A FUZZY RELATION BASED ALGORITHM FOR SEGMENTING COLOR AERIAL IMAGES OF URBAN ENVIRONMENT

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ABSTRACT:

Automated extraction of man-made objects such as buildings and roads using image analysis techniques for urban mapping and updating geographic information systems (GIS) databases has been an active research topic in photogrammetry and remote sensing community. Segmentation plays an important role in the process of digital image processing towards automatic extraction of GIS objects from aerial imagery. In digital image processing, clustering techniques are often used to segment images since segmentation is really pattern recognition, i.e., classifying each pixel. The clustering methods can be based on either crisp set or fuzzy set. The most popular fuzzy segmentation algorithm is the Fuzzy C-Means (FCM) and many of research work have been proposed to speed up the FCM algorithm. Although the FCM algorithm is powerful in image segmentation, there is still a drawback encountered, namely the desired number of clusters should be specified. This is a disadvantage whenever the clustered problem does not specify any desired number of clusters. The situation is often for the segmentation of remotely sensed images, because the ground truth is always not available for these images. In this paper, a fuzzy clustering method based on fuzzy equivalence relation is presented. The clustering technique is a hierarchical clustering method. First, a fuzzy compatibility relation is created in term of the Euclidean distance. In general, the fuzzy compatibility relation is not necessarily a fuzzy equivalence relation. Then, the transitive closure are computed and used as the fuzzy equivalence relation to cluster a given image. Finally, image segmentation is completed by computing α-cut on fuzzy equivalence relation.

1. INTRODUCTION

Given the dynamics of urban areas, their density and the type and quality of geospatial data required for their planning, high-resolution remotely sensed imagery such as large-format aerial imagery is clearly a major source of data for urban mapping and urban GIS updating. Urban land use applications require the images to be divided into segments corresponding to areas of homogeneous land use. Image segmentation is usual technical means to generate and update such land use information for urban spatial databases. It plays a key role in a wide range of applications, such as image visualization (Manduca, 1996), image coding (Bosworth and Acton, 2000; Kim and Krim, 1999), image synthesis (Terzopoulos, 1997), pattern recognition (Torre and Radeva, 2000; Devaux et al., 2000), etc. Image segmentation is a process of partitioning an image into some regions such that each region is homogeneous and none of the union of two adjacent regions is homogeneous. Mathematically, given a finite set of all image pixels *S*, and a homogeneity predicate defined over clusters of connected pixels *P*(*S*), then image segmentation is a partition of the set S into a set of connected subsets (clusters) $\{s_1, s_2, \cdots, s_n\}$, where $s_{i(i=1,2,\cdots,n)} \in S$, such that

$$s_i \cap s_j = \theta\ ,\ \forall i, j \in n \text{ And } i \neq j\ ;$$

$$\bigcup_{i=1}^{n} s_i = S\ ;$$

$$P(s_i) = true\ ,\ \forall i \in n\ ;$$

$P(s_i \cup s_j) = false$, For any two neighbours s_i and s_j , $\forall i, j \in n$.

There have been many different families of segmentation algorithms proposed in past years. These algorithms can be categorized into edge-based (Marchisio et al., 2000), clustering-based (Pham et al., 2001; Noordam et al., 2000), region-based (Fradkin et al., 1999), and split/merge (Tyagi and Bayoumi, 1989; Tu et al., 2001) algorithms. Among these algorithms, clustering-based algorithms are ones of those proved to be suited for remotely sensed image segmentation. Two main clustering segmentation approaches based on crisp and fuzzy methods have been developed. The crisp clustering segmentation algorithms generate clusters such that each pixel in an image is assigned to exactly one cluster. However, fuzzy segmentation algorithms try to cope with each cluster as a fuzzy set, and each pixel in a image has a membership value (ranging between 0 and 1) associated to each cluster, measuring how much the pixel belong to that particular cluster. In the fuzzy segmentation algorithms, the most popular is the Fuzzy C-Means (FCM) algorithm (Bezdek, 1981) and many research works have been proposed to steep up the FCM algorithm (Thitimajshima, 2000; Chen and Wang, 1999; Melek et al., 1999). Although the FCM algorithm is powerful in image segmentation, there is still a drawback encountered, namely the desired number of clusters should be specified in advance. This is a disadvantage whenever the clustering problem cannot specify any desired number of clusters. The situations are often for remotely sensed image segmentation, because the ground truth is always not available for these images. In this paper we concern with color aerial image segmentation using fuzzy equivalence relation-based clustering method.

