Pixel-based Fuzzy Classification of Aerial Images

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Abstract— This paper proposes a fuzzy approach oriented towards the classification of aerial images where the contained information is usually imprecise (it specially happens at the boundaries of the considered regions). Our pixel-based classification method produced an average accuracy of 78.73% for the considered test images when comparing the automatic results with those provided by a human expert.

Keywords- aerial images; remote sensing; pixel-based classification; fuzzy sets; nonlinear filtering; colour spaces.

I. INTRODUCTION

Remote sensing commonly refers to the acquisition of information corresponding to a geographical area and using sensing devices placed on aircrafts or satellites [1]. This makes it possible to collect data from difficult-to-access regions. In aerial photos, objects or regions are captured from an overhead position and they are taken at scales that most people are not getting used to see. Moreover, very often the infrared wavelengths are also captured with these images. The automatic classification of remotely sensed data is essential for generating or updating Geographical Information Systems (GIS) databases.

Pixel-based and object-based [2][3] are two usual classification methodologies for the analysis of remote sensing images. Pixel-based classification uses the values of the pixels themselves and classifies the images by considering the spectral similarities with a set of predefined land-cover classes. In the object-based approach, the processing units are no longer single pixels but objects. An initial segmentation of the image into regions is required to state a set of knowledge-based classification rules describing classes. According to these rules, a classification system is used to assign each image region to the appropriate class according to the proposed rules. Object-based methods are more computationally expensive than pixel-based ones but they can produce better results. In a recent study by Gao and Mas [2], object-based classification approaches take advantage in accuracy over the pixel-based ones but this only holds for high spatial resolution images. On the other hand, pixel-based methods are actually well developed and new improved techniques have been proposed like soft computing-based classifiers or sub-pixel approaches.

Pixel-based classifiers offer the advantages of simplicity and computational efficiency. However, they lack from mechanisms to incorporate the expert's knowledge and also to handle with the inherent uncertainty of the aerial image classification problem. In this sense, fuzzy sets [4] provide a suitable framework for both incorporating this problem domain knowledge offered by the expert and also for handling the imprecise categorization of pixels during the classification task. In fuzzy sets the elements have degrees of membership in the real unit interval [0,1]. These sets are a generalization of the classical crisp sets where the membership of an element in a set can be only 0 or 1. The relaxation of the restriction imposed to crisp sets makes possible to characterize the membership of a pixel to several simultaneous classes (i.e. partial membership) along the intermediate classification process.

Next, we shortly outline some related works using fuzzy sets for the classification of aerial and remote sensing images. Wang in 1990 [5] presented a fuzzy supervised classification method applied to aerial and satellite images where the geographical information is represented as fuzzy sets. His algorithm has two major steps: estimation of fuzzy parameters from training data, and a fuzzy partition of the spectral space. The use of fuzzy analysis of textures combined with the application of OWA operators has shown to improve the segmentation of aerial images [6]. Amo et al [7][8] introduced a general approach to spectral fuzzy classification for remotely sensed data that adds into the classification some multicriteria techniques. One conceptual advantage of their proposal is that the understanding of the fuzzy classes will now be easier for the decision makers. Recently, an iterative weighted fuzzy c-means method [9] has been introduced for multidimensional data clustering and aerial image classification. To increase the algorithm speed, the appropriate initial clustering centers are selected by a single point adjustment algorithm.

II. PIXEL-BASED FUZZY CLASSIFICATION SYSTEM

A. *High-level system description*

Figure 1 presents the pseudocode of the proposed pixel-based fuzzy classification system. Each function represents a stage of the method. These stages are detailed in the next subsection. The notation [.] in the algorithm means that the corresponding inputs or outputs of functions are vectors or arrays of values.

