Automated generation of urban Land Cover Maps and their enhancement and regularization

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Abstract

The aim of this article is to automatically generate and update Land Cover Map data for urban areas. The introduction examines the state of the art with a focus on enhancement of the classification results. The materials and methods of the processing are explained using a practical example. The applied classification method uses 18 features (normalized difference vegetation index, height above terrain and 16 attributes generated from four spectral bands) for each pixel of a digital true ortho-image. When training the classifier, only three small image patches per class were used. The enhancement of the classification results takes place in three steps. The first two steps create raster maps with smoothed outlines and generalized content. In the third step, straight, orthogonal, and parallel vectors are created for the outlines of buildings. The produced Land Cover Map of an urban area was checked for completeness and geometric accuracy. All buildings were detected, and the calculated standard deviations of building corner coordinates were $\sigma_E = 1.0$m and $\sigma_N = 0.8$m when the true ortho-image was used as reference. Possible improvements regarding source data, classification method, and enhancement are discussed. All processing can be done by open-source software, and a developed software package including documentation and examples can be downloaded from the Internet for own use. The results of this work can inspire both mapping organizations and amateurs to produce up-to-date thematic and topographic map data inexpensively and quickly.

Keywords Aerial image   Classification   Land Cover Map   Enhancement   Regularization   Automation

Introduction

Land Cover Maps (LCMs) may be derived from aerial and satellite imagery. Urban areas are of particular interest because there often occur changes due to construction work and the value of the ground is much higher than in other areas. Digital data of the actual land cover are of utmost importance. The data are stored in databases and can be further analysed in Geographic Information Systems. Topographic map data may also be used or derived from such data. High thematic, geometric, and cartographic accuracy is then required, and an enhancement of the classification result becomes necessary. It includes the removal of unwanted content and the generalization of the objects. Furthermore, the generation of vectors and other geometric elements must be created for artificial objects such as buildings, roads, and other man-made structures. Other requirements are high speed of operation and high degree of automation.

The task of automatically creating LCMs of high semantic, geometric, and cartographic quality has occupied several research groups. Very different methods have been developed. To achieve good geometric accuracy, the DSM-based orthoimage is used as source data. The availability of free DSM-based ortho-images may be supported by governmental mapping organizations. In this contribution only such data are used and discussed. Recent developments regarding the automated classification of imagery are presented in the following. Basically, two types of algorithms have been applied, Machine Learning (ML) or Deep Learning (DL). In ML, one must train a classifier by means of some samples for each class. Some features (attributes), which characterise the classes, are selected in advance. The class labels are known in the training areas but the class labels in other areas are predicted by a classifier using the values of the features at this position. At DL the algorithm learns on its own. It is more accurate but requires bigger amount of data than a ML-algorithm. In this article, only ML methods are discussed and used. Its algorithms are simpler and more transparent. An introduction to various ML-methods is given in (Höhle and Damodaran 2023). The book also contains the URLs of open-source software of five other ML-methods (Decision Tree, Support Vector Machine, Random Forest, PerTurbo, and Large-Scale Support Vector Machine using random Fourier Features). Supplementing data for running examples are taken from the ISPRS 2D Semantic Labelling Benchmark (ISPRS WG III/4 2012-2016). To achieve good classification results, the selection of attributes (features) that characterize the classes and distinguish them from other classes is very important. For example, the Normalized Difference Vegetation Index (NDVI) can detect vegetation. Using object height is very useful for detecting buildings and other elevated objects (Höhle and Höhle 2013). Other valuable attributes are the morphological attribute profiles (APs) which remove small gaps in object areas. The APs have been introduced to classification by (Dalla Mura 2010) and used with success by other authors, e.g., (Ghamisi et al. 2014), (Damodaran et al. 2017).