The paper is organized as follows. A short review on the concept of the proposed fuzzy relation-based segmentation algorithm is described in Section 2. Then, in Section 3 we introduce the clustering algorithm based on fuzzy equivalence relation. Segmented results are presented in section 4. We conclude the paper with an outlook on future work in Section 5.

2. BACKGROUND

In this section, we use the same symbol *A* to donate the fuzzy set and its membership function, and *R* for the fuzzy relation and its membership function.

Consider an arbitrary nonempty set *U* called a universe, a fuzzy set *A* in *U* is a function $A: U \rightarrow [0,1]$ called membership function of the fuzzy set *A*. The membership function is interpreted as the degree of membership of element *x* in the fuzzy set *A* for each $x \in X$. Each fuzzy set is completely and uniquely defined by one particular membership function.

Consider a filmy $U = \{U_i | i = 1,2,\cdots,n\}$, a n-dimensional fuzzy relation is a fuzzy set defined on the Cartesian product of the family, where n-tuples $\langle u_1, u_2, \cdots u_n \rangle$ ($u_1 \in U_1$, $u_2 \in U_2, \cdots$, $u_n \in U_n$) may have varying degrees of membership within the relation. A two-dimensional fuzzy relation is called as a binary fuzzy relation. Instead of defining a binary relation that exists between two different sets, we can also define a fuzzy binary relation among the elements of a single set *U*, namely $R: U \times U \rightarrow [0,1]$. These fuzzy relations are often referred to as binary relation on a single set. Let U be an arbitrary crisp set and $R: U \times U \rightarrow [0,1]$ be the fuzzy binary relation on U and t be a t-norm (a binary function $t :< 0,1 > \times < 0,1 > \rightarrow < 0,1 >$ is said to be a t-norm if it is associative, commutative, non-decreasing and fulfils the border condition $t(r,1) = r$ for all $r \in < 0,1 >$), then R is said to be a fuzzy compatibility relations on U, when R is reflexive on U, for every $u \in U$, $R(u,u) = 1$ and R is symmetric on U, for all $u, v \in U$, $R(u,v) = R(v,u)$. Whereas R is said to be t-fuzzy equivalence elation on U, when R is a fuzzy compatibility relation on U and R is t-transitive on U, for all $u, v, w \in U$, $t(R(u,v), R(v,w)) \leq R(u,w)$.

In our algorithm, a max-min-norm is adopted as t-norm, namely

$$t(R(u,v), R(v,w)) = \max_{v \in U} \min\big(R(u,v), R(v,w)\big) \tag{1}$$

Correspondingly the t-transitive is the max-min-transitive,

$$R(u,w) \geq \max_{v \in U} \min\big(R(u,v), R(v,w)\big) \tag{2}$$

If R is a fuzzy equivalence relation, then each α-cut of the fuzzy equivalence relation ${}^{\alpha}R$ is a crisp equivalence relation that represents the presence of similarity between the elements to the degree α. Each of α-cut of these fuzzy equivalence relations forms a partition of U. In this paper, the fuzzy clustering technique based on the fuzzy equivalence relation is used to perform the segmentation of a colour aerial image of a real world scene.

3. CLUSTERING ALGORITHM BASED ON FUZZY EQUIVALENCE RELATION

The clustering technique based on the fuzzy equivalence relation is a hierarchical clustering method. The core of the algorithm lies in computing a fuzzy equivalence relation *R* on a pixels set *X* that character the degree of similarity of the elements in the set *X*. In the algorithm proposed here, a fuzzy equivalence relation is computed by a fuzzy compatibility relation that is created in term of the Euclidean distance on RCB space.

