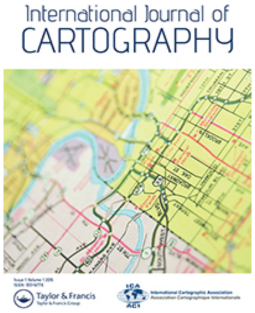

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Automatic identification of building types based on topographic databases – a comparison of different data sources

Robert Hecht[a], Gotthard Meinel[a] and Manfred Buchroithner[b]

[a]Monitoring of Settlement and Open Space Development, Leibniz Institute of Ecological Urban and Regional Development, Dresden, Germany; [b]Institute for Cartography, Dresden University of Technology, Dresden, Germany

ABSTRACT
Data, maps and services of the national mapping and cadastral agencies contain geometric information on buildings, particularly building footprints. However, building type information is often not included. In this paper, we propose a data-driven approach for automatic classification of building footprints that make use of pattern recognition and machine learning techniques. Using a Random Forest Classifier the suitability of five different data sources (e.g. topographic raster maps, cadastral databases or digital landscape models) is investigated with respect to the achieved accuracies. The results of this study show that building footprints obtained from topographic databases such as digital landscape models, cadastral databases or 3D city models can be classified with an accuracy of 90–95%. When classifying building footprints on the basis of topographic maps the accuracy is considerably lower (as of 76–88%). The automatic classification of building footprints provides an important contribution to the acquisition of new small-scale indicators on settlement structure, such as building density, floor space ratio or dwelling/population densities. In addition to its importance for urban research and planning, the results are also relevant for cartographic disciplines, such as map generalization, automated mapping and geovisualization.

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Building footprints; settlement structure; classification; machine learning

1. Introduction

The domains of urban and regional planning, land management and urban studies as well as risk assessment require detailed information about the functional, morphological and socio-economic structure of the built environment (see Aubrecht, Steinnocher, Hollaus, & Wagner, 2009; Batty 2007; Clifton, Ewing, Knaapa, & Song, 2008; Maantay & Maroko, 2009). Buildings play a key role as they determine the physical structure of a settlement, which in turn is strongly related to the distribution pattern of housing, workplaces, infrastructure or energy consumption.

Despite the importance of the built environment both for researchers and planners statistical data on buildings are often not up-to-date, strongly spatially aggregated or

CONTACT R. Hecht r.hecht@ioer.de, hechthecht@gmx.de

only very locally available. Official statistics on building stock are often available only at the municipal level. For many applications such aggregated data do not adequately describe building structure in terms of the spatial resolution. Although a few major cities provide small-scale data on the city block level, there is a lack of homogenous data on the building sector for planning purposes and comparative studies at nationwide and European level (BPIE, 2011).

National Mapping and Cadastral Agencies (NMCAs) offer various spatial base data products (vector data, raster maps, web mapping services) containing building footprint information with nationwide coverage. However, attribute information regarding the characteristics of a building (e.g. building usage, housing type, numbers of floors, building height or years of construction) is rarely included in these data. The ability of visual perception allows humans to recognize different building types in topographic maps but mapping by hand is a very time-consuming process that is often influenced by subjective factors. This raises the question whether it is possible to identify building types automatically in authoritative geospatial data from NMCAs. Hecht (2014) addresses this question in detail. The aim of this monographic study was the development of a machine learning approach for automatic classification of building footprints for the small-scale description of settlement structures. The work addresses issues of data requirements, the suitability of currently available spatial base data, measures that can be derived to characterize buildings and the capability of different classifiers as well as the factors that influence classification accuracy. The present paper highlights the developed approach and the main findings regarding the accuracies obtained for various types of data sources (e.g. topographic maps, cadastral databases or 3D city models).

2. Current state of research

During the last years various approaches have been developed to classify and describe the urban structure by means of an analysis of remote sensing imagery and topographic data. The classification of building footprints is a relatively new field and still part of basic research. With increasing availability of digital high-resolution imagery or vector data, it gained more importance within the last few years. Depending on the purpose and the field of research existing approaches strongly vary in their defined building typology (number and characteristics of the types to detect), the input data (spatial vector databases, remote sensing imagery, data from Light Detection and Ranging (LiDAR) technology, and topographic raster maps, etc.) and the applied classification approach (decision tree, cluster algorithm, support vector machines (SVMs), etc.). The existing approaches have been tested on relatively small study areas only and have not always been properly investigated, particularly in terms of the achievable accuracy using different input data types.

