Acquiring material properties of objects for tactile simulation through point cloud scans

Haocheng Yang
Supervisor(s): Kees Kroep, Dr. RangaRao Venkatesha Prasad
EEMCS, Delft University of Technology, The Netherlands
23 June 2022

A Dissertation Submitted to EEMCS faculty Delft University of Technology,
In Partial Fulfilment of the Requirements
For the Bachelor of Computer Science and Engineering

Abstract

Tactile internet enables communication in a new layer of immersion, touch. It has the potential to transform the landscape of digital communication. However, the achievable scale of tactile internet is severely limited by its 1 ms round-trip latency. We propose a workaround for the latency through tactile simulation, which can bypass the requirement by having the user interact with locally simulated force feedback instead of real ones. A real-time material estimation method is required to create such a simulation, as it needs material information such as friction and tactile texture. We, therefore, investigate whether material is estimable from point cloud scans since it provides readily available environmental data. We also explore how friction and tactile texture could be extracted from the material. Past material estimation methods rely heavily on point intensity; however, most existing point clouds do not have intensity information. Therefore, we study whether mocking intensity information could be sufficient, exchanging it with grayscale. The results demonstrate that without point intensity, the material estimation method can only discern object colour and not material properties. This finding implicates the importance of intensity and suggests future exploration of the viability of material estimation with intensity data for indoor objects.

1 Introduction

As a result of the covid-19 pandemic, we have become more aware of the importance of connecting people over the internet, primarily through video conferencing. We also realize the limitation of this type of communication, for it is still a far cry from reaching the immersion of in-person communication since only two dimensions of experience are present, audio and video. Tactile internet would be able to offer another layer of immersion by allowing touch over the internet through force feedback.

Tactile itself means tangibility, to connect via a sense of touch, which is what tactile internet aims to achieve. It aims to grant users the ability to manipulate and feel an object over the internet, such as holding a pen remotely and still feeling it in hand, as shown in Figure 1. Another example of its application could be in remote surgery, where the surgeon can accurately sense the force feedback from the scalpel, despite not holding the real thing. For such applications, a very low round-trip network latency of approximately 1 ms is desired [11], as when a human actively manipulates an object, they anticipate rapid and immediate feedback.

However, achieving such low network latency is challenging, not to mention maintaining it. Digital communications already have trouble achieving a latency of below 5ms, as most professional audio systems (e.g., wireless microphones) still use analogue by choice [11]. Even if 1 ms could be achieved, since digital communication cannot be faster than light [10], it sets a hard limit on the possible round-trip distance between terminals. The 1 ms latency requirement severely limits the scale of tactile internet that is achievable.

Figure 1: Example of tactile internet, holding a pen remotely with a robot hand but still feeling the accurate force feedback in the real hand [16].

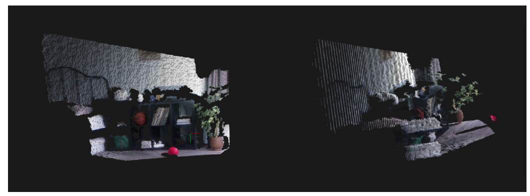


Figure 2: Point cloud scan of a room environment using Xbox Kinect in real-time, shown from two different angles. Demonstrate point cloud's ability to gather environmental information quickly.

While directly minimizing latency is difficult, it is possible to work around the problem using a local simulation to provide haptic feedback instead. If the environment users get haptic feedback from is virtual instead of real, delay would not exist, as the haptic information is not sent over the internet but from the simulated environment itself. Since the user only interacts with the local simulation, there would be no delay. As long as the simulated environment is in sync with the actual remote environment, it would achieve the same functionality as regular tactile internet and without as much demand for latency. By creating a virtual environment, the problem of latency can be bypassed.

However, how would such a virtual environment be created? It will need to provide effective haptic feedback, which means objects in the environment are simulated with physics. There will need a way to acquire visual information and then translate it into objects with accurate mass, material, and mesh structure that effectively resemble their real-world counterpart. One way such information could be acquired is through point cloud scans.

Point cloud data is a form of 3d representation that can be acquired very quickly, which suits the purpose of creating a virtual environment. It is a cloud of points in 3d space, forming structures. Xbox Kinect, for example, a motion controller designed for video game consoles, can acquire 3d colour and depth information in point cloud data in real-time, as shown in Figure 2. From that, cloud data of the objects of the environment can then be recreated. The hypothesis is that it is possible to acquire the information needed for a haptic simulation through point cloud data alone—for instance, the objects' mass, material, and mesh.

This paper aims to address one aspect of creating the simulation from point clouds, to estimate the material properties of an object, preparing it for physics simulation. Existing research on the subject already exists in the field of architecture, where it is claimed that material information such as reflectance and albedo can be accurately estimated through the point cloud's RGB information and intensity data [5]. That was used to identify material information from terrestrial scans for architectural purposes.

