OBJECT EXTRACTION AND RECOGNITION FROM LIDAR DATA BASED ON FUZZY REASONING AND INFORMATION FUSION TECHNIQUES

F. Samadzadegan

Dept. of Surveying and Geomatics Engineering, Faculty of Engineering, University of Tehran, Tehran, Iran - samadz@ut.ac.ir

KEY WORDS: 3D Objects, Extraction, Recognition, Fuzzy logic, LIDAR, Region growing

ABSTRACT:

Three dimensional object extraction and recognition (OER) from LIDAR data has been an area of major interest in photogrammetry for quite a long time. However, most of the existing methods for automatic object extraction and recognition from LIDAR data are just based on the range information and employ parametric methods and object's vagueness behaviour is basically neglected. Thus, these methods do not take into account the extraction and recognition complexities and may fail to reach a satisfied reliability level in complex situations. In this paper a novel approach based on the following strategies is formulated and implemented: (a) for a more comprehensive definition of the objects, information fusion concept is utilized, i.e., object's descriptive components such as 3D structural and textural (ST) information are automatically extracted from first/last rang and intensity information of LIDAR data and simultaneously fed into the evaluation process, (b) for a more realistic expression of the objects and also for simultaneous fusion of the extracted ST components, the fuzzy reasoning strategy is employed. The proposed automatic OER methodology is evaluated for two different object classes of buildings and trees, using a portion of LIDAR data of an urban area. The visual inspection of the recognized objects demonstrates promising results.

1. INTRODUCTION

The idea of having a fully automatic three-dimensional OER (object extraction and recognition) system to replace the human operator has been one of the main aspirations and the final goal for photogrammetry and computer vision investigators (Baltsavias and Stallmann, 1995; Brenner and Haala, 1998b; Brunn and Weidner, 1997; Collins and et. Al. 1995; Ebner and et. Al. 1999; Fua and Haanson, 1988; Gruen and et. Al. 1997; Jaynes and et. Al. 1997 ; Ameri and Fritsch, 1999; Haala and Brenner, 1999; Lemmens, 1996; Maas, 1999). The existing methods are mainly formulated using parametric approaches and just optimized for using single information. To exploit more fully all available information that contribute to the extraction and recognition process and handling the object's vagueness behaviour, we propose an OER strategy which makes use of the object information inherent both in range and intensity information through a fuzzy reasoning strategy.

2. PROPOSED OBJECT EXTRACTION AND RECOGNITION METHODOLOGY

The overall strategy for our proposed operations may be expressed, with reference to Figure. 1, by the two interrelated procedures, Extraction and Recognition.

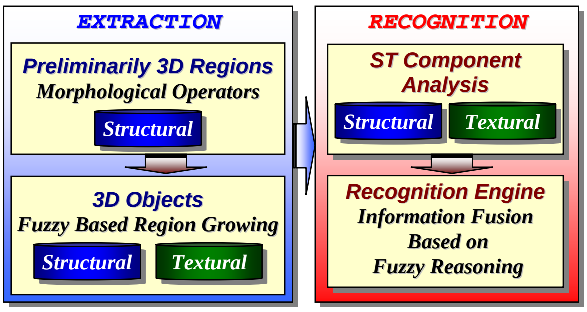


Figure 1. Extraction and recognition work flow

Extraction: In this stage an inspection is carried out to locate and extract all 3D objects that exist in the entire area irrespective of the objects identity. The morphological operators are applied to the range information of LIDAR data to delimit and isolate the individual 3D objects. In the next step each 3D candidate region is mapped into the intensity images to determine the corresponding region in the intensity space. The final decision for each individual object's boundary is made by a fuzzy-based region growing approach. Any modification of the object boundaries as an outcome of the region growing process will result a corresponding modification in the 3D geometric information in the object space. At this stage the system knows the presence and the location of the objects without a definite knowledge about their identity.