Particularly in the domain of urban modeling, remote sensing techniques are popular to detect and describe urban structures (e.g. Banzhaf & Hofer, 2008; Barr & Barnsley, 1997; Mesev, 2005; Vanderhaegen & Canters, 2010; Walde, Hese, Berger, & Schmullius, 2012; Wu, Xu, & Wang, 2006; Wurm, Taubenböck, Roth, & Dech, 2009). In digital cartography, the detection of building patterns in spatial vector databases plays an important role in cartographic generalization processes (e.g. Anders, Sester, & Fritsch, 1999; Burghardt & Steiniger, 2005; Regnauld, 2001).

Classification is the assignment of input data into one or more classes based on features (measures) and is the main goal of pattern recognition (cf. Schalkoff, 2008; Theodoridis & Koutroumbas, 2008). In the context of building classification these features can be geometrical measures such as building area, building shape or the number of neighbors of the building. Basically, two approaches can be distinguished: knowledge-based ('top-down') and data-driven ('bottom-up') approaches.

Using a top-down approach, a classifier is constructed by means of explicit knowledge derived from, for example, expert manuals, rule sets or descriptions. Knowledge-based approaches have, for example, been used by Orford and Radcliffe (2007), Meinel, Hecht, and Herold (2009), Wurm et al. (2009) or Smith and Crooks (2010). The models lead to a high level of transparency and replicability. Nevertheless, they are only applicable to simple recognition problems with a small number of classes to detect. Orford and Radcliffe (2007), for instance, use OS MasterMap® and address data to apply a rule set distinguishing the dwelling types detached, semi-detached, terraced, flat and unclassified. On the other hand, Wurm et al. (2009) use a knowledge-based fuzzy-logic approach for the recognition of five building types. They combine IKONOS satellite imagery data and a Digital Surface Model to extract and classify the building footprints, which are later used to derive Urban Structure Types. The knowledge-based models are strongly adapted to the input data and the purpose. An application to other data needs a completely new model.

With the increasing demand for semantic resolution, the complexity of the classification problem rises and data-driven (bottom-up) approaches are gaining importance. In that case, the essential part of the modeling is done automatically by a machine learning algorithm based on a given training data-set. The learning can be either supervised or unsupervised. Supervised learning assumes a labeled training set (buildings with known classes), whereas in unsupervised learning the elements do not have class labels and the algorithm (e.g. clustering) determines natural partitions (clusters) of the sample data (Schalkoff, 2008). An unsupervised classification approach, particularly the Expectation Maximization Algorithm for clustering, has been used in the work of Neidhart and Sester (2004), Werder, Kieler, and Sester (2010) and Geiß et al. (2011). A disadvantage of unsupervised approaches is that the identified clusters need to be interpreted, especially in order to compare the results with reference data. Supervised classification approaches have been proposed by Sester (2000), Raheja (2005), Steiniger, Lange, Burghardt, and Weibel (2008), Römer and Plümer (2010) and Henn, Römer, Gröger, and Plümer (2012). The first comparison of different classification algorithms (Batch Perceptron Algorithm, Minimum Squared Error Algorithm, Adaboost, SVM) was performed by Steiniger et al. (2008). In recent works, ontologies are used to support the recognition of geographic objects (Belgiu, Tomljenovic, Lampoltshammer, Blaschke, & Höfle, 2014; Lüscher, Weibel, & Burghardt, 2009; Thomson, 2009). For instance, Lüscher et al. (2009) combine ontological modeling with pattern recognition techniques to identify row houses in OS MasterMap® in the UK. However, the authors point out the need for further research in order to apply this method to other building types.

3. Methodological approach for building classification

Knowledge-based approaches use manually constructed models which are hardly adaptable to other input data or target classes. Thus, a new model must be constructed for every change in the setting. In order to keep flexibility in terms of a wide usage of the method for the assessment of the suitability of different input data we chose a data-driven pattern recognition approach with a supervised learning strategy.

The developed procedure, here called Building Footprint Classification Tool, consists of several steps and is schematically depicted in Figure 1.