However, there is no attempt to extend its use for household objects, nor exploration towards simulation with acquired material data, leaving a vacuum for exploration. Therefore, this paper explores the possibilities of finding the physical material of everyday objects from point clouds and delves into how tactile texture and physical properties could be generated from that information. Regarding that aim, several sub-questions are explored:

1. How to correctly estimate and recognize the material properties of objects represented by segmented point clouds?
2. How to identify compound materials, as household objects usually consist of multiple materials? e.g. a glass jar with a plastic lid.
3. How to acquire physical properties from the object material to be used for physics simulation, e.g. friction?
4. How to acquire tactile texture from the object material so the user can experience the object with suitable tactile sensation?

Our paper contributes the following. First, we demonstrate that it is not viable to estimate material from the point cloud's mesh texture. Second, we test the capability of material estimation with intensity and show that it can be used for compound material recognition. Third, regarding the lack of availability of intensity point clouds, we use mock intensity to test how the method fares without intensity and found intensity is too important to be omitted, as, without it, the method only discerns between colour instead of material. Finally, we propose viable ways to extend found material properties to physical properties and tactile texture.

The paper is structured as follows. First, it presents the related works in tactile internet and material estimation to put the paper's research into proper perspective. Second, the methodology is presented, going through the rationale of what is explored, what insights have been gained, and the details of the material estimation method tested. Third, the specific results from the method are presented, as well as its analysis. The responsible research section follows, reflecting on the ethical responsibility of the research methods. Finally, the suggestion for future work is discussed, following the conclusion.

2 Related Works

2.1 Tactile internet

For tactile internet, the most present research is revolved around exploring what can be done with the $1\,\mathrm{ms}$ round-trip delay as a precondition. This trend caused 5G to become the centre of the discussion since it makes it possible to achieve a $1\,\mathrm{ms}$ delay. Simsek et al., for example, discuss what 5G and tactile internet have in common and how 5G could support the architecture of tactile internet [2]. Some papers already assume the use of 5G; for instance, Gupta et al. talk about the challenges of using tactile internet with ultra-reliable low-latency applications in a 5G environment [12].

However, there is no research on finding a way around the delay or alternative methods for achieving tactile internet. Therefore, this paper proposes using simulation as a workaround for the delay problem, as mentioned in the introduction. It goes into detail to explore a sub-question that requires solving, which is the material estimation aspect of creating a convincing tactile simulation.

2.2 Material estimation

For material estimation, most research is in robotics and architecture. For robotics, it is needed for robots to walk and grasp objects and for architecture to create a comprehensive site analysis.

In robotics, research on physical material properties usually requires physical contact. Li et al. address the five critical dimensions of tactile information, for example, friction and surface texture; however, they are acquired through touch [18]. Le et al. used visual cues to acquire material properties of varying objects; however, it was combined with haptic information, as visual data alone is noted to be limited [17]. When visual information alone was used [7], it was used in context with machine learning.

In architecture, however, there are methods proposed using only visual data and without the need for machine learning. Alkadri et al. explored the potential of recognizing surface attributes from point cloud data and were able to extract albedo values to identify material types [4]. The limitation is that it relies heavily on intensity information from point clouds. In later works by Alkadri et al., the material properties that could be acquired are expanded further to reflectance and emissivity; however that made intensity information even more crucial [5]. Also, both research deal with outdoor scans for materials such as gravel, asphalt, and grass. It is unclear whether indoor object materials could be recognized through their method.

This paper, therefore, aims to explore whether the material of small, indoor objects could be estimated through only visual information. It also tries to determine the effect of lacking true intensity information on material estimation since intensity is usually unavailable through affordable scanning tools, such as Xbox Kinect. Many point cloud file types also do not feature intensity, for example, ply or most of the point formats of las file type. This severely limited the ability to use online point cloud resources for material estimation with methods that require intensity.

3 Methodology

This section presents the methodology of the paper. It lays out the process and rationale of what was explored in the paper. It goes through the different attempts to solve the material estimation problem from a segmented point cloud, first from

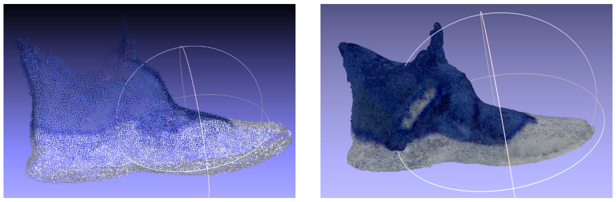


Figure 3: Segmented point cloud of a sport shoe (left). Generated mesh of the shoe after poisson surface reconstruction (right). Demonstrate how point cloud can be constructed into textured mesh.

mesh texture, second using point intensity, and finally testing the viability of material estimation without point intensity. It also discusses how the estimated material could be used to find physical properties and prepare for physics simulation. Lastly, how the material's tactile texture could be generated to simulate tactile perception is discussed.

