MODELLING QUALITATIVE AND QUANTITATIVE UNCERTAINTIES OF OBJECTS EXTRACTED FROM HIGH-RESOLUTION MULTI-SPECTRAL IMAGES AND LASER SCANNING DATA

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ABSTRACT:

An object-based approach is applied in land-cover feature extraction from high-resolution multi-spectral images and laser scanning data in this research. Objects extracted from high-resolution spectral images and laser data may have both classification errors and geometric errors. The classification errors are mainly caused by uncertainty of class definition (fuzzy classes), limited information content in the RS data and uncertainty of the validity of the decision rules for classification. These sources of uncertainty affect the quality of thematic or classification results of the information extraction from RS data, i.e. the *thematic uncertainty*. On the other hand, there are several types of errors that have an impact on the object location and the spatial extent of objects such as the geometry of object boundaries and the size of objects. These sources cause the *spatial uncertainty* of the information extracted from RS data. To assess the uncertainty of objects, we have to consider both types of uncertainty at the same time since they are interrelated. In this paper, we will firstly model these two different types of uncertainty separately and then analyse how these two types of uncertainty interact. This analysis will consider several parameters factors such as characteristics used for extracting objects, classification rules, as well as the minimum mapping units. Finally we will propose a unified framework considering both thematic and spatial uncertainty for the evaluation of the uncertainty of the results of information extraction from RS data. An overall uncertainty measure is proposed that is context-related and that will emphasise the type of quality relevant for particular applications. This will be illustrated by a case study using a 1 m resolution multi-spectral image and laser scanning data of an urban area. The experimental results confirm the effectiveness of the proposed uncertainty measures.

1. INTRODUCTION

Feature extraction from high-resolution data including laser altimetry data and multi-spectral data has become a hot topic in the past years. It is realised that the obtained results may be affected by different factors since different data and different methods are involved in acquiring such results. Therefore it is believed that good results may be obtained by applying the right methods to the right data sets, and the right parameters have to be found as well for various methods. To achieve these objectives, we have to examine and find out the relationship between these choices and quality of the acquired results by applying these choices. We expect that some of the choices made may affect the spatial extent of objects while other factors may influence the classification results. We call uncertainties caused by the former factors the spatial uncertainties and call uncertainties caused by the latter factors the thematic uncertainties. Spatial uncertainty can be better assessed by using per-pixel (per-location) methods by evaluating characteristics and their relationships to desired objects (membership functions) at each spatial location (pixel). On the other hand, thematic uncertainty can be better addressed by using per-object methods by evaluating properties of objects and their relationships to desired properties of objects for each obtained object as whole. Quality assessment of the final results should be made by using both per-pixel and per-object measures to reflect spatial and thematic aspects of quality. We conducted a case study to experimentally test the ideas and see if they fit the situation in practice. The remaining parts of this paper are organised as the follows. A brief introduction to the object-based approach for building extraction is given in Section 2. Factors that may affect the quality of extracted objects are discussed in Section 3. The case study and the test results are presented in Section 4. Section 5 is for the final remarks and conclusions.

2. THE OBJECT-BASED APPROACH FOR BUILDING EXTRACTION

In this section, we will review the object-based approach developed by Zhan for building extraction (Zhan et al., 2002). Many algorithms have been developed for this purpose from images or laser data (e.g., Brunn and Weidner, 1997; Hug and Wehr, 1997; Haala and Brenner, 1999). Many of them are per-pixel approaches and use features such as edge, texture, profile, etc. In our approach, we look at properties of image regions or segments rather than pixels. We slice the digital surface model (DSM), which is obtained by laser scanning at a fixed vertical interval (1 m in our experimental case) to obtain image segments (regions or objects) at various levels. The image segments are then subject to "vertical reasoning". The underlying assumption is that for a building certain properties of its image object hardly change from one level to the next, i.e., the sizes of image segments obtained at slightly different elevation should be more or less the same. The same properties we expect to show different behaviour for other protruding objects than buildings. We attempt to detect buildings based on two properties, i.e., the vertical change of the size of an image segment and the shift of its centre of mass. To this end, we have to link the image objects at the different levels by a tree structure. The size changes from the bottom segment to higher levels can be recorded as a variable taking a very large value at the start (size of whole image). The segment size reduces gradually up to a certain level (i.e. at the ground floor of a building). Onward from this breakpoint the segment size stabilises as we climb up the vertical wall of a building. We consider the vertical change of segment size a good indicator for discriminating buildings from other protruding objects and undulations of terrain relief.

