FUZZY IMAGE SEGMENTATION USING SUPPRESSED FUZZY C-MEANS CLUSTERING (SFCM)

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ABSTRACT

Clustering algorithms are highly dependent on the features used and the type of the objects in a particular image. By considering object similar surface variations (SSV) as well as the arbitrariness of the fuzzy c-means (FCM) algorithm for pixel location, a *fuzzy image segmentation considering object surface similarity* (FSOS) algorithm was developed, but it was unable to segment objects having SSV satisfactorily. To improve the effectiveness of FSOS in segmenting objects with SSV, this paper introduces a new *fuzzy image segmentation using suppressed fuzzy c-means clustering* (FSSC) algorithm, which directly considers object SSV and incorporates the use of suppressed-FCM (SFCM) using pixel location. The algorithm also perceptually selects the threshold within the range of human visual perception. Both qualitative and quantitative results confirm the improved segmentation performance of FSSC compared with other algorithms including FSOS, FCM, possibilistic c-means (PCM) and SFCM for many different images.

1. INTRODUCTION

Image segmentation, especially object-based image segmentation is a very challenging task because of the large number of objects and the enormous variations among them, so it is extremely difficult to approximate every object within a general framework [1], [2]. Clustering algorithms [3]-[11], use many different feature types, such as brightness (pixel *intensity* [1] of a gray-scale image) and geometric information (pixel *location*), though an algorithm's effectiveness is very dependent on the type of object and the feature used. This raises an open question about which types of feature produce better results for which type of image and hence limit the generalisation of a clustering algorithm [3]. For instance, objects having similar pixel intensities in an image cannot be separated well by FCM [3], PCM [5] and SFCM [12] by considering only their PI. They may however be able to, by exploiting PL information or a combination (CIL) of PL and PI. Similarly, clustering cannot segment asymmetrically oriented adjacent regions having different intensities by only considering PL, but may well be

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[1] The terminology *PL*, *PI* and *CIL* refer respectively to *pixel location*, *pixel intensity* and a *combination* of pixel intensity and normalized pixel location.

able to do so by considering PI. It had been reported in [14] [15] that even clustering algorithms using both features, i.e. CIL, do not necessarily produce the expected results for all images. This is the motivation of merging the initial segmented regions produced by any clustering algorithm separately using different feature sets for final segmentation. To address these issues, Ameer et al. [14] introduced an algorithm called *fuzzy image segmentation considering object surface similarity* (FSOS) which considered connectivity, objects having similar surface variations (SSV) in an image and the arbitrariness of FCM using PL. The FSOS algorithm however, was unable to segment all objects having SSV well, if objects having SSV were not well separated spatially and was also sensitive to the perceptually selected thresholds. To address these issues, suppressed-FCM (SFCM) is used to segment objects having SSV because it is insensitive to fuzzy factor. The other reason is that SFCM prizes the biggest membership values and suppresses the others. For these reasons, SFCM using PL provides better segmented results than FCM using PL. This also increases the chance that the pixels those are close together, they will be classified into the same region (object). These motivate to us use SFCM using to PL segment objects having SSV.

This paper presents a new algorithm called *fuzzy image segmentation using suppressed fuzzy c-means clustering* (FSSC) which considers each object's SSV and SFCM using PL for its segmentation to improve the effectiveness of FSOS for objects having SSV. This paper includes a numerical analysis of PCM and SFCM for all feature sets and the proposed FSSC algorithm in addition to FSOS, *fuzzy image segmentation using location and intensity information* (FSLI), *image segmentation using fuzzy clustering incorporating spatial information* (FCSI) [13] and FCM for all feature sets using one of the objective segmentation evaluation methods [1].

The paper is organized as follows: In Section 2, issues relating to the identification of SSV are discussed, while the theoretical basis of the FSOS algorithm is presented in Sections 3 and 4. A detailed qualitative and quantitative performance analysis of the segmentation results of the new algorithm is provided in Section 5, with some conclusions given in Section 6.

