Convincing stuff

Disclosing perceptually-relevant cues for the depiction of materials in 17th century paintings

Di Cicco, F.

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Francesca DI CICCO

Master of Science in Chemical Sciences,
Universiteit Utrecht, Nederland,
geboren te Rome, Italië.

Dit proefschrift is goedgekeurd door de

promotor: Prof.dr. S.C. Pont
promotor: Prof.dr. J. Dik
copromotor: Dr. M.W.A. Wijntjes

Samenstelling promotiecommissie:

Rector Magnificus	voorzitter
Prof.dr. S.C. Pont	Technische Universiteit Delft, promotor
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Dr. M.J.N. Stols-Witlox	Universiteit van Amsterdam
Prof.dr. H. de Ridder	Technische Universiteit Delft, reservelid
Overig lid:	
Emeritus Prof.dr. J.F.H.J. Stumpel,	Utrecht Universiteit

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Front: Painting by Jan Davidsz. de Heem, *Garland of Fruit and Flowers*, 1650-1660, Mauritshuis, The Netherlands.

An electronic version of this dissertation is available at
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To Sofia and Tullio for their love,
To my dad for his unconditional support,
To my mum for everything.

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1 Introduction

Study the science of art. Study the art of science.
Develop your senses - especially learn how to see.

Leonardo da Vinci

All the digital reproductions of the paintings used in this thesis are retrieved from open data collections, available in the public domain, thus free of copyright. Some of the images were downloaded from the *Materials in Painting Dataset*.

Figure 1.1: The bright, rectangular highlight elicits the convincing perception of shiny plastic for the apple hat in both scenes, even though its presence and features diverge from an accurate representation of the interaction between the optical properties of a plastic material and the daytime and nighttime illuminations of the two scenes. The illustrations are inspired by two frames from *The Simpsons* (1996) by Matt Groening. Illustrations made by Flavia Di Cicco.

The two illustrations shown in Figure 1.1 neatly sum up the topic of this thesis. In the image on the left, the scene is set in the open-air during the daytime. A mum and her daughter are walking in a park, immersed in daylight illumination, a combination of direct sunlight and diffuse skylight. In the right image, the scene is set at nighttime. The whole family is sitting in the car, thus the most likely source of illumination are the street lights. However, the two images share a common feature, a sharp, bright, rectangular-shaped highlight on the top left corner of the apple hat. Where does it come from? Neither its presence nor its shape, brightness and sharpness can be justified by the lighting and settings of the two scenes. However, not only do we not question the presence of the highlight, we even acknowledge the fulfilment of its role, i.e. providing a shiny, plastic appearance and a three-dimensional shape to the hat. This is the power of a white dab on a surface, or in the broader view of this thesis, this is the power of image shortcuts that trigger the visual perception of materials and their properties. Perceptually-relevant but not necessarily physically-accurate.

Evolution required humans to develop the ability to get information about their surroundings in a quick glance. Such ability implies that only essential information, which is enough to judge the ripeness of a fruit or the slipperiness of the ground, are seized by the eyes. According to Hoffman [1], ”Our perceptions are a user interface that evolved to guide our actions and keep us alive long enough to reproduce”.

The efficiency and speed of perception are related to beliefs (often erroneous) and assumptions about physical phenomena, and the investigation of the origin of such assumptions grew into the study of naïve or simplified physics [2–4]. The most exquisite examples of simplified physics occur in paintings. In naturalistic paintings, the persuasive representation of objects, living beings and landscapes

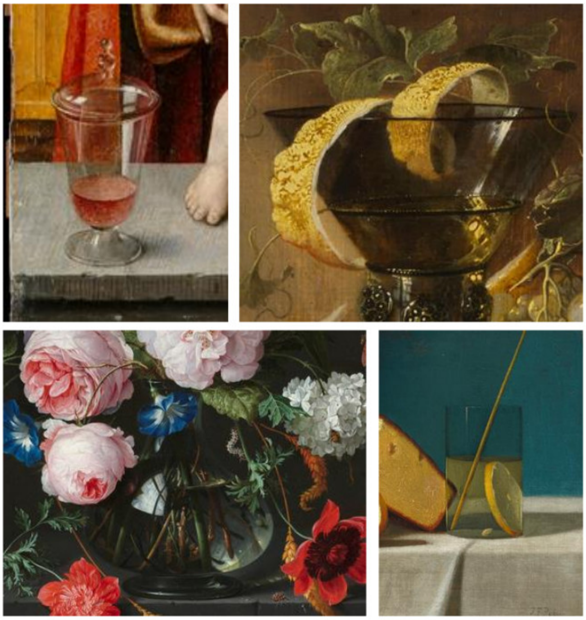


Figure 1.2: The optical distortion of objects seen through glass due to refraction of light can be usually omitted in paintings without compromising the perceived transparency of the glass. The details shown as examples are: Top left) Workshop of Joos van Cleve, *The Holy Family*, possibly 1527–33, Metropolitan Museum of Art, New York, US. Top right) Jan Davidsz de Heem, *Still Life with a Glass and Oysters*, ca. 1640, Metropolitan Museum of Art, New York, US. Bottom left) Jan Davidsz de Heem, *Still Life with Flowers in a Glass Vase*, 1650-1683, Rijksmuseum, Amsterdam, The Netherlands. Bottom right) John Frederick Peto, *Still Life with Cake, Lemon, Strawberries, and Glass*, 1890, National Gallery of Art, Washington D.C., US. Images of the paintings were retrieved from the *Materials in Painting Dataset*.

is built on employing the image features that are key to human perception and discarding the ones that, even though physically accurate, are unnecessary. An interesting example is the depiction of objects seen through transparent glass [5]. Physics teaches us that when the light propagating into a medium with refractive index (RI) n_1 (e.g. air), encounters a medium with RI n_2 (e.g. glass), it refracts, i.e. it changes direction. The refraction of light causes the optical distortion of the objects seen through a transparent medium. However, painters throughout the centuries have often skipped over the representation of such optical distortion, as shown in different examples in Figure 1.2. It is instructive to notice how the missing distortion of the objects seen through the glass does not hinder at all the perception of the glass and its transparency, indicating that the human visual system accepts and uses this simplified optics [6].

Paintings can thus help to reveal the mechanisms and the efficiency of human vision, as they represent perceptual information through economic yet effective diagnostic features.

A sharp and bright, rectangular-shaped highlight works effectively in cartoon-style illustrations as the key image cue to visually communicate an intended material

1

and its properties (smooth, shiny plastic in the case of Figure 1.1). Its use was an established convention exploited by artists throughout the centuries to convey the desired visual effect without necessarily obeying to the rules of physics. See for example the use of a specular reflection of a window in heaven to render glass in Figure 1.3.

Figure 1.3: Left) Hans von Kulmbach, *Krönung Mariae*, 1514, Kunsthistorisches Museum, Vienna, Austria. Right) Detail showing the window-like specular and inter-reflections.

One obvious physical law which is broken when depicting specular reflections, is the dependence of their position and visibility on the observer's viewpoint. If we walked around the paintings shown in Figure 1.2, the highlights on the glass would not change position nor disappear, being a static depiction of a momentary appearance. Nonetheless, they would still elicit the same shiny appearance [7, 8]. Knowing when it is acceptable to skip the physics without compromising the outcome is a skill that made art an object of research for psychologists and vision scientists, who even started to recognize painters as "neuroscientists" and paintings as a corpus of perceptual experiments [5, 9–13].

In the studies presented in this thesis, we also acknowledged the visual investigations and discoveries achieved by painters, but we took it a step further. By studying paintings, we drew connections between the perceptual knowledge of painters, the ecological optics and the pictorial procedures, posing particular attention to the rendering and perception of material properties. Throughout this thesis, I will thus present the methodological and theoretical contributions of this research to the fields of visual perception, (technical) art history, computer graphics and design.

Among all the great artworks ever produced during human history, the present thesis will focus on the narrow but flourishing period of the Dutch Golden Age, spanning the 17th century, and on a small booklet of pictorial recipes written by a Dutch painter called Willem Beurs by the end of the 17th century.

1.1. Science and art in the Dutch Golden Age

1.1.1. Learning to see

The main trait of the Dutch Golden Age paintings can be summarized with the word '*realism*'. Realism not only in the thorough reproduction of everyday life scenes and sights (which compiles an invaluable record of the Dutch 17th century culture), but also realism in the rendering of the depicted materials. *Realism* though is a problematic term, firing semantic debates when applied to art, as it can take on several meanings [14–16]. And, as explained by Hoffman [1], there is no such thing as the "true perception" of the real world, there is only our efficient interface shaped by evolution for the sake of survival of the human species. A more appropriate term in the present discussion will be *convincingness*, to clearly distinguish its subjective and perceptual nature from an 'objective' reality.

The convincing appearance of the world rendered by 17th century Dutch painters derives from a combination of factors, the first being the Scientific Revolution happening at the time. Craftsmanship, like the one of painters, is actually considered to be at the core of the Scientific Revolution and the new empirical science [17]. Painting was regarded not to be different from a scientific inquiry, since both were aiming to understand and describe the world. By learning to see, painters claimed their role "as observers, representers, and knowers of nature" [18], conducting their experiments and testing their theories via the production of images.

An amazing example of the rendering of light interacting with very different materials, through the masterful use of image features, is shown in Figure 1.4. Metal, glass and ceramic are neatly told apart by their reflections. The sharp reflection on the glass, in which a window is clearly discernible, becomes elongated and somewhat duller (compared to the glass) to reveal the metal flagon, and ends up blurred and small, completely losing the window shape in favour of a rounded spot, on the ceramic jug.

Painters' knowledge of the various ways in which light can interact with surfaces and materials, built on the observation of nature, went beyond the contemporary scientific writings on optics. Dupré [19] explains how contemporary optics was usually divided into three categories: direct vision, catoptrics (reflection of light from mirrors), and dioptrics (refraction of light by lenses). Dupré [19] also reports that Karel van Mander (1548-1606), Dutch painter and art theoretician, in his most famous work, *Het Schilder-Boek* (1604), discussed several terms to describe the interaction of light with surfaces - mirrorring (*spiegeling*), reflection (*reflectie*), polish (*glans*), re-reflection (*weerschijn*), and reverberation (*reverberatie*). The categories of contemporary optics thus failed to fully account for Van Mander's terminology.

The (re)discovery of optical tools, like mirrors and lenses, and instruments like microscopes and the *camera obscura*, allowed painters to investigate nature in the greatest amount of details, such that even the invisible world became visible to

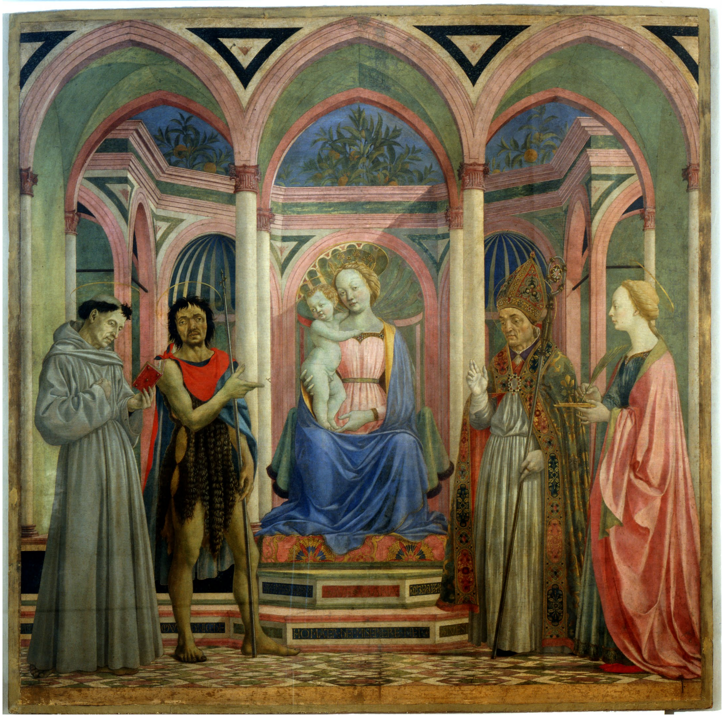
Figure 1.4: Examples of different materials (metal glass and ceramic) that reflect light in different ways, rendered and revealed by their different reflections. Johannes Torrentius, *Emblematic Still Life with Flagon, Glass, Jug and Bridle*, 1614, Rijksmuseum, Amsterdam, The Netherlands.

the eye. Snyder [20] offers the example of how Johannes Vermeer (1632-1675) could have employed the *camera obscura* to master the rendering of the light and dark values of colors. Because the human brain is capable of lightness constancy [21], meaning that we can perceive the lightness of surfaces as invariant under different illumination conditions, the *camera obscura* can help to overcome this compensation by narrowing the dynamic range of luminance values, thus making the differences in tones more apparent. Snyder [20] suggests that Vermeer could have been aided by the observations through the *camera obscura* to skillfully render the transitions between light and dark values, and in realizing that the shadows are never uniformly black.

It was Pliny the Elder [22], in 77-79 CE, who first distinguished between *splendor* (shine) and *lumen* (light) as elements that were added to the pictorial procedures. Pliny remarks how ”The opposition between shine and light on the one hand and shade on the other was called contrast, while the juxtaposition of colours and their passage one into another was termed attunement.” [22]. Leonardo da Vinci was most likely familiar with this optical knowledge when he separated *lume* (light), corresponding to the diffuse reflection of surfaces, and *lustro* (lustre) or *colmi di lumi* (literally, highest lights) [23]. Optical devices were known in The Netherlands as well as in Italy, and the same is true for the knowledge of the optical behaviour of light. However, as Gombrich points out [24], ”it was not in Italy that the first steps were made in the rendering of surface texture”. While we owe the discovery of perspective and the mathematical organization of objects in space to Italian artists such as Filippo Brunelleschi (1377–1446) and Masaccio (1401-1428), it was the Dutch who started to shift the attention to the interaction of light with materials. In this regard, it is striking the example proposed by Gombrich [24] about these different approaches to the depiction of visual phenomena. Gombrich [24] juxtaposes two altar paintings representing a similar scene and created in the same decade; one by Jan van Eyck (Figure 1.5a) and the other by Domenico Veneziano (Figure 1.5b). Van Eyck's painting offers multiple examples of the careful attention paid to the rendering of the reflective properties of each and every material, whereas in comparison, the materials depicted in Veneziano's painting look all equally matte. In Van Eyck's, the understanding of the theory of optics and the appropriate use of specular reflections emerges from the entire painting, starting from the luxurious appearance of the miter and mantle of the bishop, up to the shiny armour, both covered in lustrous jewels.

During the Dutch Golden Age, "the subject of painting became sight itself" [20], establishing art as a new method to investigate reality.

(a)



(b)

Figure 1.5: (a) Jan van Eyck, *Madonna and Child with St. Donation, St. George and the Canon van der Paele*, 1436, Groeningemuseum, Bruges, Belgium. (b) Domenico Veneziano, *Madonna and Child with Saints Francis, John the Baptist, Zenobius and Lucy*, ca. 1445, Uffizi, Florence, Italy.

1.1.2. The importance of the medium

Next to the observation of nature and the employment of optical devices, the compelling, life-like rendering of materials in Dutch Golden Age paintings has been ascribed to the use of oil paint and its methods of application. On one side, painters like Gerard Dou (1613-1675) and Frans van Mieris (1635-1681) made their hands invisible on the canvas by hiding their brushstrokes behind a neat and meticulous brushwork. On the other side, painters like Rembrandt (1606-1669) and Frans Hals (1582-1666) were applying quick and rough, visible brushstrokes. Both techniques elicit a convincing effect, though in different ways [16]. The former recalling a photographic impression in the modern viewer (Figure 1.6a), and the latter evoking a sense of immediacy and spontaneity, as if the painting was made at the moment with no apparent effort nor preparation (Figure 1.6b). Slive [25] wrote about the style of Hals that ”The single stroke of his brush, although highly individual and spontaneous, is always adjusted to the character of the surface, and takes precisely the course needed to express the variety of surfaces and substances”.

Such handling techniques of paint, able to deceive the eye, were heavily depen-

(a) (b)

Figure 1.6: (a) Frans van Mieris, *Portrait of Florentius Schuyl*, 1666, Mauritshuis, The Hague, The Netherlands. (b) Frans Hals, *The Merry Drinker*, ca. 1628-1630, Rijksmuseum, Amsterdam, The Netherlands.

dent on the physicochemical properties of oil paint. As suggested by Lehmann [26], ”materials cannot be separated from representation”. During the 15th century, following the leading efforts of Jan van Eyck (1390-1441), painters started to transition from the use of tempera to oil paint, discovering a whole new range of possibilities.

Lehmann [26], building on the theory of affordances formulated by Gibson [27], offered a novel understanding of how oily pigments could be translated on the canvas into skin, fur or bronze.

The list of oil's affordances begins with transparency, the foundation of glazing. The glazing technique consists in applying a translucent layer, made of little pigment and much oil, on top of an opaque layer of paint. Glazing allows to create new tints of deep, saturated colors, otherwise impossible to achieve. Colorimetric measurements [28] and modeling functions [29] have shown that the exceptional level of color saturation allowed by glazing cannot be achieved by merely mixing pigments. This effect is due to the optical mixing mechanism. Glazing also smooths the asperities on the surface of the painting which are due to the protruding pigments' particles, thus producing a glossy effect on the surface. Such smoothing of the surface also increases the contrast and saturation of the colors. This effect has been reported for the varnish layer [30], but it has never been investigated for glaze, to the best of our knowledge. With the addition of a number of glaze layers of different thickness, the painter could modulate the apparent values of lightness and saturation, creating a glowing effect, as if the light was radiating from within the painting [29]. It is no coincidence that Arnheim [31] identified the glaze as the illumination of the object, i.e. "the perceivable imposition of a light gradient", which the painter was able to separate perceptually from the body color of the object itself.

The following oil's affordance is malleability, due to its adjustable degree of viscosity. The manipulation of the rheological properties of oil was determinant to achieve both the smooth and invisible touch of the *fijnschilders*, by mixing the oil with thinning agents, as well as the rough and plastic style of Rembrandt or Rubens, by thickening the oil [32]. Finally, the slow-drying process of oil allows for the attainment of smooth color transitions and retouching.

These very properties of oil were suggested by Vandivere and Clarke [33] to be the root, for example, of the most convincing representations of *changeant* silk. This type of fabric is woven using warp and weft yarns with different colours, thus producing an iridescent, color-changing, and shimmering appearance. The translucency of oil paint, therefore the possibility to apply glaze layers, and the wet-in-wet procedure allowed by its slow drying time, provide for the smooth transition between the two colors of the fabric by blending the juxtaposed areas. Such smooth transition between the two colors contributed to increase the convincingness of the depiction, given that also in the real fabric the color does not abruptly change. An interesting observation made by Vandivere and Clarke [33], was that the rendering of *changeant* fabrics was most likely often based on written recipes and workshop traditions, rather than on direct observations from life. Their reasoning for such conclusion is that most of the paintings present the transition of the colors according to the direction of the light source rather than in agreement with the drapery and the viewer's direction, i.e. the color should change whether the fold is parallel or perpendicular to the viewer. However, even though the use of such conventional procedures was done at the expense of the correct representation of the optical behavior of light, the visual convincing effect worked nonetheless, indicating again the tolerance of the human visual system for physical inaccuracies.

The binding medium alone, i.e. the oil, is not the cause of the convincing visual effect. Other elements play a role. For example, the absorption and scattering properties of the pigments and their interaction with oil, need to be considered according with the desired visual outcome. A translucent glaze requires the use of pigments with a refractive index close to that of the oil medium, in order for the light to be mostly absorbed; vice versa, an opaque layer of paint is made by using pigments with higher refractive index, so that most of the light is scattered.

Finally, the layers' building up should not be ignored. It is easy to think of a painting as a 2D image, and overlooking its complex, 3D nature, resulting from the superimposition of several layers that interact with each other and all serve a visual purpose. De Ridder and Wallert [34], in this regard, presented the case of the depiction of human skin by Adriaen van der Werff (1659-1722). Van der Werff collaborated with the linguist Lambert ten Kate (1674-1731) and the painter Hendrik van Limborch (1681-1759), to develop a quantitative painterly procedure for the successful rendering of skin. This procedure was based on mixing and layering the proper pigments and binders in exact amounts, to accurately mimic the optics of skin, meaning that the ordering of the layers of paint found a qualitative correspondence to the reflection, scattering and absorption phenomena happening between the layers of human skin.

Lehmann [26] called the attention on the long neglected role of the materials employed to create a painting by art historians, who, caught in the Aristotelian hylomorphic paradigm, tended to prioritize the ideal forms made in the mind over their material representations. The study of the materials, left out of the realm of art history, specialized into the fields of technical art history and conservation. This trend, however, started to be inverted in the 1990s, with what Lehmann called a ”re-materialization” of art theory, which is still in its early stage [26]. To contribute and further develop this new role of materials, Lehmann formulated a ”theory of materials”, starting from Arnheim's idea that the properties of the medium help to mould the description of reality [26]. The starting point of this theory happens to be oil, the medium that revolutionized Western painting with all its new affordances and possibilities, but which, at the same time, was not granted the full attention of scholars until Stumpel began to investigate it in 2007 [35].

The historical written document that mostly aligns with this central view of oil as a tool to render reality, providing practical advice and how-to instructions, is a booklet written around the end of the 17th century by the painter Willem Beurs.

1.2. Willem Beurs and “The Big World Painted Small”

Thanks to Arnold Houbraken [36], painter and writer from the 17th century, we know that Willem Beurs was born in Dordrecht in 1656. Son of a shoemaker, he soon followed his passion for painting, and in 1671 he became a pupil of Willem van Drillenburg. Under his teaching, he was quickly able to paint a ”sweet landscape” [36]. He then moved to Amsterdam where he started to paint portraits, and finally to Zwolle where he mainly focused on flower still-lifes. It was in Zwolle that Beurs started to make a living out of teaching painting to four wealthy ladies, for whom he wrote his treatise on the mixtures and treatment of oil paint, with declared didactic purposes. The book, written in 1692, is called *"De Groote Waereld in 't Kleen Geschildert, of schilderagtig tafereel van 's Weerelds Schilderyen kortelijk vervat in Ses Boeken verklarende de Hooftverwen haare verscheide mengelingen in Oly, en der zelver gebruik. Omtrent de meeste vertoningen van de zigtbare nature. Leerzamelijk den liefhebbers en leerlingen der Ed. Schilderkonst medegedeelt van Wilhelmus Beurs, Schilder"* which means *"The Big World Painted Small, or painterly tableau of the World in Paintings, concisely presented in Six Books explaining the main colors, their various mixtures in oil and their use. Concerning most phenomena in visible nature. Instructive for lovers and pupils of the noble art of painting, set forth by Wilhelmus Beurs, painter"* [37, 38] (Figure 1.7). For the sake of time and

DE GROOTE
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in't kleen geschildert,
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van 's Weerelds
SCHILDERYEN.
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Verklarende de
HOOFTVERWEN,
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en der zelver gebruik.
Omtrent de meeste vertoningen van de zigt-
bare nature. Leerzamelijk den liefhebbers en leer-
lingen der Ed. Schilderkonst medegedeelt van
WILHELMUS BEURS, Schilder.
t'AMSTERDAM,
By JOHANNES en GILLIS JANSSONIUS
van WAESBERGE, 1692.

Figure 1.7: Title page of the treatise *The Big World Painted Small* (1692) by Willem Beurs.

convenience, I will refer to it as "The big world painted small", 'the treatise' or 'the book', throughout the rest of this thesis.

According to Beurs, his treatise intended to fill the "lamentable" gap "about the materials, the mixing and use of oil paints". This book is of particular interest and importance, not only because it is the first written source completely devoted to oil painting, but also because painters were careful not to share their secrets, thus we have little written documentations about the pictorial procedures [20]. It was Willem Beurs who made explicit and available to the amateurs, the tacit knowledge passed on from masters to pupils in the privacy of the painting workshops.

Similar to a cookbook of recipes to be found in a kitchen, the treatise begins with the basics and the tools: how to prepare the mixtures of oil and pigments, which brushes to use, how to prepare the support, and which colors go or do not go well together. Throughout the rest of the chapters, he instructs the reader on how to paint all sorts of materials, starting from snow to illustrate the purest white one can find in nature, up to the skin of human beings, "who — being wise and intelligent — can make amazing use of the visible world." [37, 38].

Akin to an empirical research, painters believed that the first step of the artistic creation was the close observation of the natural world [20]. Sketching and painting

Figure 1.8: Ambrosius Bosschaert the Elder, *Vase with Flowers in a Window*, 1618, Mauritshuis, The Hague, The Netherlands.

naer het leven (from life) was a regular practice [16], and Beurs was no exception to such advice. Already in the preface, he mentions that the content of the treatise was not meant to be fruitful only for the painters who are willing to practice, ”but it is also useful for all types of persons if they only want to observe and investigate visible things more closely”. When instructing on how to choose the best color combinations, Beurs recommends ”the diligent observation of the supreme teacher, nature”.

Throughout the treatise, he demonstrates a deep knowledge of the scientific theories and discoveries of the time about light and colors, mentioning the work of Robert Boyle, Christiaan Huygens and René Descartes. In a sort of literature review, he refers to several scientific facts to support the reader in better understanding the nature of things, which likely served the purpose ”to understand the means by which the eye is deceived” [20]. For example, he mentions the fact that colors ”owe all their diversity to the composition of the surfaces of the objects on which light falls and acts in various ways”, or that objects are usually seen under different light depending on the time of the day, and from different view points, changing their appearance. Knowing how light reflects and refracts when interacting with different materials, like snow or glass, would give intellectual satisfaction to the painter, but this would be of ”little or no relevance for painters, as long as they have a good understanding of the pigments and how to prepare them and paint with them” [37, 38].

Painting *naer het leven* was not the only approach, and not always feasible, especially with quickly decaying subjects like flowers and food, or with expensive goods like jewels and luxurious fabrics. The detailed observations could be enhanced and dramatized in the studio as desired, by painting *uyt den gheest* (from memory), and by relying on established recipes and conventions as the ones to be found in Beurs' treatise. A famous example is the *Vase with Flowers* painted by Bosschaert (Figure 1.8), portraying an impossible bouquet, illuminated by an impossible lighting and placed against an impossible background (i.e. mountains in The Netherlands), of flowers meticulously rendered. In this painting, the mastery of Bosschaert in the *stofuitdrukking* or 'expression of stuff', of each individual flower is the centre of attention, at the expense of realistic lighting and composition. As reported by Slive [25], each flower in this painting is like a portrait which has been the subject of an individual study, "no flower is thus left in the shadow, every corolla emerges clear and radiant, in its own local colour, in the same 'impartial' light". Once again, we have come across an optical phenomenon which can be rendered wrong, in this case the incoherent lighting distribution, without bothering the eye of the observer or even being noticed, revealing the tolerance of the human visual system for illumination incongruities. Such tolerance, found and exploited by painters, was confirmed in perceptual experiments in which participants failed to quickly identify inconsistent illumination directions [39]. These results indicate that the lighting does not need to be globally consistent to estimate the local illumination of the objects as convincing, validating Beurs' teaching approach on how to paint. In the book, each object or material is treated separately, describing how they should appear under a standard, "neutral light", meaning that one side of the object - usually the left [40] - reflects the light while the other side is shaded. Such standard chiaroscuro is also the most effective of the four illumination types proposed by Beurs [37, 38] (in sunlight, in neutral light, in shadow, at night), to obtain the most powerful rendering of depth. It has indeed been shown in psychophysical experiments that shape and relief perception depend on the lighting conditions [41, 42]. The individual pieces, thus rendered with the illumination that best serves their most convincing rendering, can be combined in the final composition, as it is the case of Figure 1.8.

What matters most in Beurs' treatise, beside the teaching of the correct use of pigments and oils, is the knowledge of the image features in the build up of the layers, the patterns of light relevant to our visual system, which resonate with our previous knowledge of materials and thus trigger the convincing appearance. The pictorial procedure is responsible for the convincing visual outcome as much as the affordances of oil, that is why they need to be studied together [26, 43]. For example, the image feature for rendering the metal of a jug is still a white, elongated highlight, both in Pieter Claesz. (Figure 1.9) and in Paul Cézanne (Figure 1.10) paintings, but the visual effect is totally different. Their intentions were clearly different as well, but we will leave the stylistic and art historical analysis out of this discussion. Different pictorial procedures can lead to very different visual outcomes. The human visual system likely relies on a combination of top-down (association) and bottom-up (estimation) approaches in order to perceive materials, and depending on the situation, one of the two approaches can dominate.

Figure 1.9: Detail of Pieter Claesz., *Still life with turkey pie*, 1627. Rijksmuseum, Amsterdam, The Netherlands.

Figure 1.10: Detail of Paul Cézanne, *Bouilloire et fruits*, ca. 1888-1890. Private collection.

In the case of Claesz., it is safe to assume that we perceive metal mostly via the estimation approach [44, 45] since the image contains all the necessary cues for the metallic sheen, i.e. bright, high-coverage reflections [46]. On the other hand, the metal in Cézanne is likely to give a stronger signal to the associative approach [44, 45], that is by recognizing a kettle with an elongated highlight we can infer it is metal.

The pictorial procedure embodies the knowledge of the visual shortcuts employed by the painter to make a mix of oily pigments look like metal, velvet or lemons to our wondering eyes.

1.3. Living in a material world

When picking the apple with the right ripeness to be crunchy and sweet, or when buying a sweater to keep us warm and cozy but not itchy, we are judging material properties. Through vision we are able to estimate the affordances [27] of objects in our environment before even interacting with them (so that we can also decide in time whether to avoid the interaction at all). We can reliably judge whether it is time to pick up our laundry or if it is still wet [47], and we can decide how cautiously we should step on that slippery floor [48]. This kind of actions are performed multiple times on a daily basis, and they do not require any (apparent) cognitive effort. Human beings are so good at it that in the span of 40 msec we can identify different material categories [49] and even tell apart real from fake materials [50]. The process of material perception is so effortless that for a long time nobody even wondered how we manage to do it. However, as noted by Köhler [51], psychologists do not need to discover unknown facts, they ”must discover facts of functional relationship with which nobody becomes spontaneously acquainted”.

The apparently trivial matter of material perception was brought to the attention of vision scientists by the influential paper of Adelson in 2001 [52], who introduced the term ’stuff’ to refer to materials, for an easy and necessary differentiation from ’things’. I keep using the word ’apparent’ because there is nothing trivial about material perception. The wide diversity of materials (both natural and artificial, and even artificially made to look natural), the (re)arrangements of their molecular structure and therefore their ability to change, the light under which we see them, their shape and surface structure, our previous experience of them, our point of view. These are all factors that contribute to the challenge of material perception for the visual system.

1.3.1. Theoretical approaches to material perception

Our visual experience of the world does not depend on a direct interaction with the 3D objects (distal stimulus) that forms it, but rather on the 2D projections of the patterns of light rays generated by these objects reaching our eyes (proximal stimulus). Using a single proximal stimulus to find a unique and stable solution to retrieve the distal stimulus among the infinite number of combinations of shapes, illuminations and materials, is an ill-posed problem which has been tackled in human and computer vision through the use of *a priori* assumptions and constraints. Such approach treats visual perception as an inverse problem [53, 54], in which the visual system discounts confounding variables such as the illumination environment, to estimate objects’ shape and reflectance [55]. For example, a common assumption about the illumination position consists in expecting the light to come from above with a bias to the left, and such prior influences the perception of convex-concave shapes [40].

However, when considering increasingly complex and ecologically valid [27] stimuli, the theory of vision retrieving physical reflectance properties by inverting the optical processes, has been deemed unlikely. According to the theory of naïve or intuitive physics, instead of accurately computing the mechanisms of physical phenomena, people hold (erroneous) beliefs about them. For example, when asked about the behavior of mirrors' reflections, participants are not able to tell correctly what and where should be visible [56–59]. People relies on these beliefs to predict optical and mechanical properties of materials and objects. Bianchi and Savardi [60] proposed that "These erroneous predictions are in fact based on generalizations of salient perceptual aspects which have been perceived in ecological conditions".

Hoffman proposed the Interface Theory of Perception [61], according to which "[Evolution] has endowed us with senses that hide the truth and display the simple icons we need to survive long enough to raise offspring" [1]. Within this framework, Hoffman coined a new term: *chromature* - image patches combining color and texture [62]. Hoffman [1] proposed the concept of chromature among the icons that guide the human perception of materials and their properties, to trigger adaptive responses and to maximize fitness payoffs.

An approach based on natural image statistics proposed that the viewing conditions encountered in the world are not completely unconstrained, as they are subject to certain statistical regularities. Such regularities disclose predictable relationships between surface reflectance and statistical image features [63–65]. Fleming, Dror and Adelson [66] argued that humans exploit statistical regularities of real-world illumination in order to discard unlikely image interpretations. Several studies have shown that the perception of optical properties can be related to luminance histogram parameters. Motoyoshi et al. [67, 68] have shown that the skewness of the luminance histogram increased with gloss perception for stucco-like surfaces. Similarly, freshness perception of fruits and vegetables was found to be related to skewness [69], whereas the visual freshness of fish was predicted both by skewness and standard deviation of the luminance histogram [70]. Wiebel et al. [71] found that the standard deviation of the luminance histogram correlated to gloss perception of natural surfaces better than the skewness. However, Kim and Anderson [72] argued that image statistics have only limited applications to understand gloss perception, as they do not account for the spatial structure and the consistency between the surface shape and the location and orientation of the highlights. Gloss perception has been repeatedly shown to interact with the perception of 3D shapes and the illumination environment [64, 66, 73–78]. This effect has been explained through the dependence of gloss perception on image cues such as coverage, contrast and sharpness of the highlights, which can be manipulated by modulating the 3D shape and the light field [79, 80].

The idea that the visual system makes use of image features of the highlights as a 'proxy' rather than estimating the physical surface reflectance through inverse optics or image statistics, led to a new theoretical approach to material perception proposed by Fleming, called the statistical appearance model [81–83]. According to this model, the goal of the visual system is to identify diagnostic image features which can be used as perceptual cues to estimate and predict the look of the material, thus shifting the focus on external features instead of intrinsic physical parameters.

According to Fleming [82], there are two main approaches that we use to perceive materials and their properties. We can use estimation and association. The estimation, or bottom-up approach, uses image features to estimate the material properties, which in this case does not mean physical properties, like reflectance for the example of glossiness, but to estimate "the extent to which a surface manifests highlights" [84]. The ensemble of such estimated material properties is then used to locate the corresponding material in a high-dimensional feature space, to finally identify it. The association, or top-down approach, directly identifies the material, and then by knowing the material, its properties are recalled from memory and previous experience.

In everyday life we can use either or both approaches, depending on the situation we are faced with. This was shown to be the case, for example, for stiffness perception of unfamiliar [44] and cubic shapes [45], rendered with different material appearances. Both studies showed that in the absence of shape cues due to deformation, the judgment of stiffness was dominated by optical cues through an associative approach ('it looks like metal, therefore it is hard'). When presenting to participants animated deformations of the objects, the estimation route became dominant to rate stiffness of the cubes, based on their degree of deformation and it was barely affected by the optical appearance [45]. However, in the case of unfamiliar shapes [44], the optics of the stimuli still had a significant effect on stiffness perception, even when participants were provided with the dynamic information about the amount of deformation. This probably indicated a combination of association and estimation in order to deal with the unfamiliarity of the objects.

Zhang et al. [85–88] further investigated the concept of image features to trigger material perception, by combining canonical modes of material and lighting via optical mixing. They analyzed the image features of a wide variety of ecologically valid appearances by combining four canonical materials (matte, velvety, specular and glittery), and three canonical lighting conditions (ambient, focus and brilliance). Using the linear weighted combination of the different modes allowed by optical mixing [89, 90], they could control and vary the contribution of the image features instead of the physical parameters, in a layering approach similar to the systematic pictorial procedures of 17th century painters.

1.3.2. Miscellaneous cues for material perception

The visual perception of material properties has many potential cues. The most well-known and most broadly investigated, is the use of optical information, i.e. the interaction of light with the material. Other types of cues for material perception that are starting to get attention, are motion and shape cues. Finally, an interesting class of cues is cross-modal correspondence, which includes both the estimation of visual material properties using senses other than vision, and, vice versa, using vision to judge material properties which belong to other sensory domains. Related to cross-modal correspondence, material perception is also studied for its association with semantic meanings.

A review of researches conducted on each of these cues, is reported in the following paragraphs. Note that this review serves to provide as much as possible a comprehensive overview of the material perception literature, rather than be strictly related to the topic of paintings (e.g. we will review motion cues which clearly do not apply to the static images of paintings).

Optical cues

The appearance of surfaces depends on their interaction with the incident light, whether it is, absorbed, reflected or transmitted. The radiometric formalization of surfaces' reflectance for opaque materials was introduced by Nicodemus [91] with the Bidirectional Reflectance Distribution Function (BRDF). A BRDF describes the optical behaviour of opaque materials at any given point for every incoming and outgoing direction of light, using four parameters, two incoming and two outgoing angles. Several BRDF models have been developed thereof, to model different materials for realistic rendering in computer graphics [92–98]. Materials that completely or partly transmit light - transparent and translucent materials - require more parameters which cannot be captured by a BRDF, and thus different descriptive functions. To this end, functions such as the Bidirectional Transmittance Distribution Function (BTDF) [99], and the Bidirectional Surface Scattering Distribution Function (BSSRDF) [100], were introduced.

Physically-based rendering (PBR) using BRDFs for the sake of realism could potentially provide an accurate radiometric representation of the spectral radiance, i.e. the flux of photons, as a function of wavelength, position, direction and time [101]. However, beside the heavy computational costs, PBR does not account for the sensitivity of human vision, that is to say, the information that is actually used by the brain. To overcome these drawbacks, more perceptually-relevant approaches have been developed, such as photorealistic rendering, aiming at triggering the same visual response as the scene, like a photo would do [102], and non-photorealistic rendering, which includes stylizations, abstraction and line drawings [103], providing the same visual information as the scene [102].

A large body of research on optical cues has focused on gloss perception. In 1937, Hunter [104] proposed six types of gloss - specular gloss, sheen at grazing angle, contrast gloss, haze, distinctness-of-reflected-image gloss, absence-of-surface-texture gloss – all contributing to the complexity of its perception to a greater or lesser extent, depending on the material. More recent works, building on the multidimensional nature of glossiness proposed by Hunter [104], have determined perceptual, rather than physical, dimensions of gloss [105, 106], measured the success and failure of gloss constancy over changes in shape [73, 75, 77], color [107] and illumination [66, 74, 108, 109], and computed image features and statistical parameters to predict gloss perception [67, 68, 71, 79, 80, 110, 111].

Other material properties that have received somewhat less attention than gloss but are still studied in relation to optical cues, are transparency [112, 113], translucency [65, 114–118], wetness [47], freshness [69, 119], and greasiness [120]. Reflectance properties can also be tell-tale of specific materials [111], like glass [121, 122], metal [46] or velvet [87, 123, 124].

Motion and shape cues

We have previously noted that one of the basic rules of specular reflections which is irremediably broken in a static representation, is the motion of the reflections on the surface relative to the position of the observer, of the light source and of the object itself. Such lack of information in static stimuli, inspired a number of studies to investigate the motion cues for gloss perception.

Sakano and Ando [125] found that both temporal cues, i.e. dynamic changes in the head's position, and binocular cues enhanced perceived glossiness. Wendt et al. [126] investigated the influence of motion, binocular disparity and color on gloss constancy, irrespective of the 3D shape. They found that all these cues increased gloss constancy, both individually and combined. Doerschner et al. [127] proposed three optical flow statistics as diagnostic cues provided by the motion to discriminate matte from shiny materials. Marlow and Anderson [128] used motion parallax and texture gradients as a source of information to modulate the perception of the 3D shape, which they previously [129] found to affect the perception of the surface as either matte or shiny.

Visual cues from shape and motion are often studied together to understand the perception of the material properties of deformable objects, such as stiffness. Dynamic information of shape deformation of real fabrics shown in videos, were first measured by Bouman et al. [130] to test human perception of cloth stiffness and density. They found that the human estimations were correlated with the ground-truth physical measurements. Bi and Xiao [131] extended on these findings by varying not only the intrinsic stiffness of the cloth but also the strength of the external force causing the deformation (wind). They confirmed the high correlation between human judgements of cloth stiffness and the physical values of stiffness, also across different external forces. Bi et al. [132] showed that such robust estimation of cloth stiffness from videos, is lowered by scrambling the order of the frames. In a following study, the same authors [133] found that the judgment of stiffness of cloths with different optical properties (e.g. cotton vs felt) was based mainly on their appearance when shown in static images. On the contrary, in the video condition, the optical appearance was discarded in favor of the dynamic information of the cloth deformation.

Similar results were obtained by Paulun et al. [45] for the visual estimation of stiffness of cubes rendered with a variety of material appearances. The effect of the optical appearance was ruled out by the dynamic information. Schmidt et al. [44] however did not find such clear-cut distinction when testing unfamiliar objects, since the optical appearance still had an effect in the video condition, in combination with the dynamic deformation cues.

Another class of deformable materials that has been researched through motion and shape cues, is liquids, in relation to viscosity perception. Kawabe et al. [134] related the visual perception of viscosity to the image motion speed of the optical flow, higher for less viscous liquids and vice versa. Paulun et al. [135] focused on the shape cues instead, testing static stimuli. They identified 2D shape image statistics that could predict human judgement of viscosity. Van Assen and Fleming [136] tested the relative contribution of mechanical and optical properties to the judgement of viscosity and of other material properties like warmth or stickiness, and for the categorization of different liquids, using both static and dynamic stimuli. They found that shape and motion cues overruled optical cues in the judgements of viscosity perception, whereas, the task of naming the liquids was dominated by their optical appearance.

All the studies mentioned so far, considered the shape cues at the macroscale, i.e. the global shape of the object [137]. Schmidt, Fleming and Valsecchi [138] instead, investigated the local shape features, at the mesoscale, that trigger the visual perception of softness and weight of unfamiliar objects. They found that more angular local shape features, such as spikes, increased the perceived hardness and heaviness compared to rounder features, like bumps, which were perceived softer and lighter. Overall, the judgements of softness and weight varied with the type, magnitude and frequency of shape feature. Schmidt et al. [138] argued that the perception of the material properties was done via an estimation approach, based on the image features, given that no semantic associations were possible. Such estimation might include inferring the causal history of the object (e.g. something that look like it has been bent is more likely to be soft than hard), a kind of inference that people have been shown to be able to do with high accuracy from shape cues [139].

Xiao et al. [116] considered the effect of local shape features, in particular thin geometric structures, which they defined as ”geometric sharpness”, on the perception of translucency. They found that objects with smoother geometric features were perceived more translucent, in agreement with previous findings on translucency perception which identified low contrast and blurriness as triggering cues [65].

Cross-modal and semantic cues

The studies reviewed above, discussing the ability to visually judge mechanical properties which belong to the haptic domain, like stiffness, viscosity, softness and weight, are examples of cross-modal correspondence.

In particular, the findings of Schmidt et al. [138] on the association of spiky, angular shapes with hardness and of rounded shapes with softness, are in agreement with a whole body of sensory research on cross-modal correspondence between shape and taste, in which sweetness is associated with roundness and bitterness with angularity [140–143]. We learn from Snyder [20] that such association is as old, at least, as the 1st century BCE, when the Roman poet Lucretius described taste in terms of the contact of particles of different shapes with the tongue, and later Cartesians argued that salt and vinegar were made of pointed shapes, causing their sharp and acidic taste.

Nowadays, cross-modal correspondence plays a key role in online retail, where people can rely on nothing else but their visual judgement to estimate all sorts of material properties, evaluate the product, and finally reach a purchase decision. As previously discussed, motion cues can add significant information and increase the accuracy of the judgement, that is why Wijntjes, Xiao and Volcic [144] recommended the use of videos to better communicate the large range of haptic material properties of jeans. Decré and Cloonan [145] also investigated the visual communication of haptic perception in an online environment, though approaching the problem from a packaging design perspective. They found that a glossy package elicits higher perception of smoothness, softness and lightness, and overall higher products' quality. They tested only self-care products though, namely shampoo, toothpaste and face cream, so this effect of glossiness cannot be generalized. In fact, in case of food products, glossy packages have been shown to be associated with unhealthy, high calories foods [120].

So far, we have seen examples of visual perception determining haptic properties, but cross-modal correspondence can also happen in the opposite direction. Adams, Kerrigan and Graf [146] found that haptic perception of friction modulated the visual perception of glossiness, so that slippery objects were perceived glossier. This is in agreement with previous findings that related visual perception of slippery floors to their reflectiveness [48].

Visual perception of materials properties can communicate more than intrinsic mechanical properties. It is also deeply related to the attribution of high-level, semantic meanings to materials (e.g. luxurious, aggressive, nostalgic, natural, etc.), pivotal for products' design and evaluation [147–149], especially to facilitate the acceptance of novel materials [150, 151].

1.3.3. When perception meets art

Most of the research on material perception discussed so far has in common the use of well-controlled, computer-rendered stimuli. It is easy to see why that is the case, since rendered stimuli allow to systematically manipulate the specific parameters under investigation. However, these stimuli are often simple or unfamiliar shapes presented in isolation against a neutral background, therefore lacking the complex interactions between shape, illumination and materials encountered in real life, and potentially missing on relevant cues and structures.

A more ecologically-valid alternative could be to use photographs or paintings as perceptual stimuli. Both are forms of representation mediated by the human brain, vision and hand. Both photos and paintings are made by humans to be seen by humans, and the knowledge of photographers is not less useful than that of painters for the sake of understanding visual perception in general, and material perception in particular. A professional photographer knows how to capture the light, how to choose the best viewpoint, and how to edit a photo in order to enhance the appearance of materials. Photographers tailor reality to their own perception and to the viewers' expectations, just like painters do. Neither of them can be deemed "true to reality", as both rely on conventions and ideal appearances. A fascinating example are the tricks used in food photography to make advertisements irresistible and mouthwatering. From giving the impression of fresh fruits by spraying deodorant on strawberries and apples to make them shine, through the cereals floating on a layer of white glue to keep their crunchy look instead of soaking in milk, all the way to liquid soap used to create the attractive foam of a beer just opened. The 'dirty' tricks of food photographers have been exposed everywhere on the internet, and while somebody may find them entertaining or shameless, what they actually are is instructive. They identified certain material properties, in this case desirable properties of food like crunchiness and freshness, and rendered them through the image features used by the visual system as perceptual cues. Just consider the fruit sprayed with deodorant with the clear aim of rendering a long-lasting shiny appearance which in turn provides a fresh look. We could argue that photographers implicitly know that freshness perception is related to glossiness, and perceptual experiments have shown it and confirmed it [69, 70].

So why did we decide to study paintings rather than photographs?

The most basic and obvious answer is because we are not merely interested in understanding the mechanisms of visual material perception, but rather to investigate the convincing appearance of 17th century paintings, by connecting the affordances of the oil medium, the knowledge of optics, the image features provided by Beurs and their role as perceptual cues. This goal automatically excludes photographs. But there is also an additional reason. Although photographs and paintings are similar in many ways, they have a crucial difference. Painters have more freedom than photographers to play with the so-called ”alternative physics” [5], which, especially when unnoticed by the observer, can help to reveal how the human brain works. As remarked by Durand [152], ”most of the indoor scenes depicted with such a realism by the Dutch Masters of the 17th century are nightmares for photography, in terms of both perspective and lighting”.

Creating and experiencing art are processes inextricably connected to vision, and the illusion of reality found in art has sparked a lot of interest among perception scientists. In 1971, Gibson [153] offered a formal definition of picture to propose a new theory of pictorial information describing the information of perception as ”formless and timeless invariants that specify the distinctive features of the object”. Gibson defined a picture as follows: ”A picture is a surface so treated that a delimited optic array to a point of observation is made available that contains the same kind of information that is found in the ambient optic arrays of an ordinary environment”. Hochberg [154], following on this definition, distinguished between two methods to represent reality: optical identity and optical equivalence. Optical identity refers to the physical equality between the light reaching the eye from an actual scene and from its representation, similar to what physically-based computer rendering is trying to achieve. Optical equivalence indicates that the arrays of light emanated from a scene and its representation are different on an optical level, but trigger nonetheless the same visual perception in the observer.

Earlier influential writings, addressing the relationship between art and reality, are the works of Arnheim [31] and Gombrich [155], representative of two distinct schools of perceptual theories, Gestaltists and constructivists, respectively. Arnheim [31], basing his reasoning on the Gestalt theory of perceptual organization, listed the visual categories that are arranged as a whole in visual perception and art production. The Gestalt principles for the structural organization of art were further developed by scientists as Koenderink [156] and Pinna [157, 158]. To Gombrich [155], visual perception and interpretation is driven by prior knowledge and expectations. He proposed that such learned experience (*schemata*) is also at the origin of artistic creation, which arises from known conventions and it is then adjusted to match the world via direct observation of reality. To use the words of Gombrich ”you cannot create a faithful image out of nothing. You must have learned the trick if only from other pictures you have seen” [155]. Priors and constraints were considered by Mamassian [159] as well, to rule not only over perception, but also art.

