

Classification of Sensor Independent Point Cloud Data of Building Objects using Random Forests

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Abstract

The Architectural, Engineering and Construction (AEC) industry is looking to integrate Building Information Modelling (BIM) for existing buildings. Currently these as-built models are created manually which is time-consuming. An important step in the automated Scan-to-BIM procedure is the interpretation and classification of point cloud data. This is computationally challenging due to the sheer size of point cloud data of an entire building. Additionally, the variety of objects makes classification problematic. Existing methods focus on specific sensors or environments to improve their results. The goal of this research is to provide a method that is sensor independent and labels entire buildings at once.

This paper presents a method to automatically identify structural elements for the purposes of Scan-to-BIM. More specifically, a Random Forests classifier is employed for the classification of the floors, ceilings, roofs, walls and beams. First, the point cloud is pre-segmented into planar primitives. This significantly reduces the data while maintaining accuracy. Both contextual and geometric features are used to describe the observed patches. By pre-

segmenting the data, more distinct features can be extracted from the input information. The algorithm is evaluated using realistic data of a wide variety of existing buildings including houses, school facilities, a factory, a castle and a church. The experiments prove that the proposed algorithm is capable of labelling structural elements with reported precisions of 85% and 87% recall in highly cluttered environments. In future work, the classified patches are processed by class-specific reconstruction algorithms to create BIM geometry.

Keywords: Classification, Semantic Labelling, Scan-to-BIM, Pre-segmentation, Point Clouds, Building

1. Introduction

The implementation of Building Information Modelling (BIM) for existing buildings is gaining popularity. Experiencing the advantage of BIM for new constructions, the industry now looks to implement as-built BIM. The need for resource efficiency, planning and communication have prompted stakeholders to adopt intelligent models that reflect the state of the asset as it was built to properly manage their data. These as-built models store an immense amount of information about a building at the varying stages of the construction's life cycle [1]. This metric and non-metric information allows the different parties in the construction process to better operate, analyse and evaluate the asset [2]. As-built BIM is currently being employed for documentation, maintenance, quality control, etc. [3].

The production of BIM models with as-built conditions is labour intensive and error prone. The existing documentation of the asset is often sparse or non-existent. Moreover, it often does not match the as-design model of the building due to construction changes or renovations [4, 5]. Current procedures rely on dense spatial measurements for the modelling of the geometry. Typically, 3D point cloud data is acquired by 3D laser scanners or photogrammetry [6]. The automated reconstruction of BIM objects is still ongoing research [7]. A key step in the workflow is the identification of observations of structural

elements. Several machine learning algorithms have been proposed to classify building objects. However, these methods often rely on specific sensors or environments [8, 9]. The goal of this research is to extend the existing approaches to be applicable to point cloud data of any source that includes both interior
25 and exterior environments of a wide variety of buildings.

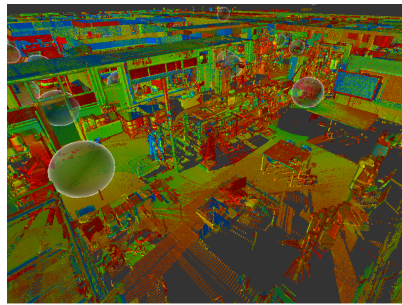
This paper presents an automated solution for the classification of point cloud data for the purposes of as-built BIM. More specifically, structural elements such as floors, ceilings, roofs, walls and beams are automatically identified in existing structures. Typically, these structures have a wide variety of
30 elements, are heavily cluttered and have problems with occlusion as depicted in Fig. 1. Machine learning techniques are proposed for the labelling of the elements. The scope of this research is focussed on the processing of metric information as it is the most consistent in point cloud data.

The remainder of this work is structured as follows. Section 2 presents a
35 background in as-built modelling. In section 3 the related work is discussed. In Section 4 the methodology is presented. The test design and experimental results are proposed in Section 5. Finally, the conclusions are presented in Section 6.

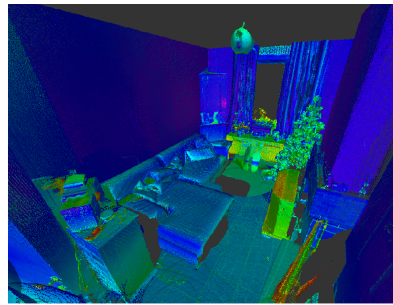
2. Background

40 The procedure of converting point cloud data to BIM geometry is referred to as Scan-to-BIM. Most automated workflows consists of three consecutive steps: Segmentation, classification and reconstruction. First, the point cloud is segmented into point clusters. It is considered as an instance of unsupervised pattern recognition and can be solved by several machine learning techniques
45 [10]. Planar clusters are often proposed [11, 12] but other primitives are not excluded.

