Enrichment and application of digital 3D city models in the context of urban mining.
A case study based on the CityGML model of Rotterdam.
Thesis proposal, MSc Geomatics

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1 Introduction

This document describes the graduation research on semantic enrichment of digital three-dimensional city models (such as CityGML LOD2 datasets) by means of point cloud analysis. On top of geometry and sometimes textures, a semantic 3D city model includes other, more thematic knowledge (by making some features and properties explicit) (Billen et al., 2014). This research will be conducted with regard to a specific application, which is optimization of material classification performed on building roof surfaces by providing a filter for spectral variations.

This research is the final part of the Master of Science program Geomatics for the Built Environment at Delft University of Technology, the Netherlands. After introducing societal and scientific relevance, this document describes different relevant academic research fields. Finally, the methodology itself, along with the research questions, a first method and planning will be introduced.

1.1 Societal relevance

A 2008 study conducted by the UK government has shown that no less than 7% of national CO2 emissions emanate from manufacturing construction products (BIS, 2010). While accounting for considerably less than the usage of buildings (about 39% of national CO2 emissions, BIS, 2010), it still has a strong potential for reduction as it copes with future constructions in contrast to existing ones which are harder to act on.

Incentives such as building certificates aiming at sustainability (e.g. BREAAM, LEEN) exist and stimulate usage of local and recyclable sources. While it creates demand, it is not sufficient as such: there also needs to be an efficient overview of the offer, of materials freed by local demolition and refurbishment. Many projects of the field ‘urban mining’ aim at doing this by mapping the materials that are present in a city (this can be building materials but also food waste, electronics etc.). Good examples are projects such as REPAiR (http://h2020repair.eu) which aims at “creating integrated, place-based eco-innovative spatial development strategies aiming at a quantitative reduction of waste flows” at a European scale. Some smaller projects can be found in the Netherlands (Blok and Faes, 2018; Blok, 2018) and use empirical observations (such as assessing building types or weighting outputs of demolition) to estimate the quantity of enclosed materials.

One building element is of particular interest due to its exposition to climate: the roof. In fact, it needs to be renewed at regular intervals which are often shorter than the ones of general refurbishments. Furthermore, promising initiatives (e.g. www.roof2roof.nl) exist to recycle freed materials such as bitumen. This can be done by reconditioning for usage on other roofs or downcycling for road asphalt (Townsend et al., 2007). In order to make such processes as efficient as possible (i.e. construction of supporting factories), spatial data (location of material flow start and end points) should aim at being as detailed as possible. Patouillard et al. (2018) discusses why aggregated approaches (such as statistical) ones can be insufficient.

1.2 Scientific relevance

Primordial for urban mining methods named above is an accurate Spatial Data Infrastructure containing information such as building location, size or volume. A strong development of the past years is the adoption of 3D city models which are a representation of the real urban world in a digital environment.

For the specific case of roofs in the context of urban mining, automatic classification of land cover materials is possible using aerial or satellite imagery as these ones are visible from the...
sky (Priem and Canters 2016). Optimally, these ones would be fused with 3D city models in order to store the building’s roof material and quantity. However, this creates rather high needs for 3D city models as relatively small objects (chimneys, roof windows, etc.) have to be included in order to avoid confusion with the roof material and accurate shadow calculation. While the automatic generation of generalized 3D-models (e.g. building represented as blocks) has proven scalable (Dukai, B. Balázs 2018) up to a national level, more detailed and complex geometries (sloped roofs, chimneys etc.) are still a challenge for research. This limitation means that higher levels of detail require more manual work, negatively impacting costs. Among the cities which have created a 3D City Model in the format CityGML, highly detailed building representations (including small chimneys, windows, etc.) are only available for some buildings (e.g. landmarks).

1.3 Reading guide

This document will first introduce some background research that has been done on the topic of urban mining (section 2) and leads to the problem statement (2.4). In a second step, an overview of related work will be provided section 3. This includes research from background fields required to facilitate efficient tackling of the problem. In section 4 the resulting research questions and sub-questions to structure it will be presented. Finally, the methodology will be explained in section 5, followed by a first method proposal (5.2) and completed by the time planning in section 6.

2 Background

2.1 Role of geographic information in life-cycle analysis

That the reuse of bituminous roofs (mentioned in part 1.1) is possible, does not indicate that it is environmentally interesting yet. In fact, the recycling/downcycling does consume energy and create flows (from or to treatment facilities) which impacts the environment. Therefore several situations including the initial situation and alternatives need to be evaluated. When doing such evaluations, the granularity of the data (the level of aggregation) deserves major attentions. In fact, for some cases, data aggregated at neighborhood level might be sufficient but for others, detailed object-level data will be necessary. This aspect is clearly formulated by Patrouillard et al. (2018) and needs to be considered within all three steps of life cycle analysis as they impact each other linearly (also see figure ??). Input data is required and needs to be obtained by analyzing either the existing objects or the past processes (step 1). This material, which gets released by demolition/maintenance would then be reused, preferably locally. To estimate the quantity and distribution of release, demolition/maintenance prediction is necessary (step 2). In the end and optimally, another material flow would be replaced, which raises the question of the impact of this change. Here questions such as ‘which criterion should be used’ arise (step 3).
2.2 Approach of statistical disaggregation

A statistical, top-down approach is possible and involves dis-aggregating historic material usage data (e.g. national bitumen coating production, not found any data yet) by using some spatial indicators such as house types, their usage of bitumen at a given period and their respective spatial distribution. A good example is Müller (2006) who has performed such analysis for concrete in the Netherlands but without being more specific geographically.

