A GEOBIA APPROACH TO MAP INTERPRETATION – MULTITEMPROAL BUILDING FOOTPRINT RETRIEVAL FOR HIGH RESOLUTION MONITORING OF SPATIAL URBAN DYNAMICS

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ABSTRACT:

This paper presents a GEOBIA approach to multitemporal map interpretation. Besides archival remote sensing imagery, cartographic representations of Earth's surface are unique sources of information on the long term evolution of geographical features. The knowledge about changes of features such as land cover, coast lines, or the extension of human settlements is essential to the understanding of their dynamics. Currently, large amounts of scanned map documents are being made digitally available through libraries or national mapping agencies. To access the information for spatial analyses and change detection, advanced pattern recognition algorithms have to be applied. Thus, automated map interpretation has been a vivid research field over the past decades. However, the acquisition of spatiotemporal information from multisource and heterogeneous image data still remains a challenging task. Algorithms have to deal with varying object representations as well as coalesced and blurred objects. In this study, we investigate the potential of an object-based image analysis and change detection methodology to deal with these issues for small areal entities. We apply a segment-based classification in order to retrieve building footprints from a multitemporal series of topographic maps. Subsequently, the objects of different points in time are compared by their geometric features to detect changes in an operational way. The achieved automation enables retrospective analyses of urban land use change on a regional and, even, national level. The combination of the retrieved historical knowledge and up-to-date information from remotely sensed imagery indicates great potential not only for decision-support and monitoring applications, but also for large scale urban land use modelling.

1. INTRODUCTION

Urban population and areas worldwide are growing at unprecedented rates causing a range of environmental and social issues (United Nations, 2010). Recently available very high-resolution (VHR) and hyperspectral remote sensing imagery and state-of-the-art image analysis techniques (Benediktsson et al., 2005; Hay et al., 2005; Blaschke, 2010) will allow monitoring of urban areas on building level (e.g., Doxani et al., 2012). However, in order to understand the underlying patterns and spatial dynamics of urban growth, detailed information on the previous evolution of human settlements are of great value and importance (e.g., Pumain et al., 1986). To date, our understanding of how cities evolve is still inadequate (Batty, 2008).

Besides archival aerial imagery, topographic and cadastral maps have, despite inherent uncertainties and generalization, proven a valuable source for retrieving the evolution of geographical features for long periods of time (Kienast 1993; Neubert & Walz, 2002; Witschas, 2003; Podobnikar & Kokalj, 2006; Perret et al., 2009). However, spatial analyses and change detection using historic geographic information are widely restricted to local case studies.

To reduce the manual digitalization and to access the map information more efficiently, sophisticated methods for automatic selective or complete map interpretation have been developed, e.g., in Yamada et al. (1993), Ablameyko et al. (1994), Samet & Soffer (1996), Frischknecht & Kanani (1998), Gamba & Mecocci (1999), Leyk et al. (2006), Chiang & Knoblock (2009), Meinel et al., 2009, and Pezeshk & Tutwiler (2011). The proposed approaches yield high recognition rates for the respective objects of interests, yet often rely on a single type of map layout. The extraction of geographical features from multitemporal, heterogeneous, and low quality scanned maps still remains a challenging task. Additionally, when aiming for long term change detection of small areal entities, inhomogeneities such as varying and blurred object representations have to be taken into account. Thus, the object extraction algorithm has to be readily adaptable as well as it has to make use of spatial context.

Template matching based approaches have been successfully used for unitemporal map interpretation (e.g., Frischknecht & Kanani 1998). However, when applied to heterogeneous data sets, the templates used for recognition have to be manually redefined. This can be a complex and time-consuming task. Easier adaptable, supervised pixel-based classification strategies are lacking the incorporation of spatial context leading to unacceptable recognition rates for complex and low quality images. Geographic object-based or object-oriented analysis techniques combined with advanced classification algorithms have proven in many studies to overcome some issues related to pixel-based approaches (e.g., Blaschke et al., 2008). The aim of this study is to investigate the potential of the object-based

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analysis concept for the interpretation of multitemporal map image data sets. To this end, an adaptable, object-based approach to automated extraction and change detection of small areal geographical entities such as building footprints is presented. Figure 1 shows an outline of the general concept.