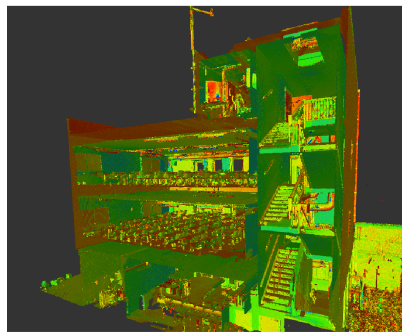
Second, each cluster is provided with a class label. This step, referred to as classification, is considered an instance of supervised learning that identi-



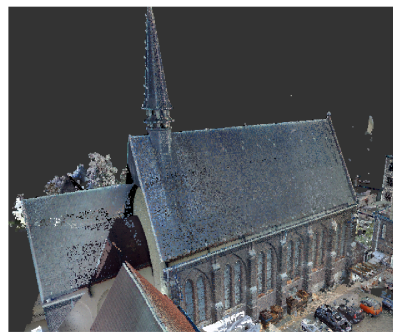
(a)



(b)



(c)



(d)

Figure 1: Example point clouds of structures used during testing: Chemical facility (a), house (b), multi-storey school building (c) and a church (d).

fies the class of new observations given a set of explanatory variables known
50 as features [10, 13]. Commonly in literature both geometric and contextual
features of the observations are employed [14, 15]. Examples of local geo-
metric features are the area, surface dimensions and orientation. Geometric
contextual features may describe the similarity, proximity, coplanarity and or-
thogonality. The set of features, grouped in a feature vector, is processed by
55 a pre-trained classification model to predict the labels. These functions are
referred to as classifiers. Both heuristics and machine learning algorithms
have been proposed for classification. Heuristic models are based on user
defined rules in a certain structure. These rules require no training of the
model parameters as they are intuitively set. While being very efficient, heuris-
60 tics are typically case specific. Alternatively, machine learning algorithms are
employed such as Discriminant Analysis (DA), Decision Trees, Support Vec-
tor Machines (SVM), Neural Networks (NN), Probabilistic Graphical Models
(PGM), etc. [8, 12, 13, 16, 17, 18, 19]. The parameters of these models are
learned from known observations. Machine learning methods often generalise
65 better than heuristics but require extensive training data to work adequately.
Currently, classification is used in a wide variety of applications such as navi-
gation, object recognition and remote sensing.

In the third step, the labelled clusters are processed by class-specific recon-
struction algorithms that create the BIM objects. Once the initial geometry has
70 been constructed, the topology of the objects is adjusted to create a realistic
BIM model. Afterwards, non-metric properties such as materials are added to
the individual elements.

3. Related Work

Semantic labelling of building geometry has been a major research topic
75 over the last decade. Both imagery and LIght Detection And Ranging (LIDAR)
data are considered for the classification of structures. The terrestrial applica-
tions are split into the processing of indoor and outdoor scenery. Most indoor

applications focus on the extraction of small scale objects for navigation and interaction purposes [5, 20, 21, 22, 23, 24]. Outdoor applications often look to
80 identify façades, windows, roads, etc. on a larger scale [9, 14, 25, 26, 27, 28, 29]
Our approach is located in between as we look to label up to several hundreds
of scans and generic point clouds of both indoor and outdoor scenery.

Closely aligned with our research is the work of Armeni et al. [30] and Xiong et al. [12, 31] who both proposed methods for the classification of struc-
85 tural elements of generic point cloud data for the purposes of 3D reconstruc-
tion. They label multiple scans of office and school facilities using machine
learning techniques. We expand their approach by investigating whether pre-
trained models can be generalised for the classification of a wide variety of
structures including castles, churches, factories, etc.

90 Related to the detection of structural elements is the classification of rooms
in a building. Mura et al. [32], Ochmann et al. [32] and Ikehata et al. [33]
consider the reconstruction to be a graph optimization problem. However,
the assumption of closed rooms is only applicable for certain cases. In this
research, the features do not specifically encode room information but describe
95 certain object configurations such as the probability of a wall being located in
between the floor and the ceiling.

Classification algorithms are often linked to a certain sensor set up or point
cloud format [8, 15, 34, 35]. This allows the integration of additional informa-
tion into the classification procedure. For instance, the sensors location pro-
100 vides cues for the positioning of certain objects. Valero et al. classifies individ-
ual scans captured by a Terrestrial Laser Scanner (TLS) for the segmentation
of rooms [36]. However, some features are excluded as each scene is labelled
individually. In our procedure, the input point cloud is considered as the sole
entity and is labelled accordingly. This allows the use of multi-scene features
105 such as the relation between walls in adjacent rooms.

