OBJECT BASED IMAGE SEGMENTATION USING FUZZY CLUSTERING

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ABSTRACT

Existing shape-based clustering algorithms, including fuzzy k-rings, fuzzy k-elliptical, circular c-shell, and fuzzy c-shell ellipsoidal are all designed to segment regular geometrically shaped objects such as circles, ellipses or combination of both. These algorithms however, are unsuitable for segmenting arbitrary-shaped objects, so in an attempt to address this issue, a *fuzzy image segmentation of generic shaped clusters* (FISG) algorithm was introduced that integrated generic shape information into the segmentation framework. It however, had a number of limitations relating to the mathematical derivation of the updated contour radius, the initial shape representation, and the impact of overlapping clusters. This paper proposes a new *object based segmentation using fuzzy clustering* (OSF) algorithm that solves these drawbacks by controlling the scaling of original shape, securing a better initial shape representation and avoids cluster overlapping, with both qualitative and quantitative results confirming the improved overall segmentation performance.

1. INTRODUCTION

Image segmentation is a vital field in image analysis, coding and understanding [1], with a wide diversity of applications, ranging from car assembly, airport security, object recognition and second generation image coding, through to criminal investigative analysis and medical imaging [2]. Segmentation is however, very challenging because of the multiplicity of objects in an image and the large variation between them. In many object based image segmentation applications from robotic car assembly through to medical imaging, the number of clusters is known *a priori,* for this reason, clustering algorithms are used for object based image segmentation, though even so, the segmentation performance of these clustering algorithms such as [3],[4] is still highly dependent on the features used and types of object in an image, which ultimately limits their generalization capability. As humans exploit shape as a perceptual attribute in both detecting and recognising objects, this motivates the exploration of ways to integrate shape-based information into the clustering framework in order to segment objects in an image. Existing shape-based clustering techniques, such *fuzzy k-ring* (FKR) [6], *circular shell* (FCS) [7], *c-ellipsoidal shells* (FCES) [8] and f*uzzy elliptic-ring* (FKE) [9] are all characterised as able to only accurately segment objects having ring, compact spherical, elliptical or a combination of ring and elliptically shaped objects. Most natural objects however, are neither ring nor elliptic in shape so the performance of these algorithms is compromised. An alternative shape-based clustering approach is the Gustafson-Kessel (GK) algorithm [5] which adopts the local topological structure of the shape of a cluster though this does not explicitly consider shape information and so is unable to segment arbitrary shaped objects satisfactorily. To achieve this goal, strategies that embed generic shape information within the fuzzy clustering framework need to be developed. Ameer et al [1] introduced the *fuzzy image segmentation of generic shaped clusters* (FISG) algorithm that attempted to incorporate generic shape information, and while it segmented certain arbitrary shaped objects well, it possessed a number of limitations including: i) inaccurate updating of the object shape contour, ii) erroneous shape representation due to using a Bezier curve with a large number of control points; and iii) the overlapping of initial shape descriptors. To explicitly address these issues, this paper introduces a new *object based segmentation using fuzzy clustering* (OSF) algorithm that reduces over-scaling and generates a shape contour representation either automatically by any clustering algorithm or using B-splines for a given set of significant shape points. To incorporate generic shape information, shape initialisation for each object has to be either manually or automatically provided, so OSF uses the GK algorithm for automatic shape initialisation because it locally adapts the distance metric to the shape of the cluster by estimating the cluster covariance matrix [5],[1].

This remainder of the paper is organized as follows: Section 2 presents the OSF algorithm including all the individual processing steps, with an analysis of its empirical performance then being provided in Section 3. Finally, some conclusions are given in Section 4.

2. STRATEGY FOR INCORPORATING GENERIC SHAPE INFORMATION

This section presents a new *object based segmentation using fuzzy clustering* (OSF) algorithm that integrates generic shape-based information seamlessly into a fuzzy clustering framework. To achieve this objective involves three steps; i) Obtain the initial shape contour representation; ii) Calculate the data distance from the contour; and iii) Integrate shape constraints into the existing fuzzy clustering algorithm. Each of these steps will now be considered.