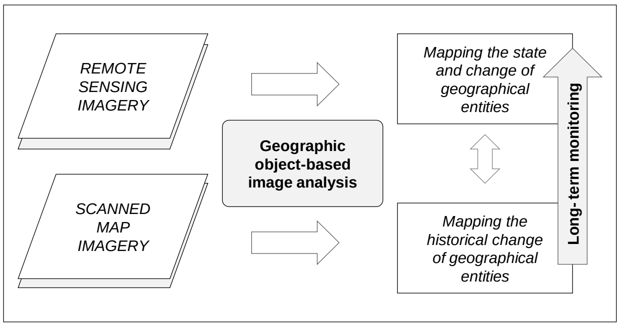

Figure 1. Concept of long-term retrospective monitoring

2. METHODOLOGY

The methodological approach comprises two fundamental steps. First, an object-based classification of each of the multitemporal map images is applied to extract the objects of interest (2.1). Second, a change detection algorithm based on features vectors of the retrieved objects in different points in time is employed (2.2). In the following, the methodology is described in detail. Figure 2 gives an outline of the overall workflow.

2.1 Image segmentation and object-based classification

In our approach we aim at a generic application to multisource data sets. The input data can be either color or grayscale imagery of varying qualities and mapping densities. Depending on the type of data, the algorithm should select the best suitable object extraction method. In order to avoid the above stated disadvantages of pure template matching based or pixel-based classification strategies, we apply color and morphological image segmentation. Subsequently, the resulting, meaningful segments are classified based on their geometric and topological features using a supervised classification strategy.

For color image segmentation we use an edge-oriented region growing algorithm proposed by Lanser (1993). The algorithm has been adapted for remote sensing imagery in Herold (2005) and evaluated to other segmentation algorithms in Marpu et al. (2010). In contrast to other segmentation approaches (e.g., Ablameyko et al., 1994), the map image segmentation is based on the CIElab color space. To separate areal from linear features in grayscale images, morphological image segmentation and filtering using a varying structure element can be applied. In many maps, buildings and other map objects are modeled as a single layer, i.e. they are represented by the same color or gray value, respectively. That is, the objects derived from primary image segmentation may comprise both building footprints and morphological similar areal entities such as characters or symbols. Thus, the resulting entities are denoted as candidate objects and have to be further classified into a set of buildings and a set of non-building objects.

The classification of candidate objects into building footprints and other areal entities is based on the object features. Thus, for all segmented objects, i.e. candidate regions, a set of normalized geometric and topological features is computed and stored in a feature vector. An object classification can be performed by applying either a knowledge-based or a data-driven, machine learning based strategy. The latter can readily be trained by user provided sample objects and, thus, adapted to varying layouts without manually rebuilding a knowledge base or iconic templates. Here, exemplarily a multilayer perceptron (feed-forward artificial neural network, ANN) based classifier with back-propagation for supervised learning (Bishop, 2006; Steger et al., 2008) is employed.

2.2 Object-based change detection

For change analyses, a spatiotemporal database has to be built from the retrieved building footprints of each time step. Starting from each object in the most recent dataset, object existence in the older data sets is checked. The procedure is referred to as backward editing in manual digitization of multitemporal data sets. To automate this process for relatively small areal objects

