Pattern recognition in building stock using geotopographic datasets

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1. Introduction

National Mapping and Cadastral Agencies (NMCAs) are collecting geotopographic datasets of the built environment of many countries [10]. In these datasets the geometry of buildings is usually represented with their 2D footprint and semantic information is limited to the address and perhaps the use of the building. While upcoming photogrammetric and remote sensing technologies were developed to facilitate the gathering of the geometries [7, 8, 27], constantly increasing urbanisation is bearing new challenges that cannot be solved with the information on hand [18].

1.1 Motivation

To satisfy the demand for higher semantic resolution and more realistic geometries, a diverse amount of techniques for mining and analysing geotopographic datasets have been developed in recent years. One example is the derivation of building typologies, that can help to model energy consumption [28] or the potential of district heat [6], determine settlement structures [29] and neighborhoud segregation [27] or infer housing prices [20]. Furthermore, knowledge about building types can help to assess seismic vulnerability [3, 5, 24]. In many areas of earthquake prone regions this information is outdated, unavailable, or simply not existent [5].

1.2 Objective

To this purpose this research aims to develop a methodology to automatically determine seismic building structural types (SBSTs) in a large urban and regional building stock using geotopographical datasets. Without extensive knowledge of structural systems, this research will focus on the classification of morphological building types. This approach is based on the assumption that similar structural system and materials can be inferred from geometric similarities [4]. In order to detect these geometric similarities they need to be quantified first. This will be done with the help of a spectral shape descriptor, namely the Laplace-Beltrami operator. However, as Sarabandi [24] points out, attributes identifying spatial, spectral (referirng to the electromagnetic spectrum) and semantic similarities should not be disregarded when trying to classify SBSTs. Thus, the usage of these features for the classification process will also be explored.

1.3 Outline of the proposal

The remainder of this proposal is structured as follows. After an introduction of related work in the area of general building classification in Section 2, the research question for this project is explained in Section 3. Section 4 discusses a possible methodology to tackle the presented problem, while Section 5 specifies the time frame for the project. Section 6 presents tools and datasets that are used in the research.

2. Related work

Pattern recognition and classification problems are not new to the GIS domain. Several techniques have been used for point cloud segmentation [17], land use classification [14], road extraction [26], 3D surface modelling [2] or the detection of plant diseases [23]. While most of this techniques follow a data driven approach, a second approach is common in the area of building classification, namely a knowledge based approach.

2.1 Knowledge-based approach

In this approach outside knowledge of experts is induced into the model. Relations between certain concepts build up an ontology that eventually allows to classify types of buildings by certain rules [1]. Knowledge-based models are strongly adapted to the input data and the purpose, and even the country they are used in. An application to other data needs a completely new model which makes the models less reproducible [10]. However, they are almost guaranteed to work, allow good control over the classification process and are easy to understand.

2.2 Data-driven approach

In a data-driven approach, the essential part of the modelling is done automatically by a machine learning algorithm. The learning can either be supervised, assuming a labeled training set (buildings with known classes) or unsupervised, whereas elements do not have class labels and the algorithm (e.g. clustering) determines natural groups (clusters) in the building stock [25]. A downside of data-driven approaches is that they often make use of geometric algorithms or statistical techniques that make it difficult to understand the mechanism of the recognition procedure. Thus, they have limited transparency [13].

2.3 Building type classification

Depending on the purpose and field of research, existing approaches for building classifications also strongly vary in their input data, the extracted features, the applied classifier and the defined building typologies [10]. Table 1 shows a detailed overview of relevant literature and their approaches in building classification. The number and characteristics of the detected building types strongly varies in present literature. One common approach is to determine a hierarchically structured typology, where buildings are first classified into residential and non-residential types. A second layer of the hierarchy can be single- or multi-family houses for residential, or industrial and factory buildings for non-residential houses. Further derivation of single-family houses are detached, semidetached or terraced houses. The achieved accuracies of the classification often depend on the different building types, in which the classification of (semi-)detached and terraced houses usually deliver the best results. Except Belgiu et al. [1], all of the presented approaches use cadastral footprints of the buildings as input data. Another common input dataset are 3D city models [9, 10, 11, 30], or raw point clouds from aerial laser scanning (ALS) [1, 4]. These datasets allow to extract geometrical features such as area, height, length, width, circumference, rectangularity or orientation of a building, as well as slope or gutter height of the roof.