Subsequent works of psychologists and neuroscientists have explored the learning possibilities offered by art [5, 9–11]. Zeki [9] defined the function of art as an extension of the function of the visual brain, which is to ”search for constancies with the aim of obtaining knowledge about the world”. In selecting such constancies, the artist needs to seize the essential features and discount the ones that are superfluous, just like the brain selects only the necessary incoming information. In light of this parallelism between art and the brain, Zeki [9] dubbed artists neurologists, as they also study the brain using their own methods. The designation of neuroscientists was later adopted also by Cavanagh [5] to describe the artists, whose use of a simplified, yet convincing physics, indicates that the visual brain employs a similar set of simplified rules to understand the world.

One major topic in this regard, is depth perception and its revealing cues. Our ability to perceive 3D space and objects in 2D representations is certainly remarkable, and has been thoroughly investigated [160–164]. In the pictorial space, monocular cues such as occlusion, texture gradient, linear perspective and relative size, are responsible for depth perception [165–169]. An additional source for perceiving depth, can be found in shades and shadows. On this topic, Casati and Cavanagh [13] provided an insightful and detailed discussion of the physical information potentially available in the shadows, the ones that we actually use and the ones that we ignore, the impossible ones that we accept and the possible ones that we discard. All these claims and findings are then backed up by a corpus of artistic work depicting shadows, demonstrating that artists had already understood long ago that the brain allows great freedom in the representation of shadows. According to Cavanagh [5], the inaccurate replication of the world and the deviations from the laws of physics which do not compromise the convincingness of the representation for the observer, is the key to understand the functioning of the visual system. He claimed that unnoticed physical errors in paintings reveal that the brain makes use of a simplified physics itself, for the sake of perceiving the world in the most efficient way. Moreover, the conventions of such “alternative physics” are well established in the human brain since prehistoric times (like the convention of line drawings of cavemen).

Vision scientists and art historians devoted a large body of research to the rendering and the perception of space in art, but they both paid less attention to the rendering of materials [19, 24]. Gombrich [24] advised the art historians to take interest in the depiction of the appearances of materials, to connect styles and their evolution of formulae to render reality. For example, before the 15th century, Gombrich [24] noted, the distinction between diffuse and specular reflections - what he called ”illumination and sparkle” - was avoided altogether. The lustrous appearance of jewellery and precious metals, or the texture of silk and velvet, were not rendered through the use of image features but via the direct application or stencil of the real materials on the canvas.

There are a few examples in the literature of material perception research exploring art. Sayim and Cavanagh [6] investigated the knowledge and the image features used by the artists throughout the centuries to depict transparency. Apart for the often-used luminance constraints, that match well the X-junctions theory of Metelli [170], they also identified material constraints. In particular the material property of glossiness can be diagnostic for transparency. They demonstrated that, in the pictorial practice, the presence of highlights on a surface can constitute the only revealing cue of its transparency. Fleming and Bülthoff [65] and Motoyoshi [114] came to similar conclusions about the role of the highlights for the case of translucent objects made via computer rendering, i.e. the perception of translucency can be enhanced by the presence of specular reflections. Wijntjes, Spoiala and de Ridder [171] identified the Number of Distiguishable Levels (NDL) and a set of image cues for translucency perception of sea waves in paintings. They found that different "*shades*", or levels, of translucency could be retrieved according to the shape of the waves, e.g. bigger waves afford more and clearer cues. Koenderink and van Doorn [172] investigated the issue of shading in case of translucent materials. They suggested that it is not necessary to know the exact physics of the subsurface scattering of the radiation at every point and direction; but rather establishing some general rules that can help to render the effect of translucency, as much as painters were able to do via image features and shortcuts.

Recently, van Zuijlen, Pont and Wijntjes [173] carried out a big scale experiment of material perception in paintings. By testing the perception of a set of properties for different materials, they concluded that the mechanism of material perception is independent of the medium of representation, as their results were in agreement with previous studies conducted on photographs [174] and computer renderings [87].

1.4. The legacy of Willem Beurs

An index of key features for material perception

Beurs' treatise is rightly valued in the field of (technical) art history as an important record of pictorial procedures [175–177]. But the real value of this book, which may not come across so explicitly at a first reading, is that Beurs compiled an *ante litteram* index of key features for material perception. The term 'key features' here means that the established image features proposed by Beurs to render different materials, work as perceptual cues regardless the illumination and viewing conditions. For example, when painting a polished ceramic jug with a shiny metal cap, it does not matter whether one places it in an outdoor shaded patio, as in Figure 1.11a, or even behind the shadow of a hung duck, as in Figure 1.11b. The jug will invariantly show sharp, high contrast specular reflections, and these cues will always trigger the intended material perception despite the (in)consistency with the illumination field or viewing direction.

We argue that there are two main reasons to explain why Beurs instructs to use the specific features reported in his recipes, and why they work so effectively on our perception. The first reason is that they capture the most likely appearance of the objects. As noted by Gombrich [24], the likelihood of a given optical phenomenon heavily influences our perception. He discusses the long known artistic convention which states that something hollow has to be painted black, in contrast to something protruding which needs to be painted white, since the former is a receding color and the latter is advancing. Such mode of representation, Gombrich continues [24], was deemed valid for paintings, because it was taken for granted to also happen in nature, i.e. "hollows are dark and ridges are light". Of course, that is not the case, since hollows can appear light and ridges dark, depending on the lighting and viewing conditions. Nonetheless, expectations make the most likely appearance also the most plausible and convincing representation. Fleming et al. [66] reasoned that the visual system exploits the regularities of natural illumination to discard unlikely interpretations of materials (e.g. a blurry surface reflection is unlikely to be interpreted as a sharp reflection of a blurry world). Under such natural illumination conditions, different materials can be recognized through their signature features profile, the set of key image features that trigger their characteristic appearances.

The second reason is that these key features, not only trigger the most likely appearances, they also allow for the best visual communication of the material properties. Consider again the examples of the ceramic jugs in Figure 1.11. It has been shown that different illumination fields can make the same object look more matte (under diffuse light) or shinier (under collimated light) [74]. So, if the painter had to create a strict, one-to-one correspondence between the physics and the depiction in order to achieve a convincing result, the most accurate rendering of the reflections on the jugs would probably look dimmer and blurrier, thus losing their convincing shiny appearance. Moreover, both jugs in Figure 1.11 show the conventional window-shape reflection on the metal cap [178].

By following the physics, the artist would depart from the most effective and convincing representation of the material he intended to show. That is why perceptually-relevant recipes were taught and preferred by the artists.

(a)

(b)

Figure 1.11: On the left is shown the detail and on the right the entire painting. (a) Jan Steen, *The Dancing Couple*, 1663, National Gallery of Art, Washington, D.C., U.S. (b) Joachim Beuckelaer, *Christ in the House of Martha and Mary*, 1568, Museo del Prado, Madrid, Spain.

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Figure 1.13: Professional photos of wine glasses. Images downloaded from Unsplash.com, released under free license.

Beurs foresaw elements of ecological optics by laying the foundations of materials' depiction onto the observation of natural illuminations and natural environments. He also understood the relevance of grasping the physics of optical phenomena, while at the same time acknowledging that there is no need for complex mathematical computations.

For example, he remarks that the painter is not required to embark on the calculations of refractive indices to paint a smooth, fragile and transparent glass of wine (as the one in Figure 1.12). Likewise, the brain has no need (and no way) to compute the physical parameters of a BRDF function in order to estimate the reflectance of that same glass. In this view, Beurs aligned with the modern theory of vision science that regards inverse optics as ill-posed and unfeasible [82, 179, 180].

Figure 1.12: Detail of Willem Claesz. Heda, *Still life with gilded beer jug*, 1634. Rijksmuseum, Amsterdam. The Netherlands.

And most important to the aim of this thesis, he provided us, scientists and artists alike, with a comprehensive list of the key image features, derived from optics but tailored to perception, which elicit the most likely, and 'the best' depiction of materials. Van Zuijlen et al. [181] reported an example of such perception-based, standard material depiction. They found that the rendering of wine glasses in paintings, like the one in Figure 1.12, was based on perceptually invariant cues, i.e. the consistent locations of the window-shaped reflections on the glass. In comparison, the photos of wine glasses taken nowadays by amateurs, under different lighting conditions and from diverse viewpoints, revealed no consistent patterns for the location of the reflections. Even though ecological environments allow for a wide variety of appearances, professional photographers, who aim like painters for the best representation of materials' appearance, might be more prone to capture the light in a way similar to the pattern used by painters (see Figure 1.13).

It was noted by Hagen [182] that applying the theory of ecological optics of Gibson [183] to the representation and perception of pictures, means that ”pictorial styles succeed as representations only to the extent that they capture invariant information for the objects and scenes pictured.” Our hypothesis is that Beurs actually seized and listed in his book the key features of the structure of light to render and perceive material properties.

He describes the features of each material under a natural, standard illumination condition, which he calls ”neutral daylight” or ”midtone” [37, 38], corresponding to chiaroscuro, i.e. transitions of light and shade on the surface of the object. In such neutral daylight, Beurs also considers the effect of interreflections on the appearance of the surfaces, in this case self-interreflections, as each object is treated separately.

Another interesting element of Beurs' treatise, is that the key features that he provides are organized in a sort of taxonomy of appearances. Very different materials are grouped in the same class according to their key image features. For example, snow, flowers, fabrics, worms, butterflies and caterpillars, all belong to the same class. Another example is the class that contains hairs, tree trunks, wood, masonry, straw, stones, chestnuts, olives and capers.

Grapes, which will dominate the first three chapters of this thesis, open another class which includes plums, cherries, berries, pomegranate seeds, oranges and lemons. The pictorial recipe for white grapes will be extensively discussed in chapter 3, but for now let me walk you through Beurs' visual formulae for this group, which start from grapes and get all the way up to citrus fruits. A schematic representation of the connections between materials is shown in Figure 1.14 (the attributions of all the paintings in the scheme are reported in [1]).

White grapes, rendered in neutral daylight, need a light color mix on the lit side and a dark one on the shaded side, to create depth via chiaroscuro. Next, the reflections are applied, i.e. the light reemerging after subsurface scattering at a different location from where it entered, thus to be placed opposite to the specular reflection. The latter will be most likely placed top left, therefore the reflections will be rendered at the bottom right. Then, a whitish, opaque layer, corresponding to the bloom, is distributed over the surface, taking care to use a darker color for the grapes in the shadow. The distribution of this opaque layer needs to be somewhat random, leaving free spots here and there, but especially making sure to leave enough space on the lit side in order to apply the specular reflection. This is placed on the lit side, where light hits the surface and it is partially absorbed and scattered and partially reflected. The highlight needs to be high contrast but with blurry edges. The final step is to make the seeds of some grapes visible through the fruit. This is done again on a spot on the surface free from the opaque layer, so that the see-through effect is more convincing.

This first visual formula is rich of details because it lays the foundation of the key features for all the following fruits in the group. Therefore, blue and Spanish red grapes will need the same exact features of white grapes, but rendered with different colors. The same is true for white and red/blue plums, no additional instructions are needed. In Figure 1.14, it can be easily seen that a plum is just a very big grape, slightly less translucent, thus with smaller reflections, because due to the increased size of the object, the light has a longer path to travel and less chances to reemerge after subsurface scattering. The features profile of red cherries is also the same as grapes, with again a difference in colors. But cherries are more shiny, so less or no bloom is needed, and they need more saturated colors. Red currants are made exactly like cherries, adding just the seeds to be seen through. And the seeds of a cracked-open pomegranate are rendered like red currants. Each segment of the mulberries is rendered like a tiny cherry. For the strawberries, the base is like the cherries, which are like the grapes, so they need a lit and a shaded side and the reflections. Instead of applying one strong specular reflection, though, strawberries need small highlights to render every seed on the surface, and their body color is less saturated than the cherries. Red gooseberries need the same key features of the grapes, plus the veins on the surface. They also need a brighter color, so less to no bloom rendered by the whitish opaque layer. The pulp of an orange is rendered like an orange gooseberry. This means that first they require a lit and a shaded side, followed by the reflections for the translucency. Like gooseberries, they do not need bloom. As in the case of strawberries, there is not a single specular reflections, but the highlights are used to mark the cells of the pulp. Their arrangement, though, still follows the scheme of the grapes, opposite to the translucent reflections. The veins of the gooseberries are used to trace the slices of the orange. The last material in this class is the lemon pulp, which is exactly like the orange, with a change in color.

A similar description would apply to the other groups of materials described in the book. Within each group, Beurs proposes features' profiles that trigger material perception, and each profile is derived by a weighted combination of key features. Such 'layered' features' combination is similar to the optical mixing of canonical material modes proposed by Zhang et al. [85–88], in which the key features are related to a limited range of common but mutually distinct appearance modes. In the following chapters we will test the perceptual relevance of the key features for material perception, listed by Beurs and employed by painters.

[1]**White grapes**: Abraham Mignon, *Still Life with Fruit, Fish and a Nest*, 1675. National Gallery of Art, Washington, DC, US. **Blue grapes**: Jacob van Walscapelle, *Still Life with Fruit*, 1675. National Gallery of Art, Washington, DC, US. **Spanish red grapes**: Abraham Mignon, *Still Life with Fruit and Oysters*, 1660 - 1679. Rijksmuseum, Amsterdam, The Netherlands. **White plums**, **Red/blue plums** and **Pomegranate seeds**: Jan Davidsz. de Heem, *Festoon of Fruits and Flowers*, 1660 - 1670. Rijksmuseum, Amsterdam, The Netherlands. **Red cherries**: Johannes Hannot, *Still Life with Fruit*, 1668. Rijksmuseum, Amsterdam, The Netherlands. **Red gooseberries**: Adriaen Coorte, *Gooseberries on a Table*, 1701. Cleveland Museum of Art, Cleveland, US. **Red currants**: Jacob van Walscapelle, *Still Life with Fruit*, c. 1670 - c. 1727. Rijksmuseum, Amsterdam, The Netherlands. **Mulberries**: Jan van Huysum, *Still Life with Fruit*, 1700 - 1749. Rijksmuseum, Amsterdam, The Netherlands. **Strawberries**: Adriaen Coorte, *Still Life with Wild Strawberries*, 1705. Maurtishuis, The Hague, The Netherlands. **Orange pulp**: Cornelis de Heem, *Fruit Still Life*, c. 1670. Maurtishuis, The Hague, The Netherlands.. **Lemon pulp**: Pieter de Ring, *Still Life with Golden Goblet*, 1640 - 1660. Rijksmuseum, Amsterdam, The Netherlands.

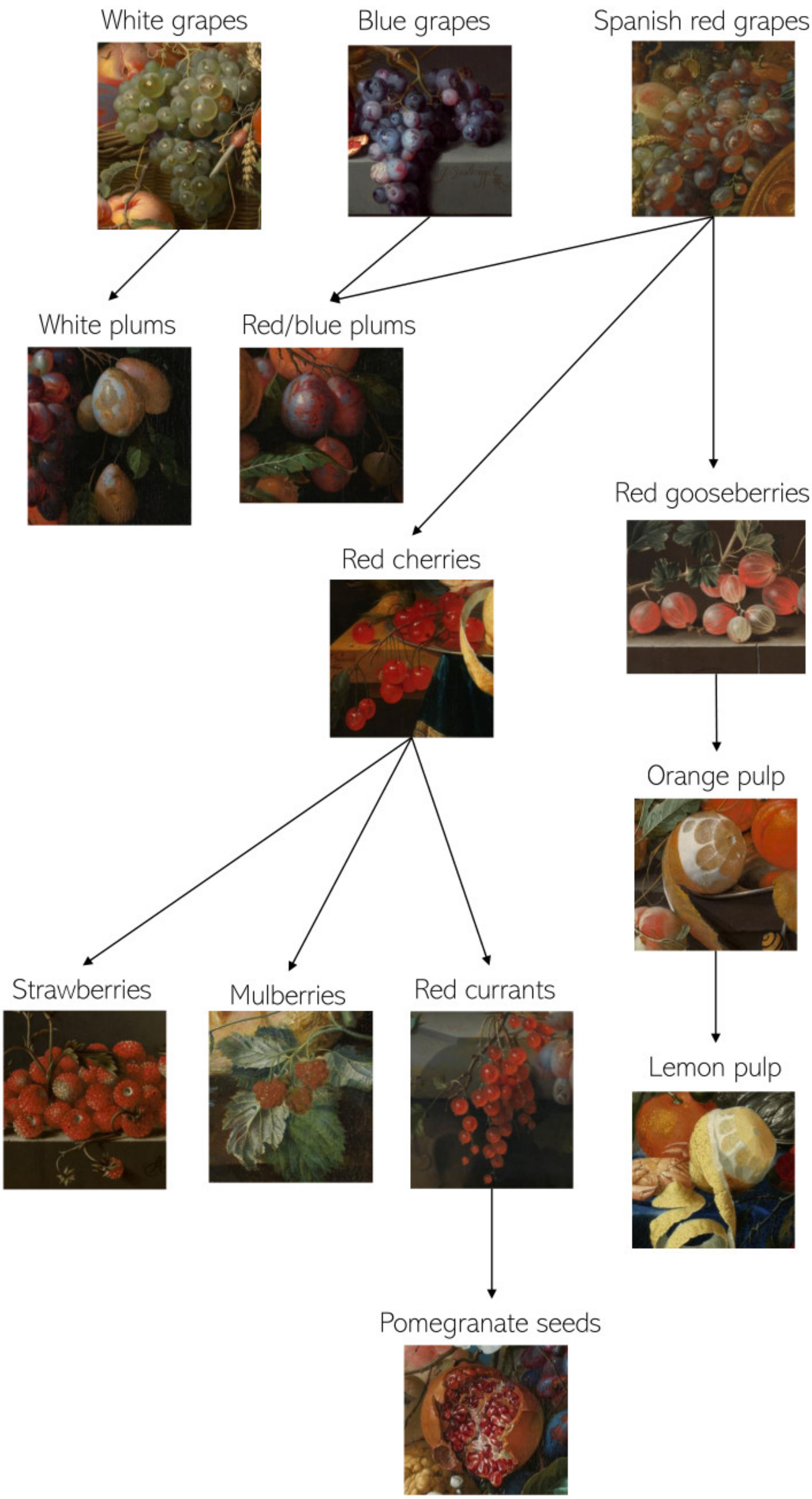

Figure 1.14: Schematic representation of the connections between different materials that, according to Beurs, can be rendered using the same image features. Attribution of each painting can be found in footnote [1].

1.5. Research aim and thesis structure

The understanding of material appearance has been mostly overlooked in art history in favour of perspective and space depiction, and it is still quite recent in the field of vision science, where the potentialities of the perceptual discoveries documented in paintings are not exploited to their fullest yet.

The objective of this thesis is:

> *To understand the convincing depiction and perception of materials in 17th century paintings, connecting the image features found in paintings and listed by Beurs to their role as perceptual cues.*

To achieve this aim, we used a novel, interdisciplinary approach, which has no precedents in literature to the best of our knowledge, integrating elements of psychophysics, computational image analysis, paintings' reconstructions, design and art history.

We formulated two overarching research questions, which have exactly the same aim (understanding convincingness), but clearly separate the two types of information exploited in this research (visual and textual):

1. *Which image features did painters use to achieve the convincing rendering of materials?*

2. *Which image features listed by Beurs work as perceptual cues to achieve the convincing rendering of materials?*

These overarching research questions raised a number of more specific research questions:

- How is the systematic pictorial procedure used by De Heem and described by Beurs, related to the convincing appearance of grapes?

In **Chapter 2** we investigate the procedural aspects of the additive, systematic building-up of layers used by the still life painter Jan de Heem to render grapes, using scientifically-based reconstructions. His pictorial procedure was shown to correspond to the recipe for grapes described by Beurs [184]. Thus, by reconstructing layer by layer the grapes of De Heem, we also visualized the effect of each key image feature provided by Beurs, and their additive effect on the final convincing appearance of the grapes. We further coupled the paintings' reconstructions with an optical mixing tool [85, 89, 90], which allows to access the temporal information of the pictorial procedure and to digitally modify each layer. This tool serves several purposes and has many potential applications, which are discussed more in depth in Chapter 2 and in Chapter 8.

- Do the material properties provided by Beurs to render white grapes, predict the convincing perception of grapes?

In **Chapter 3** we analyze Beurs' recipe to paint white grapes, and extract the material properties that, according to Beurs, would lead to a convincing bunch of grapes. The recipe advises to start with a 3D shape to which bloom, translucency and glossiness are added. We tested the perception of each of these attributes, plus convincingness, for a set of 17th century paintings. We found that, overall, only three dimensionality could predict convincingness, indicating that there is more than one way to render convincing grapes and that the optical material properties can be combined as one likes. In a second experiment, we tested the same attributes but for different versions of the same painting, a bunch of grapes by De Heem that we reconstructed following Beurs. We manipulated the weight of the layers using the optical mixing tool, to create controlled stimuli by selectively deleting certain image features. In this case, all the attributes provided by Beurs were significant predictors of convincingness, confirming that Beurs identified all the optical phenomena that can be observed in a bunch of grapes.

- Did painters use the image features of the highlights - contrast, coverage and sharpness - to trigger the glossiness of grapes? Are they to be found in Beurs' recipe as well?

In **Chapter 4**, we started from a paper by Marlow and Anderson [80] in which the authors demonstrated that the interaction between surface relief and illumination caused a systematic change in certain image features that could explain the observed variations in gloss perception of stimuli with constant reflectance. Those image features were contrast, coverage and sharpness of the highlights. We tested whether the same features were employed by painters and prescribed by Beurs to depict grapes. We computed the highlights' features directly from the images and found that gloss perception was well predicted by contrast and sharpness, but not coverage, also in agreement with Beurs instructions.

- Which image features did painters use to trigger the visual perception of juiciness and translucency of citrus fruits? Which image features did Beurs include in the recipes for oranges and lemons?

In **Chapter 5** we first determined the dimensionality of the perceptual spaces of juiciness and translucency perception of citrus fruits, to be 2D. We then used the image features identified by observers in the paintings to interpret the spaces. We found that juiciness and translucency are perceptually related, and their perception is correlated to similar, but not the same, image features. For example bumpiness was found to be important for juiciness but not for translucency, as a bumpy citrus pulp is directly related to the amount of juice. The main image features identified in this study - highlights and light gradient - were also explicitly mentioned by Beurs in his recipes.

- Does applying the perceptual cues of juiciness to packaging design of orange juice improve consumers' perception of the product?

In **Chapter 6** we tested the effect of the image features 'highlights' and 'peeled side', derived from the previous study, on juiciness perception of a cut-open orange

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shown on a package of orange juice. In this cross-disciplinary study, we aimed to address the gap of material perception in packaging design and sensory science. We thus tested the hypothesis that the image of a juicy orange, being juiciness an important food quality parameter, would improve the overall perception and expectations on the orange juice. We found that the presence of highlights on the pulp significantly increased juiciness perception of the orange, as well as the expected quality and tastiness of the juice.

- What are the material signatures used by painters and by the visual system to distinguish velvet from satin? Is their perception related to global or local visual cues?

In **Chapter 7** we tested the perception of six material attributes (warmth, softness, hairiness, heaviness, shininess and roughness) for a set of paintings depicting velvet and satin. We either showed the entire figure or object covered by the target fabric, or one region cropped from the fabric. We found that warmth, softness, heaviness and hairiness are material signatures of velvet, whereas shininess is signature of satin, but we also found that the perception of some attributes changed between the two viewing conditions. We further tested whether the observed variations in perception were related to the area chosen for the crop condition, by producing new crops that spanned the whole fabric. We found that shininess was highly related to the choice of the cropped area, as its perception changed significantly between the crops of a single fabric, and it was related to the mean luminance and coverage of highlights in each crop. Softness on the contrary, did not change across the single fabrics, indicating that softness perception is related to global perceptual cues, whereas shininess perception relies on local cues.

To borrow the words of Köhler [51]: "the most fortunate moments in the history of knowledge occur when facts which have been as yet no more than special data are suddenly referred to other apparently distant facts, and thus appear in a new light". This is what we are trying to do here, by bringing 400 years old paintings and pictorial recipes under the light of the "apparently distant" vision science, to reach a new understanding of art and of the visual system.

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2

Looking through the layers. A case study on grapes

The art of painting in addition
imitates life more precisely and naturally,
and renders everything with incomparably greater perfection.

Willem Beurs

Parts of this chapter have been adapted from: Di Cicco, F., Wiersma, L., Wijntjes, M.W.A, Dik, J., Stumpel, J., & Pont, S.C. (2019). A digital tool to understand the pictorial procedures of 17th century realism, in Leal-Taixé L., Roth S. (eds) Computer Vision – ECCV 2018 Workshops [1].
and from: Di Cicco, F., Wijntjes, M.W.A., & Pont, S.C. (2018). Beurs' historical recipe and material perception of grapes in Dutch Golden Age still-lifes. in Electronic Imaging, Human Vision and Electronic Imaging 2018, 1-6(6) [2]

My contribution in [1] was to arrange the collaboration with dr. Callewaert to perform the OCT measurements of the real paintings; to set up the controlled environment in the lab for the digitization of the reconstructions; to record and digitize the reconstruction process; to build the optical mix interfaces; to write the manuscript.

My contribution in [2] was to collect, analyze and interpret the data; to write the manuscript.

2

To unveil the mystery of the exquisitely rendered materials in Dutch 17th century paintings, we need to understand the pictorial procedures of this period. We focused on the Dutch master Jan de Heem, known for his highly convincing still-lifes. We reconstructed his systematic multi-layered approach to paint grapes, based on pigment distribution maps, layers stratigraphy, and the 17th century textual source of Beurs. We digitised the layers reconstruction to access the temporal information of the painting procedure. By combining the layers via optical mixing, we created a digital tool that can be used to answer "what if" art historical questions about the painting composition, by editing the order, weight and colour of the layers.

2.1. Introduction

Still life paintings were not as prominent as landscapes or portraits, but "no other branch of painting reveals more clearly the Dutch devotion to the visible" [3]. Indeed, still life paintings, especially the ones depicting food, glasses, knives and platters arranged on a table, demonstrate the accurate observation and the meticulous rendering of each and every surface and material. But how did they do it? How did they achieve such a successful and convincing rendering of material properties?

To answer this question, we studied the works of one of the greatest still life painters in Europe, Jan de Heem (1606–1684), especially admired for his fruits and flowers [4]. We focused on the grapes for several a reason. First, in Beurs' treatise [5, 6] the chapter devoted to food still life opens with the recipe for rendering grapes, "pleasing to the eye and a treat for the tongue, and containing the juice that, when used well, gives joy to God and humankind". But grapes are not only the sacred fruit of Bacchus, symbol of abundance and fertility. According to Roger de Piles, the bunch of grapes constitutes the metaphor of a painting. By observing a bunch of grapes, one can learn the best distribution of light and shadows to render chiaroscuro, and the sense of unity of the composition [7] (see Figure 2.1).

Figure 2.1: Illustration from "The principles of painting" (Roger de Piles, edition of the 1743).

Moreover, when considering material perception, the case of grapes is particularly interesting due to the complex combination of different properties. From daily experience with real bunches of grapes, we know that grapes are translucent and glossy, but can also be (partly) covered by a matte layer of bloom (a whitish waxy layer on the surface of the grapes). Thus, modeling an optical function to convincingly render grapes can be a computational nightmare, and attempts that claim to have reached a realistic effect still show a somewhat plastic appearance [8].

The technique of De Heem to paint grapes consisted of a multi-layered systematic approach, which was shown by Wallert, via the analysis of cross sections [9, 10], to match the painting recipe given by Beurs [5, 6]. Such systematic procedure starts with the lit and the shaded sides, continuing with the bloom and refined with the highlights.

Can his technique disclose the convincing visual effects he was able to achieve? Understanding the painting procedures underlying the masterful rendering of materials in 17th century Dutch paintings poses still a challenge for art history (but see [11, 12]). We addressed this question by combining a scientifically truthful reconstruction of De Heem paintings, based on chemical data and Beurs recipe for grapes, with imaging science to develop a digital visualisation tool of the painting procedure.

2.2. The reconstruction process

In the field of technical art history, painting methods are usually investigated by the use of diagnostic techniques to identify the pigments and layers beneath the visible surface. The development of non-destructive imaging methods, like X-ray and infrared-based techniques (see [13] for an exhaustive review), gave access to a wealth of knowledge about paintings stratigraphy and pigments' distribution. However, to the best of our knowledge, there is no available method to 'see' the layers as if one was looking over the painter's shoulder during the painting process.

Our approach provides a layer-by-layer reconstruction which is both scientifically truthful and historically accurate, and includes the digital record of the process.

We reconstructed the red grapes from two paintings by De Heem (Figure 2.2). The reconstruction process entailed that a skilled painter (Lisa Wiersma) followed the recipe using oil paint and template drawings for the De Heem grapes' outline. The order of the layers' building up was done according to Beurs recipe for Spanish red grapes [5, 6]:

> Next are the Spanish red grapes, which are pleasant to paint and are useful as a decorative element in paintings. They are laid in with only lake, or red-brown and lake, depending on how ripe they are, or with a greenish tone added if they should appear as somewhat less ripe. The reflections on the ripe grapes must be painted with vermilion or redbrown, then glazed with only lake if the reflection is very red, but if it is not, yellow lake must be mixed in with it. The grape is a shade of yellow ochre on the top, so that part has to be painted with ochre and black. The dew and the highlights require the same techniques as for blue grapes.

(a) (b)

Figure 2.2: Jan Davidsz. de Heem, (a) *Festoon of Fruits and Flowers*, 1660-1670, Rijksmuseum, Amsterdam, The Netherlands; (b) *Garland of Fruit and Flowers*, 1650-1660, Mauritshuis, The Hague, The Netherlands.

The pigments' distribution for each layer was determined by comparing Macro X-ray Fluorescence Scanning (MA-XRF) scans acquired by De Keyser [14].

Beurs advised to apply a layer of glaze made with red lake, an organic pigment made of potassium, over the reflections. However, he also instructed to lay the first layer with red lake, thus the MA-XRF map of potassium showed red lake distributed all over the grapes. This overlapping made difficult to find where De Heem actually applied the glaze just from the MA-XRF measurements. To overcome this issue, we performed Optical Coherence Tomography (OCT) analysis of the painting at the Mauritshuis (b in Figure 2.2), a technique particularly valuable to investigate (semi)transparent layers like varnish and glaze. The OCT measurements - performed by dr. Callewaert - revealed the presence of a glaze layer on the darker side of the grapes, where there is no bloom, opposite to where we expected to find it following Beurs (see Figure 2.3).

2.3. Digitalisation of the layers building-up

To reconstruct the temporal information of the multi-layered painting procedure of De Heem, we acquired high resolution digital photographs of the reconstruction process, in a controlled environment with constant lighting. To ensure light constancy during the painting process and the photos acquisition, we worked in a darkened room with no windows. The only light source in the room, pointed towards the canvas, was a lamp Rotolight ANOVA HD eco flood (color temperature set to 5000 K for a daylight-like spectrum). All the photos were taken with a camera Canon 5D s (shutter speed 1/80 s, aperture f/13, ISO 100) mounted on a tripod, using a zoom TS-E 90 mm. The photographs were shot automatically at intervals of 10 s, using

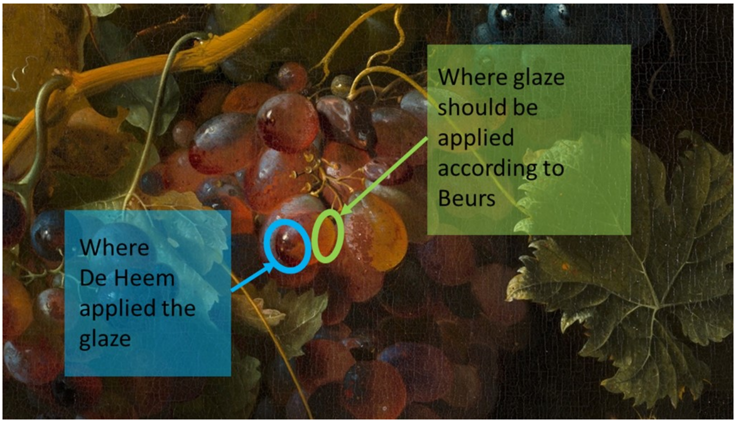


Figure 2.3: Illustration of the side of the grapes on which Beurs prescribed to apply the glaze (green spot), compared to where we found the glaze applied by de Heem using OCT (blue spot).

the program Canon EOS Utility 3 (Canon Inc., USA). The reconstructed sequence of layers are shown in Figure 2.4.

Figure 2.4: Sequence of layers reconstruction of the red grapes in *Festoon of Fruits and Flowers*.

In order to understand the success of the procedure, we need to access both the individual layers and their combination. To see the visual contribution added by each layer, one could paint the image several times leaving out one layer each time. But this would lead to inconsistent results given the impossibility to repaint the same image over and over with exactly the same colour mixtures and brushstrokes. The new versions of the painting may unconsciously be adapted to the fact that one step was being deliberately skipped.

To overcome these issues, we built an interface using optical mixing [15, 16], an image combination process that recalls the systematic layering procedure used by painters [17]. The elements combined in the optical mixing tool were obtained by subtracting the first reconstructed image in Figure 2.4 from the second, the second from the third, etc. The individual image features added with each layer, which correspond to the steps in Beurs recipe, are shown in Figure 2.5.

Reflections Unripe grapes and stem Bloom Shadows Highlights

Figure 2.5: Sequence of features obtained from the layers reconstruction and combined into the optical mixing.

2.4. The tool applications

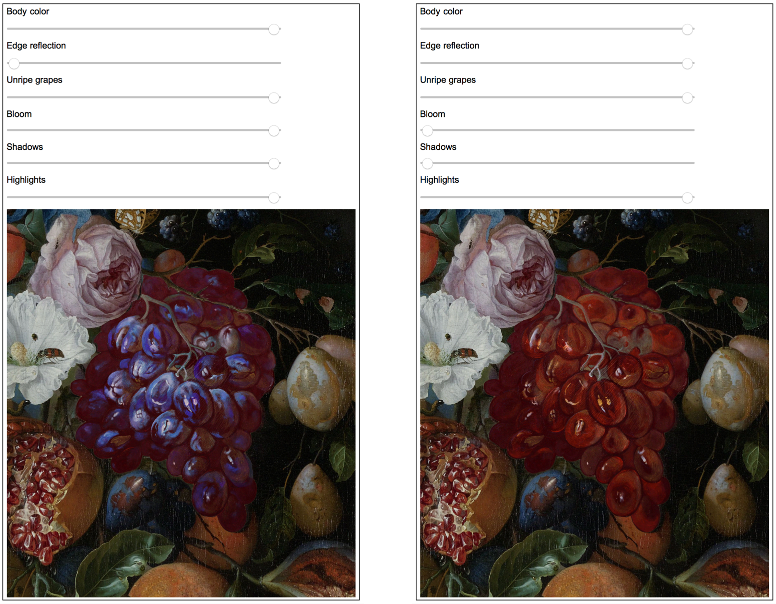
Several approaches have been used in literature to decompose images into layers via for example vectorization [18], segmentation [19], the Porter-Duff "over" operation [20, 21], or the physical Kubelka-Munk model [22, 23]. The retrieval of layers is usually done with the main intent of allowing image editing and manipulation.

Similarly, the aim of our layers' reconstruction was to provide a tool to explore the building-up of the paintings, and to open up new possibilities for different applications. The sliders can be used to manipulate and adjust the weights of the layers and therefore change the final appearance of the painting. For example, in an art historical context, we can see what the painting would have looked like if the layer of vermilion would not have been applied (Figure 2.6a). And what if the grapes would have been painted without the bloom layer (Figure 2.6b)?
Please note that the weights of all layers can be changed between 0 and 100%, allowing also subtle variations that correspond to layers thickness variations. Skipping one of the steps of De Heem's systematic procedure affects the final rendering and the realistic illusion.

Once we have access to the digitalised layers, we can also perform different types of manipulation operations, like colour editing. We can thus enable the use of counterfactual painting process scenarios to improve the knowledge and insights into the success and failure of pictorial steps. Our tool can be used by artists and art historians, conservators, scientists and a broader audience to find out how a masterpiece was made. In the context of museums, our tool can be applied for an interactive experience of the artwork. Finally, the tool can prove to be particularly useful in the field of art conservation and restoration. For example, when restoring a discoloured or damaged image, the colour editing possibilities offered by the tool can be used to check the relevance of additions or alterations.

The layers visualization resulting from our tool was used by Koppelmann [24] for a stratigraphic investigation of the *Festoon of Fruits and Flowers*. By comparing our layers' reconstruction with the MA-XRF maps [14], she could identify the layer of origin for the signal of each element, since MA-XRF analysis lacks depth and stratigraphic information.

Understanding the contribution of each layer to the convincing representation



(a) (b)

Figure 2.6: Optical mixing interface for manipulation of the layers' weights. (a) Final appearance of the grapes without the second layer that corresponds to the reflections; (b) Final appearance of the grapes when the bloom and the shadow layers are removed. The reproduction is superposed onto the real painting.

of materials is an extremely interesting question not only for art historians but also for perception scientists. We assume that every layer resonates with a certain perceived material attribute and that the layer may contain the key image cues of that material attribute.

2.5. Conclusions

By using the tool in visual perception experiments (see Chapter 3), we have showed that the compelling realism of Jan de Heem roots in a pictorial formula, consisting of the systematic application of necessary layers. De Heem was a meticulous and efficient painter: all the steps he made and that were described in the 17th century textual source of Beurs were perceptually-relevant. The computational result is an imaging technique beyond pixel values, showing actual colour layers which are editable. The assets of the digital tool, the clear-cut visualisation, practice, and testing of the Old Master's successful colour formulas, are of relevance to an interdisciplinary audience that consists of scientists, scholars, (digital) artists and interested lay persons.

2

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3

Convincing grapes: The know-how of the 17th century pictorial recipe by Willem Beurs

"I have surely painted the grapes better than the child, for if I had fully succeeded in the last, the birds would have been in fear of it". Zeuxis

Pliny the Elder

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In [1], my contribution was the conceptualization of the research idea; to design and perform the rating experiments; to create the stimuli both by collecting and cropping images of paintings and by creating optical mixtures of the reconstruction; to acquire, analyze and interpret the data; to relate the perceptual findings to Beurs' recipe; to write the main body of the manuscript.

Painters mastered replicating the regularities of the visual patterns that we use to infer different materials and their properties, via meticulous observation of the way light reveals the world's textures. The convincing depiction of bunches of grapes is particularly interesting. A convincing portrayal of grapes requires a balanced combination of different material properties, such as glossiness, translucency and bloom, as we learn from the 17th century pictorial recipe by Willem Beurs. These material properties, together with three-dimensionality and convincingness, were rated in experiment 1 on 17th century paintings, and in experiment 2 on optical mixtures of layers derived from a reconstruction of one of the 17th century paintings, made following Beurs's recipe. In experiment 3 only convincingness was rated, using again the 17th century paintings. With a multiple linear regression, we found glossiness, translucency and bloom not to be good predictors of convincingness of the 17th century paintings, but they were for the reconstruction. Overall, convincingness was judged consistently, showing that people agreed on its meaning. However, the agreement was higher when the material properties indicated by Beurs were also rated (experiment 1) than if not (experiment 3), suggesting that these properties are associated with what makes grapes look convincing. The 17th century workshop practices showed more variability than standardization of grapes, as different combinations of the material properties could lead to a highly convincing representation. Beurs's recipe provides a list of all the possible optical interactions of grapes, and the economic yet effective image cues to render them.

In the previous chapter, we have analyzed the pictorial procedure of one of the greatest 17th century still life painters, Jan de Heem, to render succulent grapes able to deceive the eye of the viewer, as much as Zeuxis' grapes could famously mislead the bird. In this chapter we will continue to investigate the source of convincingness of grapes from the point of view of material perception. We will show that the ingredients provided by Beurs to paint grapes reveal all the image cues to trigger the necessary material properties. What is left to us, is mixing them to our own taste to get the most convincing grape.

3.1. Introduction

What does it take to paint convincing grapes? According to Willem Beurs [2, 3], convincingly painted grapes look three-dimensional, glossy, translucent and partly covered with bloom (a waxy coating that naturally occurs on grapes, resulting in a whitish, matte appearance). Here, we studied whether these material properties explain the perceived convincingness of grapes depicted in 17th century paintings, and how the pictorial cues that Beurs prescribed to trigger their perception relate to the perceived material properties.

With the advent of the 'psychology of art' [4, 5], art became an object of scientific interest, worth investigating to disclose new perspectives on our understanding of the human visual system [6–9]. However, collaborations between artists and scientists are developing at a slow pace due to differences in methods and languages

[10]. Perception studies referring to the knowledge of painters have mostly focused on depth perception of 3D space and objects in 2D representations [11–16]. Little attention has been paid to what artists have already discovered about material perception, a recent core topic in vision science [17, 18]. Material perception investigates the relationships between optical properties, image cues, and perception of materials from their appearance (see [19] for a comprehensive review).
Sayim and Cavanagh [20] studied the cues used by artists throughout the centuries to depict transparency. Wijntjes et al. [21] identified the Number of Distinguishable Levels (NDL) of translucency perception of sea in paintings, and a set of image cues related to it. Di Cicco et al. [22] (see Chapter 4) found that some of the image features diagnostic for gloss perception, proposed by Marlow and Anderson [23], were already part of the 17th century pictorial conventions for depicting grapes, namely the contrast and blurriness of highlights.

The exceptional realism of Dutch 17th century paintings is widely acknowledged by scholars in art history [24–29]. While seeking the most life-like representation of reality, Dutch painters became masters in the *stofuitdrukking*, a Dutch term that can be translated as 'rendering of texture' [1] or 'expression of stuff'. According to De Vries [30], the *stofuitdrukking* is distinctive of Dutch Golden Age paintings, given that "nowhere else was so much effort expended on attaining the greatest possible likeness between a real object and its depiction with regard to surface structure, colour, and the play of light".

Painters understood long before the advent of vision science that the human visual system seizes key information from the surroundings, discarding unnecessary details and physical inaccuracies [31–33]. They have exploited the capability of the visual system of disregarding impossible and simplified physical phenomena, to abbreviate the rendering of materials with perception-triggering pictorial shortcuts [6]. Such a perception-driven approach has been also used for photo-editing applications by Khan et al. [34]. Schmidt et al. [35] reviewed art-based material editing methods that discount the laws of physics when necessary to achieve the desired appearance. This is the case for, for instance, the artist-friendly hair rendering system developed by Sadeghi et al. [36]. They proposed an intuitive hair shader method based on visual cues whose colour, shape or position can be manipulated separately, rather than relying on intrinsic physical parameters, like the refractive index, that affect the whole final appearance in unpredictable ways. Bousseau [37] reported that artistic principles and image shortcuts can vividly represent the appearance of materials in computer graphics, optimizing the time-consuming task of rendering algorithms. Convincing (but not necessarily physically realistic) rendering of fruits and vegetables finds a wide range of applications, from movies and animations [38], to virtual reality experiments for food loss reduction [39].

[1] The term 'texture' is often used by art historians to indicate all material properties, not limited to the more formal statistical meaning often used in vision science.

3

3.1.1. The pictorial recipe for grapes in “The Big World Painted Small”

While the number of perceptual experiments using paintings as stimuli is limited, the use of art historical writings in material perception science is virtually nonexistent. Lehmann et al. [40] investigated the texture of trees and found that the attributes that best describe the appearance of foliage were already noted by Leonardo da Vinci in his *Trattato della pittura*. Written sources are used in technical art history to shed light on the painters' practices [25, 41], and to analyze and reconstruct the artworks [42, 43]. As such, they can serve as complementary information to disclose the perceptual knowledge inherent in paintings. In contradistinction, understanding the mechanisms behind our perception of paintings can help to systematically describe paintings.

The depiction of surfaces and materials during the 17th century was determined by workshop traditions and by the standardization of recipes [44]. For example, the method for painting grapes deployed by Jan Davidsz. de Heem is similar to the recipe given by Beurs in the art treatise ”The Big World Painted Small” from 1692 [45–47]. This treatise is a compilation of colour recipes for oil painting, a recapitulation of 17th century practice. It describes the best choice of colour (pigment) combinations for the defining visible properties of several phenomena, objects and beings. Recipes for objects and edibles that occur in still-life paintings received most attention in the treatise. The recipe for grapes is one of the most extensive in the book; it requires nine to ten steps, depending on the colour of the bunch. When describing plums, berries and even lemons, Beurs (indirectly) refers to how the translucent pulp of the grape is depicted, treating this fruit recipe as the template for many others. Given the number of surface effects and material properties grapes display, this makes sense. Grapes have a multilayered structure (Figure 3.1), so the

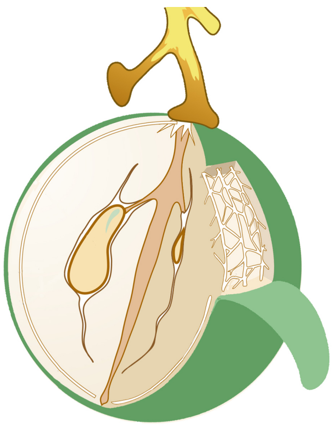


Figure 3.1: Schematic representation of the multilayered structure of a grape (adapted from an illustration by Mariana Ruiz Villarreal, released to the public domain).

relationship between the optical properties of glossiness, translucency and bloom can be complex and not easily predictable. The skin covers the pulp, which is made of cells containing the juice and comprehends a vascular system for transportation of water and nutrients, and the seeds. The skin is naturally covered with bloom, that (partly) diffusely reflects light hindering the process of subsurface scattering and the specular reflections. However, the influence of bloom on translucency and glossiness is not straightforward, since the bloom can be unevenly spread over the surface and can be of varying thickness. The process of subsurface scattering is further complicated by the heterogeneous internal structure of the grapes, adding to the complexity of the grapes' appearance.

The recipe for white grapes is as follows [2, 3]:

> White grapes are laid in with English ash [a greyish blue], yellow lake [a translucent bright yellow paint], and white for the lit side. But for the shadows, ash, yellow lake, and black have to do the work. The reflections however, require only a little ash but somewhat more yellow lake. After white grapes have been painted in this way the bloom can be created with ultramarine and white, or with a little lake mixed into a white oil, which is scumbled over the grapes. But to render the bloom in shadows, black, lake, and white are needed. Once all this has been done, the grapes have to be given a sheen on the lit side (where there is no bloom) with white that is gently blended in, and the reflections glazed with only yellow lake, as the occasion demands. But the seeds in the grapes, which shine through in the ripe ones as they are usually painted, must not be forgotten. These are made visible by mixing light ochre with a little ash and white into the yellow lake, and for the shadows, black.

The recipe starts with instructions to paint the lit and shaded side of the grapes, providing the first impression of their three-dimensional shape [48]. The following step is to render the internal reflections along the edges of the grapes, a cue of the permeability to light which provides the translucent look. When the paint is dry, the bloom layer is scumbled on top, not too opaque, following a seemingly random design per grape to keep the translucent peel visible here and there and apt for highlights — the next step. Highlights are the basic visual cues for glossiness [49, 50]. A glaze deepens and saturates the pulp's shadow colour where the edge reflections are visible. The glaze is made using a translucent pigment and a fairly large amount of binding medium [51]. Last in the recipe, the impression of a seed within the pulp is given by defining part of its shape. A visible seed is a further indication of the translucent property of the grapes.

In this discussion it is important to distinguish between the physical properties of materials, lighting and shape, their depiction, and their perceptions. These three domains must be systematically related, but their mutual relationships do not have to be dictated by physics in the sense that perceived physical realism can only be attained by physically realistic rendering. Perceived physical realism is a perceptual entity and therefore determined by perception or intelligent interpretations. Therefore, 'physical realism' is replaced by 'convincingness' in this paper, to clearly distinguish it as a perceptual attribute.

In paintings, it needs understanding of which key image features trigger certain perceptions. The aim of this paper is to understand which features those are for grapes, and how those are related to the perceived material attributes prescribed by Beurs to paint a convincing bunch of grapes [2, 3].

3.2. Methods

We investigated whether Beurs's material attributes explain convincingness of grapes via three rating experiments. We tested the perception of convincingness, three-dimensionality, glossiness, translucency, and bloom for images of 17th century paintings in experiment 1, and for optical mixtures of layers obtained reproducing one of the 17th century paintings in experiment 2. In (control) experiment 3, only the convincingness of the 17th century paintings was rated. These data were correlated to the convincingness ratings of experiment 1 to test if raters, provided and not provided with the material attributes that should explain convincingness, agreed on how convincing the painted grapes looked.

3.2.1. Participants

Different groups of observers took part in each experiment. Two groups of nine, and a group of ten naïve observers, with normal or corrected vision, participated in experiments 1, 2 and 3 respectively. They provided written consent prior to the experiment and received a financial compensation. The experiments were conducted in agreement with the Declaration of Helsinki and approved by the Human Research Ethics Committee of the Delft University of Technology.