2.1 Initial Shape Contour Representation

In order to integrate generic shape information into the formal segmentation process, it is necessary to determine the contour (boundary) of each object in an image. The contour can be either automatically generated or represented by a prescribed set of significant points. For the former, objects are initially segmented using a clustering algorithm, such as the GK technique which adapts a cluster to the local topological structure of the shape [5], while in the latter case, the shape contour is generated using parametric curve generation techniques such as Bezier curves (BC) or B-splines [10]. Being a member of the parametric curve family, B-splines are used to generate shape contour points in the new OSF algorithm since they provide greater control flexibility and it is possible to achieve a desired level of local optimality with shape parameters, not achievable with BC [10], [11]. Since the distance of any arbitrary datum from the shape contour is pivotal to any shape-based clustering algorithm, it is necessary to develop strategies to locate the *intersection points* between a contour and the data.

2.2 Calculating the Intersection Points

An important consideration in any segmentation strategy is how the distance d_{ij} of a datum is determined for subsequent use in an objective function (Section 2.3). For example, in the fuzzy c-means (FCM) algorithm [3], d_{ij} is calculated from the cluster centre in order to segment objects in an image based on some predefined features, while for FKR and FKE, d_{ij} is calculated from the contour of the circle and ellipse respectively. As the OSF algorithm focuses upon arbitrary shapes, d_{ij} is calculated from the respective contour shape points. An algorithm for computing the intersection points is provided in [1].

2.3 Integrating Shape Constraints

There are no shape constraints in existing clustering algorithms such as FCM and existing shape-based algorithms like FKR, FCS, FKE and FCES consider only circular and elliptical features in the clustering framework by using standard geometric equations. It is feasible however, to integrate arbitrary shape information into the fuzzy clustering framework by optimizing the objective function of a clustering algorithm that incorporates arbitrary shape constraints. For this reason, the following shape constraint $r_{ij} \Big/ \sum_{t=1}^{n} r_{it} = k_{ij}$ is introduced [1] to ensure that it preserves the original shape during scaling, where r_{ij} is the Euclidian distance between the intersection point S'_{ij} and the i^{th} cluster centre v_i and k_{ij} is a constant of the j^{th} datum in the i^{th} cluster. It has been mathematically proven that the initial shape does not deform during scaling, and in order to reduce the effects of overlapping caused by over-scaling, the convergence rate of the OSF algorithm is reduced by trading-off between the initial and current r_{ij} values according to [5]. The objective function of the OSF algorithm is based upon FCM and is formally defined as:-

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

$$\text{subject to } \sum_{i=1}^{c} \mu_{ij} = 1 \text{ and } r_{ij} \Big/ \sum_{t=1}^{n} r_{it} = k_{ij} \tag{2}$$

where $d_{ij} = d(S_j, v_i) - r_{ij}$. $d(S_j, v_i)$ 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. The objective function and its constraints (1) and (2), is iteratively minimised using the (3), (4) and (6), which are all derived from Lagrangian optimisation techniques:-

$$\text{IF } d_{ij} = 0 \text{ THEN } \mu_{ij} = 1 \text{ maintaining } \sum_{i=1}^{c} \mu_{ij} = 1 \tag{3a}$$

$$\text{ELSE} \quad \mu_{ij} = 1 \Big/ \sum_{k=1}^{c} \left(\frac{d_{ij}}{d_{kj}} \right)^{\frac{2}{q-1}} \tag{3b}$$

The contour radius r_{ij} is updated using (4) and (5):-

$$r_{ij} = d(S_j, v_i) - \frac{k_{ij} \sum_{t=1}^{n} d(S_t, v_i) - d(S_j, v_i)}{k_{ij} \sum_{t=1}^{n} \frac{1-k_{it}}{\mu_{it}} - \frac{1-k_{ij}}{\mu_{ij}}} \left(\frac{1-k_{ij}}{\mu_{ij}} \right) \tag{4}$$

and as (4) upholds the shape constraint (2) then during each iteration, the segmented object shape derived during initialization is preserved.