Inputs: - Color RGB (or HSV) image I
- (Optional) Number of classes k

Output: Image I' with pixels labeled to one of k classes

Algorithm:

```
k = ComputeNumberOfClasses (I); (*optional*)
[z]= ObtainCentroidsOfClasses (I,k);
[vk] = ComputeParameterVectorFuzzySets ([z]);
(* an array of 3×k images is now available *)
for all 3×k images do (*apply separately *)
  [I1] =ComputeFuzzyMembershipOfPixels(I,[vk]);
  [I2] = SimplifyFuzzyMemberShipOfPixels([I1]);
  [I3] = SortClasses([I2]);
end;
[I4] =MergeChannels([I3]); (*one image per class*)
for all k class images do (* apply separately *)
  [I5] = DefuzzifyPixels ([I4])
end;
I' = Combine ([I5]) (* produce result image I' *)
```

Figure 1. Pixel-based fuzzy classification algorithm.

B. *Description of involved fuzzy classification stages*

This subsection summarizes the stages of the proposed pixel-based fuzzy classification system applied to aerial 3-channel color images. In general, our approach can also be adapted in a straight forward way to any type of multi-band images.

- Compute the number of classes k for a test image I.

This value is optional and it is computed off-line. An expert user of the system can state the suitable number of classes for a given test image. Otherwise, this number is obtained by the average sum of squared differences $v_k(I)$ between each image pixel and the centroid of each estimated class. The number of classes k is computed using the fuzzy c-means algorithm [10]. If the value of $v_k(I)$ is smaller than a empirical threshold the algorithm returns the appropriate number of classes; otherwise, the procedure is repeated increasing k by one. An experimental threshold is obtained by training on a large collection of images and taking into account the number of classes determined by an expert at any of the training images. This threshold represents the maximal allowed difference between a pixel in a class and the corresponding class centroid value.

- Obtain the centroids of the k classes.

If the estimated number of classes is provided by the user, we apply the fuzzy c-means algorithm [10] to compute these centroids. When the system computes this number, the corresponding centroids are obtained at the previous stage.

- Compute parameters of the fuzzy sets.

The membership function m_{kf} for each pixel I_{ijf} (where i and j correspond to spatial coordinates) to each class k ($k \in [1,2,,..., K]$) and image plane f ($f \in [1,2,3]$) is defined as in [7][8] using the corresponding trapezoid-shape fuzzy sets. These fuzzy sets need from four parameters (i.e. the corresponding trapezoid vertices) which again calculated like in [7][8].

- Compute fuzzy membership for each image pixel.

Once obtained the four parameters for all fuzzy sets defining each of the considered classes in the image, the membership degree of each image pixel I_{ijf} to each class is obtained. This is independently done for each of the $3\times k$ generated images where 3 are the number of color channels and k is the number of classes. Consequently, each pixel I_{ijf} will have associated a set of three membership vectors v_f (one for each color channel $f \in [1,2,3]$) with size equal to the possible class values $k \in [1,2,,..., K]$. As it is usual, the partition of unity [4] is considered in our approach.

$$v_f(I_{ijf}) = (m_{f1}(I_{ijf}),...,m_{fK}(I_{ijf})) \wedge (\sum_{k=1}^{K} m_{fk}(I_{ijf}) = 1) \quad (1)$$

- Simplify the fuzzy membership vectors.

At this point, it is not realistic at all that a pixel could be classified as belonging to a high number of classes (i.e. four of more). However, it is possible that a given pixel could have very low membership values for many of the considered classes. The aim of this stage is to reduce in a realistic way the number of classes to which a pixel has a membership different from zero. This is done by proportionally redistributing the smallest class membership values into the classes with higher membership for the considered pixel according to the algorithm of Figure 2. It corresponds to a nonlinear rule-based filtering. The first rule is applied when the membership difference between the third and fourth decreasingly sorted components of any of the class-membership vector corresponding to a pixel is greater of equal than an experimental threshold th (in our approach th=0.15 produced good results). The second rule is applied when the previous condition fails; in this case, we compute the threshold th' as the average among all membership values. Next, the first position of v whose value is smaller than th' is searched and all the smaller membership values are again redistributed among the larger ones like in the previous rule.

- Sort classes:

Next, it is necessary to sort the identified classes for each color channel due to the independent classification of the pixels at each image channel. The idea is to state the numbering of classes at the first image channel (i.e. the R-channel image in the RGB space) as reference for the other image channels. This stage requires $\mathbf{O}((f\text{-}1)\cdot k!)$ comparisons between pairs of component images.