3.2.2. Stimuli

Experiments 1 and 3

In experiments 1 and 3, we used 78 high-resolution digital images of 17th century paintings, downloaded from the online repositories of several museums [2]. The stimuli were presented as squared cut-outs containing the target bunch of grapes (Figure 3.2).

Experiment 2

A bunch of grapes painted by Jan de Heem (Figure 3.3), judged among the most convincing in experiment 1 and 3, was reconstructed according to Beurs's recipe, to make the stimuli for experiment 2. The pictorial procedure of De Heem, especially

[2] A numbered list of all the squared cut-outs used in the rating experiments can be found in Supplementary Figure S1 in 3.7. Each image in the list has an embedded link to the relative museum repository website, where the original images can be found.

Figure 3.2: Example of a stimulus presentation, as squared cut-out around the target bunch of grapes. Abraham Mignon, *Still Life with Fruit, Fish and a Nest*, 1675. National Gallery of Art, Washington, DC, USA.

Figure 3.3: Bunch of grapes representing Beurs' recipe, which formed the example for the reconstruction and stimuli of experiment 2. Jan Davidsz. de Heem, *Garland of Fruits and Flowers*, ca. 1650-1660. Mauritshuis, The Hague, The Netherlands.

for grapes, was shown to match rather well the recipe of Beurs via scientific analysis of his paintings [45–47]. Hence, the second author, who is also an experienced painter, implemented Beurs's procedure in a reconstruction.

The bunch was painted on fine linen, prepared with a coloured ground following Beurs: a mixture of umber and white was applied by hand in several layers. This is not how De Heem prepared his canvas: there, a grey or grey-brown was applied on top of a red ochre. Since the laboratory where the painting was made was not equipped with a fume hood, no historical pigments were used, but modern tube paints. For the yellow glaze, boiled linseed oil was added to a bit of bright yellow tube paint. The colours were selected to match the paints mentioned in Beurs' text visually.

We digitized the reconstruction process to provide access to images of the painting layers, corresponding to the pictorial cues given in the recipe. The painting reconstruction and its digitization were carried out in a darkened room with no windows to ensure a constant lighting. The only light source present in the room was a professional studio LED lamp, a Rotolight ANOVA HD eco flood (colour temperature, 5000 K). All the photos, for a total of 1124, were taken with a camera Canon 5D Mark II (shutter speed 1/80 s, aperture f/8.0, ISO 500). High-resolution images were acquired automatically every 10 s, using the program Canon EOS Utility 3 (Canon Inc., USA). Figure 3.4 (top) shows the six stages of the reconstruction corresponding to each step given by Beurs [2, 3].

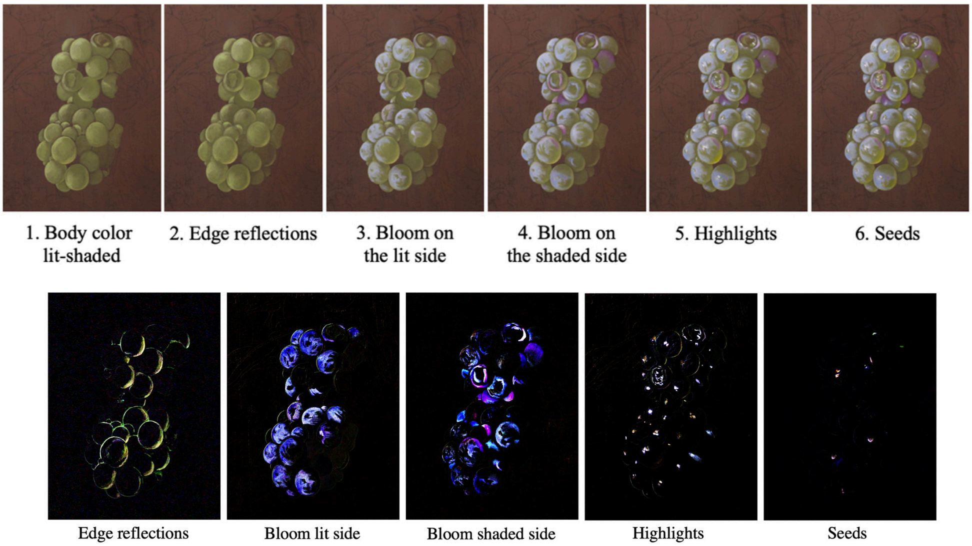


Figure 3.4: (Top) Sequence of reconstruction steps of the bunch of grapes in *Garland of Fruits and Flowers* according to Beurs' recipe, made by Lisa Wiersma. Each image corresponds to a step in the recipe. (Bottom) Layers representing pictorial material cues for edge reflections, bloom, specular highlights and seeds, obtained by subtraction of the steps in the reconstruction process.

To generate the stimuli for the experiment we used the optical mixing procedure [52, 53], an image combination technique that resembles the systematic layering approach of painters [54]. The layers recombined via optical mixing were obtained by subtracting the first image in Figure 3.4 (top) from the second, the second from the third, etc. The resulting layers, carrying the individual cues, are shown in Figure 3.4 (bottom). Using the optical mixing interface, we made 162 stimuli [3]. We used the interface to control and manipulate the weights of each layer, which

[3] The images of the 162 combinations and their corresponding layer weights are available in Supplementary Figure S2 and Supplementary Table S1 in 3.7

could be placed anywhere between 0 and 100%. The stimuli were made via the following combinations of the layers' weights: the first layer, corresponding to the body colour, was kept constant at 100%; the layers 2 to 5 (edge reflections, bloom on the lit and on the shaded side, and highlights) were taken with weights of 0, 50 or 100%; the layer of the seeds was either 0 or 100%. Some examples of the stimuli and their change in appearance according to the weights of the layers are shown in Figure 3.5.

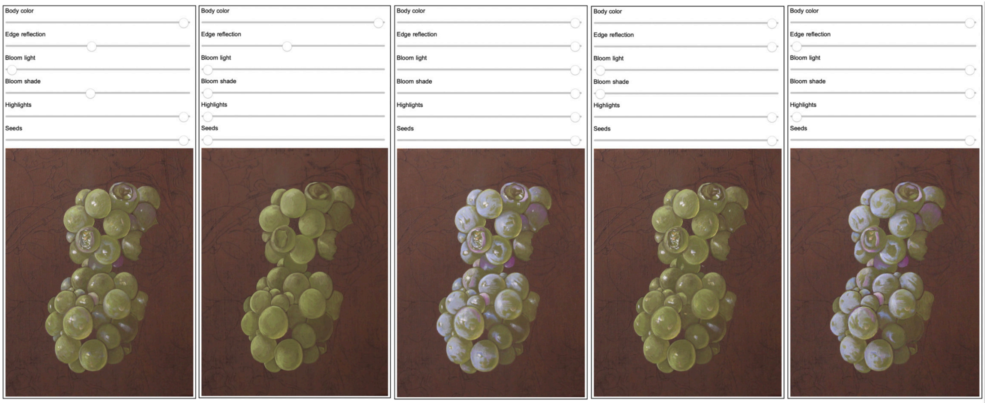


Figure 3.5: Examples of the stimuli obtained with the optical mixing interface by combining different weights of the layers. From left to right the weights of the layers edge reflections, bloom on the lit side, bloom on the shaded side, specular highlights and seeds, are: (1) 50%, 0, 50%, 100%, 100%; (2) 50%, 0, 0, 0, 0; (3) 100%, 100%, 100%, 100%, 100%; (4) 100%, 0, 0, 100%, 100%; (5) 0, 100%, 100%, 0, 100%.

3.3. Procedure

The procedure was the same for experiments 1 and 2, with the only difference being the stimuli presented. Participants were asked to rate on a continuous seven-point scale the five attributes derived from Beurs: three-dimensionality, translucency, glossiness, bloom and convincingness. A written definition of each attribute and an explanation of the polarity of the scale were provided before starting the experiment. The attributes were defined as follows:

- Translucency: how translucent do the grapes appear to you? Low values indicate that no light passes through the grapes and the appearance is opaque; high values indicate that some light passes through the grapes.
- Glossiness: how glossy do the grapes appear to you? Low values indicate a matte appearance; high values indicate a shiny appearance.
- Bloom: it is the whitish layer covering the surface of the grapes. How much bloom appears to be on the grapes? Low values mean that there is no bloom at all; high values indicate that the grapes are completely covered with bloom.

- Three-dimensionality: how three-dimensional do the grapes look? Low values indicate a flat appearance; high values indicate that the grapes look three-dimensional.
- Convincingness: how convincing is the representation of the grapes' appearance? To what extent do you recognize the features that you would expect to see in a real bunch of grapes? Low values mean that the representation is not convincing at all; high values indicate that all the expected features necessary to recognize a real bunch of grapes are present.

The understanding of the meaning of translucency, glossiness and bloom was verified with a two-alternative choice test. A pair of photographs of real grapes was shown to the participants to test the three attributes, with one photo having the attribute and one not. Observers were asked to choose which one was more translucent, bloomy or glossier. They were given feedback on the answer, and if they were able to choose the right options they could start the experiment. The question presented on the screen was "How [attribute] is this bunch of grapes on average?".

The attributes were rated separately in five blocks, in a random order (between and within each block), resulting in 390 trials per observer for the 78 stimuli of experiment 1, and 810 trials for the 162 stimuli of experiment 2. In experiment 3, participants rated convincingness only, for the same stimuli as in experiment 1, on a continuous seven-point scale. The 78 stimuli were rated three times in random order in one block, for a total of 234 trials per observer.

The experiments were conducted in a darkened room. The stimuli were presented against a black background, on an EIZO LCD monitor (CG277). Colour consistency was ensured by calibrating the monitor before each session, with the software Color Navigator 6 (EIZO Hakusan, Ishikawa, Japan; version 6.4.18.4; brightness 100 cd/m2, colour temperature 5500 K). The interfaces of the experiments were programmed in MATLAB R2016b (Math-Works, Natick, MA, USA), using the Psychtoolbox Version 3.0.14 [55–57]. Prior to the experiments, participants had the possibility to go through all the stimuli in order to get an overview of the stimulus range. No time limit was given to complete the tasks.

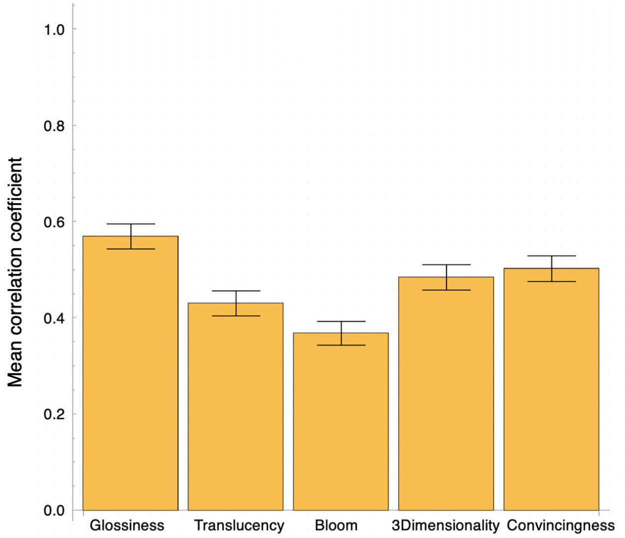
3.4. Results

3.4.1. Consistency between subjects

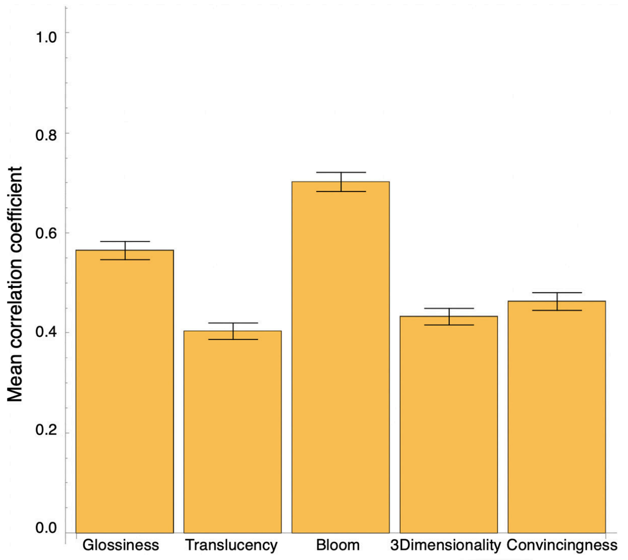
We checked for the consistency between raters of each experiment. To minimize possible effects of unequal interval judgements, the data of all observers were normalized before averaging. To measure the agreement between observers, the ratings of each participant were correlated with the mean ratings of the other participants.

For experiment 1, all correlations were positive and significant ($p<0.001$), ranging from 0.81 to 0.52 for glossiness, 0.72 to 0.39 for translucency, 0.63 to 0.37 for bloom, 0.77 to 0.41 for three-dimensionality and 0.71 to 0.48 for convincingness.

In Figure 3.6a we plotted the mean correlations of the ratings to visualize the dependency of the agreement between participants on the attributes. Participants



(a)



(b)

Figure 3.6: (a) Mean correlations of the attributes rated in experiment 1. (b) Mean correlations of the attributes rated in experiment 2. The error bars indicate the standard error of the mean.

were most consistent when rating glossiness, and next for convincingness and three-dimensionality. The least agreement was found for translucency and bloom.

For experiment 2, the correlations were all positive and significant ($p<0.001$), ranging from 0.82 to 0.39 for glossiness, 0.72 to 0.30 for translucency, 0.87 to 0.62 for bloom, 0.76 to 0.36 for three-dimensionality and 0.77 to 0.46 for convincingness. In Figure 3.6b, the mean correlations of the ratings for each attribute are plotted. The inter rater agreement again depended on the attribute rated. To the contrary of what we found for experiment 1, people agreed most on the rating of bloom. The order of the other mean correlations was the same as in experiment 1, and the attribute translucency was rated again less consistently across participants. Overall the agreement on convincingness was somewhat lower than in experiment 1.

The inter rater agreement was calculated also for experiment 3. In this experiment participants were asked to rate convincingness three times per stimulus. We took the median of the three repetitions to account for potential outliers, and then calculated the correlations between observers. All correlations were positive and significant ($p<0.001$) ranging from 0.85 to 0.53. The mean intra rater correlations ranged between 0.8 and 0.48 ($p<0.001$). The high agreement between and within subjects suggests that convincingness perception was consistent and stable.

3.4.2. Convincingness perception explained by Beurs's recipe

In experiment 1, convincingness was highly correlated with three-dimensionality, it was moderately but significantly correlated with glossiness and translucency, and it showed no correlation with bloom (Figure 3.7). To predict perceived convincingness from the attributes' ratings, we used multiple linear regression. The best-fitting model (equation 3.1) carries only glossiness and three-dimensionality as significant predictors. This model explains 66% of the variance of perceived convincingness:

$$Convincingness = 0.01 + 0.1 Glossiness + 0.8 ThreeD \tag{3.1}$$

However, the semi-partial correlation between convincingness and glossiness is 0.065, meaning that the term glossiness in the model does not explain any additional variance of convincingness above what is already explained by three-dimensionality. The contribution of glossiness, which appears to be redundant, can be deleted. The best-fitting model for convincingness of the 'average' bunch of grapes has only three-dimensionality as significant predictor (equation 3.2), with an explained variance of 65%:

$$Convincingness = 0.04 + 0.84 ThreeD \tag{3.2}$$

In experiment 2, convincingness was highly and positively correlated with glossiness, translucency and three-dimensionality, and negatively with bloom (Figure 3.8). A multiple linear regression of the rated attributes resulted in the best-fitting model carrying all the attributes as significant predictors of perceived convincingness (equation 3.3). The variance explained by this model is r^2 = 84%:

$$Convincingness = 0.07 + 0.3 ThreeD - 0.14 Bloom + 0.24 Translucency + 0.4 Gloss \tag{3.3}$$

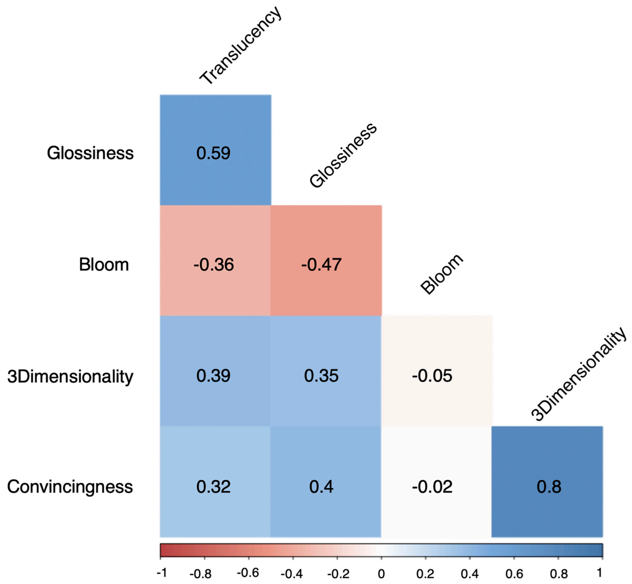


Figure 3.7: Correlation matrix of the mean ratings of the attributes in experiment 1. Each cell reports the value of the non-partial correlation coefficient.

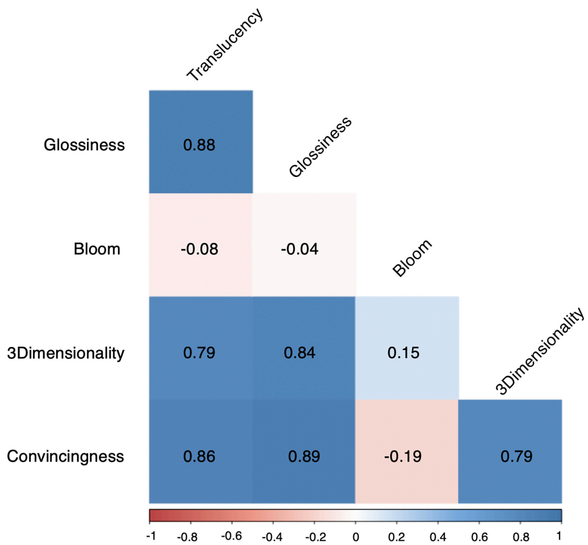


Figure 3.8: Correlation matrix of the mean ratings of the attributes in experiment 2. Each cell reports the value of the non-partial correlation coefficient.

3.4.3. Pictorial cues for convincingness

We found that for the bunch of grapes reproduced in experiment 2, convincingness on average was related to all the attributes. Now we want to know which combinations of pictorial cues produced the most and the least convincing representations of the bunch. By manipulating the weights of the layers, we could control for the presence of the cues in the images.

The weights of the layers' (edge reflections, bloom on the lit side, bloom on the shaded side, specular highlights and seeds) combinations for the least and most convincing grapes on average were (50%, 0, 0, 0, 0) and (50%, 0, 50%, 100%, 100%), respectively. The corresponding images are shown in Figure 3.5 (the first two images from the left). The least convincing bunch had (excluding the base) none of the layers and related cues of the material properties given by Beurs [2, 3]. The only exception was the weight of the edge reflections layer, being 50% instead of 0. However, a *t*-test showed that for the bunch perceived to be least convincing the convincingness rating was not significantly different ($p>0.05$) from that of the bunch having all layers set to 0.

The most convincing bunch, instead, presented all the prescribed layers except for the bloom. Following Beurs, we expected the image with all the layers set to 100% (see Figure 3.5, third image) to be the most convincing, but a *t*-test showed that those two images were significantly different ($p<0.01$) in perceived convincingness.

The weights of the pictorial cues were also correlated to the material properties that they were supposed to trigger. The weights of the layers bloom on the lit side and bloom on the shaded side had, respectively, $r = 0.92$ ($p<0.001$) and $r = 0.33$ ($p<0.001$) with perceived bloom. The weights of the highlights' layer correlated highly and significantly both with glossiness ($r = 0.94$, $p<0.001$) and translucency perception ($r = 0.87$, $p<0.001$). The weights of the edge reflections layer had a moderate but significant positive correlation with translucency ($r = 0.19$, $p<0.001$).

3.4.4. Correlation between convincingness ratings in experiment 1 and 3

To test the assumption that convincingness was judged consistently, regardless of the amount of information given or actively directing attention towards certain aspects, we plotted the correlation between the average ratings of experiments 1 and 3, i.e. with and without specifying the material attributes (Figure 3.9). The correlation coefficient between the ratings was high, positive and significant ($r = 0.87$, $p<0.001$). However, when comparing the Cronbach's alpha values of the two experiments (0.98 for experiment 1 and 0.91 for experiment 3) with a *t*-test, we found a significant difference between the two values ($p<0.05$). This suggests that participants in experiment 1 were more consistent with each other when rating convincingness compared to participants of experiment 3.

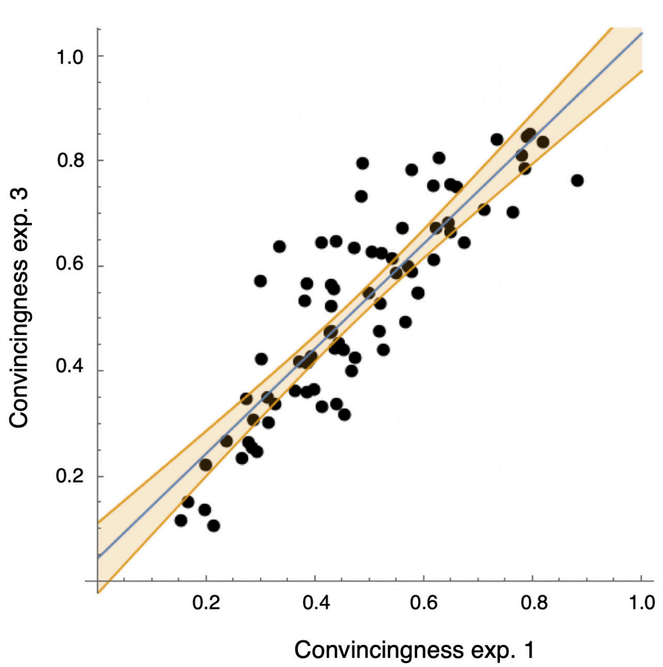


Figure 3.9: Scatterplot of the correlation between the average convincingness ratings of experiment 1 and of experiment 3. r = 0.87, p<0.001; the area around the fit line represents the 95% confidence interval.

3.5. Discussion

The order of the mean correlations of the attributes in experiments 1 and 2 was the same except for bloom. Bloom was perceived least consistently across subjects in experiment 1 (Figure 3.6a), but it had the most agreement in experiment 2 (Figure 3.6b). To the contrary of experiment 1, the stimuli of experiment 2 represented variations of the same bunch of grapes, with a clear depiction of the confirmed by the high correlation between bloom perception and the weights of the bloom layer in experiment 2, indicating that the bloom cue was a clear trigger of bloom perception for the reproduced bunch of grapes. However, the bloom cue might have been less obvious in the stimuli of experiment 1, probably due to the different painting techniques and the diverse variety of depicted grapes. This could result in different styles to render the bloom layer, which may have been perceived as a diffuse reflection when applied thinly, rather than something covering the surface, and vice versa. This was maybe the case for the bunch shown in Figure 3.10, whose bloom perception caused the most disagreement.

Translucency was perceived the second least consistently in experiment 1 (Figure 3.6a) and the least in experiment 2 (Figure 3.6b). The optical phenomenon that elicits translucency is subsurface scattering, i.e., light enters a body, it is partly absorbed and partly scattered within the body, and it reemerges at different locations

Figure 3.10: Stimulus whose bloom perception was rated the least consistently in experiment 1. Jan van Huysum, *Fruit Piece*, 1722. J. Paul Getty Museum, Los Angeles, CA, USA.

of the surface. The physics of translucency is well known, but the visual cues that trigger its perception are less well understood (but see [58]). Koenderink and Van Doorn [59] investigated the shape from shading theory for translucent objects and concluded that determining general laws to explain the appearance of translucent objects is far from trivial, given that it depends on illumination and viewing directions and on the object's shape. Since the appearance of translucent objects is dependent on so many factors, it varies enormously in ecologically valid conditions, which might explain the relatively low consistency found in our experiments.

On the other hand, the agreement between participants on glossiness was the highest in experiment 1 (Figure 3.6a) and the second highest in experiment 2 (Figure 3.6b). In case of experiment 2, the high agreement can be easily explained by the highlight cue, whether it was present or absent from the layers' combinations. In experiment 1, the high agreement shows that participants were relying on a common set of cues to make their judgements. In the stimuli of experiment 1, the way of rendering the highlights on the grapes was dependent on the personal style of the painter. Differences in the application of the brushstrokes, e.g., fine and invisible or rough and discernible, could have affected the perceived magnitude of glossiness, if people were basing their judgements on the realism of the highlights. In another study [22] (see Chapter 4), we found the main predictor of glossiness perception to be the contrast of the highlights, followed by their blurriness, despite how realistically the highlights were depicted. An example is shown in Figure 3.11. The bunch on the left was perceived to be significantly glossier ($p<0.05$) than the one on the right, even though its highlights look poorly realistic, and are recognizable as white dubs of paint, but with high contrast and sharp nonetheless.

Figure 3.11: Two stimuli showing that glossiness perception was dependent mostly on the contrast and sharpness of the highlights rather than on how realistically the highlights were depicted. The bunch on the left was perceived as glossier than the one on the right. (Left) Abraham Hendricksz. van Beyeren, *Still Life with Silver-gilt Bekerschroef with Roemer*, 1640–1670. Rijksmuseum, Amsterdam, The Netherlands. (Right) Jan Davidsz. de Heem, *Garland of Fruits and Flowers*, ca. 1650–1660. Mauritshuis, The Hague, The Netherlands.

The agreement was medium on the perception of three-dimensionality in experiment 1 (Figure 3.6a). In this case, it is possible that the realism of the 3D depiction was confounded with the magnitude of the perceived depth. An increase in the magnitude of depth perception is known to be associated with increased perception of realism of three-dimensionality [11, 60], but the latter also depends on the precision of depth representation and perception [61], which might cause inconsistencies.

To test whether Beurs' attributes explained convincingness perception of grapes, we performed multiple linear regressions of the ratings, both from experiments 1 and 2. For experiment 1, we found that three-dimensionality was the only significant predictor for perceived convincingness (equation 3.2). In real life grapes are three-dimensional, providing a straightforward explanation for the fundamental role of three-dimensionality in convincingness perception. However, a further explanation for the high correlation between three-dimensionality and convincingness could be ascribable to a confounding effect of the realism of the 3D depiction being rated instead of its magnitude. The material properties, translucency, bloom and glossiness, could not be encompassed in a single regression model with defined weights that could fit each and every bunch of grapes. Due to the wide variety of grapes, the best combination of material attributes needs to be tailored on the single case. Figure 3.12 shows three examples extracted from the 15% most convincing grapes of experiment 1. The bar charts of the average ratings, paired with the corresponding stimulus, show very different patterns in the material attributes, all leading to a judged-to-be-convincing appearance.

Note that, even though on average we found convincingness to be positively

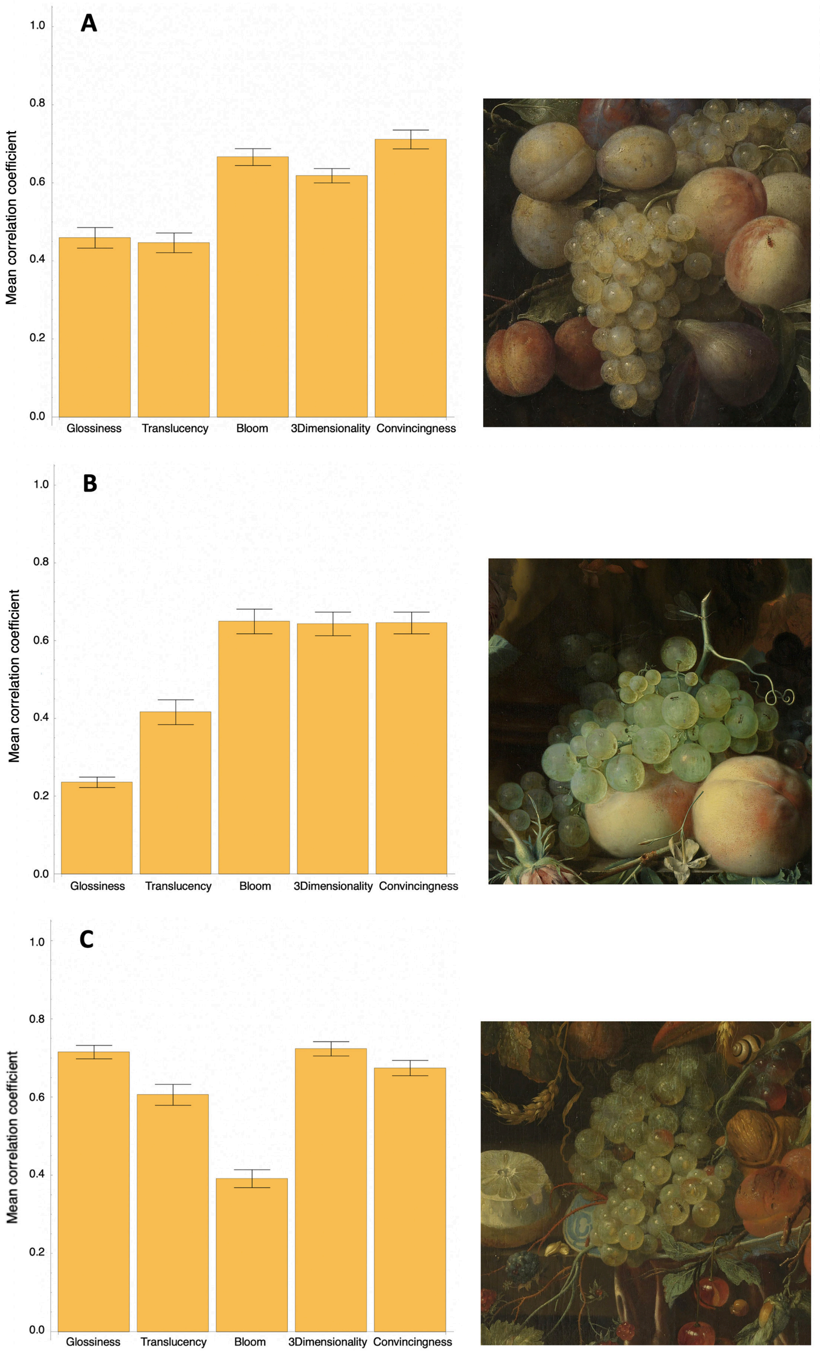


Figure 3.12: Mean ratings of the attributes rated in experiment 1 for three of the 15% most convincing stimuli. The error bars indicate the standard error of the mean. (A) Jan Frans van Son, *Marble Bust surrounded by a Festoon of Fruit*, 1680–1718; (B) Jan van Huysum, *Still Life with Flowers and Fruit*, 1721; (C)(copy after) Jan Davidsz. de Heem, *Still Life with Fruit and a Lobster*, 1640–1700. Rijksmuseum, Amsterdam, The Netherlands.

correlated with glossiness and translucency (Figure 3.7), this does not imply that these material properties should be increased to their maximum in order to trigger the most convincing appearance. We could not define the appropriate amounts of glossiness, translucency and bloom, we could just recognize, as Beurs also did in his recipe [2, 3], that grapes can show all these optical interactions, but the weights of their combination for the most convincing result is left to decide to everybody's own "schema" [5] of grapes.

The convincingness of the reconstruction of the bunch of grapes tested in experiment 2, was best predicted by all the attributes (equation 3.3), even though the bloom had a more nuanced contribution compared to Beurs's instructions — the most convincing grapes were found to have no bloom on the lit side and 50% on the shaded side. The bloom layer naturally occurs on grapes, and it is even considered a parameter for postharvest fruit quality measurement [62]. However, the presence of bloom on the surface of the grapes often leads to a negative impression of the naturalness and quality of the fruit [63]. To meet consumers' expectations, grapes are usually sold polished in supermarkets, reducing our interaction and association of bloom with grapes. Participants may have also not associated bloom with convincingness because the bunch in the reconstruction was painted out of context. It was placed isolated against an umber ground, which may have overdone the visual effect of the cues, especially the bloom. In future reconstructions, we intend to include (part of) the background so as to avoid this possibility. Furthermore, it might be possible that the bloom layer was simply painted too thick in the reconstruction.

We further studied the relationship of Beurs's pictorial cues with perception of convincingness and the material attributes, in experiment 2. The combination of layers perceived as least convincing implicitly complied with Beurs's prescription given that they were all set to 0, or it was not significantly different from the one with all the layers set to 0. The only slight exception concerned the weight of the edge reflections layer. This might be due to the fact that during the painting of

Figure 3.13: The three weights of the edge reflections layer: left 0%, center 50%, right 100%.

the first step of the recipe, a light part was already laid down along the edge of some of the berries as preparation for the second step, i.e. the application of the edge reflections. The colours prescribed to paint the lit side and the reflections are almost the same. Thus, it could be visually misleading as if also with weight zero of the edge reflections layer, the reflections were already there; and the difference between 0 and 50% is rather subtle (Figure 3.13). The most convincing combination had all the layers except bloom, confirming the result of the predictive model. Its convincingness rating was significantly different from the image with all the layers set to 1, which according to Beurs should result in the most convincing appearance. Beurs's recipe, though, is not a strict set of rules and there is no definition for how the weights of the layers should be distributed to get the optimal result, leaving room for the artist's personal interpretation. Additionally, as discussed above, the effect of the bloom cue may have been exaggerated by the lack of context and background or too thick painting.

We tested the assumption that convincingness was judged consistently despite the amount of information given and attentional focus on specific aspects. In experiment 3, the observers were not explicitly attending our candidate attributes next to convincingness, but we still found high correlation with the convincingness ratings of experiment 1 (Figure 3.9). Therefore, we assume that their judgements were based on similar features. An interesting exception is the bunch shown in Figure 3.10, which was rated moderately convincing in experiment 1 but highly convincing in experiment 3. As already noticed, this bunch caused the most disagreement on the perception of bloom in experiment 1. When the patina on the surface of the grapes was identified as bloom, the perception of convincingness dropped, contributing negatively to the overall mean convincingness which resulted to be moderate. In experiment 3, the same bunch was perceived to be highly convincing probably because participants were not questioning the nature of the haziness of these grapes, since they were not instructed to look for bloom. The Cronbach's alpha values of perceived convincingness in both experiments were above 0.9, demonstrating the high inter rater agreement, but these values were also significantly different. Participants of experiment 1 were more consistent among each other than participants of experiment 3. Actively looking for the material attributes in experiment 1 may have made it easier for participants to judge convincingness, probably due to a process of perceptual learning and selective attention for the relevant cues [64].

3.6. Conclusions

In the present study we aimed to determine which properties, among the ones prescribed by Beurs in his recipe, are relevant for a convincing depiction of grapes.

The prototype of 'convincing grapes' does not exist. The material properties prescribed by Beurs present a wide range of combinations that can lead to convincing appearances. We have shown that convincingness of grapes painted throughout the 17^{th} century by different artists was predicted by three-dimensionality only; whereas the influence of glossiness, translucency and bloom was case-dependent. The 17^{th} century workshop traditions and recipes thus show more variability than standardization for grapes. However, when we considered only one bunch of grapes, all the attributes prescribed by Beurs were predictors of convincingness, with bloom being a negative predictor. This was contrary to what we expected, but likely ascribable to a limitation of our stimuli. We showed that people judged convincingness consistently, but they tended to agree more when also the material attributes were provided. This might be due to processes involving more understanding and attention for the pictorial cues with regard to the material.

Beurs grasped the basic optical interactions of grapes with light and translated them into those effective pictorial cues. Disclosing and making explicit the pictorial cues and the visual dimensions along which perceptual convincingness was achieved by painters, is an important contribution not only for vision science and art history, but also for the field of computer rendering. We have shown that research on material perception can benefit from the study of art historical writings and from the body of 17^{th} century naturalistic paintings.

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3.7. Supplementary material

Figure S1.

Numbered list of all the squared cut-outs used for rating experiments 1 and 3. Each image in the list has the embedded link in the caption to the relative museum repository website.


Stimulus 1

Stimulus 2

Stimulus 3

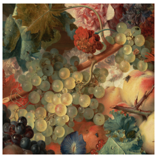
Stimulus 4

Stimulus 5

Stimulus 6

Stimulus 7

Stimulus 8

Stimulus 9

Stimulus 10

Stimulus 11

Stimulus 12

Stimulus 13

Stimulus 14

Stimulus 15

Stimulus 16

Stimulus 17

Stimulus 18

Stimulus 19

Stimulus 20

Stimulus 21

Stimulus 22

Stimulus 23

Stimulus 24

Stimulus 25

Stimulus 26

Stimulus 27

Stimulus 28

Stimulus 29

Stimulus 30


Stimulus 31


Stimulus 32


Stimulus 33


Stimulus 34


Stimulus 35


Stimulus 36


Stimulus 37


Stimulus 38


Stimulus 39


Stimulus 40


Stimulus 41


Stimulus 42


Stimulus 43


Stimulus 44


Stimulus 45


Stimulus 46


Stimulus 47


Stimulus 48


Stimulus 49


Stimulus 50


Stimulus 51


Stimulus 52


Stimulus 53


Stimulus 54


Stimulus 55


Stimulus 56


Stimulus 57


Stimulus 58


Stimulus 59


Stimulus 60

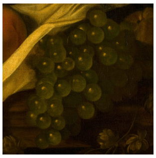

Stimulus 61


Stimulus 62


Stimulus 63


Stimulus 64


Stimulus 65


Stimulus 66


Stimulus 67


Stimulus 68


Stimulus 69


Stimulus 70


Stimulus 71


Stimulus 72


Stimulus 73


Stimulus 74

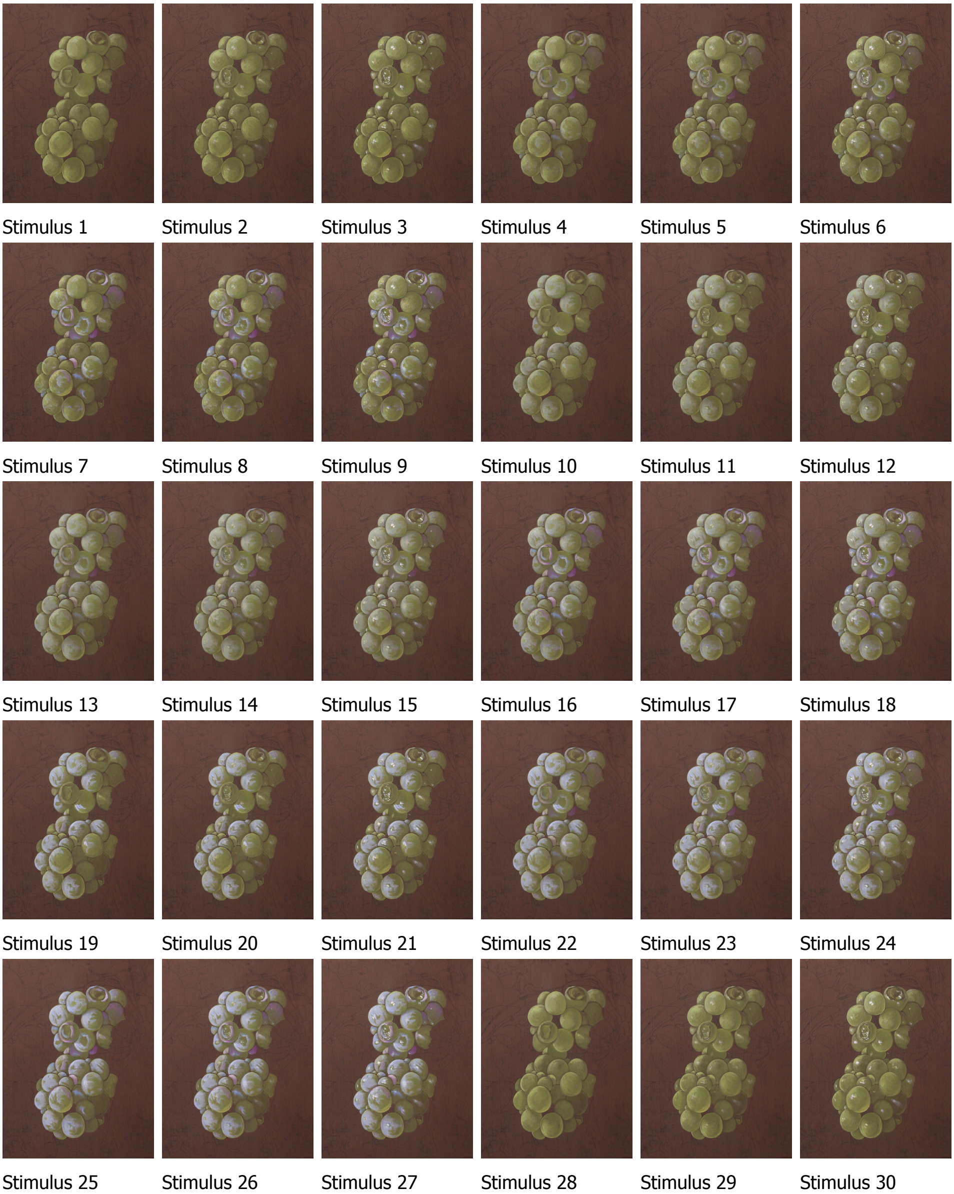

Stimulus 75

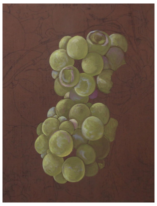

Stimulus 76


Stimulus 77


Stimulus 78

Figure S2.
List of the stimuli used in experiment 2, made by layers' combination using optical mixing.

