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## Image segmentation using fuzzy clustering incorporating spatial information

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#### How to cite:

Ali, Ameer; Karmakar, Gour C. and Dooley, Laurence S. (2004). Image segmentation using fuzzy clustering incorporating spatial information. In: International Conference on Artificial Intelligence and Applications (AIA '04), 16-18 Feb 2004, Innsbruck, Austria.

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# IMAGE SEGMENTATION USING FUZZY CLUSTERING INCORPORATING SPATIAL INFORMATION

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## Abstract

Effective image segmentation cannot be achieved for a fuzzy clustering algorithm based on using only pixel intensity, pixel locations or a combination of the two. Often if both pixel intensity and pixel location are combined, one feature tends to minimize the effect of other, thus degrading the resulting segmentation. This paper directly addresses this problem by introducing a new algorithm called *image segmentation using fuzzy clustering incorporating spatial information (FCSI)*, which merges the segmented results independently generated by fuzzy clustering-based on pixel intensity and the location of pixels. Qualitative results show the superiority of the FCSI algorithm compared with the fuzzy c-means (FCM) algorithm for all three alternatives, clustering using only pixel intensity, pixel locations and a combination of the two.

**Keywords** – Image Segmentation, Fuzzy Clustering, Spatial Information.

## 1. Introduction

Image segmentation is a very important research area because it plays a fundamental role in image analysis, understanding and coding [1]. It can be formally defined as the process of separating mutually exclusive regions (objects) of interest from other regions (objects) in an image. However, it is the most challenging task because there are often an inordinate number of objects and huge variations between them that make it almost impossible to approximate all the objects using a general frame. Most real-world images possess a certain amount of ambiguity and hence the segmentation produces fuzzy regions. Fuzzy image segmentation techniques are much more adept at processing such uncertainty than classical techniques and in this context, fuzzy clustering algorithms are the most popular and extensively used image segmentation techniques [2].

Clustering methods [3], [4], [5], [6], [7] utilize many different feature types, such as brightness (the pixel intensity of a gray scale image) and geometrical (the spatial location of the pixels). Clustering however cannot

separate image regions which have similar pixel intensities by considering only their pixel intensity, though they may be able to by exploiting information on the location of pixels. In the same way, clustering cannot segment adjacent regions having different pixel intensities by only considering pixel locations, but may well be able to do so by considering respective pixel intensities. From the observations, it was also found that clustering algorithm using both features i.e. the combination of pixel intensity and pixel locations could not produce the expected results for the image comprising of various regions having different pixel intensities. The above mentioned facts demand to introduce a new algorithm, which can combine the similar segmented regions independently produced by the clustering algorithm based on pixel intensity and pixel locations and refine the merged regions.

This paper introduces a new algorithm called *image segmentation using fuzzy clustering incorporating spatial information (FCSI)*. This merges similar regions produced by any clustering algorithm based on using the pixel intensity and pixel locations separately. FCSI then attempts to remove redundancies between the combined regions. In this paper all the clustering results are presented using the fuzzy c-means (FCM) algorithm [3] for pixel intensities only, pixel locations only and a combination of the two.

The paper is organized as follows: In Section 2, the basic mathematical principles of the FCM algorithm are outlined; while the underlying theory of the new FCSI algorithm is discussed in Section 3. Some experimental results and discussions are presented in Section 4. Finally, the conclusions are given in Section 5.

## 2. Fuzzy C-Means Algorithm (FCM)

FCM is the most popular fuzzy-based clustering technique [2]. It was developed by Bezdek (1981) and is still widely used in features analysis, pattern recognition, image processing, classifier design and clustering [8]. The FCM algorithm is mainly based on the iterative minimization of the following objective function and constraints [2], [3]:

$$J_q(\mu, \nu) = \sum_{j=1}^n \sum_{i=1}^c (\mu_{ij})^q d_{ij}^2 \quad (1)$$

$$0 \leq \mu_{ij} \leq 1; \quad i \in \{1, \dots, c\} \text{ and } j \in \{1, \dots, n\} \quad (2)$$

$$\sum_{i=1}^c \mu_{ij} = 1; \quad j \in \{1, \dots, n\} \quad (3)$$

$$0 < \sum_{j=1}^n \mu_{ij} < n; \quad i \in \{1, \dots, c\} \quad (4)$$

where  $c$  and  $n$  are the number of clusters and data respectively.  $\mu$  is a set of membership values  $\mu_{ij}$ .  $\nu$  is a vector containing the values of cluster centers  $\nu_i$ .  $q$  is the fuzzifier  $1 < q \leq \infty$ .  $d_{ij}$  is the Euclidean distance between a datum  $x_j$  and the centre of the  $i^{\text{th}}$  cluster  $\nu_i$ . The objective function (1) is iteratively minimized using the following two equations for  $\mu$  and  $\nu$  respectively:

$$\mu_{ij} = \frac{1}{\sum_{k=1}^c \left( \frac{d_{ij}}{d_{kj}} \right)^{\frac{2}{q-1}}} \quad (5)$$

$$\nu_i = \frac{\sum_{j=1}^n (\mu_{ij})^q x_j}{\sum_{j=1}^n (\mu_{ij})^q} \quad (6)$$

The cluster centers are initialized either randomly or by an approximation method. The membership values and cluster centers are updated through an iterative process until the maximum change in  $\mu_{ij}$  becomes less or equal to a specified threshold.

### 3. The FCSI Algorithm

As mentioned in the previous section, the clustering algorithm could not produce good results using pixel intensity only, pixel location only and a combination of the two for all images. To address these drawbacks, this section presents a new algorithm called *image segmentation using fuzzy clustering incorporating spatial information (FCSI)*, which is able to find and combine the similar regions and refine the combined regions by removing the overlapping among the regions.

The various detailed steps involved in the FCSI algorithm are summarized in Table I. Initially an image is segmented into regions using a fuzzy clustering algorithm based on individually considering the pixel intensities and location of pixels. Similarly segmented regions produced by the pixel intensity and pixel location clustering are then merged (Steps 1 and 2). The overlapping between the two merged regions is then determined (Step 3) and if the

**Table 1: Image segmentation using fuzzy clustering incorporating spatial information (FCSI) algorithm**

**Precondition:** Initially segment regions  $R^I$  and  $R^L$  utilizing the pixel intensity and pixel locations respectively produced by any fuzzy clustering algorithm. The number of segmented regions ( $\mathfrak{R}$ ).

**Postcondition:** The final segmented regions  $R$ .

1. Determine the similar (closest) regions of  $R^I$  to  $R^L$ :

$$\text{similar}(R_j^I) = \min_{1 \leq k \leq \mathfrak{R}} \left\{ \sum |P_j^I(x, y) - P_k^L(x, y)| \right\}$$

where  $P_j^I(x, y) \in R_j^I$  and  $P_k^L(x, y) \in R_k^L$ .

2. Merge similar regions between  $R^I$  and  $R^L$ :

$$R_j = \left\{ P(x, y) \mid P(x, y) \in R_j^I \text{ OR } P(x, y) \in R_k^L \right\}$$

where  $P(x, y)$  is the pixel at location  $(x, y)$  and  $R_j^I$  is similar to  $R_k^L$ .

3. Calculate the overlap between the two merged regions:

$$R_{ij}^O = \left\{ P(x, y) \mid \begin{array}{l} P(x, y) \in R_i \text{ AND } P(x, y) \in R_j \\ \text{AND } i \neq j \text{ AND } 1 \leq i, j \leq \mathfrak{R} \end{array} \right\}$$

4. Either remove or redistribute the overlap by considering the locations of pixels using a threshold. This threshold is defined as the ratio of overlap for the merged regions  $R_i$  and  $R_j$  as:-

$$\eta_i = \frac{|R_{ij}^O|}{|R_i|}; \quad \eta_j = \frac{|R_{ij}^O|}{|R_j|}$$

IF  $((\eta_i > 0.5) \text{ or } (\eta_j > 0.5))$  THEN

Find the index  $k$  of the merged region containing less overlap:

$$k = \begin{cases} i & \text{if } \eta_i \leq \eta_j, \\ j & \text{otherwise.} \end{cases}$$

Remove the overlap from the merged region  $R_k$ .

ELSE

Redistribute the overlap by considering the spatial locations of pixels.

$$R_k = \left\{ P(x, y) \mid P(x, y) \in R_k \text{ AND } P(x, y) \notin R_{ij}^O \right\}$$

ratio between the number of overlapping and respective region pixels is greater than 0.5, the overlapping region is removed from the merged region which possesses the minimum ratio, otherwise the overlapping region pixels are redistributed between the two regions using FCM considering only pixel locations (Step 4). Finally, it should be highlighted that the FCSI algorithm is independent of the actual clustering algorithm employed.