A similar approach but at smaller scale (8 and 11 km²) was conducted by (Tanikawa and Hashimoto, 2009). They used historic data to estimate the material inflow and linked that to historic building construction and demolition data. Moreover, this data was used to predict lifetime by construction period and future demolitions/release of material flows.

2.3 Usage of remote sensing data for material identification

A much more detailed approach is the usage of remote sensing data to identify materials using their spectral characteristics. The field of land cover classification is not new and can be divided in several levels of detail (figure 2), similarly to 3D city models:

![Hierarchical classification of urban surface materials](image)

Figure 2: Hierarchical classification of urban surface materials (Heiden et al., 2007)

Numerous studies have been conducted for classification but level IV only became possible
with higher resolution images. On one hand, spatial resolution has considerably increased (Frick, 2007) and created opportunities for more detailed classification as less pixels are affected by spectral mixing. On the other hand, new technologies appeared for spectral classifiers: the range and the number of bands was increased by including numerous visual, VNIR (visible and near-infrared) and SWIR (short-wave infrared) bands at identical, below 10m resolutions. A good illustration are research projects conducted with hyperspectral imagery (such as HyMap in figure 3 or the airborne prism experiment - APEX used by Priem and Canters (2016)).

Table 2

<table>
<thead>
<tr>
<th>Spectrometer</th>
<th>No. of bands</th>
<th>Wavelength range [nm]</th>
<th>Bandwidth [nm]</th>
<th>Detector material</th>
</tr>
</thead>
<tbody>
<tr>
<td>VIS</td>
<td>32</td>
<td>400–900</td>
<td>15</td>
<td>Si</td>
</tr>
<tr>
<td>NIR</td>
<td>32</td>
<td>885–1350</td>
<td>16</td>
<td>In Sb</td>
</tr>
<tr>
<td>SWIR I</td>
<td>32</td>
<td>1400–1800</td>
<td>16</td>
<td>In Sb</td>
</tr>
<tr>
<td>SWIR II</td>
<td>32</td>
<td>1900–2500</td>
<td>20</td>
<td>In Sb</td>
</tr>
</tbody>
</table>

Heiden et al. (2007) conducted a determination of spectral features using remote sensing for Dresden and Potsdam. This one included bitumen (green/gray, red and gray) and tar paper as well as other materials. Identifying bitumen was seen as a challenge: “In contrast, some of the dark materials, such as asphalt and roofing tar paper do not show distinct absorption features. Their separation from other materials is only possible based on brightness.”. The results are indeed much better for the gray value than for the spectral feature analysis concerning commission errors. However, omission errors reach 41.26% of which 28.16% by roofing polyethylene which is still an unsatisfying result. Nevertheless, a solution is suggested as for PE commission errors were only 7.6% in total when using gray values. Grey values might therefore be used for first classification, followed by a correction using spectral features.

Another study which uses a different method than the previous separability analysis and shows promising results was published by Priem and Canters (2016). Here a form of machine learning, support vectors are used to classify pixels of urban land cover materials. Before applying spectral analysis, a shadow filter is applied (for more details see part 3.5). After classification, correction using LiDAR data is performed using height, roughness and slope attributes is applied.

The performance for identifying flat bituminous roofs is rather good: only 6% of omission errors (pixels which in reality belong to the category ‘dark shingle’) and 19% of commission errors (all from pixels of bitumen classified as fiber cement).

A challenge which is only slightly addressed by both studies is the link to real world objects (e.g. buildings). Heiden et al. (2007) does perform the study (thus both training and validation) on a pixel-basis, which is scientifically correct but does not address the pepper and salt effect which Priem and Canters (2016) does briefly: classification is very sensitive to small spectral variations within pixels. As the latter study was not performed on a pixel but on a polygon level (polygons were created for training and validation, these pixels could not simply be omitted. The solution employed in this study is a 3*3 majority filter applied before validation. One might note that this solution only works if a critical share of the 8 neighbors are indeed of the correct class. This issue is also addressed in a bachelor thesis (Thiel, 2016)
where the majority filter is replaced by a moving window approach, including pixel’s neighborhood information in the classification process directly.

2.4 Problem statement

Automatic classification of roofs using aerial imagery requires pixels containing roof material deviations and shadow to be identified as such. While a highly detailed 3D city model would fulfill such criterion, it is often unavailable. A potential alternative on which no research has been conducted yet is to use a less detailed 3D city model and semantically enrich with the required data.

3 Related work

First, the concepts of the CityGML standard and methods to generate it using remotely sensed data will be introduced. Finally, the application of such city models will be discussed, mainly with regard to roof material classification.

3.1 CityGML, Levels of Detail (LODs) and semantics

CityGML is an open and standardized data model recognized by the Open Geospatial Consortium for the storage of urban and landscape 3D city models. As its name suggests, it bases on the GML (geographic markup language) which is an extensible international standard for spatial data exchange.

Inclusion of semantics was one of the project’s core priorities: "One of the most important design principles for CityGML is the coherent modeling of semantics and geometrical/topological properties." (Gröger et al., 2012). In fact, even at most basic level, clear distinguishing between modules (such as terrain and buildings) requires more than geometric information. One of CityGML strengths is therefore that thematic and geometric data can be queried in the same way, making navigation between hierarchies easy (Gröger et al., 2012).