The approach is described in detail by Hecht (2014). At this point, only the basic procedure is presented. After the definition of *building typology* and *input data types* the approach follows five processing steps. These are data preparation, feature extraction, pre-processing, feature selection and classifier design. *Data preparation* includes the integration of the defined input data types as well as the collection of training samples. In the *feature extraction* process various numerical features are derived by means of digital image processing techniques and spatial analysis. For the characterization of the buildings, geometric, topological, statistical and semantic measures (e.g. a given land-use category) are calculated. For each data type a set of features has to be defined. The size of the feature sets ranges from 72 features (data type I) to 87 features (data type V) (cf. Hecht, 2014, Table 8–8). To avoid falsification of some features values all small annexes such as garages and extensions are eliminated in advance using a knowledge-based rule set. In the feature extraction process, urban block geometry and official house coordinates are included as auxiliary data. The urban block geometry provides a useful reference when calculating contextual features such as the building density or the mean distance between buildings. House coordinates are used to determine the number of addresses per building object. In a *pre-processing* step, the feature measurements are cleaned up, scaled and transformed. In order to reduce dimension and redundancy a filter-based *feature reduction* based on a

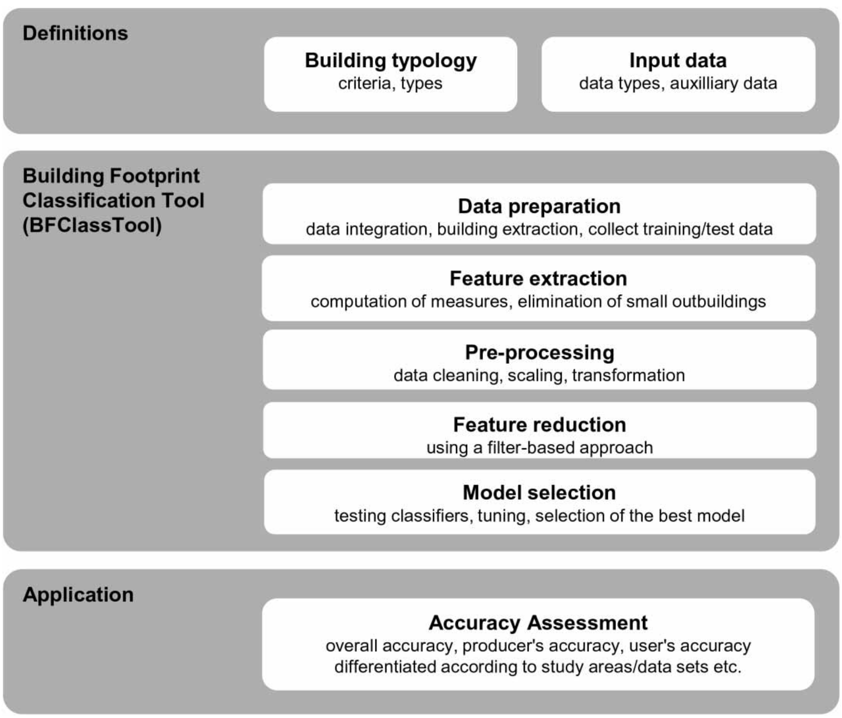


Figure 1. Methodological approach (adapted from Hecht, 2014).

Principal Component Analysis (Jollife, 1973) is applied only to highly correlated features. In a *model selection* process, 16 different machine learning classifiers (e.g. linear discriminant analysis, artificial neural networks, SVMs, decision trees and ensemble methods) were tested and compared to each other in terms of the generalization ability and computational efficiency. The Random Forest (RF) Algorithm introduced Breiman (2001) was identified as the best learning algorithm for building classification (cf. Hecht, 2014) and is used in this study. The RF Algorithm is an ensemble classifier consisting of a multitude of trained decision trees. The individual trees are constructed by a random bootstrap selection of the training data. Compared to the strongly linked Bagging Algorithm by Breiman (1996) only a random feature set is used for the decision tree construction. The RF Algorithm is implemented in an R software package called 'randomForest' (Liaw & Wiener, 2002). The basic parameters are *mtry* (the number of features randomly selected for training a decision tree) and *ntree* (the number of trees to be constructed). While the parameter *ntree* is set at 200, the parameter *mtry* is tuned in a particular tuning process. After RF has been chosen as the best algorithm for building classification, a detailed *accuracy assessment* is carried out through testing the algorithm on different data-sets (different study areas, input data and training data sizes). In this step, error matrices and accuracy measures such as the overall accuracy as well as the producer's accuracy (PA) and the user's accuracy (UA) representing individual accuracies for each class (Congalton & Green, 1998) are calculated. The PA gives the ratio between correctly classified objects and the total number of reference objects in the respective reference class. The UA is the ratio of the correctly classified objects of a certain class to the total number of all objects predicted as belonging to the class.

