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FUZZY IMAGE SEGMENTATION OF GENERIC SHAPED CLUSTERS

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ABSTRACT

The segmentation performance of any clustering algorithm is very sensitive to the features in an image, which ultimately restricts their generalisation capability. This limitation was the primary motivation in our investigation into using shape information to improve the generality of these algorithms. Fuzzy shape-based clustering techniques already consider ring and elliptical profiles in segmentation, though most real objects are neither ring nor elliptically shaped. This paper addresses this issue by introducing a new shape-based algorithm called *fuzzy image segmentation of generic shaped clusters* (FISG) that incorporates generic shape information into the framework of the fuzzy c-means (FCM) algorithm. Both qualitative and quantitative analyses confirm the superiority of FISG compared to other shape-based fuzzy clustering methods including, *Gustafson-Kessel algorithm*, *ring-shaped*, *circular shell*, *c-ellipsoidal shells* and *elliptic ring-shaped clusters*. The new algorithm has also been shown to be application independent so it can be applied in areas such as video object plane segmentation in MPEG-4 based coding.

Keyword: Image segmentation, Clustering, Fuzzy c-means

1. INTRODUCTION

Image segmentation is an important research area because it plays a fundamental role in image analysis, understanding and coding [1]. To accurately segment an image within a general framework is a challenging task because there exist many diverse objects and large variations between them. The performance of a clustering algorithm such as in [2, 3, 4], is highly dependent on the type of the features used and domain information concerning the objects in that image. This raises an interesting question about which features produce the best results for which type of image, thereby limiting the generalization capability of such clustering algorithms. This drawback provided the motivation to explore embedding shape information within the segmentation process. Popular fuzzy shape-based clustering techniques include the *Gustafson-Kessel* (GK) algorithm [5], *ring-shaped* (FKR) [6], *circular shell* (FCS) [7], *c-ellipsoidal shells* (FCES) [8] and *elliptic ring-shaped clusters* (FKE) [9]. The GK algorithm does not explicitly consider shape information, while both FKR and FCS only take into account objects which are ring, compact spherical or a combination of ring-shaped. To generalize the FKR and FCS algorithms, FKE and FCES were respectively proposed as alternative algorithms that broadened the application area of

shape-based segmentation to both detect and separate elliptical or a combination of ring and elliptical shaped objects as well as ring-shaped objects. The main problem is however, that most natural objects are neither ring nor elliptical in shape, so existing image segmentation techniques are unable to be successfully applied to generically shaped objects. To address this specific issue, a new shape-based technique called *fuzzy image segmentation of generic shaped clusters* (FISG) is presented which exploits object-based shape information. The basis of the new FISG algorithm is to integrate generic shape information into the framework of the fuzzy c-means (FCM) algorithm [2] with the aim of being able to detect and separate arbitrary shaped objects in an image. The FISG algorithm is expected to be used in two of the most challenging problems in multimedia research; (i) the segmentation of video object planes (VOP) in real video for object-based video coding in MPEG-4, which has already been implemented, but only for synthetic video; (ii) fast object-based content retrieval in MPEG-7 [10]. This paper is organized as follows: Section 2 details the FISG algorithm including all relevant processes, with the empirical results being fully analysed in Section 3. Finally, some conclusions are provided in Section 4.

2. THEORETICAL BASIS FOR THE FISG ALGORITHM

Existing fuzzy clustering algorithms which incorporate shape information, including FKR, FCS, FKE and FCES are all restricted from a segmentation perspective, to only ring and elliptical type shapes. This paper introduces a new *fuzzy image segmentation of generic shaped clusters* (FISG) algorithm, with the following sub-sections exploring some of the core elements that underpin this algorithm, including the initial shape contour representation and location of the intersection point, before the formal mathematical model and complete FISG algorithm are presented.

2.1 Initial Contour Representation

In order to integrate generic shape information into the formal segmentation process, it is firstly necessary to derive a contour point representation of each object in the image. For this reason, objects were initially segmented using the GK algorithm as this automatically adopts the local topological structure of the shape [5]. A set of significant points for a shape were then generated using the convex hull of the respective initial segmentation and either a Bezier Curve (BC) or B-spline [11] approximation used to generate the final contour points. The B-spline approach, while computationally efficient obtains a local optimum compared with the BC which achieves a global optimum. This

latter property is especially attractive in being able to represent global curve information and for this reason the BC was in contour point generation.