For every attempt mentioned in this section, it assumes that we start with a segmented point cloud of an object and need to recognize the material of that cloud. It seeks to find a method suitable for material estimation that is then extendable to finding the object's physical properties and tactile texture.

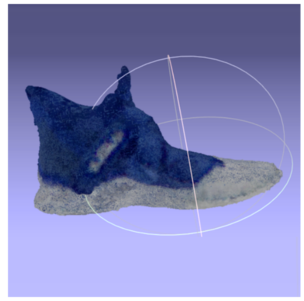
3.1 Material recognition from mesh texture

For the first attempt, we tried to acquire the colored texture from the segmented point cloud and then recognize the material from the texture. This method was considered because we hypothesized that the texture generated from the point cloud would contain distinct features. Therefore we could use feature matching methods such as Scale-Invariant Feature Transform (SIFT) to match with an existing library of textures. We could then use the matched texture to interpret the material of the point cloud. For example, if a wooden texture is matched, then part of the material of the point cloud would be wood. If multiple textures are matched, we could then use the UV map of the mesh to see which part of the point cloud mesh is which material. The problem of recognizing compound material would then also be solved.

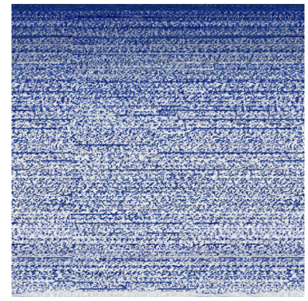
We then attempted to test the hypothesized workflow with an existing mesh processing tool Meshlab [8]. It provides visualizations and is equipped with state-of-the-art utilities for point cloud processing, which suits our purpose of doing experimentation.

For the specific steps taken, we first calculated the normal of each point cloud point to ensure the faces of the generated mesh would face the correct direction concerning the viewpoint. Secondly, we generated the point cloud to mesh, as shown in Figure 3, through Poisson surface reconstruction [14], since it is the standard method used in point cloud libraries such as PCL [22]. Thirdly, we textured the generated mesh by assigning the colour of the cloud points to the closest vertex of the mesh. From that, we were able to acquire the mesh's colored texture.

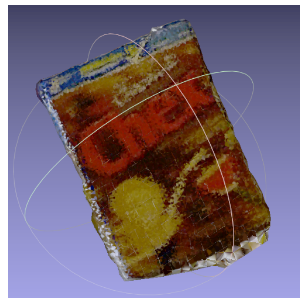
However, the acquired texture was proven to be unusable for feature detection. For the sports shoe, for example, its generated UV does not have any logical arrangement, causing the colour information to also be in complete disorder, as shown in Figure 4(b). This distortion is the case for different



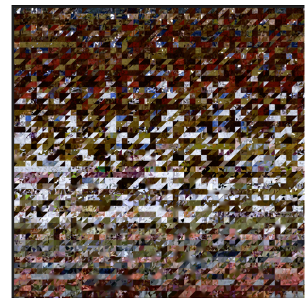
(a) sport shoe mesh



(b) sport shoe texture



(c) cereal box mesh



(d) cereal box texture

Figure 4: Textured meshes constructed from segmented point clouds of a shoe and a cereal box (left). The unfolded mesh textures of the shoe and the cereal box (right). The generated textures are unfit for any feature extraction for material recognition due to the UV distortions.

meshes as well. For instance, Figure 4(c) shows the cereal box. It contains fewer faces as its point cloud was downsampled. However, that does not improve the distortion of its texture. No recognizable features could be extracted from colored textures like these. Therefore, it is impossible to recognize material from point cloud textures.

3.2 Material estimation with intensity

For the next attempt, we tried to calculate the material for every point of the point cloud. Through that, we either get the average if the object is of a single material or use k-means clustering on the material to section out compound materials. This method was based on the architectural site analysis method proposed by Alkadri et al., where site materials such as asphalt and cement could be recognized, and distinguished [5]. It was considered for its flexibility and applicability, for it relies on primarily easy-to-acquire data, for example, the colour and depth information of the point cloud.

However, the method also relies heavily on point intensity, as Alkadri et al. focus on point cloud data acquired from Light Detection and Ranging (LiDAR) technology [5]. LiDAR is a laser-based method which shoots a laser pulse targeting object and surface and measures the return strength and time used for the laser to return to the receiver. The laser's returning strength is intensity, reflecting the Emissivity of the material. For a perfect reflector, the intensity would be 1, and for a perfect emitter, 0. If the intensity is missing, then the material's Emissivity is missing, making estimating material attributes difficult. Therefore, intensity plays an integral role in ensuring successful material recognition for this method.

To test the method's viability, we acquired a point cloud with intensity information, shown in Figure 5, and calculated the Emissivity, Albedo, and Reflectance of every point of the cloud [5]. Details of the formula used will be elaborated on in the following sections. We used the materials as input vectors for k-means clustering and acquired a visualization of the compound material it recognizes, as shown in Figure 6. It was a promising result as the material segmentation matches the cloud's material make-up.