Several researchers have presented results for the labelling of built envi-

ronments using heuristics [37, 38, 39, 40, 41, 42]. However, to classify a wider variety of buildings, more complex models are considered. For instance, Support Vector Machines (SVM) have been a popular approach in the past few years [43, 44, 45]. SVM have been successfully implemented for the classification of both indoor and outdoor point cloud data. Non-linear models such as Decision Trees are also considered for the identification of building elements [12, 29, 46, 47]. These weak learners are often bootstrap aggregated or boosted to produce stronger classification algorithms [48]. In our research a similar Random Forests classifier is proposed for the semantic labelling. Additionally, Probabilistic Graphical Models (PGM) are considered [8, 15, 28, 49, 50]. By representing the data as nodes in a graph, probabilistic reasoning allows the likelihood maximisation of the labels of the nodes. Both implementations of Markov Random Fields (MRF) and Conditional Random Fields (CRF) have been presented for the classification of point cloud data [15, 34, 51, 52, 53, 54, 8]. Their ability to model pairwise and higher order edge potentials between the nodes increases the model performance and aids classification regularity. The pairwise terms smooth the labelling as most CRF implementations favour associative classification [28]. This is especially useful in point-wise classification methods that have weaker features [9]. Currently, Probabilistic Graphical Models are not implemented into our approach as we incorporate the contextual information such as the topology as unary terms.

Prior knowledge has also been proposed for semantic labelling of buildings. Existing plans or models significantly reduce the search area of object recognition algorithms and aid the scene understanding. Several methods have been proposed for model matching between the as-built and as-designed conditions [55, 56]. However, our approach does not rely on prior knowledge as it is typically scarce and error prone.

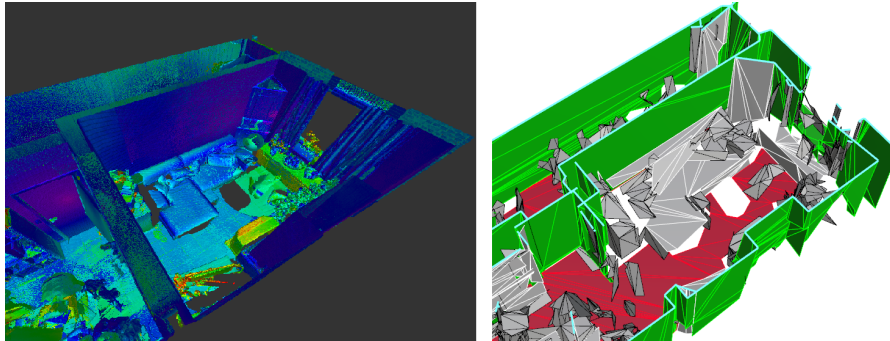


Figure 2: Pre-segmentation: Registered point cloud (Left) and the resulting planar patches (Right).

135 4. Methodology

In this research, a classification procedure is presented for the labelling of structural objects in built environments. More specifically, a Random Forests (RF) is implemented with geometric and contextual features for the semantic labelling. First, the data is pre-segmented into planar patches for data re-
140 duction. This is a well understood problem and thus the Pointfuse engine of Arithmetica is utilised [57]. After loading the points into the software, planar patches are incrementally fit through each point cluster with similar normals (Fig. 2). The resulting planar patches are processed by the classification model.

145 4.1. Feature Extraction

Distinct features are computed for each observed patch s_i similar to Weinmann et al. [14]. Both geometric and contextual characteristics are exploited. The former encodes the object's individual geometric information such as shape, size and orientation. The latter encodes both associative and non-associative information in relation to a group of reference surfaces. In addition to the nearest neighbours, class-specific nearby patches are considered for the features. For instance, the repetitivity and frequent topological configurations of certain reference groups is captured. Table 1 summarizes the different types

Table 1: List of all features calculated for each observed patch

Local features	Count	Contextual features	Count
Surface Area	1	Normal Similarity	1
Orientation	2	Coplanarity	1
Dimensions	2	Parallellity	1
		Proximity	4
		Topology	5

and the number of features used in the experiments. The context differs for the varying feature descriptors (Fig. 3). Both the immediate neighbourhood of the observed surface is exploited as well as larger reference groups. Additionally, several features only employ surfaces with specific characteristics such as orientation as context (Fig. 3 b,c). For instance, the vertical topology feature $D_z(u \in s_i, v \in s_j)$ evaluates the vertical distance between the observed surface s_i and the large horizontal surfaces s_j within its vicinity (Fig. 3 b). The normal similarity feature computes $\vec{n}_i \cdot \vec{n}_{large}$ between the normal vector of the surface \vec{n}_i and the normals of the nearby large surfaces \vec{n}_{large} . Coplanarity is defined as

$$Coplanarity(s_i, s_j) = \begin{cases} -1 & \vec{n}_i \cdot \vec{n}_j < \cos \theta_t \\ |(\vec{c}_i - \vec{c}_j) \cdot \vec{n}_i| & else \end{cases} \quad (1)$$