2. SFCM ALGORITHM

Wei and Xie [16] originally proposed an algorithm called *rival checked fuzzy c-means clustering algorithm* (RCFCM) which magnified the largest membership value and suppressed the

second largest membership value μ. Since RCFCM gives priority to the biggest and the second biggest membership values of μ, μ is dependent on the value of the parameter α $(0 \leq \alpha \leq 1)$. This causes distortion of the original order of the membership values when the selection of α is unsuitable. To address this issue, Jui-Lun et al. [12] proposed an algorithm *called suppressed fuzzy c-means clustering algorithm* (SFCM) which gave the highest priority to the biggest membership and suppressed the others. Assume X_j is a datum. If the membership value of X_j belonging to cluster p is the biggest cluster, the value is noted as μ_{pj}. The modified membership value can then be defined as:

$$\mu_{pj} = 1 - \alpha \sum_{\substack{i=1 \\ i \neq p}}^{c} \mu_{ij} = 1 - \alpha + \alpha \mu_{pj} \qquad (1)$$

$$\mu_{ij} = \alpha \mu_{ij}, \quad i \neq p \qquad (2)$$

where $0 \leq \alpha \leq 1$ and c is the number of clusters. This modification does not disturb the original order and eliminates the drawback in RCFCM. When $\alpha = 0$, the algorithm provides hard clustering, while $\alpha = 1$ it gives the same results as FCM.

3. IDENTIFICATION OF OBJECTS HAVING SIMILAR SURFACE VARIATIONS (SSV)

To effectively segment objects having SSV, it is very important to identify similar and dissimilar object surfaces in an image, though this is a challenging task [15]. Two possible cases exist by which surfaces may be considered as similar with respect to brightness perspective. These are that the surfaces have: (i) similar intensity and (ii) possess SSV. In case (i), FCM using CIL produces similar results to FCM using PL [15]. For the later case, when objects have SSV i.e., objects with repeated patterns of bright and dark pixels, FCM using CIL is unable to separate them [15]. In this case one cluster covers the whole area of these objects. This motivated the use of FCM using CIL to determine the type of objects surface variations, such that when FCM using CIL cannot separate a group of objects, all these objects have SSV.

4. THE MODIFIED FCSI ALGORITHM

As mentioned in Section 1, since many objects contain ambiguous information, no single feature or combination of them is suitable for segmenting every object in an image. This was the rationale behind independently merging the segmented results produced by FCM using PL, PI and CIL in [13]-[15]. However, the FCSI algorithm is very sensitive to the threshold used for merging and the higher level features of an object are not considered. To merge the initial segmented results effectively, the original FCSI algorithm has been modified by incorporating connectedness [14]. In the modified FCSI (MFCSI) algorithm, misclassified pixels are distributed using 8-connected objects and 8-connectivity property to the corresponding merged pair. The reason for using 8-connectivity is to ensure all weak object connections are considered. If there still remain any non-connected pixels, these are redistributed by

FCM using CIL. CIL is used as the feature because it is a combination of PI and PL, which reduces the sensitivity of the perceptual threshold. The steps of MFCSI algorithm is given in Algorithm 1

5. THE FSSC ALGORITHM

The FSOS algorithm [15] was unable to segment objects having SSV well, because it considers FCM using PL for segmentation. Since FCM using PL gives an arbitrary decision it does not provide superior results for objects having SSV which are not suitably oriented and connected for FCM. As outlined in Section 1, SFCM using PL always gives better segmented results than FCM using PL. For this reason, to address this limitation and also reduce the arbitrariness of FCM using PL (Section 2), this paper introduces a new algorithm (Algorithm 2) called *fuzzy image segmentation using suppressed fuzzy c-means clustering* (FSSC) which considers object surface similarity and SFCM using PL.