On top of providing content information, semantics in CityGML are also used to store metadata related to store specifications required by the CityGML standard. A good example is the level of accuracy, of which 5 versions are supported and denominated “Level of Detail” (short: LOD) 0 till 4 (0 is most coarse, 4 most detailed). The specifications defined by the standard for building roofs are as follows (CityGML version used here is 2.0, Gröger et al. (2012)):
- LOD0: The entire building is represented by a horizontal surface (gml:MultiSurfaceType). The main difference with (conventional 2D) cadastral registration datasets is that this surface is embedded in 3D space (for instance by including a digital terrain model). The horizontal surface can either represent the footprint (and be located at ground level) or a horizontal projection of the building roof (and are then located at the height of the eave) as shown in figure 4.

![Figure 4: Representations of a building as a polygon in LOD0 (Gröger et al., 2012)](image-url)
- LOD1: From this level on, the buildings are represented as a volume. In LOD1, entities are aggregated to a simple block (the outer shell) which can either be expressed as solid (gml:SolidType) or multiple surfaces (gml:MultiSurfaceType). From LOD1 buildings might also be split in building parts but each of these might only have one height value. Therefore, the outer shell does not contain additional details such as the roof shape.
- LOD2: From this level on, semantic objects are required to compose the exterior shell of a building. These ones are all of classes _BoundarySurface or BuildingInstallation_. The first class contains special functions like walls, roofs, ground plates, outer floors, outer ceilings or closure surfaces. The latter class is used to store building elements like balconies, chimneys, dormers or outer stairs which are “strongly affecting the outer appearance of a building” (as a threshold 4 by 4m is proposed for LOD2, 2 by 2m for LOD3) (Gröger et al., 2012). Furthermore, roof overhanging parts should be modeled if known.
- LOD3: On top of being more detailed/representing smaller exterior objects, openings (windows, doors) should be modeled separately, creating a hole in the surface within which they lie (AbstractOpeningType). From LOD3 on, overhanging roof parts must be modeled as such (this is recommended but optional in LOD2).
- LOD4: LOD4 is the highest level of detail as it covers the building interior too. Rooms and interior installations are therefore modeled too. Moreover, although not formally part of the standard, an increase in absolute 3D point accuracy and decrease in shape generalization is proposed as in figure 6.
As the CityGML format is extensible, semantic information of virtually any application field can be stored in it. A number of cases are covered by the standard itself, while others can be added by creating a *GenericAttribute*. Similarly, a new object type can be added by adding a *GenericCityObject*. Before doing so, it might be worth examining existing application domain extensions (ADEs) such as the EnergyADE or NoiseADE. If the desired semantic has already been created somewhere else, reusing it might be beneficial for interoperability.

### 3.2 Characteristics of LiDAR acquisition

LiDAR stands for *Light Detection And Ranging* which is an optical measurement technique that uses light to measure time-of-flights and/or phases. In fact, as the speed of light is known, the time taken by a light pulse to be reflected (i.e. travel back to the emitter) can be measured and converted into a distance. In combination with the position and orientation of the emitter/receiver, the reflection point position can be determined. LiDAR systems can perform static measurements (on a pole, similarly to total stations) but also be mounted on moving vehicles or planes (in which case a inertial measurement unit is usually required on top of the GPS receiver) (Vosselman and Maas, 2010). The fact that LiDAR is an optical system means that more than one return can be registered. By registering the full return waveform, several echoes can be identified. This is specially practical for objects which partially transmit light, such as trees (Vosselman and Maas, 2010). Depending on the wavelength, LiDAR signals might also be absorbed (Lemmens, 2011) by materials such as water. This mainly depends on the wavelength of the signals: a special application of LiDAR is bathymetry where two pulses are used: one in the longer infrared (e.g. 1060 nm) and another in the green spectrum (e.g. 530 nm). While the first one is reflected by water, the latter is transmitted and reflected by seabed (Vosselman and Maas, 2010). Another advantage of LiDAR being an optical system is that intensity (often called amplitude) measurements can easily be performed. To do so, the amplitude of the pulse, which characterizes the reflectance of the spot, must be recorded. This value depends on the material reflectivity (which again depends on the wavelength), and on the reflection type (which can either be specular, diffuse or a mix of both) (Vosselman and Maas, 2010).
3.3 Automated detection of buildings/roof surfaces using 2D data

Identification of buildings is not an entirely new topic as before airborne laser scanning scaled up in the 1990s ([Lemmens 2011]), research was already conducted using aerial and satellite imagery (and is still nowadays). Although being limited to 2D (except for stereo-images) and being more structured than point clouds (in raster files, neighborhood is explicit), many research aspects show similarities. An extensive overview of research conducted in 1980-1999 with much lower resolutions than nowadays is provided by [Mayer 1999]. One might note that aspects such as the paradigm of data vs. model driven approaches (which can be found back in part 3.4.1) already existed.

Another good example is the identification of edges as performed by [Wei et al. 2004] which is using unsupervised classification followed by canny edge detection and Hough transform to detect building shapes in panchromatic images. With higher spectral and spatial resolutions, research in this field is still strong, now often being published under the term 'object-based image analysis' ([Blaschke 2013]). A good example is [Khosravi and Momeni 2018] with a similar but more extensive approach than [Wei et al. 2004]. Unsupervised classification is performed with a Otsu threshold, followed by morphological operators to remove noisy regions, small objects and fill holes (which might result of foreign objects on roofs or shadows). Finally a canny edge detection is applied followed by skeletonization and connected component labeling to create primary edge (geometric) objects. In a final step area and shape attributes are used to select buildings.

Finally, one might also note that analysis of aerial imagery and LiDAR data can also be fused with the aim to take advantage of the strengths of both to obtain better results ([Li and Wu 2008; Gilani et al. 2015]).