This approach works well in areas with large buildings as in our test site in Amsterdam (Zhan et al., 2002). In this test site, most buildings have been successfully extracted when a threshold of 15% is applied for probing the size change between segments at two adjacent levels. In another test site (Ravensburg, Germany), things are different. There are many small houses with gable roofs, many trees close to relatively small and low houses, and there is varying terrain relief. In such a case, we better use a larger threshold to ensure that we obtain segments that may contain buildings. As a result, the extracted segments may contain other features that have similar characteristics to buildings such as trees. The second feature, NDVI (Normalised Difference Vegetation Index) derived from multi-spectral image, is then used for refining the segments extracted from elevation slices. The underlying assumption for using the NDVI is that building roofs do not contain vegetation. Only if segments and pixels in these regions meet both criteria, they are considered to relate to buildings. A detailed description of the object extraction approach can be found in (Zhan et al., 2002) and (Zhan, 2003).

We pursue our research on building extraction, aiming at minimising human intervention such as choosing a suitable threshold and producing information for uncertainty assessment. To do so, we will focus on the effects of applying different thresholds and utilizing the gained information to improve quality of the extracted objects and for uncertainty assessment. Other efforts include the study of effectiveness of using NDVI data in refining the spatial extent of objects and the influences of choosing different minimum mapping units (MMU) on the quality of the classification results.

3. FACTORS THAT MAY AFFECT THE QUALITY OF EXTRACTED OBJECTS

To assess the uncertainty of extracted objects, we need to investigate which factors may have affected the obtained results and to what degree they have done so. The thresholds that are used in building reasoning, the use of NDVI in refining the obtained results, and the minimum mapping unit (MMU) are considered the major factors; we will investigate them.

3.1 Thresholds used in building reasoning

We use only one parameter now to explain our concept, i.e., the size change between the upper-layer segment and the current-layer segment as indicator for reasoning on buildings from image segments at elevation levels. We believe that a tight threshold (a small threshold should be valid for regularly shaped buildings with vertical walls) is likely to produce reliable results (high correctness) while a loose threshold (a larger threshold) will produce more complete results (higher completeness). In most cases, we are interested in keeping a balance between correctness and completeness in order to obtain a good overall quality. If so, we should use segments that are produced according to a membership function. The membership function should portray the effect of applying different thresholds and indicate uncertainty.

The proposed membership function for building reasoning results is determined by counting how often a pixel has been identified as a building pixel when applying different thresholds. The range of thresholds used to produce the membership function is sequentially chosen from 10 % to 20 % … up to 60 %. The idea is that few objects may be extracted when using a threshold of 10 % and too many false objects may be produced when using a threshold that is larger than 60 %. The membership function based on the results of applying different thresholds is designed as:

$$MF_{Seg} = \mathrm{smf}(NO\_Seg,\ [0\ \ 6]) \tag{1}$$

where smf denotes the “S-shape” membership function. It returns the lowest membership value 0 at the location of the first argument (0) and the highest membership value 1 at the location of the second argument (6). NO_Seg denotes frequency of a pixel being identified as building one when using different thresholds.

3.2 The use of NDVI data in building refinement

In this research, NDVI data is used to refine the spatial extent of the extracted objects with the aim to distinguish tree and building in a segment, which is necessary if trees stand very close to buildings. The fuzzy membership value assigned to each pixel is used to determine if a pixel (a location) is a part of a building. Based on the knowledge of the relationship between NDVI and vegetation, the membership function is constructed as:

$$MF_{NDVI} = \mathrm{zmf}(NDVI, [0\ \mathrm{Cluster}(2)]) \tag{2}$$

where zmf denotes the “Z-shape” membership function. It returns the highest membership value 1 at the location of the first argument (0) and the lowest membership value 0 at the location of the second argument (Cluster(2)). To our knowledge, pixels that have NDVI values of zero must not be considered as vegetation. Cluster(2) denotes the centre of the second cluster, which is used to represent the cluster of pixels that have higher NDVI values (vegetation) in the histogram of NDVI values of the image. To reduce human intervention, the centre of the second cluster is determined automatically by using a clustering algorithm called fuzzy c-means based on the NDVI data.