Algorithm 1: The Modified Image Segmentation using Fuzzy Clustering Incorporating Spatial Information (MFCSI) Algorithm

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Precondition: A selected pair of the initial segmented regions R^I, R^L and R^C ; $\Re$, connectivity.
Post-condition: The segmented regions R.
1. Determine similar regions.
2. Merge these similar regions.
3. Calculate the overlap between the two merging regions and remove overlapping pixels from them.
4. IF (connectivity) THEN distribute 8-connected objects of the overlap to merging regions using 8-connectivity.
5. Redistribute any remaining overlapping pixels by a clustering algorithm using CIL.

For object-based image segmentation, any image may contain objects with both SSV and DSV; any clustering algorithm that is able to identify between them in the segmentation process has the potential to offer superior results. A detailed description of how separating the object having SSV and DSV is presented in Algorithm 2. R^C the segmented regions produced by FCM using CIL is used as the initial segmented regions to determine whether the objects have either SSV or DSV. To locate SSV regions, the area $A^{R_i^C}$ of the segmented region R_i^C is calculated using a convex hull:-

$$A^{R_i^C} = Area\left(Convexhull\left(R_i^C\right)\right) \qquad (3)$$

where $Area(\bullet)$ and $Convexhull(\bullet)$ determine the area and the vertices of the convex hull of a region respectively. To identify objects having SSV, the regions are merged with each other. The merging of the two regions of R^C to form a new region R_k^M can be expressed as :

$$R_k^M = \left\{P(x,y) \middle| P(x,y) \in R_i^C \vee P(x,y) \in R_j^C\right\} \qquad (4)$$

where M is the number of merged regions in R_k^M, $2 \leq M \leq \Re$, $1 \leq k \leq \Re/2$, $i \neq j$ and $1 \leq i,j \leq \Re$, $\Re$ is the number of

segmented regions. The ratio between the difference between the area of the largest merged region $A_i^{'C}$ and $A^{R_k^M}$, the area of the kth merging region and the $A_i^{'C}$, is a measure of shape distortion (Step 5 Algorithm 2), because the merging region R_k^M always contains the largest merged region. If shape distortion is within $0.5\ dB$ the human eye cannot detect the change of shape. This implies if the shape distortion between the largest merged region and its corresponding merging region is less than $0.5\ dB$, the segmentation algorithm cannot separate the objects. This means that in the case described in Section 3, all merged regions will have SSV. To find if all objects have SSV, this hypothesis is applicable to all possible merging regions. Finally, objects having DSV are separated from those with SSV which are represented by region R^D, where D is the number of objects having DSV and $0 \le D \le \Re$. The clusters which are not merged to form similar regions are treated as clusters containing objects having DSV.

In the FSOS algorithm, multiple objects having DSV are segmented using the MFCSI algorithm since they have distinctive PIs. For $\Re$ regions, since the degree of arbitrariness of FCM using PL increases in $O(\Re^2)$ [15], for more than two objects with DSV, FCM using CIL produces better segmented results than FCM using only PL. In this case therefore, MFCSI is used with R^C and R^I where R^I is the initial segmented regions by FCM using PI. However, for two regions it is important to make a decision about which feature (either CIL or PL) is used in conjunction with PI. This decision has been considered by taking account of the superiority of using CIL and PI over PL. This is illustrated in Figure 1 (a) and (b), where

Algorithm 2: Separation of objects having similar and dissimilar surface variations Algorithm

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Precondition: Initially segmented regions R^C and $\Re$.

Post condition: A list of objects having similar and dissimilar surface variations are R_i^M and R^D respectively.

1. Set $M = 1$ and $k = 1$.
2. Form region R_k^M by combining R_i^C and R_j^C using (4).
3. Calculate areas $A^{R_k^M}$, $A^{R_i^C}$ and $A^{R_j^C}$ using (3).
4. Find the maximum area $A_i^{'C}$ of $(M+1)$ regions in R_k^M.
5. IF $\dfrac{\left| A^{R_k^M} - A_i^{'C} \right|}{A_i^{'C}} \le T_{max}$ THEN the two regions R_i^C and R_j^C have SSV and increment M
6. Repeat Steps 2-5 for forming R_k^M by merging R_k^M and another region from R^C except the earlier merged regions.
7. IF $(M \ge 2)$ THEN increment k and repeat Steps 1-6.
8. Separate region R^D having D objects with DSV from R^C.