The resulting LCMs will need improvements regarding the smoothing of lines and generalizing of the content. Furthermore, man-made objects like buildings, roads, bridges, and walls should be resolved by points, lines, and other geometric elements. For example, all buildings should be represented by straight, parallel, and orthogonal lines. This regularization is the major contribution of this article. Research on this subject has been published by various authors, including Wang (2016), Tasar et al. (2018) and Mousa et al. (2019). Later articles on this topic are published by Höhle (2021) and Kong et al. (2023).

In (Höhle 2021), buildings are vectorized one by one after labelling connected pixels that represent building outlines. Using the Hough transform, several line segments are obtained, which may be part of the outline. An algorithm finds the right line segments. Their parameters are determined using least-squares adjustment and their sequence is derived by one of three methods. The successive lines are then intersected, and preliminary corner coordinates of the building corners are obtained. The orthogonality and parallelism of the lines are calculated again by least-squares adjustment. Multiple tests of intermediate results ensure reliable results. Standard deviations $\sigma_x = 1.2$m and $\sigma_y = 1.0$m were determined with the ISPRS test data "Vaihingen". The methods and results of the above authors were discussed.

Kong et al. (2023) deal exclusively with buildings with orthogonal lines. Their applied methodology overlays the derived outline with a dense grid and determines for each cell of the grid whether it contains building information or not. The applied algorithms reconstruct all segments of the outline and sorts them thereafter. The generated outline is simplified by selecting a threshold for the minimal length of the line segments. The method is tested on a large data set and the obtained results are compared with the methods of other authors (Wang and Lee 2000; Yan et al. 2017; Bayer 2010; Shen et al. 2019).

There are many publications on detection and enhancement of buildings when airborne laser scanning (ALS) is used as an additional data source. Using ALS data in combination with images offers several advantages. Disadvantages are costs and therefore reduced availability of ALS data. There are also technical reasons for only using imagery. For example, if the images and laser footprints are not captured simultaneously, the elevation and position accuracy may decrease. Using ALS exclusively to generate LCMs may affect the detection of multiple objects (classes) because laser light is mono-colour light. In comparison, images can have multiple spectral bands and large spectral ranges in each of the bands. In addition, not all materials in the object space reflect the laser light sufficiently strongly, which can lead to gaps in the point clouds or inaccuracies in the elevation models due to interpolation.

The major goal of this investigation is the automatic generation of an urban LCM with many classes and of high geometric, thematic, and cartographic quality. The applied methodology classifies a true ortho-image of very high resolution. The focus in the article is on the enhancement and regularizing of the classification result. The processes involved in generating the LCM are illustrated using a practical example. The generated LCM with five classes ('building', 'impervious surface', 'low vegetation', 'tree', 'clutter/background') is automatically enhanced so that correct and geo-referenced land cover and topographic data of high quality can be transferred to databases and GIS.

Materials and Methods

In the following subsections, the methodology of the applied mapping method is presented and applied to a practical example. The source data and software tools are explained. The steps of the preparation and processing works are covered in detail.

Data sources

The data of the practical example comprise open-source data of the German mapping organization (LVermGeo Sachsen-Anhalt)[1]. The following test data were downloaded from their portal.

-Digital Ortho-image
-Digital Surface Model
-Digital Terrain Model
-Digital Topographic Map

[1] https://geodatenportal.sachsen-anhalt.de

The Digital Surface Model (DSM) and the ortho-image are produced from aerial images, which overlap 80% in flight direction and 60% across the flight direction. The aerial images have four bands (Red, Green, Blue, and Near Infra-Red). The relevant characteristics of these source data are given in the following subsections. The abbreviated names of the producer are in brackets.

Digital Ortho-image (DOP20)

The ortho-image has a patch size of 2km x 2km. Its pixels size corresponds to 0.2m x 0.2m on the ground. The ortho-images are generated with the help of the DSM. Hidden areas behind elevated objects, e.g., buildings, bridges, are filled with image detail from other images. Such ortho-images are also referred to as True Digital Orthophotos (TrueDOPs).