$$\mathrm{Cluster} = \mathrm{fcm}(NDVI, 2) \tag{3}$$

3.3 Joint membership function and uncertainty assessment of using both data

The integrated membership function (MF_{OA}) that considers both membership functions the one for building reasoning (MF_{Seg}) and the one for NDVI (MF_{NDVI}) should take the minimum value of both:

$$MF_{OA} = \min(MF_{Seg}, MF_{NDVI}) \tag{4}$$

The accuracy of a classification may be expressed by the way in which the probability of class membership is partitioned between the classes (between 1 – yes and 0 – no in this case). This can be achieved by entropy measures. The cross-entropy was proposed as a means of evaluating the accuracy of a 'soft' classification (Foody, 1995, Duda et al. 2001). We suggest applying the entropy for uncertainty assessment of our building extraction

$$\begin{aligned} \text{Uncertainty}_{OA} &= -\sum_{i=1}^{2} P_i \log_2 P_i \\ &= -MF_{OA} \cdot \log_2 MF_{OA} - MF_{OA}^c \cdot \log_2 MF_{OA}^c \\ &= -MF_{OA} \cdot \log_2 MF_{OA} - (1 - MF_{OA}) \cdot \log_2 (1\text{-}MF_{OA}) \end{aligned} \tag{5}$$

P_i: is the probability belonging to and not belonging to end-member class i - building
MF: is the fuzzy membership function value for a class – building
MF^c: is the complement of the fuzzy membership function value for a class – building or MF^c =1-MF

3.4 Minimum mapping unit

The size of the MMU is a factor that may affect the quality of extracted objects. A smaller MMU usually leads to a large number of small objects, thus it may help to increase the completeness of object extraction. Often, however, such small objects are noise and unwanted objects. This implies that a small MMU is likely to yield low correctness. On the other hand, a larger MMU can eliminate noise thus increase correctness of obtained results, this at the costs of decreasing completeness.

3.5 Quality assessment of extracted results

To assess how these factors affect the quality of the extracted objects, we need to measure the quality of the extracted objects using reference data. In this research, we use both per-pixel and per-object measures. Per-pixel measures use pixels or locations as units for quality assessment whereas per-object measures count the number of objects that fall in different classes. In the following we review the quality measures; a detailed discussion of these measures is presented in (Zhan et al., 2004).

Per-pixel quality measures

$$\text{User's accuracy for class k}: UA_k = \frac{\mathbf{n}_{kk}}{\mathbf{n}_{k+}} \tag{6}$$

$\mathbf{n}_{kk}$ denotes the number of sample pixels that are supported by both classified results and reference data.
$\mathbf{n}_{k+}$ denotes the total number of sample pixels that are supported by the classified results.

$$\text{Producer's accuracy for class k}: PA_k = \frac{\mathbf{n}_{kk}}{\mathbf{n}_{+k}} \tag{7}$$

$\mathbf{n}_{kk}$ denotes the number of sample pixels that are support by both classified results and reference data.
$\mathbf{n}_{+k}$ denotes the total number of sample pixels that are explained by the reference data.

$$\text{Overall quality for class k}: OQ_k = \frac{1}{\frac{1}{UA_k} + \frac{1}{PA_k} - 1} \tag{8}$$

Per-object quality measures

$$\text{Correctness for class k} = \frac{\mathbf{N}_{kk}}{\mathbf{N}_{k+}} \tag{9}$$

$\mathbf{N}_{kk}$ denotes the number of sample objects that are supported by both classified results and reference data.
$\mathbf{N}_{k+}$ denotes the total number of sample objects that are supported by the classified results.

$$\text{Completeness for class k} = \frac{\mathbf{N}_{kk}}{\mathbf{N}_{+k}} \tag{10}$$

$\mathbf{N}_{kk}$ denotes the number of sample objects that are supported by both classified results and reference data.
$\mathbf{N}_{k+}$ denotes the total number of sample objects that are supported by the classified results.