However, we could not apply this method directly to indoor objects because of its heavy reliance on intensity. Scans of indoor objects available online are usually in a file format that does not contain intensity information, such as ply. The scans that can be made ourselves are only through Xbox Kinect, and it does not have any direct method to create point clouds with intensity. It could be possible to use its infrared camera to create a point cloud of only intensity and then combine it with its RGB point cloud; however, that was proven difficult to achieve due to the limited time frame of the research. Therefore, we sought to test whether material estimation would still be possible if intensity information is not known.

Figure 5: The input house point cloud used for material estimation, shown in RGB colors.

3.3 Material estimation with mock intensity

In the final attempt, we explored the viability of estimating material without intensity information. Intensity aside, the rest of the method remains the same. The material is still calculated for every point cloud point, allowing average material calculation of the cloud or clustering to distinguish compound materials.

Mock intensity As mentioned in the previous section, since point intensity is not usually available, it is necessary to test whether it is still possible to estimate material in its absence. This paper proposes to substitute intensity information with grayscale values and leave the rest of the method unchanged. The substitution is because visualized intensity looks similar to grayscale, with intensity 1 being white and intensity 0 being black. Figure 7 shows a visualisation of it. However, this substitution only works under the assumption that objects will be relatively well-lit.

Lighting is of concern because it now directly affects how intensity is estimated. For LiDAR scans, lighting condition is not of significant concern because it relies on its infrared laser beams to gather information instead of visible light, so the light from the environment does not affect its judgment. However, scanning tools like Xbox Kinect uses an RGB video camera to judge colour information. When a room is subjected to a powerful light, objects it scans from that room will appear to have brighter colours than if the room is poorly lit. This difference, in turn, would mean higher or lower estimated intensity values. It is challenging to assume how much lighting would be optimal; therefore, the experiments in this paper use standard indoor lighting.

After lighting is established, the problem that's left is RGB to grayscale conversion. It is done with the formula proposed and used in the image editing software GIMP and numerical computing software Matlab [23], for the method models the human's brightness perception, albeit simple. The formula proposes a coefficient to multiply each colour channel to output the grayscale intensity:

$$I = 0.3R + 0.59G + 0.11B \tag{1}$$

However, this formula does not normalize the intensity within the 0 to 1 range. Therefore, the RGB values were normalized, resulting in the formula:

$$I = \frac{0.3R}{255} + \frac{0.59G}{255} + \frac{0.11B}{255} \tag{2}$$

After the intensity value has been acquired, the estimation of the material can begin.

Intensity correction Three material properties can be acquired from intensity data, Emissivity, Albedo, and Reflectance [5]. Emissivity and Albedo rely on intensity, while Reflectance does not. Before the material properties can be calculated, intensity correction must be taken into consideration [5].

Intensity correction is needed for LiDAR scans. The lasers' range and angle of incidence have a direct influence on the intensity acquired, and the correction makes the intensity equivalent to when all points are in a defined range with the angle of incidence zero [13]. It would make the intensity values less dependent upon the scanner location.

However, because the intensity value is now mocked, intensity correction is no longer necessary. While Kinect and LiDAR utilize laser, the point cloud colour from our scans is determined solely by its RGB camera. Therefore, the grayscale mock intensity is not dependent upon incidence angle or range, making correction redundant.

Emissivity Emissivity is calculated as the inverse of intensity, the first material property we can acquire. It refers to the amount of heat radiated by the material surface [5]. A perfect emitter surface would have an intensity value of 0 since no energy would be reflected. For a perfect reflector, it would then have an intensity value of 1. Emissivity goes directly in contrast to this as it would have a high value for

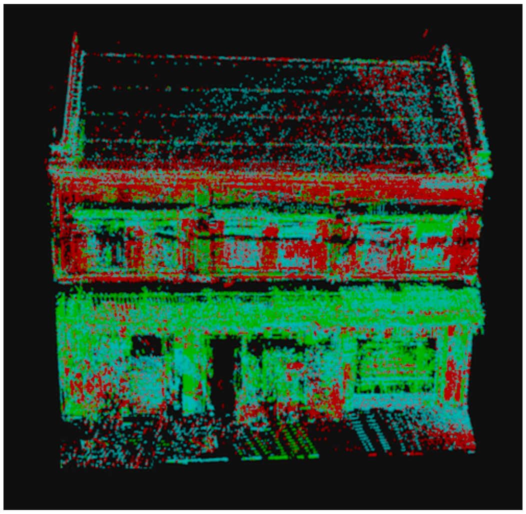


Figure 6: Recognized compound material from the house point cloud, assuming it has three materials. Each material is represented by a different colour, red, green, or blue. It shows that it is possible to recognize compound material using material estimation with intensity.