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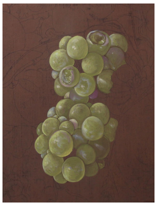
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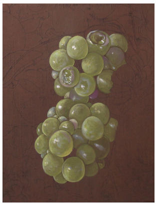
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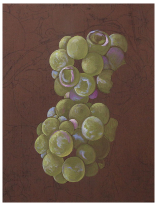
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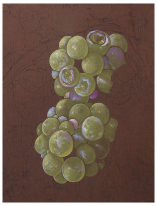
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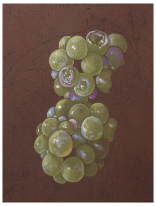
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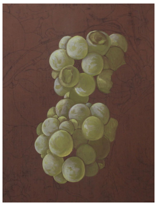
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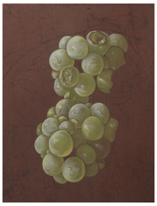
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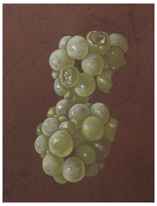
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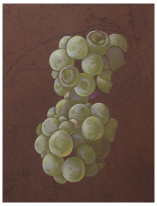
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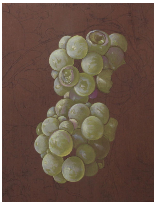
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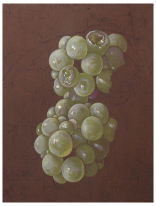
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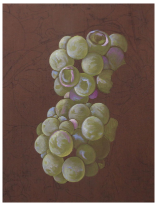
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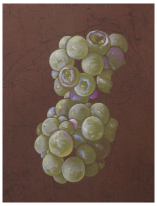
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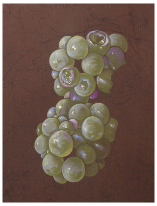
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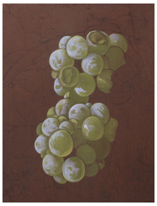
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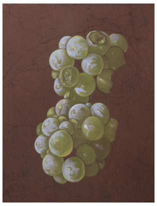
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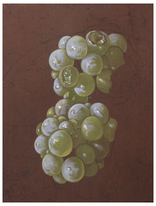
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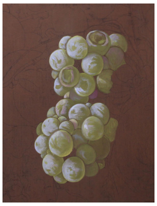
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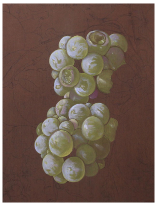
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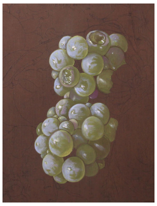
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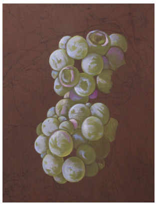
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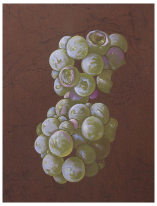
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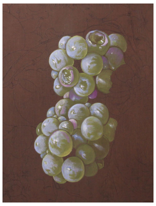
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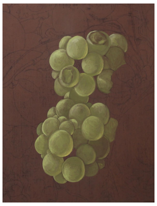
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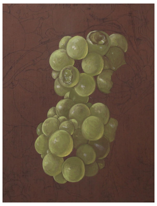
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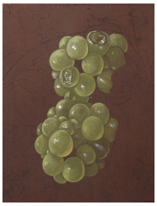
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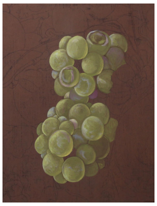
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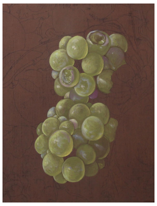
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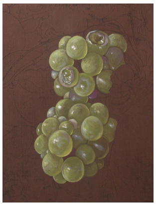
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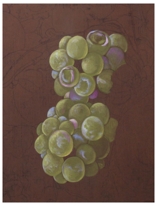
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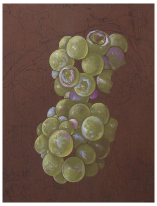
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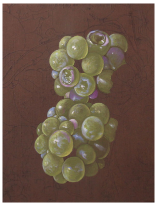
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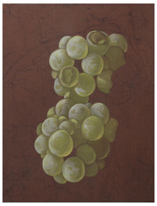
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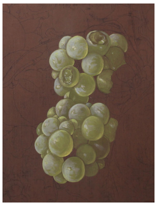
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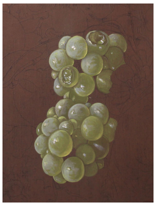
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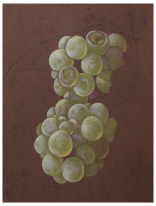
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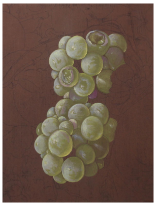
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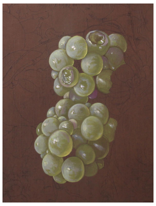
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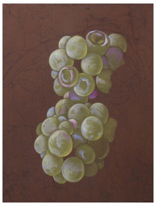
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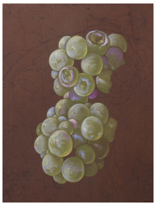
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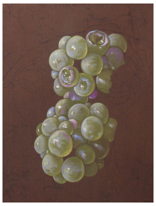
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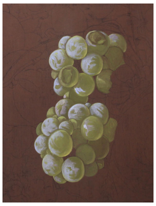
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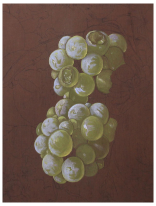
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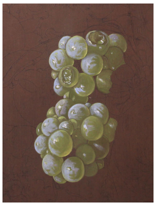
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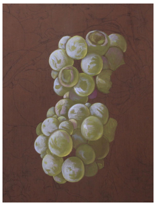
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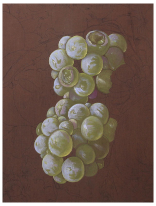
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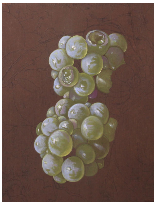
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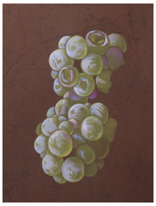
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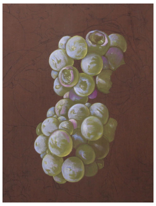
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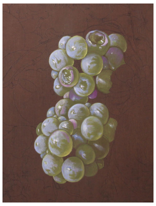
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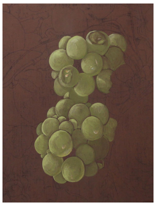
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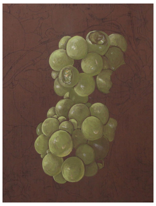
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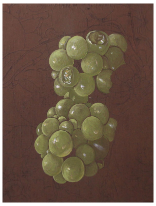
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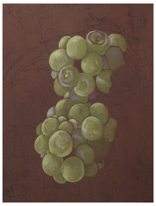
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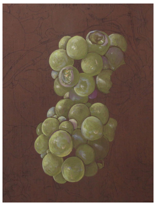
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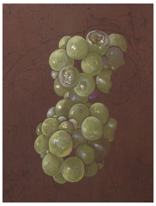
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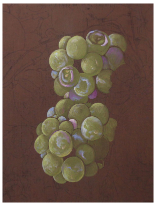
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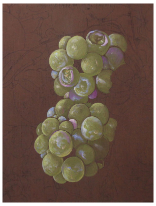
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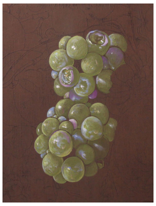
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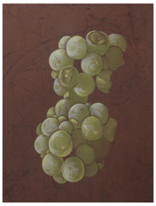
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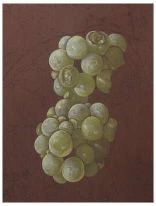
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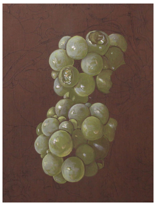
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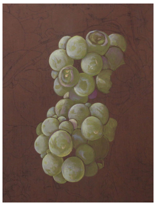
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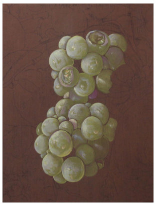
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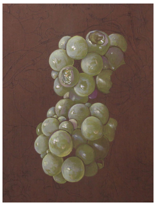
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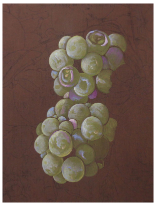
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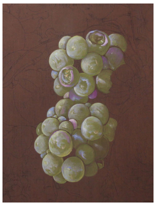
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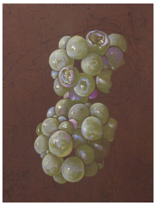
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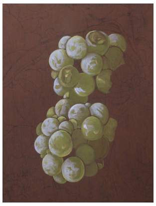
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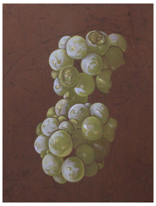
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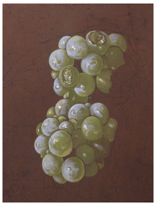
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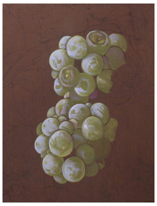
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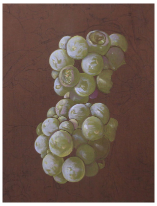
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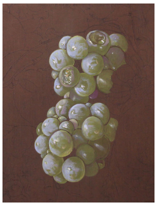
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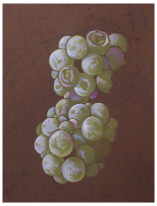
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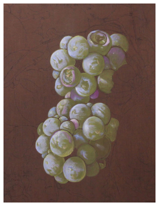
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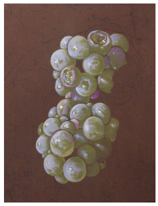
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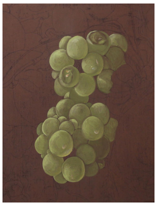
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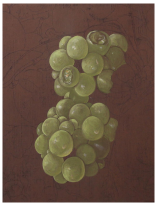
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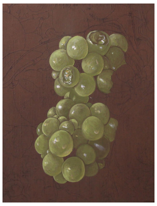
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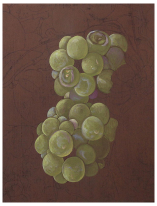
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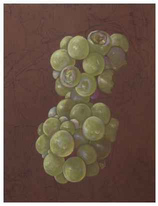
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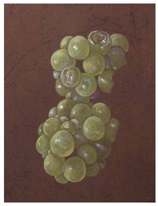
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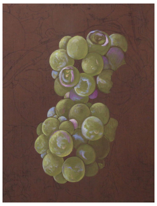
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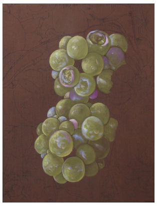
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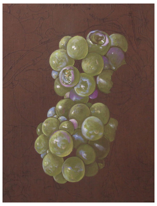
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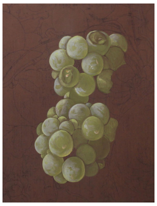
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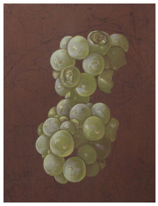
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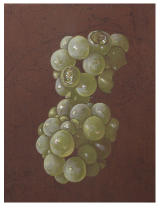
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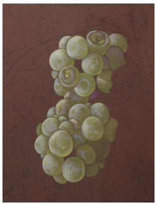
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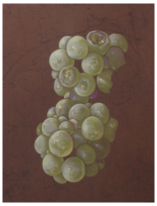
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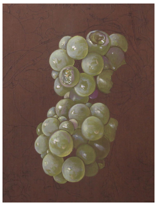
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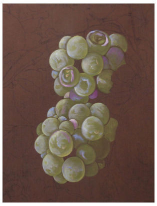
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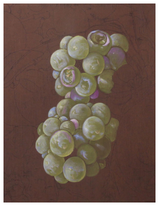
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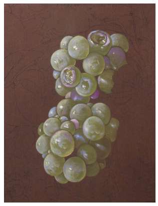
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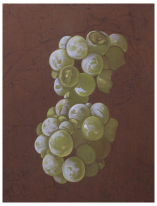
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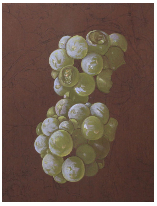
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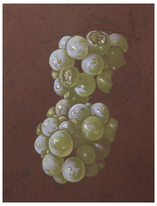
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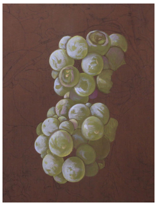
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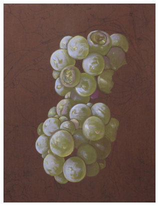
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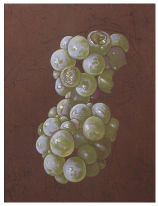
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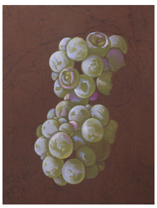
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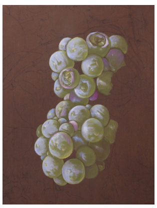
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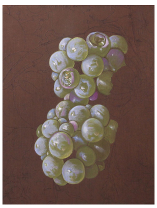
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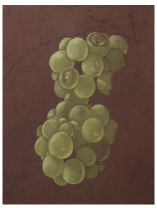
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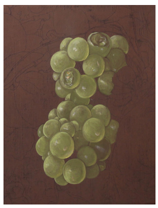
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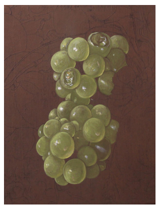
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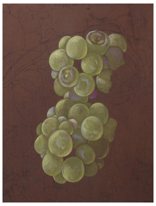
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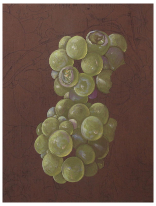
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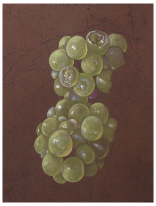
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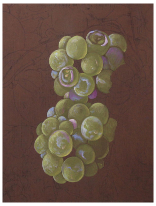
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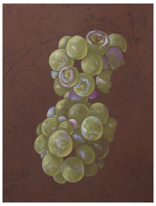
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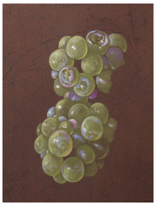
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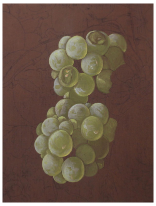
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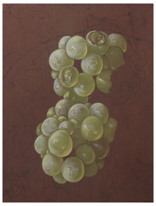
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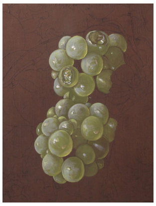
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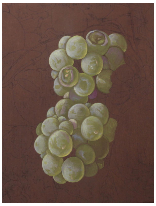
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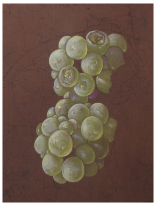
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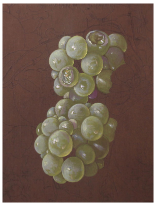
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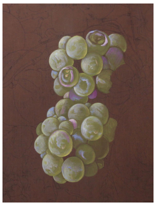
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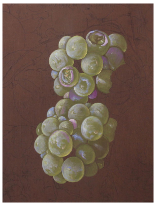
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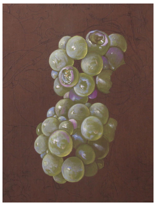
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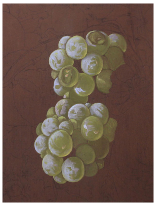
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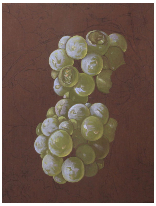
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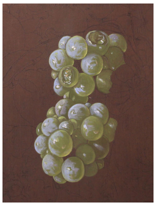
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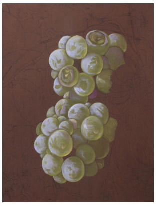
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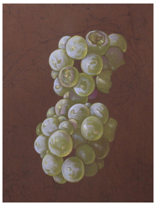
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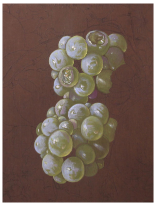
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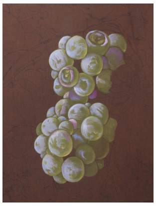
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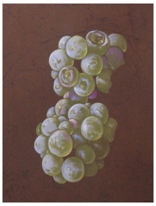
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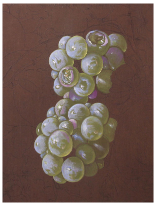
Stimulus 162

Table S1.
Weights of the layers combined to make the stimuli of experiment 2. The numbers correspond to the numbers of the images in Figure S2.

Stimuli	Edge reflection	Bloom lit	Bloom shade	Highlights	Seeds
1	0	0	0	0	0
2	0	0	0	0.5	0
3	0	0	0	1	0
4	0	0	0.5	0	0
5	0	0	0.5	0.5	0
6	0	0	0.5	1	0
7	0	0	1	0	0
8	0	0	1	0.5	0
9	0	0	1	1	0
10	0	0.5	0	0	0
11	0	0.5	0	0.5	0
12	0	0.5	0	1	0
13	0	0.5	0.5	0	0
14	0	0.5	0.5	0.5	0
15	0	0.5	0.5	1	0
16	0	0.5	1	0	0
17	0	0.5	1	0.5	0
18	0	0.5	1	1	0
19	0	1	0	0	0
20	0	1	0	0.5	0
21	0	1	0	1	0
22	0	1	0.5	0	0
23	0	1	0.5	0.5	0
24	0	1	0.5	1	0]
25	0	1	1	0	0
26	0	1	1	0.5	0
27	0	1	1	1	0
28	0.5	0	0	0	0
29	0.5	0	0	0.5	0
30	0.5	0	0	1	0
31	0.5	0	0.5	0	0
32	0.5	0	0.5	0.5	0
33	0.5	0	0.5	1	0
34	0.5	0	1	0	0
35	0.5	0	1	0.5	0
36	0.5	0	1	1	0
37	0.5	0.5	0	0	0
38	0.5	0.5	0	0.5	0
39	0.5	0.5	0	1	0
40	0.5	0.5	0.5	0	0
41	0.5	0.5	0.5	0.5	0

42	0.5	0.5	0.5	1	0
43	0.5	0.5	1	0	0
44	0.5	0.5	1	0.5	0
45	0.5	0.5	1	1	0
46	0.5	1	0	0	0
47	0.5	1	0	0.5	0
48	0.5	1	0	1	0
49	0.5	1	0.5	0	0
50	0.5	1	0.5	0.5	0
51	0.5	1	0.5	1	0
52	0.5	1	1	0	0
53	0.5	1	1	0.5	0
54	0.5	1	1	1	0
55	1	0	0	0	0
56	1	0	0	0.5	0
57	1	0	0	1	0
58	1	0	0.5	0	0
59	1	0	0.5	0.5	0
60	1	0	0.5	1	0
61	1	0	1	0	0
62	1	0	1	0.5	0
63	1	0	1	1	0
64	1	0.5	0	0	0
65	1	0.5	0	0.5	0
66	1	0.5	0	1	0
67	1	0.5	0.5	0	0
68	1	0.5	0.5	0.5	0
69	1	0.5	0.5	1	0
70	1	0.5	1	0	0
71	1	0.5	1	0.5	0
72	1	0.5	1	1	0
73	1	1	0	0	0
74	1	1	0	0.5	0
75	1	1	0	1	0
76	1	1	0.5	0	0
77	1	1	0.5	0.5	0
78	1	1	0.5	1	0
79	1	1	1	0	0
80	1	1	1	0.5	0
81	1	1	1	1	0
82	0	0	0	0	1
83	0	0	0	0.5	1
84	0	0	0	1	1
85	0	0	0.5	0	1
86	0	0	0.5	0.5	1

87	0	0	0.5	1	1
88	0	0	1	0	1
89	0	0	1	0.5	1
90	0	0	1	1	1
91	0	0.5	0	0	1
92	0	0.5	0	0.5	1
93	0	0.5	0	1	1
94	0	0.5	0.5	0	1
95	0	0.5	0.5	0.5	1
96	0	0.5	0.5	1	1
97	0	0.5	1	0	1
98	0	0.5	1	0.5	1
99	0	0.5	1	1	1
100	0	1	0	0	1
101	0	1	0	0.5	1
102	0	1	0	1	1
103	0	1	0.5	0	1
104	0	1	0.5	0.5	1
105	0	1	0.5	1	1
106	0	1	1	0	1
107	0	1	1	0.5 1	
108	0	1	1	1	1
109	0.5	0	0	0	1
110	0.5	0	0	0.5	1
111	0.5	0	0	1	1
112	0.5	0	0.5	0	1
113	0.5	0	0.5	0.5	1
114	0.5	0	0.5	1	1
115	0.5	0	1	0	1
116	0.5	0	1	0.5	1
117	0.5	0	1	1	1
118	0.5	0.5	0	0	1
119	0.5	0.5	0	0.5	1
120	0.5	0.5	0	1	1
121	0.5	0.5	0.5	0	1
122	0.5	0.5	0.5	0.5	1
123	0.5	0.5	0.5	1	1
124	0.5	0.5	1	0	1
125	0.5	0.5	1	0.5	1
126	0.5	0.5	1	1	1
127	0.5	1	0	0	1
128	0.5	1	0	0.5	1
129	0.5	1	0	1	1
130	0.5	1	0.5	0	1
131	0.5	1	0.5	0.5	1

132	0.5	1	0.5	1	1
133	0.5	1	1	0	1
134	0.5	1	1	0.5	1
135	0.5	1	1	1	1
136	1	0	0	0	1
137	1	0	0	0.5	1
138	1	0	0	1	1
139	1	0	0.5	0	1
140	1	0	0.5	0.5	1
141	1	0	0.5	1	1
142	1	0	1	0	1
143	1	0	1	0.5	1
144	1	0	1	1	1
145	1	0.5	0	0	1
146	1	0.5	0	0.5	1
147	1	0.5	0	1	1
148	1	0.5	0.5	0	1
149	1	0.5	0.5	0.5	1
150	1	0.5	0.5	1	1
151	1	0.5	1	0	1
152	1	0.5	1	0.5	1
153	1	0.5	1	1	1
154	1	1	0	0	1
155	1	1	0	0.5	1
156	1	1	0	1	1
157	1	1	0.5	0	1
158	1	1	0.5	0.5	1
159	1	1	0.5	1	1
160	1	1	1	0	1
161	1	1	1	0.5	1

3

4

Understanding gloss perception through the lens of art

It's the mystery of reflection itself that continues to captivate us.

Jonathan Miller

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My contribution in [1] was the conceptualization of the research idea; to design and perform the rating experiments; to create the stimuli by collecting and cropping images of paintings; to acquire, analyze and interpret the data; to perform the image analysis to quantify the image features; to relate the perceptual findings to Beurs' recipe; to write the manuscript.

To understand the key image features that we use to infer the glossiness of materials, we analyzed the pictorial shortcuts used by 17th century painters to imitate the optical phenomenon of specular reflections when depicting grapes. Gloss perception of painted grapes was determined via a rating experiment. We computed the contrast, blurriness, and coverage of the grapes' highlights in the paintings' images, inspired by Marlow and Anderson [2]. The highlights were manually segmented from the images, and next the features contrast, coverage, and blurriness were semi-automatically quantified using self-defined algorithms. Multiple linear regressions of contrast and blurriness resulted in a predictive model that could explain 69% of the variance in gloss perception. No effect was found for coverage. These findings are in agreement with the instructions to render glossiness of grapes contained in the painting manual written by Beurs [3, 4], suggesting that painting practice embeds knowledge about key image features that trigger specific material percepts.

4

Like Bacchus, we never get tired of grapes. We have seen which material properties are to be expected in a convincing bunch of grapes, and how painters achieved it. A white dab on the top left and there you have a highlight for a shiny grape. But is that enough? In this chapter we will see that convincing glossy grapes require more fine tuning of the highlights. Make them too dull and you might compromise their fresh and juicy look. Make them too sharp and you will get a bunch of glass beads instead of grapes.

4.1. Introduction

In the last two decades, artists and vision scientists have boosted joint efforts to mutually profit from each other's knowledge [5–13]. Via careful observation of the world, painters have developed implicit knowledge of the key image features needed to render different materials, and they have transferred this knowledge to the canvas. Vision scientists can thus use artworks produced throughout the centuries to extract these features and understand visual perception. Naturalistic paintings offer novel learning possibilities to the ongoing research on gloss perception.

When rendering glossy materials, painters did not retrieve the exact reflectance function of the object they were depicting. Most likely, they rather portrayed the optical phenomenon representing its most salient characteristic, namely its specular peak, by applying a bright spot following the curvature of the surface [10]. Specular highlights are, indeed, the most common monocular cues used by painters to induce a glossy impression [14, 15]. Here we assume "real world illumination", allowing reliable and accurate estimations of the gloss [16], from one primary light source (e.g., a window, as was common in 17th century painting studios), and we ignore illumination variations.

According to Marlow, Kim, and Anderson [17], the key visible features of a highlight that affect gloss perception are coverage, sharpness, and contrast. They represent respectively the width, steepness, and height of the specular peak of the reflectance function. Perceptual effects of contrast, coverage, and sharpness of the specular reflections were already considered separately in literature [18–20], and found to influence gloss perception. Marlow et al. [17] investigated their combined effect. Following the study of Ho, Landy, and Maloney [21], Marlow et al. [17] extended the research on the perceptual interaction between bumpiness and glossiness, as a function of the illumination geometry. By varying the surface reliefs and illumination directions, but keeping constant the reflectance function, they observed variations in perceived glossiness. Such variations could be predicted by modeling the perceived values of contrast, sharpness, and coverage of the specular reflections. In a follow-up study, Marlow and Anderson [2] tested the efficacy of perceptual ratings of these highlights' features as predictors, by systematically varying their contribution in the stimuli. By tuning the extrinsic factors of surface geometry and illumination, they could manipulate the highlight features. They demonstrated that the weighted combination of the perceived highlight features can generate and predict the glossy appearance of spherical and planar rendered objects.

Here, we tested if the same holds for glossy materials depicted in paintings. We tested glossiness perception of grapes in Dutch 17th century paintings via a rating experiment, and whether those data can be predicted by the image features of the highlights. To do this, we developed a novel method to semi-automatically compute the features directly from segmented images of the paintings. The reason for preferring paintings from the 17th century over other periods is the accurate rendering of reality that characterizes this age. We chose to study grapes because they represent an accessible starting point, given their more or less spherical shape. Moreover, grapes offer the advantage of having been painted often during the 17th century, allowing us to collect a high number of stimuli. In addition to linking perceptual judgments and image analyses, we investigated whether we could find hints to the three highlights' features in the pictorial recipe for grapes contained in a 17th century treatise on oil painting, ”The big world painted small” [3, 4]. This treatise represents one of the most valuable art historical records of the 17th century studio practice. Throughout the six chapters that make up the treatise, Beurs[3, 4] provides detailed instructions and practical tips on how to render all kind of materials and surface textures. As the recipes of Beurs [3, 4] were shown to match the painting practice of some of his contemporaries [22–24], we can use this written source to grasp 17th century painters' implicit knowledge.

4.1.1. Previous work

It is known that gloss perception interacts with the 3D shape of the target object [21, 25, 26], its surface structure [27], and the light field in which it is embedded [16, 28–30]. Certain combinations of illumination directions and surface reliefs can even render a matte Lambertian surface to look glossy [31]. The presence of either highlights or lowlights is recognized to be the minimum requisite to convey a glossy impression [15, 18, 20, 32], as long as they are placed at the ”right” position on the surface, i.e., along the direction of minimal curvature [18, 33–36]. Moreover, highlights with simple shapes, as squares or circles, were found to be more effective than complex ones in producing a glossy impression [15]. In 1937, Hunter [37] pioneered the idea of the multidimensionality of glossiness, identifying six classes of gloss that differ in their appearance. In doing so, he laid the groundwork for the perceptual dimensions often used in the subsequent investigations on gloss. Ferwerda et al. [19] revealed the limitations of the dimensions proposed by Hunter, as being defined a priori. They suggested, instead, a psychophysically based model to predict gloss perception. Via multidimensional scaling, Ferwerda et al. [19] built a visual gloss space, whose perceptually meaningful axes were contrast and sharpness of the reflected image, for the specific set of conditions and stimuli they used. This gloss space should probably be extended with more dimensions, for extensions of the range of stimuli beyond dielectrics.

One popular approach to understand material perception from low-level image cues involves image statistics. For gloss perception, it has been proposed that the statistical moments of the luminance histogram of the image, such as the skewness, could be used as predictor [38, 39]. However, further researches have demonstrated that the skewness is not enough to explain perceived glossiness [35, 40, 41], and it fails to account for the influence of illumination geometry [42, 43]. Wiebel, Toscani, and Gegenfurtner [44] found an effect of skewness on glossiness, but only for computer rendered stimuli. When they tested photographs of natural surfaces, the main discriminative statistic for glossiness was the standard deviation of the luminance histogram, a measure for the contrast. Given the wide variety of glossy materials present in the world, Wiebel et al. [44] proposed the use of photographs of real surfaces as alternative to the time-consuming procedure of computer rendering.

Here, we aim to extend the study of gloss perception to true-to-life paintings, starting with paintings of grapes. We tested the three highlight features proposed by Marlow and Anderson [2], but instead of relying on human judgment to estimate them, we developed a new method to semi-automatically compute them from the segmented images of the paintings. Previous research concerning the influence of image cues on material perception have hitherto either used human judgments [2, 17] or luminance histogram-based moment statistics [38, 39]. The former approach appears to be motivated by difficulties designing robust algorithms that capture image properties like coverage, contrast, and sharpness of the highlights (but see also [45]) for segmentation of highlights based on pixel intensity threshold and pixel wise calculation of the features for the case of rendered surfaces with identical parameters settings). Yet, the drawback of relying on human judgments is that there could be interaction effects (e.g., an object appears glossier, causing the contrast to be perceived higher). Please note that the computation of these features also involves more than only the luminance histogram; in order to determine the coverage, sharpness, and contrast, the spatial characteristics of highlights need to be taken into account too, complicating the computation. Therefore, we propose an intermediate approach where human annotations assist the computation of the image properties. Understanding the effectiveness of this approach will not only answer our specific research questions but may also be useful for other studies concerning the relation between image cues and material perception.

4.2. Methods

Glossiness rating experiments were conducted on the cropped (A) and original (B) versions of the stimuli. The first experiment (A) was performed as main experiment, while the second (B) was done to investigate the influence of context of the whole painting on the gloss judgment of grapes. The highlights of the grapes were manually segmented from the images of the paintings. The luminance profile of each segmented highlight was semi-automatically extracted to quantify the features.

4.2.1. Stimuli

The stimuli used were high-resolution, digital images of 17th century paintings (78 in total), downloaded from the online repositories of several museums (see Figure S1 in 3.7 for a numbered list of all the squared cut-outs used for rating experiment A. Each image in the list has the embedded link to the relative museum repository website, where the original images used in experiment B can be found). For experiment A, the stimuli consisted of squared cut-outs containing the target bunch of grapes (Figure 4.1, left). The gloss rating experiment B was conducted using images of the entire paintings (Figure 4.1, right). The segmentation task was performed using the latter (Figure 4.1, right).

Figure 4.1: Left, squared cut-out (experiment A); Right, whole painting (experiment B). Abraham Mignon, *Still Life with Fruit and Oysters*, 1660–1679. Rijksmuseum, Amsterdam, The Netherlands.

4.2.2. Experimental set up

For both rating experiments and the highlights segmentation task, the stimuli were presented in a darkened room, on an EIZO LCD monitor (CG277), with built-in self-calibration sensor. To ensure color consistency across the experiments, the monitor was calibrated before each session, using the software "Color Navigator 6" (EIZO, version 6.4.18.4). The brightness level was always set to 100 cd/m2 and the color temperature to 5500 K. The interfaces of the experiments were programmed in

MATLAB R2016b, using the Psychtoolbox Version 3.0.14 [46–48].

4.2.3. Observers

The two rating experiments were conducted with different groups of participants. Nine observers took part in rating experiment A, using the cut-out stimuli containing the grapes. For experiment B, six observers were asked to rate glossiness for the images of the entire paintings. All participants had normal or corrected-to-normal vision. They were naïve to the purpose of the experiments. They provided written consent prior to the experiment and received a compensation for their participation. The experiments were conducted in agreement with the Declaration of Helsinki and approved by the Human Research Ethics Committee of the Delft University of Technology.

4.2.4. Procedure rating experiments

Rating experiments A and B differed in that either a part of the painting or the whole was shown (Figure 4.1), and in the number of material properties rated. For both experiments, the images were presented against a black background. Before starting the experiments, participants went through all the stimuli in order to get an overview of the stimulus range. No time limit was given to complete the task.

Experiment A

In experiment A the squared cut-outs containing the target grapes were used as stimuli. The rating of gloss was part of a larger experiment. Observers were asked to rate five different attributes on a continuous 7-point scale. Apart from the attribute glossiness, they also rated translucency, bloom, three-dimensionality, and convincingness. The ratings of the other four attributes were not considered in the analysis since they are not relevant for the purpose of the current discussion. Before starting the experiment, a written definition of each attribute was provided to the observers, and their understanding of the meaning of glossiness, translucency, and bloom was verified with a paired comparison test. A pair of photographs of real grapes was shown to the participants to test the three attributes, with one photo having the attribute and one not. Observers were asked to choose which one was glossier (or more translucent/bloomy). They were given feedback on the answers and, if they were able to choose the right option, they could start the experiment. The question presented on the screen was "how [attribute] is this bunch of grapes on average?" The attributes were tested separately in five blocks, in a random order (between and within each block). Altogether the 78 stimuli were rated five times, once for each attribute, resulting in 390 trials per observer. In the data analysis, the possible differences in rating due to having rated glossiness as first attribute or as last, i.e., after having seen a certain stimulus for the first time or the fifth time, were tested via inter rater reliability analysis.

Experiment B

Rating experiment B, using the entire paintings, was performed to check the assumption that the context of the painting does not play a significant role on judging the grapes' glossiness. The term "glossiness" was explained to the observers, and their understanding was checked as in experiment A, with the same two alternative choice test. If multiple bunches were depicted, the researcher indicated to the observer the bunch of grapes in the painting to be rated. The images were presented in a random order to each participant. The rating was done on a continuous 7-point scale.

4.3. Procedure image segmentation

For the segmentation analysis of the stimuli, the full images of the paintings were used. The highlights' segmentation was performed by the first author. On average, 17.64 grapes were segmented from the images of the bunches used in the rating experiments, in order to have a representative set of samples. The segmentation procedure consisted of drawing a polygon around the grape's contour (blue line, Figure 4.2), followed by another polygon around the outline of the corresponding highlight (green line, Figure 4.2). The image could be freely zoomed in (up to the pixel level) and out in order to perform the segmentation.

Figure 4.2: Full painting with one grape and its highlight manually segmented. Abraham Mignon, *Still Life with Fruit and Oysters*, 1660–1679. Rijksmuseum, Amsterdam, The Netherlands.

4.4. Procedure computation of highlights' features from the images

Since no conventional method can be found in literature on how to compute the image features that are diagnostic for material properties, we propose a novel approach. We developed a series of functions in Mathematica (version 11.2) for the semiautomated computation of the contrast, coverage, and sharpness of the highlights, which were manually segmented from the images. Although we tried to make the algorithm to extract the highlights' features fully automated, a manual inspection of the luminance profiles was still needed to correct the data. Because of the extremely uncontrolled nature of the stimuli, several factors interfered with the analysis of the images. The major factor was that, since we used photographs of old paintings, cracks on the surface of the paint (visible as dark lines) added noise to the pixel wise analysis of the highlights. The coverage was calculated as the ratio between the area of the highlight and the total area of the grape. Sharpness and contrast were derived from the luminance profiles of the segmented grapes. We extracted the luminance profile from a cross-section of the segmented grape, centered in the middle of the highlight. The cross-sections covered the width of the grapes and were 3 pixels high; the luminance profiles were averaged over these 3 pixels, smoothing out potential outliers. Contrast values were calculated as the Michelson's contrast [49], taking the maximum and minimum luminance values of the peak profile as shown by the horizontal lines pink and yellow in Figure 3. The choice of the orientation for the extraction of the luminance profile (blue line crossing the highlight on the grape in Figure 4.3) will be addressed later. Instead of sharpness we considered the inverse, which we named the blurriness and quantified as:

$$Blurriness = (\frac{\Delta y}{\Delta x} \cdot \frac{1}{\Delta y})^{-1} = \Delta x \tag{4.1}$$

where Δy is the difference between the maximum and minimum luminance values of the peak and Δy/Δx corresponds to the maximum derivative, taken and averaged over the two sides of the highlight profile (oblique red and green lines in Figure 4.3). The Δx values were normalized to the visual size of the grapes shown on the screen during the rating experiment A. Δx represents the transition area from the background (diffuse scattering) to the highlight (specular reflections). The relationship between Δx and blurriness is illustrated in Figure 4.4. Δx increases with the blurriness, and thus it is inversely related to sharpness. Throughout the rest of the chapter, we will refer to blurriness instead of sharpness. Figure 4.4 also shows that changing the contrast does not affect Δx.

Because of the irregular shapes of the highlights, the luminance profiles were extracted at 36 different angles, between 0° and 175°, in steps of 5°. The results were averaged over the different angles. Two examples of luminance profiles acquired at 0° and 90° are shown in Figure 4.5.

The highlights do not only show irregular shapes, but many also show an internal spatial structure. They were often rendered as a window reflection [15]. Thus, the inner structure of the window, visible in the reflection, constitutes an additional term of variation in the luminance profile, depending on the angle of computation. This is evident in Figure 4.5. Extracting the profile either perpendicular or parallel to the internal line of the window drastically changes the shape of the luminance profile. Hence, in some cases the maximum derivative is detected in the middle of the highlight instead of at the outer edges. We assume that the visual system detects the sharpest edges and they do not necessarily need to be the outer ones.

Finally, the features' values for each bunch of grapes were obtained from the

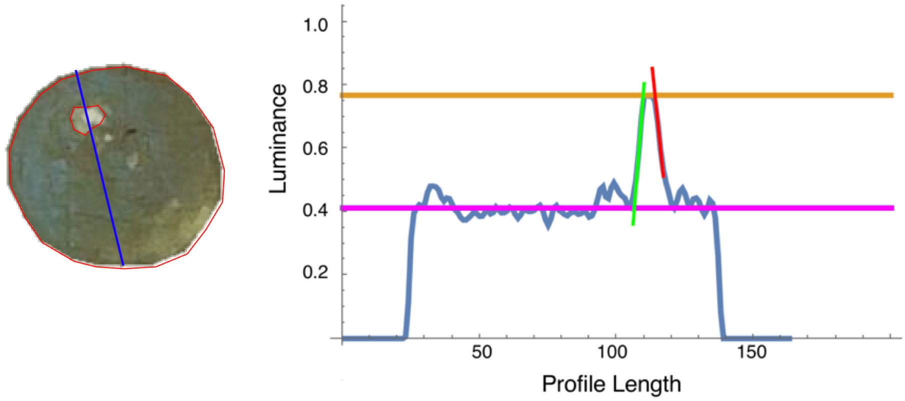

Figure 4.3: Illustration of the values extraction from a luminance profile for the computation of Michelson's contrast and of the slope on the two sides of the peak. The horizontal lines pink and yellow show how the minimum and maximum values of the highlight's peak were extracted, whereas the oblique lines green and red show the computation of the maximum derivative. Note that the x axis shows the pixel width of the grape from the original image, but for the data analysis all the values were normalized for the pixel width of the grape shown on the screen.

average of the segmented grapes, analyzed as just described.

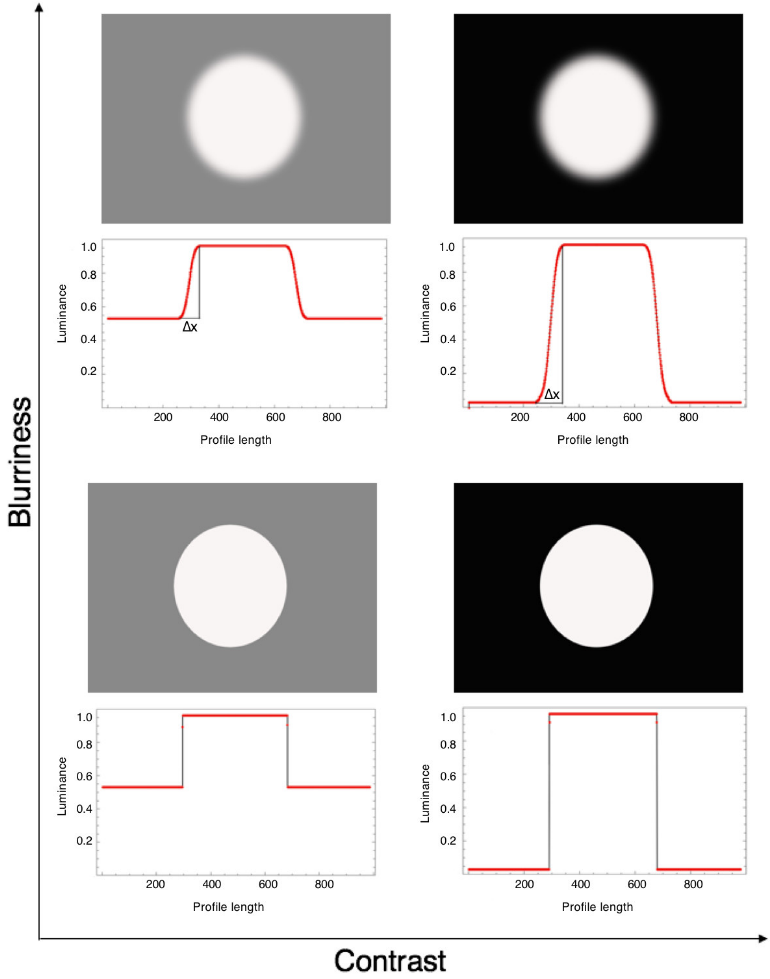

Figure 4.4: Illustration of the relationships of Δx with blurriness and contrast. For the sharp circles, the luminance profile shows a step, with Δx=0. As blurriness increases, the transition becomes more gradual and Δx increases. Δx is not dependent on the contrast.

4.5. Results

4.5.1. Glossiness rating experiments

As mentioned before, the gloss rating experiment was performed once using the squared cut-outs containing the target grapes, and again with the entire images of the paintings.

Before comparing the data, we analyzed the internal consistency of the ratings in experiment A. Here, glossiness was rated as part of a larger experiment in which observers were asked to judge also four other attributes, in random order (see experiment 1 in 3). Their evaluation of glossiness may thus have been biased by

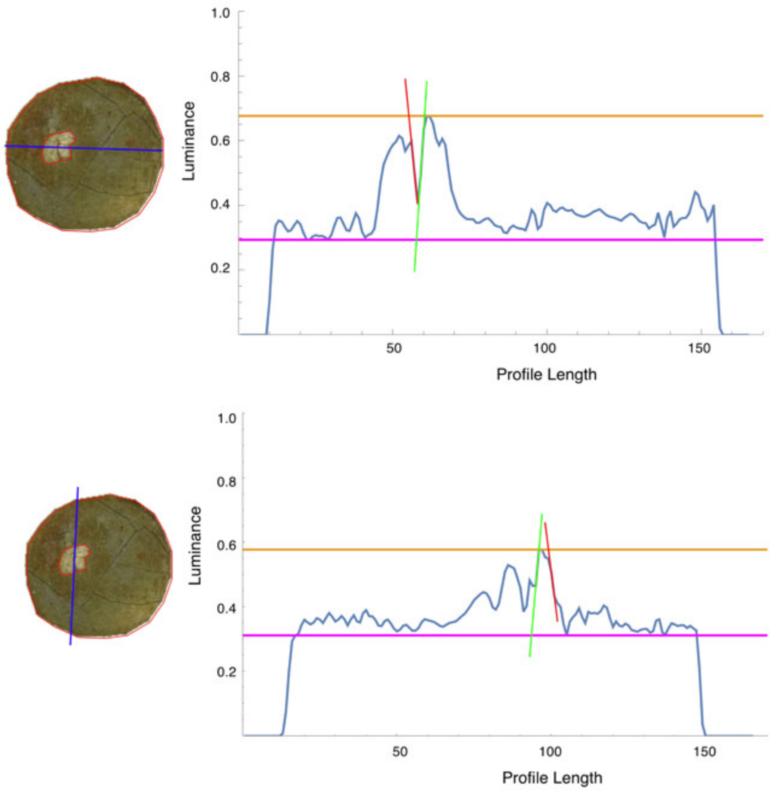

Figure 4.5: Example of a segmented grape and its highlight. The luminance profile above was taken at 0°, the one below at 90°.

the order of the attributes and the number of times the stimuli were seen before rating glossiness. A reliability analysis resulted in a Cronbach's alpha coefficient of 0.83, demonstrating high consistency in the ratings. A Spearman rank test was also performed, showing that all the observers' data were significantly correlated ($p<0.05$) with each other. Nevertheless, the reliability analysis between observers of experiment B, who rated only glossiness of the grapes seeing the entire paintings, gave a Cronbach's alpha coefficient of 0.97. *T* test showed that the two Cronbach's alpha values were significantly different ($p<0.05$). This may indicate that increasing the number of material properties to be rated decreased the agreement between observers, but gloss ratings from experiment A are still reliable.

To minimize possible effects of unequal interval judgments, the data of each observer for both rating experiments were rescaled from the 7-point scale to the 0–1 range before averaging. The average gloss ratings of experiments A and B were correlated, in order to test possible effects of the painting context on the judgment. The trend of the correlation is shown in Figure 4.6. The ratings resulted in a strong

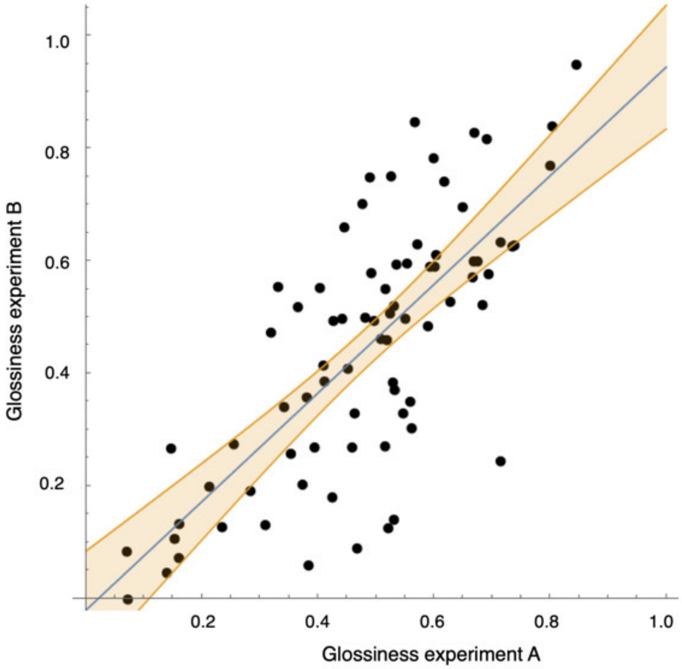

Figure 4.6: Scatterplot of the correlation between the average glossiness ratings of the squared cut-outs (experiment A) and of the whole paintings (experiment B). Results show r=0.74, p<0.001; the area around the fit line represents the 95% CI.

and significant correlation (r = 0.74, p<0.001). The regression line that best fit the data gives an offset of -0.02 nonsignificantly different from 0, but a slope of 0.96 significantly (p< 0.05) different from 1. This means that the participants of experiment A perceived a wider range of glossiness levels than the ratings used by participants in experiment B. Such systematic effect of the slope may be due to the grapes' bunch size shown in the two experiments. They were clear and close-up in the cut-outs (A), but small when shown in the entirety of big paintings (B). In Figure 4.7, a bar chart shows average ratings from experiment A for the three stimuli judged most and the three judged least glossy. We do not know the ground truth of the glossiness levels of the painted grapes, but since the average minimum and maximum levels were more than 0.6 apart, whereas random data would have shown both the minimum and maximum around 0.5, we can conclude that the ratings were internally consistent and the stimuli obviously covered a perceptual well distinguishable range.

4.5.2. Glossiness prediction based on the segmented highlights' features

Using the image processing technique described in the method section, we quantified the features of the segmented highlights. To explore the relationships between

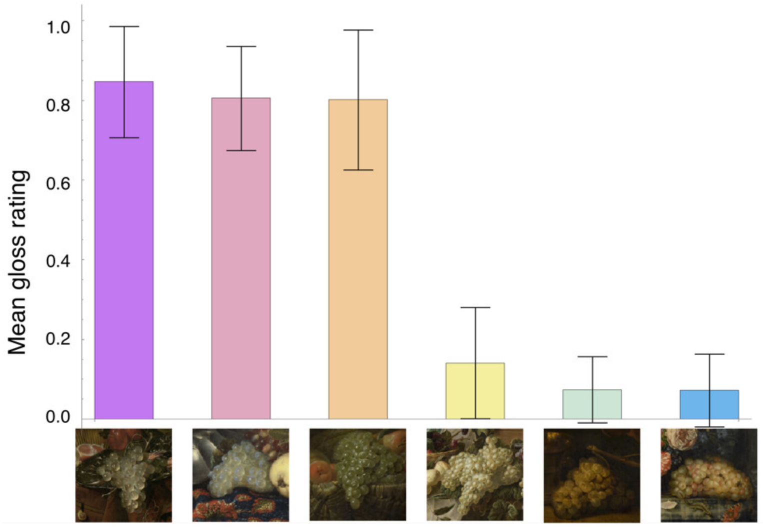

Figure 4.7: Mean ratings for experiment A (cut-outs) of the three bunches of grapes judged most glossy and the three least glossy. The corresponding images are shown below each bar. The error bars indicate the standard errors of the mean.

the features contrast, blurriness, and coverage and the perceived glossiness, we employed principal component analysis (PCA) and multiple linear regression. In the PCA biplot, shown in Figure 4.8, we can see how the scores, i.e., the images (numbered points; see Supplementary Figure S1 in 3.7 for the image corresponding to each number) were distributed with respect to the variables. The variables represent the three highlight features and the mean gloss rating from experiment A (a PCA biplot representing the relationships between only the three highlight features is shown in Supplementary Figure S1, with the corresponding factor loadings in Supplementary Table S1 in 4.8). To account for the different scales of the variables, we performed the PCA based on the correlation matrix.

	PC1	PC2
Gloss	-0.61	0.02
Contrast	-0.59	0.03
Blurriness	0.53	-0.04
Coverage	0.054	0.99

Table 4.1: Factor loadings of the first two principal components.

The first two principal components together account for 83.4% of the variance. From the factor loadings (Table 4.1), we see that the first component is strongly loaded by contrast and perceived gloss in one direction and by blurriness in the opposite direction. This means that glossiness varied positively with contrast and

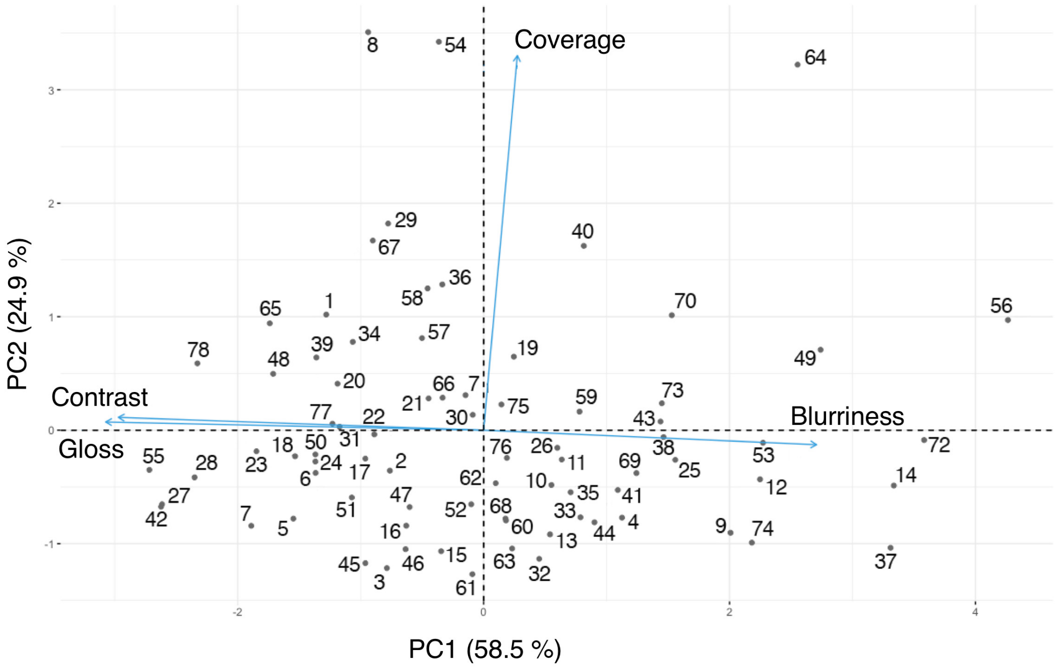

Figure 4.8: PCA biplot showing the scores (images) distribution with respect to the variables (highlights' features and gloss ratings), and the relationships between the variables themselves.

negatively with blurriness. The correlation between perceived gloss and contrast is indeed positive and significant with r = 0.80, $p<0.001$, and it is negative and significant between perceived gloss and blurriness with r = -0.61, $p<0.001$. On the second component, the variable with the highest loading is coverage. This suggests that coverage was not correlated with glossiness, and indeed r = 0.03, $p>0.05$ between glossiness and coverage. Correlation plots for each highlight feature with perceived glossiness are shown in Supplementary Figure S2 (in 4.8). To predict the perception of glossiness based on the highlight features, we used multiple linear regression. We found the best fit (Equation 4.2) for a model carrying contrast and blurriness as significant ($p<0.001$) predictors. This model explains (r^2) 69% of the variance of perceived glossiness.

$$Perceived gloss = 0.32 + 1.1 Contrast - 2.05 Blurriness \tag{4.2}$$

4.6. Discussion

One aim of the study presented in this paper was to test whether the diagnostic power of highlight features proposed by Marlow and Anderson [2] could be transferred from computer rendered to painted stimuli. We therefore first measured the perception of glossiness of grapes in bunches, extracted as squared cut-outs from the images of the paintings. Alongside this rating experiment, a second experiment was performed, showing to the observers the entire images of the paintings in order to test whether the context influences the perceived glossiness of the grapes. The strong and significant correlation, and the lack of systematic effect of the fit offset that we found for the average ratings of the two experiments, show that a potential influence due to the context was not critical. However, the systematic effect of the slope indicates that a wider range of ratings was used for the cut-outs compared to the entire paintings. The different sizes of the bunches of grapes shown in the two experiments may have caused this effect. In the cut-outs of experiment A, they were all shown with similar, close-up sizes; thus, smaller variations of glossiness image cues may have been more visible.

To measure the three highlight features (contrast, blurriness, and coverage), we segmented the grapes from the images and computed the features via image analysis. Contrast and blurriness were found to be the predictors for the best fit model of gloss perception, accounting for 69% of the explained variance. The amount of explained variance (r^2) given by Marlow and Anderson [2] for their set of experiments ranged between 0.91 and 0.97. We cannot make a direct comparison with their r^2 values because of the fundamental difference with our stimuli and for the method used to quantify the highlight features. However, we assume that the main explanation for our lower r^2 can be imputed to the uncontrolled nature of the paintings. As a future step, the algorithms we used to quantify the highlight features should be correlated to their perceptual measures (i.e., via human estimation of the cues), in order to validate the psychophysical relevance of our method.

The high negative correlation observed between contrast and blurriness in the PCA biplot (Figure 4.8 is in agreement with previous research on the effect of the smoothness of the boundaries of color patches on the perceived brightness of the patch itself [50]. They found that patches with sharper edges appear brighter than ones with blurrier edges, indicating that the perceived contrast of the patch is related to the amount of blurriness of its boundaries.

Contrast and blurriness were found to be the main contributors regarding gloss rendering of grapes in paintings, as shown by their high correlations with glossiness in the PCA biplot (Figure 4.8).

Dutch 17th century painters may have been aware of the importance of the highlights' contrast and may have intentionally emphasized such feature by placing a dark line or area along the highlight contour as a pictorial trick (Figure 4.9). The importance of contrast for rendering glossiness in paintings is also confirmed by the findings of Cavanagh et al. [10]. They found that in paintings the only requirements for highlights on curved surfaces are to be brighter than the surrounding and to be appropriately curved.