Recognition and training: The geometric and radiometric contents of each segmented region are analyzed to derive the double descriptive attributes that define the objects in an integral manner, these are: structural and textural (ST) descriptive attributes. Simultaneous fusion of these parameters yields the object's identifying signature. Because of the vagueness nature of the ST elements, the recognition engine is designed based on a fuzzy reasoning strategy. The training potentials are also embedded into the recognition engine to be used for unrecognized objects. Having stated the general working principal of the proposed OER method, in the following sections detailed treatments of the main individual modules that govern the OER process are presented.

2.1 Object Extraction methodology

The proposed object extraction method is designed to perform two sequential procedures, namely: (a) preliminary extraction of all candidate objects of interest from first and last range pulses LIDAR data, i.e., 3D candidate region extraction, and (b)

3D object extraction by means of a region growing process based on all of first/last pulse of range and intensity data.

2.1.1 *3D regions extraction based on morphological operators*

In this study we have adapted morphological operators for extraction and refinement of the 3D regions (Gonzaless and Woods, 1993). The adapted process may be outlined as follows: in the first step the initial regions are extracted by a top-hat morphological operator:

$$Regions = DSM - (DSM \circ b) \quad (1)$$

where b is the structuring element function, and $\circ$ denotes the opening operator given by:

$$f \circ b = (f \ominus b) \oplus b \quad (2)$$

$$\therefore (f \oplus b)(s,t) = \min\{f(s-x,t-y) - b(x,y) | (s-x),(t-y) \in D_f ; (x,y) \in D_b\}$$

$$\therefore (f \ominus b)(s,t) = \min\{f(s+x,t+y) - b(x,y) | (s+x),(t+y) \in D_f ; (x,y) \in D_b\}$$

where Θ and $\oplus$ denote the grey scale *Erosion* and *Dilation* operators and D_f , D_b are the domains of *f* and *b*, respectively.

The output of this process will be binary data with the values one and zero denoting the 3D objects and the background respectively. This stage is then followed by the binary cleaning and the opening morphological operators. In this way only the objects of interest will remain and insignificant objects and artefacts are excluded from the extracted regions.

The 3D regions that are extracted from the range data may be quite close and thus morphological operators may fail to isolate them as 3D individual objects and hence they may be erroneously classified as a single 3D object. This defect is resolved by exploiting other information available in the data set. That is, the relief and textural information. To utilize these information, the extracted 3D regions are mapped into the intensity information of LIDAR data. This leads to the generation of the preliminary regions.

2.1.2 *Object Extraction Based on Simultaneous Fusion of RTS Information*

This stage is designed to extract of all objects of interest in the object space, by means of a region growing process. It is assumed that a region that belongs to a single object should demonstrate a uniform variation of the structural values for all pixels included in the region. For example for a 3D region that belongs to a tree, the fluctuation of the values of the structural components should remain relatively uniform for all pixels on the region. This means that if the structural variation exceeds a certain level, the possibility of the presence of a second object in the region is signalled. To express the relief variations for a 3D object, a relief descriptor is determined using the following strategy: A normal vector is computed for a local surface defined by a 3×3 or 5×5 window array constructed around the position of each point on the 3D region. Texture metrics are computed over a local collection of facets, and represent how the directions of the normals are distributed about the local mean normal (Figure 2).

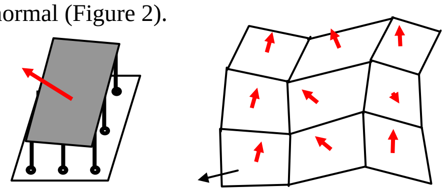


Figure 2. Analytical description of the surface based on normal vectors.

The three components of the normal vector are given by:

$$\begin{bmatrix} K_i \\ L_i \\ M_i \end{bmatrix} = \frac{1}{\sqrt{\alpha_i^2 + \beta_i^2 + 1}} \begin{bmatrix} \alpha_i \\ \beta_i \\ -1 \end{bmatrix} \quad (3)$$

where, α_i and β_i are the coefficients of the surface given by:

$$P_i(w,h) = \alpha_i \cdot w + \beta_i \cdot h + \gamma_i \quad (4)$$

This surface is determined within a predefined limit specified by the window size, $w = 1 : Width, h = 1 : Height$. Based on these vector components, the relief descriptor, *k*, can be defined as:

$$k = \frac{N-1}{N-R} \quad (5)$$

where $R^2 = \left(\sum_{i=1}^{N} K_i\right)^2 + \left(\sum_{i=1}^{N} L_i\right)^2 + \left(\sum_{i=1}^{N} M_i\right)^2$ and N is the local surface window size (Besl and Jain, 1988).