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angles θ_1 and θ_2 represent the discrepancy between the two decision boundaries separately produced by FCM, using *PL and CIL* and *PL and PI* respectively. For this case, the proper selection of feature sets and connectivity are given in Table 1
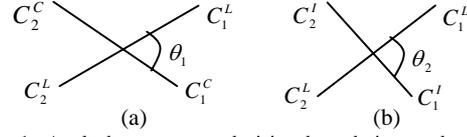

Figure 1: Angle between two decision boundaries produced by FCM separately using (a) *PL and CIL*, (b) *PL and PI*.

For objects having SSV, FCM using PL was used for segmentation because they cannot be separated by FCM using CIL and PI. As mentioned in Section 1, SFCM using PL provides better segmented results than FCM using PL, SFCM is used to segment objects having SSV in the FSSC algorithm (Step 3, Algorithm 3).

Note, the value of threshold T_{max} in Algorithm 2 is determined by considering human visual perception. The steps of the FSSC algorithm are given in Algorithm 3 where R^I and R^L are the initial segmented regions independently produced by FCM using PI and PL.

Algorithm 3: The fuzzy image segmentation using suppressed fuzzy c-means clustering (FSSC) algorithm

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Precondition: The foreground region f to be segmented, $\Re$, θ_1 and θ_2.

Post condition: The final segmented regions R.

1. Segment f by FCM using a combination into $\Re$ regions represented by R^C.
2. Find R_k^M and R^D applying Algorithm 2 for R^C.
3. IF $(k \ge 1)$ THEN FOR $i = 1, \cdots, k$
     Segment R_i^M into M regions by SFCM using PL.
4. IF $(D \ge 2)$ THEN
     connectivity=TRUE
     IF $(D = 2)$ THEN
       IF $(\theta_1 > 45^o)$THEN
       Connectivity=FALSE
       Segment R^D into D regions by MFCSI for R^I and R^C.
       ELSE IF $\left((\theta_1 \le 45^0)\ AND\ (\theta_2 > 45^o) \right)$ THEN
             Segment R^D by MFCSI for R^I and R^C
       ELSE segment R^D by MFCSI for R^I and R^L.
   ELSE segment R^D by MFCSI for R^I and R^C.

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6. EXPERIMENTAL RESULTS

The new FSSC, FSOS, FSLI, FCSI, fuzzy c-means (FCM) [3], PCM [5] and SFCM [12] algorithms were implemented using Matlab 6.1 (The Mathworks Inc.). The feature sets: PI, PL, and CIL were used for FCM, PCM and SFCM. A total of 146 different types of natural and artificial 8-bit gray-scale images were used in the experiments. These comprised different regions (objects) having similar and dissimilar PI and surface variation[2] and up to five separate regions. To segment only foreground

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

objects, the background was manually removed from all images. Since the background of an object is filled with zeroes, all foreground zeros were replaced by 1 to differentiate them. PL in the form of the (x, y) coordinates of a pixel were normalized within the range [0, 255] in order to keep them within the same range as the pixel intensities and reduce the effect of image size. All the presented results for the new FSSC algorithm were produced using a perceptually selected threshold T_{max} set to 5% shape distortion of the largest merged region (Section 4). The quantitative analysis was conducted using *discrepancy based on the number of misclassified pixels* [1]. The Type I, $errorI_i$ is the error percentage of all ith region pixels misclassified into other regions, while Type II, $errorII_i$ is the error percentage of all region pixels that are misclassified into ith region. The original images and their manually segmented reference regions are shown in Figures 2(a)-2(b) and 3(a)-3(b) respectively. Note, that the manually referenced and segmented regions are displayed using different gray levels to their original intensities, so as to provide a better visual interpretation of the segmentation results. For the space limitations, only the best two results of FCM, PCM and SFCM with the results of the FSOS and FSSC algorithms are provided in this paper.

