FUZZY IMAGE SEGMENTATION USING LOCATION AND INTENSITY INFORMATION

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Abstract

The segmentation results of any clustering algorithm are very sensitive to the features used in the similarity measure and the object types, which reduce the generalization capability of the algorithm. The previously developed algorithm called *image segmentation using fuzzy clustering incorporating spatial information* (FCSI) merged the independently segmented results generated by fuzzy clustering-based on pixel intensity and pixel location. The main disadvantages of this algorithm are that a perceptually selected threshold does not consider any semantic information and also produces unpredictable segmentation results for objects (regions) covering the entire image. This paper directly addresses these issues by introducing a new algorithm called *fuzzy image segmentation using location and intensity* (FSLI) by modifying the original FCSI algorithm. It considers the topological feature namely, connectivity and the similarity based on pixel intensity and surface variation. Qualitative and quantitative results confirm the considerable improvements achieved using the FSLI algorithm compared with FCSI and the fuzzy c-means (FCM) algorithm for all three alternatives, namely clustering using only pixel intensity, pixel location and a combination of the two, for a range of sample of images.

Keywords – Image Segmentation, Fuzzy Clustering, Connectivity, Location.

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] use many different feature types, such as brightness (the pixel intensity of a gray scale image) and geometrical (the spatial location of the pixels) for measuring the similarity but the segmented results are very much dependent on the types of feature used in clustering and the types of the objects in an image. This raises the question as to which type of feature is most suitable for which type of object so limiting the generalization of a clustering algorithm [3]. For instance, FCM 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 or a combination of pixel intensity and location. In the same way, clustering cannot segment adjacent regions having different pixel intensities by only considering pixel location, but may well be able to do so by considering respective pixel intensities. From the observations, it was also found that in the most cases, clustering algorithms using both features, i.e. a combination of pixel intensity and location did not produce the expected results for the objects of an image having the same pixel intensity and surface variations and in some cases, it also was unable to separate the objects having distinguishable pixel intensities. These issues were addressed by Ali *et a*l. [8] who introduced an algorithm called *image segmentation using fuzzy clustering incorporating spatial information* (FCSI). The main drawback of this algorithm is that it uses a perceptually selected threshold, which redistributes the overlap between two regions without considering any semantic information about an object. It also does not handle well the situation where an object covers almost the entire image.

This paper introduces a new algorithm called *fuzzy image segmentation using location and intensity information (FSLI).* It considers the connectivity topological feature, and an object's similarity based on pixel intensity and surface variation. The original FCSI algorithm has also been modified and integrated within the new algorithm. A numerical analysis of FCM, FCSI and the proposed FSLI is performed using one of the efficient objective segmentation evaluation methods, namely *discrepancy based on the number of misclassified pixels* [9]. In this paper all the clustering results are presented using the fuzzy c-means (FCM) algorithm [3] for pixel intensity only, pixel location 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 theoretical concepts of the modified FCSI and the new FSLI algorithms are discussed in Sections 3 and 4 respectively. The numerical evaluation of the experimental results is analysed in Section 5. Finally, some conclusions are given in Section 6.

2. Fuzzy C-Means Algorithm (FCM)

FCM is the most popular and oldest fuzzy-based clustering technique [2]. It is still widely used in features analysis, pattern recognition, image processing, classifier design and clustering [10]. The FCM algorithm is mainly based on the optimization of the following objective function and constraints [2], [3]:

$$J_q(\mu, v) = \sum_{j=1}^{n}\sum_{i=1}^{c}\left(\mu_{ij}\right)^q d_{ij}^2 \qquad (1)$$

$$0 \le \mu_{ij} \le 1; \quad i \in \{1,\ldots,c\}\ and\ j \in \{1,\ldots,n\} \qquad (2)$$

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

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

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

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

$$v_i = \frac{\sum_{j=1}^{n}\left(\mu_{ij}\right)^q x_j}{\sum_{j=1}^{n}\left(\mu_{ij}\right)^q} \qquad (6)$$

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

3. The Modified FCSI Algorithm

A detailed description of the original *image segmentation using fuzzy clustering incorporating spatial information (FCSI)* algorithm is given in [8]. The main drawback of this algorithm concerns the perceptually selected threshold used to redistribute the overlap between two regions without considering any semantic information of an object. To address this issue, the FCSI algorithm has been modified to redistribute the overlap by using 8-connected objects and the normalized pixel locations with a range from minimum to maximum gray level pixel intensity, thereby eliminating the threshold. The modified FCSI algorithm (Algorithm 1), is embedded in the new FSLI algorithm, which is described in the next section.