a perfect emitter and vice versa. Material characterized with high-intensity values, such as polished metals and ceramics, would, in turn, have low Emissivity values [5]. Therefore, this paper calculates the normalized Emissivity value by subtracting the intensity from 1.

$$\text{Emissivity} = 1 - \text{Intensity} \tag{3}$$

Albedo Albedo is the second material property we can acquire, defined as the fraction of sunlight that a surface can reflect [9]. It is valued between 0 and 1, where 0 would present a black body, absorbing all incoming solar radiation [5]. It can be calculated by combining RGB information and Intensity [5], as shown in equation 4.

$$\text{Albedo} = \left(\frac{\sqrt{\frac{(R^2+G^2+B^2)}{3}}}{255} \right) \cdot I, \tag{4}$$

where I represents intensity, the front bracket captures reflected light from RGB colours, combined with intensity through multiplication.

While Albedo is a material property, its application for indoor objects is scrutinized. Albedo is solely a measure of the effect of sunlight, therefore valuable for remote sensing atmospheric and surface properties [9]. While it can be calculated and used as a factor for material recognition, it needs to be taken into account that Albedo is not used to describe indoor materials. It is more commonly used to describe urban environments or vegetation. It is still a factor because the paper aims to see whether it could help distinguish materials from one another.

Reflectance Reflectance is the final material property we could acquire. There are two types of Reflectance, spectral

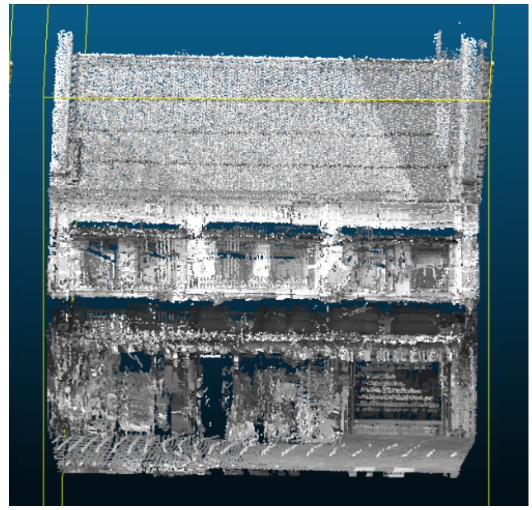


Figure 7: The intensity of the house point cloud is visualized as grayscale. It shows that intensity resembles the grayscale of RGB information.

Figure 8: A transparent glass mug; the object to be scanned into a point cloud using Xbox Kinect. The resulting point cloud after the scan (right). It demonstrates that Xbox Kinect is bad at scanning transparent objects.

reflectance and diffuse reflectance [3]. This paper only considers diffuse reflectance, as spectral reflectance deals with reflective materials such as mirrors, which is beyond this paper's scope. Therefore, Reflectance in this paper only refers to diffuse reflectance.

Diffuse reflectance is the ratio of light energy reflected from a material relative to the amount of light incident on the material. The material must also be opaque, as Reflectance does not take internal reflections into account [5]. This limitation suits the purpose of point cloud scans as the scanning tools available do not fare well with transparency, as shown in Figure 8.

Reflectance is calculated with the below formula [5], with the precondition that the material is both diffuse and opaque.

$$\text{Ref} = \left(0.2125 \cdot \frac{R}{255}\right) + \left(0.7154 \cdot \frac{G}{255}\right) + \left(0.0721 \cdot \frac{B}{255}\right), \tag{5}$$

where Ref refers to Reflectance.

Result acquisition The method was tested using segmented point clouds of individual objects, shown in Figure 9. To acquire the results, we calculated the mock intensity first. Then using it in combination with RGB information, we acquired the Emissivity, Albedo, and Reflectance for every point cloud point. Under the assumption that the input point cloud consists of a single material, we calculated the material average of every point to get the final output material.

3.4 Friction estimation from material

Another central question requiring exploration was how to acquire physical properties such as friction from the estimated material properties. Without physical properties, we would be unable to use our material data for any form of physics simulation. Therefore, we looked into whether a friction model exists that inputs material properties and outputs friction coefficients.

However, it was discovered that such a friction model does not yet exist. Friction could be estimated with a model in specific circumstances such as a mining tunnel using fluid dynamics; however, that does not apply for most cases [24]. Otherwise, it was done with black-box machine learning methods, trained using an image data set [7]. Friction coefficients are solely an empirical measurement and can only be acquired experimentally, as opposed to through calculations [19].

Because we cannot calculate friction, the only way to acquire friction coefficients from material properties is to have a pre-made library of already acquired coefficients and get the coefficients based on the materials in contact. For example, if we have a ceramic mug placed on a wooden table, we would recognize their material, which is ceramic and wood, and find the friction coefficient corresponding to ceramic against wood existing in the library.