2.4 Seismic building structural types

While most of the approaches classify the buildings according to similarities based on these features, this might not be sufficient when trying to infer the structural type of a building. Experiments conducted in the beginning of this research have shown that experts are not always capable of inferring the structural type by looking at a single untextured geometrical model of a building. Geiß et al. [5] are using a supervised learning algorithm to automatically classify seismic building structural types (SBSTs). Next to geometrical and spatial features on building level, they also use spatial features, as well as semantic features on building blocks. Additionally attributes from multispectral satellite images, such as brightness, contrast or colour of the buildings are taken into account. Ending up with almost 80 features per building, Geiß et al. [5] also describe different feature selection techniques to identify the most relevant features.

The difficulty when using a supervised learning algorithm is that training samples for each target class need to be collected [10]. When determining structural systems this imposes an even bigger challenge. Ground truth data is costly and time consuming to obtain and can be afflicted with many uncertainties [5]. To tackle this problem Geiß et al. [5] are proposing to generate synthetic training samples, by oversampling existing ground truth data. Depending on the specific structural system an accuracy between 50% (steel frame) and 96% (confined masonry) is reached. However, they also acknowledge that accuracy estimates are very optimistic. The accuracy assessment is based on the synthetically generated building samples and do unlikely reveal accuracies on unseen data. Another approach used by Christodoulou et al. [4] first classifies buildings into geometric groups, before inferring the structural system based on certain relations. This allows to train and assess the first part of the classification with labelled data of geometric building types, instead of the more difficult to obtain SBSTs.

Table 1: Overview of building classification approaches

	Ref.	input data: thematic	input data: 2D	input data: 3D	features	classifier	classes	purpose	accuracy
data-driven	[9, 10]	address, building use	footprints	city model (LoD1)	area, no. of neighbours, mean length, orientation, ...	Random Forest	hierarchically structured typology	-	62-94%
	[29]	-	footprints	-	area, dist. to neighbour, rectangularity, no. of neighbours, compactness	Maximum Likelihood Estimation	10 clusters	determine settlement structure	-
	[27]	-	footprints	-	area, orientation, longest axis to area ratio, squareness, no. of corners, elongation	Batch Perceptron, Minimum Squared Error, AdaBoost, SVM	rural, industry, inner city, urban, suburban,	urban modelling, map generalisation	75%
	[16]	-	footprints	-	area, height, length, width	Maximum Likelihood Estimation	one-family, row-house, small multi-family, large multi-family	-	-
	[11]	address	-	city model (LoD1)	length, width, area, volume, no. of rightangles, no. of corners, distance to neighbour, distance to POI	Support Vector Machine	(semi-)detached, terraced, Wilhelminian-style, villa, apartment, huge dimensional	-	54-94%
	[30]	-	footprints	city model (LoD1)	area, perimeter, length, width, roundness	Linear discrim- inant analysis	(perimeter) block development, (semi-)detached, terraced, halls	-	90-94%
knowledge-based	[19]	address	footprints	-	no. of addresses, no. of neighbours, length of neighbouring border	decision-rules	detached, semi- detached, terraced, flat, unclassified	-	-
	[8]	address, land use	footprints	-	no. addresses in a polygon, land use type, area, no.adjacent polygons	Decision Tree	hierarchically structured typology	-	-
	[20]	address	footprints	-	area, no. of neighbours, no. of addresses	decision-rules	middle/end in a row, free-standing, two-under-a-roof, apartment, special	housing index, infer price	-
	[15]	-	footprints	-	area, circumference, compactness, dist. fr. neighbouring buildings, distance from block boundary, ...	decision-rules	hierarchically structured typology	determine settle- ment structure	70-94%
mixed	[13]	-	footprints	-	area, presence of yard, no. of neighbours, distance to neighbours	Bayesian inference	terraced	map generali- sation	90-96%
	[1]	-	-	ALS	slope (of roof), height, area	Random Forest (feature selection), decision tree (classification)	residential, apartment, blocks, industrial, factory	-	-
	[4]	address data, year of construction	footprints	ALS	gutter height, slope, area, year of construction	Maximum Likelihood Estimation, Decision Tree	hierarchically structured typology	determine structural system	-