Algorithm 1: The modified fuzzy clustering incorporating spatial information (FCSI) algorithm.

Precondition: Initially segment regions R^I and R^L utilising pixel intensity and normalised pixel location or a combination of pixel intensity and normalised pixel location respectively produced by any fuzzy clustering algorithm. The number of segmented regions ($\Re$).

Postcondition: The final segmented regions R.

1. Determine the similar (closest) regions of R^I to R^L:
   $$similar(R_j^I) = \min_{1 \le k \le \Re}\left\{\sum\left|P_j^I(x,y) - P_k^L(x,y)\right|\right\}$$
   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:
   $$R_j = \left\{P(x,y) \middle| P(x,y) \in R_j^I\ OR\ P(x,y) \in R_k^L\right\}$$
   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:
   $$R_{ij}^O = \left\{P(x,y) \middle| \begin{array}{l} P(x,y) \in R_i\ AND\ P(x,y) \in R_j \\ AND\ i \ne j\ AND\ 1 \le i, j \le \Re \end{array}\right\}$$
4. Redistribute the overlap by considering 8-connected objects.
5. Redistribute again the overlap using normalized pixel location and pixel intensity if there are any more pixels in the overlapping region.

4. The FSLI Algorithm

As mentioned in Section 1, the segmented results of a clustering algorithm depend on the features of the similarity measure and the types of object in an image. The original FCSI algorithm did not consider topological information about an object and was sensitive to the value of the threshold. In this section an algorithm *called fuzzy image segmentation using location and intensity information* (FSLI) is presented (Algorithm 2) to reduce the aforementioned limitations.

Algorithm 2: The fuzzy image segmentation using location and intensity (FSLI) algorithm

Precondition: The foreground of the image to be segmented and the number of segmented regions ($\Re$).

Postcondition: The final segmented regions R.

1. Calculate the areas A^w and A^f of the entire image (I) and the foreground (f) respectively.

$$A^w = \left|\{P(x,y) \mid P(x,y) \in I\}\right|$$

$$A^f = \left|\{P(x,y) \mid P(x,y) \in f\}\right|$$

2. Segment the image.

IF $\left(\left|A^w - A^f\right| \le \mathit{Threshold}\ T\right)$ THEN

Execute the modified FCSI algorithm (**Algorithm 1**) using pixel intensity and a combination of pixel intensity and normalized pixel location for initial segmented regions.

ELSE

Find the initial regions R^L using FCM with a combination of pixel intensity and normalised pixel location. Determine the area $A^{R_i^L}$ for each segmented region R_i^L.

$$A^{R_i^L} = \left|\left\{P(x,y) \middle| P(x,y) \in R_i^L\right\}\right|$$

where $i \in \{1,\ldots,\Re\}$.

IF $\left(\left|A^f - \max_{1\le i\le \Re}\left(A^{R_i^L}\right)\right| \le \mathit{Threshold}\ T_{\max}\right)$ THEN

The objects to be segmented are similar with respect to pixel intensity and surface variation and hence perform segmentation using FCM with normalised pixel location.

ELSE

The objects are dissimilar and hence segment the image using the modified FCSI algorithm (**Algorithm 1**) using pixel intensity and normalised pixel location.