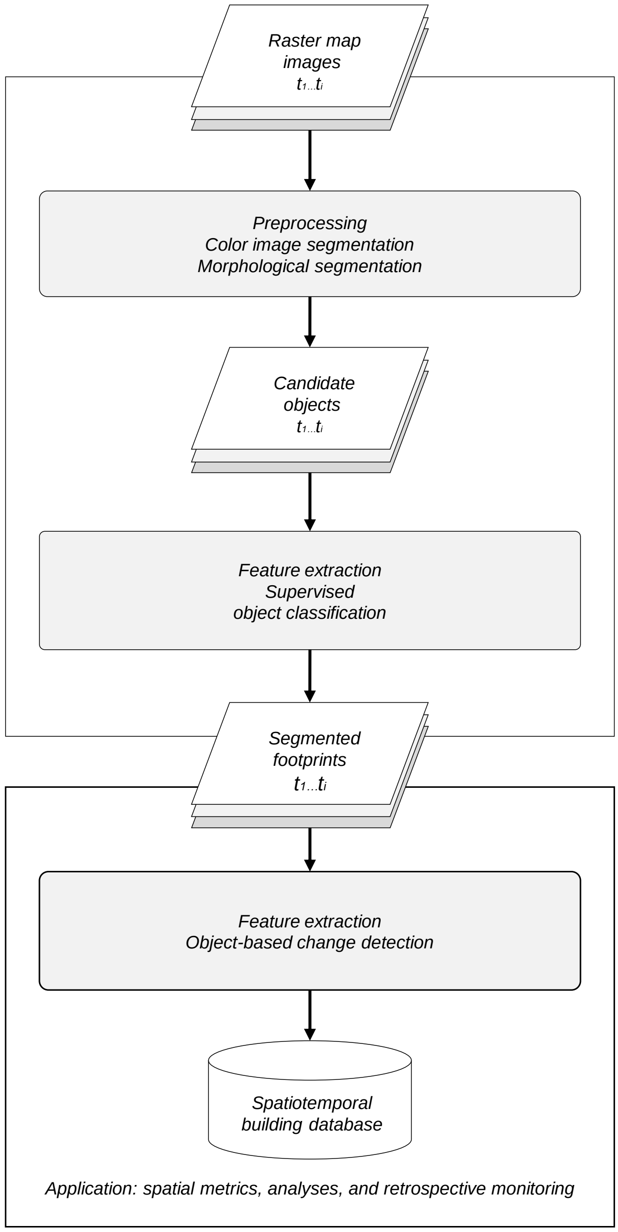

Figure 2. Conceptual outline of the proposed methodology

such as buildings, an object-based instead of a pixel-based strategy is suggested (Niemeyer et al., 2007). Object-based change detection has successfully been applied for building footprints derived from remote sensing data, e.g, multitemporal LiDAR data (Rutzinger et al., 2010). When applied to objects extracted from heterogeneous data sets, location based object comparison may fail since they considerably overestimate the amount of new buildings. This is because non-overlapping but homologue object representations in different points in time may occur. Spatially non-overlapping objects are caused by:

- differences in object representation between the multisource data sets, and,
- the maximum spatial uncertainty can be larger than the dimension of the objects of interest.

In these cases, the comparison of potentially homologue (identical) objects has to be based on not only proximity but also geometric similarity measures. For fuzzy comparison of multilevel data, the following similarity measures have been suggested and applied in studies (Maruca et al., 2002; JCS, 2003; Revell & Antoine, 2009): (1) the *centroid distance* as the distance between the centroids of the two objects; (2) the *Hausdorff distance* as the greatest local deviation between two geometries; (3) the *symmetric difference* as the total area of the non-overlapping portions of the two geometries; (4) the *symmetric difference centroids aligned* as the distance between the centroids of the two objects that have been shifted such that their centroids are coincident; (5) the *compactness* as the ratio of object area to object perimeter, and (6) the *angle histogram* as the histogram of the angles that the objects outline segments have with the positive x-axis, weighted by segment length. Potentially homologue objects are rated by similarities of the six measures. Objects with low matching rates, i.e., potentially without representation in the old data set, are marked as new objects within the respective time period. Thus, the number of misclassified objects will be reduced.

3. RESULTS AND DISCUSSION

The methodology has been implemented using the machine vision and image analysis software MVTec HALCON and geoprocessing scripting engine in ESRI ArcGIS. For change detection considering non-overlapping identical objects, the Java Conflation Suite (Vivid Solutions) has been tested within the open source GIS framework OpenJUMP. As a proof of concept, we employed the proposed methodology to a series of German 1:25K topographic map images covering varying layouts and a time span of three decades. The temporal resolution of the data sets averages five years. The resolution of the imagery was 20 lines/mm, which equivalents to 508dpi. To reduce the computational efforts, the area of interest in each map data set was limited to the recent extension of built-up areas using land use data from a digital topographic database.

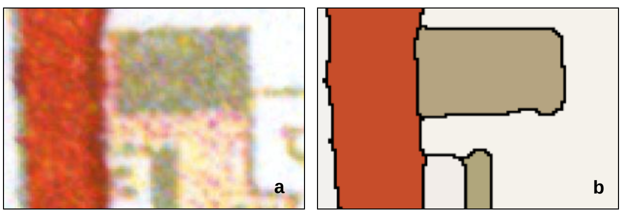

Figure 3. Subset of the original (a) and the segmented image (b)