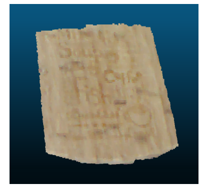
3.5 Tactile texture from material

The final problem this paper explored was acquiring the tactile texture of the object material and allowing users to feel the texture when they interact with the object. For example, they would feel the wood grain when they move their hand across a wooden table. Due to the limited time frame, we were unable to test its effect on users; however, we have made hypotheses that could be useful as a guide for future exploration.

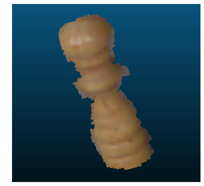
We hypothesize that users would be satisfied with basic tactile sensations as long as they correlate with their vision. In the case of tactile internet through simulation, as mentioned in the introduction, a user would look at camera footage and interact with a simulated environment. They will not come into contact with the remote object and will only interact with simulated ones. Therefore, their expectation of object tactile texture comes solely from vision.

We believe that as long as their visual expectation of the tactile texture is satisfied, the user would not doubt the fidelity of the simulation. Even if a wooden table does not have wood grain, if it looks like it does, we can have the users feel wood grain when they touch the table without losing immersion. Wastiels et al. have found that when a person judges whether material is warm or cold, the perception is dominated by vision [1]. We hypothesize that could be the same for roughness and textural perception. If valid, it would save work in simulating object material as now we have a lot more margin for error in simulating the textural sensation. We could assign pre-prepared tactile texture based on the material, for example, wood grain texture if the visually recognized material is wood. We would then be able to disregard the real texture of the material. However, this idea requires future testing.

(a) wood bat

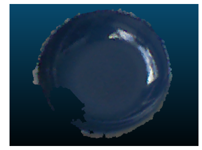


(b) cutboard



(c) salt shaker

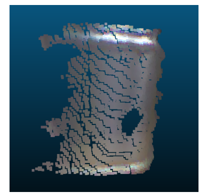
(d) white plate



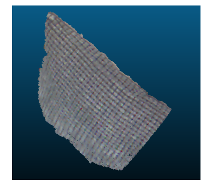
(e) blue plate

(f) beige plate

(g) metal plate



(h) plastic jar



(i) cushion

Figure 9: Visualization of input point clouds for material estimation. For the first row, (a) (b) (c) are all point clouds of wood material. For the second row, (d) (e) (f) are also of the same material, ceramic, but with more significant colour differences. For the final row, (g) (h) (i) are instead all of the different materials, metal, plastic and cloth, but of similar colour. They are organized as such to test how well the material estimation method accounts for colour differences.

4 Results

4.1 Experimental setup

The experiment's aim is to test how well the material estimation method without intensity work adjusts for colour differences and whether it is capable of recognizing the material properties despite the colour variation. Regarding this aim, three distinct batches of point clouds were used as input, each testing a different aspect. The point clouds used are shown in Figure 9.

The first batch consists of three wooden objects, assuming they would be recognized as the same material. The second batch is placed under the same assumption, as all three objects are ceramic, despite having different colours. For the final batch, all three objects are of different materials, the first one metal, the second one plastic, and the third one cloth. If the material estimation is functional, they should produce distinct material properties despite being very close in colour.

4.2 Data analysis

The resulting data of material estimation through mocking intensity are presented here, where grayscale is used as inten-

Index	Object	Estimated Material properties		
		Emissivity	Albedo	Reflectance
(a)	Wood Bat	0.62	0.15	0.38
(b)	Cutboard	0.39	0.36	0.60
(c)	Salt shaker	0.56	0.19	0.43
(d)	White plate	0.11	0.80	0.89
(e)	Blue plate	0.81	0.04	0.19
(f)	Beige plate	0.06	0.97	0.94
(g)	Metal plate	0.55	0.21	0.45
(h)	Plastic jar	0.58	0.19	0.42
(i)	Cushion	0.55	0.21	0.45

Table 1: Material properties of segmented point clouds using mock intensity. The method is shown to be bad at dealing with colour differences; for example, Metal plate and Cushion is recognized as having the same material due to similar colour.

sity, and the average Emissivity, Albedo and Reflectance of every input point cloud is calculated.

For the first batch of three wooden objects, we could see that objects (a) and (c) from Table 1 produced similar values, while the object (b) differs quite a bit from the two. This finding violates the assumption that all three objects should have similar material properties, as they are all wood. If only looking at the three objects, we could still argue that object (b) is of a different type of wood since its appearance differs from (a) and (c), as shown in Figure 9. However, it could also mean that the method cannot recognize the same material if colour variations exist. Therefore, a more noticeable colour difference is used in the second batch to gain a more concrete view.

For the second batch, all three plates are ceramic, and each of different colour, white (d), blue (c), and beige (f). As seen from Table 1, the same pattern is shown again as in batch one, that the material property differs significantly if their colour differs greatly, and similar if their colours are similar. Plate (c) differs by a large portion from the other two plates, with Albedo close to 0, while the other two close to 1. Under the current method, the three plates will not be recognized as the same material.