FSLI segments the foreground objects by considering semantic information about these objects and considers two types of information – the image, which does not contain considerable number of background pixels and the similarity of the objects based on pixel intensity and surface variation. Firstly, the calculation of the area of the whole image A^w and the foreground A^f, in terms of the number of the pixels is described in Step 1, Algorithm 2. If the area of the foreground is approximately the same as the image, FCM using only pixel locations arbitrarily divides the image without considering semantic information about the image. To avoid this scenario, the difference between the foreground and entire image areas is perceptually thresholded and the segmentation performed using the modified FCSI algorithm (**Algorithm 1**) using pixel intensity and a combination of pixel intensity and normalized pixel location for initial segmented regions shown in Step 2, Algorithm 2. In all other cases, the segmentation is performed by considering the similarity and dissimilarity based on pixel intensity and surface variation of the objects of an image using a perceptually defined threshold $T_{\max}$. If FCM does not effectively separate the objects using a combination of pixel intensity and normalised pixel locations, the objects are similar in pixel intensity and surface variation and hence FCM with normalised pixel location is applied in segmentation (Step 2, Algorithm 2). Otherwise the objects are dissimilar and separated by the modified FCSI algorithm using pixel intensity and normalised pixel location. While the two thresholds T and $T_{\max}$ are perceptually determined by a small percentage (1%) of the foreground and the largest segmented region respectively, the new algorithm is not very sensitive to them.

5. Experimental Results

The new FSLI, FCSI and fuzzy c-means (FCM) [3] algorithms were implemented using Matlab 6.1 (The Mathworks Inc.). For FCM, only the pixel intensity, normalised pixel location, and a combination of both features were used. Since the FSLI and FCSI algorithms are based on clustering, the prior number of clusters c has to be manually chosen. A representative sample of three different types of natural grey-scale image consisting of different regions (objects) having similar and dissimilar pixel intensity and surface variation, used in the experiment, were obtained from IMSI[↑] and from the Internet. The backgrounds have been manually removed from all images for segmenting the foreground regions using their normalised pixel locations. Location in the form of the x, y coordinates of a pixel are normalised within the range [0, 255] in order to keep them within the same range of pixel intensities for 8-bit gray scale images.

[↑] IMSI's Master Photo Collection, 1895 Francisco Blvd. East, San Rafael, CA 94901-5506, USA.

The quantitative analysis was conducted using one of the most efficient segmentation evaluation methods, namely *discrepancy based on the number of misclassified pixels* [9]. The confusion matrix M is a $\Re$ *by* $\Re$ square matrix, where M_{ij} represents the number of pixels misclassified into the ith region from the jth region. The two types of error, namely Type I, $errorI_i$ and Type II, $errorII_i$ are defined as follows:

$$errorI_i = \frac{\left(\sum_{j=1}^{\Re} M_{ji} - M_{ii}\right)}{\sum_{j=1}^{\Re} M_{ji}} \times 100 \qquad (7)$$

$$errorII_i = \frac{\left(\sum_{j=1}^{\Re} M_{ij} - M_{ii}\right)}{\left(\sum_{i=1}^{\Re}\sum_{j=1}^{\Re} M_{ij} - \sum_{j=1}^{\Re} M_{ji}\right)} \times 100 \qquad (8)$$