where $|(\vec{c}_i - \vec{c}_j) \cdot \vec{n}_i|$ is the distance between centroids along the normal to the neighbouring parallel surfaces (Eq. 1). The parallellity is similar but with the reference surfaces conditioned to be directly in front of or behind of the observed surface. The proximity feature captures the repetitivity of certain
150 object configurations. It is defined as the minimum distance $D_{min}(u \in s_i, v \in s_j)$
between the boundary of the observed surface s_i and a set of reference surfaces s_j . The following distances are evaluated: the vertical distance to the closest
large horizontal surface above (1), the vertical distance to the closest large hor-
izontal surface underneath (2), the distance to the closest large vertical surface
155 (3), and the number of connected surfaces (4). The topology features encode

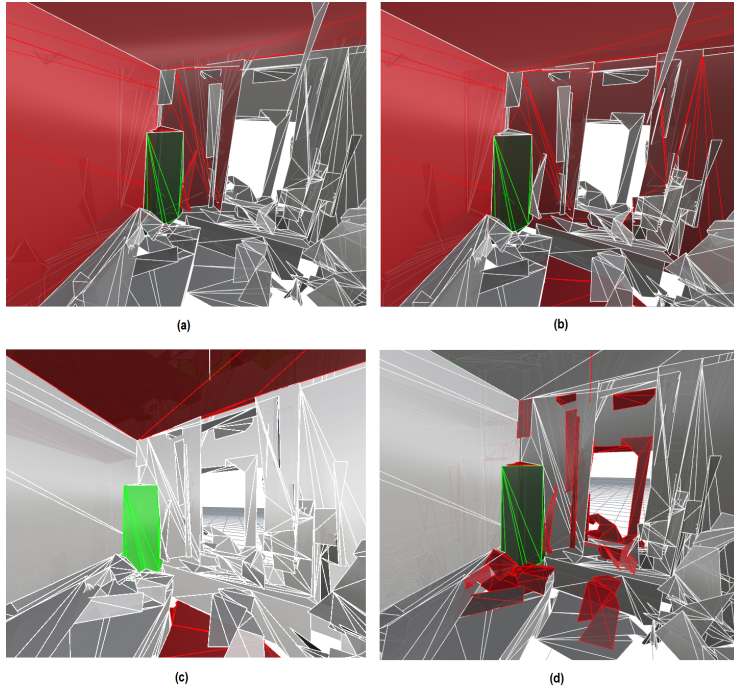


Figure 3: Visualisation of class specific neighbours: Conventional nearest neighbours (a), significantly large nearby surfaces (b), significantly large horizontal surfaces above/below (c) and nearby small surfaces (d).

the presence of object configurations. These binary predictors serve as discriminative features between classes. For instance, a horizontal patch is more likely to be a ceiling when there are large horizontal patches directly above it. Five relations are observed describing the presence of horizontal and vertical surfaces: Small surfaces above (1) and below the patch (2) (Fig.4a), the position of vertical patches (3) and the position of horizontal patches above (4) and below (5) (Fig.4b). Finally, all features values are combined in feature vectors $\mathbf{x} = \{x_1, \dots, x_n\}$ and are passed to the classifier for further processing.

4.2. Model formulation

Each observed surface is assigned a class label $y \in \mathbf{Y} = \{l_1, \dots, l_k\}$ given the feature vectors \mathbf{x} . The label prediction $p(y|\mathbf{x})$ is computed by a pre-trained Random Forests (RF) classifier similar to Munoz et al. [58], Vosselman et al.

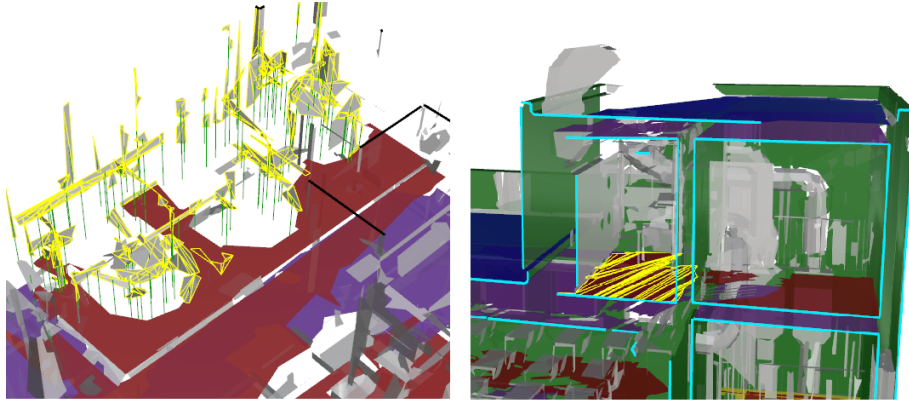


Figure 4: Representation topology predictors: Topology small surfaces (Left), evaluation topology nearby significantly large horizontal surfaces (Right).