Digital Surface Model (bDOM20)

The used DSM is generated from aerial images by Dense Image Matching. It is structured as a regular grid of elevations. The spacing between the elevations is 0.2m on the ground. The accuracy of the elevations is quoted with σ_Z = 0.6m at non-vegetated areas. The elevation data are supplemented by the producer with the four channels of the orthoimage containing the intensity values in the range 0-255.

Digital Terrain Model (DGM2)

The acquired Digital Terrain Model is derived by laser scanning (lidar). The density of laser scanning is 4 to 12 points/m^2. The derived grid model has a spacing of two meters. Its accuracy is given by the producer as σ_Z = 0.2m for flat areas and σ_Z = 0.5m for areas with steep slopes or of dense vegetation.

Digital Topographic Map (DTK10)

The analogue map in scale 1:10000 has been scanned and is available from the data provider as digital raster map. The resolution is 0.5m per pixel. The map contains buildings, roads, and vegetation. The content of the map has been updated in 2022, which is the same year as the photography for the DOP20 production took place. The updating has been done by means of the true ortho-image (TrueDOP) and manual digitizing. The planimetric accuracy is quoted with ± 3m for well-defined objects. In our investigation the DTK10 will be used as reference.

Preparation work

The source data must be modified for our task. It concerns changes in the content, size of area, number of channels, and the resolution of the data.

Selection of example

The selected example must contain an urban area with buildings, roads, and vegetation. These objects should be different in size and shape. Most important, the data should be open-source.

Reduction in size and bands

The downloaded ortho-image has 10000 x 10000 pixels. Processing matrices of this size can cause delays in operations. Therefore, in our case, a computer with 16 GB of RAM, the example is reduced to 1250 x 1300 pixels, which in nature corresponds to 250m x 260m. The reduction is carried out by image processing software. The downloaded orthoimage contains four bands (R,G,B,NIR). For representation of the ortho-image in natural colours the infra-red band is removed. The selected test area is depicted in Fig. 1. It has several detached houses, roads, grass and bush areas, high trees, and some other objects (cars, swimming pools, etc.) Only completely imaged houses will be mapped in the example. Large trees are present in the ortho-image, some cover the edges of the buildings. The enhanced LCM must have the complete outline of all buildings after the principle in mapping that harder objects have priority.

Densification

The pixel size of the ortho-image is 0.2m x 0.2m. The other data for the generation of the LCM must have the same density. The given DTM with a spacing of 2m must therefore be densified to 0.2m spacing. This is carried out by applying linear interpolation.

Derivation of normalised DSM (nDSM)

The availability of the DGM and DSM, both now with the same density, allows the derivation of the nDSM. This is achieved by differencing the two vectors (see Eq. (1)).

$$nDSM = DSM - DGM \tag{1}$$

Each cell has then a height above ground, which is used as a feature in the classification. The maximum value in the test area is 21m.

Derivation of the Normalized Difference Vegetation Index (NDVI)

The NDVI is derived from the intensities in the NIR-band and the Red-band according to Eq. (2).

$$NDVI = \frac{I_{NIR} - I_R}{I_{NIR} + I_R} \tag{2}$$

where

I_{NIR} = intensity in the NIR-band,
I_R = intensity in the R-band.

The units of I_{NIR} and I_R are digital numbers (DN) in the range 0-255.

The NDVI values are used in the classification as features.

Methodology

There are two tasks to solve in our topic, the generation of the LCM by classification and the enhancement of the generated LCM. The methods used are described in the following four subsections. Their presentation is based on the example data.

Classification

For each pixel of the LCM a class value must be derived. It is found by the classifier Decision Tree (DT) which analyses several attributes (features) to be generated for each pixel of the LCM. The classifier must be trained by some samples for each of the selected classes. The DT is a method of ML. A detailed description and open-source scripts of the DT-method is given in (Höhle and Damodaran 2023).