$$\text{Overall quality for class k}: OQ_k = \frac{1}{\frac{1}{\text{Correctness}} + \frac{1}{\text{Completeness}} - 1} \tag{11}$$

4. CASE STUDY

4.1 Study area

We have selected the Ravensburg study site, the difficult one of our test areas (see Section 2), to test the proposed quality assessment measures. It is an area of 1 km × 1 km in the south of Germany with various types of vegetation and both urban and rural land-use. For this area TopoSys has supplied us with high-resolution data produced simultaneously by a laser scanner and a four-channel multi-spectral scanner. The data used for the experiment are DSM1 (digital surface model acquired from the first pulse of the laser beam), DSM2 (digital surface model acquired from the second pulse of the laser beam), a colour infrared image, and a real-colour image. The detailed description of the study area and data can be found in (Zhan, 2003). The reference data for the quality analysis have been obtained by digitizing on top of high-resolution images on the computer screen.

4.2 Accuracy and membership function in building extraction

To examine if the proposed membership function values are proportional to correct results, we apply the proposed membership function (Formula 1) and obtain the image of the membership function (MF_{Seg}). We select samples from pixels that have MF values in different ranges, compare with the reference data, and obtain figures of the corresponding accuracies (percentage of correct detection) as shown in Table 1 and Figure 1. The test results indicated that the proposed fuzzy membership function is proportional to the accuracy, thus it is a valid measure for building reasoning. The tendency line is determined from the average of samples from 5 different ranges of the MF_{Seg} values using the least squares method as shown in Figure 1.

Table 1. Relationship between accuracy and membership function values (MF_{Seg})

MF_{Seg}	0 – 0.2	0.2 – 0.4	0.4 – 0.6	0.6 – 0.8	0.8 – 1.0
Accuracy (%)	0.35567	3.2512	15.636	11.983	27.953

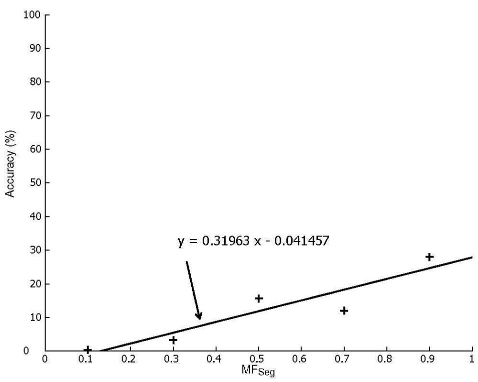

Figure 1. Relationship between accuracy and membership values (MF_Seg).

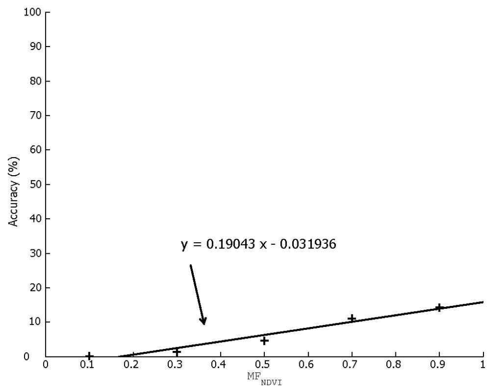

Figure 2. Relationship between accuracy and membership values (MF_{NDVI}).

4.3 Accuracy and membership function in the use of NDVI

To examine if the NDVI data is useful in refining the spatial extent of buildings and if the proposed membership is positively correlated to accuracy of classification results, we apply the proposed membership function (Formulas 2 and 3) and obtain the image of the membership function (MF_{NDVI}). We then select sample pixels from different ranges of the MF_{NDVI} values and produce figures of the corresponding accuracies (percentage of correct detection) as shown in Table 2 and Figure 2. The test results indicate that the proposed fuzzy membership function is positively correlated to the accuracy, therefore we conclude that the MF is a valid measure for the use of NDVI in the refinement of the spatial extent of buildings. The tendency line is determined from the average of samples from 5 different ranges of the MF_{NDVI} values using the least squares method as shown in Figure 2.

