AUTOMATIC EXTRACTION OF URBAN ROAD NETWORKS FROM IKONOS IMAGES USING A FUZZY MATHEMATICAL MORPHOLOGY APPROACH

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ABSTRACT:

High-resolution commercial imaging satellite such as IKONOS provides an important new data sources for urban mapping and geographic information systems (GIS) applications. This paper presents a fuzzy mathematical morphology method for automated extraction of urban road networks from IKONOS imagery. In this proposed method, the road networks in a complex urban scene are firstly modeled, followed by modeling other different types of undesirable structures such as buildings and trees, both of which are based on their geometric and radiometric properties in the IKONOS imagery. Then, the shape, size, and gray-scale values of the structuring elements are selected based on their geometric and radiometric properties in order to determine which objects should be retained or eliminated. A series of fuzzy morphological operators combined with the different structuring elements are used in order to retain bright, long rectangular structures such as roads and eliminate other undesirable non-road structures.

1. INSTRUCTION

Automated extraction urban road networks from high-resolution remotely sensed imagery is in particular motivated by the increasingly demand for accurate and up-to-date information for applications related with urban planning, traffic flow analysis and simulation, estimation of air and noise pollution, road maintenance and upgrading. Acquiring mapping quality digital imagery from imaging satellites to permit frequent GIS database updating is half the battle in urban environmental management. The other half is extracting information from the imagery. Automating these processes provides significant challenges for geomatics or mapping engineers. Automated extraction of urban road networks is currently very active research topic in remote sensing and computer vision and has been intensively studied. Many automatic and semiautomatic road extraction algorithms using satellite or aerial images have been proposed in the past (Trinder and Wang, 1998; Zhang and Baltsavias, 1999; Huber and Lang, 2001, Lee et al., 2000; Hinz el al., 2001; Oddo et al., 2000; Dell'Acqua and Gamba, 2001). However, many of the developed road extraction approaches would presumably fail when applied to high-resolution remotely sensed imagery taken over densely built-up areas, although they show good results in rural areas. In these proposed methods, most of them rely on road models that describe the appearance of roads in the studied area. It is a great challenge to model urban roads in high-resolution satellite or aerial images, because their spectral and radiometric properties in these images sometimes are similar to other objects such as buildings or parking lots. Generally, road models are related to two factors: the spatial resolution of imagery and the area of study. In low-resolution satellite imagery such as Landsat and SPOT, roads can be defined as long linear feature even if there are curve-like roads. However, it is not possible to use the line-shaped road model to extract urban road networks from high-resolution satellite imagery such as IKONOS with a 1 m spatial resolution and QuickBird with a 70 cm spatial resolution, This is because in high-resolution satellite imagery the roads are long rectangular structures, so the roads have to be modeled as the long rectangular segments. For road modeling, the area of study can be divided into two broad types: rural and urban. Differing from rural areas, urban areas generally have higher density of roads with a brighter structure property.

In this paper, the problems in automated extraction of urban road networks from high-resolution IKONOS imagery are considered and an automated road extraction approach using a combination of fuzzy mathematical morphology and model-based extraction techniques is presented. This model-based road extraction method may be achieved by three steps: (1) the road networks are modeled in terms of their geometric and radiometric properties in IKONOS imagery, (2) the other different types of undesirable structures in the IKONOS imagery are modeled based on their geometric and radiometric properties, and (3) a fuzzy mathematical morphology method is used to extract automatically urban road networks from the IKONOS imagery.

The paper is organized as follows. Some basic concepts on fuzzy mathematical morphology (FMM) are reviewed in Section 2. A road model and some fuzzy morphological operators are described in Section 3. Implementation and results are shown in Section 4. Finally, concluding remarks with an outlook on future work are given in Section 5.

2. PROPOSED FMM APPROACH

Mathematical morphology, introduced initially by Matheron (1975) and developed later by Serra (1982), is the study of shape or form using simple concept based on classical set theory. As one of the branches of non-linear image processing, mathematical morphology uses the morphological operations to process and analyze images and extract useful information. A morphological operation transforms an image by means of a structuring element into a new image. There are four basic morphological operations: dilation, erosion, opening and closing. Depending on the different image representations, either binary images (only two possible pixel values 0 and 1 are allowed in the images, respectively corresponding to black and white) or gray-scale images (the pixel values are also allowed in the unite interval $[0,1]$), there are two kinds of mathematical morphologies: binary morphology and gray-scale morphology. Recently, several FMM approaches (De Baets, 1977; Bloch and Maitre, 1995; Sinha and Dougherty, 1993; Nachtegael and Kerre, 2000) have been proposed as alternative extensions of binary morphology to gray-scale morphology. The basic idea in the FMM approaches are using fuzzy set to represent gray-scale images and using fuzzy tools to define fuzzy morphological operations. The FMM is a very rich and powerful tool used for the representation and analysis of gray-scale images. In this paper, we use the FMM approach developed by De Baets (1977). His idea was based on using the notions of negator, conjunctor and implicator on the unit interval $[0,1]$ to obtain a successful fuzzification.