[58], Niemeyer et al. [59], etc. [8, 54]. This classifier bootstrap-aggregates a number of weak learners [48]. The training data is copied into M different bootstrapped data sets and a predictive discrete decision tree $y_m(\mathbf{x})$ is trained for each subset. Each tree consists of a series of binary splits that separate the input variables. The split is the result of the best fit partitioning of the feature vector space for the classes along one of the major axes. Typically, a single tree has the tendency to overfit. By bagging a large number of trees, the variance is significantly reduced which aids the generalisation of the model. Once the Random Forests classifier is trained, future observations are classified by a majority vote of the hypotheses of the decision trees.

The Random Forests model is trained using leave-p-out cross validation. Consecutively, p known observations are used for validation and the remaining observations are used for training. The final optimized model is achieved by averaging the model parameters. A regularization parameter λ is introduced that penalises overfitting. The feature extraction and prediction algorithm are implemented in the Rhinoceros plug-in Grasshopper[60]. This intuitive procedural programming platform allows for flexible data processing and evaluation. The classified patches are exported to the Rhinoceros model space for validation and further processing.

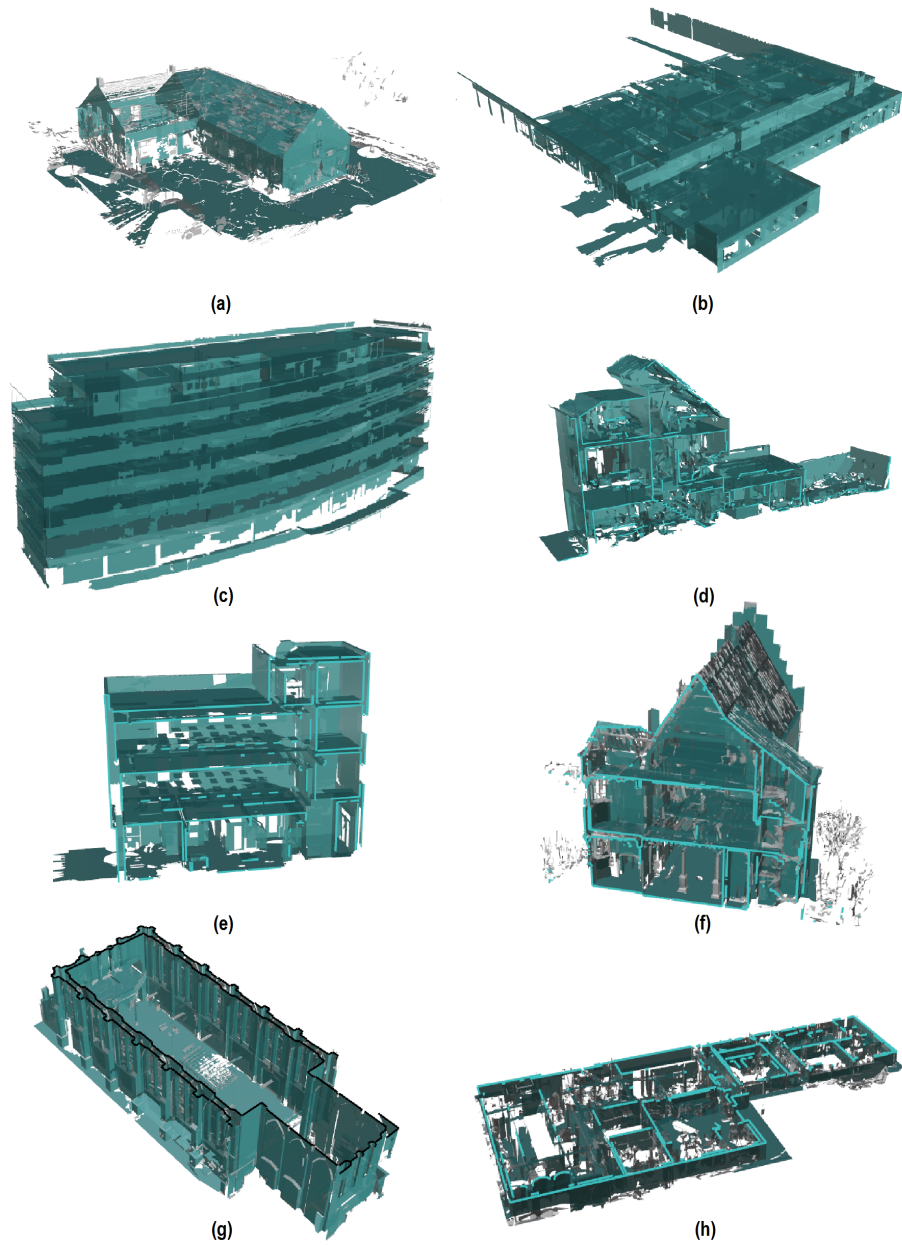


Figure 5: Example test cases with reconstructed surfaces: House 4000 surfaces (a), Campus 30000 surfaces (b), Office 26000 surfaces (c), Row house 1800 surfaces (d), Multi-storey office 3000 surfaces (e), heritage site 10000 (f), church 6500 surfaces (g) and chemical plant 15000 surfaces(h).