2.2 Locating the Intersection Point

In any segmentation strategy, a vital consideration is how the datum distance d_{ij} is calculated. All fuzzy clustering algorithms concomitantly seek to both minimize the intra- and maximize the inter-cluster distance, so in order to segment an image with respect to a given shape contour, d_{ij} must be calculated along a line (l_1) from datum S_j to its respective shape contour point. This contour point is referred to as the *intersection point* S'_{ij} along (l_1) between S_j and the cluster centre V_i . S'_{ij} can be calculated as follows:- i) Find two points on the contour of the curve that are closest and lie on opposite sides of (l_1) between v_i and S_j . ii) As the BC produces a straight line between two consecutive contour points, the intersected point of these two points and (l_1) will then be S'_{ij} . All the various steps in locating the intersection point are formalized in **Algorithm 1**.

Algorithm 1: Determining the intersection point between a datum and its corresponding cluster centre.

Precondition: cluster contour points, cluster centre v_i and datum S_j .

Post condition: Intersection point S'_{ij} .

1. Convert all contour points into polar form (r'_{ij}, θ'_{ij}) with respect to their corresponding cluster centre.
2. Convert all data points into polar form (r_{ij}, θ_{ij}) with respect to their corresponding cluster centre.
3. Calculate the difference $(\Delta\theta_{ij} = \theta_{ij} - \theta'_{ij})$
4. Using $\Delta\theta_{ij}$, find two points on opposite sides of the line (l_1) for S_j .
5. Calculate intersection point S'_{ij} of the line between two points and line (l_1) .
6. STOP

2.3 Mathematical Modelling

The objective function of the FISG algorithm is defined as follows:-

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

$$\text{subject to } \sum_{i=1}^c \mu_{ij} = 1 \text{ and } r_{ij} / \sum_{i=1}^c r_{ij} = k_{ij} \quad (2)$$

where $d_{ij} = d(S_j, v_i) - r_{ij}$. r_{ij} is the Euclidian distance between intersected point S'_{ij} and the i^{th} cluster centre v_i . $d(S_j, v_i)$ is the distance between datum S_j and v_i . μ_{ij} is the membership value of j^{th} datum for i^{th} cluster, while n and c are the number of data points and clusters respectively, and q is a fuzzifier. k_{ij} is a constant of the j^{th} datum in the i^{th} cluster. The constraints in (2), force the objective function to change each value of r_{ij} by its ratio from the previous iteration, thereby preserving the initial shape as well as scaling it by considering all previous r_{ij} . The algorithm iteratively minimizes (1) using the following equations. The membership value μ_{ij} is:-

$$\mu_{ij} = 1 / \sum_{i=1}^c \left(\frac{d_{ij}}{d_{ij}} \right)^{\frac{2}{q-1}} \quad (3)$$

From (1) and (2), using the Lagrangian optimization technique, r_{ij} is derived as:-

$$r_{ij} = d(S_j, v_i) - \frac{k_{ij} \sum_{i=1}^n d(S_i, v_i) - d(S_j, v_i)}{k_{ij} \left\{ \mu_{ij}^{q-1} / \sum_{i=1}^n (\mu_{ij}^{q-1}) \right\} - 1} \quad (4)$$

The i^{th} cluster centre v_i is then calculated as:-

$$\begin{aligned} f_x &= S_{j1} - d(S_j, v_i) \frac{S'_{ij1} - v_{i1}}{d(S'_{ij}, v_i)} + S'_{ij1} - d(S'_{ij}, v_i) \frac{S_{j1} - v_{i1}}{d(S_{j1}, v_i)} \\ f_y &= S_{j2} - d(S_j, v_i) \frac{S'_{ij2} - v_{i2}}{d(S'_{ij}, v_i)} + S'_{ij2} - d(S'_{ij}, v_i) \frac{S_{j2} - v_{i2}}{d(S_{j2}, v_i)} \\ v_i &= \frac{\sum_{j=1}^n (\mu_{ij})^q \begin{pmatrix} f_x \\ f_y \end{pmatrix}}{2 \sum_{j=1}^n (\mu_{ij})^q} \end{aligned} \quad (5)$$

where for an image, the 2-D data and cluster centre are given by

$$S_{jl} = \begin{bmatrix} S_{j1} \\ S_{j2} \end{bmatrix} \text{ and } v_{il} = \begin{bmatrix} v_{i1} \\ v_{i2} \end{bmatrix} \text{ respectively for } l = 1, 2.$$

2.4 The FISG Algorithm

The complete FISG algorithm is now formally summarised in **Algorithm 2**.

3. EXPERIMENTAL RESULTS

The FKR, FKE, GK, FCS, FCES and new FISG algorithms were all implemented using Matlab 6.1 (The Mathworks Inc.). Different natural and synthetic gray-scale images were randomly selected for the experimental analysis, comprising varying

number of regions (objects) with different shapes, (obtained from IMSI¹ and the Internet). As the image size is rectangular in shape, the segmentation process using pixel location will always arbitrarily divide the number of given clusters if the background

Algorithm 2: A Fuzzy Image Segmentation of Generic Shaped Clusters (FISG) algorithm.