3. Research questions

The research question is proposed as follows:

- To which extent is it possible to estimate the structural type of many buildings from geotopographic datasets by means of automatic classification?

To answer this question several subquestion need to be answered:

- Is it possible to determine geometric similarities of buildings by using a spectral shape descriptor?

The current methodology (see Section 4) is based on the assumption that geometrically similar buildings have similar structural systems. Thus, in a first step buildings are classified as different geometrical types.

- How are geometrically similar buildings linked to structural systems?

However, in order to determine meaningful geometrical groups it is important to know how the geometries are linked to the structural systems. First, it is important to know what are the attributes for inferring structural systems from the geometry of the buildings. Only then relevant features can be selected.

- Can structural systems be classified without first classifying their geometries?

However, if these links are based on specific attributes the question rises to why not include those attributes into the model from the beginning and determine structural systems without determining geometries first?

4. Methodology

The following section will show an overview of the methodology used in this project. Additionally a PERT chart in Figure 1 shows preferred and alternative ways to solve the given problem.

A previously developed methodology by Christodoulou et al. [4] will serve as the starting point of this research. Christodoulou et al. [4] follow a mixed approach (cf. Section 2) in classifying buildings according to their structural system. In a first step a small training sample of five geometrical types is gathered by visual inspection. Next geometric features such as the footprint area, gutter height, span length, width of maximum enclosed rectangle and roof steepness are measured. The probability distribution of these features given the 5 different classes is modelled with a normal distribution, i.e. parameters for mean and standard deviation are calculated. The classification is done with a maximum likelihood estimation.

In a next step, certain relations are establish that connect the geometric layouts to possible structural systems. However, these rules are weak links that are mostly based on assumptions. Furthermore, the mix between algorithmic and relations is complicated to implement, difficult to reproduce and transfer, and computationally expensive. Considering this and the advantages and disadvantages presented in Section 2, the aim of this research is to develop a pure data-driven approach that goes as far towards the classification of structural building types as possible. This way the assumptions that are made when inferring structural systems can be included into the data model. Additionally a data-driven approach is more flexible, e.g. when a new type needs to be determined or new data is added to the model. Instead of making the existing model more complicated by adding a new set of rules and relations, the data-driven approach can be adjusted more easily.