3.4 Automated detection of buildings using 3D point clouds

According to [Nguyen and Le 2013], the field of structure recognition in point clouds can be divided into six subfields as shown in figure 7.

![Figure 7: Taxonomy of 3D point cloud segmentation methods as proposed by Nguyen and Le (2013)](image)

Figure 7: Taxonomy of 3D point cloud segmentation methods as proposed by [Nguyen and Le 2013]

3.4.1 Taxonomy of 3D point cloud segmentation methods

1. **Edge based methods** These methods aim at outlining boundaries by detecting geometric or intensity properties. To do so, mainly edge-detection algorithms from computer vision area are used (e.g. canny edge detection using sobel operator). Therefore, 3D data needs to be converted into a 2.5D range image, which often implies a loss of information ([Wang and Shan 2009]).
2. **Region based methods.** This category which uses neighborhood information to combine nearby points with similar properties can be divided into two subcategories: seeded and unseeded methods. The first one identifies a number of characteristic surface patches (using attributes such as planarity or curvature) and then gradually extends these patches to sufficiently similar points (basing on measures such as proximity, slope, curvature, normals). A big challenge of these methods is optimal seed selection (Nguyen and Le, 2013) and sensitivity to noise (Nguyen and Le, 2013; Nurunnabi et al., 2012; Gilani et al., 2016). Unseeded methods use an alternative top-down approach. First all points are in a single group which is split until all parts satisfy the given threshold criteria. Challenges here are avoiding over-segmentation and prior knowledge requirements which usually cannot be satisfied in complex scenes (Nguyen and Le, 2013).

3. **Attributes based methods** In this method, first an attribute computation is performed: each point is associated a feature vector which consists of one or several geometric or radiometric measures. In a second step, unsupervised clustering is performed (popular methods include k-means, fuzzy clustering, maximum likelihood). As it is carried out on the feature space, this method can be used on point clouds, raster data and TINs directly. Reliable results can be achieved but depend on the quality of the attributes, the computation of the feature vectors and the clustering technique. Also, the dimensionality of the feature vector can be a challenge for computation speed (Nguyen and Le, 2013; Wang and Shan, 2009).

4. **Model based approaches** These approaches are also known as “direct extraction of parameterised shapes” (Vosselman et al., 2004) and rely on geometric primitives such as planes, cylinders or spheres. Popular examples are the 3D Hough transform (for planes, with variants for cylinders) and RANSAC (for RANdom SAmple Consensus). Advantage of these methods is their speed and their robustness with regard to outliers (Nguyen and Le, 2013).

5. **Graph based methods** In this category, the point cloud is represented as a graph with the points as vertices and edges representing connections with a weight attribute for their similarity. Segmentation is then achieved by decimating (partitioning) the graph, for instance where connections are weakest. Popular techniques include normalized cut, minimum spanning tree and spectral graph partitioning (Wang and Shan, 2009).

One might note that the classification provided by Nguyen and Le (2013) is not the only possible perspective as it focuses on mathematical techniques. Other ones focus on type of output (part-type or primitive geometries vs. patch-type or homogeneous regions) (Vosselman et al., 2004; Wang and Shan, 2009) or on representation used (edge/boundary vs. surface based) (Wang and Shan, 2009). One might note that some mathematical techniques might be used for both types of representation, so the latter is rather characterizing than classifying.

### 3.4.2 Challenges of point cloud data segmentation

Three recurring challenges of point cloud data segmentation are discussed by Nurunnabi et al. (2012):
1. Types of edges  
Three different types of edges can be considered (illustrated in figure 8): (a) crease edges which can for instance be found at the meeting of planes of a same roof. While there is a proximity between the planes’ edge points, a difference between surface normals can be observed. (b) jump edges can for instance be found between roof’s eave and ground surface. As the name indicates, there is a discontinuity between the planes: planes’ edge points show no proximity but the normals of the surfaces might be the same (such as in the case of a flat roof above flat ground). (c) a third type are smooth edges which are characterized by surface continuity but show a change of curvature. (Nurunnabi et al., 2012; Wang and Shan, 2009)

![Figure 8: Illustration of the different types of edges (Nurunnabi et al., 2012)](image)

2. Gaps  
As point clouds are scattered and unorganized (Wang and Shan, 2009), gaps in the data are no exception. Occlusion depending on the geometry and the scan angle or absorption by presence of water (for some laser beam with near-infrared wavelengths) occur in nearly all datasets (Vosselman and Maas, 2010) p.36. Robust methods therefore need to be designed to handle gaps, for instance avoiding splitting an affected surface (Nurunnabi et al., 2012).

3. Ouliers/noise  
As mentioned in the explanations of the region based methods, outliers (which are a form of noise) can be very challenging for point cloud surface reconstruction. In fact, they can contaminate statistics calculated on the local neighborhoods, resulting in for instance a tangent plane biased in the direction of the outlier (Nurunnabi et al., 2012). Nurunnabi et al. (2012) and Gilani et al. (2016) proposed region based methods with the aim to be more robust to outliers using respectively Projection Pursuit combined with Minimum Covariance Determinant and Low-Rank-Subspace with prior Knowledge methods.

3.5 Shadow identification and estimation methods  
A topic of 3D city models which is strongly linked but not exclusive to APEX imagery (introduced in section 2.3) is shadow identification. In fact, many materials show a different spectrum in shadow, requiring a parallel classification to be identified (Priem and Canters, 2016). In order to send the pixels to the right classification process, shadow first needs to be identified. This can be calculated either geometrically or using LiDAR intensity values (using an invariant color model).