The third batch takes a different approach from the first two batches, as every object is of a very different material but similar in colour. If the method can discern different materials, the results should be very different, despite the colour similarity. However, the results showed the opposite. From Table 1, we can see that (g) and (i) are considered to have identical material, even though (g) is entirely metal, and (i) is a cloth cushion. From this, we can conclude that the method cannot discern objects of different materials but of the same colour.

In conclusion, the method cannot recognize objects of different materials and can only discern them between colours. We cannot compare the current results with results where intensity is available, however, as we do not yet have the capability of creating point clouds with intensity, nor is there an existing data set available of indoor objects. Therefore, we also do not know whether the method would be viable if we have intensity. Two possible hypotheses could be drawn, first is that while discerning between materials of different colours is impossible without intensity, it would be possible with intensity. The second is that it would still be impossible, at least with the three material properties we can acquire.

5 Responsible Research

This paper did not involve external participants for its experiment nor collaborators for data collection and is strictly a standalone exploration. Therefore, the author of the paper shoulders full responsibility for research integrity. The main aspects that need to be addressed are scientific integrity, the necessity to highlight negative results, and the reproducibility of the experiments, which in turn upholds the epistemic virtues of honesty, humility and objectivity, as well as the Scientific ethos of disinterestedness and communism.

This paper's results were primarily negative, as the explored method turned out to be too limited to sufficiently answer the research question. While giving more emphasis to positive results would make the paper seem more attractive to potential readers, that was dutifully avoided. Negative results are just as valuable as positive results, and to falsely highlight positive results violates the disinterestedness principle of scientific ethos because the research results should not be influenced by personal interests.

While the result of this paper might not seem worth celebrating, it can avoid other researchers repeating the same failed experiments and delay genuine progress [20]. The limitations on imitating intensity for material estimation mean it can be improved in future works. It is also necessary to remain truthful and objective for scientific research to counter the positive result bias rampant in published studies [20].

Reproducibility is also a big issue in various research fields [6]. It is a crucial aspect as easily reproducible results make it easier for future research to build on existing research and uphold the Communism scientific ethos. Considering that, the methodology of this paper is made to be reproducible, as well as results. It lists in full what tools were used. The math used is thoroughly presented in the methodology. The point cloud data used for the experiments will be made public, as well as the executable code. It must be noted that the point cloud data set explored is small and manually processed due to the scanning device's flaws so the method might produce different results with unfiltered and unprocessed point cloud data.

6 Future Work

Based on the current result, two next steps can be taken. The first is to examine the viability of material estimation with intensity for indoor objects, and the second is an experiment to pinpoint the user's requirement for tactile texture fidelity.

While the method does not produce desired results without intensity, its performance with point clouds is still unclear. To validate this, a way of independently creating intensity point clouds is necessary, and we believe it could be done with a slight improvement in hardware.

Kinect V2 can produce infrared intensity images of much higher quality than Kinect V1. It could be a viable way of producing intensity point clouds without needing a high-cost LiDAR scanner [21]. The intensity acquired could also be used for roughness estimation, making more accurate tactile texture simulation possible [15]. For example, if the object material is wood, a wood grain texture can be felt when the user touches the object and is scaled based on the actual roughness of the surface.

This implication leads to the question of how sensitive the users are to the accuracy of tactile texture simulated. To gain insight on this, we propose a wizard of oz experiment setup to test the fidelity needed for tactile texture. We could let the user experience the texture in simulation, where we could control the fidelity of the texture they experience. At the same time, they can only see an image of the object with the texture. Then, we let the users rate how much they thought the simulated texture accurately represented the tactile texture of the object they had seen. This experiment can then narrow down the quality of tactile texture users expect based only on visual information without needing full working material recognition.

7 Conclusion

Tactile internet opens the opportunities for another form of interaction across the internet, touch, and has numerous applications such as immersive video conferencing and remote surgery. However, it is limited by a round-trip latency requirement of $1\,\mathrm{ms}$. The requirement can be worked around using a simulation to provide force feedback instead of real-time force feedback. However, this leaves the problem of creating a simulation with enough fidelity to pass for real force feedback, and material estimation is one crucial step to ensure simulation fidelity.

This paper sought to find a method to estimate the material properties of an object from its point cloud so that it can be simulated in a physics simulation. Point clouds are used because point cloud scans can capture information about the environment in real-time and do not require costly equipment. From the material properties found, physical and textural properties should also be able to be acquired from that information to prepare the object for simulation. Also, the method should be capable of discovering the compound material of an object. Regarding this aim, several discoveries were made.

Firstly, we discovered that it is not viable to estimate point cloud material from its mesh texture, as the colour information is too distorted to be used for classification. Secondly, we found that the architectural method of using cloud intensity and RGB information to infer material properties fits our purpose. However, we could not produce point cloud data set of indoor objects with intensity information. Because of it, we sought to mock intensity with grayscale to test the method's limit. After experimenting, we concluded that the method could not discern objects with the same colour but different material through intensity mocking. This finding indicates that the estimated material from the method is insufficient without intensity information and cannot adjust for colour differences.