Blurriness had the expected negative correlation with gloss perception. For coverage we found no significant effect. This is comparable with what Marlow and Anderson [2] reported for rendered spheres. They did find an effect of perceived coverage on glossiness, but this effect and the perceived variation of the highlights' coverage were the lowest compared to perceived contrast and sharpness. If the light source has one main direction, only a small part of a spherical surface will be covered by highlights, because a sphere has a uniform distribution of surface

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Figure 4.9: Details of two bunches of grapes used as stimuli showing an example of the use of dark lines around the contour of some of the highlights. Left: Nicolaes van Gelder, *Still Life*, 1664. Right: Pieter de Ring, *Still Life with Golden Goblet*, 1640–1660. Rijksmuseum, Amsterdam, The Netherlands.

normals. Grapes are spherical (or ellipsoidal) objects, and in still life paintings it was common practice to suggest the presence of a single source of light coming from a window, usually placed top left [51]. Thus, the coverage is rather small and constant throughout the various paintings and the different levels of glossiness.

From previous works it is clear that the research on gloss perception cannot be reduced to the highlights only, since the appearance of the highlights is influenced by other factors like the illumination field [16, 28–30] and the 3D shape of the object [21, 25, 26]. However, it is also known that painters often abstract the rules of physics into an ”alternative physics” [7], which allows portraying just the key information for an efficient recognition of the scene, leaving errors and incongruences unnoticed at first glance.

This is, for example, the case for the congruency between the orientation of the highlights and of the grapes' shapes. It is well known in literature that one of the fundamental requisites for highlights is to be placed at the ”right” position on the surface [18, 33–36]. Still, when we measured the orientation of an ellipse fitted onto the highlight and that of an ellipse fitted on the grape, we did not find a correlation for the set of bunches perceived as highly glossy. The orientations were found to be more congruent instead ($r = 0.57$, $p<0.001$) for the medium to low glossy grapes. This finding contradicts the literature as well as the physics. Figure 4.10 shows on the left a photo of a real bunch of grapes and on the right one of the painted bunches considered among the glossiest. In the photo, each grape has its own orientation, as indicated by the black arrows, and their highlights are always coherently aligned (red arrows). The painting, on the other hand, shows visible incongruences. Nonetheless, such inaccurate orienting of the highlights does

Figure 4.10: Left: Photo of a real bunch of grapes taken by the authors in the lab. Right: A bunch of grapes considered among the glossiest of our set of stimuli (Pieter de Ring, *Still Life with Golden Goblet*, 1640–1660. Rijksmuseum, Amsterdam). The black arrows indicate the orientation of the grapes while the red arrows show the orientation of the highlights. The arrows were drawn by hand. In the photo, the grapes are oriented differently, but each highlight follows the shape orientation of the grapes; in the painting, the orientations of the highlights appear to be randomly scattered across the bunch, and they are not consistently congruent with the grapes' shape.

not seem to hinder the perception of glossiness, nor improve it when they are more coherently aligned on the low and medium glossy grapes.

Another discrepancy between the laws of physics and the "physics of paintings" concerns the elongation of the highlights' shape with respect to the distance of the highlight from the center of the grape, which is related to the slant angle of the light direction.

Assuming a spherical shape for the grapes, we calculated the highlights' position. We retrieved the light direction as the tilt and the slant angle. With an average of 143° for the tilt angle and of 51° for the slant angle (Figure 4.11), we could confirm the top-left convention for the illumination orientation, which is a well-known perceptual prior [52, 53], also found in paintings [51, 54, 55]. We found that the highlights' elongations were not consistent with the slant angles of the illumination. Nevertheless, this did not influence gloss judgments throughout our stimulus set, as no correlation was found. We found that breaking the rules of the orientation congruency and of the elongation of highlights with the light slant do not affect glossiness perception. We assume that this is the case, because the highlights' contrast has the predominant effect in our set of stimuli.

As will be discussed later, the artistic conventions, including the recipes given by Beurs [3, 4], state to use white to render the highlights on grapes. This can be an example of the above-mentioned key information representing statistical regularities of real scenes and transferred to the canvas by the painter. In fact, grapes are dielectric materials, so they have specular highlights of the same color as the light source [56, 57]. Measuring the chroma of the segmented highlights, we found a significant negative correlation with glossiness ($r = -0.35$, $p<0.01$), which means that the more colored the highlights are (which can also be due to ageing and yel-

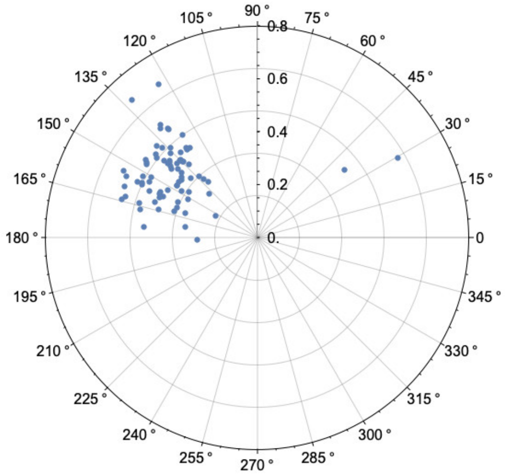

Figure 4.11: Polar plot of the average tilt and slant angles. The plot shows the top-left convention of the light orientation used in paintings.

lowing of the painting), the less glossy the grapes will be perceived. One of the next steps would be to include the perceptual attribute of ”haze gloss” [37, 58] to the representation of the glossy appearance of grapes. Grapes are naturally covered by bloom, a waxy coating that looks like a whitish matte layer. Usually, it is not evenly spread over the fruit surface, since it can be easily deleted by handling or transportation, and it can also have various thickness, but in general the more bloom is present, the less glossy the fruit appears [59, 60]. However, the highlight can be also placed next to a highly bloomy area, making the role of bloom in tuning gloss perception far from trivial.

Our findings on the use of the highlights' features to render glossiness of grapes in 17th century painting practice are supported by the painting manual of Beurs [3, 4]. In his recipe for grapes, no instruction can be found on how much of the fruit surface should be covered with highlights. He may not have mentioned it, either because experience and observation would have been enough to get this notion, or because, as we found, the coverage has no significant role in the case of grapes. The recipe contains less ambiguous indications for what concerns contrast and blurriness. It states that the highlight should be placed where the surface is not covered with bloom, and it should be painted white. In the area where no bloom is present, the skin color of the grape is visible. Applying a white spot on a colored background mainly affects the contrast. For blurriness, Beurs [3, 4] specified that care should be taken, when applying the white highlight, to "gently blend it in." He referred to the edges of the reflection, blending the white of the specular reflection with the color of the diffuse body scattering, resulting in more gradual edges. Since grapes are not mirror-like materials, this procedure would increase the natural appearance of the fruit and thus its convincingness. It would be interesting to apply the model, having contrast, blurriness, and coverage of the highlights as predictors, to other glossy materials depicted in paintings, and see whether the contributions of the predictors change.

Lastly, we showed that it is possible to extract image cues by manually indicating the highlight and the contour of the grape. Using this input, highlight profiles can be generated that contain information about contrast, blurriness, and coverage. To our knowledge, this approach is relatively new and seems a valuable addition to research on visual material cues. Until now, research has either focused on the physical parameters (that lead to the image cues, e.g., [19]), global image statistics [38] or human estimates of cue strength [2]. Almost all of these studies were performed on well-controlled computer rendered stimuli. Although our stimuli are clearly also artificial, they are uncontrolled. Our approach can be readily generalized to "natural images", like the Flickr Material Database (FMD) [61].

4.7. Conclusions

We have measured the amount of glossiness perceived in paintings of grapes from the Dutch Golden Age, a period characterized by the detailed realistic imitation of nature. We have predicted perceived glossiness using the key features of the highlights, which can be observed in the image [2, 17]. The novelty of our work consisted in the use of uncontrolled stimuli and in the method we have used to measure the features. Contrast, coverage, and blurriness were mathematically defined, and calculated directly from the segmented stimuli. Contrast and blurriness were found to be the main predictors for gloss perception. Coverage, on the other hand, was found to have no influence at all. We could find hints to the same conclusions in the painting instructions for grapes given by Beurs [3, 4]. We also found support for the idea that painters used to sacrifice the true physics of light and instead use key factors of the optical phenomena, and that does not affect glossiness perception (or perhaps even enhance it). We have shown that the research on gloss perception can be extended to paintings, and eventually also to the study of historical sources. Via image analysis, we have demonstrated that two of the three cues proposed by Marlow and Anderson [2], were used by 17th century painters to elicit gloss perception of grapes.

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4

4.8. Supplementary material

Figure S1.

PCA biplot showing the scores (images) distribution with respect to the variables (highlights' features), and the relationships between the variables themselves.

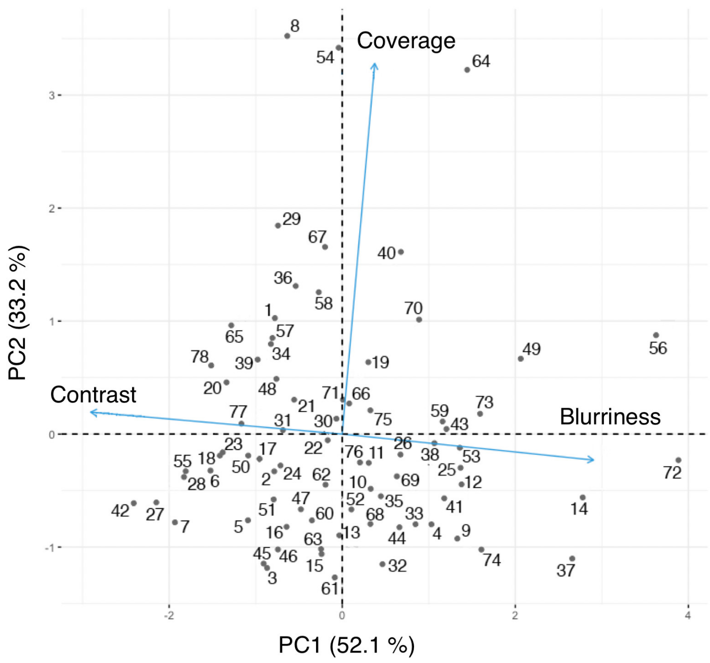
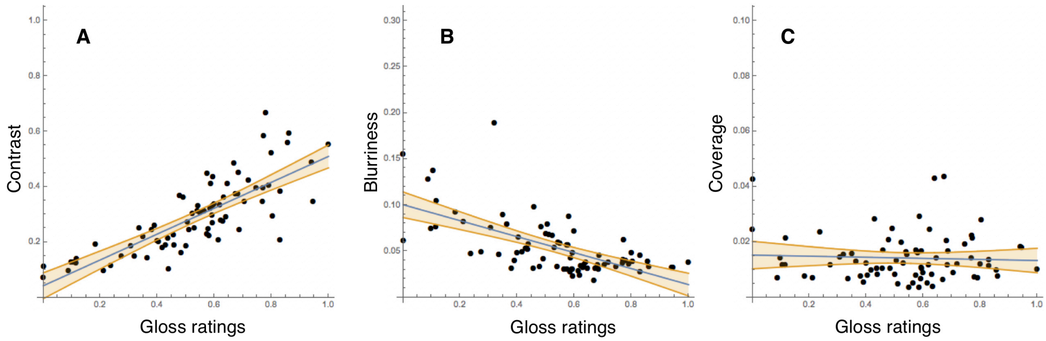


Table S1.

Factor loadings of the first two principal components in Figure S1.

	PC1	PC2
Contrast	-0.70	0.06
Blurriness	0.70	-0.07
Coverage	0.09	0.99

Figure S2.
Scatterplots of the correlation between the average glossiness ratings of the squared cut-outs and A) contrast (r = 0.80, $p<0.001$), B) blurriness (r = -0.61, $p<0.001$), C) coverage (r = 0.03, $p>0.05$). The area around the fit line represents the 95% confidence interval.



5

If painters give you lemons, squeeze the knowledge out of them

Consider the lemon, one of the favored objects of Dutch vision. Its representation characteristically maximizes surface: the peel is sliced and unwound to reveal a glistening interior from which a seed or two is frequently discarded to one side.

Sventlana Alpers

This chapter has been published as: Di Cicco, F., Wijntjes, M.W.A., & Pont, S.C. (2020). If painters give you lemons, squeeze the knowledge out of them. A study on the visual perception of the translucent and juicy appearance of citrus fruits in paintings. Journal of Vision, 20(13):12, 1–15 [1].

My contribution in [1] was the conceptualization of the research idea; to design and perform the rating and the pairwise comparison experiments; to create the stimuli by collecting and cropping images of paintings; to acquire, analyze and interpret the data; to relate the perceptual findings to Beurs' recipe; to write the manuscript.

Citrus fruits are characterized by a juicy and translucent interior, important properties that drive material recognition and food acceptance. Yet, a thorough understanding of their visual perception is still missing. Using citrus fruits depicted in 17th century paintings as stimuli, we ran three rating experiments. In Experiment 1, participants rated the perceived similarity in translucency or juiciness of the fruits. In Experiment 2, different groups of participants rated one image feature from a list obtained in a preliminary experiment. In Experiment 3, translucency and juiciness were rated. We constructed 2D perceptual spaces for both material properties, and fitted the ratings of the image features into the spaces to interpret them. 'Highlights', 'peeled side', 'bumpiness' and 'color saturation' fitted best the juiciness space, and were high for the highly juicy stimuli. 'Peeled side', 'intensity of light gradient', 'highlights' and 'color saturation' were the most salient features of the translucency space, high for the highly translucent stimuli. The same image features were also indicated in a 17th century painting manual for material depiction [2, 3]. Altogether, we disclosed painters' expertise on material perception by identifying the image features that trigger a visual impression of juiciness and translucency in citrus fruits.

5

There are not only grapes in life, which notoriously hands you lemons. Many advice have been given on what to do with these lemons: make lemonade, throw them back, squeeze them into people's eyes. My advice is to look at them. See its taste. Maybe better, estimate. We know from previous experience that citrus fruits are juicy (that's why we make juice out of them), and we can estimate just by looking if we are reaching for the juiciest orange in the bowl. How do we do that? This chapter will reveal the image cues for juiciness and translucency perception of citrus fruits, learning from paintings, and guided as always by Beurs.

5.1. Introduction

Eating is a multisensory experience. Often, the first interaction people have with food is visual, setting intentions to buy and consume a certain food. Several researchers have shown that vision can even affect taste perception by creating expectations [4]. Food appearance drives quality perception and consumers' acceptance, making it a fundamental problem for food industries and manufacturers. Despite its importance though, this problem has seldom been approached from the perspective of vision to answer the question of how people visually estimate food material attributes.

Here, we focused on understanding the perceptual spaces of the visual perception of translucency and juiciness, for the case of citrus fruits. Translucency and juiciness represent important quality parameters not only for citrus fruits, but also for other types of fruits, like apples [5], and even more so for meat [6]. Juiciness especially is an attribute that needs to be right in meat and meat substitutes in order to be accepted [7].

Translucency and juiciness can be readily estimated from visual information, but while some research has been done on how we perceive translucent materials [8–

13], no work to our knowledge has investigated the visual perception of juiciness. Local objects' features have been associated with translucency perception, especially edges and thin areas [9, 14, 15] enhanced by back lighting [16]. However, a thorough understanding of translucency perception of 3D objects is still missing. Translucency is due to the complex optical phenomenon of subsurface scattering, and how it appears depends on the 3D shape of the object, the extinction coefficient of the medium (due to absorption and scattering), and the lighting and viewing directions [8]. While other optical properties like color [17] and glossiness [18, 19] have received more attention, and perceptual spaces have been constructed to relate bidirectional reflectance distribution function (BRDF) parameters to human perception of glossiness [20, 21], the only attempt to find a perceptual embedding of translucency was done by Gkioulekas et al. [11]. In their study, they focused on the effect of the phase function (i.e. the angular distribution of light scattering) on the appearance of translucency, to unravel which physical parameters can be used to elicit the desired translucent effect. Using classical multidimensional scaling (MDS), they found a 2D space of translucency perception that could well be represented by the square of the average cosine of the phase function and by a function inversely related with the second moment of the cosine of the phase function. These corresponded respectively to a change in light diffusion and sharpness of the light gradient.

We assumed that the properties of translucency and juiciness are perceptually related. Juiciness is a complex food textural attribute dependent on the structure and the strength of the plant tissue [22], and corresponding to the amount and the rate of juice release during mastication [23]. Translucency is the optical phenomenon of light partially travelling through a medium, being scattered, then absorbed or transmitted. When light enters a citrus fruit, the juice contained in the vesicles making the pulp [24], is the scattering medium. A dry fruit would hardly appear translucent. Translucency and juiciness are also indicators of the fruit ripeness, and thus quality. Unripe oranges, for example, exhibit low transmittance (i.e. low translucency) and they contain the least amount of water (i.e. low juiciness) [25]. Note that in food science, the term 'texture' refers to the mechanical and structural properties of food which are experienced on a multisensory level while eating (e.g. crispiness, stickiness, tenderness, juiciness, etc.) [26]. This differs from the meaning of 'texture' in vision science, as a statistically defined surface property of image regions (e.g. wavy, like water, like wood, etc.) [27]. In art history, 'texture' takes yet another meaning, referring rather indistinctly to all the material properties of a depicted object (e.g. shiny, rough, etc.). In this paper we will use the term 'texture' as it is used in food science.

Our approach to understand the visual perception of material appearance is based on unravelling the image cues identified and exploited by painters to render different materials. This is based on the hypothesis that painters captured the triggers of material percepts – not necessarily realistically representing all optical details but phenomenologically depicting the key features. A painting is as ecologically valid as a photograph in representing reality, given that a photograph is a construction of lightings and viewpoints as much as a painting is. The same holds for computer renderings, which appearance is even more constructed, being totally controlled by the input parameters. In this study, we sought to determine whether visual perception of translucency and juiciness of citrus fruits rendered in 17th century paintings could be embedded in perceptual spaces, and in how many dimensions. We further aimed to identify which image features present in the paintings were used to estimate translucency and juiciness perception. Several researchers have referred to realistic painters in order to understand the mechanisms of human visual perception [8, 12, 28–31]. Painters are regarded as "early vision scientists" [32], because the way they represented the world taps into the processes of the human visual system via abbreviations of the laws of physics [33]. Computer graphics is also turning towards more art-based and perception-driven approaches [34–36], given the human vision tolerance for some physical inaccuracies [37–39], and to avoid the computational costs [40] and the artificial, too perfect look of physically-based rendering [41]. Moreover, using simplified depictions containing just perceptual triggers and ignoring what the visual system is insensitive to, might also enhance experience. For example, as suggested by Parraman [42], the highly convincing representation of material attributes achieved by painters from the 15th century on, can be ascribed to their economical and almost gestural brushworks, since "too much information possibly hinders the appearance".

Dutch painters from the 17th century were masters in the expression of stuff [43]. Cut-open lemons and oranges, revealing their juicy and translucent inside, became a recurring motif in Dutch still lifes since Pieter Claesz. (1597-1661) painted the first peeled lemon in the second decade of the 17th century [44]. Lemons and oranges, like many other objects in the 17th century, were painted according to standard, systematic recipes [45–47]. Instructions of this kind are to be found in the 17th century manual, "The big world painted small", composed by Willem Beurs [2, 3]. This manual provides a collection of shortcuts to render the optical behavior of materials, by tweaking features of their highlights, like color, contrast or sharpness. Parametric changes of such image features have been shown to affect not only gloss perception [48], but also the perceived material category [49]. In previous work, Beurs' manual has offered supporting indications that contrast and blurriness, but not coverage of the highlights were the image features used to render glossiness of grapes in 17th century paintings. The grapes recipe contained in the manual, also confirmed the artistic convention to use white to render the highlights on grapes, showing an example of the use of key perceptual information for an efficient yet effective rendering of material properties [50] (see Chapter 4). Here, we also considered Beurs' recipes for additional insights into the image features and perceptual shortcuts exploited by painters to render translucency and juiciness.

5.2. Methods

The study consisted of three parts. In the first part (Experiment 1), we ran two similarity rating experiments, one on juiciness and one on translucency. In the second part (Experiment 2), participants each rated one of seven features from a list collected during a questionnaire in a preliminary experiment. The features were rated to find a meaningful interpretation of the perceptual spaces of translucency and juiciness. In the last part (Experiment 3), participants rated translucency and juiciness of all the stimuli.

5.2.1. Stimuli

The stimuli consisted of 55 digital images of 17th century paintings depicting citrus fruits. The images were downloaded from the online repositories of several museums and collections. The stimuli were presented on the screen as cut-outs containing the target citrus and part of the background, as shown in Figure 5.1 (see Figure S1 in supplementary material 5.7 for a numbered list of all the squared cut-outs used in the experiments. Each image in the list is linked to the relative museum repository website, where the original images can be found). To ensure that the visual size of the citrus fruits was kept consistent between stimuli, the cut-outs were made so as to keep a constant ratio between the width of the pulp and the width of the resulting image.

Figure 5.1: Example of a stimulus presentation, as squared cut-out containing the target citrus. Abraham Mignon, *Still Life with Fruit and a Goldfinch*, 1660-1679. Rijksmuseum, Amsterdam, The Netherlands.

5.2.2. Observers

Two groups of seven and six observers participated in Experiment 1, one group rated the similarity in translucency and the other group the similarity in juiciness, respectively. The participants were students recruited via email within Delft University of Technology. Experiments 2 and 3 were conducted on Amazon Mechanical Turk (AMT). Seven different groups of ten participants each, took part in Experiment 2, and two different groups of 10 participants participated in Experiment 3. For the data collected on AMT, participants whose rating time was below 1 second were removed from the analysis. After such participants' sampling, the data of seven different groups of six participants resulted from Experiment 2, and of two groups of six participants from Experiment 3. All participants were naïve to the purpose of the experiments. They agreed with the informed consent prior to the experiment, and received a compensation for their participation. The experiments were conducted in agreement with the Declaration of Helsinki and approved by the Human Research Ethics Committee of the Delft University of Technology.

5.2.3. Procedure Experiment 1

Experiment 1 was conducted online using p5.js [51]. A link to the code of the experiment was sent to the participants via email. They also received video instructions in which they were shown all the images before starting the experiment, to get an overview of the stimuli range. Next in the instructions they were provided with a written definition of the attribute to rate (see S1 in supplementary material 5.7), an explanation of the task, and of the polarity of the scale (1=low similarity; 7=high similarity). At the end of the experiment, participants could automatically download the data, which they sent back to the experimenter via email. The task was to rate on a continuous 7-point scale the similarity of either translucency or juiciness of two fruit pulps. The 55 stimuli provided a total of 1485 pairs of images, which were rated once. The trials were randomized across participants. The question shown on the screen was "How similar is the [attribute] of the pulps of these citrus fruits?". In the instructions, participants were explicitly told to focus on the pulps only, and to avoid to base their judgements on similarities in shape or orientation of the whole fruit.

5.2.4. Procedure Experiment 2

Experiment 2 consisted of rating a list of image features obtained from a questionnaire conducted during a preliminary experiment in the lab. In the preliminary experiment, two groups of six participants rated the similarity in juiciness or translucency for a subset of 38 stimuli. After finishing, they were asked to fill in a questionnaire with two questions: "Describe how you rated the similarity of the [attribute] of the pulps" and "Which features of the object did you use?". During the questionnaire, prints of all the stimuli were available for the participants to allow pointing out things with specific stimuli to the experimenter. The answers to the questionnaire were evaluated by the authors via frequency analysis (data not shown), and they were used to generate a list of image features that might relate to the perceptual spaces of translucency and juiciness. The list included: intensity of the light gradient, sharpness of the light gradient, color saturation, surface bumpiness, highlights, visible seeds, and peeled side of the pulp.

In this study, we need to distinguish between the physics, the (pictorial) representation and the visual perception of material properties. They are closely related, but not exclusively determined by physics. Optical properties such as translucency can most directly be visually interpreted, thus perceived, based on the features of the image structure rather than by retrieving exact physical parameters. We tested the perception of such image features in Experiment 2. The experiment was conducted online on AMT. The selection criteria for participants was an approval rate of minimum 95% over at least 1000 completed tasks. Participants were randomly assigned to one of the seven features. The order of the stimuli was randomized across participants. Prior to the experiment, participants were shown all the images to get an overview of the stimuli range. Afterwards, they received written instructions regarding the question, the definition of the feature to rate, and the explanation of the scale polarity (see S2 in supplementary material 5.7). 'Intensity of the light gradient', 'sharpness of the light gradient', 'color saturation' and 'bumpiness' were rated on a continuous 7-point scale, three times for each of the 55 stimuli for a total of 165 trials per task. The features 'highlights', 'peeled side' and 'visible seed' were judged via yes/no questions. The three yes/no questions were answered once for each of the 55 stimuli.

Hereafter, we will, for readability, refer to the ratings of the image features simply by the term for the feature, e.g. the rating of the intensity of the light gradient as the 'intensity of gradient', but please note that these all concern perceptual ratings and not actual image measures.

5.2.5. Procedure Experiment 3

The procedure of Experiment 3 was the same as Experiment 2 (see S3 in supplementary material 5.7 for the instructions). Participants on AMT rated either translucency or juiciness on a continuous 7-point scale, three times for each of the 55 stimuli for a total of 165 trials per task.

5.3. Results

5.3.1. Internal consistency

To analyze the internal consistency between participants for all the experiments, we normalized the data of each participant rescaling to the 0-1 range, to account for possible effects of unequal interval judgments. The yes/no data on the presence of highlights, seeds and a peeled side, were converted to YES=1 and NO=0.

For Experiment 1, the inter-rater agreement, calculated as the mean correlation of the ratings of all observers, was r = 0.51 ($p<0.05$) for translucency, and r = 0.53 ($p<0.05$) for juiciness. In Experiment 2, the features 'intensity of gradient', 'sharpness of gradient', 'color saturation', and 'bumpiness' were rated three times per stimulus. To smooth out the effects of potential outliers we took the median over the three repetitions. The mean intra-rater correlations ranged from 0.65 to 0.89 ($p<0.001$) for the intensity of gradient; from 0.64 to 0.85 ($p<0.001$) for the sharpness of gradient; from 0.39 to 0.66 (p<0.05) for color saturation; and from 0.47 to 0.71 ($p<0.01$) for bumpiness. The agreement between participants was r = 0.7 ($p<0.001$) for the intensity of gradient; r = 0.73 ($p<0.001$) for the sharpness of gradient; r = 0.44 for color saturation ($p<0.05$); and r = 0.62 ($p<0.05$) for bumpiness. The three yes/no questions about the presence of highlights on the pulp surfaces, of seeds in the pulps, and whether the citrus fruits were peeled showing the pulp on the side, were answered once per stimulus. Fleiss' kappa showed that there was moderate inter-rater agreement on the presence of visible seeds (k = 0.47, $p<0.001$) and of highlights (k = 0.43, $p<0.001$), and there was substantial agreement on the presence of the peeled side (k = 0.75, $p<0.001$). Finally, the intra-rater agreement in Experiment 3 ranged from 0.57 to 0.77 ($p<0.001$) for translucency and from 0.66 to 0.77 ($p<0.001$) for juiciness. The inter-rater agreement was r=0.66 ($p<0.001$) for translucency, and was $r = 0.67$ ($p<0.001$) for juiciness.

Overall, the agreement between participants in the three experiments was at a level that allowed for further analysis.

5.3.2. Dimensionality of the perceptual spaces of translucency and juiciness

The similarity data of Experiment 1 were analyzed via non-metric multidimensional scaling (NMDS). NMDS represents similarity data, or in general proximities, in a new configuration with the least possible number of dimensions to achieve the best fit, while still reproducing the distances of the data as close as possible. NMDS addresses the limitation of applicability of metric MDS to human rating data, in that it does not rely on the magnitude of the dissimilarities but rather on their rank order [52]. Thus, the reason for using NMDS was to handle perceptual data whose actual distances are unknown.

The analysis was run using the function *metaMDS* from the 'vegan' package (v2.5-5) in R [53]. The similarity ratings were converted to dissimilarity distance matrices by subtracting the ratings from 1. To determine the dimensionality of the translucency and juiciness spaces, we calculated the stress as defined by Kruskal [54] for 1D configurations to 6D. The resulting scree plots are shown in Figure 5.2.

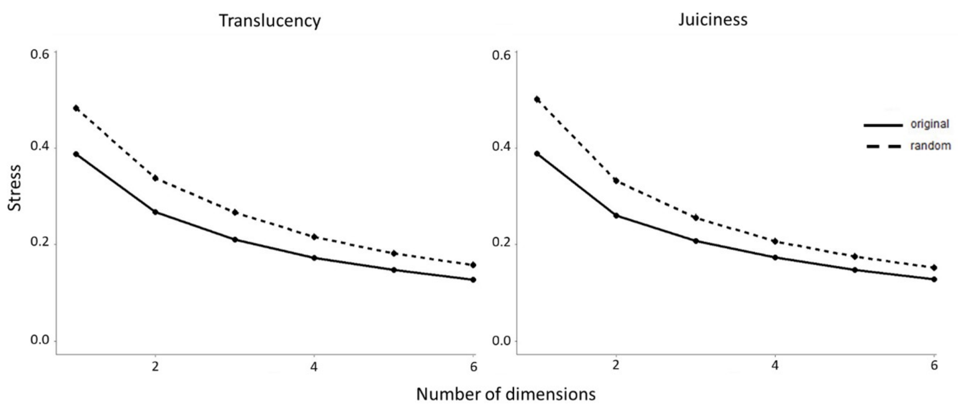


Figure 5.2: Scree plots showing the stress values as a function of the number of dimensions. The solid line represents the scree plot for the original values, whereas the dashed line shows the scree plot of the random data obtained from the average of the permutations. Left) Scree plot for translucency NMDS space. Right) Scree plot for juiciness NMDS space.

One criterion to choose the optimal number of dimensions is to look for an "elbow" in the scree plot, i.e. a steep decrease of stress followed by a plateau, which indicates that the addition of dimensions to the space would just fit noise and not significantly reduce the stress. Our scree plots do not show a clear elbow, as often is the case with human data [55]. Another approach is to pick the number of dimensions that allow for a stress value below 0.2, indicating an adequate fit [54].

The stress values for two dimensions were 0.27 for translucency and 0.26 for juiciness, thus higher than the threshold of 0.2 proposed by Kruskal [54]. However, the appropriateness of the strict cutoff at 0.2 has been questioned by several researchers. Borg et al. [55] stated that "An MDS solution can be robust and replicable, even if its Stress value is high. Stress, moreover, is substantively blind; i.e., it says nothing about the compatibility of a content theory with the MDS configuration, or about its interpretability." The stress value depends on several factors, including the number of points, the number of dimensions and the amount of noise in the data [56]. Dexter, Rollwage-Bollens and Bollens [57] proposed a permutational-based null model for the evaluation of the stress. According to this model, we generated 100 permutations for the similarity matrices of translucency and juiciness, we then calculated the stress values for these random datasets and compared them with the stress of the original data. The scree plots for the original (solid line) and the random (dashed line) data are compared in Figure 5.2. A t-test showed that the stress values obtained for the original data were significantly (p<0.001) different from the random ordinations. We can thus conclude that the 2D configurations hold some meaningful structure.

5

We further analyzed the dimensionality according to the criterion of interpretability of the coordinates proposed by Kruskal [54]. We compared via visual inspection, the distribution of the stimuli in 2D and 3D spaces for both translucency and juiciness. Since the third dimension did not reveal any further structure, we opted for the 2D space in both cases.

5.4. Interpretation of the perceptual spaces of translucency and juiciness

Figure 5.3 and Figure 5.4 show the 2D embeddings of the perceived similarities of translucency and juiciness respectively, together with the vectors of the features fitted onto the spaces. The ordination of the juiciness space shown in Figure 5.4 was matched via Procrustes analysis to the translucency space shown in Figure 5.3. The significance of the Procrustes result was tested by permutation, resulting in high and significant correlation between the two ordinations (r=0.78, p<0.001).

To interpret the underlying structure of the multidimensional spaces, we performed property vector fitting [58]. For property vector fitting, we used the function *envfit* from the 'vegan' package (v2.5-5) in R [53], to fit vectors of the features rated in Experiment 2 onto the spaces, such as to maximize the correlations of the projections of the scores onto the vectors with the corresponding rated features. The length of the vectors illustrates the strength of the correlation, and the orientation indicates the direction that maximizes the correlation.

We computed the correlations given by the vectors fitting to interpret the configurations of the translucency and juiciness spaces.

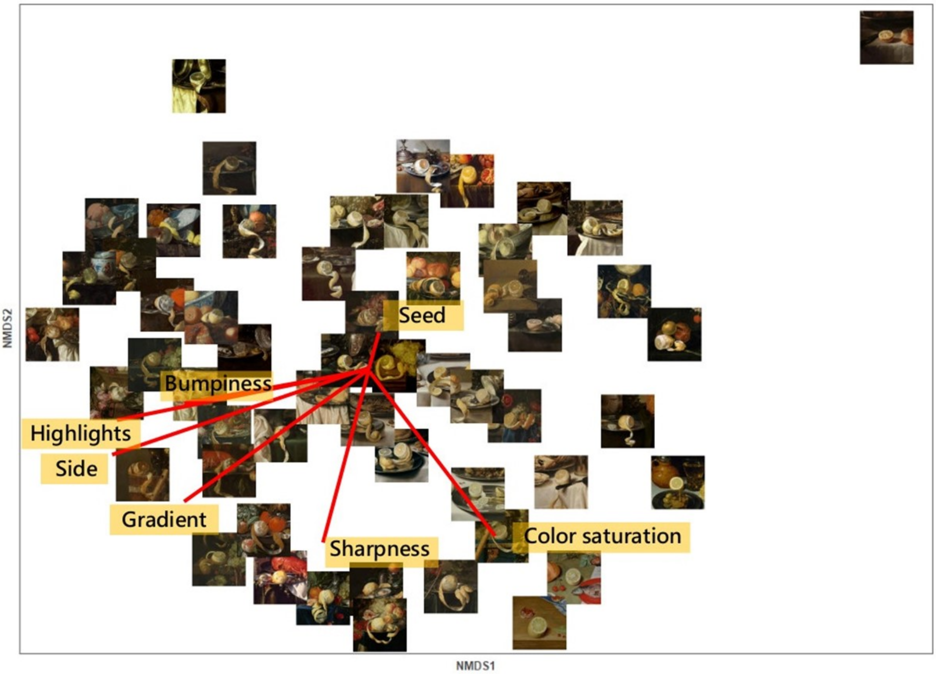


Figure 5.3: 2D space of translucency perception with the stimuli shown at the corresponding coordinates. The red lines represent the vectors of the image features fitted in the space.

The projections of the scores were calculated as the distance d_i from the origin to the scores projected onto the vectors, using the formula [59]:

$$d_i = \left(\frac{\vec{p} \cdot \vec{x}_i}{|\vec{p}|}\right) \tag{5.1}$$

where $\vec{p}$ is the vector of a rated feature and $\vec{x}_i$ is the score representing a stimulus in the NMDS space. The correlation coefficients between the features rated in Experiment 2 and the projections of the scores onto their vectors, together with their significance level, are reported in Table 5.1.

All image features showed high and significant correlation with both spaces, except for the presence of seeds in the pulp, which did not correlate with neither of the spaces. In Table 5.2 we reported the correlations between the ratings of translucency and juiciness from Experiment 3, with the ratings of the image features. The stimuli rated most translucent and juicy in Experiment 3 also had high values of intensity and sharpness of the light gradient; the images showed fruit that was peeled on the side, was bumpy, and had highlights, as shown by the positive and significant correlations in Table 5.2.

Figure 5.4: 2D space of juiciness perception with the stimuli shown at the corresponding coordinates. The red lines represent the vectors of the image features fitted in the space. The space was rotated using Procrustes analysis for better comparison with the ordination of the stimuli in the translucency space in Figure 5.3

	Scores translucency	Scores juiciness
Intensity gradient	0.64 ***	0.59 ***
Sharpness gradient	0.49 ***	0.50 ***
Color saturation	0.58 ***	0.69 ***
Bumpiness	0.50 ***	0.59 ***
Highlights	0.70 ***	0.72 ***
Peeled side	0.77 ***	0.77 ***
Visible seeds	0.08	0.12

Table 5.1: Correlations between the distance of the scores projected onto the vector of each attribute and the corresponding ratings from Experiment 2, in the 2D translucency space (first column) and in the 2D juiciness space (second column) (*p<0.05; **p<0.01; ***p<0.001).

5.5. Discussion

In this study, we first aimed to determine the dimensionalities of the perceptual spaces of human visual perception of translucency and juiciness of citrus fruits pulps depicted in 17th century paintings. Secondly, we intended to identify and evaluate the perceptual relevance of image features found in the paintings, for the

	Translucency	Juiciness
Intensity gradient	0.65 ***	0.41 **
Sharpness gradient	0.31 *	0.42 **
Color saturation	0.10	0.15
Bumpiness	0.40 **	0.38 **
Highlights	0.61 ***	0.61 ***
Peeled side	0.70 ***	0.65 **
Visible seeds	-0.11	0.17

Table 5.2: Correlations between the ratings of the features from Experiment 2 with the ratings of translucency (first column) and juiciness (second column) from Experiment 3 (*$p<0.05$; **$p<0.01$; ***$p<0.001$).

interpretation of the spaces.

We found that 2D embeddings were the optimal solutions for both perceptual spaces, based on the evaluation of the stress values compared to random configurations. We further relied on the criterion of interpretability of the coordinates proposed by Kruskal [54] to opt for the 2D solutions, given that a visual inspection of the third dimension of both spaces did not lead to additional understanding of translucency and juiciness perception.

We assumed that the translucency and the juiciness spaces were perceptually related and we found that similar features were associated with the perception of both attributes. Procrustes analysis showed that the ordination of the stimuli was similar above chance between the translucency and the juiciness spaces, demonstrating the robustness of the underlying structures of the data. The interpretation of the two dimensions of the spaces was drawn from vector fitting of the image features rated in Experiment 2, and by correlating the ratings of translucency and juiciness in Experiment 3 with the ratings of the features. As for vector fitting, the norm of the vectors represented the importance of each image feature for the perceptual judgement of translucency and juiciness.

The vectors that best fitted the translucency space were the presence of highlights on the pulp, the peeled side, the intensity and the sharpness of gradient, and color saturation. Because we tested a limited and specific set of stimuli, we cannot draw conclusions about the space of translucency perception which can be generalized to every translucent material. Different translucent materials might need additional dimensions and features to fit into the space. Nonetheless, the list of image features that we used to interpret our translucency space of citrus fruits, agreed with previous research on translucency perception. Fleming and Bülthoff [9] compiled a list of image features that they found to contribute to the visual appearance of translucency, using computer rendered stimuli evaluating a bidirectional scattering surface reflectance distribution function (BSSRDF) [60]. Their list included highlights, color saturation, important image regions, image contrast and blur. Image contrast and image blur correspond to our intensity of gradient and sharpness of gradient; whereas, the important image regions can be related to what

we called 'peeled side', which is an image feature specific for citrus fruits. When the pulp is visible also from the side, it allows to easily perceive the light bleeding through the edges of the object [15], increasing the translucent impression. The relation between the light gradient and translucency perception was found also by Wijntjes, Spoiala and de Ridder [61] for the case of sea waves depicted in paintings.
Gkioulekas et al. [11] proposed a two-dimensional perceptual space for translucency, corresponding to two parameters of the phase function that mainly affected light diffusion and sharpness. These may be qualitatively related to what we called 'intensity of gradient' and 'sharpness of gradient', which we also found to be important parameters for the ordering of the stimuli in the translucency space, but not independent dimensions. However, it is difficult to draw a direct comparison with their study, given the essential difference with their choice of well-controlled computer rendered objects as stimuli. By using totally uncontrolled stimuli like paintings, we allowed for variations across a wide range of (unknown) features. This may have disclosed different relationships between perceptual dimensions.

The present study is the first, to our knowledge, to investigate the visual perceptual space of juiciness. The vectors that best fitted the juiciness space were the peeled side, the presence of highlights, the bumpiness, the intensity of gradient, and color saturation. Bumpiness, together with the presence of highlights and the peeled side were oriented towards the first dimension of the juiciness space (Figure 5.4). The function *metaMDS* that was used to construct the space, also rotated the configuration to maximize the variance of the points along the first dimension [53], meaning that these features were the most salient to sort juiciness perception. The bumpiness of the pulp surface is a straightforward indication that the cells are full of juice. A peeled side allows to better perceive whether the cells of the pulp are swollen and bumpy, or empty and flat. The presence of highlights serves as an additional information to retrieve the 3D shape of the pulp [62, 63], hence the bumpiness. These three image features can be all observed in the pulp of the fruit that was perceived to be the juiciest, which was also the bumpiest, had a peeled side, and it was among the ones with most highlights (Figure 5.5, left). All the small white dots mimicking the highlights on the peeled side give a stronger 3D appearance to the juice cells, compared to the same image from which the highlights have been removed (Figure 5.5, right).

Among our list of image features, only the visible seeds seem to not contribute to the interpretation of the perceptual spaces of translucency and juiciness. A visual inspection of the stimuli showed that seeds could be visible in pulps with a dry and non-translucent appearance (Figure 5.6, left), as well as in translucent and juicy pulps (Figure 5.6, right). Even though visible seeds were not found to be a cue, it was probably reported by our participants because the property of seeing inner parts is often associated with transparent and translucent media.

The value of the implicit knowledge of painters for material perception has been widely recognized [8, 12, 28–30, 32], but the actual use of paintings as stimuli to research and understand how we perceive material properties is novel and still in its infancy [50, 61, 64]. Our approach was also new in measuring the perceived

Figure 5.5: Detail of the stimulus perceived as bumpiest. The black box indicates the part that was manually modified by the authors to remove the highlights. Left) original painting; Right) modified version without highlights on the side of the pulp. Cornelis de Heem, *Fruit Still Life*, 1670. Mauritshuis, The Hague, The Netherlands.

Figure 5.6: Examples of two stimuli with the seeds visible inside the pulp. The one on the left was perceived among the least translucent and least juicy, whereas the one on the right was rated highly translucent and juicy. Left) Willem Claesz. Heda, *Still Life with a Broken Glass*, 1642. Right) Abraham Mignon, *Still Life with fruit and a Beaker on a Cock's Foot*, 1660-1679. Rijksmuseum, Amsterdam, The Netherlands.

similarity of a specific material property (either translucency or juiciness), uncovering the complexity of its perception.
For example, by correlating the ratings of translucency and juiciness from Experiment 3 with the ratings of the image features from Experiment 2 (Table 5.2), we observed that neither translucency nor juiciness were correlated with color saturation (r=0.1 for translucency and r=0.17 for juiciness, both $p>0.05$). However, the

vector fitting in their 2D perceptual spaces (Figure 5.3 and 5.4), revealed that color saturation could be identified with the second dimension of both spaces. As argued by Fleming and Bülthoff [9], even though color saturation can have an effect, it is neither necessary nor sufficient to trigger a translucent impression. Nonetheless, color saturation was spontaneously reported in the questionnaire by participants of the preliminary experiment, and we found that the stimuli were consistently ordered along such higher dimension.

The psychophysical measurements of the features used to interpret the spaces might be considered a limitation of this work. We believe, however, that this approach is justified by the nature of some of our features (bumpiness, presence of highlights, peeled side, visible seeds), being distal visual cues which cannot be easily and correctly quantified via image analysis. Image statistics, like skewness [65], have been shown to not be adequate predictors of surface reflectance properties, as they fail to take into account the consistency between the perceived 3D shape and the positions and orientations of highlights on the surface [66]. As argued by Wijntjes et al. [61], quantifying the visual cues from the image without considering the 3D shape would be meaningless. The other three features in our list, magnitude and sharpness of the light gradient and color saturation, could be measured via image analysis but again the measurement would not be complete. Especially in the case of the light gradient other factors beside the change in the luminance values, play a role, like the shading pattern and its distribution around the pulp. This effect would need to be calculated together with the luminance gradient, but to our knowledge no algorithm can do it yet. Finally, the measurement of the features via image analysis would need to be proven valid via correlation with the psychophysical estimations.

5.5.1. Beurs' instructions on the material properties of lemons and oranges

Historical painting instructions represent a great source of information, not only for the purpose of technical art history [67, 68], but also to complement the implicit perceptual knowledge inherent in paintings. For example, Lehmann, Pont and Geusebroek [69] investigated the texture appearance of tree bark and foliage combining the findings that Leonardo da Vinci reported in the *Trattato della pittura*, with computer vision and ecological optics to understand tree depictions. Here, we referred to the painting manual "The big world painted small" [2, 3], which is a collection of pictorial recipes for rendering objects and materials in the most convincing way, using oil paint. The book has a descending structure, so once the basics have been explained and practiced in the beginning, there is no need to repeat them in every recipe, and the same is valid for similarities between materials. That is why Beurs' instructions on how to paint the pulp of a lemon or an orange consist of a series of references to previous recipes, up to the grapes, the first food treated in the book [2, 3]. Beurs aimed to teach how to paint materials rather than objects, so he instructed that the layers composition of grapes could be reapplied to paint gooseberries, oranges and lemons. From the grapes recipe we could derive the image features prescribed to render citrus fruits pulps, i.e. the light gradient, the

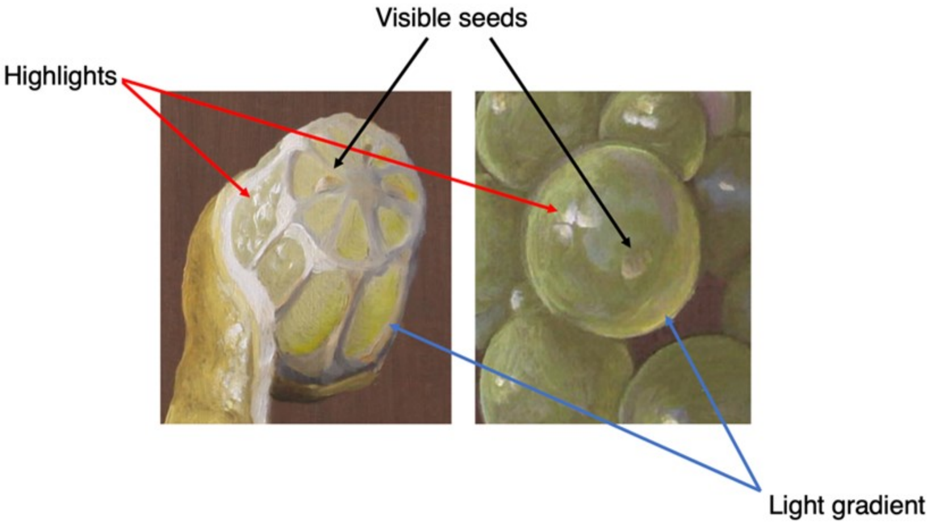


Figure 5.7: Visualization of how the pictorial recipe of the grapes was reapplied to render the pulp of a lemon, according to Beurs' recipe. The image features explicitly addressed by Beurs are marked with an arrow (paintings by Lisa Wiersma).

highlights placed opposite to the brighter contours along the edges, and the visible seeds (Figure 5.7). Beurs also implicitly referred to the use of bright colors when listing the color pigments to employ.

Given that in still life paintings the light source is conventionally placed top left [70], the lighter part of the gradient is usually painted at the bottom right of the pulp. The top left lighting also means that the bottom right side of the lemon is shaded, and when the side is peeled, the contrast between the pulp and the white pith of the citrus fruit increases. Such contrast produces an appearance even lighter along the edges of the fruit pulp, confirming the importance of a visible light gradient through the pulp to trigger an impression of translucency (see Figure 5.8 for examples from our stimulus set).

5.6. Conclusions

In this study, we determined the optimal embeddings for the perception of translucency and juiciness of the pulps of citrus fruits depicted in 17th century paintings to be two dimensional. We then identified the image features that provided a perceptually-meaningful interpretation of these spaces. We assumed a perceptual relationship between translucency and juiciness, and we found that similar image features were related to their perceptual spaces. The present study is the first, to our knowledge, to investigate the visual space of juiciness perception, a food textural attribute usually studied in relation to in-mouth perception [71], and physical

Figure 5.8: Examples of stimuli peeled on the side, showing top-left lighting and bottom-right shading. The shade on the white pith increases the contrast with the pulp seen through, making it appear lighter. Top left) Abraham Mignon, *Still Life with fruit and a Beaker on a Cock's Foot*, 1660-1679. Top right) Pieter de Ring, *Still Life with Golden Goblet*, 1640-1660. Bottom left) Johannes Hannot, *Still Life with Fruit*, 1668. Bottom right) Jan Davidsz. de Heem, *Still Life with Fruit and a Lobster*, 1640-1700. Rijksmuseum, Amsterdam, The Netherlands.

measurements for fruit quality determination [72, 73].
Visual perception is known to affect the overall sensory experience of food, but the effect of visual perception of food textural properties is still unknown (with the exception of [74]). Thus, recovering the visual dimensions that people use to infer the textural properties of food, can forward the current understanding of human multisensory perception of food. Our findings could contribute to the fields of human-food interaction influenced by the visual appearance of food, such as expectations of liking and flavor [75], eating behavior [76], and purchase intentions [77].