The experiments were performed upon the peacock image shown in Figure 2(a) which has two different objects with SSV: the peacock (R_1) and tree branch (R_2). The three best

Figure 2: (a) Original peacock image, (b) Manually segmented reference of (a). (c)-(i) Segmented results of (a).
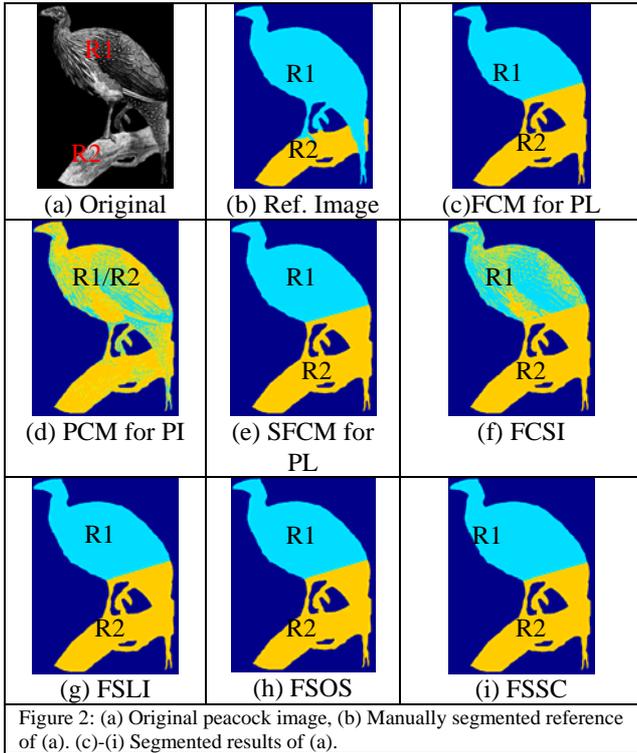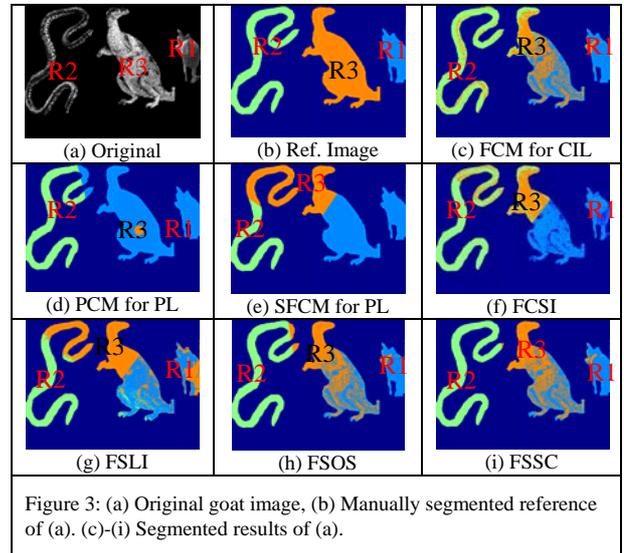
segmented results for FCM, PCM, and SFCM are taken for each algorithm with the results of FCSI, FSLI, FSOS and FSSC shown in Figure 2 (c)-(i). If the segmented results in Figure 2 (c)-(d), (f)-(h) are compared with the manually segmented reference regions in Figure 2 (b), it is visually apparent that a

considerable number of pixels in (R_1) are misclassified into region (R_2) since both regions have SSV.

Most of the misclassified pixels are correctly classified by the FSSC algorithm (Figure 2 (i)) since using SFCM for PL for segmentation is effective since they have SSV. The numerical results (average of Type I and Type II errors) of FCM, PCM and SFCM for all feature sets (PI, PL and CIL), FSSC, FSOS, FSLI and FCSI for the peacock image are shown in Table 2. This shows that the average percentage error = 12.5% for FSSC and SFCM using PL, while the second best average percentage error was achieved by FCM for PL, FSLI and FSOS = 13%. This confirms the superiority of FSSC over other algorithms using any of the three feature sets and SFCM for the other feature sets.