#### 4. Simulation Results

The new FCSI and fuzzy c-means (FCM) [3] algorithms were implemented using Matlab 6.1 (The Mathworks Inc.). The pixel intensity, location of the pixels, and the combination of both features were each examined. All experiments were conducted using three natural gray-scale images comprising various types of objects, which were obtained from IMSI<sup>†</sup>. The backgrounds have been manually removed from all images for segmenting the foreground regions using their pixel locations.

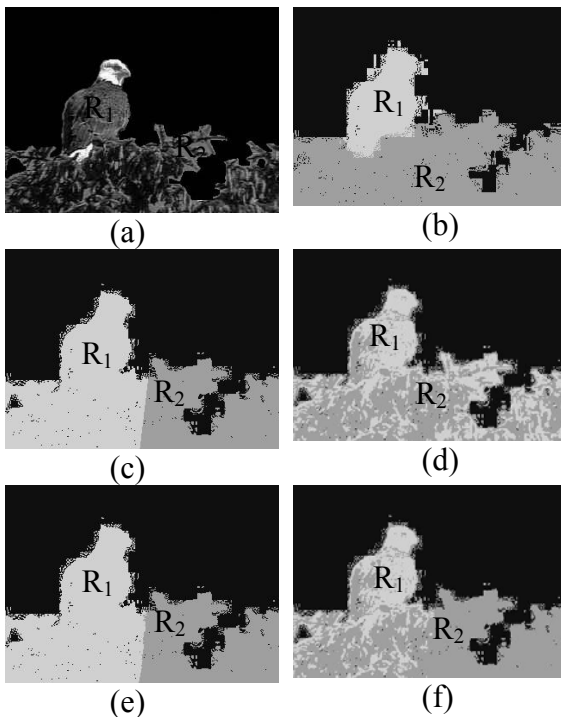


Figure 1: (a) Original tree image, (b) Manually segmented reference image of (a). Figures (c) – (e) the segmented results for the tree image into two regions using FCM with pixel locations only; pixel intensity only and both features respectively. (f) Segmentation result using FCSI.

The original images and their respective manually segmented regions (labeled  $R_1$  and  $R_2$ ) are shown in Figures 1(a)-1(b), 2(a)-2(b) and 3(a)-3(b). Note that the two manually reference and segmented regions are presented by two different gray level intensities instead of original region intensities in order to be clearly visible the segmented results.

The segmentation results obtained using the FCSI and FCM algorithms for the image comprising two regions, namely the bird ( $R_1$ ) and the tree ( $R_2$ ), are presented in Figure 1. If the segmented results produced by FCM for three cases (Figures 1(c)-1(e)) are compared with the corresponding region (object), it is visually obvious that the bird ( $R_1$ ) region contains a large number of misclassified pixels, which should have been segmented in the tree ( $R_2$ ) region. In contrast, the bird ( $R_1$ ) region in Figure 1(f) produced by the FCSI algorithm has far fewer misclassified pixels.

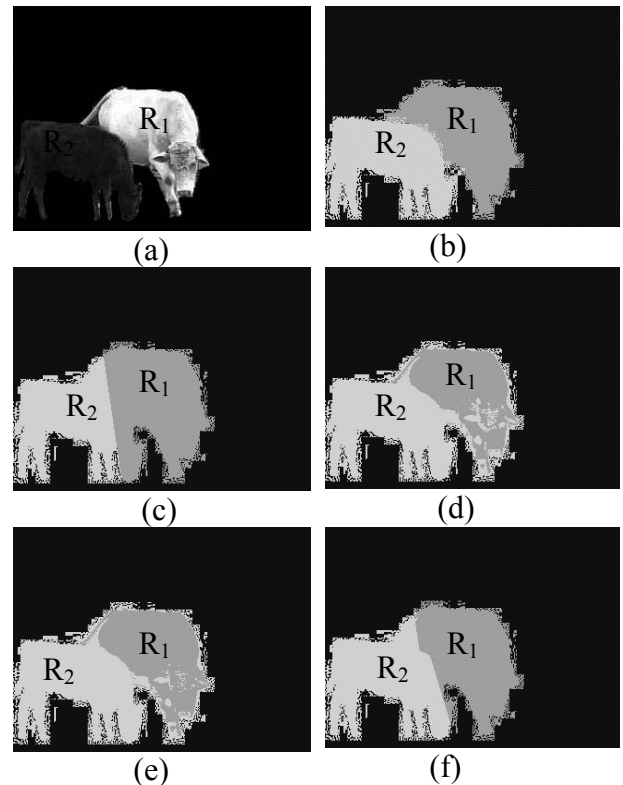


Figure 2: (a) Original cow image, (b) Manually segmented reference image for (a). Figures (c) – (e) the segmented results of the cow image into two regions using FCM with pixel locations only; pixel intensity only and both features respectively. (f) Segmentation result using FCSI.