Finding image features that are perceptually significant to trigger specific material properties could be also beneficial for computer graphics. Working with scientifically informed, perception-based visual cues, like the ones found in this study, could reduce the time spent on trial and error, allowing to tune the parameters to directly obtain the desired appearance.

The translucency space was interpreted via image features that agreed with previous literature [9] and may thus be generalized to: light gradient, highlights, color saturation and edges. The first three cues were also prescribed by Beurs [2, 3] in his recipes to paint cut open lemons and oranges, showing how research on material perception could be complemented by art historical writings and by the implicit knowledge of painters.

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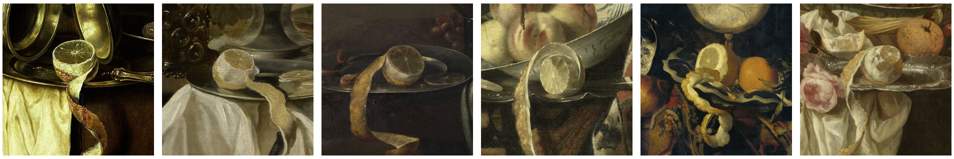
5.7. Supplementary material

Figure S1.

Numbered list of all the squared cut-outs used for rating experiments 1,2 and 3. Each image in the list has the embedded link in the caption to the relative museum repository website.

Stimulus 1 Stimulus 2 Stimulus 3 Stimulus 4 Stimulus 5 Stimulus 6

Stimulus 7 Stimulus 8 Stimulus 9 Stimulus 10 Stimulus 11 Stimulus 12



Stimulus 13 Stimulus 14 Stimulus 15 Stimulus 16 Stimulus 17 Stimulus 18

Stimulus 19 Stimulus 20 Stimulus 21 Stimulus 22 Stimulus 23 Stimulus 24

Stimulus 25 Stimulus 26 Stimulus 27 Stimulus 28 Stimulus 29 Stimulus 30

Stimulus 31 Stimulus 32 Stimulus 33 Stimulus 34 Stimulus 35 Stimulus 36

Stimulus 37 Stimulus 38 Stimulus 39 Stimulus 40 Stimulus 41 Stimulus 42

Stimulus 43 Stimulus 44 Stimulus 45 Stimulus 46 Stimulus 47 Stimulus 48


Stimulus 49


Stimulus 50


Stimulus 51


Stimulus 52


Stimulus 53


Stimulus 54


Stimulus 55

S1. Instructions experiment 1

"How similar is the translucency/juiciness of the pulps of these citrus fruits?"

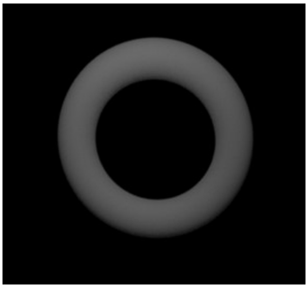
TRANSLUCENCY: Indicates that light can pass through the pulp of the citrus. It is the opposite of opaque.

JUICINESS: Indicates that the pulp of the citrus appears full of juice. It is the opposite of dry.

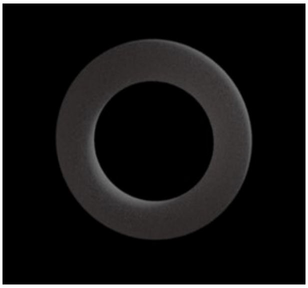
S2. Instructions experiment 2

"How big is the difference between the light and the dark part in the pulp of this citrus?"

LIGHT GRADIENT: magnitude of the change between the part of the pulp (surface + side when visible) in the light and the part of the pulp in the dark. Low values indicate that the light on the pulp looks uniform with no transition between light and dark; high values indicate that there is a big difference between the light and the dark parts of the pulp.



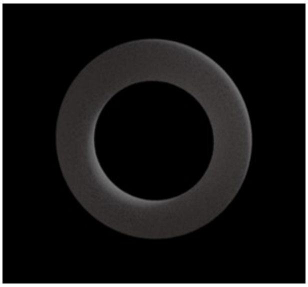
(a) Uniform light



(b) Light gradient

"How sharp is the gradient between the light and dark part of the pulp surface of this citrus?"

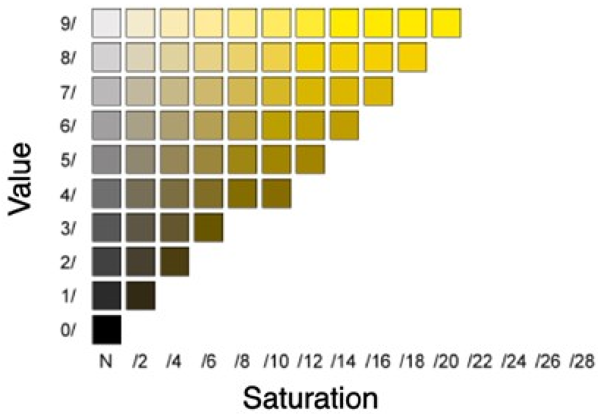
SHARPNESS OF GRADIENT: refers to the sharpness of the transition between the part of the pulp in the light and the part of the pulp in the dark. Low values indicate that the transition looks blurred; high values indicate that the transition looks very sharp.



(a) Blurred gradient

(b) Sharp gradient

"How saturated is the color of the pulp of this citrus?" COLOR SATURATION: defines the intensity of the color. Low values indicate that the color looks poorly saturated; high values indicate that the color looks highly saturated.



"How bumpy is the surface of the circular cross section of the pulp of this citrus?" Low values indicate that the surface of the pulp looks completely flat; high values indicate that the surface of the pulp looks very bumpy. Bumpiness includes also the small cells in each slice.

"Do you see highlights on the pulp of this citrus?"
"Do you see the seed(s) in the pulp of this citrus?"
"Do you see the (peeled) side of the pulp of this citrus?"

S3. Instructions experiment 3
"How translucent does the pulp of this citrus look?"
TRANSLUCENCY: Indicates that light can pass through the pulp of the citrus. It is the opposite of opaque. Low values indicate an opaque appearance, high values indicate a translucent appearance.

"How juicy does the pulp of this citrus look?"

JUICINESS: Indicates that the pulp of the citrus appears full of juice. It is the opposite of dry. Low values indicate a dry appearance, high values indicate a juicy appearance.

6

From paintings to packaging design

The customer's perception is your reality.

Kate Zabriskie

This chapter has been published as: Di Cicco, F., Zhao, Y., Wijntjes, M.W.A., Pont, S.C., Schifferstein, H.N.J. (2021). A juicy orange makes for a tastier juice: The neglected role of visual material perception in packaging design. Food Quality and Preference, 88, 104086 [1].

My contribution in [1] was the conceptualization of the research idea; to design the rating experiments; to analyze and interpret the data; to write the manuscript.

Food appearance sets intentions and expectations. When designing packaged food much attention is devoted to packaging elements like color and shape, but less to the characteristics of the images used. To our awareness, no study has yet investigated how the appearance of the food shown on the package affects consumers' preferences. Often, orange juice packages depict an orange. Juiciness being one of the most important parameters to assess oranges' quality, we hypothesized that an orange with a juicier appearance on the package would improve the overall evaluation of the juice. Using image cues found to trigger juiciness perception of oranges depicted in 17th century paintings, we designed four orange juice packages by manipulating the highlights on the pulp (present vs. absent) and the state of the orange (unpeeled vs. peeled).

In an online experiment, 400 participants, each assigned to one condition, rated expected naturalness, healthiness, quality, sweetness and tastiness of the juice, package attractiveness and willingness to buy. Finally, they rated juiciness of the orange for all four images. A one-way ANOVA showed a significant effect of the highlights on juiciness. A MANOVA showed that the presence of highlights, both in isolation and in interaction with the peeled side, also significantly increased expected quality and tastiness of the juice.

The present study shows the importance of material perception and food texture appearance in the imagery of food packaging. We suggest that knowledge from vision science on image features and material perception should be integrated into the process of packaging design.

The quote by the business trainer Kate Zabriskie "the customer's perceptions is your reality", could be adapted to "the customer's perception is *THE* reality", especially when it comes to food. It is known already that 'what we see is what we get', our eyes have a great influence on our taste perception. Color, shape, plates' arrangement, were all shown to play a role. But what about the eternal forgotten material perception? Building on the findings from the previous chapter, here we will show that the picture of a juicy orange on orange juice packaging can boost consumers' expectations on quality and taste, and should therefore not be ignored.

6.1. Introduction

Product packaging plays an influential role in guiding the in-store purchase decisions of consumers. For instance, the packaging shape and color contribute significantly in guiding consumers' first impression of a product seen from a distance and at an angle on retail shelves [2]. The processing of visual packaging cues tends to dominate the purchase decision process [3]. On the basis of the packaging characteristics people see, they try to predict how the product will taste [3]. Hence, the design of food product packages can have a major effect on how its content is experienced during consumption. Studies have demonstrated that packaging shape [4] and color [2] affect the expectations consumers have when they open a package and consume its content.

Besides shape and color, imagery is another extrinsic cue contributing to build expectations and sensory experiences [5]. A congruent and pleasant image on orange juice packaging has been shown to affect its taste, by improving palatability, freshness and aroma perception [6]. In a recent review, Gil-Pérez, Rebollar and Lidón [7] summarized the last decade of research on the effect of various elements of packaging imagery on consumers' perception and expectations, offering a framework to use these findings to promote healthy eating behaviors.

In the current paper, we are particularly interested in the role of images on orange juice packages. Orange juice is consumed worldwide, and a glass of 100% fruit juice can account for one of the five daily recommended portions of fruits and vegetables, representing a healthier alternative to carbonated beverages. Images on orange juice packages usually depict a glass of juice or an orange shown either entire or cut in half. A topic that has been largely neglected thus far is the role of the visualization of the material properties of the objects depicted in the package image. Material perception can be easily overlooked, since it is something that people evaluate effortlessly on a daily basis when, for example, they judge the ripeness of an apple or the slipperiness of a floor. Studies on material perception in food packaging have considered only the material properties of the packaging itself, showing that glossy packaging materials are associated with high fat levels [8] and tastiness [9].

No study, to the best of our knowledge, has looked into the perceived material properties of the product presented in the packaging imagery. Studies have shown that the visual features of food can affect the perception of properties responsible for food quality, like freshness. Changes in freshness perception of fish [10], fruits and vegetables [11] were shown to be related to the luminance distribution of the food image. Despite this critical role that food appearance plays on consumers' perception and acceptability of products, a thorough understanding of its effect in packaging imagery is still missing.

In this paper we aim to address this gap by investigating how the visual perception of juiciness of an orange shown on the package of orange juice affects the inferred properties of the product. Juiciness is a key textural property of food, mainly dependent on the amount of juice and its rate of release during chewing [12]. It is usually studied in relation with in-mouth perception using trained sensory panels ([13], or via physical measurements to determine food quality [14]. To understand how juiciness can be visually communicated and how it is estimated, it is necessary to know the image cues that trigger its perception. One research approach consists in unraveling the implicit knowledge of painters by using images of paintings as experimental stimuli. Paintings are considered a corpus of perceptual experiments by vision scientists [15], since painters have been studying the key image cues exploited by the human visual system to perceive material properties for centuries. In a psychophysical study on visual perception of the juiciness of citrus fruits depicted in 17th century paintings [16] the authors identified the 'highlights on the pulp' and the 'peeled side' of the fruits as the image features that most contributed to perceived juiciness. Therefore, the hypotheses of the present study are:

- H1: The presence (absence) of the features 'highlights' and 'peeled side' in the image would result in a significantly higher (lower) perception of juiciness of the orange shown in the packaging imagery.

- H2: The image of an orange with a juicier (less juicy) appearance on the packaging would enhance (decrease) the expected quality, naturalness, healthiness, and tastiness of the juice, and therefore the willingness to buy.

6.2. Method

6.2.1. Stimuli

To systematically vary the visual perception of juiciness, we adopted the image features found to be associated with it, 'highlights on the pulp' and the 'peeled side' of the fruits [16]. In agreement with these findings, we designed four stimuli following a 2 × 2 design via digital manipulation of the highlights on the pulp (present vs. absent) and physical manipulation of the state of the orange (unpeeled vs. peeled). The digital manipulation and the design of the packages were done using Adobe Photoshop (CC 2017.0.1). The stimuli are shown in Figure 6.1.

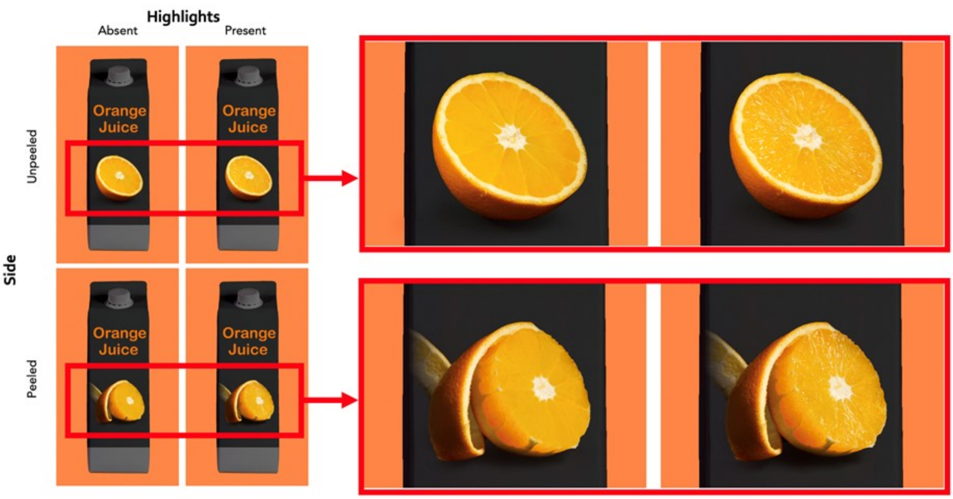


Figure 6.1: Stimulus set with zoomed-in version of the orange images and the features manipulated.

6.2.2. Participants

Four groups of 100 participants were recruited online through the Amazon Mechanical Turk (AMT) platform. Each participant was randomly assigned to one of the four conditions and rated a set of attributes. Participants with a rating time below 1 s were removed, as we assumed they were just rushing through the experiment to increase their financial gain. Such participants' sampling resulted in a total of 359 participants, circa 90 per condition. All participants were naïve to the purpose of the experiment. They agreed to the informed consent prior to the experiment. The experiment was conducted in agreement with the Declaration of Helsinki and approved by the Human Research Ethics Committee of Delft University of Technology.

6.2.3. Procedure

The experiment was coded in Python, using the Boto3 package to communicate to Amazon Mechanical Turk. The experiment consisted of two parts. In the first part, participants were presented with one of the packages from the four conditions following a between-subject design. In this part of the experiment they were asked to rate naturalness, healthiness, quality, and the expected sweetness and tastiness of the juice, the attractiveness of the package, and the willingness to buy. The ratings were done using a slider on a continuum, ranging from 0 to 100, with the anchoring points being 'low' and 'high', respectively. In the second part of the experiment, all participants rated the perceived juiciness of the orange in the image for all four conditions following a within-subject design. Before starting the actual rating in the second part, participants did four practice trials that were meant to give them an overview of the stimuli to set an internal scale for the ratings. After the practice trials, they rated the juiciness of the orange shown in the image, using the same slider as in the first part, ranging on a continuum from 0 (low) to 100 (high). The four trials in the second part were randomized across participants.

6

6.3. Results

We will first report the outcomes of the second part of the study about juiciness perception of the four stimuli, before reporting the outcomes of the first part of the study about the overall evaluation of the juice in each of the four conditions.

6.3.1. Effect of visual cues on juiciness perception

In the second part of the experiment, all participants rated juiciness for all four conditions. To test whether the manipulation of the visual cues affected the visual perception of the juiciness of the oranges shown on the packages, we performed a two-way repeated measures ANOVA, with 'highlights on the pulp' and 'peeled side' as independent variables and perceived juiciness as dependent variable. Juiciness perception of the orange increased significantly with the presence of the highlights ($F(1, 358) = 34.05$, $p<0.001$, $\eta^2_{partial} = 0.087$), whereas the peeled side caused no significant increase ($F(1, 358) = 0.305$, $p>0.05$, $\eta^2_{partial} = 0.001$). The mean values and the standard errors of the four conditions are reported in Table 7.1. The interaction effect between highlights and peeled side was also not significant ($F(1, 358) = 0.5$, $p>0.05$, $\eta^2_{partial} = 0.001$). This indicates that highlights on the pulp of the orange triggered a significantly higher perception of juiciness than if they were not present, regardless of the state of the orange being peeled or not.

Condition	Mean	Standard error
Highlights – peeled side	0.65	0.014
No highlights – peeled side	0.58	0.016
Highlights – unpeeled side	0.64	0.014
No highlights – unpeeled side	0.56	0.016

Table 6.1: Mean and standard errors of the juiciness ratings in the four conditions.

6.3.2. Effect of visual cues on product's assessment

We conducted a MANOVA to examine the effect of the presence of the visual cues 'highlights on the pulp' and 'peeled side' as independent variables, on the expected naturalness, healthiness, quality, sweetness and tastiness of the juice, attractiveness of the package, and the willingness to buy, as dependent variables. We found a main effect of the presence of the highlights on expected quality ($F(1, 355) = 4.1$, $p<0.05$, $\eta^2_{partial} = 0.011$) and tastiness of the juice ($F(1, 355) = 4.7$, $p<0.05$, $\eta^2_{partial} = 0.013$). The main effect of peeling the side of the orange was not significant for any of the attributes (F ranged from 2.1 to 0.1, $p>0.05$).

However, there was a significant interaction effect of the presence of the highlights with the peeling of the orange for the quality and taste of the juice ($F(1, 355) = 5.1$, $\eta^2_{partial} = 0.014$ for quality and $F(1, 355) = 3.7$, $\eta^2_{partial} = 0.01$ for tastiness, $p<0.05$). Peeling the orange resulted in a larger effect on the quality and tastiness of the juice for oranges with highlights (M = 0.58, SE = 0.29 for quality; M = 0.73, SE = 0.26 for tastiness), than for oranges without highlights (M = 0.45, SE = 0.30 for quality; M = 0.61, SE = 0.27 for tastiness).

6.3.3. Mediation analysis

We found that the presence of highlights on the pulp of the orange shown in the package's imagery was related to a significant increase in juiciness perception of the orange in the image, as well as an increase in expected quality and tastiness of the juice. Therefore, we were interested to know whether consumers expected the juice to be of higher quality and taste better for images of oranges with highlights, because they perceived the orange to be juicier. Or, in other words, we wanted to test whether juiciness perception of the orange acted as a mediator on expected quality and tastiness of the juice. To test the significance of the indirect effect we performed a biased-corrected bootstrapping procedure with 10.000 samples (PROCESS, model 4 [17]). The 95% confidence interval (CI) of the indirect effect included zero both for quality (-0.02 to 0.06) and for tastiness (-0.02 to 0.08), indicating that the indirect effect of the highlights on expected quality and tastiness of the juice through juiciness perception of the orange, was not significant. However, a linear regression with juiciness predicting quality and taste, showed that the juiciness of the orange on the package was related to the tastiness (b = 0.29, $p=0.000$) and quality (b = 0.22, $p=0.002$) of the juice.

6.4. Discussion

Building on the research on material perception and on food packaging imagery, in this study we investigated the role that juiciness perception of an orange displayed on the package of orange juice plays in product evaluation. We first tested how the perceived juiciness of the orange changed when manipulating the presence of the image features found to trigger juiciness perception, i.e. the presence of highlights and the peeled side [16]. The visual perception of juiciness may not be an often discussed topic in the scientific perception literature, but it is well-known to professionals who convincingly render material properties, like painters, graphic designers or food photographers. For example, to make a burger look juicy in a photo, the trick is to spray it with oil to increase the amount of specularly reflected light.

In agreement with this "implicit" knowledge, our results showed a significant effect of highlights on juiciness perception. The presence of highlights on the pulp of the orange reveals the three-dimensional shape of the cells [18], i.e. whether they are round and swollen with juice or flat and dry. This gives a straightforward indication of the amount of juice present, that people can adopt to estimate how juicy the orange would be. The peeled side on the contrary, had no significant effect on juiciness perception of the orange in the image. Peeling an orange on the side adds a cue for translucency perception by increasing the visibility of the light gradient. Juiciness is related to translucency, since the juice contained in the cells acts as medium that allows the light to scatter within the orange pulp. However, the present study suggests that translucency alone is not strong enough as a cue to increase juiciness perception. A peeled side can also reveal the bumpiness of the cells swollen with juice, and thus contribute to juiciness perception, but the bumpiness may be perceived to be more articulated in combination with the highlights [18].

The MANOVA results indicated that the presence of highlights on the orange pulp significantly increased expected quality and tastiness of the juice. The peeled side showed no significant effect in isolation, but it showed a significant interaction effect where peeling in the presence of highlights increased the expected quality and taste of the juice. The MANOVA also showed that the image manipulations did not affect the other attributes. Naturalness and healthiness were likely not influenced because an image of an orange was shown in all four testing conditions, and showing the ingredient in its unprocessed form is often associated with the perception of a natural and healthy product [19].

The non-significant effect on purchase intentions was unexpected, considering the increase in expected quality and taste evaluation. Possibly, our stimulus set did not offer sufficient variations to induce a significant difference in willingness to buy, since the image of the orange was always congruent with the product category. Mediation analysis did not confirm that the presence of highlights increased expected quality and taste evaluations, because the orange in the image was perceived to be juicier. However, the regression coefficients of juiciness on taste and quality evaluations were both positive and significant, suggesting that as juiciness perception of the orange image increased, the expected quality and tastiness of the juice also tended to increase.

Even though no studies so far have looked into the effect of the material properties of the food shown in packaging imagery, several researchers have investigated the role of food textural properties on consumers' liking and acceptance. Our results on the effect of the highlights are in good agreement with studies that identified glossiness as a critical surface property for consumers' liking and sensory evaluation of diverse food products, like chocolate [20], fruits and vegetables [11], and fish [10].

One limitation of our approach, which should be addressed in a future study, was that our stimulus set relied solely on attributes inference based on implicit cues, i.e. the image features. This could have required an enhanced cognitive effort, which not all participants may have been able or willing to make [19]. It would be interesting to see if including explicit textual information could increase the effect on product quality and tastiness expectations.

The main aim of the present study was to draw the attention of packaging designers and food industries to the importance of the visual appearance and material perception of food presented in the packaging imagery. It is a popular saying that "we eat with our eyes first", as the visual experience of food appearance is usually the first way how we interact with a product, setting intentions and expectations [3]. As surface textural properties of food can deeply affect consumers' perception of the product [21], we propose to integrate multidisciplinary insights from vision science and material perception into making better informed decisions in the process of packaging design. The first step should be finding which image cues trigger the perception of an intended material property, and then integrate these cues in the imagery shown on the package. This study, for example, demonstrated that adding highlights on the pulp of the depicted orange contributes to communicate the juiciness of the oranges squeezed to make the juice. This is necessary because only by knowing which image cues trigger the perception of the desired material property, it is possible to visually communicate the intended message to consumers effectively.

6.5. Conclusion

In this study, we showed that material perception of the food shown on the package influences consumers' evaluation of the packaging content. More specifically, we manipulated the image features that contribute to the visual perception of juiciness of oranges, i.e. the highlights on the pulp and the peeled side. We hypothesized that the image of a juicy orange on the package, would elicit a better overall impression of the orange juice. This hypothesis was confirmed, at least for certain attributes, as we found that juiciness perception was positively correlated with expected quality and tastiness of the juice. The presence of the highlights on the orange pulp significantly increased juiciness perception of the orange, and the interaction of highlights with the peeled side, showed a significant effect on expected quality, and tastiness of the juice. In terms of practical applications of this study, we recommend to include insights from vision science to improve design decision making for packaging design.

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7

Soft like velvet and shiny like satin

In contrast to your other textile, where you render with light paint all the relief in the folds, this is completely different with velvet [drapery], as you make these entirely dark and paint flat highlights only on the reflecting side.

Karel van Mander

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In [1], my contribution was to the conceptualization of the research questions; to create the stimuli for all the experiments; to compute the image features via image analysis. MJPVZ and I contributed equally to design the rating experiments; to analyze and interpret the data; to write the manuscript. We both share first authorship on the paper.

Dutch 17^{th} century painters were masters in depicting materials and their properties in a convincing way. Here, we studied the perception of the material signatures and key image features of different depicted fabrics, like satin and velvet. We also tested whether the perception of fabrics depicted in paintings related to local or global cues, by cropping the stimuli. In Experiment 1, roughness, warmth, softness, heaviness, hairiness and shininess were rated for the stimuli shown either full figure or cropped. In the full figure, all attributes except shininess were rated higher for velvet, while shininess was rated higher for satin. This distinction was less clear in the cropped condition, and some properties were perceived significantly different between the two conditions. In Experiment 2 we tested whether this difference was due to the choice of the cropped area. Based on the results of Experiment 1, shininess and softness were rated for multiple crops from each fabric. Most crops from the same fabric differed significantly in shininess, but not in softness perception. Perceived shininess correlated positively with the mean luminance of the crops and the highlights' coverage. Experiment 1 showed that painted velvet and satin triggered distinct perceptions, indicative of robust material signatures of the two fabrics. The results of Experiment 2 suggest that the presence of local image cues affects the perception of optical properties like shininess, but not mechanical properties like softness.

In 1976, Gombrich [2] observed "the demise of highlights" in the works of 14^{th} century Italian masters like Duccio di Buoninsegna (1255-1319), who was able to skillfully render the illumination in the scene and sculpt the shape of objects with chiaroscuro. However, rendering the 3D shape of objects is not quite the same as rendering their materials. That is why Gombrich [2] wondered clueless "But are the draperies silk or are they wool?" when discussing *The Healing of the Man born Blind* (1307, The National Gallery, London, UK). With the "demise of highlights" it is indeed impossible to tell fabrics apart, because, as we will show in this chapter, different fabrics have distinctive material signatures and perceptual features, among which the highlights are one of the most tell-tale.

7.1. Introduction

Fabrics serve a wide array of functions in our daily life. We use fabrics to hold and carry things, to clean and dry surfaces, for decoration, and for clothing. With this wide array of functions, the material category of 'fabric' also comes with a wide variety of appearances. The visual appearance of fabrics depends on the type of fiber (e.g., natural or synthetic), the yarn (the continuous segment of fibers), and the weaving method [3–5]. Materials' appearances are strongly dependent on light [6, 7] and shape [8–10]. This is true also for the appearance of fabrics, which has been shown to depend on the illumination environment [11, 12] and on the folding shape [13]. Nonetheless, we can visually discriminate and identify different types of fabrics on the basis of their characteristic visual qualities, also known as "material signatures" [14].

In this paper we focus on the appearance of velvet and satin. Velvet and satin both belong to the material category of fabric, but large differences exist within this same material class. Upon visual observation, one could find more similarities between the appearance of satin and aluminum foil, than between satin and velvet (Figure 7.1). However, despite the visual similarity, nobody would classify aluminum as a fabric.

Figure 7.1: Satin (left)is visually more similar to aluminum foil (middle) than to velvet (right). However, satin certainly belongs to a different material class than aluminum. The first two images were downloaded from Morguefile.com and the third image from pxfuel.com, released under free license.

In this study, we studied the perception of painted fabrics in 17th century Dutch paintings, a class of paintings unanimously acknowledged for the convincing representation of materials and their properties. The economical yet effective rendering of material properties exploited by 17th century painters [15] resonates with the mechanisms of the human visual system [16–25]. Painters carefully chose the image features to include and could choose to omit perceptually irrelevant or hindering features, as it was shown to be the case for the orientation of the highlights on grapes which do not need to be congruent with the object shape in order to communicate a glossy appearance [22]. Materials were often painted according to standard, well-established instructions which assured the painter of getting the best possible rendering. Velvet, for example, could be convincingly depicted by simply inverting the typical patterns of light and shade [26, 27]. Written records of such visual tricks can be found in "Het Schilder-boek", a book describing the life and work of several painters, composed by Dutch painter and art historian Karel van Mander in 1604. He wrote: "In contrast to your other textile, where you render with light paint all the relief in the folds, this is completely different with velvet [drapery], as you make these entirely dark and paint flat highlights only on the reflecting side" [28, 29]. Another relevant art historical source is "The big world painted small" by Willem Beurs [30, 31]. This book has already proven to be a useful tool to help understand pictorial procedures and the relevant image features for the rendering of materials [32]. In this collection of pictorial recipes, Beurs described how to paint satin and velvet emphasizing the different rendering of specular reflections, sharp and high contrast for satin and somewhat blurrier and with less contrast for velvet [33]. These are examples of the value of investigating paintings and art historical writings for the sake of understanding the functioning of the human visual system.

Understanding the material attributes that form the signatures of the representation of different fabrics, like velvet and satin, is important for several applications.

One example is online shopping, in which visual communication of the material qualities of fabrics is crucial to guide the consumers' choice. The appearance in the image should match as closely as possible the appearance that would be perceived in a real shop. Failing to capture and convey the material attributes of the fabric is one of the major concerns of online retailing [34]. On this topic, it has been shown that dynamic stimuli (videos) can better communicate the haptic properties of fabrics compared to static stimuli (images), because of the greater availability of information [35, 36]. Xiao et al. [13] found that when observers can only rely on images to infer the material properties of fabrics, color and folding information interact to enhance the accuracy with which tactile properties are estimated. In the absence of folds, i.e., if the fabric is shown flat, chromatic information was found not to be discriminative enough. In perception-based computer graphics, it has been shown that the optical appearance of different fabrics contributes to the realism of the rendering more than their dynamics [37]. The digital rendering of fabrics is gaining importance in the entertainment industry for movies and games [38], and in online shopping with the option to virtually try-on clothes [39].

Velvet and satin have different mechanical and optical properties which give rise to their distinctive appearances. The appearance of velvet is due to asperity scattering, where light is scattered by the hairy layer on the surface, leading to a brightening of the contours [3, 4]. The reflectance properties of satin, which lead to its shiny appearance, depend on its constructional parameters (e.g., the yarn density and the weave pattern) [40]. In particular the weave pattern of satin is based on "floating" yarns, yarns that are weaved vertically over a horizontal weft. These floating yarns reflect the light from the fabric creating specular or split-specular reflections causing the shiny appearance [11]. The specular peaks for satin are located at the regions of highest curvature, and under generic lighting conditions are pointed towards the light source. For velvet however, the brightest regions are typically placed along its occluding contours, under generic lighting condition [11]. The position of highlights, being related to the 3D shape of the object, also reveals the folding configuration of the fabric. This folding configuration is informative when estimating the optical and mechanical properties of a piece of fabric when presented with visual information only [13].

Some physical properties of an object or material, such as softness or warmth, are not directly apparent by the optical cues present in the image. To infer these properties, the human visual system can either employ a bottom-up or a top-down approach. The first relies on the profile of image features that triggers material perception. The second approach would first require recognizing the object and the material class it belongs to, and then inferring the material attributes via prior knowledge and learned associations. However, it is not always necessary to identify the object in order to infer the material attributes. Schmidt et al. [41, 42] showed that identifying the material class already provides enough cues to derive material attributes via an "associative approach". They conducted a rating experiment of several material attributes using unfamiliar shapes rendered with materials with different optical properties (e.g., marble, steel, velvet, etc.). They found that softness estimation relied on recognizing the different materials via the associative approach (e.g., it is velvet therefore it is soft). These two approaches, i.e., bottom-up and top-down, typically, but not necessarily exclusively, use local and global visual information respectively. This then raises the question whether material perception relies on global or local visual information, or a combination of both. According to Schwartz and Nishino [43], material attributes are inherently local, which is why a classifier trained on human similarity judgements could recognize these attributes from small image patches, like image crops. Marlow and Anderson [44] proposed that human perception of glossiness depends on local image features of the highlights, such as coverage, contrast and sharpness, but these features are in turn dependent on the global information of the shape and the illumination environment. Balas et al. [45] proposed that the use of global or large scale visual information for material perception is developed with age, as they found that children's performance in distinguishing between real and fake food was impaired when local information was disrupted but that this impairment was reduced or even absent when global information was disrupted. They found that the disruption of global information affected the latency in the response of children rather than their accuracy. Since missing global information did not affect the outcome, it indicates that children rely more on local cues than on global ones. Schmidt, Fleming and Valsecchi [10] showed that local shape features affect the visual perception of softness and weight of unfamiliar, static objects.

It is evident from the literature that the understanding of the visual systems' use of local vs global visual information is still an open problem, therefore in this paper we tested and compared material perception providing either global or local information.

Another field in which it is relevant to distinguish and identify different fabrics is art history, as every element within paintings usually carries meaning. For example, in some drawings made around 1490 by a German artist known as the Master of the Coburg Roundels, the lively "fluttering loincloth" of the crucified Christ may signify his imminent resurrection [46]. Another example is the dress of Eleanor of Toledo, painted by Bronzino in 1546, which symbolized the wealth and power of Florence and de Medici family in the 16th century [47]. According to Thomas [47], "in order to understand the origin and purpose of the dress, we must first know the nature of the fabric" and he wondered whether the fabric was velvet or satin. The original hypothesis that the fabric was brocaded satin was later confirmed when the tombs in de Medici's mausoleum were opened, as the dress was the burial gown of the Eleanor of Toledo [47]. However, it should be noted that art historical examples where the depictions of an object or material can actually be compared with the original object or material, are for obvious reasons extremely rare.

The first aim of this paper was to determine the perceptual material signatures of velvet and satin depicted in 17th century paintings. In Experiment 1, we further explored whether cropping the fabric out of its global form and providing only local information, caused a change in perception of its material properties. This indeed happened. In Experiment 2, we investigated whether the observed changes in material perception when judging a cropped image could be related to the choice of the cropped area, due to the presence or absence of triggering image cues. Finally, to explore which cues observers relied on to make their judgments, we correlated the perceived material properties in the different crops with image features of the highlights.

Experiment 1

7.2. Methods

In Experiment 1 six material attributes were rated for a set of paintings of fabrics, depicting either velvet or satin, to measure the extent of association of each attribute with the two types of fabric. The stimuli were presented in two viewing conditions, either with context where the full figure was presented or without context/object shape information, where crops of the fabric were presented. The different viewing conditions were aimed to test whether showing a fabric embedded in a recognizable object, such as a dress or a tablecloth, rather than in an anonymous form without context, would affect the perception of the material attributes.

7.2.1. Stimuli

We selected 19 fabrics from 17 high-resolution digital images of 17th century oil paintings. Two paintings depicted both velvet and satin and were therefore used twice. All paintings reproduced within this paper are available under open access at a CC0 or CC BY 4.0 license. The full list of all paintings used within this study, including those reproduced in this paper, can be found in Figure S1 in the supplementary materials 7.8.

The fabrics were categorized as either velvet ($n = 8$) or satin ($n = 11$) by the experimenters. The categorization was based on the expertise of all the authors in vision science and optics. We further supported this categorization with art historical sources identifying the fabrics of some of the paintings in our set of stimuli, as either satin or velvet [33, 48, 49].

In one viewing condition, the entire figure or object, including the background, was shown with a red arrow indicating the target fabric to rate (see the left image in Figure 7.2). In the other viewing condition, each target fabric was cropped to a 600x600 pixels patch and presented on the screen at the same visual size as in the full figure condition against a grey background (see the right image in Figure 7.2). The cropped areas were chosen to be as informative as possible about the folding shapes. Throughout the rest of the paper, we will refer to the two viewing conditions as full figure condition and crop condition, respectively. See Figure S1 in the supplementary material 7.8 for all the stimuli in both viewing conditions.

7.2.2. Observers

Each participant rated all the stimuli in one viewing condition and for one material attribute. We collected data from 10 participants for each combination of the two viewing conditions and six attributes, for a total of 120 participants. Data were collected through the Amazon Mechanical Turk (AMT) platform. While AMT provides some benefits over conventional lab-settings, it is known to possibly result in noisy

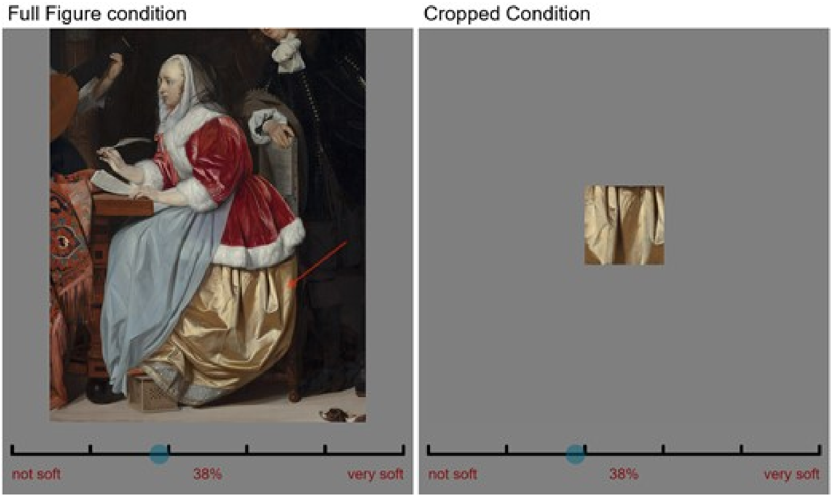

Figure 7.2: An example of each of the two conditions, within the interface. Left) the full figure condition, in which the figure or object with the target fabrics is fully visible. Right) the crop condition, where only a patch from the target fabric is visible, which is intended to deprive the visual system from context and shape information. Note that a participant would see only the left or right screen, never both.

data as a result of a small, but considerable portion of participants that appear to perform badly in experiments. Based on previous experience with the AMT platform [23], we set an exclusion criterion to automatically remove data from participants whose median trial time was below 1 second (i.e., responding too fast). For each participant removed this way, we collected one more participant until we reached the targeted 10 participants per viewing condition/attribute combination. In total, 48 participants were removed this way, which in hindsight signals that this exclusion criterion might have been too strict. Participants were excluded in this way before any data analysis was performed. All participants were naïve to the purpose of the experiment. They agreed with the informed consent prior to the experiment. The experiments were conducted in agreement with the Declaration of Helsinki and approved by the Human Research Ethics Committee of the Delft University of Technology.

7.2.3. Procedure

Experiment 1 consisted of a between-subjects design, with two viewing conditions and six perceptual attributes, namely roughness, shininess, softness, weight, warmth and hairiness. Before starting the experiment, participants received written instructions explaining the task. They were informed that they would be shown images of fabrics but not which type of fabric. Prior to the actual experiment, participants performed 15 practice trials, not only to become familiar with the interface but also to get an idea of the range of stimuli. Participants were randomly assigned to one of the viewing conditions and they were asked to rate one of the attributes. Each attribute was rated using a slider on a continuum ranging from 0 to 100:

smooth vs. rough, matte vs. shiny, hard vs. soft, cold vs. warm, hairless vs. hairy, and light vs heavy. In both viewing conditions, each of the 19 stimuli was rated three times for a total of 57 trials. The trials were randomized across participants.

7.3. Results

7.3.1. Consistency between and within observers

In Experiment 1 each attribute was rated three times. The consistency within observers is visualized in Figure 7.3 (left) and was calculated as the average pairwise (Pearson) correlation between the ratings over the three repetitions per observer, again averaged across observers. Next, we took the median across the three repetitions to smooth out the effects of potential outliers. Then, we normalized the data for each participant between 0 and 1 to rule out possible effects of unequal interval judgments. We used this median, normalized data for the remainder of the result section. For the consistency between participants, we calculated the intraclass correlation coefficient (ICC) using an average rating, consistency, two-way random effects model for each attribute and each condition [50, 51]. The ICC values and the 95% confidence intervals have been visualized in Figure 7.3 (right). A full report of the ICC statistics can be found in Table S1 in supplementary material 7.8. In Figure 7.3 there is a clear trend of higher inter- and intra-rater agreement in the full figure condition compared to the crop condition, with the exception of roughness in the inter-rater agreement (Figure 7.3, right). For the ratings of roughness, some participants in the crop condition may have attended to the visible roughness of the brushstrokes instead of judging the fabric. Furthermore, the ICC calculations show that the consistency between participants is significantly different from zero, thus above chance, for all attributes and in both viewing conditions, with the only exception of hairiness in the crop condition. However, the intra-rater agreement on hairiness was high and significant in both viewing conditions.

7.3.2. Material signatures

We ran a two-way MANOVA to examine the effect of the viewing condition and the fabrics' material on the perception of the material attributes. We found a main effect for both viewing condition (i.e., full figure vs crop) at $F(6, 29) = 2.78$, $p < .05$, and material (i.e., velvet vs satin) at $F(6, 29) = 23$, $p < .001$. We also found an interaction effect between the two factors at $F(6,29) = 6.56$, $p < .001$. In Figure 7.4, we visualized the average judgments of the material attributes, split by viewing condition (top) and material (bottom) and indicate significant differences (Bonferroni corrected) between the conditions. The perception of warmth and hairiness of satin, and hairiness and softness of velvet changed significantly between the two viewing conditions. For the full figure condition, velvet was judged to be significantly warmer, hairier, softer, heavier, and rougher, while satin was perceived to be shinier. For the crop condition, velvet was significantly warmer, hairier and heavier, whereas satin was rated significantly shinier. There were no significant differences between satin and velvet, for the attributes of softness and roughness, in the crop condition.

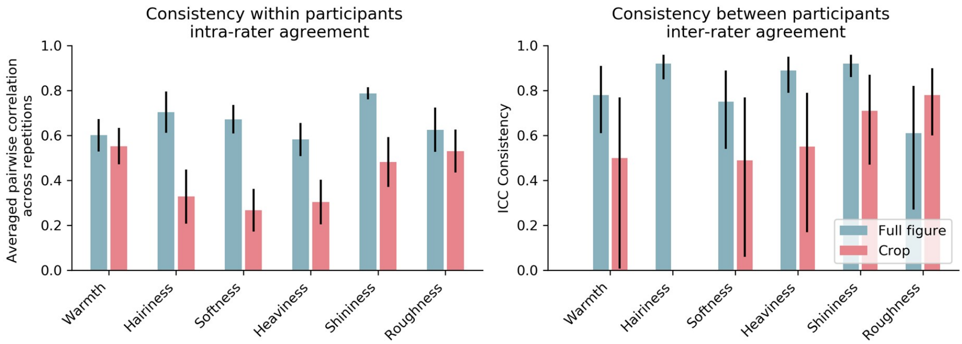

Figure 7.3: Consistency within and between participants. Left) The consistency within participants is calculated as the averaged pairwise correlation between each participants repetitions of the stimuli, and the error bars indicate the standard error. Right) The consistency between participants was calculated using intraclass correlations, and the error bars indicate the 95% confidence interval. The full report of the ICC analysis can be found in Table S1 in 7.8. Note that non-significant ICC are not visualized (i.e., hairiness in the crop condition).

To check if the material attributes were independent of each other or belonged to an underlying subset of dimensions, we computed a correlation matrix for both viewing conditions and visualized them in Figure 7.5. The correlation coefficients are reported in the cells of the matrices. Significant correlations at $p < .05$ are marked with an asterisk (*).

In the full figure condition, shininess was the only attribute that showed a negative significant correlation with each other attribute. All other attributes showed mutual positive, significant correlations except for roughness, which only correlated (negatively) with shininess.

In the crop condition, fewer correlations were found across all attributes. Roughness was again negatively and significantly correlated with shininess, as well as with softness and positively correlated with heaviness. Shininess was no longer correlated with hairiness, nor softness. Overall, this shows that the material attributes are not completely independent of each other, which implies they might be captured by a smaller set of dimensions.

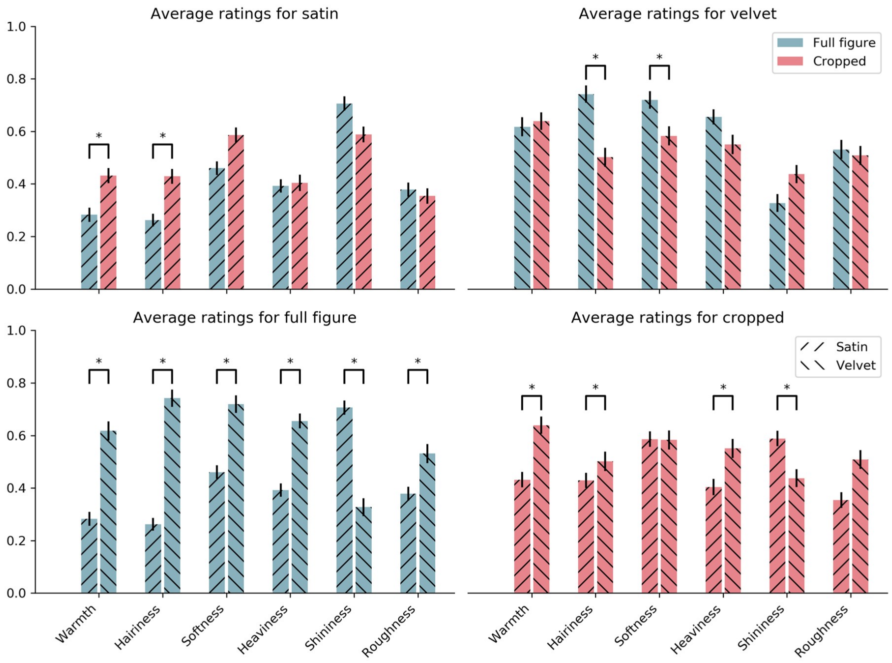

Figure 7.4: The perceptual judgments of satin and velvet, for both conditions. In the top plots, the data is split by viewing condition, while in the bottom plots data is divided by material. For each participant, we took the median rating across the stimuli repetitions, and then averaged across these values. Significance between condition (top) and material (bottom) is indicated at $p < .05$, Bonferroni corrected. Note that besides the significance, the top and bottom display the same data, only differently presented to make interpretations across conditions easier, and to avoid visual clutter of displaying all significant differences within a single plot.

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7.3.3. Principal component analysis and Procrustes analysis

To visualize whether the two materials, velvet and satin, were perceived as having different material properties, we ran a PCA for both viewing conditions. Figure 7.6 and Figure 7.7 show the PCA biplots of the full figure and the crop conditions, respectively. These biplots indicate how the stimuli are related to the attributes. The stimuli were clustered using 95% confidence covariance ellipses, according to the depicted material, satin (light blue ellipse), or velvet (yellow ellipse).

To further compare the effect of cropping on the material properties perception, we performed Procrustes analysis. The PCA of the crop condition shown in Figure 7.7 was matched to the PCA of the full figure condition (Figure 7.6).

In the full figure condition, the first two principal components account for 84.2% of the variance. The factor loadings listed in Table 7.1, show that the first principal component is positively loaded by a cluster of attributes including hairiness, warmth and heaviness. In the negative direction, shininess loads on the first component. The second principal component is mostly loaded by roughness.

In the crop condition, the first two principal components explain 77% of the

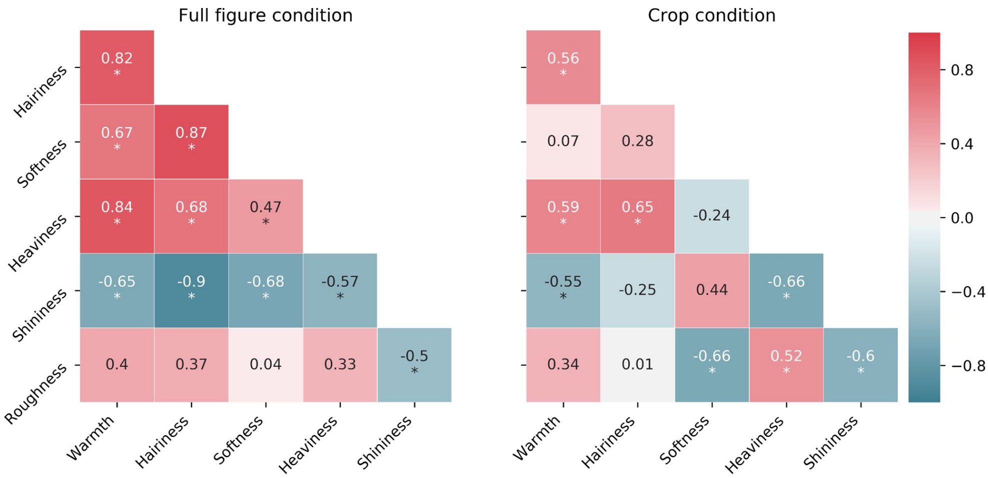

Figure 7.5: Correlation matrices of the attributes for both conditions. Color indicates the magnitude of the correlation coefficient. Asterisk (*) indicates a significant effect at p < .05.

variance. The first component is mostly loaded in the positive direction by hairiness, heaviness, and warmth and by shininess in the negative direction. The second component is mostly loaded positively by softness and negatively by roughness.