For acquiring friction from the material, it was found to be impossible, as friction coefficients are empirical measurements. The only way to still approximate friction is to have already available data for various material types and use that data when the material matches. Obtaining objects' tactile texture would be done similarly, where existing tactile textures are matched given the material properties.

References

[1] Relating material experience to technical parameters: A case study on visual and tactile warmth perception of indoor wall materials. *Building and Environment*, 49:359–367, 3 2012.

[2] 5g-enabled tactile internet. *IEEE Journal on Selected Areas in Communications*, 34:460–473, 3 2016.

[3] Reflectance, reflectivity, and the solar reflectance index, Oct 2020.

[4] Miktha Farid Alkadri, Michela Turrin, and Sevil Sariyildiz. Identifying the surface materials of the existing environment through point cloud data attributes. pages 1–8, 2018.

[5] Miktha Farid Alkadri, Michela Turrin, and Sevil Sariyildiz. A computational workflow to analyse material properties and solar radiation of existing contexts from attribute information of point cloud data. *Building and Environment*, 155:268–282, 5 2019.

[6] Monya Baker and Dan Penny. Is there a reproducibility crisis? *Nature*, 533:452–454, 5 2016.

[7] Martim Brandão, Kenji Hashimoto, and Atsuo Takanishi. Friction from vision: A study of algorithmic and human performance with consequences for robot perception and teleoperation. pages 428–435. IEEE Computer Society, 12 2016.

[8] Paolo Cignoni, Marco Callieri, Massimiliano Corsini, Matteo Dellepiane, Fabio Ganovelli, and Guido Ranzuglia. MeshLab: an Open-Source Mesh Processing Tool. In Vittorio Scarano, Rosario De Chiara, and Ugo Erra, editors, *Eurographics Italian Chapter Conference*. The Eurographics Association, 2008.

[9] J A Coakley. Reflectance and albedo, surface, 2003.

[10] Phillippe H Eberhard and Ronald R Ross. Quantum field theory cannot provide faster-than-light communication. *Foundations of Physics Letters*, 2:127–149, 1989.

[11] Gerhard P. Fettweis. The tactile internet: Applications and challenges. *IEEE Vehicular Technology Magazine*, 9(1):64–70, 2014.

[12] Rajesh Gupta, Sudeep Tanwar, Sudhanshu Tyagi, and Neeraj Kumar. Tactile internet and its applications in 5g era: A comprehensive review. *International Journal of Communication Systems*, 32, 9 2019.

[13] Alireza G. Kashani, Michael J. Olsen, Christopher E. Parrish, and Nicholas Wilson. A review of lidar radiometric processing: From ad hoc intensity correction to rigorous radiometric calibration, 11 2015.

[14] Michael Kazhdan and Hugues Hoppe. Screened poisson surface reconstruction. *ACM Transactions on Graphics (TOG)*, 32(3):29, 2013.

[15] Jungjun Kim, Hwasup Lim, Sang Ahn, and Seungkyu Lee. Rgbd camera based material recognition via surface roughness estimation. pages 1963–1971, 03 2018.

[16] H. J. C. Kroep, V. Gokhale, J. Verburg, and R. Venkatesha Prasad. Etvo: Effectively measuring tactile internet with experimental validation. 7 2021.

[17] Tran Nguyen Le, Francesco Verdoja, Fares J. Abu-Dakka, and Ville Kyrki. Probabilistic surface friction estimation based on visual and haptic measurements. 10 2020.

[18] Qiang Li, Oliver Kroemer, Zhe Su, Filipe Fernandes Veiga, Mohsen Kaboli, and Helge Joachim Ritter. A review of tactile information: Perception and action through touch. *IEEE Transactions on Robotics*, 36:1619–1634, 12 2020.

[19] Vladimir Malyshev. *Tribological aspects in friction stir welding and processing*, pages 329–386. 12 2014.

[20] Devang Mehta. Highlight negative results to improve science. *Nature*, 10 2019.

[21] MReza Naeemabadi, Birthe Dinesen, Ole Kæseler Andersen, and John Hansen. Investigating the impact of a motion capture system on microsoft kinect v2 recordings: A caution for using the technologies together. *PLoS ONE*, 13, 9 2018.

[22] Radu Bogdan Rusu and Steve Cousins. 3D is here: Point Cloud Library (PCL). In *IEEE International Conference on Robotics and Automation (ICRA)*, Shanghai, China, May 9-13 2011.

[23] Yi Wan and Qisong Xie. A novel framework for optimal rgb to grayscale image conversion. volume 2, pages 345–348. Institute of Electrical and Electronics Engineers Inc., 12 2016.

[24] Curtis W A Watson and Robert M Buchan. Towards estimating friction factors of mine drifts from low density point clouds, 2016.