- Merge color channels:

Once the images with labelled pixels are sorted for the considered classes, they are merged along the channels. The goal is to have one unique image for the whole set of channels (but maintaining one image per each class). Several simple merging strategies [11] that do not show any dependence on the results were considered. In particular, we tested the maximum, median and average of votes. The average strategy was adopted for providing good results.

Input: Membership vector v of a pixel to the k classes
Output: Simplified sorted membership vector v'
Algorithm:

Sort decreasing membership values of v;
if $v_3 - v_4 \geq th$ **then** (*Rule 1 *)

distribute $\sum_{j=4}^{K} v_j$ among v_i ($i \in [1,2,3]$):

$$v'_i = v_i + (v_i \times \sum_{j=4}^{K} v_j)/(v_1 + v_2 + v_3)$$

else (* Rule 2 *)

compute $th' = \frac{1}{K}\sum_{j=1}^{K} v_j$;

search l such that $v_l < th'$;

distribute $\sum_{j=l}^{K} v_j$ among v_i ($i \in [1,.., l-1]$):

$$v'_i = v_i + (v_i \times \sum_{j=l}^{K} v_j)/(v_1 + ... + v_{l-1})$$

end

Figure 2. Algorithm to simplify the membership vectors of pixels

- Defuzzify and combine classes:

Defuzzification produces the crisp result for the pixels (at all the class images) such that they only belong to one class. We applied the largest of maximum (LOM) deffuzification method [4]. Consequently, the corresponding class with the highest membership value is assigned to the pixel. Combination obtains the result image where pixels belonging to the same class are drawn using the same gray-level intensity.

III. EXPERIMENTS

Different experiments were performed on a collection of around 100 aerial images from different types (i.e. rural, urban, cartographic and satellite images) obtained from the web. These images, having different spatial resolutions (varying from 320×240 to 1024×768), are stored without loss of information in BMP format. Two types of experiments were carried out on them: (a) experiments to automatically determine the optimal number of classes to state for a given test image and (b) experiments to automatically segment an image and classify their pixels in the stated classes. For the first type, we used the method explained in Subsection II.B. For the second type of experiments, we have used images in two usual color spaces: RGB and HSV, respectively. Due to space restrictions, we only show and comment some results corresponding to the second class of experiments on some test images.

Figure 3 shows the results for a RGB image using different number of classes (four, six and seven classes, respectively). We notice that six or seven classes produce appropriate results. Figure 4 compares the results for two test images by setting the number of classes equal to four. For both examples, the results produced in the respective RGB and HSV spaces are shown. Classification results are promising for test images. In general, we observed that images with brighter color tonalities are better classified in the RGB space (first example) while the images with darker tonalities are better classified using the HSV space. This can be caused because in the HSV, the V channel (representing the brightness) was not used in the classification.

To accomplish quantitative results, we compared the classification results reported by a human expert (who generated the ground truth images) to those produced by our method on the same test images where the number of classes was initially set. A median filter was firstly applied on the images to remove some small regions that could not be selected by the expert. The average correct pixel classification for the considered 10 test images was a 78.73%. This result was achieved by comparing pixel-by-pixel the automatic classification provided by the method for test images with the corresponding ground truth images. Figure 5 shows a sample RGB test image that was segmented into four classes, the result automatically produced by the algorithm and the corresponding result presented by the expert for this image. For the sake of a better visualization, segmented regions produced by the expert are displayed in different colors (instead of using different grayscales like for the automatically segmented images). For this particular example with four classes, an 89.42% of the pixels were correctly classified when compared to the expert criteria.

IV. CONCLUSION

We presented a pixel-based fuzzy method to classify aerial images where the information is usually imprecise, specially the boundaries among the different considered regions. This method produced an average overall accuracy of 78.73%. In next works, the extension of this approach could handle different types of satellite multi-spectral images.