The first one uses 3D city models or digital terrain and surface models (DTM/DSM) by projecting objects’ occlusion of daylight. While virtually any shadow situation can be computed
(the only input required is solar height), it is highly dependent on the completeness of the digital surface model. This completeness does not only apply to the type of objects (for instance whether trees are included) but also to the degree of generalization (which can be linked to the CityGML LODs mentioned in part [3.1]), which can be crucial for long linear objects such as cranes or power lines (specific cases mentioned by [Priem and Canters, 2016]).

The second option involves the usage of an invariant color model: [Priem and Canters, 2016] apply this by using LiDAR intensity as an external indicator for inherent material brightness. In fact, LiDAR being an active system, the effect of shadow on intensity can be expected to be lower. By comparing it with the first approach, [Priem and Canters, 2016] nevertheless identify some weaknesses: “For materials with rough surface or on tilted roofs, a considerable fraction of the inbound pulses will be lost due to scattering, resulting in an underestimation of intensity for those surfaces” ([Priem and Canters, 2016], p.11.). As the latter method appears weak for non-flat rooftops, the study decided to use it for ground surface only and to combine it with a geometric approach for rooftops. Also, from a practical point of view, this method can only be performed on the aerial imagery data directly. This one’s resolution must therefore be sufficient to avoid too many pixels with partial shadow (which the threshold method might have difficulties to identify).

Another related topic of 3D city models and shadow identification can be found in the field of solar potential estimation. In fact, most studies focus on the available roof surface and neglect foreign objects such as chimneys, dormers, roof windows ([Jochem et al., 2009] [Nguyen et al., 2012]). This is problematic as it can lead to an over-estimation of solar potential, mainly for two reasons: i) foreign objects situated on the roof might cast significant shadows on solar panels (for instance, a box-like ventilation installation located on the south side of a flat roof) ii) the amount of free space is over-estimated because the foreign objects appear as regular parts of the roof, additionally an accurate position of the foreign objects might allow estimations including solar panel dimensions (usually not the entire roof surface can be filled, as figure 9 shows). These errors might be approximated by using generalized correction factors (for instance, using only a % of the solar potential) - which would however diminish the accuracy of the results, especially on a big scale.

Figure 9: Houses with solar panels in Horben, close to Freiburg(Germany). One might note that i) objects such as chimneys or roof windows interrupt the pattern of solar panels ii) standard solar panel sizes result in surfaces close to the roof edges being uncovered (own photography).
4 Research questions

4.1 Relation with work presented in section

Following the current stage of scientific research, one might note that there is an alternative approach to the pepper and salt effect in part 2.3 which has not been considered yet. In fact, the 3D city model which is already required for geometric shadow filtering (see part 3.5) might as well store and facilitate identification of spectral variations (in the case of roofs, typical examples are chimneys, roof windows, etc.). The idea is that affected pixels should be filtered out beforehand - allowing a lower critical share of correctly classified pixels than required for 3*3 majority filter. A critical number of ‘clean pixels’ (without spectral variations) might be identified beforehand and used to classify the roof surface of the 3D model. Moreover, the border between materials might then be sourced from the 3D city model, potentially allowing sub-pixel accuracy. Additionally, the usage of a 3D city model might allow more accurate quantification for tilted surfaces as a 3D surface can be used instead of 2D projection in aerial imagery (allowing quantification in square meters instead of pixels).

4.2 Research question and subquestions

Basing on the previous observation, the main research question to be answered by this thesis is “How can a CityGML LOD2 model be semantically enriched with regard to material classification performed on roof surfaces”. To answer the latter, several sub questions can be formulated, illustrating different steps:
1. Which method(s) is/are suitable (computationally efficient and accurate) to detect and classify deviations of LiDAR compared to LOD2.
2. To which extent does CityGML and its ADEs facilitate the storage of such “deviations”? Are additional components (GenericObject and GenericAttribute) needed?
3. To which extent can the storage of such “deviations” improve accuracy of shadow calculations?
4. How suited is the method with regard to identification for bituminous roofs using a ‘clean pixel’ approach?

4.3 Research scope

Basing on the MoSCoW method, the scope of the study can be defined as follows:

4.3.1 Must-haves

The core of the research will be to develop at least two approaches (one geometric, one intensity-based) to identify “deviations” between CityGML LOD2 models and LiDAR point clouds. These methods should be robust for the critical mass of buildings but might exclude particularly complex cases (such as smooth edges, advertisements printed on roofs). The core further includes finding a way to store these deviations within the framework of the CityGML data format. For this thesis a research area of slightly more than 12 km² has been defined in the south of Rotterdam (see figure 10). This one has been chosen in order to include as many building typologies as possible: it covers high rise buildings on Kop van Zuid, big industrial hangars on...
the docks, apartment blocks, as well as semi-detached houses of different sizes (reaching from closed blocks to few attached bungalows).

Figure 10: Research area of this thesis, located in the south of Rotterdam (imagery source: google earth).

4.3.2 Should-haves

Along with the identification and storage of “deviations”, additional attributes such as the type (geometric, intensity-based or both) or the distribution (height difference with regard to the surface, expressed in several percentiles) should be stored as well. This is important with regard to shadow identification which is essential for material classification (and uses height values). While this thesis does not aim at creating a LOD3 city model and reaching such level of accuracy, it does aim at improving the shadow calculation accuracy of LOD2 towards the level of LOD3.