The attributes should characterize the selected classes and increase the discrimination between the classes. In this contribution we use the intensity values of the four bands, nDSM, NDVI, and Attribute Profile (AP). The APs are generated for the four bands of the ortho-image applying three thresholds for an area-attribute. A thinning operation (maxTree) is applied which merges the connected pixels of smaller areas to the connected pixels of lower intensity. This filtering will remove small bright areas in the ortho-image bands. In our example 18 attributes (features) are applied and the selected thresholds of the area attribute (also denoted as area-criterion) are 1.4m x 1.4m, 2.4m x 2.4m, and 5.5m x 5.5m on the ground. This filtering is a spatial operation which takes the neighbourhood information in the ortho-image into account. To train the classifier, some pixels of known value must be collected. In the example, three patches per class are taken. Each patch consists of 11x11 pixels, resulting in a sample size of 1815 pixels for the five classes. By means of the true values of pixels and the feature vector the DT is derived. Fig. 1 depicts the ortho-image together with the selected patches. The selection of the patches of pixels should be taken with great care. For example, places in the shadows behind buildings or trees should be avoided. Furthermore, the selected pixels should not be neighbours in the patches.

Enhancement

The enhancement can be carried out in three steps. In the first step, morphological operators are applied, in the second a generalization of the content and in the third the formation of vectors. Each class is processed separately and not all classes need to have all three steps. Artificial objects consisting of geometric elements require the third step. The morphologic operations of step 1 are dilation and erosion. In our example, they are carried out in this sequence. This process, also called closing, smoothes the object's boundaries and closes small gaps within areas. The selected structuring element has a diamond shape and a size of 5 x 5 pixels. The second step generalizes the content. This is achieved by segmentation. Connected sets of pixels get a label and the enclosed area is filled with pixels of foreground (I=1). A threshold for area removes all objects of smaller size. In the example, the threshold is selected with 300 pixels (=3.5m x 3.5m) for class ‘building’ or with 500 pixels (diameter of circle = 5m) for the other classes. In the third step, the artificial objects such as buildings, roads and walls are vectorized. The used methodology is based on straight lines which are described by the Hesse normal form. The user of the software prepares the processing by selecting appropriate methods and parameters to adapt to the specifics of the imaged objects.

Fig. 1 Ortho-image and patches of pixels for the selected classes (green: 'building', red: 'impervious surface': white: 'low vegetation', yellow: 'tree', blue: 'clutter/background') for the derivation of the DT.

The detection of the lines that form the outline of the object is done using the Hough transform. Each object is processed separately. Its main line is selected from the range of the ten longest lines, the other lines of rectangular objects are found automatically. Short lines of other orientation than the main line may need to be determined by measurements. The final line parameters (angle and distance of the normal to the line) are derived by minimizing the orthogonal distances to the line. The derivation of the equations can be found in (Borre 1992).

The order of the lines in the polygon can be done using three different methods (angle, distance, line following). A decision tree selects the most likely one. Subsequent lines are intersected, and parallelism and orthogonality of the lines are established by least-squares adjustment. The applied method is published in (Kraus 2000). The
user can monitor the intermediate results, which are displayed graphically along with a section of the ortho-image.

A collection of open-source scripts is provided (see subsection 2.4.2). Default values for the resolution of the Hough parameter space are five degrees and five pixels, and fifteen pixels (=3m) for the shortest line segment to be detected.

Generation of a vector with all classes

To derive the final LCM, a single vector with all class labels must be formed. Each class with its label (1-5) is extracted from the LCM generated in steps 1 and 2. Fig. 2 shows the matrices of the five classes. The matrices are converted into vectors, which are added one by one to a 0-vector. This vector with all class labels is then again transferred to a matrix and the LCM can be plotted using a palette of suitable colours. At the end the polygons of the man-made objects (buildings) are added.

Quality control and checking

To achieve optimal results for the final LCM, quality control is an important part of the processing. It should be done for the input data, the intermediate results and for the LCM. The methods may be visual or by metrics.