3.1. *Building typology*

In a supervised classification approach, training samples for each target class (building type) need to be collected. This requires a priori knowledge about the existence of certain building types. With respect of the area under investigation, in our case in Germany, a hierarchically structured typology was defined largely based on established criteria in urban and housing research (e.g. Buchert et al., 2004; Institut Wohnen und Umwelt, 2003; Müller & Korda, 1999). On the first level residential and non-residential buildings are differentiated. Residential buildings are further subdivided into single/two family houses (SFH), multi-family houses (MFH) and miscellaneous housing (e.g. rural houses, RH). On the next level, the SFH can be differentiated in detached (SFH-D), semi-detached (SFH-SD) or terraced (SFH-T) houses. With respect to the arrangement of buildings the MFH are in turn initially classified into open structures, closed structures or ribbon developments. Ribbon developments are, for instance, traditional row houses (MFH-TR) or industrial row houses (MFH-IR). Non-residential buildings are differentiated into industrial or commercial (IC) and buildings of special purpose (SP) such as for administration, education and research, culture or health. Figure 2 shows the typology in its entirety. The gray-colored classes were not taken into consideration in the study.

3.2. *Input data types*

Building footprints can be found in various spatial data-sets, such as topographic maps, digital landscape models, cadastral databases, but also in Volunteered Geographic

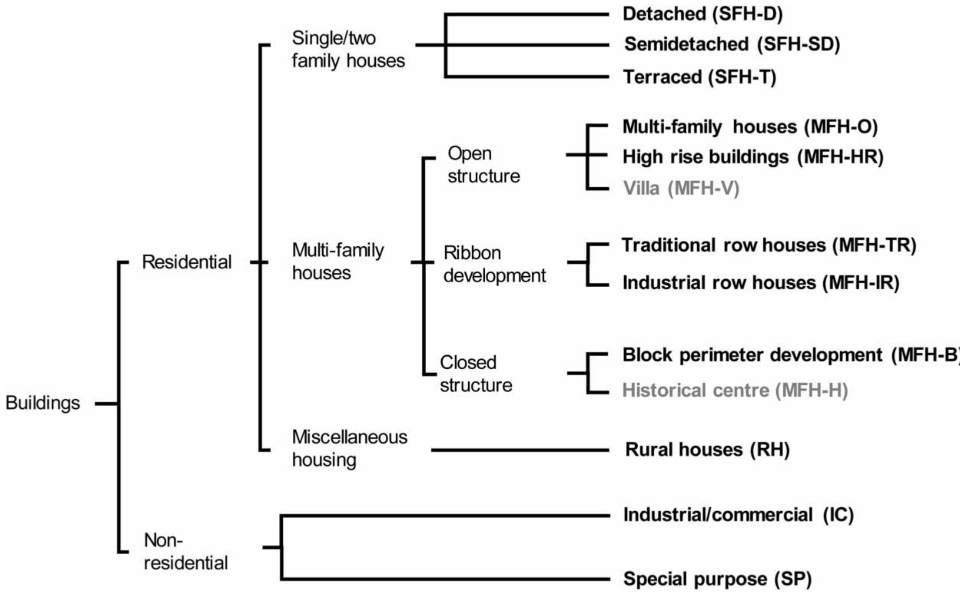
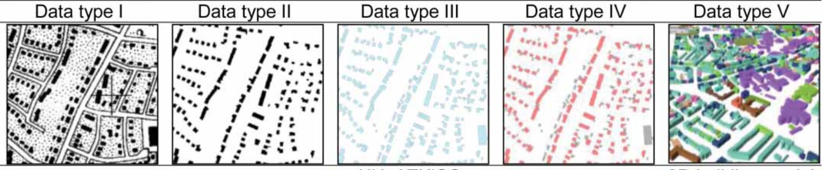


Figure 2. Building typology (adapted from Hecht, 2014).