Thus, the value of k quantitatively expresses the overall relief variation of a region. The large value of k indicates that the region comprises rather uniform relief variations. The large value of k, on the other hand, denotes the non uniformity of the relief fluctuations (Samadzadegan, 2002).

Taking into account the complexities and the fuzziness behaviour associated with these consistency checks, a fuzzy based region growing approach is adapted as follows: The region growing starts from the pixel located in the centre of the gravity of the 2D regions. For all neighbouring pixels, based on a fuzzy reasoning strategy and Mamdani inference type, a consistency check is carried out (Zimmermann, 1993).

The linguistic variables to be fed into the fuzzy reasoning module are: (1) the pixels and relief fluctuation values in both of intensity and range data (the value of k), (2) the size of the region, and (3) the difference of the pixel values (*TextureDiff*) and the height value (*ReliefDiff*). The "Size" item is used to exclude the objects that are smaller than a predefined size. By the region growing process the regions undergo one of the following changes: (a) the region remains unchanged if it satisfies the consistency criteria, (b) the region is subdivided into two or more regions if consistency criteria are not satisfied, (c) different regions are merged if they are consistent. The

Table 1. Linguistic variables and labels of fuzzy reasoning structure in region growing process

	Linguistic Variable	Linguistic Labels
Input	Texture	*SoIrregular, Irregular,Regular,SoRegular*
	Relief	*SoIrregular, Irregular,Regular,SoRegular*
	Size	*SoSmall , Small , Medium , Large , SoLarge*
	TextureDiff	*SoSmall , Small , Medium , Large , SoLarge*
	ReliefDiff	*SoSmall , Small , Medium , Large , SoLarge*
Output	Grow	*NotGrow , ProbablyNotGrow , ProbablyGrow , Grow*

linguistic variables, labels and the corresponding membership functions for the fuzzy region growing process are given in Table 1.

As an example, suppose that a building with its nearby tree in the object space is extracted and classified as a single 3D object. This inevitable miss classification, is revised by the fuzzy based region growing in the image space. After the fuzzy based consistency check, the region is subdivided into two uniformly varying sections and subsequently will be treated as two different objects.

2.2 Recognition

As mentioned above, our recognition strategy is based on the concept of information fusion. These descriptors are important elements for a comprehensive recognition process and they need to be fed simultaneously into the recognition engine (Samadzadegan, 2002). In order to make it quite clear, it should be emphasized that in the previous stage the structural parameter was used to determine only the presence and the location of the objects. In the recognition stage, however, the structural parameters are used for the object recognition process. Thus, the extracted parameters are regarded as the signatures expressing the object's identity.

The structural descriptors of a 3D object are: height, area, shape and relief variations. The shape of an object is expressed by the length to the width ratio. To express the relief variations for a 3D object, a relief descriptor is determined using the indicator *k* expressed by Equation 5. The object's structural descriptors are indeed an efficient mechanism by which a reliable recognition of many 3D objects can be conducted without further involvement with the textural complications.

As mentioned earlier, the object recognition potentials can be enhanced by a simultaneous fusion of the extracted STS parameters. However, these descriptors are not crisp in their nature and hence can not be realistically described by a rigorous mathematical model. Therefore, our proposed method again takes advantage of the fuzzy logic concepts to describe the objects more realistically and consequently to perform objects recognition process based on the fuzzy decision making approach.

It is important to mention that, in principle, the descriptors are not necessarily limited to the STS values. That is, the information fusion process may also include other types of descriptors if they are available. If, on the other hand, there are only one or two descriptors (e.g. only spectral, or spectral and structural), the recognition process can still be executed, but this time, of course, giving rise to a less reliable result. The first step in proposed recognition process is to determine the degree to which the STS descriptors belong to each of the appropriate fuzzy sets via membership functions. The linguistic variables which are used for each of structural, textural and spectral descriptors are presented in Table 2.
Once the STS components have been fuzzified, the sequential fuzzy reasoning procedures, comprising: Implication, aggregation, and deffuzification, are performed (see Section 3.1.2).