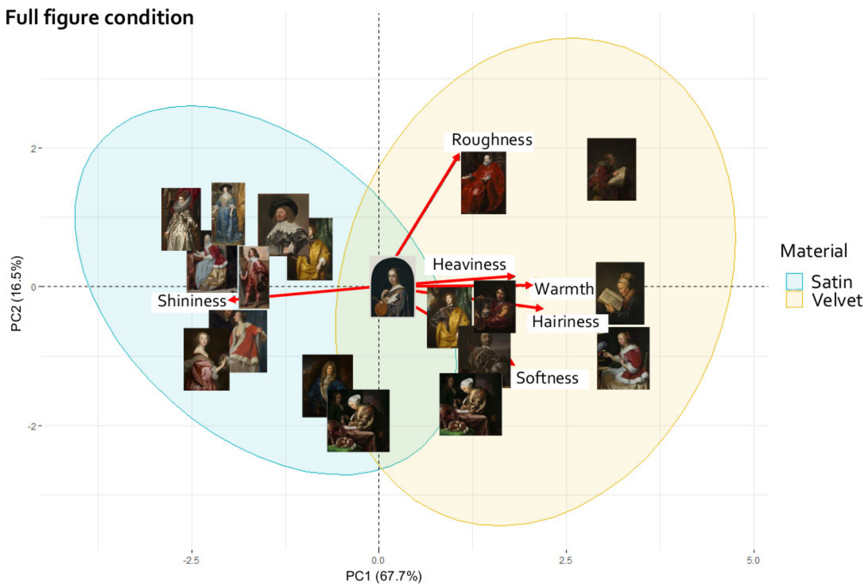

Figure 7.6: PCA biplot for the full figure condition. The materials are clustered within 95% confidence ellipses.

A permutational test to check the significance of the Procrustes result (r = 0.72, p

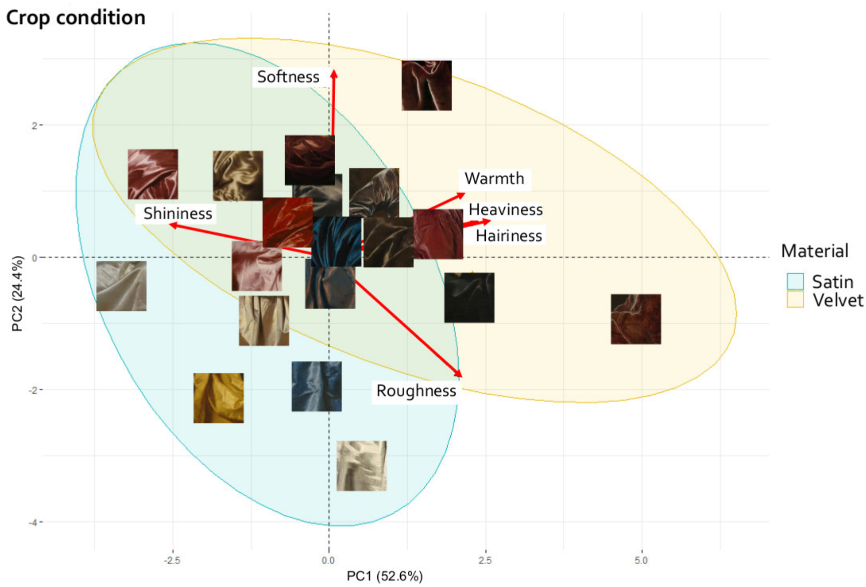

Figure 7.7: PCA biplot for the crop condition. The materials are clustered within 95% confidence ellipses.

	PC1 Full figure	PC2 Full figure	PC1 Crop	PC2 Crop
Warmth	0.45	0.01	0.41	0.27
Hairiness	0.48	-0.14	0.49	0.16
Softness	0.39	-0.50	0.015	0.78
Heaviness	0.40	0.06	0.45	0.15
Shininess	-0.44	-0.1	-0.48	0.14
Roughness	0.24	0.85	0.40	-0.51

Table 7.1: The factor loadings for the first two principle components of two PCAs, one for each condition.

$< .001$), indicated that the overall distribution of the stimuli was similar between the PCA of the full figure condition and of the crop condition. However, the distribution of the stimuli in the PCA biplot (Figure 7.7) shows much more overlap of the velvet and satin clusters, compared to the PCA of the full figure condition (Figure 7.6). In addition, some stimuli clearly changed location between the two PCA spaces, indicating that their perception differed in the two viewing conditions. One example is the crop shown in Figure 7.8. The mean ratings of all the attributes for this fabric, averaged over the median rating of each participant, are shown in Figure 7.8 for the two viewing conditions. The asterisk indicates that hairiness and shininess were perceived to be significantly different at $p < .05$ between the two viewing conditions.

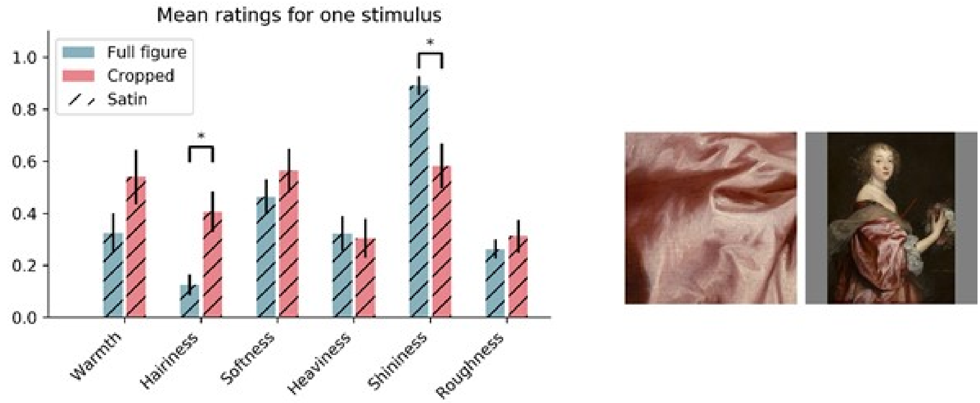

Figure 7.8: Left) The mean ratings on the y-axis of the attributes for one specific stimulus. An asterisk (*) indicates a significant difference at $p < .05$. Right) the crop and full figure stimuli represented in the left bar chart. Error bars indicate the standard error. Painting: Anthony van Dyck, *Catherine Howard, Lady d'Aubigny*, 1638, National Gallery of Art, Washington, DC, US.

7.3.4. Intermediate conclusions and discussion

We conclude that, within the attributes that we tested, the material signatures of depicted velvet included warmth, heaviness, hairiness and softness, and the signature of depicted satin included shininess. We further conclude that depriving the visual system of context and shape information significantly changed the perception of fabrics as depicted in 17^{th} century paintings. Specifically, when depriving the visual system of shape and object information, the perception of material attributes can drastically change, as exemplified in Figure 7.8. Moreover, the percepts became less consistent and more subjective as observed from the decrease in both inter- and intra-rater agreement. Furthermore, differences between materials expressed as the distributions of perceived material attributes became less distinct.

The cropped areas shown in the crop condition were chosen according to the amount of folding, in an attempt to maximize the amount of visual information. Considering that, we wondered to what extent the differences in perception found between the crop and full figure conditions were affected by this choice. One could argue that the depicted dress or robe from which crops are taken presents a certain shininess, roughness, etc., and thus different crops from it would present these properties quite consistently, without qualitative changes in perception between crops. However, on the other hand, local variations in shape (drapery) and effective lighting can cause major appearance variations, thereby causing differences in perception between the full figure condition, where participants could attend to all image features anywhere on the clothing, and the selected crop condition. For instance a crop that coincidentally captures many highlights might be perceived to be shinier relative to a crop with few or no highlights, and, vice versa, it might also be possible that key image features were absent in our crops.

We follow-up on this question in Experiment 2 where we tested if the perception of crops changed depends on the choice of cropped area.

Experiment 2

7.4. Methods

In Experiment 2, we investigated the extent to which perception of material attributes varies depending on the content of the crop and the presence or absence of local image features. We tested this with two material attributes that we also used in the previous experiment. The experiment consisted of a rating task of the two material attributes, followed by image analysis of the crops to extract highlights' features that could relate to the variation in perception between crops of the same fabric.

7.4.1. Stimuli

We used the 19 fabric stimuli from the full figure condition in Experiment 1 to make the stimuli in Experiment 2. From each image, we extracted a set of 9 to 21 equally sized crops, which covered the whole fabric (see Figure 7.9 for an example). Thus, we made 19 sets of crops (velvet n = 8 and satin n = 11). To keep the visual size of the folds in the crops as consistent as possible across different sets, the images were cropped with a constant ratio between the width of the whole fabric in the original image and the width of the crops. Images of all the crops can be found in the supplementary materials Figure S2 in 7.8.

7.4.2. Observers

Identical to Experiment 1, data were collected on the AMT platform. Each of the 19 sets of crops was judged by a group of 5 participants for either shininess or softness. That is, participants would rate one set of crops for one material attribute. A total of 190 AMT users participated in the second experiment. All participants were naïve to the purpose of the experiment, and none had participated in the first experiment. Each participant agreed with the informed consent prior to performing the experiment. The experiments were conducted in agreement with the Declaration of Helsinki and approved by the Human Research Ethics Committee of the Delft University of Technology.

7.4.3. Material attributes

We used two material attributes in this experiment, both of which were also measured in Experiment 1. The first attribute was shininess, and the second was softness. Softness was found to be not correlated (see Figure 7.5) with shininess and it can be seen to be nearly perpendicular to shininess in the crop condition PCA (Figure 7.7). We interpreted this to mean that the majority of variability captured by softness is not explained by shininess, and vice versa, and that these two represented two main underlying dimensions of a perceptual material attribute space. Roughness was found to not be significantly different between velvet and satin and thus is unlikely to represent an underlying feature in this material space. The three remaining attributes used in Experiment 1 (warmth, hairiness, and heavi-

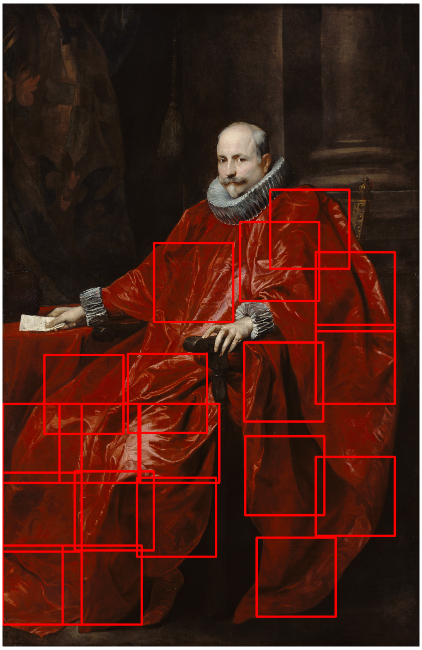

Figure 7.9: The original full figure stimulus, with red boxes that indicate the crops made for this stimulus. Each of the 19 stimuli from experiment 1 was subdivided into a set of crops as shown here. These sets of crops were used as stimuli in experiment two. Each crop within a set was the same size.

ness) all inter-correlate and likely compose one underlying dimension. Therefore, with choosing shininess and softness we hope to capture the majority of the variation and underlying dimensions of the material feature space for fabrics with the least amount of attributes.

7.4.4. Procedure rating experiment

In Experiment 2, participants were asked to rate one material attribute for each crop in one set of crops, taken from one of the 19 fabrics used in Experiment 1. After having read the instructions and having agreed to the informed consent, participants were asked to perform a size calibration, by adjusting a digital image of a credit card until it matches a physical payment card in the possession of the participants. Since all payment cards adhere to the standard set size forth by the International Organization for Standardization's 7810 ID-1 format (ISO/IEC 7810-ID-1), this allows us to rescale all images, so that each stimulus was presented at the same size, across different display settings for different participants. After the size calibration, participants performed a 10 second free-viewing task of the crops to get an idea of the range of the stimuli. Next, participants performed five practice trials followed by the actual experiment. For each trial, participant were tasked with rating shininess or softness with a slider on a continuum ranging from 0 to 100, corresponding to matte to shiny and hard to soft, as in Experiment 1.

Each crop was rated three times, for a total number of trials ranging from 27 to 63 depending on the number of crops. The trials were randomized across participants.

7.4.5. Procedure image analysis of highlights

One way painters distinguished the depiction of velvet from satin, is through the rendering of the key image features of their reflectance properties [2]. We hypothesized that, when judging the material properties of such depicted fabrics, humans attend to similar image features as perceptual cues. Via photometric measurements of fabric samples, Barati et al. [11] assigned satin to a reflectance category combining specular and split-specular scattering, and velvet to the category of asperity scattering materials. From a perceptual rating experiment, Barati et al. [11] also found that the samples belonging to the asperity scattering category were perceived to be the softest, whereas the samples in the specular and split-specular scattering class were perceived to be the shiniest and the least soft. These findings support our hypothesis that softness and shininess are key attributes of velvet and satin, respectively.

The different scattering behaviors of velvet and satin result in distinctive optical cues. Previous studies have shown that image features of the highlights, such as coverage, contrast and sharpness, can influence the perception of glossiness [22, 44, 52–54]. To test whether the perception of shininess and softness depended on the choice of the cropped area, and therefore on the image features of the highlights present in the crop, we computed the mean luminance of the crops, the relative coverage of the highlights and the mean contrast of the highlights. We did not measure sharpness because that was assumed to be relatively consistent between crops of the same painting.

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The calculations of the highlight features, i.e., coverage and contrast, were done using binary images of the crops. The threshold values to binarize the images and isolate the highlights for the computations, were manually derived from the luminance histogram of each crop. Figure 7.10 A shows the luminance histogram of the crop shown in Figure 7.10 B. The highlight mode, one of the three general modes for a histogram-based measure of the surface structure proposed by Pont [55], is indicated by a black bar (note that here the width and height of the bar have no other meaning beside providing a clear visual indication of the threshold value used to binarize the image, whereas in Pont [55] these parameters were related to the width and the height of the mode). To binarize the images, we manually selected the threshold at the minimum value of the highlight mode (indicated by the red line in Figure 7.10 A). The manual selection was done for every crop. Figure 7.10 B shows the original crop and its binary image.

The contrast was calculated as Michelson contrast, taking the 95^{th} and the 5^{th} percentiles of the luminance values instead of the absolute maximum and minimum for robustness; the percentage of coverage was calculated as the ratio of the areas covered by white and by black pixels in the binarized image.

All image analyses were done in Matlab 2018a (The MathWorks Inc., Natick, MA).

Note that the measures of the highlights' features reported here should be considered only rough approximations, due to the complexity of automatically and accurately segmenting the image regions that correspond to the highlights, especially in the case of paintings for which the ground truth is not known. Designing a robust algorithm to measure the image features of highlights that is generalizable to natural images such as photographs or paintings, is still an unsolved problem in the literature, due to the difficulty of defining and identifying what the visual system considers to be a highlight. In a previous study [22], we addressed this issue by combining manual annotation of the highlights and self-developed algorithms for the semi-automatic computation of highlights' features directly from images of paintings. However, the paintings analyzed in that study were exclusively depicting grapes, meaning that each object showed a single, mostly round, specular reflection. This simplified the annotation and computation, and made the method more difficult to apply to paintings of fabrics with multiple reflections of various shapes. Marlow, Kim and Anderson [52] approached the problem by using psychophysical measurements of contrast, coverage and sharpness of highlights. They further compared the human judgements of the highlights' features with measures obtained via direct image computation, finding high correlations between the two types of measurements. Qi et al. [53] employed a pixel-wise computation of the highlights' features based on luminance threshold for stimuli rendered with the same reflectance and illumination parameters. Recently, Schmid, Barla and Doerschner [54] developed a series of image-based calculations of the highlights' features that could be applied to stimuli with different shapes, but only with rendered images for which the diffuse and specular components can be defined.

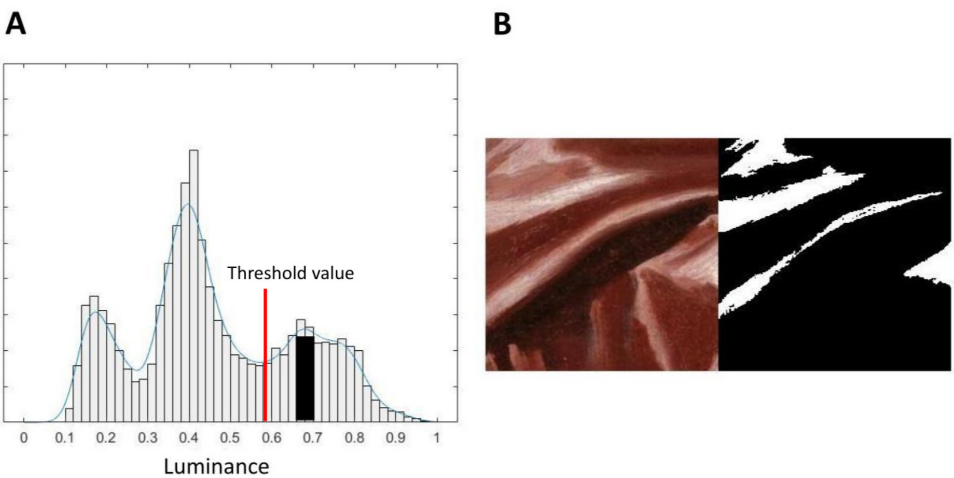

Figure 7.10: A) Luminance distribution and the highlight mode used as threshold value (black bar) to create the binarized image. B) The original stimulus, as presented to the participants in the rating experiment, and its binarized version.

7.5. Results

7.5.1. Consistency between and within observers

The intra- and inter-rater agreement (Figure 7.11) were calculated for each of the 19 sets of crops for both material attributes. Because shininess and softness were rated three times per crop, prior to the data analysis we took the median over the three repetitions of the ratings to smooth out the effects of potential outliers. Then, the data were normalized to rule out possible effects of unequal interval judgments. Consistency within observers was calculated as the average correlation between the ratings over the three repetitions for each observer. The consistency between participants was calculated as the mean correlation between all participants.

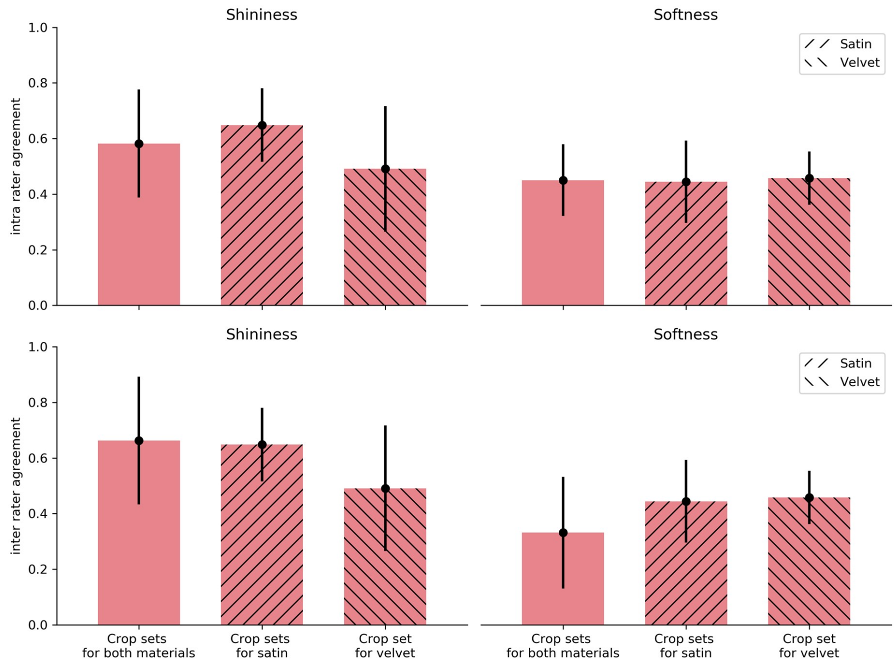

Figure 7.11: The intra- and inter rater agreement. The top contains the intra rater agreement(consistency within observers) with shininess on the left and softness on the right. The same ordering is applied at the bottom for the inter rater agreement (agreement between observers). The error bar indicates the standard deviation.

First, we report the consistency within and between participants split on material attribute.

The agreement both within and between participants, varied greatly. This indicates that some sets of crops triggered a clear and consistent perception, whereas other sets were perceptually ambiguous.

Stimuli	Shininess		Softness	
	F value	*p* value	*F* value	*p* value
1 S	F(10, 55)=1.8	> .05	F(10, 55)=0.5	> .05
2 S	F(16, 85)=3.8	< .001 *	F(16, 136)=1.1	> .05
3 S	F(12, 52)=8.1	< .001 *	F(12, 91)=3.2	< .01
4 S	F(14, 60)=10.1	< .001 *	F(14, 45)=0.6	> .05
5 S	F(16, 136)=23.1	< .001 *	F(16, 85)=6.7	< .001 *
6 S	F(19, 60)=3.7	< .001 *	F(19, 60)=9.9	< .001 *
7 S	F(11, 48)=8.3	< .001 *	F(11, 84)=5.7	< .01
8 S	F(20, 84)=15.8	< .001 *	F(20, 126)=1.3	> .05
9 S	F(12, 91)=32.0	< .001 *	F(12, 65)=0.7	> .05
10 S	F(11, 96)=6.2	< .001 *	F(11, 84)=1.2	> .05
11 S	F(16, 119)=24.5	< .001 *	F(16, 136)=1.7	> .05
12 V	F(18, 76)=13.1	< .001 *	F(18, 133)=0.9	> .05
13 V	F(10, 77)=13.3	< .001 *	F(10, 66)=2.7	< .01
14 V	F(14, 90)=10.7	< .001 *	F(14, 75)=0.5	> .05
15 V	F(8, 45)=16.2	< .001 *	F(8, 27)=0.2	> .05
16 V	F(11, 84)=3.4	< .001 *	F(11, 72)=1.8	> .05
17 V	F(12, 52)=1.5	> .05	F(12, 52)=5.8	< .001 *
18 V	F(12, 52)=1.2	> .05	F(12, 117)=0.7	> .05
19 V	F(12, 52)=0.9	> .05	F(12, 52)=0.6	> .05

Table 7.2: Results one-way ANOVAs of Experiment 2. The numbering of the stimuli corresponds to that of Figure S2 reported in italic in the supplementary materials 7.8. The ANOVAs significant after Bonferroni correction are indicated by *. As can be seen, a significant effect (and thus a varying percept across the same fabric) was found more often for shininess than softness. Stimuli material identity is marked by an S for satin and a V for velvet.

7.5.2. ANOVA

The median ratings of shininess and softness were averaged over all participants for each set of crops, to calculate a one-way ANOVA to measure the effect of varying the cropped area. A significant effect for a set of crops indicates that the perceptual ratings differed between crops taken from a single fabric. Significant differences were evaluated at p = .001 after Bonferroni correction. The results of each individual ANOVA are reported Table 7.2. Overall, the crops of fifteen crop sets were significantly different for shininess, ten of which depicted satin, and five depicted velvet. Softness was significantly different for only three sets of the crops, two of which depicted satin and the remaining one velvet.

The results from the ANOVAs showed that crops were perceived to vary significantly in shininess within most of the crop sets. We hypothesized that the observed variation in shininess perception can be related to the image features of the highlights available in the different crops.

7.5.3. Correlation with highlights' features

We performed correlation analysis to evaluate the relationships between the mean ratings of shininess and softness of the crops and the features calculated from the images, namely the mean luminance of the crops, and the coverage and contrast of the highlights. We only performed the correlations for the sets of crops in which we found significant differences with the one-way ANOVA, i.e., fifteen sets for shininess and three for softness.

In Figure 7.12 we reported the correlation coefficients of the image features with shininess (top) and softness (bottom). Only the values significant at $p < .05$ were reported. The stimuli corresponding to the crop sets are reported in Figure S2 in the supplementary material in 7.8. Note that the crop sets 1-3 for softness do not correspond to the crop sets 1-3 for shininess.

The top of Figure 7.12 shows that for fourteen out of fifteen significantly different sets, shininess was positively and significantly correlated with the mean luminance of the crops. For eleven crop sets, shininess was also positively and significantly correlated with the coverage of the highlights. Three of the sets showed a significant positive correlation with the contrast of the highlights, whereas for one set the correlation with contrast was negative and significant.

The three sets with crops significantly different in softness reported in Figure 7.12, were all positively and significantly correlated with the mean luminance. Two of them were also significantly and positively correlated to the coverage of the highlights. None of them was related to the contrast of the highlights.

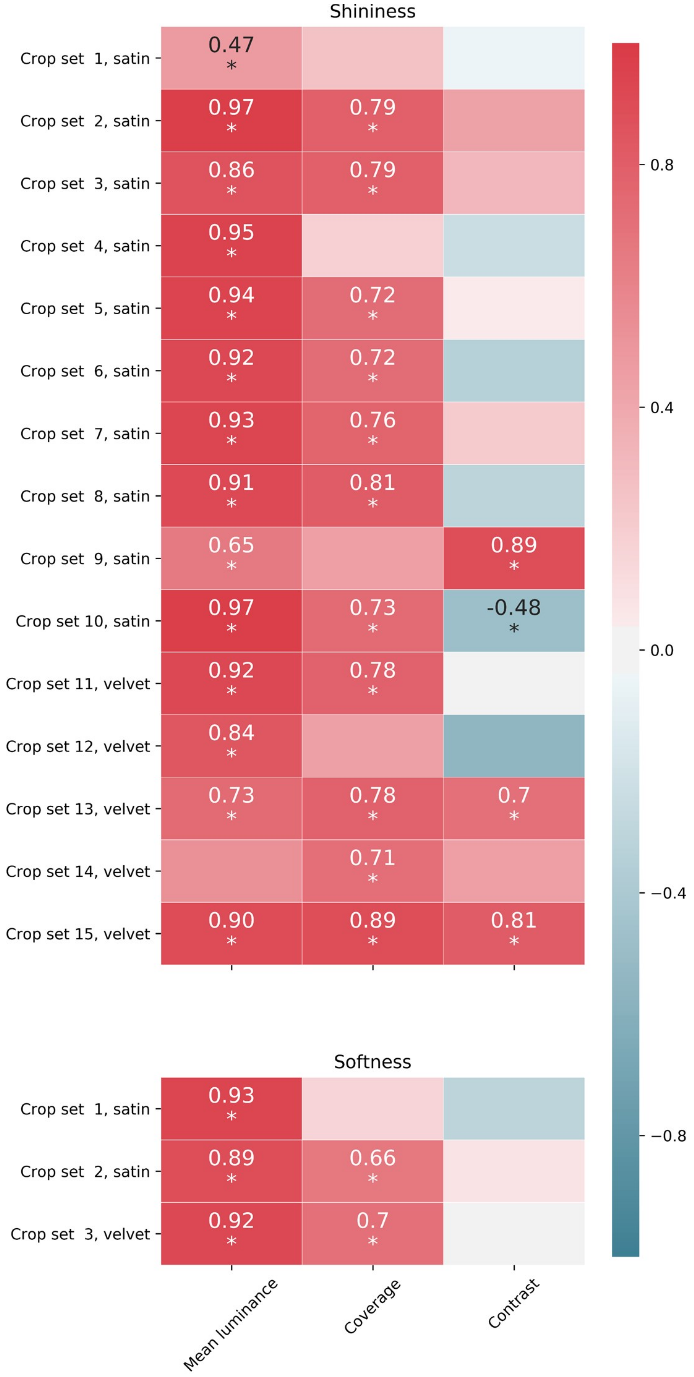

Figure 7.12: Correlation coefficients of shininess (top) and softness (bottom) with the image features highlights' contrast, highlights' coverage, and mean luminance of the crops. The values reported are significant at $p < .05$.

7.6. General discussion

In Experiment 1, we aimed to determine which material attributes belong to the signatures of velvet and satin depicted in 17^{th} century paintings. We further tested if removing shape and context information by only presenting crops of the fabric, caused a change in perception.

We found that velvet and satin were judged to have different material attributes, as indicated by the two-way MANOVA (Figure 7.4) and the PCAs (Figures 7.6 and 7.7), and that the commonalities in the judgments were based on robust material signatures that are specific for velvet and satin. In the full figure condition, velvet was judged to be warmer, hairier, softer, heavier, and rougher, while satin was perceived to be shinier. In the PCAs for both conditions, shininess appears to be directed towards the satin cluster while the remaining attributes point more towards the velvet cluster. When we look at the velvet and satin clusters in the PCA for the full figure condition (Figure 7.6) we also see that the materials are separated. In the crop condition (Figure 7.7), this separation became less, implying that the distinction between satin and velvet decreases in the crop condition relative to the full figure condition. This is also shown in our finding that all material attributes were significantly different between satin and velvet in the full figure condition, but only part of them in the crop condition. This leads to the following result: satin and velvet depicted in 17^{th} century paintings are perceptually distinct, but the distinction decreases when only viewing local information. But what is this perceptual distinction between satin and velvet based based on?

In the rating tasks, participants were consistent in both conditions but less so in the crop condition. The agreement between participants varied depending on the perceptual attribute, which has been reported before [14, 23]. Within the domain of computer vision, Schwartz and Nishino [43] argued that visual material properties, such as shininess and hairiness, should be inherently local. Indeed, Geirhos et al. [56] showed that CNNs are strongly biased towards texture, i.e., local image features. This implies that computer vision algorithms currently rely on local information. However, Geirhos et al. [56] showed that CNNs trained to learn a shape-based representation (i.e., a bias for global information) improve on accuracy and robustness. Similarly, providing global and context information decreases the idiosyncrasy for our human data in our experiments. This implies that while both computer and human vision can form a clear or robust response, the responses' robustness can be improved by providing global information.

The correlation matrices in Figure 7.5, showed that roughness was negatively correlated to shininess in both viewing conditions. This is in agreement with many reflectance distribution models such as for instance the microfacets model [57], in which rough surfaces are modeled as a distribution of specular microfacets, which orientation distribution determines the surface roughness and resulting width of the reflectance lobe (the rougher, the less glossy, see also for instance [58, 59]. We also see this negative correlation in the two PCA biplots (Figures 7.6 and 7.7).

For roughness we found no correlation with softness for the full figure condition, which is in agreement with several studies that have shown that the main perceptual dimensions of tactile perception of texture are roughness/smoothness and hardness/softness [12, 60, 61]. However, in the crop condition, we found a negative correlation between roughness and softness. This negative correlation might be ascribed to one outlier: a crop with clearly visible rough brushstrokes (Figure 7.13) which was on average perceived to be the second roughest fabric and the least soft. Indeed, removing this crop from the data made the correlation no longer significant. Possibly the roughness of the brushstrokes for this specific stimulus introduced an element of ambiguity in the judgment of the surface roughness of the fabric.

Figure 7.13: One crop that was identified as a possible outlier. With this stimulus included, a strong negative correlation was found between softness and roughness, which is surprising based on the literature. With this crop removed, the correlation is no longer significant. This might be due to the visibility of the individual brushstrokes, which gave rise to a perceptual ambiguity.

Heaviness was significantly negatively correlated with shininess in both viewing conditions. In the crop condition, no size information was available. If participants were able to retrieve the material identity, heaviness could have been inferred through an "associative approach" [41]. One possible association could have been that darker objects are perceived to be heavier than brighter ones [62, 63]. From additional analysis, we found that ratings of heaviness in the crop condition were indeed highly negatively correlated (r = -0.73, $p < .001$) with the mean luminance of the stimuli. Shininess, on the other hand, was highly and positively correlated with the mean luminance (r = 0.75, $p < .001$).

Softness, a material property relying on haptic information, is physically unrelated to the visual property of glossiness. However, they can be perceptually related since a perceptual association can be learned when intentionally induced [64, 65], or from prior experience, since glossy materials tend to be hard [66]). In the full figure condition, there was indeed a high and significant negative correlation between shininess and softness, likely due to the identification of the objects and of the materials they were made of. Paulun et al. [67] showed that the optical appearance of familiar materials creates expectations and influence stiffness perception. This might explain the lack of correlation between softness and shininess in the crop condition, where participants knew they were judging fabrics, but they were missing contextual information to recognize the fabrics' material, and thus were unable to draw from expectations.

In Figure 7.4 (top), we reported the attributes that were perceived to be significantly different between the two viewing conditions, per material. If we considered a single fabric, we observed additional variations of attributes between conditions (see Figure 7.8). This raised the question whether such variation in perception was due to our choice of the area to crop in the fabrics. Thus, in Experiment 2 we tested the relationship between the perception of shininess and softness and different areas cropped within the same fabric, spanning the whole fabric as much as possible.

If different perceptions were triggered, they might be the result of the presence or absence of local image features within the crop. On the other hand, if all crops were perceived similarly, we might argue that local image features tend to be stable across the entire surface of the materials, at least within our set of stimuli.

The consistency within participants fluctuated greatly for different sets of crops, from 0.16 to 0.81 and from 0.18 to 0.77, for shininess and softness respectively. The consistency between participants showed similar fluctuations, from 0.13 to 0.87 for shininess, and from 0.08 to 0.78 for softness. The high agreement found for some sets of crops indicates that these crops evoked a clear and consistent perception. Simultaneously, the low agreement on other sets showed the opposite, namely that these crops were perceptually ambiguous. In the first experiment, stimuli presented with context and shape information, evoked a more consistent perception. It appears that cropping stimuli reduces the uniqueness of the evoked perception in some, but not all stimuli. The size, aspect ratio and area relative to the original image was kept constant within each set of crops, and can thus not explain the differences found. The local content of the crops within sets of crops must have caused the variety: the presence (or absence) of local image features in the crops of each set might be (in)sufficient to elicit a clear, consistent perception.

The results from the ANOVAs showed that crops were perceived to vary significantly in shininess within most of the crop sets. The presence of highlights on a surface is a well-known image feature for the perception of glossiness. According to Beck and Prazdny [68], glossiness perception depends on the local presence of highlights, meaning that the direct area surrounding the highlight is perceived to be glossy, but not the whole surface per se. That is, they argue that glossiness perception is the direct response to local visual information, and not the result of some perceptual inference about the reflectance properties of the whole surface. Similar results are discussed by Berzhanskaya et al. [69]. They found that perceived gloss decreases as a function of the distance from the highlight. Thus when different parts of an object are considered, gloss perception will differ among the different parts depending on their vicinity to the highlights. This local quality of glossiness is in agreement with our results on the perception of shininess differing between the crops of a fabric.

We used three image features (mean luminance, coverage of the highlight, and contrast of the highlight) to further analyze this relationship between the local image content and the evoked perception. In Figure 7.12 (top) we showed that the mean luminance of the crops was highly and positively correlated with almost all the crop sets for shininess. This finding is in line with Wiebel, Toscani and Gegenfurtner [70], who found that the mean luminance of photographs of real materials was a high-performance predictor, followed by the standard deviation of luminance, to differentiate between glossy and matte materials. Highlights are high-luminance regions of the surface, explaining the high correlation we observed between the mean luminance of the crops and the perceived shininess. Coverage of the highlights was also highly correlated with the perceived shininess for most of the crop sets. Coverage of highlights has been shown to be strongly associated with glossiness perception [44, 52], especially when coverage is the most reliable cue for the judgement of glossiness. This happens with objects whose shapes create higher variability in highlights' coverage rather than contrast or sharpness, under the same illumination. For our stimuli, within the same fabric, the folding configuration caused high variations of coverage that we found to be related to significant variations in shininess perception between the different crops of a fabric. High highlights' coverage is also related to higher mean luminance, given that the area of the surface covered with highlights, i.e., the high-luminance regions, increases. We indeed found the correlation between the mean luminance and the coverage averaged over all the crop sets, to be high and significant ($r = 0.78$, $p < .001$). The third image feature that we measured, the highlights' contrast, overall, was not strongly correlated with perceived shininess. In the three cases in which high and significant positive correlations were found, the contrast was also positively correlated with coverage. The opposite occurred for the only crop set that showed a significant negative correlation between contrast and shininess, i.e., the high contrast highlights covered the smallest regions of the fabrics' surface.

For softness perception, the ANOVAs showed no significant differences for most of the crop sets. So, while the perception of shininess might depend on local image features, this might not hold for softness. A possible explanation for this finding could be that softness is a mechanical property, rather than an optical property and therefore less associated to the image features. Another related possibility is that the image features that were analyzed are simply not the key triggers for softness. The question then arises whether other local features might explain the data, or whether mechanical attributes such as softness requires global features to explain the judgments.

In the bottom section of Figure 7.12 we reported the three crop sets that were significantly different for softness perception. They all showed a high and significant positive correlation with the mean luminance of the crops. Two sets were also significantly positively correlated with the coverage of the highlights and one of these sets (crop set 2) is shown in Figure 7.14. The crops in the top row were perceived to be significantly softer that the crops in the bottom row. What is apparent from these two rows of crops is that in the top row, the high luminance and the high coverage of the highlights allow to clearly see the folding shape of the fabric, in contradistinction to those in the bottom row. Local shape features, like textiles' folding, have been shown to play a role in the visual estimation of softness perception [10]. For the stimuli shown in Figure 7.14, the visibility of the shape deformation due to the folding could have been the driving cue for the perception of different levels of softness between the crops. This is in agreement with Xiao et al. [13], who showed that the 3D folding configuration increases the accuracy of estimation of tactile material properties of fabrics.

Other cues, like the brightened contours', might be related to visual perception of softness via a cognitive association with velvet [12, 41, 67]. Further research is needed to understand how local and global information contribute to and possibly interact in material perception, and whether such mechanisms are dependent on the material and property under consideration.

Figure 7.14: Visualization of the crop set 2 from the bottom of Figure 7.12. The image on top shows the locations where the crops were taken from the whole fabric. The crop in the top row were perceived to be significantly softer than the crops in the bottom row.

Since the 15th century, with the introduction of oil painting and a whole new range of possible visual effects, Netherlandish painters started to shift the attention from the rendering of space and volume to the rendering of materials, reaching their "golden age" in the 17th century. When the separation between diffuse and specular illumination started to be acknowledged and exploited [2], painters could visually differentiate velvet from satin, instead of rendering all the fabrics equally matte. This novel use of the highlights is what we quantified in Experiment 2 via image analysis, and related to the perception of shininess and softness. However, there is a stylistic aspect of the paintings that we selected for our stimuli set, which we did not address here, in order to focus on the discussion on material perception. The paintings were made either with a neat, almost invisible brushwork (see Figure 7.15 left) or with loose brushstrokes (see Figure 7.15 right). These opposite pictorial manners were equally valued to produce a convincing effect [71], but their mechanisms are completely different. Paintings with the neat brushstrokes can be appreciated from a distance or from close by in a similar way, whereas paintings with loose brushstrokes are unintelligible when one stands close or zooms in, but they make perfect sense and trigger a powerful convincing effect when seen in their entirety, at a proper distance.

The different brushworks might have introduced an additional source of noise in our data, but they also raised further questions, like, how is the pictorial style (neat vs loose) related to the use of local and global image cues for material depiction and perception? Future work in this direction could contribute to the emerging field of art and perception.

Figure 7.15: Examples from our stimuli set of a neat (left) and a loose (right) use of brushstrokes, to illustrate the difference in these two styles which becomes apparent when moving closer to the physical painting – or when zooming in. The two crops (below) are from the crop-set that correspond to the paintings (above). Left) Adriaen van der Werff, *Self-portrait with the Portrait of his Wife, Margaretha van Rees, and their Daughter Maria*, 1699, Rijksmuseum, Amsterdam, The Netherlands. Right) Frans Hals, *Portrait of a Man, Possibly Nicolaes Pietersz Duyst van Voorhout*, ca. 1636–38, The Metropolitan Museum of Art, New York, US.

7.7. Conclusions

In this study, we found that warmth, heaviness, hairiness and softness are key attributes of the material signatures of velvet, whereas shininess is a key attribute of the signature of satin, when studying the depiction of both fabrics in 17th century paintings. We further showed that the two fabrics, and their material signatures were clearly perceptually distinct when the stimuli were presented in the full figure condition. On the other hand, the cropped condition, depriving the visual system of object shape and context information, caused higher ambiguity and made the distributions for the measured perceptual attributes of the two materials less distinct.

In Experiment 2, we showed that the perceived shininess is not stable across one single fabric. The perception of the optical property shininess based on a cropped area of the fabric was shown to be correlated to the presence of diagnostic image features in the crop, namely highlights. Moreover, shininess perception increased with the coverage of the highlights and their mean luminance. The haptic property of softness, instead, did not differ significantly between crops of the same fabric. Further analysis of the softness data suggested that perception of this haptic property might be driven by local and global shape cues.

In conclusion, we have shown that velvet and satin were depicted with distinct perceptual material signatures, which painters started to employ around the 15th century, and highlights started to be exploited to render the characteristic appearance of different textiles [2]. Highlights can be used to render the luster of satin and the softness of velvet, by indicating not only how the fabric reflects light but also by revealing the shape of the folds. Local image features of the highlights were found to be sufficient to trigger significant variations in shininess perception, but not for softness. This indicates that shininess is a local material property, whereas softness might require more global visual information relating to shape.

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7.8. Supplementary material

Figure S1.

All the stimuli used in Experiment 1. For stimuli we display the full figure condition on the left, and the crop condition on the right. Note that both images are resized to fit the page while in the experiment stimuli were presented at 600x600 and 200x200 pixels for the full figure and crop condition, respectively. The first 11 are the satin stimuli, the remaining 8 are the velvet stimuli. All images reproduced here are are available under open access at a CC0 or CC BY 4.0 license. Two paintings (and the crops thereof) have not been reproduced here due to copy rights restraints.

Stimulus 1

Stimulus 2

Stimulus 3

Stimulus 4

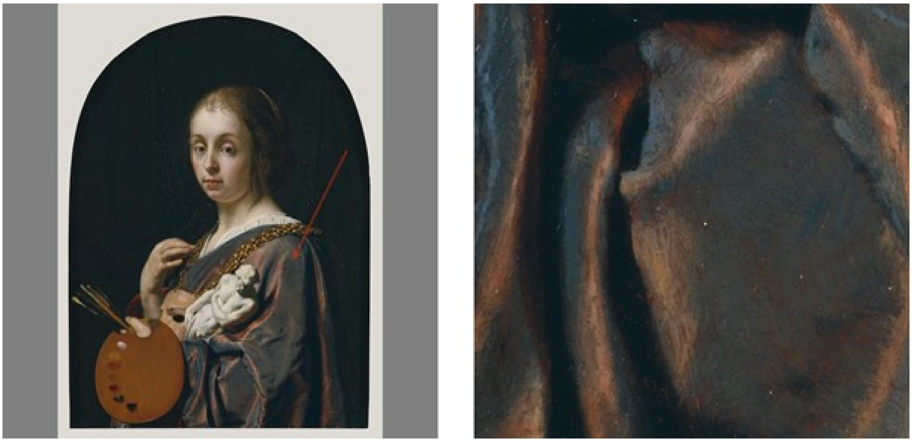
Stimulus 5


Stimulus 6


Stimulus 7

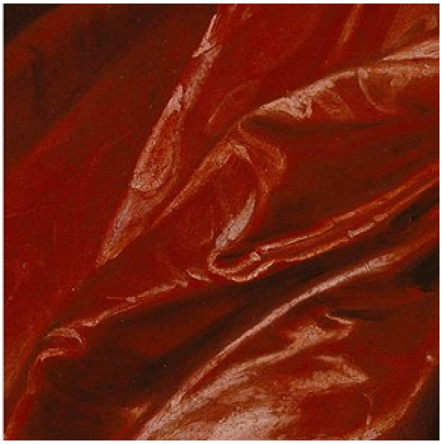

Stimulus 8

Stimulus 9



Stimulus 10

Stimulus 11



Stimulus 12

Stimulus 13. Images not reproduced due to copy-rights restrictions.

Stimulus 14


Stimulus 15


Stimulus 16

Stimulus 17. Images not reproduced due to copy-rights restrictions.

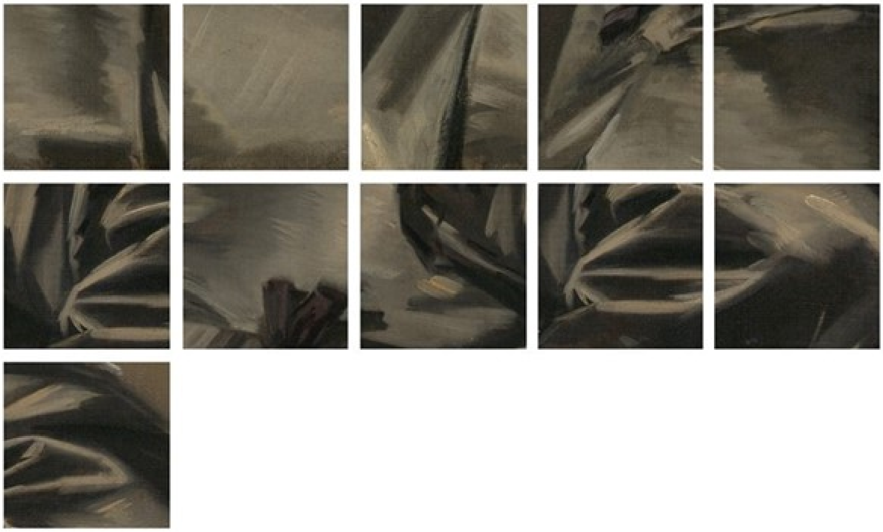
Stimulus 18

Stimulus 19

Table S1.
ICC calculations for the inter-rater agreement in Experiment 1. The calculation was done using average rating, consistency agreement, two-way random effects model.

	ICC	95% CI		F test with true value 0			
		Lower Bound	Upper Bound	Value	*df1*	*df2*	Sig.
Full figure							
Warmth	0.78	0.61	0.91	4.74	18	162	<.001
Hairiness	0.92	0.85	0.96	12.3	18	162	<.001
Softness	0.75	0.54	0.89	3.97	18	162	<.001
Heaviness	0.89	0.79	0.95	9.05	18	162	<.001
Shininess	0.92	0.86	0.96	12.8	18	162	<.001
Roughness	0.61	0.27	0.82	2.54	18	162	<.01
Crop							
Warmth	0.5	0.08	0.77	1.99	18	162	<.05
Hairiness	-0.7	-2.25	0.21	0.56	18	162	>.05
Softness	0.49	0.06	0.77	1.97	18	162	<.05
Heaviness	0.55	0.17	0.79	2.22	18	162	<.01
Shininess	0.71	0.47	0.87	3.5	18	162	<.001
Roughness	0.78	0.6	0.9	4.63	18	162	<.001

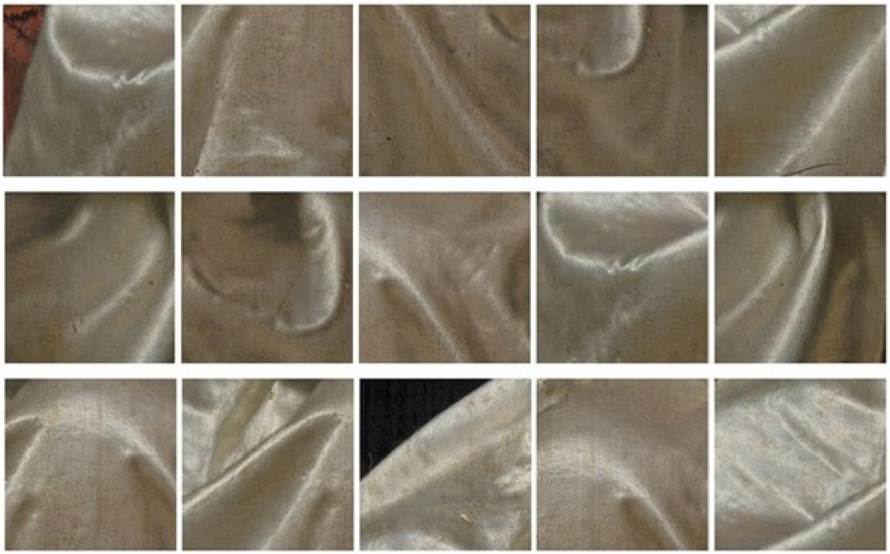
Figure S2.
All the stimuli used in Experiment 2.



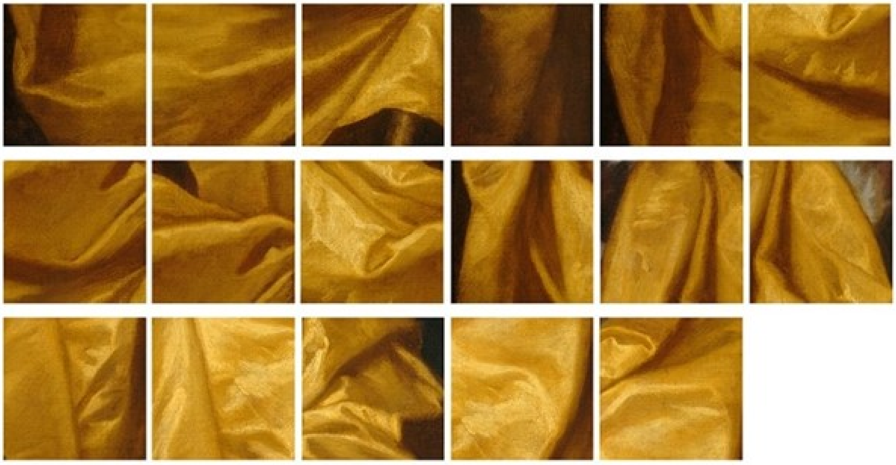
Stimulus 1

Stimulus 2. Crop set 1 in Figure 7.12 shininess.