Information (VGI) platforms such as the popular OpenStreetMap (OSM). OSM data contain building footprints but are currently not suitable for large area applications due to the low degree of completeness and a strong heterogeneity in the geometrical modeling of the buildings (Hecht, Kunze, & Hahmann, 2013). With regard to a nationwide applicability, in the present study five types of German authoritative spatial base were taken into account (Figure 3). These are, at first, topographic raster maps at a scale of 1:25,000, either scanned from analogue sources (TK25, DTK25-V – data type I) or digitally produced (DTK25 – data type II). Further, vector data-sets from NMCAs data types III–V, were considered. Data type III is building footprints without any attributes (e.g. including the



	Data type I	Data type II	Data type III	Data type IV	Data type V
German data sets	TK25, DTK25-V	DTK25	HU, ATKIS® Base-DLM	ALK, ALKIS®	3D building model in LoD1
Data structure	Raster data	Raster data	Vector data	Vector data	Vector data
Geometric representation	regions of buildings together with other map symbols	regions of buildings in a separate layer	single buildings	single buildings	single buildings
Usage information	no	no	no	yes	yes
Height information	no	no	no	no	yes

Figure 3. Types of spatial base data with building footprint information (adapted from Hecht, 2014).

Digital Landscape Model of the Authoritative Topographic-Cartographic Information System (ATKIS® Basic DLM) or the official building polygon data-set called 'Amtliche Hausumringe Deutschland' (HU-DE)), whereas data type IV includes semantic information, respectively, the building usage (e.g. included in the Automated Real Estate Map (ALK) or the Authoritative Real Estate Cadastre Information System (ALKIS®)). The last data type V is a 3D building model in Level of Detail 1 with building usage information and an attribute containing building height information usually gathered by airborne laser scanning. The data types vary in data structure, geometric building representation and information content and finally in terms of data costs.

In addition to the building data-sets, urban block geometries are used to derive additional measures for the characterization of the urban context. Urban blocks (sometimes also referred to city or street blocks) are defined as built-up areas that are confined by topographic lines, in particular streets or pathways (Luft & Bender, 1998).Their geometry can be obtained from the German Digital Landscape Model (ATKIS® Basic DLM) by selecting the object group '2100' (built-up area). The ATKIS® Basic DLM also offers semantic information on land use. Four main land-use classes can be distinguished on the urban block level: residential area, industrial/commercial area, mixed use area and specific functional area. This categorical information can be transformed into a numerical feature which can later be used in the classification process to separate residential from non-residential buildings. Further, official house coordinates are used as auxiliary data. They contain points representing all addressed buildings in Germany. This information is used for the exclusion of irrelevant buildings and helps to describe the buildings by the number of addresses per building footprint.

4. Results

In the following, after an introduction of the study areas, the used data-sets and their preprocessing, the results of the achieved classification accuracies for different input data types are presented.

4.1. *Study areas, data-sets and pre-processing*

The classification approach was tested on different data-sets for different settlement types in Germany. The areas selected for the study are the city of Dresden (large city), Halle and Krefeld (medium-sized town), Stolpen (small town) and rural areas in Saxony (municipalities Diera-Zehren, Crostwitz and Rechenberg- Bienenmühle). The selection of the study areas was carried out based on the availability of geospatial data as well as a sufficiently large amount of existing reference data (buildings with class labels) for training and validation.

Building footprint data of all five input data types as well as the urban block data from the ATKIS® Basic DLM and the house coordinates have been processed and integrated in a database. To retrieve building footprints from topographic raster maps (data types I and II), building footprints are extracted and subsequently converted into a vector format by means of image processing techniques. While for data type II a thresholding operator is adequate, a more sophisticated procedure is necessary for the footprint retrieval from scanned topographic maps (data type I) due to overlays and joins with other map features (e.g. street lines, vegetation symbols). The methodology of this cartographic pattern recognition process is described in Meinel et al. (2009).

Table 1. Number of reference buildings with building type information.