The evaluation comprised both the detection of objects at each point in time and the correct detection of change. Manually segmented footprints and an up-to-date cadastral building database serve as reference. Precision rates (*true positive* / (*true positives* + *false positives*) $\in [0;1]$) and recall rates (*true positives* / (*true positives* + *false negatives*) $\in [0;1]$) are used as quality measures. The measures correspond to correctness and completeness, respectively, suggested in Heipke et al. (1997). Experiments yield very low omission and acceptable commission error rates (precision = 0.943, recall = 0.997, number of reference objects = 4,452). In general, the precision rate for change detection heavily depend on the object size, correct delineation and the positional accuracy of the source data. Here, ancillary data such as the street network could be supportive to minimize the commission errors in case of low quality or poorly georeferenced data sources. Figures 4 and 5 exemplarily show visualizations of the change detection result. Table 1 gives the precision rates for different building footprint sizes.

Figure 4. Building object-based visualization of urban growth. The temporal information on the construction period of newly constructed buildings (in red) is inferred by operational object-based comparison of segmented footprints from historic maps.

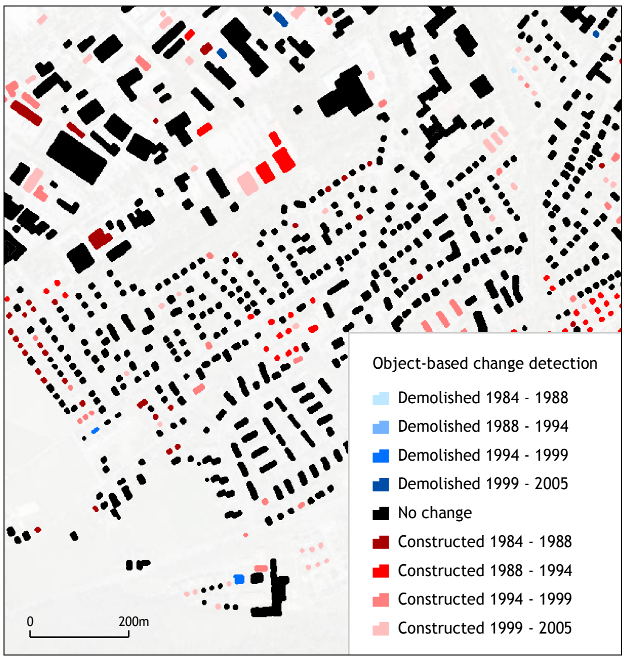

Figure 5. Sample result of building-based change detection

Building footprint size a (in m²)	Precision (Correctness)
$50 < a \leq 200$	.8429
$200 < a \leq 300$	.9667
$300 < a \leq 400$	.9623
$400 < a \leq 500$	.9905
$500 < a \leq 600$	.9425
$600 < a \leq 700$	.9740
$700 < a \leq 800$	.9831
$800 < a \leq 900$	.9902
$900 < a \leq 1{,}000$	.9772
$1{,}000 < a \leq 10{,}000$	.9859

Table 1. Precision rates for different building footprint sizes

In contrast to the recall rate, the precision rate gradually varies across different footprint sizes. This is because the amount of areal objects representing non-building objects varies across the classes leading to differing commission errors (false positives) within the respective size range.

To date, the approach is limited to the proof of object existence. Structural changes of buildings over time are not yet considered in the model. For further optimization, the segmentation result of the most recent data set could be used to refine parameterizations of the algorithm for the older data sets.

4. CONCLUSIONS

This study presented an object-oriented approach to multi-temporal map image interpretation. We developed and applied a methodology in order to detect the evolution of urban areas on building level from historical data sources in an operational way. The findings and the achieved automation enable micro-scale retrospective analyses of urban land use dynamics on a regional and, even, national level. The operational application of the approach and its results will support a nationwide land use monitoring system for Germany, proposed in Meinel (2010). The combination of retrieved historical knowledge of geographical features and up-to-date information retrieved from remotely sensed imagery indicates great potential for decision-support, monitoring applications, and large scale urban land use modelling. Furthermore, the research suggests that the concept of GEOBIA is not only suitable for the analysis of very high resolution remote sensing imagery, but also for the multi-temporal interpretation of cartographic representations of the Earth’s surface.

Current research encompasses further generalization of the segmentation algorithm, its hierarchical extension, the optimization of the change detection algorithm, and a machine learning approach to the building type classification. Future research will focus on the extraction of linear geographical objects such as urban blocks and streets as well as a spatial data mining approach to detect patterns in the retrieved urban change information.

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