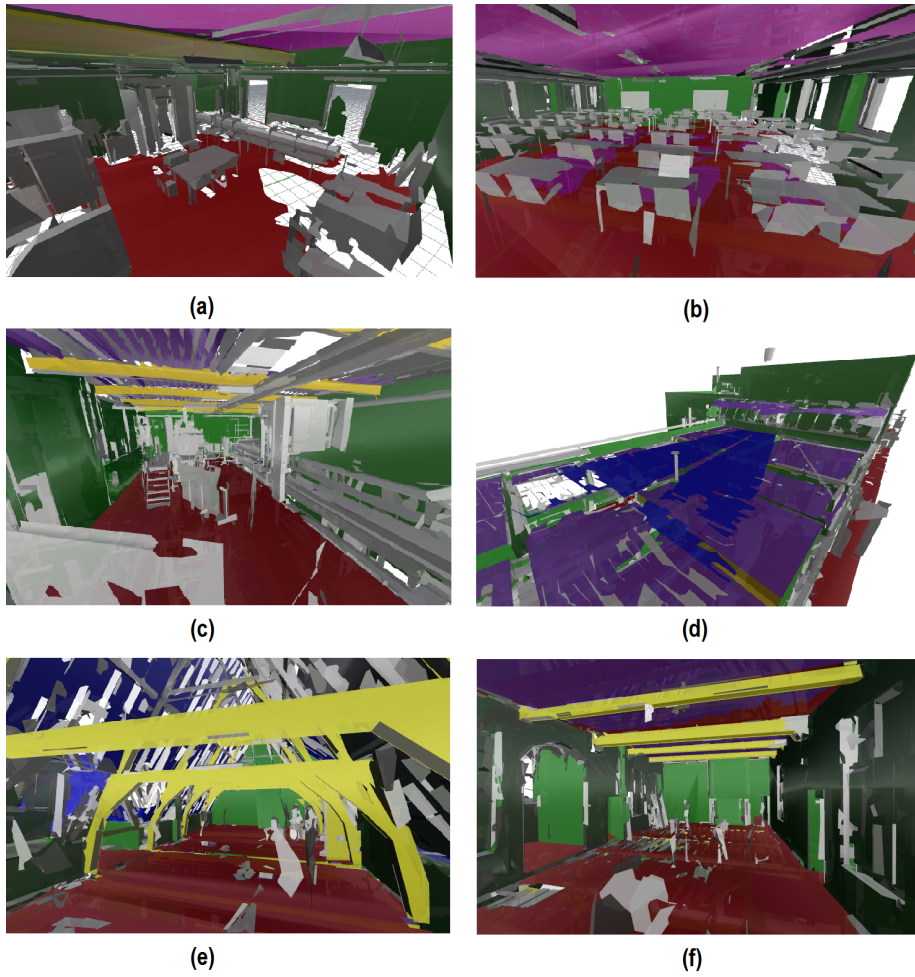


Figure 6: Example test data with ground truth: Laboratory (a), classroom (b), chemical plant (c), flat roof structure (d), heritage roof beam structure (e) and heritage room (f). Red=floors, purple=ceilings, blue=roofs, green=walls, yellow=beams and grey=clutter.

5. Experiments

The algorithm was tested on a wide variety of buildings. 10 structures including houses, offices, industrial buildings and churches were used for training and testing (Fig 5). The size of the projects varies between 300 million and 1,4 billion points and were acquired with different sensors such as Terrestrial Laser Scanners. The test sites were acquired under realistic conditions including clutter, occlusions, traffic, etc. The pre-segmentation was performed with the Armitica's Pointfuse software [57]. The point clouds were subsampled with a 1cm spacing and processed on an Intel®Core i7-4900MQ CPU @ 2.80Ghz with 4 cores and 4 hyperthreads and 32GB RAM. Over 90,000 surfaces were computed for the projects. On average, the patch creation had a standard deviation of 1mm compared to the initial point clouds. A subset of the data was used for the experiments. Only the surfaces larger than $0.4m^2$ were considered since the smaller surfaces mainly consisted of clutter and furniture pieces. The remaining 7000 surfaces were labelled manually and served as ground truth for the classification (Fig. 6). The available classes included floors, ceilings, roofs, walls, beams and clutter. All 17 predictors from table 1 were considered for the classification of the observations. The Random Forests classifier was trained with a $p = 5$ cross-validation. In order to obtain an unbiased classification model, the training data set was balanced by sampling the same number of observations for each class.