Another image used in the experiments was the goat image (Figure 3 (a)) which has three different regions: the goat (R_1), snake (R_2), and kangaroo (R_3). Note both regions (R_2) and (R_3) have SSV and the other region (R_1) has DSV. The seven best segmented results taken one from each algorithm for this image are shown in Figure 3 (c)-(i) respectively. FSLI, FCSI were unable to separate the objects because they do not consider SSV (Figure 3 (f)-(g)), while FSOS failed because it segmented the objects by FCM using PL (Figure 3 (h)). The results shown in Figure 3 (i) show that FSSC completely separated the snake from the kangaroo using SFCM for PL. This confirms that FSSC produced better results than FCM, PCM and SFCM for all three cases and FCSI, FSLI and FSOS because it utilized the concept of SSV and DSV for individual object and selection of SFCM using PL for objects having SSV. FSSC also generated a much lower average error (12.3%) compared with the 13.8% produced by FSOS as shown in Table 2.

Figure 3: (a) Original goat image, (b) Manually segmented reference of (a). (c)-(i) Segmented results of (a).

In total, experiments were conducted on 146 real and synthetic images including up to 5 regions. Of the 146 test images, FSSC produced superior results for 51 while FCM, SFCM and PCM provided better results for only 29, 24 and 13 images respectively (Table 2). The average error percentages for the new FSSC algorithm for all 146

images is 16.87% compared with the best average percentage errors for FCSI, FSLI, FSOS, FCM, SFCM and PCM of 28.9%, 20.2%, 18.1%, 20.5%, 24.6% and 33.7% respectively, again endorsing the improved performance of the FSSC algorithm compared with the other clustering algorithms for all three feature sets. An analysis of the distribution of images where superior results were obtained revealed a high dependency upon the actual number of clustering algorithms used for comparative purposes, the different features selected and number of objects used in the experiments. Since the test image set was specifically constructed so that all possible data sets were considered, embracing different types of objects and features using different clustering algorithms, the overall superiority of the FSSC algorithm is considerably significant.

Table 1: Selection of proper feature sets

$\Re$	θ_1	θ_2	Feature Sets	Connectivity
$\Re > 2$	X	X	CIL, PI	YES
$\Re = 2$	$\theta_1 > 45^o$	X	CIL, PI	NO
$\Re = 2$	$\theta_1 \leq 45^o$	$\theta_2 > 45^o$	CIL, PI	YES
$\Re = 2$	$\theta_1 \leq 45^o$	$\theta_2 \leq 45^o$	PL, PI	YES

Table 2: Average error percentages and the number of images for the superior results of different algorithms

Image\ Average error	Algorithms												
	FCM			PCM			SFCM			FCSI	FSLI	FSOS	FSSC
	PL	PI	CIL	PL	PI	CIL	PL	PI	CIL				
Peacock	13	32.8	19.5	49.3	38.2	46.1	12.5	32.8	32.8	26.7	13	13	12.5
Goat	27	38.3	19.6	28.2	41.2	49.4	32.5	49.7	38.4	21.6	33.1	13.8	12.3
146 Im	24.8	30.1	20.5	36.8	33.7	33.9	24.7	29.8	30.1	28.9	20.2	17.9	16.8
Best Results	19	4	29	13	9	8	24	6	5	8	29	41	51

7. CONCLUSIONS

This paper has introduced a new algorithm called *fuzzy image segmentation using suppressed fuzzy c-means clustering* (FSSC) which has proven superior segmented performance and results for objects having SSV compared to FSOS, FSLI, FCSI, FCM, PCM and SFCM both qualitatively and quantitatively. For the objects having SSV, SFCM using PL provides better results than FCM using PL since SFCM strengthens the higher membership values and hence weakens the other values, which also increases the possibility of classifying the neighbor pixels into the same object. The value of T_{max} (0.05) used in FSSC algorithm is perceptually selected from a range of values by considering shape distortion based on the human visual perception. Since the FSSC algorithm is based on clustering initially the prior number of clusters is needed to be provided.

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