According to Baets (1977), a unary operator N on $[0,1]$ is a negator if it is a decreasing mapping that coincides with the Boolean negator on $\{0,1\}$ i.e. $N(0)=1$ and $N(1)=0$; a binary operator C on $[0,1]$ is a conjunctor on $[0,1]$ if it is an increasing mapping (i.e. a mapping with increasing partial mappings) that coincides with the Boolean conjunction on $\{0,1\}^2$, i.e. $C(0,0)=C(0,1)=C(1,0)=0$ and $C(1,1)=1$; a binary operator I on $[0,1]$ is a implicator on $[0,1]$ if it is an hybrid monotonous mapping (i.e. a mapping with describing first and increasing second partial mappings) that coincides with the Boolean implication on $\{0,1\}^2$, i.e., $I(0,0)=I(0,1)=I(1,1)=1$ and $I(1,0)=0$.

In the FMM approach, n-dimensional gray-scale objects (images and structuring elements) can be represented as $R^n \rightarrow [0,1]$ functions.

Let C is a conjunctor on $[0,1]$, let I be an implicator on $[0,1]$, let A be a gray-scale image ($A: R^n \rightarrow [0,1]$) and let B be a gray-scale structuring element ($B: R^n \rightarrow [0,1]$). The fuzzy dilation $D_C(A,B)$ and the fuzzy erosion $E_I(A,B)$ are the gray-scale images defined by:

$$D_C(A,B)(y) = \sup_{x \in T_y(d_B) \cap d_A} C(B(x-y), A(x)) \tag{1}$$

$$E_I(A,B)(y) = \inf_{x \in T_y(d_B)} I(B(x-y), A(x)) \tag{2}$$

where d_A and d_B are respectively the domains of image A and structuring element B,

$$d_A = \{x \in R^n | (\exists t \in [0,1])(A(x)=t)\} \tag{3}$$

$$d_B = \{x \in R^n | (\exists t \in [0,1])(B(x)=t)\} \tag{4}$$

$T_y(d_B)$ is the translation operation of d_B by the vector $y \in R^n$,

$$Ty(d_B) = \{x \in R^n | x - y \in B\} \tag{5}$$

Let C is a conjunctor on $[0,1]$, let I be an implicator on $[0,1]$, let A be a gray-scale image and let B be a gray-scale structuring element. The fuzzy closing $C_{C,I}(A,B)$ and the fuzzy opening $O_{C,I}(A,B)$ are the gray-scale images defined by:

$$C_{C,I}(A,B)(y) = E_I(D_C(A,B), -B)(y) \tag{6}$$

$$O_{C,I}(A,B)(y) = D_C(E_I(A,B), -B)(y) \tag{7}$$

where $-B$ is the reflection of the fuzzy structuring element B defined as:

$$(-B)(x) = (B)(-x), \ \forall x \in Z^2 \tag{8}$$

In this paper, we use the standard negator N_S :

$$N_S(x) = 1 - x, \ x \in [0,1] \tag{9}$$

as the negator N, the minimum M:

$$M(x,y) = \min(x,y), x, y \in [0,1] \tag{10}$$

as the conjunctor C, and the Lukasiewicz implication I_L :

$$I_L(x,y) = \min(1, 1-x+y) \quad x, y \in [0,1] \tag{11}$$

as the implicator I respectively.

3. MODELING URBAN ROAD NETWORKS

3.1 Road Model

An urban road network consists of junctions and road links connecting junctions. Road links are constructed from road segments. The urban road networks can be modeled in terms of their geometric and radiometric characteristics in IKONOS imagery. Traditionally, in low-resolution satellite imagery, e.g., Landsat (15 m or 30 m spatial resolution) and SPOT (10 m or 20 me spatial resolution), urban roads can be defined as long linear features even if there are curve-like roads. However, it is not possible to use the line-shaped road model to extract urban road networks from 1 m spatial resolution IKONOS imagery. This is because in the IKONOS imagery the roads are long rectangular structures. Like the approach presented by Chanussot et al., (1999), the urban roads are also modeled as the combination of bright, connected long rectangular segments in this study, that is:

- The road segments in the IKONOS imagery have long rectangular structures with a maximum width $w_{\max}$ and minimum length $l_{\min}$.
- Each road segment is a bright structure with respect to its surroundings.

According to the road network model presented above, the problems in urban road network extraction may be considered as finding long rectangular, bright structures in the IKONOS imagery.