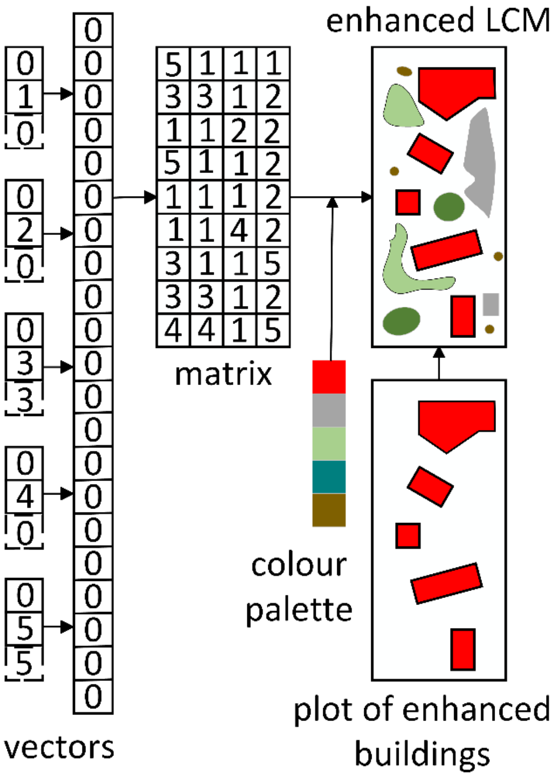

Fig. 2 Derivation of enhanced LCM from vectors for each class labelled by a number

Both tests require reference data, which should preferably be independent. The applied methods should follow statistical rules.

In general, the differential rectification and the mosaicking deteriorates the image quality available in the aerial images. The visual check of the other input data (DSM, DTM, DTK) is carried out to detect missing and obsolete data or displacements. The checking of the LCM's thematic accuracy requires a sample of reference data. These test pixels must be independent of the pixels used for training. The size of the sample must comply with statistical rules to obtain reliable results. A formula for sample size (n) is given in (Congalton and Green 2009). The desired confidence level, precision, and the size of the classes are the parameters in Eq. (3).

$$n = \frac{B}{4 \times b^2} \tag{3}$$

where

n = sample size
$B = \chi^2_{(1-\alpha/k,\, m)}$
$1 - \alpha$ = desired confidence level
k = number of classes
m = degree of freedom
b = desired precision of the entire sample

The value for B can be taken from a χ^2-table, which is contained in textbooks of statistics or adjustment theory, e.g., in (Mikhail 1976). At Eq. (3) is assumed that the class area is 50% of the entire population (worst-case scenario). A provided open-source program will calculate the required sample size (see section 2.4.1).

As accuracy measure of the thematic accuracy, we use the F1 score (see Eq. (4)) together with its 95% confidence interval (CI).

$$F1 = \frac{2tp}{2tp + fp + fn} \tag{4}$$

where

tp = number of true positives
fp = number of false positives
fn = number of false negatives.

The values tp, fp, and fn are contained in the confusion matrix.

Determination of thematic accuracy for the enhanced LCM (after steps 1-3) is not performed because smoothing of lines and generalization of content introduce errors. The test of the geometric accuracy of the derived LCM requires references of superior accuracy. The applied accuracy measures in the example are the standard deviation and the number of gross errors. Gross errors are defined by $>3\sigma$. All available corners of a selected area shall be tested. Only corresponding corners will be compared.

Applied software

The applied software is a combination of existing tools and scripts for the classification, enhancement and quality control written in "R", which is a free software environment for image processing, graphics, and statistical computing (R Core Team 2024). Many open-source R-packages are available on the Comprehensive R Archive Network (CRAN)[2] and can be downloaded from a nearby server.

Software for classification

A collection of classification software including DT is described in (Höhle and Damodaran 2023). The DT software is based on the R-package "rpart", which is described in the documentation of "R". Free R-software for DT and other classification methods are available on the Internet.[3] Software for deriving APs as well as example data for classification work are included in the free tools.

Software for enhancement

A collection of R-scripts for improving classification results called "buildenh_v1.3" is open source and can be downloaded from the Internet at the same address as before[4]. Example data are included.