3.1 Colour Image Description

To perform colour image segmentation, a colour model must be selected. The purpose of the colour model is to facilitate the specification of colours in some standard manner. In general, a colour model is a specification of a three-dimensional coordinate system where each colour is represented by a point (Pratt, 1991). The most known colour model is the RGB (Red, Green and Blue) model. With the RGB model, a colour is described in term of the percentage of three primary colours (Red, Green and Blue) in the colour. For example, combining 100% red, 100% green and 100% blue creates white, i.e., <255, 255, 255> in RGB values. Conversely, black can be obtained by combining 0% red, 0% green and 0% blue, <0, 0, 0> in RGB values. Thus, in RGB system, a colour image can be represented with n-array vectors set $X = \{\mathbf{x_1}, \mathbf{x_2}, \cdots \mathbf{x_n}\}$ in a RGB system, where n is the number of pixels in the image. Each element in the set is a three-dimensional vector representing three primary colours (Red, Green, Blue) of the pixel in the RGB coordinate system, namely $\mathbf{x}_i = (x_{i1}, x_{i2}, x_{i3})$, $i = 1,2,\cdots,n$.

3.2 Computing the Fuzzy Binary Relation

The aim of this step is to compute a fuzzy binary relation R_c on *X*, which will measure the similarity between the pixels in an image in RGB system. The fuzzy binary relation is represented by $n \times n$ matrix R_C. The element in the matrix is denoted by

$$r_{ij} = 1 - \frac{\left[\sum_{k=1}^{3} \left(x_{ik} - x_{jk}\right)^2\right]^{\frac{1}{2}}}{\max_{i,j \in n} \left[\sum_{k=1}^{3} \left(x_{ik} - x_{jk}\right)^2\right]^{\frac{1}{2}}} \tag{3}$$

Obviously, the fuzzy binary relation R_C is a fuzzy compatibility relation.

Actually, there are much appropriate distance functions on X can be used as membership grade of a fuzzy compatibility relation R_c on X. The reason, using (3) as the measurement of similarity between any two pixels in a given image, is based on the ideal, namely, in an image the identical pixel should have the maximum similarity, i.e. its membership grade should be 1. Conversely, two pixels with the maximum distance in the RGB space are not similar, i.e., its membership grade should be 0.

3.3 Computing the Fuzzy Equivalence Relation

In general, fuzzy relation R_C computed by (3) is a fuzzy compatibility relation, but not be necessarily a fuzzy equivalence relation. According to the fuzzy compatibility relation R_C computed by above step, the following algorithm (George and Bo Yuan, 1995) is used to compute a fuzzy equivalence relation,

Step 1: $R' = R_C \cup (R_C \circ R_C)$;

Step 2: If $R' \neq R_C$, make $R_C = R'$ and go to Step 1;

Step 3: If $R' = R_C$, then stop and R_C is a fuzzy equivalence relation, denoted by R_T.

Where operator $\circ$ is the standard composition operation (Let $P = [p_{ik}]$, $Q = [q_{kj}]$ and $R = [r_{ij}]$ are binary relation matrixes such that $R = P \circ Q$, then $r_{ij} = \max_k \min(p_{ik}, q_{kj})$). Operator $\cup$ is the max operator for set union (Let $P = [p_{ij}]$, $Q = [q_{ij}]$ and $R = [r_{ij}]$ are binary relation matrixes such that $R = P \cup Q$, then $r_{ij} = \max(p_{ij}, q_{ij})$). It can be proved that R_T is a fuzzy equivalence relation on X.

3.4 Image Segmentation

Image segmentation can be completed by computing α-cut of R_T.