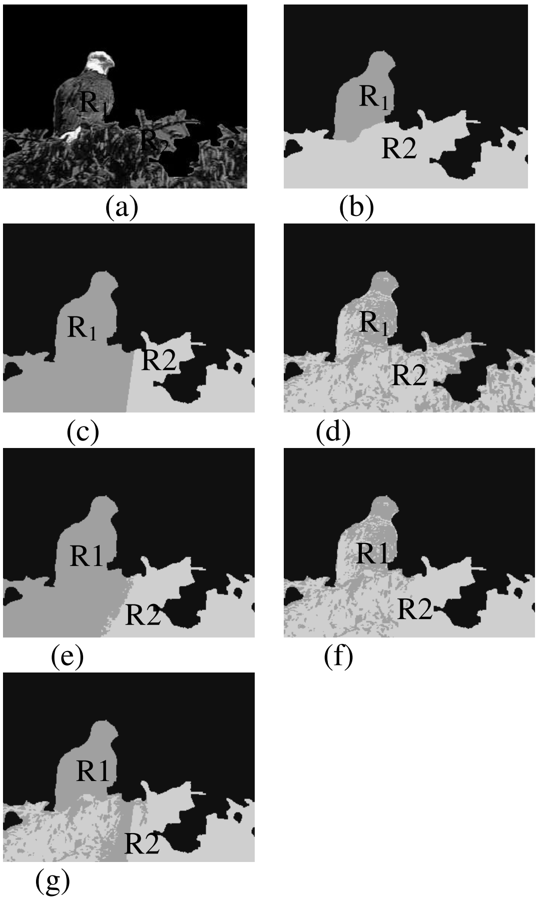


Figure 1: (a) Original tree image, (b) Manually segmented reference image of (a). Figures (c) – (e) the segmented results for the tree image into two regions using FCM with pixel locations only; pixel intensity only and both features respectively. (f) Segmentation result using FCSI. (g) Segmentation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

Type I, $errorI_i$ is the error percentage of all ith region pixels that are misclassified in the other regions, while Type II, $errorII_i$ is the error percentage of all region pixels that are misclassified into ith region. The manually segmented reference regions with their respective original image 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 levels instead of the original region intensities, in order to provide a better visual interpretation of the segmented results.

Experiments were performed using the bird image (Figure 1(a)) having two regions: the bird (R_1) and the tree (R_2) and its segmented results produced by FCM, the original FCSI [10] and FSLI are shown in Figure 1(c)-(g). If the results produced by the FSLI algorithm are compared with the other results (Figure 1(c)-(f) and manually segmented reference regions (Figure 1(b)), it is shown that the FSLI algorithm completely separated the bird (R_1) region from the tree (R_2) region. Figure 1(c) and 1(e) prove that FCM arbitrarily divides the foreground objects for normalized pixel location and a combination of pixel intensity and normalized pixel location. The corresponding numerical results for the bird (R_1) region shown in Table 1 confirm the superiority of the new FSLI algorithm to the other analysed algorithms and shows that FCM using location and location and pixel intensity produced no Type I error i.e. no pixels of the bird (R_1) region were misclassified into another region, because, as mentioned before, FCM using them arbitrarily divided the image (Figure 1(c) and 1(e)). For this reason, Type II error was also very high for the bird (R_1) region as a large number of pixels from the tree (R_2) region were misclassified into (R_1) region. The FSLI algorithm reduced the Type II error significantly while slightly increasing the Type I error. Overall, the mean error percentage of FSLI (12.28%) is considerably lower than for the other algorithms examined.

Table 1: Error percentages for the bird region (R_1) segmentation in Figure 1

Algorithm	Error		
	Type I	Type II	Mean
FCM (location)	0	53.2926	26.6463
FCM (Intensity)	34.5845	33.7895	34.1870
FCM (location & Intensity)	0	48.5902	24.2951
FCSI	34.5845	13.4322	24.0084
FSLI	2.3275	22.2309	12.2792

Another series of experiments was performed using the image (Figure 2(a)) containing two cows having different pixel intensities. The results shown in Figure 2 (c)-(g) illustrate that the FSLI almost separated the two cows (Figure 2(g)), while the other algorithms did not (Figure 2(c)-(f)). The average percentage error (2.88%) shown in Table 2 for the FSLI algorithm of this image is also noticeably lower compared with the others (10.9%, 8.36%, 3.73% and 4.5%).