Table 2. Relationship between accuracy and membership function values (MF_{NDVI})

MF_{NDVI}	0 – 0.2	0.2 – 0.4	0.4 – 0.6	0.6 – 0.8	0.8 – 1.0
Accuracy (%)	0.14555	1.3815	4.679	11.107	14.325

4.4 Accuracy and the joint membership function (MF_{OA})

To examine if the joint membership function is useful in extracting buildings and if the proposed membership is positively correlated to the accuracy of classification results, we apply the proposed membership function (Formula 4) and obtain the image of the membership function (MF_{OA}) as shown in Figure 3. We select sample pixels from different ranges of membership function (MF_{OA}) values and produce figures of the corresponding accuracies (percentage of correct detection) as shown in Table 3 and Figure 4. The test results indicated that the joint membership function is very positively correlated to the accuracy, therefore we conclude that the MF_{OA} is a valid measure for extracting building. The tendency line is determined from the average of samples from 5 different ranges of the MF_{OA} values using the least squares method as shown in Figure 4.

Table 3. Relationship between accuracy and the integrated membership function values (MF_{OA})

MF_{NDVI}	0 – 0.2	0.2 – 0.4	0.4 – 0.6	0.6 – 0.8	0.8 – 1.0
Accuracy (%)	0.38775	7.4847	36.677	63.831	88.605

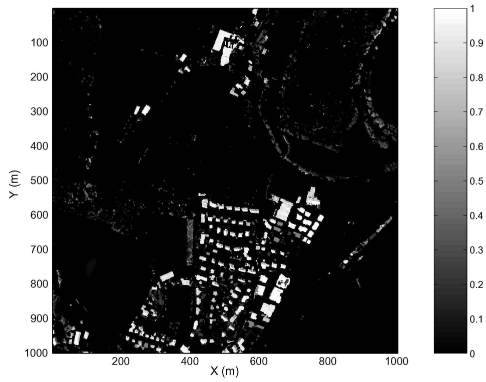

Figure 3. The joint membership function (MF_{OA}) for extracting buildings based on both measure (MF_{Seg} and MF_{NDVI}).

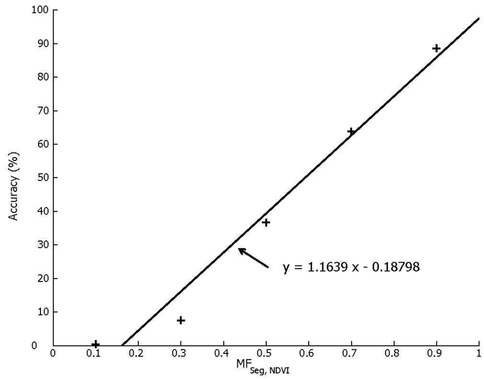

Figure 4. Relationship between accuracy and membership values (MF_{OA}).

4.5 Minimum mapping unit (MMU)

Since many small objects are likely to be noisy objects that are produced during image segmentation and refining spatial extent of objects, we need to investigate the relationship between the quality of extracted results and the MMU used. In this experiment, a sequential increased MMU is applied and the corresponding results are obtained. Both per-object and per-pixel quality measures as introduced earlier (Formulas 6 to 11) are used to assess these results. The figures obtained by per-object measures of quality are presented in Table 4 and Figure 5. The figures obtained by per-pixel measures of quality are shown in Table 5 and Figure 6. The experimental results confirm that a reasonable MMU (40 to 60 m^2) can increase the quality of extracted objects, especially correctness.

Table 4. Accuracy (per-object measures) obtained by applying different MMU

MMU (m^2)	10	20	30	40	50	60	70	80	90	100
Correctness	0.604	0.773	0.838	0.879	0.913	0.933	0.943	0.960	0.972	0.978
Completeness	0.937	0.937	0.937	0.937	0.920	0.903	0.880	0.840	0.811	0.771
Overall quality	0.580	0.735	0.793	0.830	0.846	0.848	0.836	0.811	0.793	0.758

Table 5. Accuracy (per-pixel measures) obtained by applying different MMU

MMU (m^2)	10	20	30	40	50	60	70	80	90	100
User's accuracy	0.804	0.820	0.828	0.835	0.841	0.846	0.848	0.853	0.858	0.858
Producer's accuracy	0.853	0.853	0.853	0.853	0.850	0.846	0.840	0.828	0.819	0.803
Overall quality	0.706	0.719	0.725	0.730	0.732	0.733	0.730	0.725	0.721	0.709

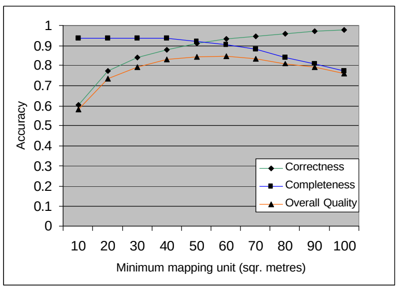

Figure 5. Relationship between accuracy (per-object measures) and the use of different MMUs.