Software for image processing and GIS

Other open-source tools used for achieving our goal are EBImage, spatstat, and Quantum GIS (QGIS). EBImage[4] is a processing and analysis toolbox for "R". A description of the functions is available from the producer. It is applied in our example for the enhancement of all classes in raster format (steps 1 and 2). Spatstat is a family of R-packages for the statistical analysis of spatial point patterns. It is applied to solve the order of lines at the enhancement of buildings (step3). QGIS[5] is a widespread Geographic Information System. The visual check of the input data is carried out by this tool.

Software for quality control and testing

The quality control requires checkpoints. A script for the size for the sample, which realizes Eq. (3), is 'samplesize_1.R'. The thematic accuracy (F1-score) of the derived LCM is calculated by the script 'bh_confusionmat.R' together with its confidence intervals (CI). Both tools are contained in the free GitHub repository 'buildenh_v1.3'.

Results

Results of the selected example are presented in the following. Firstly, some observations regarding the quality of the input data are shared. Thereafter, the results of classification and of the three steps of enhancement are presented. The final LCM is tested on the geometric accuracy. In addition to the visual inspection, accuracy measures are derived.

Input data

Visual inspection of the ortho-image shows dense foliage in the vegetation and long shadows behind the elevated objects, which affect the results of DSM-generation and classification. In addition, some image errors are visible (see Fig. 1).

[2] CRAN - Mirrors (r-project.org)
[3] https://github.com/JoaHoe/EduServ17Mat/
[4] EBImage.pdf (bioconductor.org)
[5] https://qgis.org/

Some border lines of the buildings have wide white edges. The latter may be noticed on the short sides of the four long buildings in the centre of the ortho-image. The elevations behind tall buildings cannot be derived if the side overlap of 60% is used. Assuming an aerial camera with a field of view = 57°, the distance behind a building without ground elevations is then up to 22% of the buildings' height. In our example, where some buildings reach 16m in height, the distance is 3.5m or 17.5 pixels. This is the maximum value when the building is situated near the short side of the "net image". These gaps are closed by interpolation. The consequence of such stereo occlusion and inaccuracies due to interpolation is unsharp building edges. If the positions of all perspective centres are available, a visuality map can be generated where the obscured areas are shown (Nielsen 2004).

Classification

By means of the normalized feature vector generated for 1815 pixels, the DT is derived. Fig. 3 depicts the derived DT.

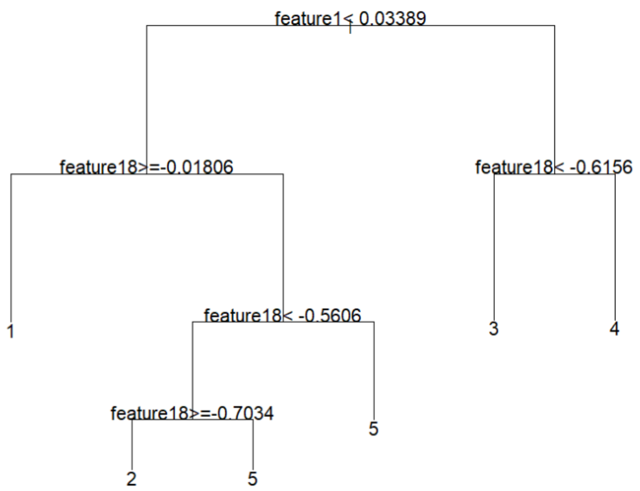

Fig. 3 Derived DT (class 1: 'building', 2: 'impervious surface', 3: 'low vegetation', 4: 'tree', 5: 'clutter/background')

The pruned tree uses thresholds for the feature 1 (NDVI) and feature 18 (nDSM) to decide which class value (1-5) is assigned to the pixel. The other 16 features (OrgImgAPs) do not appear in the final tree.