Precondition: c , v_i , the initial segmented regions R_i , the significant points P of an object shape and the number of points m representing the shape contour.

Post condition: Final segmented regions \mathfrak{R} .

1. Generate m points on the contour of the shape for R_i using the Bezier curve.
2. Find intersection point using **Algorithm 1** and calculate initial r_{ij} .
3. Calculate k_{ij} using (2).
4. Repeat Steps 4-8 for each iteration $l = 0, 1, \dots$,
 5. Update μ_{ij} using (3).
 6. Update r_{ij} using (4).
 7. Update v_i using (5).
 8. IF $\|\mu_{ij}^l - \mu_{ij}^{l+1}\| < \xi$ THEN STOP
ELSE GOTO 4.

is not removed. For this reason, the background pixels of each image were manually removed by setting them to zero. Any zero-valued foreground object pixels were replaced by 1, which had no effect upon visual perception and avoided the possibility of foreground pixels merging with the background.

To quantitatively appraise the performance of all the various fuzzy clustering algorithms, the efficient objective segmentation evaluation method, *discrepancy based on the number of misclassified pixels* [12] was used. Two types of error, namely Type I, $errorI_i$ and Type II, $errorII_i$ are computed, the former being the percentage error of all i^{th} region pixels misclassified into other regions, while the latter is the error percentage of all region pixels misclassified into i^{th} region. Representative samples of the manually segmented reference regions together with their original images are shown in Figures 2(a)-2(b) and 3(a)-3(b). To provide a better visual interpretation of the segmented results, both the reference and segmented regions are displayed using different colours rather than their original gray-scale intensities.

The *snake* image in Figure 2(a) has two regions: the snake (R_1) and kangaroo (R_2). The segmented results of FKR, FKE, GK, FCS, FCES and FISG are respectively shown in Figures 2(c)-(h). If the segmentation results in Figures 2(c)-(g) are compared with the manually segmented reference regions in Figure 2(b), it is visually apparent a large number of pixels of (R_2) have been misclassified into (R_1) for the FKR, FKE, GK, FCS and

FCES algorithms, since both regions are neither circular nor elliptic in shape, thereby leading to a high number of misclassified pixels. In contrast, all misclassified pixels have been correctly classified by the FISG algorithm in Figure 2(h) because of the strategy employed of considering the shape produced using the initially segmented regions produced by FCM and Bezier curve approximation, together with the new

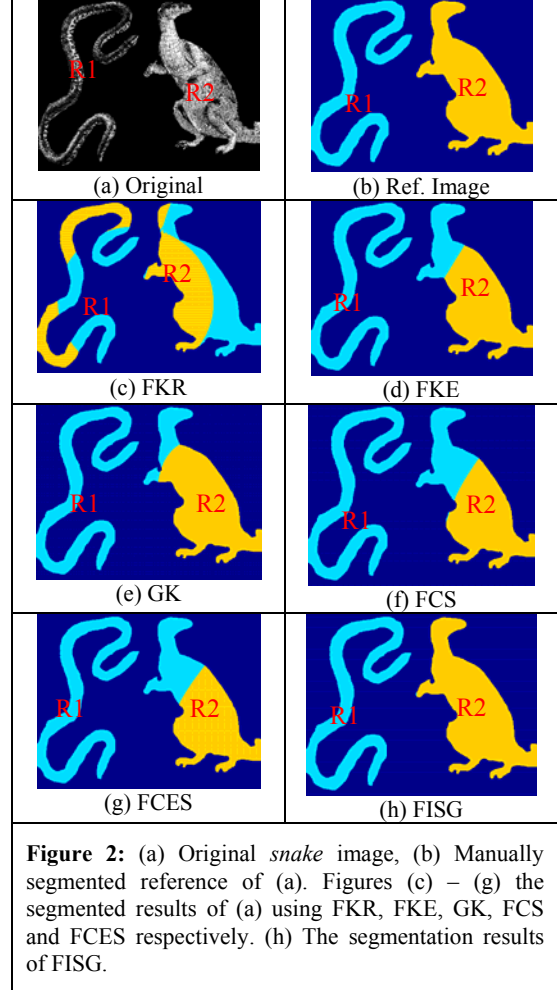


Figure 2: (a) Original *snake* image, (b) Manually segmented reference of (a). Figures (c) – (g) the segmented results of (a) using FKR, FKE, GK, FCS and FCES respectively. (h) The segmentation results of FISG.