$$r_{ij}(new) = \lambda r_{ij} + (1-\lambda) r_{ij}^0 \tag{5}$$

where r_{ij} is current value, r_{ij}^0 is the initial value of r_{ij} and λ is an empirically selected constant derived from the data which is a trade-off between the current and initial shapes. The i^{th} cluster centre v_i is then calculated as:-

$$f_x = S_{j1} - d(S_j, v_i) \frac{S'_{ij1} - v_{i1}}{d(S'_{ij}, v_i)} + S'_{ij1} - d(S'_{ij}, v_i) \frac{S_{j1} - v_{i1}}{d(S_{j1}, v_i)}$$

$$f_y = S_{j2} - d(S_j, v_i) \frac{S'_{ij2} - v_{i2}}{d(S'_{ij}, v_i)} + S'_{ij2} - d(S'_{ij}, v_i) \frac{S_{j2} - v_{i2}}{d(S_j, v_i)}$$

$$v_i = \frac{\sum_{j=1}^{n} (\mu_{ij})^q \begin{pmatrix} f_x \\ f_y \end{pmatrix}}{2 \sum_{j=1}^{n} (\mu_{ij})^q} \tag{6}$$

All the steps in the OSF algorithm are provided in Algorithm 1.

3. EXPERIMENTAL RESULTS

In analyzing the segmentation performance of the OSF algorithm, empirical results were both qualitatively and numerically compared with other shape-based clustering algorithms, namely FKR, FKE, GK, FCS, FCES and FISG. Different natural and synthetic gray-scale images[1] as well as medical images and video frames from the *football* test sequence

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[1] *Obtained* from IMSI (Master Photo Collection, San Rafael, CA 94901-5506, USA.) and the Internet.

comprising arbitrary shapes were randomly selected for analysis. As the image size is rectangular, clustering algorithms that employ only pixel location arbitrarily divide the number of clusters [1], so to circumvent this problem, the background of each image were removed so that only foregrounds objects were segmented. This necessitated the manual setting of all background pixels to zero, with zero-valued foreground object pixels being replaced by 1 to avoid the possibility of foreground pixels merging with the background, while not impacting upon visual perception.

Algorithm 1: O*bject based segmentation using fuzzy clustering* (OSF).

Precondition: c , v_i , the initial shape contours, the number of clusters n .
Post condition: Final segmented regions $\Re$.
1. Find Intersection Point (Section 2.2)
2. Calculate initial r_{ij} .
3. Calculate k_{ij} using (2).
4. Repeat Steps 5-6for each iteration $l = 0,1,\cdots,$
    5. Update μ_{ij} , r_{ij} and v_i using (3a), (3b), (4), (5) and (6) respectively.
    6. IF $\left\| \mu_{ij}{}^{l} - \mu_{ij}{}^{l+1} \right\| \geq \xi$ THEN GOTO 5.
7. STOP.

To quantitatively appraise the performance of all the fuzzy clustering algorithms, the objective segmentation evaluation method, *discrepancy based on the number of misclassified pixels* [1] was used. Two types of error, namely Type I, $errorI_i$ and Type II, $errorII_i$ were computed, the former being the percentage error of all i^{th} region pixels misclassified into other regions, while the latter is the percentage error of all region pixels misclassified into the i^{th} region. Representative samples of the manually segmented reference regions together with their original images are shown in Figure 1(a)-(b) and 2(a)-(b). To provide an improved visual interpretation of the segmented results, both the reference and segmented regions are displayed in different colours rather than their original gray-scale intensities.

Before analysing the results in detail, a brief outline is made upon the initialisation strategies used for each clustering method. GK, FCS and FCES algorithms were initialised using random membership values μ . The FKR algorithm used a *fuzzy k-means* (FKM) [12] algorithm, while for the FKE algorithm, the same initialisation approach in [9] was used, namely 10 iterations of FKM followed by 10 iterations of FKR. For both the FISG and OSF algorithms, any clustering algorithm can in principle be applied. However, as the potentiality of these algorithms depends upon prior shape information, the GK algorithm was selected for its automatic shape initialization, i.e. the results in Figures 1(e) and 2(e) respectively, because GK has consistently been proven to provide superior results for object based segmentation compared with FKR, FCS, FKE and FCES. In the experiments, $\lambda = 0.1$ so giving a higher priority to the initial shape while reducing over-scaling of the shape in each iteration.