After all preparations the LCM has been generated. Fig. 4 depicts the derived (preliminary) LCM. The visual check reveals some misclassifications. The large buildings have all been detected, but some of them are deformed. Balconies and sunroofs have been classified as 'building'. The dark shadow areas behind buildings were in some cases classified as trees. Several cars have not been detected or were not assigned to the class 'clutter/background'. But cars are not permanent objects and are not part of the data used in topographic databases.

Fig. 4 Preliminary LCM. (red: 'building', grey: 'impervious surface', green: 'low vegetation', dark green: 'tree', brown: 'clutter/background')

The thematic accuracy is tested by check pixels. The required number of check pixels (sample size) using Eq. (1) and the parameters (k=5, m=1, α=5%, b=0.05) is n = 665 pixels or n_c=133 pixels/class. The practical test of thematic accuracy is carried out using six patches from which 22 pixels are randomly selected. The accuracy measure F1-score is calculated from the comparison between predicted and reference value at 660 pixels using Eq. (4). The 95% CI is derived from the confusion matrix using the function 'binom'. Table 1 displays both accuracy measures for the five classes.

Table 1 Thematic accuracy of the (preliminary) LCM

class	F1-score [%]	95% CI [%]
building	77	74-83
impervious surface	86	82-89
low vegetation	58	51-65
tree	74	69-78
clutter/background	53	46-59

The F1-score for the important class 'building' is 77% with 95% CI=74%-83%. The calculated CI of the F1-score is less than ±5%. The result can be considered as satisfactory for the enhancement of the classes using generalization and vectorization.

Enhancement by image processing and generalization

In the first step, the object's boundaries are smoothed and the small gaps within areas are removed. All classes still have irregular shapes and contain very small objects. Buildings smaller than 12m² and detached trees smaller than 20m² were removed in step 2. A combination of the generalized and preliminary result may be used to see the effect of the generalization. The class 'impervious surface' contains a mixture of topographic objects (roads, paths, parking places). Its use is mainly in hydrological studies. The classes 'low vegetation' and 'tree' are subject of continuous change in the real world. The images of the five classes after enhancement by steps 1 and 2 are raster maps. The class 'building' will be processed further to vector data.

Enhancement by vectorization and adjustment

The visual check of class 'building' revealed that all buildings larger than $12m^2$ have been detected. The buildings are still deformed, which is partially caused due to overhanging trees. After step 3, the building outlines are reconstructed and consist now of straight, orthogonal, and parallel lines (see Fig. 5). This is done by vectorizing and least-squares adjustment using the program package "buildenh". Before the generation of the final LCM the geometric accuracy of the class 'building' is tested. Two references will be used. The first reference is the digital topographic map (DTK10), the second one is the true ortho-image (see Fig. 1). The coordinates of 120 and 135 building corners are compared. Table 2 displays the results. Using the ortho-image as reference, the standard deviations of the coordinates are σ_E = 1.0m and σ_N = 0.8m. When the DTK10 is the reference, the standard deviations are slightly bigger (σ_E = 1.0m and σ_N = 1.4m). In both cases gross errors were excluded before the computation of the standard deviation. The digitized and transformed corner coordinates of the DTK10 are not of superior accuracy. The ortho-image is not an independent reference. The results correspond to the results which are obtained by other test material and similar methodology in the processing (Höhle 2021).

Table 2 Geometric accuracy of derived corner coordinates (E=Easting, N=Northing, σ=standard deviation, n=number, na=not available)

reference	**DTK 10**		**ortho-image**	
coordinate	E	N	E	N
σ **[m]**	1.0	1.4	1.0	0.8
n_{corner}	102		135	
$n_{gross\ error}$	5		4	
n_{na}	16		0	

After assessment of the enhanced class 'building', the final map is processed according to the methodology described in section 2.3.3. Fig. 5 depicts the result.

Fig. 5 Derived LCM with five enhanced classes (red: 'building', grey: 'impervious surface', green: 'low vegetation', dark green: 'tree', brown: 'clutter/background').

The final LCM is a considerable improvement of the classification result. The outlines of the buildings are reconstructed, and the other classes have smoothed line segments and generalized content.