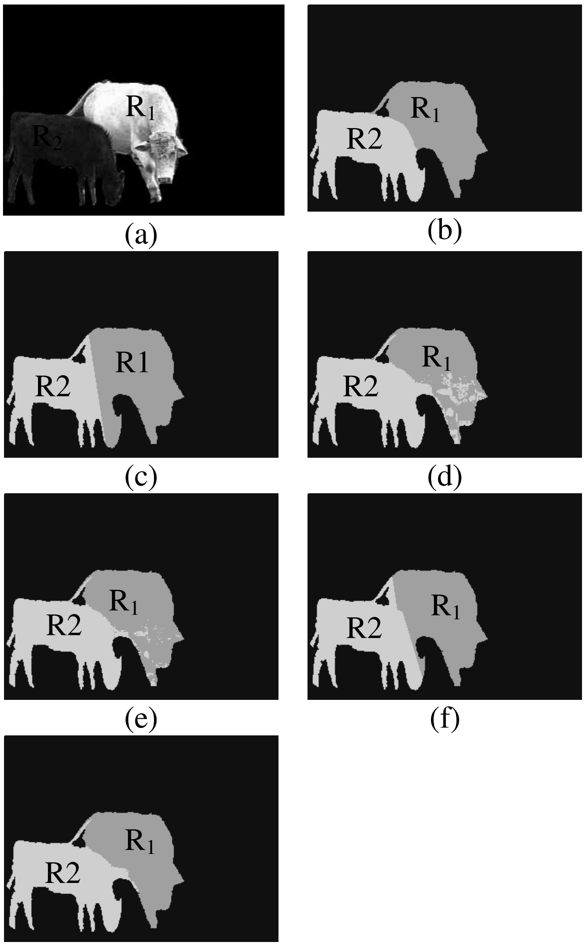
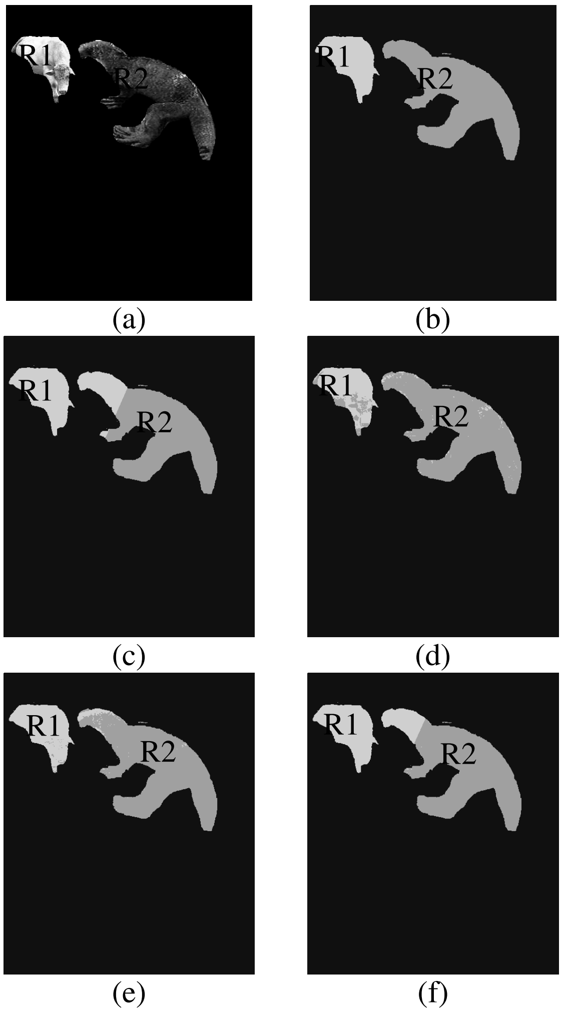


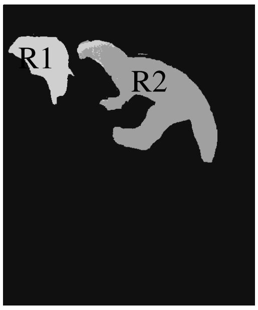
Figure 2: (a) Original cow image, (b) Manually segmented reference image for (a). Figures (c) – (e) the segmented results of the cow image into two regions using FCM with pixel locations only; pixel intensity only and both features respectively. (f) Segmentation result using FCSI. (g) Segmentation result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

Table 2: Error percentages for the cow region (R_1) segmentation in Figure 2

Algorithm	Error		
	Type I	Type II	Mean
FCM (location)	4.4310	17.3835	10.90
FCM (Intensity)	16.6476	0.0839	8.3657
FCM (location & Intensity)	7.4193	0.0479	3.7336
FCSI	4.4539	4.5525	4.5032
FSLI	5.7477	0.0120	2.8798

The final experiment was performed using the dinosaur image (Figure 3(a)) having two regions: the cow (R_1) and the dinosaur (R_2). Again the segmented results produced by the FSLI algorithm (Figure 3(g)) separated the entire cow (R_1) and the dinosaur (R_2) except for a few pixels of the dinosaur. The segmentation error percentage for the dinosaur image is shown in Table 3, which again confirms the improvement of the FSLI algorithm having average error of only 1.59%, whereas the average error for the other algorithm was 7.88%, 10.23%, 2.66% and 5.97%.