Other different types of undesirable structures in a complex urban scene are then modeled based on their geometric and radiometric properties. The following cases are examined:

- The linear features that can be confused with roads in some extent, but they do not satisfy all requirements for roads, for example, they are darker or lighter than their surroundings, or too wide (more than $w_{\max}$).
- Irregularly bright structures.

3.2 FMM Operations

Image Fuzzification

To employ the proposed FMM approach, a process of fuzzification that scales the value of the pixels of image and the elements of structuring element to unit interval $[0,1]$ is necessary (Nachtegael and Kerre, 1999). In the gray-scale images, the gray levels of pixels do not belong to the unit interval $[0,1]$. In this paper, we consider a finite sub-chain of $[0,1]$ defined by

$$C_\lambda = \left\{0, \frac{1}{\lambda-1}, \cdots, \frac{\lambda-2}{\lambda-1}, 1\right\} \tag{12}$$

where $\lambda \in N \setminus \{0,1\}$, and then two-dimensional gray-scale imagery will be fuzzified as $Z^2 \to C_\lambda$ functions.

Fuzzy Morphology Operators

As long, rectangular, bright structures, roads can easily be identified using fuzzy opening. A bright road segment or part of it will be removed if the structuring element cannot be included inside the road segment. For example, in the case when the structuring element is orthogonal with the road segment and it is longer than the road segment. To detect the roads being bright structures with respect to their surroundings, a directional opening in successive directions with a gray-scale structuring element with sizes $(w_{\max}/4) \times l_{\min}$ are used. And irregularly bright structures can also be removed by the directional opening.

To remove the linear structures that are more than $l_{\min}$ pixels long, but wider than $w_{\max}$ width, an $D_C(A,B) - E_I(A,B)$ operation with the gray-scale structuring element with size $w_{\max} \times w_{\max}$ is used.

To remove the structures that are lighter than their surroundings, a fuzzy opening is adopted with a gray-scale structuring element of size $w_{\max} \times w_{\max}$.

4. IMPLEMENTATION AND RESULTS

To test the proposed model-based FMM approach, two section of a georeferenced IKONOS imagery with a spatial resolution of 1 m from the Toronto dataset acquired in summer 2001 were used in this study. Figure 1 shows a typical residential area in Toronto, Ontario, Canada, where the scene consists mainly of roads, individual houses, and trees. Figure 3 shows an industrial

Figure 1. Section of a georeferenced IKONOS image of a residential area in Toronto, Canada.

Figure 2. Extracted road networks in the residential area depicted in Figure 1 (long bright objects are road networks).

Figure 3. Section of a georeferenced IKONOS image of an industrial area in Toronto, Canada.

area near the Person International Airport in Toronto, where the scene consists of roads, industrial buildings, parking lots, and other non-road objects, e.g., vegetation area and water body.

The FMM algorithm mentioned in the previous section was implemented using Visual C++. Figures 2 and 4 show the extracted road networks in the residential area and the industrial area, respectively. In the process of image analysis, we fixed the minimum $l_{\min}$ to 43 pixels corresponding to approximately 100 m, which is a realistic minimum straight-line length for typical urban areas. We fixed the minimum width $w_{\min}$ to 5 pixels, which is the typical maximum width for common roads in urban areas in the IKONOS images.

Figure 4. Extracted road networks in the industrial area depicted in Figure 3 (long bright linear objects are road networks).

Depending on our experiments, we note that the influence of the directional fuzzy morphological opening to extract the roads highly depends upon the choice of the structuring element. In the experiment, we took 0.90 as the gray-scale value of the structuring element. As can be seen in Figure 2, major parts of the road networks of the residential area have been extracted (white long rectangular structures indicate extracted road networks). Buildings, trees and their shadows are generally shown in the dark areas.

For the industrial scene, we fixed the minimum $l_{\min}$ to 91 pixels and the minimum width $w_{\min}$ to 7 pixels. The gray-scale value of the structuring element was also set as 0.90. As can be seen in Figure 4, both major parts of the road networks and other bright objects have been extracted because roads and non-road objects in this industrial area have similar spectral and radiometric characteristics. Comparing Figure 2 with Figure 4, the proposed FMM approach works better in the residential area than the industrial area.

5. CONCLUSIONS

In this paper, a model-based fuzzy mathematical morphology approach for automated extraction of the urban road networks from IKONOS imagery has been presented. The results indicate that the proposed FMM method, as a local image analysis approach, can extract road networks even in a complex urban residential environment. However, for accurate mapping purposes, accurate delineation techniques are further required. One of our next steps will be directed towards developing more effective fuzzy operators and a global image analysis approach to improve the performance of road network extraction. The focus will be placed on integrating local and global grouping to construct urban road networks.

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