Another important part of the research is the validation of the results which will take place in several ways:

a. completeness and position validation of “deviations” by comparing automatically and manually identified surfaces (the latter using point clouds or textures provided by the CityGML model). The scientific validity of this method is to be determined with regard to the accuracy, especially of the textures.

b. quantitative validation comparing surface sizes of the CityGML textures (or aerial imagery) and the identified “deviations”.

c. quantitative validation comparing shadow surfaces created by the “deviations” and on aerial imagery (both position and sizes). It seems important to note that validation, at least for a part, will focus on bitumen as this material shows a high relevancy within the field of land cover material classification (as mentioned in 1.1).
4.3.3 Could-haves

If time allows it, following extensions to the research project can be considered:
a. Providing a connection to raster datasets used for land cover material classification. Taking the semantically enriched 3D city model (with the “deviations”) and an orthocorrected (and georeferenced) aerial imagery (including acquisition date and time for shadow calculation) as inputs, this one would return a binary indicator whether a pixel is expected to be ‘clean’ or affected by spectral variations.
b. The research core could be extended to some buildings which have characteristics of above average complexity. This might be done by extending the method, or alternatively by making the existing methods robust by triggering an error messages to create user awareness (e.g. if construction work was going on on the roof and geometric/intensity values show no statistical patterns, an error message pops up).

4.3.4 Won’t-haves

A number of topics will certainly not be covered by this thesis and it is safe to name them here:
a. The goal is to create a semantically enriched LOD2 level, which considerably differs from LOD3 where smaller objects are represented geometrically. Therefore, visualization within this research will be kept rather simple.
b. A foreseeable limitation which will not be addressed is arising by fusion of the CityGML 3D model with aerial imagery data. In fact, both the APEX data but also the yearly updated multispectral aerial imagery are only orthorectified (using a DTM) but not orthocorrected (eliminating the shift of buildings that are off-nadir, which requires a DSM). Performing this orthocorrection is beyond the scope of this study. Therefore, every data fusion (including validation) will have to consider accuracy of the datasets involved. For validation of “deviation” positions, alternatives will have to be considered (such as textures of the 3D city model).
c. For the same reason, even if point a of the could-haves is covered, no validation of the clean-pixel identification method will be done.
d. For accurate shadow calculations, a CityGML model covering other classes than buildings (such as trees) would be needed. As this study focuses on buildings, this topic will not be covered by the scope. Validation of the improved shadow estimation will therefore use roof surfaces that are not affected by non-building shadows.
5 Methodology and methods

5.1 Methodology

As shown in Figure 11, the methodology can be seen as a structure with several shells:

1. First, a literature study to cover the existing research on point clouds, 3D city models and their applications is done (major topics have been presented in parts that might be added are semantics from a more conceptual approach and how ADEs store it).
2. By making choices in the first part, the theoretical framework is established and leads to the research question.
3. To answer the research question, a method is designed and made explicit. There will globally be 4 steps in the method: dataset selection and filtering, attribute computation and extraction, semantic storage, and result validation.
4. Especially for the computation part, the method needs to be adapted and tested. Basing on the outcomes, the method is modified for improvements.
5. The obtained results will finally have to be discussed.

Concerning point number 4, a choice for two approaches has been made: one geometry and one intensity-based. For the first one (see figure 12), the approach is to use a maximum of data from the CityGML file. By providing clearly labeled roof surface geometry, one can also calculate normal vectors and curvature belonging to the respective surface.
5.2 Proposed methods

An existing CityGML LOD2 model will be used as a starting point, along with a LiDAR point cloud which is the medium containing the ‘deviations’. In fact, existing roof surface geometry is a strong advantage by indicating the approximate position and normal vector of the points effectively belonging to it. Additionally, such a surface can minimize conversion loss when opting for 2.5D data as it provides a robust first selection buffer.

Two approaches will be developed and compared within this thesis: the first uses all three spatial attributes (x,y and z coordinates) while the second uses return intensity instead of the z coordinate attribute.

Within this approach, geometrical “deviation” will be defined as foreign volumes placed on the roof surface. The point belonging to it therefore have a shortest distance to the roof plane which is higher than normal. Furthermore, depending on the geometry, the following characteristics might apply (but do not necessarily need to):
- their normal vector (basing on the point’s neighborhood covariance matrix, see the principal components analysis below) is not the same as the roof geometry.
- their curvature (which can be deduced from the same method) is not the same as the roof geometry.

Therefore, the first step will consist in selecting all the points belonging to the roof by applying a big selection buffer (points have previously been filtered to include only building class). Subsequently, clusters of points whose shortest distance to the roof plane are bigger than a given threshold will be selected by applying a smaller buffer (the buffer size will depend on the noise in the data).

These clusters will then be extended starting at the border points (to be identified using convex hull testing for instance) using neighborhood operators (k-nearest neighbors). For each new point, the normal vector will be calculated using the following approach (principal components analysis as described by Nurunnabi et al. (2012); Gilani et al. (2016)). First, the covariance matrix is computed:

Figure 12: Main steps of the two computational approaches.
\[ C_{3x3} = \frac{1}{k} \sum_{i=1}^{k} (p_i - \bar{p})(p_i - \bar{p})^T, \bar{p} = \frac{1}{k} \sum_{i=1}^{k} p_i \] (1)

Then, the eigenvalues \( \lambda \) can be extracted along with the eigenvectors \( V \) (if three dimensions, three of each):

\[ \lambda V = CV \] (2)

The smallest of all three eigenvalues can then be used to identify the normal vector which is the eigenvector corresponding to that eigenvector. The curvature can be calculated using the eigenvalues \( \lambda \):

\[ \sigma = \frac{\lambda_0}{\lambda_0 + \lambda_1 + \lambda_2} \] (3)

If the new point has an eigenvalue and a normal vector which are not matching the roof surface as defined in the CityGML, the point is added to the cluster. If the normal vector and the curvature do match, then growing is stopped and the last added points are used to generate the border (e.g. using a minimum spanning tree as done by Wang and Shan (2009)). In a last step, this one is simplified and additional attributes (e.g. height difference percentiles) are kept for storage.