	Study area				
	Dresden (large city)	Halle (medium-sized town)	Krefeld (medium-sized town)	Stolpen (small town)	Rural areas in Saxony
Data type I	18,180	14,750	640	230	730
Data type II	–	25,610	6470	–	–
Data type III	19,370	39,630	26,040	370	920
Data type IV	19,590	–	26,040	430	1030
Data type V	–	–	26,040	–	–

For a set of building footprints corresponding building type information was gathered from other existing databases. This reference information was collected in other projects based on the interpretation of aerial photographs and ground truthing. Due to semantic and geometric differences between the data-sets a transformation, spatial matching and recording were carried out to receive homogenous building data-sets with corresponding building type information as a basis for training and testing in the accuracy assessment. Table 1 presents the number of reference buildings used in the study. The different number of objects for data-sets of the same study area is due to the fact that buildings in the data-sets are represented differently. On the other hand not all attributes could be spatially assigned due to positional differences between the data-sets.

4.2. *Classification accuracy for each data-set*

In order to assess the accuracy of the classification approach for each data-set the overall accuracy was determined using a 10-fold cross-validation (Alpaydin, 2004). To achieve this the training data are divided into 10 equal-size and random subsamples (bootstrap samples), with 9 samples used for training and the remaining subsample for the evaluation of the classifier quality. The average of the 10 resulting values gives the overall accuracy.

Table 2 summarizes the results in terms of the overall accuracy and their standard deviations (in brackets). The table shows that accuracy increases from data types I–V. With respect to the cities of Dresden, Halle and Krefeld, 90–95% of all building footprints are classified correctly as long as they are type III, IV or V (e.g. HU, ALK, 3D buildings). The

Table 2. Overall accuracy and standard deviation (in brackets) obtained from 10-fold cross-validation differentiated according to the input data type and study area. The accuracy is color-coded from green (very good), via yellow (good) to red (not satisfactory).

	Study area				
	Dresden (large city)	Halle (medium-sized town)	Krefeld (medium-sized town)	Stolpen (small town)	Rural areas in Saxony
Data type I	78.90% (±0,3)	76.60% (±1,2)	76.60% (±6,9)	67.40% (±11,5)	56.40% (±7,0)
Data type II	–	88.90% (±0,4)	78.20% (±2,2)	–	–
Data type III	90.40% (±0,6)	91.80% (±0,5)	93.60% (±0,5)	72.20% (±9,0)	62.40% (±3,4)
Data type IV	94.30% (±0,4)	–	94.30% (±0,3)	84.20% (±4,5)	78.70% (±6,0)
Data type V	–	–	94.90% (±0,3)	–	–

Figure 4. Input data (left) and classified building footprints (right) for a small section of the city of Krefeld (data type III).

accuracy of 76–88% for buildings extracted from topographic raster maps (types I and II) is considerably lower. The highest accuracy was achieved for the 3D building data-set (data type V) from Krefeld.

With a sufficiently large training data-set in urban areas for the buildings from ALK (data type IV) an accuracy of about 94% (Dresden, Krefeld) and for the building of the input data type III (ATKIS® Basic DLM) an accuracy of at least about 90% (Dresden, Halle, Krefeld) was measured (see also Figure 4). For the small town of Stolpen and the rural areas a lower accuracy was observed. However, the lower accuracies are apparently due to the smaller number of training objects available.

4.3. *Class-specific accuracy*

Considering the overall accuracy alone does not reveal sufficient information to assess the quality of a classifier. Therefore, confusion matrices have been computed for each data-set. Based on the misclassifications in the matrix the PA and UA are calculated in order to investigate the quality of each class. Table 3 summarizes the PA and UA for each class based on the results obtained using input data type III.

Table 3. PA and UA for each building type. The results were obtained using input data type III (German official building polygon data-set).

	Study area									
	Dresden (large city)		Halle (medium-sized town)		Krefeld (medium-sized town)		Stolpen (small town)		Rural areas in Saxony	
Building type	PA (%)	UA (%)	PA (%)	UA (%)	PA (%)	UA (%)	PA (%)	UA (%)	PA (%)	UA (%)
SFH-D	74.8	77.5	87.4	86.0	90.7	91.3	71.8	64.6	75.0	66.8
SFH-SD	95.1	97.2	97.0	96.0	95.4	95.4	52.4	68.8	31.8	87.5
SFH-T	98.6	99.8	99.1	98.6	97.7	97.9	57.1	57.1	57.1	100.0
MFH-O	85.6	84.2	61.9	77.3	56.5	75.0	70.3	63.4	35.2	48.1
MFH-HR	84.2	100.0	92.3	100.0	74.4	93.6	–	–	–	–
MFH-TR	97.5	98.6	96.8	97.9	93.1	90.2	–	–	–	–
MFH-IR	99.8	99.6	98.6	98.9	85.5	94.4	–	–	–	–
MFH-B	96.4	97.7	95.7	94.4	93.0	92.1	92.5	86.0	–	–
RH	45.4	63.2	61.7	74.9	74.5	97.4	26.3	62.5	65.8	57.0
IC	94.5	90.5	91.0	87.9	93.0	90.8	71.2	75.0	66.7	68.3
SP	82.3	94.0	95.0	96.1	91.9	97.9	75.0	80.0	40.9	90.0