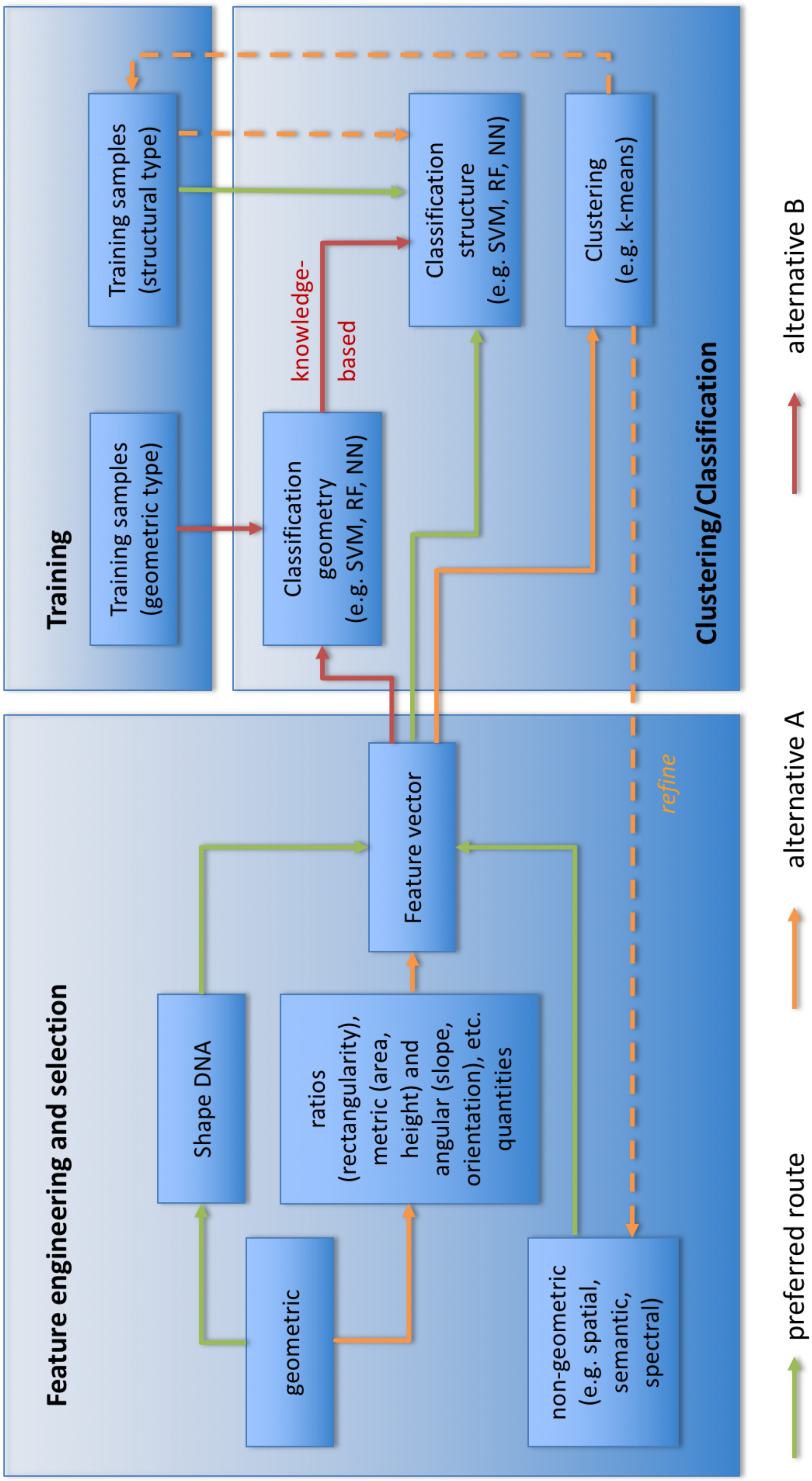

Figure 1: PERT chart

4.1 Feature engineering and selection

The following section describes the process of mapping relevant characteristics of the buildings onto a numerical vector that will serve as the basis for the classification.

4.1.1 geometric-topologic features

Since morphologically similar buildings can occur with many different dimension and orientations, an approach that is able to truly understand the geometry of the buildings is needed [12]. The eigenfunction and the corresponding eigenvalues of the Laplace-Beltrami operator provide a good basis to get insight into the morphological shape of an object [21]. Reuter et al. [22] use the Laplace-Beltrami operator to extract what they call "Shape-DNA" of 2D and 3D manifolds. Based on this approach, the Laplace-Beltrami operator will be applied on a polygonal mesh created from the AHN point cloud (see Section 6.2). In the continuous case, the Laplace-Beltrami operator is defined as:

$$\Delta f := div(grad f), \tag{1}$$

where grad and div are the gradient and divergence on the manifold. The Laplacian eigenvalue problem is given as [22]:

$$\Delta f = -\lambda f. \tag{2}$$

In the discrete case this can be written as:

$$L\mathbf{f} = \lambda \mathbf{f}, \tag{3}$$

where **f** are a set of vectors representing the values of the eigenfunctions at the nodes of the polygonal mesh. By solving Equation 3 the eigenvalues (i.e. the spectrum) can be determined, which then serve as features for the classification process. The advantage of this approach is that the spectrum is isometric and, by normalising the eigenvalues, scaling invariant [22].