The second approach, based on point-cloud intensity values is a bit different as the ‘standard’ intensity (for the wavelength used by the laser scanner) is not unknown. The only purpose the CityGML can still be used for here is point selection by creating a buffer around the roof surface for point selection. The idea is that not all three-dimensions need to be geometric: dimensionality is reduced by ‘replacing’ the z-coordinate by intensity values. By doing so, jump edges are expected to appear where a strong change in intensity between points that are close in (x,y) space occurs. These jump edges could then be identified using local convex hull testing (using k-nearest neighbors) and subsequently used to segment the point cloud (as done by Wang and Shan (2009)). Using a morphological analysis, the cluster representing the ‘standard’ intensity of the roof surface should then be identified (in order not to map it as a deviation). Finally, just as with the geometric approach, storage preparation takes place by simplifying geometry and extracting borders.

The results then need to be compared in order to determine and merge “deviations” that have been identified in both processes. Finally, the results have to be saved back to the CityGML data model and shadow calculations performed to prepare validation.

5.3 Tools

5.3.1 Algorithms

As main programming language, Python 3.7 along with its numerous libraries will be used. Good example codes of among others, several point cloud segmentation techniques can be found at \( \text{http://pointclouds.org/documentation/tutorials/} \). Another interesting library which directly integrates a number of computational geometry algorithms (PCA, convex hull testing, etc.) in Python is CGAL-bindings(\( \text{https://pypi.org/project/cgal-bindings/} \)). As pointed out on \( \text{https://www.cgal.org/exact.html} \), one needs to be aware of robustness and exact computation paradigm for many geometric computational applications, including to some
extent point cloud segmentation.
Among the more basic libraries scipy.spatial (https://docs.scipy.org/doc/scipy/reference/spatial.html) might be useful for tasks such as indexing and neighbor querying.

5.3.2 Data reading, writing and storage

For the storage of CityGML data, 3DCityDB will be used (https://www.3dcitydb.org/). This tool is standard for storage of big databases (used by the city of Rotterdam) and supports extensions (ADEs) as well as file formats of other programs. As 3DCityDB is a PostgreSQL database, it can be queried directly using python libraries such as psycopg2.

5.3.3 Visualization

For visualization of the results the only tool that allows simultaneous visualization of CityGML and point clouds that could be found is the FME (https://www.safe.com/) data inspector. For some purposes such as quick computation and customized visualization, the viewer Cloud Compare (http://cloudcompare.org/) can be used.

5.4 Datasets

5.4.1 Core Datasets

**AHN - Actueel Hoogtebestand Nederland**  The AHN (“Actueel Hoogtebestand Nederland” - Dutch for actual height data of the Netherlands) is an open point cloud dataset that can be downloaded from https://www.pdok.nl/nl/ahn3 – downloads. It provides the following attributes for each point (information obtained from [for Photogrammetry & Remote Sensing](2013)):
- x,y,z coordinates in the local reference system (EPSG:28992)
- intensity of the return (pulse return magnitude)
- return number
- total number of returns
- classification (using the LAS standard classes and a custom one, code 26 that is used for infrastructure such as bridges)
- gps time of the acquisition moment
some other, less interesting characteristics are also included:
- scan direction (this one is 0, for a negative scan direction, 1 for a positive one)
- scan angle (output angle of the beam, seems to always be 0)
- flight line edge (is usually 0, 1 only if point is at end of scan)
- point source id (indicates the file from which the point originated)
a last characteristic is unknown:
- user data (this is a custom field, meaning has to be asked to the data owner)
The flight path of data acquisition can be found on http://www.ahn.nl/index.html.

**Rotterdam 3D city model**  The city of Rotterdam has published it’s 3D city model at https://www.3drotterdam.nl/. Within the online viewer (which uses cesium), a download function is available (with object or area selection). Several formats, among which CityGML are offered. Data is provided in LOD2 and includes textures. Information about the creation of the city model is not available, the only indication is that software of https://www.virtualcitysystems.de/ was used. Outdated files at http://rotterdamopendata.nl/dataset/rotterdam – 3d – bestanden indicate that AHN point clouds were used as source in the past, along with public aerial imagery for the textures.
One might note that although the city model is officially labeled as LOD2, considerable differences can be observed in the aggregation level of buildings. As shown in figure 13, detail is sometimes below the recommended threshold of 4*4 m or 16 $m^2$ while buildings where much bigger elements have been omitted (figure 14) can also be found. Basing on observations, it seems that buildings in the port are less detailed.

Figure 13: Example of a building of the Rotterdam 3D city model (Fenix Food Factory/Paul Nijghkade 19DD) with a detail of only 13 $m^2$ (source: https://www.3drotterdam.nl/).

Figure 14: On the left: example of a building of the Rotterdam 3D city model (Waalhaven Noordzijde 11) where a rather big object on the roof has been omitted (source: https://www.3drotterdam.nl/). On the right: for comparison, aerial imagery of 2016 (http://www.beeldmateriaal.nl/index.html).