Data type III (Halle)

Classification \ Reference	MFH-B	MFH-O	MFH-TR	MFH-IR	MFH-HR	SFH-D	SFH-SD	SFH-T	RH	IC	SP	Sum	UA[%]
MFH-B	5774	30	49	30	0	13	0	2	8	207	7	6120	94,4
MFH-O	9	771	4	6	0	62	3	1	25	114	2	997	77,3
MFH-TR	33	4	2514	0	0	1	4	2	0	11	0	2569	97,9
MFH-IR	17	2	0	4436	0	0	0	0	0	30	0	4485	98,9
MFH-HR	0	0	0	0	12	0	0	0	0	0	0	12	100,0
SFH-D	5	159	6	0	0	4308	19	3	188	317	2	5007	86,0
SFH-SD	0	22	3	0	0	46	3792	12	29	45	0	3949	96,0
SFH-T	2	11	5	0	0	3	16	3410	2	8	0	3457	98,6
RH	9	30	0	0	0	97	10	0	977	182	0	1305	74,9
IC	180	203	15	25	1	386	65	11	347	9283	48	10564	87,9
SP	6	13	0	3	0	11	0	0	7	5	1120	1165	96,1
Sum	6035	1245	2596	4500	13	4927	3909	3441	1583	10202	1179	39630	
PA[%]	95,7	61,9	96,8	98,6	92,3	87,4	97,0	99,1	61,7	91,0	95,0		

Ø Overall Accuracy (SD) 91,8 %(±0,5)

Ø Cohen´s Kappa κ (SD) 0,90 (±0,01)

Figure 5. Confusion matrix of the data-set of the city of Halle (data type III).

In urban areas a PA of more than 90% could be achieved for the majority of classes using the input data types III–V. In particular, the classes of residential buildings MFH-B, MFH-TR, MFH-IR, SFH-D, SFH-SD, SFH-T and the non-residential classes IC and SP can be predicted very well. A lower accuracy is observed for the frequently underrepresented classes of multi-family houses (MFH-O), rural houses (RH) and high-rise buildings (MFH-HR). The class-specific accuracy of the building footprints from topographic maps (input data types I and II) is lower for all classes. As an example, Figure 5 shows the confusion matrix of the data-set of the city of Halle (data type III).

4.4. *Influence of training data size*

A variation of the training data-set size shows that the overall accuracy is increasing and converges to the accuracy achieved with a theoretically infinite training data-set (cf. Hecht, 2014, Section 8.4.3.2). Experiments on data type III show that 625 training objects in total (buildings with class labels) are sufficient to train a classifier with an accuracy of about 80%. Using 2500 training objects, the achievable accuracy raises up to 85%. In case of 10,000 available training objects, an accuracy gain of 5% points (total 90%) could be observed. The collection of training data is a time-consuming process and induces costs for human resources. Of course, this data-rich situation requires much more human resources for training data collection and consequently leads to higher costs.

5. Discussion

The type of data-set used has a great influence on the classification accuracy, since they differ in information content and geometric representation of the buildings. The classification accuracy increases with the amount of information provided by the numerical features. For all three cities comparable accuracies could be observed. Using buildings from ATKIS® Basic DLM (data type III) the accuracy was 93.6% for Krefeld, 91.8% for Halle and 90.4% for Dresden. Using buildings from DTK25-V similar accuracy ratios could be obtained for Dresden (78.9%), Krefeld (76.6%) and Halle (76.6%). Assuming the availability of a sufficiently large training data-set, comparable accuracy rates can be expected for other German cities, too.

Transferability plays an important role in practice. Experiments have shown that the transferability of trained classification models to other cities is limited due to regional factors on urban structure (Steiniger et al., 2008). Transferability is only given for cities with a similar building culture and history (see also Hecht, 2014). For a German-wide building classification, regional differentiation and the collection of training data in these regions is necessary.