4.1.2 non-geometric featues

As Sarabandi [24] points out, attributes identifying spatial, spectral (referring to the electomagnetic spectrum) and semantic similarities should not be disregarded when trying to classify SBSTs. A good example for a spatial attribute that is important to consider when determining different types of buildings is the neighbourhood relation between buildings. Spectral features can allow inferences towards material of buildings, while semantic features such as the year of construction are also very important.

4.2 Pattern recognition and machine learning

While Christodoulou et al. [4] use a probabilistic maximum likelihood estimation for the classification, a discriminative classifier, like Support Vector Machines (SVMs) or Random Forests (RFs) can be used to be able to deal with a possibly large feature set [5]. However, in order to train these classifiers, enough training datasets are necessary in which all relevant phenomena can be measured in the feature space with regard to the classes to be learned. A way to circumvent this problem is to first follow an unsupervised learning approach, namely clustering. A possible approach for the clustering is the k-means algorithm. Hereby, a user defined number (k) of arbitrary starting points in feature space are determined as the centre of new clusters. Afterwards data samples get assign to their nearest cluster and the centre of the clusters are calculated as new starting points. The algorithm is iteratively repeated, minimising the variance of the clusters. After this unsupervised approach the identified clusters need to be interpreted. They will be examined with the help of structural engineers to see if the clusters include relevant information towards the identification of a structural system.

The final methodology of this research is still to be determined. Often in machine learning problems a model is constructed through trial and error [8]. For this reason several approaches will be tested in the coming weeks (see Section 5).

5. Time planning

Figure 2 shows a detailed time plan of the project. The aim is to graduate in November. However, if it turns out that more time is needed after P3 in August, then P4 and P5 can be shifted to December and January respectively. The research will be conducted at a company, where daily meetings with experts in the field of structural engineering are possible.