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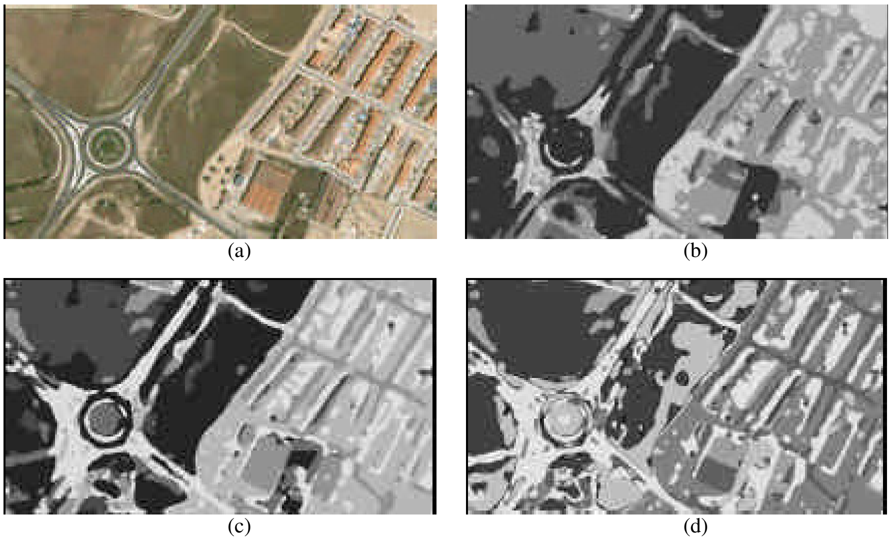

(a) (b) (c) (d)

Figure 3. (a) Original image and its automatic segmentation into (b) four, (c) six and (d) seven classes.

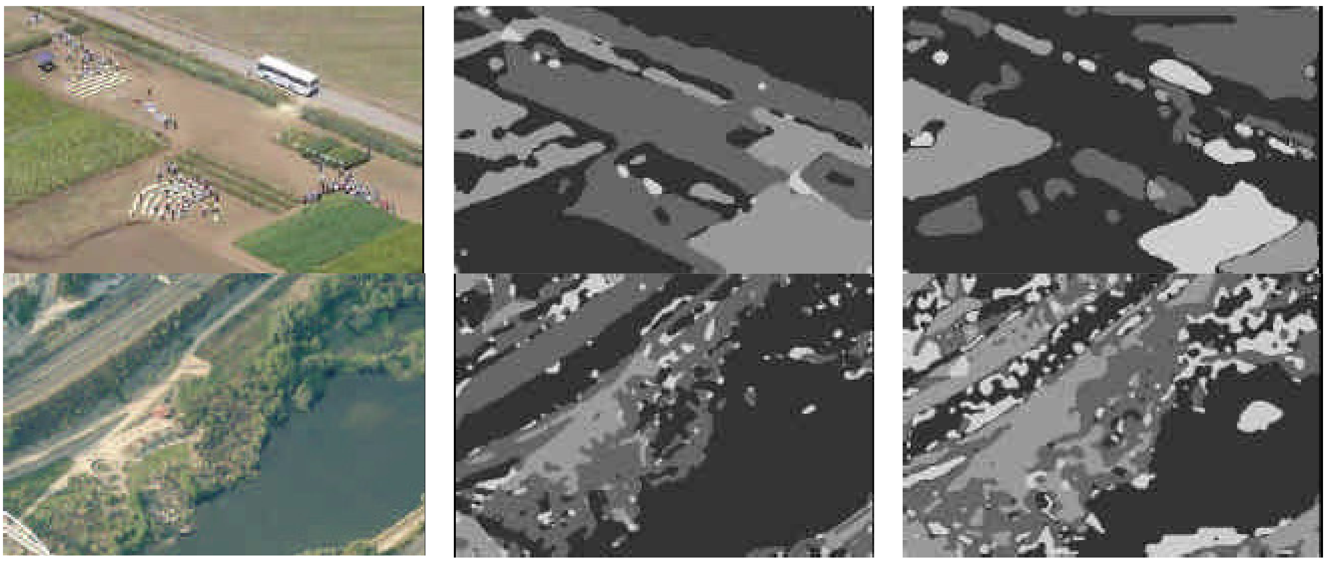

Figure 4.Segmentation of two test images into four classes: (left) original image, (centre) result in RGB space and (right) result in HSV space.

Figure 5. (Left) Original test image, and four class segmentation: (centre).automatic method and (right) manual result from an expert.