Table 1: Percentage errors for the *snake and cow* reference test images in Figures 2 and 3.

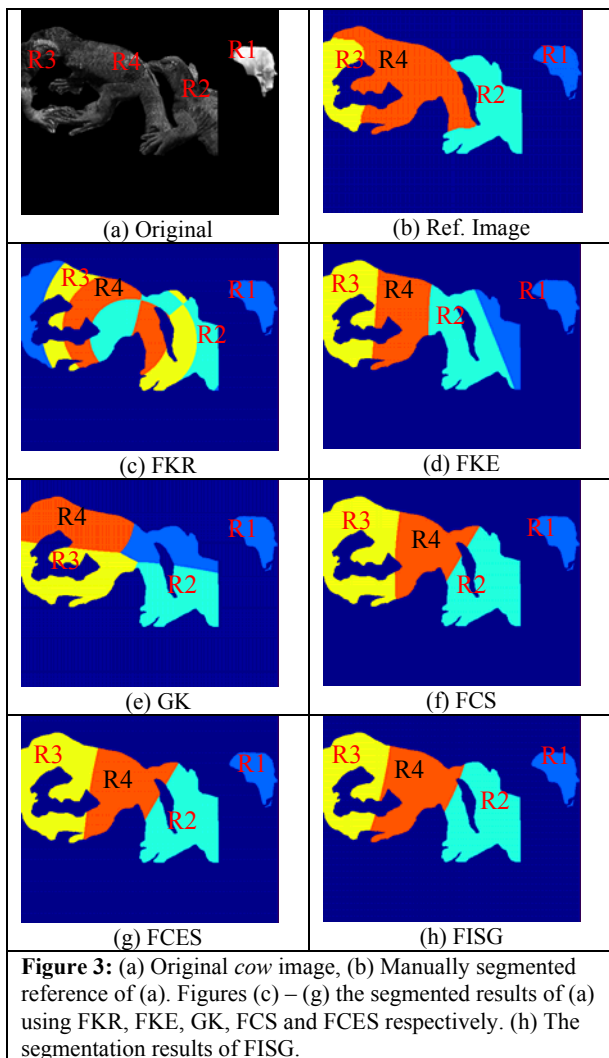
Algorithm	Error			
	Snake			Cow
	Type I	Type II	Mean	Mean
FKR	48.1	44.5	46.3	28.9
FKE	0	25	12.5	15.8
GK	0	16	8	25.3
FCS	0	34.2	17.1	11.8
FCES	0	32.8	16.4	11
FISG	0	0.04	0.02	8.2

constraints in (2) which limit the shape from arbitrary scaling. The corresponding average Type I and Type II errors for all algorithms analysed are presented in Table 1, which confirms

¹ IMSI's Master Photo Collection, 1895 Francisco Blvd. East, San Rafael, CA 94901-5506, USA.

the improvement of using FISG with an average error of only 0.02%.

A second sample image is shown in Figure 3(a) that comprises four different regions: the *cow* (R_1), and three separate *reptiles* on the right (R_2), on the left (R_3) and in the middle (R_4), each having a significantly differing shape. The segmented results for FKR, FKE, GK, FCS, FCES and the FISG are shown in Figure 3(c)-(h) respectively. For the results produced by FKR, FKE, GK, FCS and FCES reveal a considerable number of pixels from R_4 being misclassified into both R_3 and R_2 and a portion of R_2 being misclassified into R_4 . The FISG algorithm using the initial shape produced by FCM (Figure 3(h)) again reduced the number of misclassified pixels of R_2 and R_3 due to considering the shape of objects, with the corresponding quantitative improvement shown in Table 1. This shows the average errors of FISG, FCES, FCS, GK, FKE and FKR were 8.2%, 11%, 11.8%, 25.3%, 15.8% and 28.9% respectively.



Finally, to evaluate the overall performance of the new FISG algorithm, the experiment was performed using 178 different images. The FISG algorithm provides best result for 84 images while FKR, FKE, GK, FCS and FCES algorithms produce better results for 5, 23, 57, 16 and 45 respectively.

4. CONCLUSIONS

This paper has presented a new shape-based image segmentation algorithm called *fuzzy image segmentation of generic shaped clusters* (FISG) which incorporates generic shape information into the framework of the fuzzy c-means (FCM) algorithm. A formal qualitative and quantitative analysis has been conducted to compare the performance against existing shape-based algorithms and experimental results have proven the superiority of the FISG algorithm. This is because the shape is retained by the strategy of incorporating a series of constraints upon the objective function, which consistently generates fewer misclassified pixels in the segmentation process.

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