6. Conclusion and outlook

The current state of research shows that only a few studies exist that make use of methods of pattern recognition and machine learning for building classification. Many approaches rely on knowledge-based models and are less flexible in practice (e.g. changes in input data or the building types to recognize). Furthermore, most approaches lack a critical accuracy assessment using independent validation data. Therefore, emphasis was put on flexibility, automation and reliable validation. The approach draws upon spatial base data from NMCAs. Therefore, the procedure is area-wide applicable in Germany and countries with comparable data. VGI and the Open Data Initiative in Europe open up new possibilities of application. Several EU countries already provide free access to vector building footprint data, such as Denmark, Great Britain, Finland, France and the Netherlands. Further, large amounts of historical topographic maps are digitally available through libraries and NMCAs. This offers the possibility of multi-temporal analysis at the building level. However, the acquisition of building footprint information from topographic maps of different ages with heterogeneous graphical representations remains a challenging task (Herold, Meinel, Hecht, & Csaplovics, 2012). This requires more enhanced and adaptive cartographic pattern recognition approaches for building footprint retrieval currently investigated by Herold (2015).

The results show that automatic classification of building footprints is possible with an accuracy of about 90% combining spatial analysis, methods of pattern recognition and machine learning. It opens up a wide range of application scenarios (quantitative urban research, urban and regional planning, infrastructure planning, geomarketing, energy modeling, risk assessment, monitoring, etc.). Further research on the applicability to other problems, building typologies, data and research areas is needed. Particularly, the integration of additional data (roof type information from 3D city models in LoD2, parcel geometry, remote sensing imagery, semantic information from OSM, company data) may enhance the model in future.

The automatic classification contributes to the small-scale description of settlement structures relevant for research and planning. It is therefore possible to implement it within the framework of existing monitoring systems such as the *Monitor of settlement and open space development* (www.ioer-monitor.de) (Krüger, Meinel, & Schumacher, 2013). Based on the classified building stock estimates of the floor area ratio, building volumes or other dwelling/population densities can contribute to a more detailed representation of the settlement. However, for a nationwide classification of all building footprints more research is needed. Thus, suitable strategies should be developed to overcome the regional differences in the urban structure.

ORCID

Robert Hecht http://orcid.org/0000-0001-8420-7233
Gotthard Meinel http://orcid.org/0000-0002-9201-7664
Manfred Buchroithner http://orcid.org/0000-0002-6051-2249

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Disclosure statement

No potential conflict of interest was reported by the authors.

Notes on contributors

Robert Hecht studied cartography with focus on GIS. He received his Ph.D. degree from the Faculty of Environmental Sciences, Dresden University of Technology, Dresden, Germany, in 2013. He is now a researcher at the Leibniz Institute of Ecological Urban and Regional Development in Dresden. The main emphases of his research are on applied spatial modeling, machine learning, geovisualization, indicator development, remote sensing and LiDAR technology.

Gotthard Meinel received his Ph.D. degree in image processing from Dresden University of Technology in 1987. Later he has been a postdoctoral researcher in biomathematics und technical informatics. Since 1992 he has been the project leader in the field of informatics, GIS and remote sensing at the Leibniz Institute of Ecological and Regional Development in Dresden and since 2009 Head of the research area 'Monitoring of settlement and open space development'. He is a specialist in the field of land-use monitoring, indicator development, spatial analysis and visualization technologies. He has published more than 100 research papers in journals and refereed conference proceedings.

Manfred Buchroithner received a degree in geology and paleontology from the University of Graz, Graz, Austria, a degree in cartography and remote sensing from the University of Twente, ITC, Enschede, NL, and his Ph.D. degree from the University of Graz in 1977. In 1982, he was Fulbright Postdoc in Fort Worth, TX, Denver, CO, and Stanford, CA. He is currently Full Professor at and Director of the Institute for Cartography, Dresden University of Technology, Dresden, Germany. Before joining TUD he was Director of the Institute for Image Processing and Computer Graphics of Joanneum Research, Graz. His main research interests cover all aspects of the use of geovisualization, multisensoral remote sensing data for cartographic applications, autostereoscopic cartographic displays and high-mountain cartography, specializing in glacier monitoring.

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