Stimulus 3. Crop set 2 in Figure 7.12 shininess.



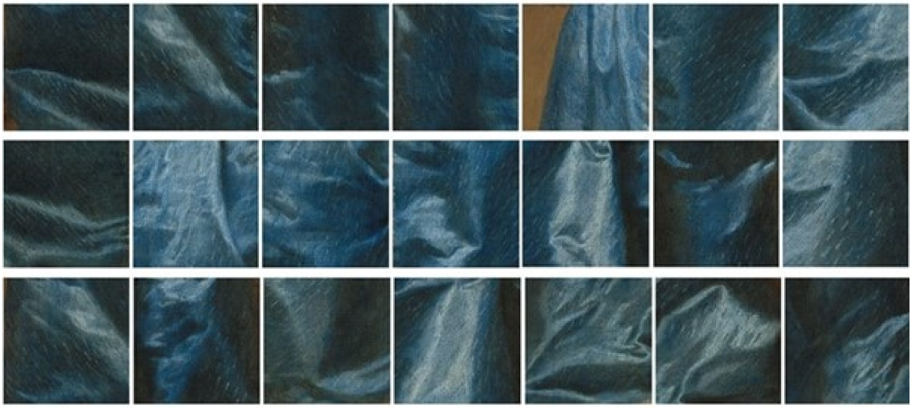
Stimulus 4. Crop set 3 in Figure 7.12 shininess.



Stimulus 5. Crop set 4 in Figure 7.12 shininess. Crop set 1 in Figure 7.12 softness.

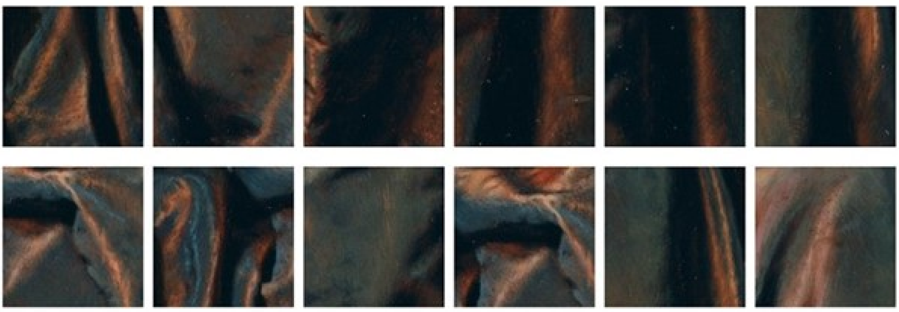
Stimulus 6. Crop set 5 in Figure 7.12 shininess. Crop set 2 in Figure 7.12 softness.

Stimulus 7. Crop set 6 in Figure 7.12 shininess.



Stimulus 8. Crop set 7 in Figure 7.12 shininess.

Stimulus 9. Crop set 8 in Figure 7.12 shininess.

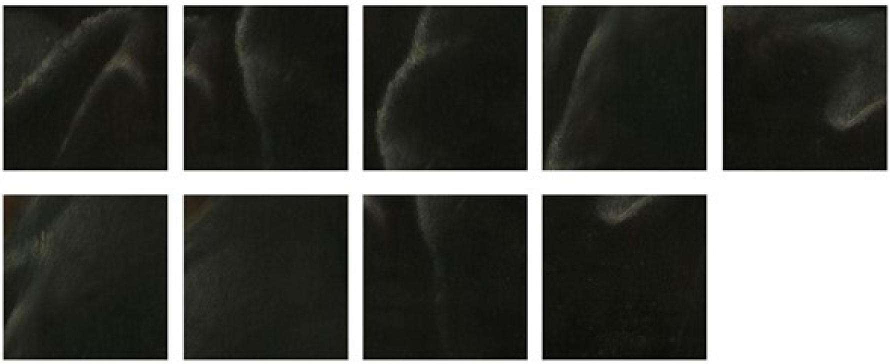


Stimulus 10. Crop set 9 in Figure 7.12 shininess.

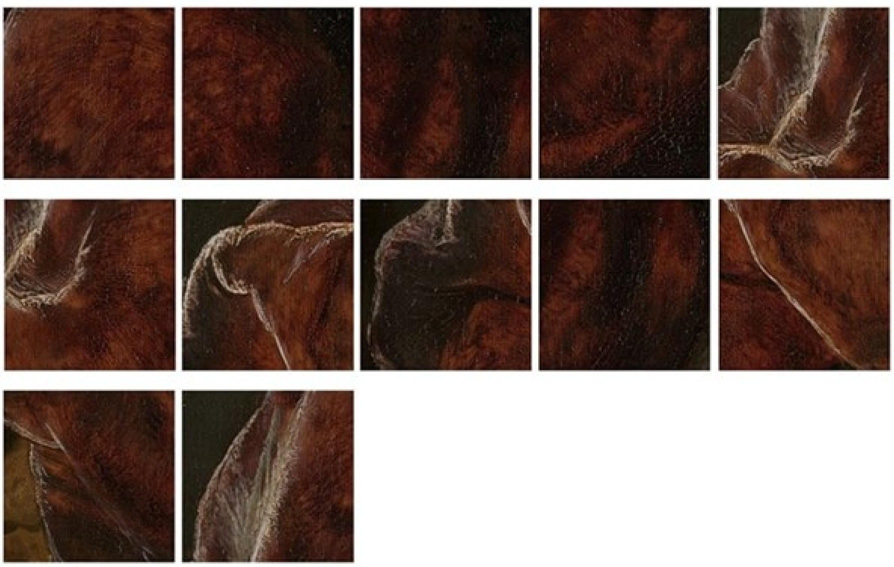
Stimulus 11. Crop set 10 in Figure 7.12 shininess.

Stimulus 12. Crop set 11 in Figure 7.12 shininess.
Stimulus 13. Crop set 12 in Figure 7.12 shininess. Images not reproduced due to copy-rights restrictions.

Stimulus 14. Crop set 13 in Figure 7.12 shininess.

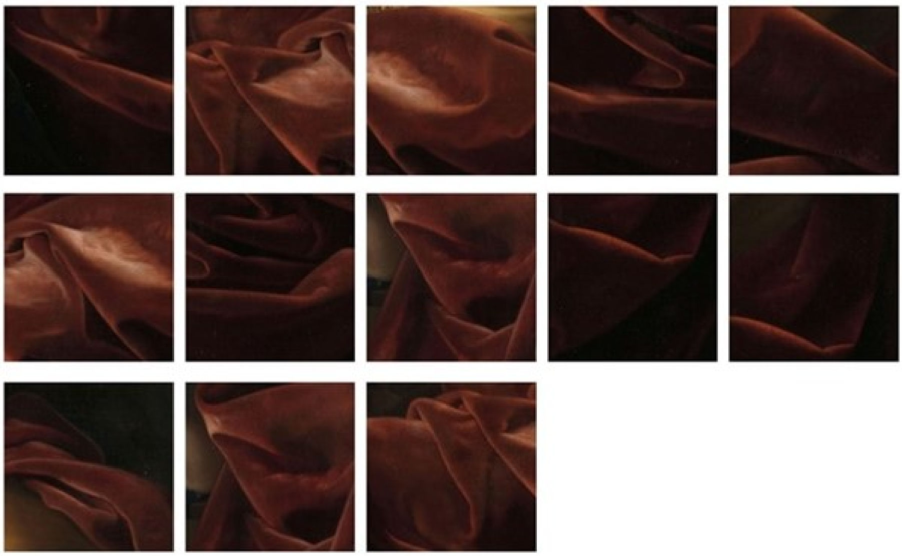


Stimulus 15. Crop set 14 in Figure 7.12 shininess.



Stimulus 17. Crop set 3 in Figure 7.12 softness. Images not reproduced due to copy-rights restrictions.

Stimulus 18



Stimulus 19

8

Conclusion

For color is the key to all the eye beholds.
Without the painter's brush, how much would disappear!

Willem Beurs

What emerged from these chapters, is that the convincing depiction of materials, so typical of 17th century paintings, relies on sets of image features that simplify the physics, even to the point of rendering it wrong, in order to get the appearance right. We have proposed that the human visual system exploits a similar set of image features as perceptual cues to effortlessly estimate the wealth of materials surrounding us. The main argument of this thesis was that artistic representations can efficiently communicate perceptual information to the human brain, tapping into the fundamental functioning of the visual system. Paintings and pictorial procedures should therefore become an integral part of the study of vision science. Likewise, theories and findings from perception studies should be considered by art historians, curators, conservators and other museum professionals to better understand the intentions of the artists and to thoroughly address the issue of materials' depiction.

How this thesis contributes to such mutual integration of knowledge is discussed below.

8.1. Theoretical and methodological contributions

This thesis contributes to bridging the fields of vision science and (technical) art history to gain a holistic understanding of materials' depiction and perception.

The idea of combining art and perception is not new, it constitutes a developing research field that has already its own specialized conference since 2012 (Visual Science of Art Conference, VSAC) and journal since 2013 (*Art & Perception*, Brill). However, the works related to the field of art and perception seldom address the issues of materials depiction and material perception, and even when they do so, there is a lack of quantitative and computational analysis (see for example [1, 2]). The present thesis offers theoretical and methodological contributions both to the emerging field of art and perception, and to the established fields of visual material perception and art history. Moreover, our findings have multifaceted implications for computer graphics, education, product and food design, photography, advertisements and e-commerce, which will be discussed later in this chapter.

8

The main theoretical contribution of this thesis is based on Beurs. The book of Beurs is not as popular as the more well-known *Schilder-Boeck* by Karel van Mander, but his instructions about how to prepare the ground layer [3, 4] or which pigments' mixtures should be applied where [5, 6], have already been used in art historical studies. In [5] in particular, we read that the pictorial recipes written between the 15th and the 18th century, including Beurs, provided "systems [...] to render the modelling of the objects and their textural characteristics in the quickest, best and easiest way", and that "The great advantage of following these and other instructions was that the rendering of effects did not continually have to be reinvented".

Like painters had a system to depict materials in the "quickest, best and easiest way", similarly the human brain has a system to perceive materials in a way that is fast, efficient and effortless. This thesis contributes to the current literature about the theoretical approaches to visual material perception, by proposing that Beurs' pictorial recipes compile an index of key image features exploited by the visual system to perceive materials and their properties. Such index of diagnostic features can enrich and complement theoretical models such as the statistical appearance model proposed by Fleming [7–9]. We have shown throughout the thesis that Beurs' features work as perceptual cues.

We focused a lot of attention on grapes, demonstrating that Beurs' recipe describes, in terms of key features, all the optical phenomena that define the appearance of grapes. By manipulating the weights of the image features listed by Beurs - highlights, edge reflections, and bloom - we inferred a causal relationship with the perception of the material properties glossiness, translucency and bloom (see Chapter 3). The highlights were used as perceptual cues for glossiness and translucency perception, in agreement with the literature [10, 11], the edge reflections also increased the translucent appearance, again in agreement with literature about the cues for translucency [11–15], and the image feature of the bloom was the direct trigger of bloom perception. We further showed that the glossiness of grapes is predicted by high contrast, blurry highlights, in accordance with Beurs' instructions (see Chapter 4).

These findings might seem limited, since they were derived for grapes only, but because Beurs grouped the materials according to their communal features, we assume that they will hold valid for all the materials which share the same features as grapes (see Figure 1.14). This was confirmed for the perception of juiciness and translucency of citrus fruits (see Chapter 5), for which the main perceptual cues that we identified - highlights for juiciness and light gradient (or edge reflections) for translucency - are also to be found in Beurs' grapes recipe. Future research should be carried out to analyze the perceptual relevance of all the recipes in the book, to conclusively confirm our hypothesis.

As noted by van Eikema Hommes [5], the use of standard recipes offers the advantage of not having to reinvent the right image features for the convincing rendering of materials every time. We thus propose that the study of material perception could greatly benefit from consulting Beurs to identify candidate image features, to be then tested with psychophysical methods, without having to reinvent the wheel every time.

Our analysis of Beurs also contributes to fill the gap in art history about the depiction of materials. By relating the image features found in paintings and listed by Beurs to their perceptual effects, we answered the question *How did painters achieve the convincing rendering of materials?* for the case of grapes, citrus fruits and fabrics. We provided information about the functioning of the visual system which can be used to understand the pictorial procedures. For example, the following step in Berus' grapes recipe [16, 17]

```
The reflections however, require only a little ash
but somewhat more yellow lake.
```

instructs that to add the edge reflections, a lighter color (yellow lake) should be applied. This step will create the visual impression of the light reemerging from the edges of the grapes, which is what happens after subsurface scattering. Being the edges the regions of an object that are most affected by variations in light scattering and diffusion, they constitute also the quickest and best shortcut to depict translucency. We found that this trick of lightening the edges was regularly used to render translucent materials in paintings, like grapes and pearls. We propose that by adding knowledge of optics and perception, art historians could reach a comprehensive understanding of the artworks and the historical recipes.

To further investigate the visual effect of each layer, we carried out reconstructions of painted grapes, based on scientific examinations of the real paintings and on Beurs' recipe (see Chapter 2). Reconstruction of recipes is a common practice in art history, not only to shed light on the materials and methods of the artists [3, 5, 18–20], but also to understand the meaning of the recipe itself, which may not be so straightforward just by reading it [21]. In art historical literature it has been noted that in order to understand the visual effect of different pictorial procedures, a multidisciplinary approach is required, coupling technical examinations with historical recipes [22]. However, the art historical discussion in this regard, is mostly limited to the illusion of space and volume [23].

What was new in our approach, was that we took a step beyond the reconstruction itself, by digitizing the whole painting process so that we could access each individual layer. To do so, we created an interface based on optical mixing [24–26], with several potential applications.

By being able to systematically manipulate the weight of each pictorial layer, we showed that every step in De Heem's procedure and in Beurs' recipe, provides an essential perceptual element to the overall convincingness of the grapes. If, for example, the layer adding the edge reflections is removed, as in Figre 2.6a, the grapes suddenly look like a bunch of plums, having lost most of their translucency.

This tool contributes to the realm of computer techniques devoted to the understanding of artworks. Stork and others have used computer vision and image analysis to explore a series of art historical questions regarding perspective [27], illumination [28] and shape [29], but not materials. Our tool, by allowing the visualization of the layers underneath the surface, their individual contribution and how they combine with each other, can be exploited to answer ”what if” questions that would be difficult to answer otherwise. Eventually, this could open up the field of virtual technical art history, with application potential in art history, conservation science and museology. Already, this study has been included in the book ”Pixels and Paintings” by David Stork (Wiley, 2020), among some of the "most powerful and useful computer techniques in the service of art."

Our tool has already shown to be valuable in the technical art historical research by Koppelmann [30], in order to add stratigraphic information to pigments' distribution obtained via MA-XRF scans of De Heem grapes. The visualization of the individual layers of our grapes is also currently being used in a project applying computer graphics and machine learning for painting analysis, carried out at the Computer Graphics and Visualization group, at TU Delft.

The layers' visualization method and the resulting interface proposed in this thesis could become a common tool in conservation and art historical research, if it could be extended to more paintings and developed to easily control more than just the weight of the layers (e.g. modulate the individual features in each layer). This, of course, cannot be easily and instantly generalized to every existing painting, because every painting would require its own reconstruction. But since reconstructions are already diffuse in art historical studies, our tool could be easily integrated in the process.

The methodological contribution of this thesis is to promote the use of quantitative analysis and image statistics in art. As for the theory, this contribution adds both to vision science and art history. Doing quantitative analysis in vision science is no breakthrough, but applied to uncontrolled stimuli, such as paintings, it offers the possibility to uncover unexpected findings, because it allows variations across a range of unknown features. For example, when investigating the highlights' features for gloss perception of grapes (Chapter 4), we found, outside the primary scope of that study, that painters could break the fundamental rule of highlights' orientation congruence [31–35], without hindering the perception of glossiness. This was demonstrated by applying quantitative image analysis to the highlights, by measuring and correlating the orientations of ellipses fitted onto the highlights and the grapes, for different levels of perceived glossiness.

When using only computer rendered stimuli it is more difficult, if not impossible, to reveal hidden information because all the features available in the stimulus are carefully tuned and controlled by the input parameters during the rendering. We recommend the use of computer renderings in combination with more uncontrolled and ecologically-valid stimuli, like paintings or photos, in order to maximize the availability of potential visual cues.

Quantitative and statistical analysis of paintings to measure material perception have been conducted, to the best of our knowledge, only within our lab [14, 36, 37]. The methodology proposed in this thesis can be used to advance the art historical inquiry on the depiction of materials [38]. For example, it has long been observed that 17th century painters could adopt a neat and precise brushwork, typical of the *fijnschilders* like Gerard Dou and Adriaen van der Weff, or use loose and coarse brushstrokes with a sense of immediacy, like Frans Hals and the late Rembrandt. What might have been gone unnoticed though, is that both pictorial manners employ the same image features to depict, for example, the shininess of fabrics, i.e. high coverage and high luminance highlights (Chapter 7). Future research in the art history of materials depiction will need to include multidisciplinary quantitative analysis of the paintings, to relate the image features to their deviation from the optics, and consequently to the evolution of pictorial styles.

8.2. Implications of this thesis

An index of key image features that act as perceptual cues for convincing material perception, like the one proposed in this thesis, has implications for computer graphics, a field that strives to ”generate an image that evokes from the visual perception system a response indistinguishable from that evoked by the actual environment” [39].

However, in realistic image synthesis, there is no agreed standard of realism to judge the success or failure of the final result [40]. Computationally-expensive, physically-based renderings are increasingly replaced by perceptually-relevant renderings, approximating details that would anyway be unnoticed by human observers [40], especially in the case of real-time and interactive renderings, like virtual reality [41] and video games [42]. By understanding the image features that act as perceptual cues for the convincing representation of materials, rendering algorithms could be developed to enhance these cues that are relevant for our visual system. A study that we conducted within this project on the perception of pearls [43], provides a clear example. The optics of pearls is highly complex, requiring their physically-based rendering to compute structural, radiometric and photometric parameters [44]. However, people that have no extensive experience of real pearls, which probably includes the majority of the world population, are satisfied with a bright highlight in order to perceive a pearl as convincing.

In product design, next to functionality, safety and price, the visual appearance is one of the most important parameters that designers and manufacturers need to consider, in order to meet or anticipate the needs of consumers [45]. A lot of research in this direction is devoted to the semantic meaning and symbolic association of materials, and the aesthetic appreciation of the products [46–49]. The knowledge of which image features consumers attend to when judging the materials of a product, to determine that something looks 'old' or 'luxurious' or 'cozy', can help product designers to focus on and enhance those features that make the product most appealing to the consumer.

Creating an appealing product appearance is a matter of interest at all the stages of a product lifetime, from the sketching to the sale, the latter holding especially valid when the product is sold online. Sketching, photography, advertisement and e-commerce, are all fields that would benefit from knowing and applying the key image cues for convincing material depiction, since they all rely on the visual communication of material properties. Focusing on the perceptually-relevant image features, would make the representation of the product and its intended materials more intuitive and persuasive for a potential stakeholder or consumer, thus increasing the chances of a successful pitching or sale that meet the expectations of the buyer.

Given the ubiquity of products of all kinds in our daily life, there is an increasing need for industrial designers [50] specialized in formgiving [51]. Part of their professional training should be targeted to learn how to see materials, and how the people at the center of human-centered design, perceive materials. The relevance of this topic is still largely underestimated in design education (but see [52, 53]). To learn formgiving in design, several sketching courses are provided, in which the depiction of materials is mainly addressed as part of the product presentation phase. However, in presentation sketching, materials and surface properties are just one element of a set information about the product, where the main goal is to show the possible interactions and intended use of the product. Instead, learning to visualize shapes, light and color is done in dedicated courses.

It is interesting to note how neglecting the importance of material perception and depiction, constitutes a recurring factor in all the disciplines that are most affected by it. Vision science has made huge progresses to catch up, but art history, industrial design and, as we will discuss next, food industries, have still a long way to go. Visual expertise about material depiction and perception should be taught in their own specialized course, and we believe that the knowledge provided in this thesis represents an adequate starting point for this purpose.

Finally, in this thesis we have devoted particular attention to food, and while analyzing the perceptual cues to render the glossiness of grapes and the juiciness of lemons, we identified the research gap in food science about material appearance. Some fundamental research has been done to understand the relationship between glossiness and freshness perception [54, 55], but applied research, addressing consumers' needs and preferences, is barely concerned with the surface appearance of foods. Once again, color [56] and shape [57] have monopolized the attention of researchers for the visual parameters able to modify taste perception through expectations. However, the textural properties of food [1] are equally important to set and alter taste perception.

A relevant example to our current situation comes from the foreseen food trends post-pandemic. A transition is expected towards healthy eating, with a major growth of consumption of alternatives to animal products. Research on the acceptance of meat and dairy alternatives has highlighted the importance of textural parameters [58], such that liquid dairy alternatives, like milk or drinking yogurt, should not be too watery and runny, and meat alternatives are often expected to be juicy. Food manufacturers usually run tests to assess whether the new food formulation got the desired textural properties, by asking panels to taste and rate the products. However, as the common saying recites *"We eat with our eyes first"*, which means that in usual, everyday situations we first interact with food visually, to set expectations and make decisions that in the long run can affect our health. It has been shown that we are attracted by appealing looking foods [59]. Thus, whether one aims to facilitate the transition towards animal products alternatives, or nudging the choice and consumption of healthy foods in a school/university/work place cafeteria, where the prepared food is directly displayed, and in supermarkets, where food is judged from the packaging (see Chapter 6), knowledge of the image features triggering the material (or textural) properties of interest, is crucial.

8.3. Limitations and future research

No research can ever be considered really finished, since every novel finding generates new questions, and in the time span of four years we could just start scratching the surface of the vast topic of art and material perception. Even if we would keep focusing on just one century and one country - the Dutch Golden Age - and leave out the rest of thousands of years of art ever produced by the mankind worldwide, several lines of research would still be left unexplored.

One crucial point of our research was the use of digital images of the paintings. Digitization of art galleries and museums' collections comes with many benefits, like allowing a more democratic experience of art, making feasible to test paintings in

[1]Note that 'textural properties' is the food science equivalent of 'material properties' in vision science.

the controlled environment of the lab or via online experiments, and it even turned out to be a great advantage during a worldwide pandemic. However, seeing a digital reproduction of a painting is not the same as seeing the original artwork.

We might argue that the viewing conditions of the stimuli in our research oversimplified and neglected a crucial aspect of the production of paintings, namely the light under which they were painted and intended to be seen [60]. The uniform, diffuse light sources which usually illuminate the paintings when photographed for the digital archives, may flatten the texture of the painting surface, causing the observer to miss the richness of 3D details that enhance the perception of the depicted materials [61]. Inadequate lighting conditions can also induce a misperception of the intended colors. Carbon and Deininger [62] demonstrated that for medieval paintings, where gold leaves were applied on the surface to render the luster of gold, candle light was intended and it is needed to bring out the splendor of the gold. Moreover, paintings made on commission were intended to be seen in a specific room, which means that the lighting depicted in the scene was coherent with the illumination of the room. Van de Meerendonk et al. [63] wrote about a series of paintings commissioned to Theodoor van Thulden (1606-1669) for the town-hall of 's-Hertogenbosch, that "The light in the painting comes from the right, which means the work was placed to the left of the windows". Nowadays, most of these paintings have been moved from their original location, impairing the intended perception and thus the appreciation.

With the novel opportunities offered by the fast growing fields of 3D scanning and 3D printing, which allow to obtain high-fidelity copies of the original paintings [61], one could test the effect of directional daylight (or daylight-like illumination) and candle light on the perception of the materials depicted in the paintings. Our hypothesis is that seeing the paintings as they were intended to be seen, would add another dimension to the perception of convincingness, by revealing further unknown cues.

Locher et al. [64] compared the perception of a number of structural qualities of the composition, like symmetry, homogeneity and complexity, when seeing the original painting in a museum or a reproduction, either projected or on a computer screen. They found that there was a "pictorial sameness" of these attributes between the originals and the reproductions, indicating that the reproductions can be as perceptually valuable as the originals and observers are able to "look past the medium" [64, 65]. However, the pictorial sameness did not hold when they tested the aesthetic experience, for which the original paintings resulted to be significantly more pleasant [66].

Future research should investigate the "pictorial sameness" of material perception to validate our results and the use of electronic surrogates of paintings. This could be done by conducting rating experiments, like the ones discussed in this thesis, by having a laptop or tablet in front of the original paintings hanging in the museums, and by engaging visitors to perform the experiment.

Another limitation of this thesis is that we have not addressed enough the connection between the optics, the affordances of oil, and the perception. For example, a fascinating topic that is worth investigating in future research, is the relation between the translucency of the oil medium, the subsurface scattering between the layers of the painting, and the resulting perceived translucency of the depicted materials. In other words, the question that we aim to answer in future research is *How does the perception of translucency of the depicted materials depend on the translucent property of the oil?* To this purpose, skin would be an interesting case study. Skin is humans' largest organ, and it plays a fundamental role in our social interactions [67]. It is also a translucent material that interacts with light via subsurface scattering, an interaction that was formalized into the bidirectional surface scattering distribution function (BSSRDF) by Jensen [68]. We have already seen that Adriaen van der Werff used to depict skin by ordering the layers of paint like the layers of skin, to recreate similar optical phenomena [69]. In future research, reconstructions of the pictorial procedures to depict skin, like the recipe given by Beurs, could be used to systematically vary the translucency of the glaze layers, by changing the pigment to oil ratio. The optical properties of these glaze layers relevant for subsurface scattering (i.e. absorption and transmittance) could be quantified using micro-spectrophotometry [70]. Finally, the reconstructed samples varying in the physical translucency of the paint, should be used as stimuli for psychophysical experiments. This would allow to relate the perceived translucency of the skin to the physical translucency of the paint, using, for example, psychometric curves.

8.4. Final remarks

In this thesis, we have observed art under the lens of material perception, and used the lens of art to understand material perception. We have discussed how these two disciplines are complementary, and can therefore reveal of each other more than what is apparent with traditional research methods.

To put it into the beautiful words of Meadows [71]:

> *Each way of seeing allows our knowledge of the wondrous world to become a little more complete.*

8

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Summary

This thesis explores *convincing stuff* depicted in 17th century paintings, with the primary aim of understanding their visual perception. "Stuff" is the term first introduced by Edward Adelson in 2001 to differentiate materials from objects, and to call attention on the research gap in material perception. In an interesting parallel, the representation of materials in paintings constitutes a knowledge gap in art history as well. Both gaps have only recently been recognized and started to be addressed in their respective research fields.

In this thesis, representation and perception come together to create a virtuous circle in which the knowledge of painters about the representation of materials is used to understand the mechanisms of the visual system for material perception, and this is in turn used to explain the pictorial features that make the representation of materials so convincing.

The common thread used here to connect representation and perception, is "The big world painted small", a long-forgotten booklet of pictorial recipes written by the Dutch painter Willem Beurs in 1692. We argue that this book represents an index of key features for material perception, that means an index of image features that always work as perceptual cues regardless of the illumination and the viewing conditions of the depicted scene.

The main research objective of this dissertation is:

> *To understand the convincing depiction and perception of materials in 17th century paintings, connecting the image features found in paintings and listed by Beurs to their role as perceptual cues.*

In order to achieve this objective, we employed a novel, interdisciplinary research approach, merging science of human and computer vision, technical art history, and the historical textual source of Beurs.

In **Chapter 1** we provide a multidisciplinary literature review and a historical background to understand how Dutch Golden Age painters became experts in seeing and depicting materials convincingly. The first part of the Introduction, traces the origin of the convincingness of materials' depiction to the Scientific Revolution, and the establishment of the use of oil paint. It is in this chapter that we get to know a bit about the life of Willem Beurs, a painter who also taught how to paint, and we discuss at length his book. In the second part of the Introduction, we present a review of the literature in vision science that has researched material perception, the existing theoretical frameworks proposed to understand the mechanisms of material perception, and the different types of cues that have been shown to trigger the perception of materials. We complete the literature review

by reporting the studies of vision scientists who have investigated art in order to understand material perception. Finally, we describe how Beurs fits into the vision science community. Beurs' recipes connect different materials according to their shared key image features, and offer the features profiles, i.e. the weighted combinations of these features, to render a wide range of materials. His index of key features for material perception lays the foundation for the present thesis.

In **Chapter 2**, we addressed the question "How is the pictorial procedure related to the convincing rendering of materials?", by reconstructing layer by layer the systematic approach of Jan de Heem to paint grapes. We often regard a painting as a 2D representation of the world, forgetting that a painting is actually a composition of layers, chemically and physically interacting with each other. Each layer fulfills a visual function and their sum results in the final appearance. The field of technical art history is responsible for identifying and characterizing these layers, but the understanding of their contribution to the visual effect of the painting requires a multidisciplinary study. The reconstructions were based on technical examinations of the real paintings and on the order of layers provided by Beurs. The whole painting process was recorded and digitized, in order to access each individual layer. To do so, we created an interface based on optical mixing, with several potential applications. By being able to systematically manipulate the weight of each pictorial layer, we showed that every step in De Heem's procedure and in Beurs' recipe, provides an essential perceptual element to the overall convincingness of the grapes.

To quantify and model the perceptual convincingness of the grapes' recipe in Beurs book, in **Chapter 3** we describe a series of rating experiments. These experiments were run on images of paintings of 17^{th} century grapes and on optical mixtures of layers derived from a reconstruction of De Heem's painting, made following Beurs' recipe. The attributes to be rated were derived from Beurs' recipe as well: three-dimensionality, glossiness, bloom, translucency and convincingness. The main findings of this study were that for the convincing appearance of grapes there is not a "one size fits all" solution, and that 17^{th} century workshop traditions showed more variations than standardization. All the material properties prescribed by Beurs were found to contribute to the overall convincingness, but their weight in the contribution was case-dependent. However, regardless of their weights in the depiction, we concluded that Beurs' key features for the material properties of grapes include and simplify all the optical phenomena needed to render convincing grapes. By manipulating the weights of the image features listed by Beurs - highlights, edge reflections, and bloom - we could infer a causal relationship with the perception of the material properties glossiness, translucency and bloom.

In **Chapter 4**, we focused on the highlights of the grapes and on the different contributions of their image features - contrast, coverage and blurriness - to gloss perception. We derived the highlights' features from literature, but we quantified them using self-developed algorithms and image analysis. We found that the glossiness of grapes was predicted by contrast and blurriness, the first with a positive and the latter with a negative contribution. We did not find any significant effect of coverage, most likely due to the (quasi)spherical shape of the grapes in combination with the assumption of a standard light source from a window, which caused a uniform and rather small coverage across all the stimuli. Beurs' grapes recipe points towards the same conclusions. He instructs to paint the highlights on the grapes using only white, thus high contrast, and to blend them in, thus with blurry edges, and he doesn't give any instruction about the coverage. One of the basic constraints for a highlight to be perceived as a specular reflection instead of pigmentation of the surface, is to be congruent with the orientation of the object shape and the shading pattern. However, we found that painters often broke this rule when depicting the highlights on grapes without affecting the perception of glossiness, which was dominated by the contrast cue.

In **Chapter 5**, we analyzed the perception of juiciness and translucency of citrus fruits' pulps, because according to Beurs, the pulps of lemons and oranges require the same key features as grapes. The pulps of cut-open citrus fruits depicted in 17^{th} century paintings were judged in their similarity in translucency or juiciness, in a pairwise comparison experiment. The perceived translucency and juiciness of each fruit and a set of image features, were rated in following experiments. We constructed a 2D perceptual space for juiciness and one for translucency, which resulted to be very similar to each other indicating a perceptual relationship between the two attributes. Among the image features that we tested, "highlights", "peeled side", "bumpiness", and "color saturation" fitted the juiciness space best and were high for the highly juicy stimuli. "Peeled side", "intensity of light gradient", "highlights", and "color saturation" were the most salient features of the translucency space, being high for the highly translucent stimuli. The main difference between juiciness and translucency was that juiciness was more related to the image feature of bumpiness - revealed by the highlights -, and translucency to the presence of a light gradient. These two main image features, light gradient and highlights, are the only ones prescribed by Beurs, together with the option of making the seeds visible, to render the pulps of oranges and lemons. This demonstrates that Beurs listed only the key perceptual cues for convincing material depiction.

In **Chapter 6**, we applied our findings about juiciness perception to the fields of packaging design and consumer science. We contributed to extend the scope of these fields, which are mostly concerned with the effect of color and shape, but less with appearance and visual material perception. We investigated how the juicy appearance of a cut-open orange affects consumers' preferences when shown on the package of orange juice. Juiciness perception was triggered by manipulating the presence of highlights and of the peeled side on the orange. According to our hypothesis, the image of an orange with a juicier appearance on the package would improve the overall evaluation of the juice. We found that the presence of highlights had a significant effect on increasing juiciness perception of the orange. Moreover, the highlights, both in isolation and in interaction with the peeled side, significantly increased the expected quality and tastiness of the juice.

Finally, in **Chapter 7** we moved away from the topic of food and investigated the material signatures of velvet and satin, that is the material properties that are characteristic of the two fabrics. Next to investigating the material signatures of velvet and satin, we also tested their perception in relation to local and global features. Rating experiments were conducted showing the stimuli either including the entire figure with the target fabric, or by showing just one crop of the fabric. We found that, among the set of material properties that we tested, shininess was the signature of satin, whereas softness, warmth, heaviness, hairiness and roughness were characteristic of velvet. Because we also found that some of the material properties were perceived significantly different between seeing the stimuli in full figure or cropped, we further tested whether this difference was due to the choice of the cropped area. In another experiment, the fabrics were divided in multiple crops which were rated for their shininess and softness for each fabric. We found that shininess varied significantly within one fabric, indicating that its judgement mainly relies on local features (i.e. the highlights). Softness instead, was not perceived significantly different between crops of the same fabric, showing that its perception is better related to global features, which probably include the overall shape and deformation of the fabric.

With the studies presented in this thesis, we show the mutual benefits that material perception and art history can gain from each other, and we provide practical examples of how the knowledge and methods from one field can be implemented into the other. Insights about material depiction and perception, derived by merging these two disciplines, find applications in all the fields that deal with appearance, from product design to computer graphics.

Samenvatting

In dit proefschrift wordt stofuitdrukking in de 17de -eeuwse schilderijen onderzocht, met als primair doel hun visuele waarneming te begrijpen. "Stuff'is de term die in 2001 door Edward Adelson voor het eerst werd geïntroduceerd om materialen van objecten te onderscheiden en om aandacht te vragen voor deze onderzoekskloof. Een interessante parallel vormt de weergave van materialen in schilderijen: in de kunstgeschiedenis is er sprake van eenzelfde kennislacune. Beide hiaten zijn pas onlangs onderkend en begonnen te worden aangepakt in hun respectievelijke onderzoeksgebieden.

In dit proefschrift komen representatie en perceptie samen om een cirkel te creëren waarin de kennis van schilders over de representatie van materialen wordt gebruikt om de mechanismen van het visuele systeem voor materiaal perceptie te begrijpen, en dit wordt op zijn beurt gebruikt om de picturale kenmerken te verklaren die de weergave van materialen zo overtuigend maken.

De rode draad die hier wordt gebruikt om representatie en perceptie met elkaar te verbinden, is 'De Groote Waereld in 't Kleen Geschildert', een lang vergeten boek met picturale recepten geschreven door de Nederlandse schilder Willem Beurs in 1692. We stellen dat dit boek een index is van de belangrijkste kenmerken van materiaalperceptie, dat wil zeggen een index van beeldkenmerken die altijd als perceptuele aanwijzingen werken, ongeacht de verlichting en de kijkomstandigheden van de afgebeelde scène.

De belangrijkste onderzoeksdoelstelling van dit proefschrift is:

> *De overtuigende weergave en perceptie van materialen in 17e-eeuwse schilderijen begrijpen, de beeldkenmerken die in schilderijen worden gevonden en door Beurs worden vermeld, verbinden met hun rol als perceptuele aanwijzingen.*

Om dit doel te bereiken, pasten we een nieuwe, interdisciplinaire onderzoeksbenadering toe, waarbij we wetenschap van mens- en computervisie, technische kunstgeschiedenis en de historische tekstuele bron van Beurs samenvoegen.

In **Hoofdstuk 1** geven we een multidisciplinair literatuuronderzoek en een historische achtergrond om te begrijpen hoe Nederlandse schilders uit de Gouden Eeuw experts werden in het overtuigend zien en weergeven van materialen. Het eerste deel van de inleiding beschrijft de oorsprong van de overtuigingskracht van de materiaalafbeeldingen tot de Wetenschappelijke Revolutie en de vaststelling van het gebruik van olieverf. In dit hoofdstuk maken we kennis met het leven van Willem Beurs, een schilder die ook anderen leerde schilderen, en bespreken we uitvoerig zijn boek. In het tweede deel van de inleiding presenteren we een overzicht van de perceptie literatuur die materiaal waarneming heeft onderzocht, de bestaande theoretische kaders die zijn voorgesteld om de mechanismen van materiaalperceptie te begrijpen, en de verschillende soorten beeldeigenschappen waarvan is aangetoond dat ze de perceptie van materialen beïnvloeden. We eindigen het literatuuronderzoek door de studies te rapporteren van perceptie-wetenschappers die kunst hebben onderzocht om materiaalperceptie te begrijpen. Tot slot beschrijven we hoe Beurs past in de vision science community. De recepten van Beurs verbinden verschillende materialen op basis van hun gedeelde belangrijkste beeldkenmerken, en bieden de kenmerkenprofielen, d.w.z. de gewogen combinaties van deze kenmerken, om een breed scala aan materialen weer te geven. Zijn index van de belangrijkste kenmerken voor materiaalperceptie legt de basis voor dit proefschrift.

In **Hoofdstuk 2** gingen we in op de vraag “Hoe verhoudt de schilder procedure zich tot het overtuigend weergeven van materialen?”, door laag voor laag de systematische benadering van Jan de Heem om druiven te schilderen te reconstrueren. We beschouwen een schilderij vaak als een 2D-weergave van de wereld, waarbij we vergeten dat een schilderij eigenlijk een compositie is van lagen die chemisch en fysiek met elkaar in wisselwerking staan. Elke laag vervult een visuele functie en hun som resulteert in het uiteindelijke uiterlijk. Het vakgebied van de technische kunstgeschiedenis is verantwoordelijk voor het identificeren en karakteriseren van deze lagen, maar het begrijpen van hun bijdrage aan de visuele werking van het schilderij vereist een multidisciplinaire studie. De reconstructies zijn gebaseerd op technisch onderzoek van de echte schilderijen en op de door Beurs aangeleverde lagen. Het volledige schilderproces werd geregistreerd en gedigitaliseerd om toegang te krijgen tot elke afzonderlijke laag. Om dit te doen, hebben we een interface gecreëerd op basis van optische menging, met verschillende mogelijke toepassingen. Door het gewicht van elke picturale laag systematisch te kunnen manipuleren, toonden we aan dat elke stap in De Heem’s procedure en in het recept van Beurs een essentieel perceptueel element vormt voor de algehele overtuigingskracht van de druiven.

Om de perceptuele overtuigingskracht van het druivenrecept in het Beurs-boek te kwantificeren en te modelleren, beschrijven we in **Hoofdstuk 3** een reeks beoordelingsexperimenten. Deze experimenten werden uitgevoerd op afbeeldingen van schilderijen van 17de-eeuwse druiven en op optische mengsels van lagen afgeleid van een reconstructie van De Heems schilderij, gemaakt volgens Beurs’ recept. Ook de te beoordelen attributen zijn ontleend aan het recept van Beurs: driedimensionaliteit, glans, ‘bloom’ (de poederachtige waslaag), translucentie en overtuigingskracht. De belangrijkste bevindingen van dit onderzoek waren dat er voor de overtuigende uitstraling van druiven geen ’one size fits all’-oplossing is, en dat 17e-eeuwse werkplaatstradities meer variatie dan standaardisatie vertoonden. Alle door Beurs voorgeschreven materiaaleigenschappen bleken bij te dragen aan de algehele overtuigingskracht, maar hun gewicht in de bijdrage was gevalafhankelijk. Ongeacht hun gewicht in de afbeelding, kwamen we tot de conclusie dat de belangrijkste kenmerken van Beurs voor de materiaaleigenschappen van druiven alle optische verschijnselen omvatten en vereenvoudigen die nodig zijn om druiven overtuigend te maken. Door de gewichten van de door Beurs genoemde beeldkenmerken - hooglichten, randreflecties en 'bloom' - te manipuleren konden we een causaal verband afleiden met de perceptie van de materiaaleigenschappen glans, translucentie en 'bloom'.

In **Hoofdstuk 4** hebben we ons geconcentreerd op de hooglichten van de druiven en op de verschillende bijdragen van hun beeldkenmerken - contrast, dekking en wazigheid - aan glansperceptie. We hebben de kenmerken van de hooglichten afgeleid uit de literatuur, maar we hebben ze gekwantificeerd met behulp van zelfontwikkelde algoritmen en beeldanalyse. We ontdekten dat de glans van druiven werd voorspeld door contrast en wazigheid, de eerste met een positieve en de laatste met een negatieve bijdrage. We vonden geen significant effect van bedekking, hoogstwaarschijnlijk vanwege de (quasi) bolvorm van de druiven in combinatie met de aanname van een standaard lichtbron uit een raam, wat een uniforme en vrij kleine dekking over alle stimuli veroorzaakte. Het druivenrecept van Beurs leidt tot dezelfde conclusies. Hij instrueert om de hooglichten op de druiven te schilderen met alleen wit, dus een hoog contrast, en ze in te mengen, dus met wazige randen, en hij geeft geen instructies over de dekking. Een van de basisbeperkingen voor een hooglicht om te worden waargenomen als een spiegelreflectie in plaats van een pigmentatie van het oppervlak, is congruent te zijn met de oriëntatie van de objectvorm en het schaduwpatroon. We ontdekten echter dat schilders deze regel vaak overtreden bij het weergeven van de hooglichten op druiven zonder de perceptie van glans te beïnvloeden, die werd gedomineerd door het contrast.

In **Hoofdstuk 5** hebben we de perceptie van sappigheid en doorschijnendheid van de pulp van citrusvruchten geanalyseerd, omdat volgens Beurs de pulp van citroenen en sinaasappels dezelfde hoofdkenmerken nodig heeft als druiven. De pulp van opengesneden citrusvruchten afgebeeld in 17e-eeuwse schilderijen werden beoordeeld op hun gelijkenis in doorschijnendheid of sappigheid, in een paarsgewijs vergelijkingsexperiment. De waargenomen doorschijnendheid en sappigheid van elke vrucht en een reeks beeldkenmerken werden beoordeeld in de volgende experimenten. We construeerden een 2D-perceptuele ruimte voor sappigheid en een voor translucentie, die erg op elkaar leken, wat wijst op een perceptuele relatie tussen de twee attributen. Onder de beeldkenmerken die we hebben getest, pasten ″hooglichten″, ″gepelde zijde″, ″hobbeligheidën ″kleurverzadiging″het beste bij de sappigheidsruimte en waren ze hoog voor de zeer sappige stimuli. ″Gepelde zijde″, ïntensiteit van lichtgradiënt″, ″hooglichtenën ″kleurverzadiging″waren de meest opvallende kenmerken van de translucentieruimte, omdat ze hoog waren voor de zeer doorschijnende stimuli. Het belangrijkste verschil tussen sappigheid en doorschijnendheid was dat sappigheid meer gerelateerd was aan het beeldkenmerk van hobbeligheid - onthuld door de hooglichten - en doorschijnendheid met de aanwezigheid van een licht verloop. Deze twee beeldkenmerken, lichtverloop en hooglichten, zijn de enige die Beurs voorschrijft, samen met de mogelijkheid om de zaden zichtbaar te maken, om de pulp van sinaasappels en citroenen weer te geven. Dit toont aan dat Beurs alleen de belangrijkste perceptuele aanwijzingen voor een overtuigende materiaalweergave opsomde.

In **Hoofdstuk 6** hebben we onze bevindingen over de perceptie van sappigheid toegepast op het gebied van verpakkingsontwerp en consumentenwetenschap. We hebben bijgedragen aan het vergroten van de reikwijdte van deze velden, die vooral betrekking hebben op het effect van kleur en vorm, maar minder op het uiterlijk en de perceptie van beeldmateriaal. We onderzochten hoe het sappige uiterlijk van een opengesneden sinaasappel de voorkeuren van de consument beïnvloedt wanneer deze op de verpakking van sinaasappelsap staat. De perceptie van sappigheid werd veroorzaakt door het manipuleren van de aanwezigheid van hooglichten en van de gepelde kant van de sinaasappel. Volgens onze hypothese zou de afbeelding van een sinaasappel met een sappiger uiterlijk op de verpakking de algehele evaluatie van het sap verbeteren. We ontdekten dat de aanwezigheid van hooglichten een significant effect had op het verhogen van de sappigheidsperceptie van de sinaasappel. Bovendien verhoogden de hooglichten, zowel afzonderlijk als in interactie met de geschilde kant, de verwachte kwaliteit en smaak van het sap aanzienlijk.

Ten slotte hebben we in **Hoofdstuk 7** afstand genomen van het onderwerp voedsel en de materiaalsignatuur van fluweel en satijn onderzocht, dat zijn de materiaaleigenschappen die kenmerkend zijn voor de twee stoffen. Naast het onderzoeken van de materiaalsignaturen van fluweel en satijn, hebben we ook hun perceptie getest in relatie tot lokale en globale kenmerken. Er werden classificatie-experimenten uitgevoerd waarbij de stimuli werden getoond, ofwel de hele figuur met de stof, of door slechts één uitsnede van de stof te tonen. We ontdekten dat onder de reeks materiaaleigenschappen die we hebben getest, glans het kenmerk was van satijn, terwijl zachtheid, warmte, zwaarheid, beharing en ruwheid kenmerkend waren voor fluweel. Omdat we ook ontdekten dat sommige van de materiaaleigenschappen significant verschilden tussen het zien van de stimuli in volledige vorm of bijgesneden, hebben we verder getest of dit verschil te wijten was aan de keuze van het bijgesneden gebied. In een ander experiment werden de stoffen verdeeld in meerdere gewassen die werden beoordeeld op hun glans en zachtheid voor elke stof. We ontdekten dat de glans aanzienlijk varieerde binnen één stof, wat aangeeft dat het oordeel voornamelijk afhangt van lokale kenmerken (d.w.z. de hooglichten). Zachtheid daarentegen werd niet significant verschillend ervaren tussen gewassen van dezelfde stof, wat aantoont dat de perceptie ervan beter gerelateerd is aan globale kenmerken, waaronder waarschijnlijk de algehele vorm en vervorming van de stof. Met de onderzoeken die in dit proefschrift worden gepresenteerd, laten we de wederzijdse voordelen zien die materiaalperceptie en kunstgeschiedenis van elkaar kunnen halen, en we geven praktische voorbeelden van hoe de kennis en methoden uit het ene vakgebied in het andere kunnen worden geïmplementeerd.

Inzichten over materiaalweergave en perceptie, verkregen door het samenvoegen van deze twee disciplines, vinden toepassingen in alle gebieden die met uiterlijk te maken hebben, van productontwerp tot computer graphics.

Curriculum Vitæ

Francesca DI CICCO

22-05-1991	Born in Rome, Italy.
2010–2014	BSc Industrial Chemistry “La Sapienza” University, Rome, Italy
2014–2016	MSc Chemical Sciences Utrecht University, Utrecht, The Netherlands
2016–2021	PhD. Material perception Delft University of Technology, Delft, The Netherlands *Thesis:* Convincing stuff. Disclosing perceptually-relevant cues for the depiction of materials in 17^{th} century paintings. *Promotors:* Prof.dr. S.C. Pont, Prof.dr. J. Dik *Copromotor:* Dr. M.W.A. Wijntjes

List of Publications

9. **F. Di Cicco**, *An index of key image features for material perception. The legacy of Willem Beurs*, Manuscript in preparation.

8. **F. Di Cicco**, M. Van Zuijlen, P. Barla, M. Wijntjes, S. Pont, *On perceiving the lustre of pearls. When less is more*, Manuscript under review.

7. **F. Di Cicco**, M. Van Zuijlen, M. Wijntjes, S. Pont,*Soft like velvet and shiny like satin: perceptual material signatures of fabrics depicted in 17th century paintings*, Manuscript in publication.

6. **F. Di Cicco**, M. Wijntjes, S. Pont, *If painters give you lemons, squeeze the knowledge out of them. A study on the visual perception of the translucent and juicy appearance of citrus fruits in paintings*, Journal of Vision, **20**(13):12, 1-15 (2020).

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