(g)

Figure 3: (a) Original dinosaur 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. (g) Segmentation result using FSLI.

Table 3: Error percentages for the dinosaur region (R_1) segmentation in Figure 3.

Algorithm	Error		
	Type I	Type II	Mean
FCM (location)	15.7643	0	7.8822
FCM (Intensity)	2.0159	18.4423	10.2291
FCM (location & Intensity)	3.2277	2.0946	2.6612
FCSI	11.9585	0	5.972
FSLI	3.1758	0	1.5879

From both the qualitative and quantitative analysis, it can be concluded that for all the test images used (Figures (1)-(3)), the proposed FSLI algorithm obtains considerable improvement in its segmentation performance compared with FCM for all three cases, that is using clustering based on pixel intensity, on pixel location and the combination of the two, as well as in comparison with the original FCSI algorithm.

6. Conclusions

This paper has presented a new algorithm called *image segmentation using location and intensity information* (FSLI) by applying connectivity, a topological feature and object similarity based on the pixel intensity and surface variation. Both qualitative and quantitative analysis of the results produced by all algorithms has exhibited the considerable improvement of the new algorithm compared with FCM using only pixel locations, only pixel intensity, and a combination of the two as well as the original FCSI algorithm. The main advantage of this algorithm is that it can separate any type of object from an image, to a certain extent. From the experiments, it has also been shown that the proposed FSLI algorithm is insensitive to the values of the thresholds T and $T_{\max}$. Since the new algorithm is based on clustering, it is required that initially the number of clusters to be used has to be specified for this algorithm.

References

[1] I. Gath, andA. B. Geva, Unsupervised Optimal Fuzzy Clustering, *International Journal of Pattern Analysis and Machine Intelligence, 2*(7), 1989, 773-781.

[2] G.C. Karmakar, L. Dooley, and M. R. Syed, Review on fuzzy image segmentation techniques, *Design and Management of Multimedia Information Systems: Opportunities and Challenges,* (USA, Idea Group Publishing Copyright, 2001).

[3] J.C. Bezdek, *Pattern Recognition with fuzzy objective function algorithm* (New York: Plenum Press, 1981).

[4] R. Krishnapuram and J. M. Keller, A Possibilistic Approach to Clustering, *International Journal of Fuzzy Systems, 2*(2), 1993, 98-110.

[5] Y. A. Tolias and M. Panas, On applying Spatial Constraints in Fuzzy Image Clustering Using a Fuzzy Rule-Based System, *IEEE Intern. Con. on Signal Processing Letters*, 1998, *5*(10), 245-247.

[6] A. W. C. Liew, S. H. Leung and W. H. Lau, Fuzzy image clustering incorporating spatial continuity, *IEE Proc.-Vis on Image Signal Process*, 2000, *147*(2),185-192,

[7] Z. Chi, H. Yan, and T. Pham, *Fuzzy Algorithms: With Applications to Image Processing and Pattern Recognition* (Singapore: World Scientific Publishing Co. Pte. Ltd. 1996).

[8] Ameer Ali, G.C. Karmakar and L. S. Dooley, Image segmentation using fuzzy clustering incorporating spatial information, *IASTED Intern. Con. on Computer Graphics and Imaging*, accepted for the publication, 2003.

[9] G.C. Karmakar, L. Dooley, A generic fuzzy rule based image segmentation algorithm, *Pattern Recognition Letters, 23*, 2002, 1215-1227.

[10] Jian Yu, Houkuan Huang and Shengfeng Tian, An Efficient Optimality Test for the Fuzzy C-Means Algorithm, *IEEE Intern. Con. on Fuzzy Systems*, 2002, 98-103.