5.1. Performance

The classification results are depicted in the confusion matrices in Fig.7. The average recall and precision is 87% and 85% respectively, resulting in an overall average accuracy of 86%. This is very accurate given the large variety of buildings and objects that were evaluated. Typical objects such as floors, ceilings and walls were extracted with over 88% accuracy. This proves that while buildings have many unique objects and are heavily cluttered, their structural elements are reliably detected.

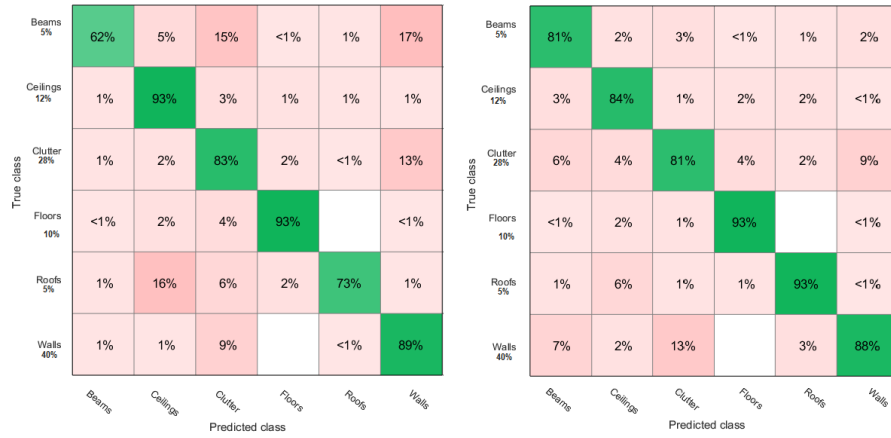


Figure 7: Classification results Random Forests classifier: Recall (Left), Precision (Right). The percentage defined under the 'True Class' is the amount of available test data.

Not-surprisingly, a large number of evaluated surfaces are objects for which the classes are not available (28%). Combined with the small surfaces, over 90% of the pre-segmented patches are non-structural objects. However, the feature predictors are sufficiently distinct for the Random Forests classifier to properly differentiate the structural from the non-structural patches.

The confusion matrices show that the beams class underperforms (Fig. 7). This is expected due to the increased feature variance of this class. Beams have no obvious direction and are prone to occlusions. Increased confusion rates are observed between the walls and clutter classes as well as the ceiling and roof classes. The confusion rate of walls and clutter is approximately the same for both classes (avg. 10%). This is mainly due to the misclassification of wall-like objects such as built-in closets and blackboards and actual wall objects such as niches and wall details (Fig.8a,c,d & e). In contrast, the confusion between the ceilings and roofs is only observed for the roofs (16%). This is due to the fact that several data sets do not have roofs making the top ceilings harder to interpret (Fig.8b). Several misclassifications are due to our sensor independent approach. For instance, the ceiling in Fig.8f was misclassified as a floor as it was the most likely state given the context. Information regarding the position