A second experiment was conducted using the image containing two cows, regions ( $R_1$ ) and ( $R_2$ ) shown in Figure 2(a). Figure 2(c) shows that the cow ( $R_1$ ) region produced by FCM using only the locations of pixels

<sup>†</sup> IMSI's Master Photo Collection, 1895 Francisco Blvd. East, San Rafael, CA 94901-5506, USA.

includes a considerable number of pixels from the other ( $R_2$ ) region and vice versa. Note that FCM arbitrarily divided the regions shown in Figure 2(c) using only pixel locations. For the segmented results produced by FCM using the pixel intensity and both the pixel intensity and the locations of pixels, the cow ( $R_2$ ) region clearly possesses a large number of the other region's ( $R_1$ ) pixels (Figures 2(d)-(e)). If the segmented results produced by the FCSI algorithm (Figure 2(f)) are contrasted with the corresponding results of the manually segmented results shown in Figure 2(b), it again reveals the superior performance of the algorithm in separating the two regions with far fewer misclassified pixels, especially in region ( $R_2$ ).

The final experiment was performed using the sun image (Figure 3(a)) having two regions: the sun ( $R_1$ ) and the tree branch ( $R_2$ ). Again the segmented results produced by the FCSI algorithm (Figure 3(f)) contain fewer misclassified pixels especially for the tree ( $R_2$ ) region compared with all the corresponding FCM results in all cases (Figures 3(c)-(e)).

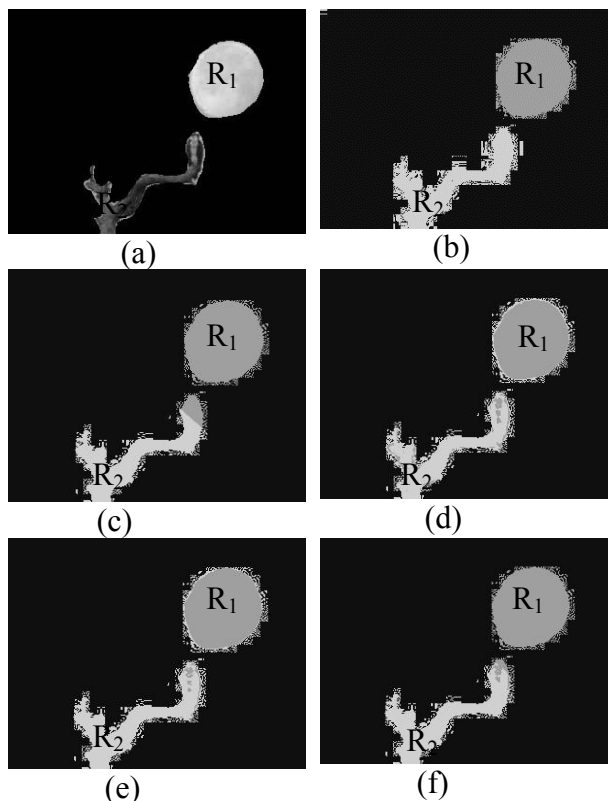


Figure 3: (a) Original sun image, (b) Manually segmented reference image for (a). Figures (c) – (e) the segmented results of the sun image into two regions using FCM with pixel locations only; pixel intensity only and both features respectively. (f) Segmentation result using FCSI.

From this qualitative-based analysis, it can be concluded that for all the test images used (Figures (1)-(3)), the new FCSI algorithm exhibits significant improvement in its segmentation performance compared to FCM for all three cases, that is using clustering based on pixel intensity, on pixel location and the combination of the two. Currently a quantitative analysis is being undertaken to also provide an objective evaluation and metric of the performance improvement of using the FCSI algorithm for fuzzy clustering.

## 5. Conclusions

This paper has presented a new algorithm called *image segmentation using fuzzy clustering incorporating spatial information* (FCSI). The fuzzy c-means (FCM) algorithm has been used to obtain the segmented results based on using pixel intensity, the locations of pixels and a combination of the two. The qualitative analysis of the results produced by the FCSI algorithm has been presented and has shown it provides considerable overall improvement over the FCM algorithm for all cases. The main advantage of the proposed algorithm is that it can be used to combine the segmented results using any number of independent features. Since the new algorithm is based on clustering, initially the prior number of clusters has to be specified.

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