### 5.4.2 Auxiliary datasets

**Yearly updated multispectral imagery from the Dutch Government**  The government of the Netherlands conducts a yearly nationwide acquisition of multispectral aerial images. Since 2016, these ones are open and can be accessed using a WMS (for more details see https://www.pdok.nl/introductie?articleid = 1954278). For each of the years, two three-band raster services exist: one with reg-green-blue and another one with reg-green-infrared. The flight paths can be found on http://www.beeldmateriaal.nl/index.html. The images are georeferenced but not orthocorrected: facades of buildings can be seen and roofs are shifted in oblique...
parts.

**APEX hyperspectral imagery - Airborne Prism Experiment of Rotterdam from 2014** Upon request, a hyperspectral dataset of a flight above the city of Rotterdam in 2014 was provided by Dr. Andreas Hueni from University of Zurich. The dataset itself is owned by the *Swiss Federal Laboratories for Material Science and Technology* who ordered the acquisition for air pollution studies. The dataset was acquired at a flying height of approximately 7000m and has a pixel size of about 4m (it is unclear to which extent this is suitable to identify roof materials, in constrast - the study by Priem and Canters (2016) has been conducted with a pixel size of 2m). It has a total of 284 bands covering wavelengths from 380 to 2500 nm (each band does thus cover less than 10nm). Next to the raw imagery which is a raster file without interpolation artifacts but with distortions, the corrected coordinates after orthorectification (with a DEM) have been obtained. The dataset does therefore still show facades and roofs are shifted in oblique parts.

### 5.5 Expected challenges

A first, general challenge has been observed in part 3.4.1: the identification and storage of “deviations” is not a research topic that has explicitly been addressed yet. Instead, approaches of the well developed field of point cloud segmentation have to adapted, the main difference being that this thesis is mainly interested in mapping the borders of “deviations”, rather than reconstructing them geometrically (which can be a challenge for object which are relatively small with regard to the point cloud density). Other challenges, of which have already been named are: irregular point cloud distribution and occlusion, noise in geometric and intensity data (see section 3.4.2), variations in intensity due to LiDAR characteristics (see section 2.3 and) and computing speed, basing on finite computation and dimensionality (see section 3.4.1 and 3.2).

### 6 Time planning

#### 6.1 Frequency of meetings

Meetings every two weeks will be held with the first supervisor (Rusnė Šilerytė) and every four weeks with the second supervisor (Giorgio Agugiaro).

#### 6.2 Table

The following schedule is proposed for the different steps needed to meet the research objectives:
<table>
<thead>
<tr>
<th>Start</th>
<th>End</th>
<th>Activity</th>
<th>Subquestion</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Sept</td>
<td>31 Oct</td>
<td>Exploring graduation topics &amp; literature</td>
<td>-</td>
</tr>
<tr>
<td>1 Oct</td>
<td>5 Oct</td>
<td>GeoDelft conference</td>
<td>-</td>
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<tr>
<td>1 Nov</td>
<td>30 Nov</td>
<td>Request first datasets (APEX) and their metadata</td>
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<tr>
<td>15 Nov</td>
<td></td>
<td><strong>P1 presentation: draft graduation plan assessment</strong></td>
<td>-</td>
</tr>
<tr>
<td>15 Nov</td>
<td>14 Dec</td>
<td>Testing and development of methodology, final framing choice</td>
<td>-</td>
</tr>
<tr>
<td>5 Dec</td>
<td>6 Dec</td>
<td>10th Workshop on the CityGML Energy ADE</td>
<td>-</td>
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<tr>
<td>14 Dec</td>
<td>4 Jan</td>
<td>Explore existing point cloud segmentation techniques</td>
<td>-</td>
</tr>
<tr>
<td>1 Jan</td>
<td>9 Jan</td>
<td>Writing of the formal methodology, design computation approach</td>
<td>-</td>
</tr>
<tr>
<td>16 Jan</td>
<td></td>
<td><strong>P1 presentation: formal graduation plan assessment</strong></td>
<td>-</td>
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<td>17 Jan</td>
<td>10 Feb</td>
<td>Implement a geometry-based algorithm for “deviation” detection</td>
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<td>24 Jan</td>
<td>4 Feb</td>
<td>Build link to 3DCityDB</td>
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<td>28 Jan</td>
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<td>Presentation at the municipality of Rotterdam</td>
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<tr>
<td>11 Feb</td>
<td>7 Mar</td>
<td>Implement an intensity-based algorithm for “deviation” detection</td>
<td>1</td>
</tr>
<tr>
<td>11 Feb</td>
<td>18 Feb</td>
<td>Define semantics for storage of results</td>
<td>2</td>
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<td>7 Mar</td>
<td>14 Mar</td>
<td>Implement a shadow-calculation algorithm</td>
<td>3</td>
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<tr>
<td>15 Mar</td>
<td>23 Mar</td>
<td>First validation of results</td>
<td>4</td>
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<tr>
<td>24 Mar</td>
<td></td>
<td><strong>P2 presentation: formal graduation plan assessment</strong></td>
<td>-</td>
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<tr>
<td>23 Mar</td>
<td>23 Apr</td>
<td>Last changes to the computation algorithms</td>
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<tr>
<td>24 Apr</td>
<td>31 Apr</td>
<td>Final validation</td>
<td>4</td>
</tr>
<tr>
<td>1 May</td>
<td>15 May</td>
<td>Preparation of P4</td>
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<tr>
<td>16 May</td>
<td></td>
<td><strong>P4 presentation: formal process assessment</strong></td>
<td>-</td>
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<tr>
<td>1 Jun</td>
<td>23 Jun</td>
<td>Finalization of thesis, prepare final presentation</td>
<td>-</td>
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<tr>
<td>24 Jun</td>
<td></td>
<td><strong>P5 presentation: final public presentation and assessment</strong></td>
<td>-</td>
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**References**


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