Discussion

The major goal of this article is to produce and update digital LCM data automatically. The task is solved by enhancement of a classified ortho-image using generalizing the content and vectorizing man-made objects. Overlapping aerial photographs served as initial data. At many places they are taken at short intervals of time to ensure that derived products are up to date. The major advantage of this approach is that objects including all elevated ones (buildings, bridges, etc.) are correctly positioned, hidden parts are replaced, and that the processing is largely automatic. The other approach in photogrammetric mapping, to compile map data from aerial images by human operators using expensive stereo-systems is avoided. The consequences regarding completeness and geometric quality of the automatically processed map data must be known and this is another goal in this contribution. The article focuses on enhancement and vectorizing of the classification result. This enhancement may become necessary when the generated data should be used in databases and Geographic Information Systems. A practical example was used to demonstrate the potential of the selected approach.

The final LCM contains all buildings larger than the selected threshold ($12m^2$). The other classes have objects larger than $20m^2$. The test of the geometric accuracy revealed standard deviations of σ_E =1.0m and σ_N = 0.8m corresponding to 5.0 and 4.0 pixels respectively. The automated derived LCM is less accurate than one compiled by the traditional method. For example, the ISPRS test of digital aerial cameras yielded subpixel accuracy when well-defined objects like manhole covers were mapped by operators using stereo workstation (Spreckels et al. 2010). Improvements in the automated approach are still possible. They regard the source data, the preparations, the classification, and the enhancement. Image taking at overcast sky would eliminate long dark shadows behind the elevated objects, which will benefit the classification. The 80% side overlap for urban areas with building heights of 16 m could improve the building edges in the LCM and thus the geometric accuracy of the building corner coordinates. The quality of the DSM and of the ortho-image would improve, but additional costs are then also a consequence.

The generation of the nDSM required a densification of the digital terrain model (DGM). This processing took additional time but a density of 25 cells/m^2 is an advantage in comparison with other methods of data acquisition. The derivation of the preliminary LCM can be carried out by many other classification methods. DT is a simple but effective method. More important than the classification method is the selection of proper features. In our approach, Attribute Profiles (APs) were used for the four bands of the images. Another possibility is the use of APs on derived features like the NDVI. In (Damodaran et al. 2017) improvements in the overall accuracy of up to 7% have been achieved when using NDVIAP instead of the simple NDVI.

Improvements in enhancement are also possible. Steps 1 and 2 may become unnecessary if the classification result has better line quality and generalized content. And again, the quality of the classification result depends very much on the quality of the input data and the selected features. Regarding step 3, the enhancement of buildings and of other artificial objects, the reliable determination of small lines of arbitrary orientation need to be improved. The manual selection of parameters could be reduced in the applied software package ("buildenh") by using ML or other methods. Currently, only the method for line-sequence is selected using a decision tree.

All the mentioned possibilities for improvement may give better and faster results. Further tests with other data, other urban areas are necessary to define the limits of this method of mapping. There are disadvantages with this approach. First, the ortho-images do not have the quality of the original aerial images. Second, the abandonment of stereovision and human intelligence will result in loss of completeness and geometric accuracy of the derived map data.

Conclusions and Outlook

The results of the practical example show that the generation of urban LCMs from true ortho-images can be done almost automatically and with submeter accuracy. Improvements in thematic and geometric accuracy and operational speed are still possible. The derived data for buildings is a collection of georeferenced vectors that can also be used as topographic map and GIS data. Only aerial imagery is used as initial data; expensive equipment and stereo-observations are not necessary. Therefore, the method is a cost-effective and has the potential for fully automated processing. It can be used by both mapping organizations and laypeople. Only open-source software was used in this article. The author hopes that further improvements to the methodology and scripts will be made by people with an interest in the topic. Other landscape types and specific user requirements will require modifications. The provided software tools, including examples and documentation, are a good starting point for these endeavours.

Acknowledgements

I want to thank the LVermGeo Sachsen-Anhalt for the provided test data.

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