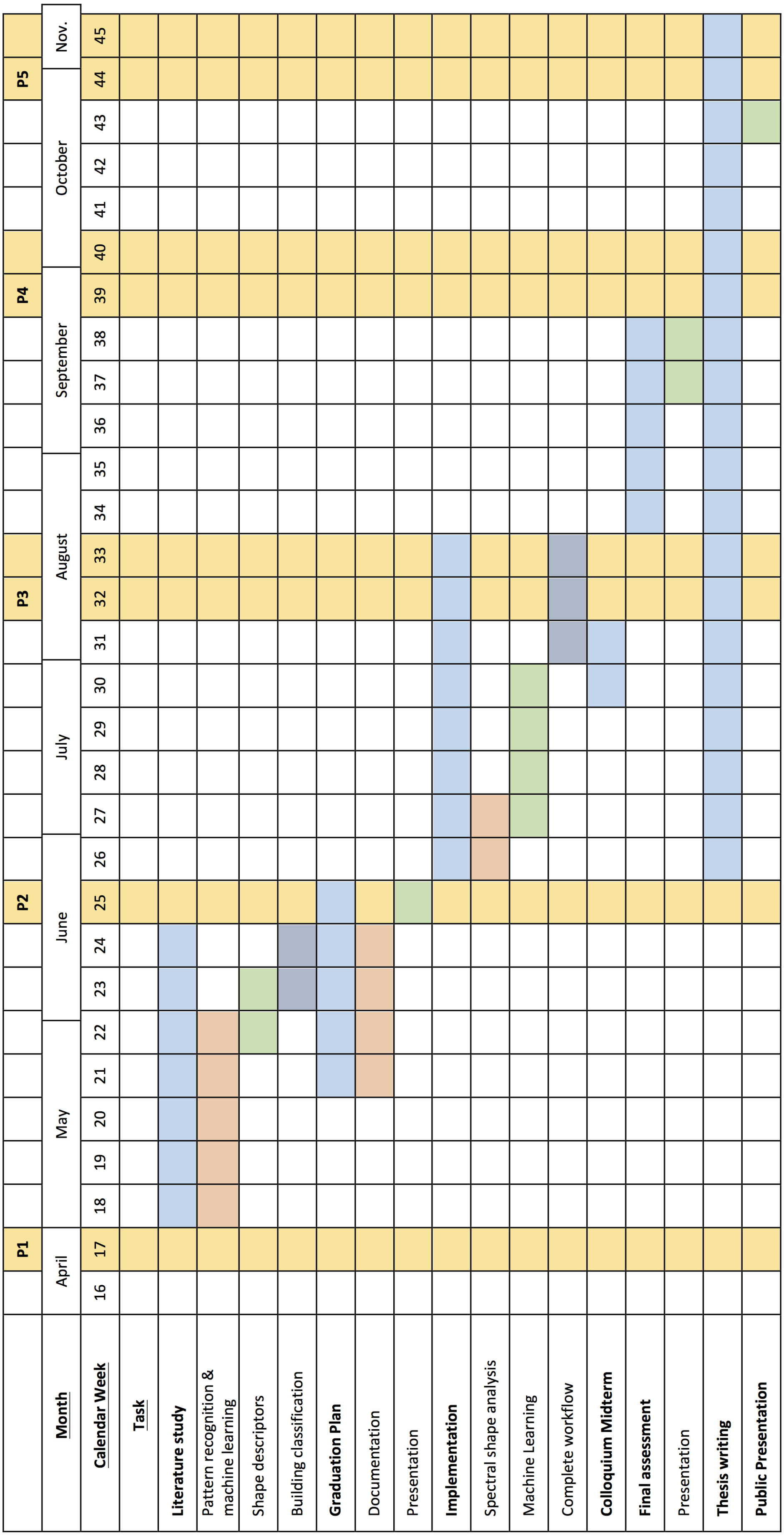

Figure 2: Time planning

6. Tools and datasets

The following subsections describe the tools and datasets that will be used in this project.

6.1 Datasets

The idea of this project is to use publicly available dataset for the classification process. The Height Model of the Netherlands (AHN - Actueel Hoogtebestand Nederland), contains 639 billion elevation points covering the whole country. The AHN dataset is obtained by airborne laser scanning (ALS). This method will generally result in a point cloud that represents the roof of buildings accurately, but will have less points on the walls of buildings. If it turns out that this is a problem for the classification process, additional information from building data from the national register of addresses and buildings (BAG - Basisregistraties Adressen en Gebouwen, which is collected and maintained by each municipality, and disseminated as country-wide dataset through the NMAC of the Netherlands can be used. The building footprint geometry is generally more accurate in this dataset then it can be obtained by ALS. A combination of the two datasets is, at least in the Netherlands, feasible. In other countries there is however, the danger of mismatches in the two different datasets. Furthermore the BAG dataset contains building use, year of construction, and floorspace information, which could be used for the classification. Additionally, aerial images can be used. All input datasets are publicly available on the Dutch geoportal.

6.2 Tools

For testing different approaches based on the spectral shape analysis the 3D graphics design software Rhinoceros 3D including the script language add-on Grasshopper will be used. The advantage of this combination is that it allows to implement spectral analysis and machine learning ideas and immediately visualise their result on 3D models. If a promising approach was found a complete implementation can be done in a variety of programming languages. Python offers many machine learning libraries, such as scikit or TensorFlow, that are easy to use and well suited for this project. At the last stage it is also possible to implement a workflow in C++. Since the complete building stock of a city can be very big this could be beneficial for the performance of the classification.

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