3. EVALUATION OF THE PROPOSED OER STRATEGY

To assess the capabilities of the proposed OER method a sample LIDAR data of an urban area of city of Castrop-Rauxel which is located in the west of Germany, was selected (Figure 3). The selected area was suitable for the evaluation of the proposed OER method because the required complexities (e.g. proximities of different objects: building and tree) were available in the image (Figure 4).

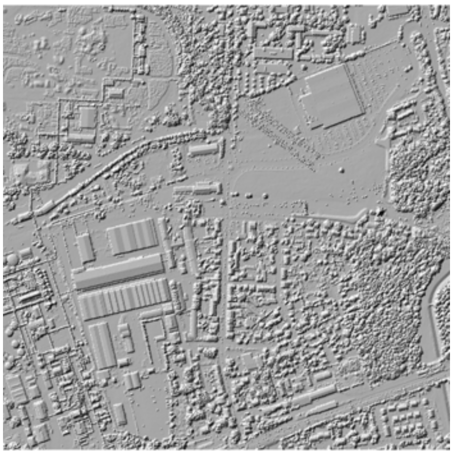


Figure 3. Sample area

Before the system operation is started it is necessary to set up the fuzzy reasoning parameters. For the BT object classes, the preliminary membership functions for the ST components are defined based on the knowledge of an experienced photogrammetric operator (Figure 5 and Figure 6).

3.1 Operational stages

The OER process was initiated with fuzzy based region extractions operation and hence effectively regions are constructed (Figure 5). In the next step the extracted regions are analyzed to derive the ST descriptors. In the next stage, the recognition operation is activated by which all BT objects in the sampled area patch were successfully recognized. Figure 7. shows the output of each stage for a sample image patch and all recognized BT objects for the entire test area.

Table 2. Linguistic variables and labels of fuzzy reasoning structure in recognition process

	Type	Linguistic Variable	Linguistic Labels
Input	Structural	*Height*	*SoShort ,Short , Medium , High , SoHigh*
		Area	*SoSmall , Small , Medium , Large , SoLarge*
		Relife	*SoIrregular, Irregular , Regular , SoRegular*
		Shape	*NonStretched , Stretched , soStretched*
	Textural	*Texture*	*SoIrregular, Irregular, Regular , SoRegular*
Output	Object	*Object Type*	*Not , ProbablyNot , ProbablyYes , Yes*