Step 1: Computing the level set of R_T,

$$\Lambda_{R_T} = \{\alpha \,|\, r_{ij} = \alpha,\ \forall r_{ij} \in R_T\} \tag{4}$$

Step 2: For $\alpha \in \Lambda_{R_T}$ computed by Step 1, the α-cut of R_T is a matrix ${}^{\alpha}R_T$ and can be computed with the following formula:

$${}^{\alpha}r_{ij} = \begin{cases} 1 & r_{ij} \geq \alpha \\ 0 & r_{ij} < \alpha \end{cases} \tag{5}$$

where

$${}^{\alpha}r_{ij} \in {}^{\alpha}R_T \text{ and } r_{ij} \in R_T .$$

Step 3: By constructing a partition tree for all α-cut matrixes, a hierarchical partition can be obtained.

Clearly, all partitions associated with $\partial \in (0,1]$ are nested. The partition $P({}^{\partial}R_T)$ is a refinement of other partition $P({}^{\beta}R_T)$, if and only if $\partial \geq \beta$.

4. IMPLEMENTATION AND RESULTS

The proposed fuzzy relation-based segmentation algorithm mentioned in the previous section has been implemented using Visual C++ on the colour orthoimagery with a spatial resolution of 1 m. We present here results on two typical urban subscenes: an urban green area and an urban residential area, in the Greater Toronto Area, Canada. The images consisting of 100 by 100 pixels each as shown in the Figures 1. The left image in Figure 1 consists of two roads, five individual houses, three swimming pools, trees and green areas covered by grasses, in which roads look like line-shaped structures. The right image in Figure 1 shows a typical Toronto residential area that consists of individual houses, trees and roads, in which roads look like long, rectangular structure rather than line-shaped structures. Trees along one road-side lead to the fragments of the street.

Figures 2 shows the segmented results of the colour orthoimages depicted in Figure 1, using the proposed approach, which set the α-cut parameter α=0.9. Figures 3 shows the segmented results presented by false colours, in which we can see that the presented algorithm gives the better results for all object classes, the segmented areas have the clear boundaries. Bright, long linear objects in Figure 2 (left) are segmented roads.

5. CONCLUSIONS

A fuzzy clustering method based on fuzzy equivalence relation was proposed. In experiments, the proposed method demonstrated promising performance even in a complex urban environment. In particular, the proposed approach gives a better shape description of the roads in a urban green area than that in a residential area where similar spectral and radiometric properties between roads and some buildings lead to misclassification. Currently, our work is addressing on the extension of the proposed approach by defining more effective rules to construct the fuzzy relation, analysing the effectiveness of the segmentation algorithm, and examining the traits of the fuzzy partitions being isomorphic to the fuzzy equivalence relations.

Figure 1. Two sections of a colour orthoimagery covering an urban area (left: urban green area; right: urban residential area).

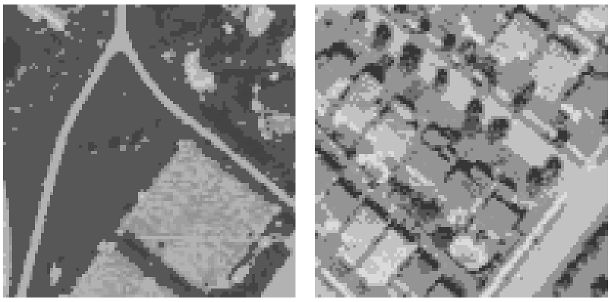

Figure 2. Segmented results derived by FCM approach.

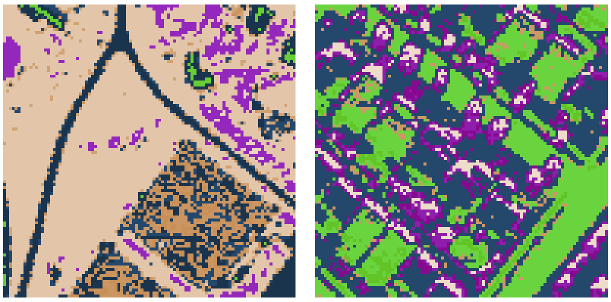

Figure 3. Segmented results displayed by false colours.

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