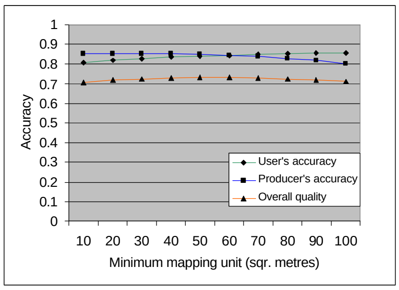

Figure 6. Relationship between accuracy (per-pixel measures) and the use of different MMUs.

4.6 Uncertainty measure and its effectiveness

Uncertainty assessment is made based on the joint membership function as defined by Formula 5 and shown in Figure 7. Uncertainty assessment is meaningful only if it is presented in correspondence to the results of extraction and classification. The presented uncertainty assessment is corresponding to the results of using 40 m^2 as the MMU. To examine if the uncertainty figures are valid to represent the quality of the extracted object, we select sample pixels from different ranges of the uncertainty values and produce figures of the corresponding accuracies (percentage of correct detection) as shown in Table 6 and Figure 8. The test results indicated that the proposed uncertainty measure is correctly correlated to the accuracy, therefore it supports that it is valid uncertainty measure. The tendency line is determined from the average of samples from 10 different ranges of the uncertainty values using the least squares method as shown in Figure 8.

Table 6. Relationship between accuracy and uncertainty values

Uncertainty	0 -0.1	0.1-0.2	0.2-0.3	0.3-0.4	0.4-0.5	0.5-0.6	0.6-0.7	0.7-0.8	0.8-0.9	0.9-1.0
Accuracy	0.94583	0.93622	0.91473	0.88263	0.87384	0.87825	0.80854	0.73488	0.74291	0.65013

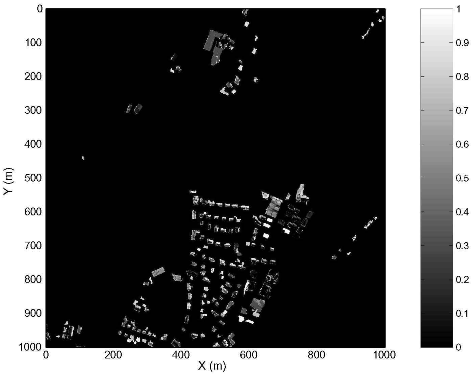

Figure 7. Uncertainty assessment result (per-pixel) of extracted buildings.

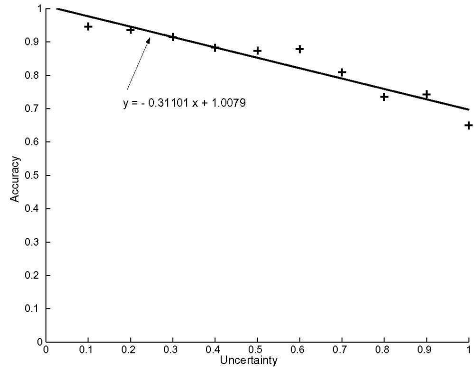

Figure 8. Relationship between accuracy (per-pixel measures) and uncertainty values.

5. DISCUSSIONS AND CONCLUSIONS

In this study, we have made the validity check for both fuzzy membership function for building reasoning and for the use of NDVI, and the integration of these two. The test results have confirmed that the proposed membership functions are effective. Our experimental results also indicate that the MMU can largely affect the quality of extracted buildings. Proper selection of the MMU can significantly improve the classification accuracy, especially the correctness of extracted objects. The uncertainty assessment results show that higher uncertainty values tend to represent lower accuracy, which in turn indicates that the proposed uncertainty measure is valid. These relationships are useful for better understanding in developing an automatic approach for extracting features from high-resolution data.

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