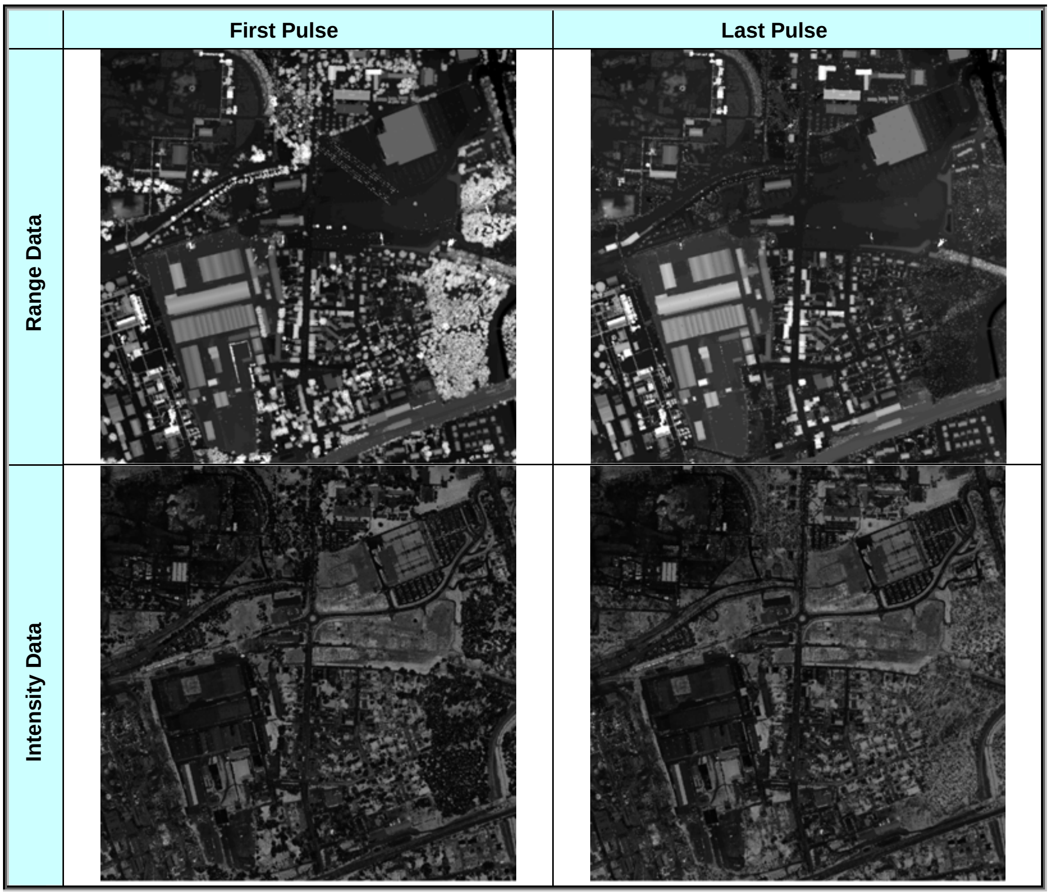
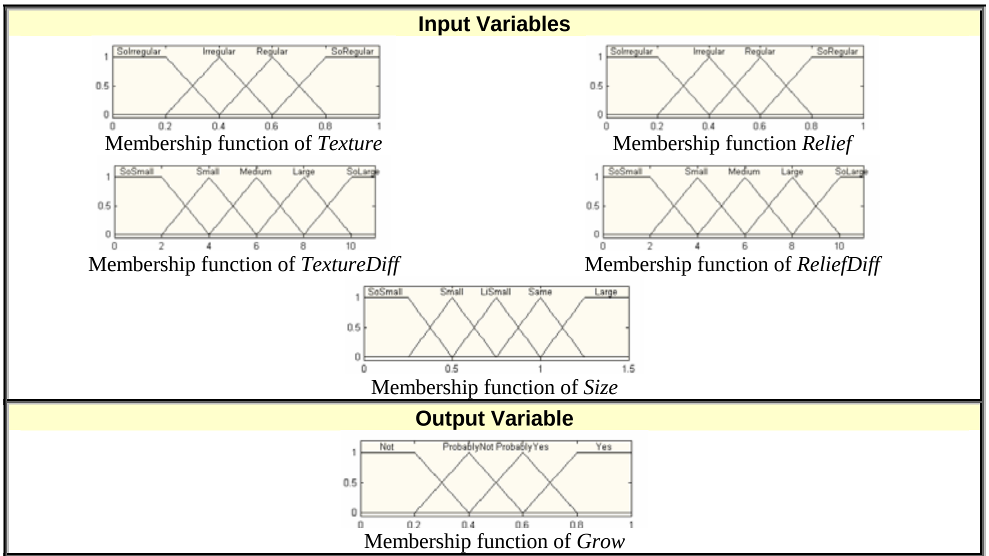


Figure 4. LIDAR data from sample area

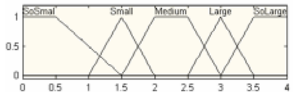


Some Sample Rules:

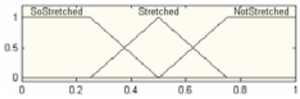
- IF *Area* Is *So Small* AND *Texture* Is *SoRegular* AND *Relief* Is *SoRegular* THEN *Grow*
- IF *Area* Is *Small* AND *TextureDiff* Is *Small* AND *ReliefDiff* Is *Small* AND *Texture* Is *SoRegular* AND *Relief* Is *SoRegular* THEN *Grow*
- IF *Area* Is *Large* AND *TextureDiff* Is *Large* AND *RelierDiff* Is *SoLargel* THEN *NotGrow*
- IF *Area* Is *Large* AND *TextureDiff* Is *Large* AND *RelierDiff* Is *medium* THEN *ProbablyNotGrow*