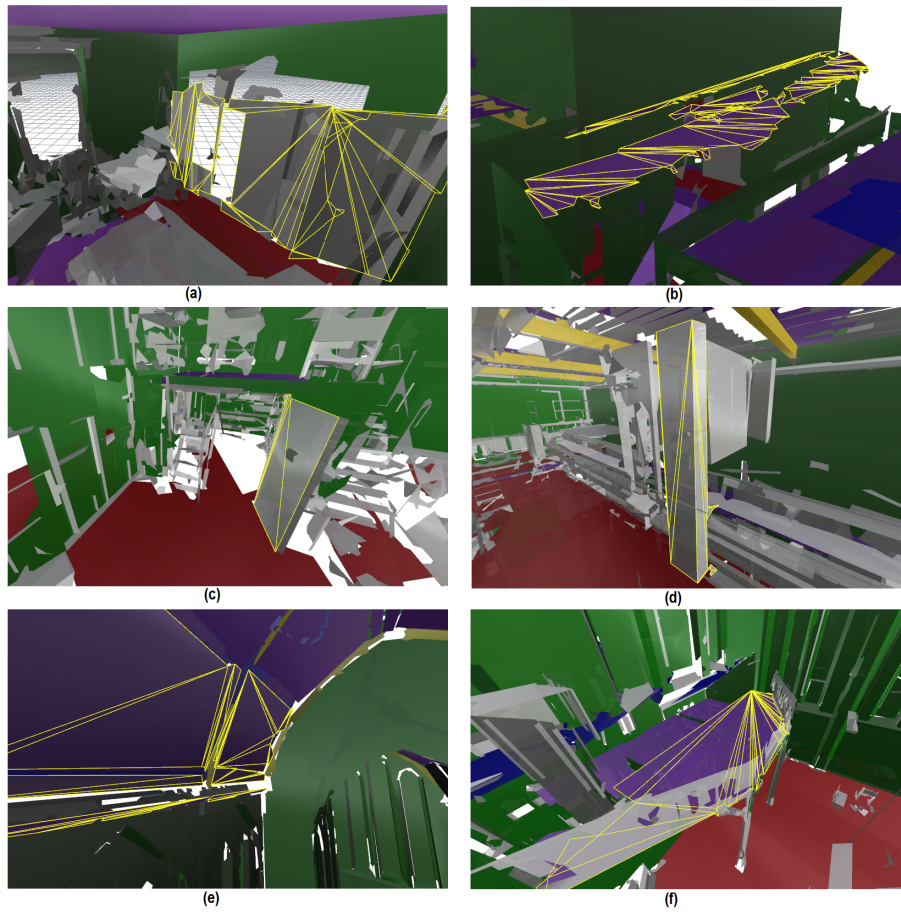


Figure 8: Several misclassification examples. Large closets, doors and machinery labelled as walls (a,c and d), unobstructed ceilings labelled as roofs (b), near vertical ceilings labelled as walls (e) and unobstructed ceilings labelled as floors (f).

Table 2: Averaged classification results of Random Forests compared to K-Nearest Neighbours, multiceptron Neural Network, Linear Support Vectors Machines and Boosted Decision Trees.

Classifier	Training [s]	AUC [%]	Recall/Precision [%]					
			Beams	Ceilings	Clutter	Floors	Roofs	Walls
Random Forests	13.7	86	62/81	93/84	83/81	93/93	73/93	89/88
KNN	2.1	78.7	53/70	74/70	78/76	82/72	61/78	85/87
Neural Network	1.2	69.6	61/29	65/84	73/74	87/78	74/59	83/85
SVM	15.8	74	13/51	78/59	71/71	76/86	52/69	85/80
Boosted Trees	14.4	77.8	27/70	80/72	76/69	91/83	46/88	85/84

of the sensor would have avoided this misclassification but would make the
 235 approach dependent on a specific sensor set up.

5.2. Comparison

We compared the results of the Random Forests classifier with other com-
 mon machine learning methods. Table 2 depicts the results of the model per-
 formance for K-Nearest Neighbours (KNN), a multiceptron Neural Network
 240 (NN), Support Vector Machines (SVM) and boosted decision trees. All models
 were tested with the same predictors and data as the proposed model. Both the
 recall and precision values were observed. From table 2 is derived that most
 classifiers had fast training speeds and were able to properly label the candi-
 date data. This proves that the used predictors are both distinct and robust
 245 for the detection of structural elements in cluttered and noisy environments.
 When comparing Random Forests to the other classifiers, it is observed that
 the used model outperforms the other classifiers. When comparing against
 a Neural Network, a clear trade off is observed between speed and perfor-
 mance. However, since our approach focusses on post-processing applications,
 250 the training time is of lesser concern.

6. Discussion and Conclusion

In this paper, a method is presented for the automated classification of
 point cloud data of structural objects in buildings. More specifically, the data

is pre-segmented and processed by machine learning algorithms to label the
255 floors, ceilings, roofs, beams, walls and clutter in noisy and occluded environ-
ments. This step is crucial in the automated procedure of creating Building
Information Modelling (BIM) objects from raw metric information.

By pre-segmenting the point cloud data, the amount of observations is dras-
tically reduced while maintaining the metric accuracy. This allows for the
260 processing of larger data sets and provides additional features. A Random Forests
classifier is implemented that exploits both geometric and contextual features.
A variable neighbourhood search is presented to encode various contextual
relations. The results show that the proposed classifier is able to reliably la-
bel the pre-segmented patches given the feature observations. However, some
265 classes underperform due to the large variance in feature values within the
class. Classes such as beams consist of a wide variety of possible objects and
suffer from occlusions. The results can be improved by narrowing down the
possible objects of a single class by splitting the class into various subclasses
such as pillar, beam, pipe, etc. Additionally, while the sensor independent ap-
270 proach generalises well, the lack of additional information such as the sensors
position affects the model performance.

From the comparison to other classifiers is derived that most classification
methods are capable of identifying the correct class of new observations given
distinct and robust descriptors and a large number of known observations. The
275 experiments prove that the feature values of observations in different buildings
and configurations are similar and discriminative.

In future work, the method will be investigated further to improve the la-
labelling performance. Additionally, More types of primitives will be considered
along with appropriate features. This will enhance the current classification
280 and allows for the processing of non-planar classes such as cylindrical beams
and pipes as well as furniture. Also, research will be performed towards the
integration of probabilistic graphical models to increase the methods perfor-

mance.

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