Figure 5. Linguistic variables and labels, membership functions and some sample of presented rules in region growing process

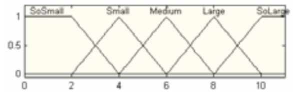
Structural Components



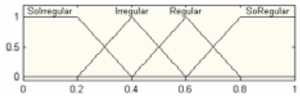
Membership function of *Height(meter)*



Membership function of *Shape*

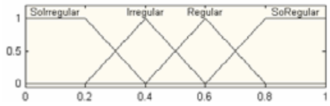


Membership function of *Area(meter)*



Membership function of *Relief*

Textural Components



Membership function of *Texture*

Some Sample Rules:

- IF *Texture* is *Regular* AND *Relief* is *Very Regular* AND *Height* is *Very Tall* AND *Area* is *Very Large* THEN *Object* is *Building*
- IF *Texture* is *Irregular* AND *Relief* is *Regular* AND *Height* is *Tall* AND *Area* is *Large* AND *Shape* is *Not Stretched* THEN *Object* is *Probably Building*
- IF *Texture* is *Very Irregular* AND *Relief* is *Very Irregular* AND *Green Colour* is *Deep* AND *Height* is *Medium* AND *Area* is *Small* THEN *Object* is *Tree*
- IF *Texture* is *Irregular* AND *Relief* is *Regular* AND *Green Colour* is *Medium* AND *Height* is *Medium* AND *Area* is *Small* THEN *Object* is *Probably Tree*

Figure 6. Linguistic variables and labels, membership functions and some sample of presented rules in recognition process

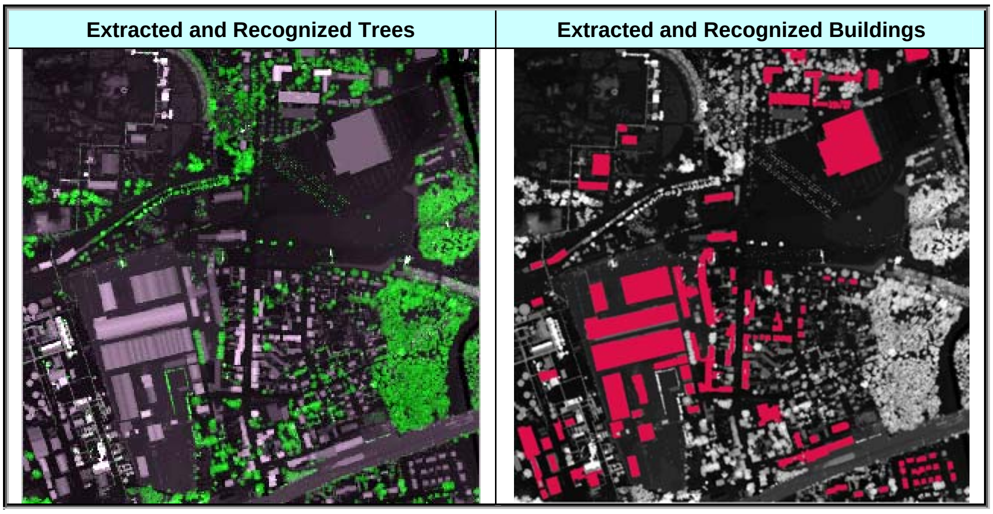


Figure 7. Linguistic variables and labels, membership functions and some sample of presented rules in region growing process

4. CONCLUSION

We believe the foregoing sections and the presented test results have demonstrated a promising and comprehensive solution to a complicated problem and the evaluation of our OER method has indicated its high potentials for extraction and Recognition of the 3D GIS objects.

It should be emphasized, however, that in the preceding sections the main intention was to express the general structure of the proposed OER strategy. The principle feature of this strategy is not so much its individual modules that perform different tasks, but the methodology itself that governs the entire system.

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