The first set of results relate to the *X-ray* image in Figure 1(a) which has two objects (regions), namely the *femur* (R_1) and *tibia* (R_2) with both regions being arbitrarily shaped. The segmentation results for all the aforementioned algorithms are given in Figure 1 (c)-(i). If the results in Figure 1(c) and (e) are compared with the manually segmented reference regions in Figure 1(b), it is visually apparent a large number of pixels of R_1 have been misclassified into R_2 and vice versa by FKR and GK respectively, because both objects are neither circular in shape nor consider any specific shape information. The results for FKE also produced a large number of misclassified pixels for R_2 (Figure 1(d)) because neither region is elliptically shaped, and similar observations being also made about the results in Figure 1(f) and (g) for FCS and FCES respectively. While the FISG algorithm attempted to segment the two arbitrary shaped objects, it generated a high number of misclassified pixels for both regions (Figure 1(h)) due to aforementioned problem of shape over-scaling and an inaccurate initial shape representation. In contrast, the results for the new OSF algorithm in Figure 1(i) reveal that it correctly classified both regions R_1 and R_2 with a minimal number of misclassified pixels in R_1 . The corresponding numerical results for the *Type I* and *Type II* errors for region R_1 for all six algorithms are shown in Table 1, confirm the improved performance of the OSF algorithm which generated the lowest overall average error of 3.3%.

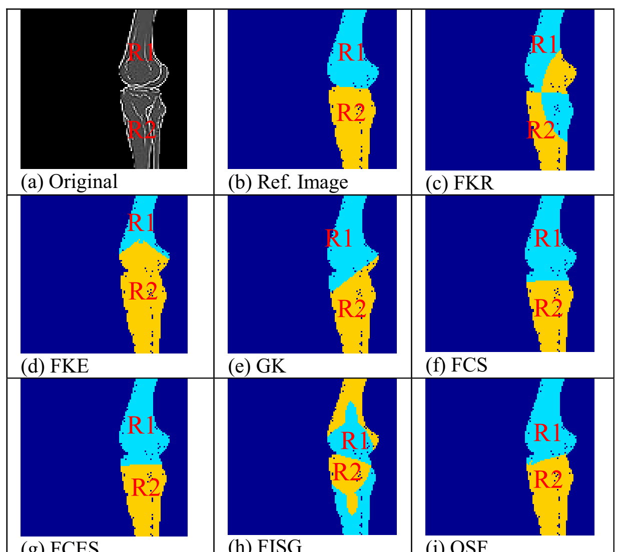

Figure 1: (a) Original *X-ray* image, (b) Manually segmented reference of (a). Figures (c) – (h) the segmented results of (a) using FKR, FKE, GK, FCS, FCES and FISG respectively. (i) Segmented results for OSF.

A second series of experiments were undertaken on a frame taken from the popular *football* video test sequence used by researchers in the field of video coding. This frame, shown in Figure 2(a), contains three arbitrary-shaped objects (R_1) (*left player*), (R_2) (*player on the ground)* and (R_3) (*right player*), each having a different shape and orientation, with some occlusion between R_2 and R_3. The results produced by the FKR, FKE, GK, FCS, FCES, FISG and OSF algorithms are shown in Figure 2(c)-(i) respectively. The segmented results for FKR and FCS in Figure 2(c) and (f) respectively, reveal when compared with the reference image (Figure 2(b)), a significant number of misclassified pixels from R_1 into both R_2 and R_3, and vice versa, because once again none of the three objects are circular in shape. A similar conclusion can be drawn concerning the results for both the FKE and FCES algorithms (Figure 2(d) and (g)) because none of the objects are ostensibly elliptical in shape. While the GK algorithm performed better, it still has a number of misclassified pixels from R_2 into R_3 and from R_3 into R_2 due to the occlusion and also from R_1 into R_2 (Figure 2(e)). The arbitrary generic shaped clustering algorithm (FISG) however generated a large number of misclassified pixels as shown in Figure 2(h) because of the recurring problem of over scaling the initial shape, while in comparison, the results for the new OSF algorithm (Figure 2(i)) reveal that R_1 has been correctly classified in its entirety, and both R_2 and R_3 have a negligible number of misclassified pixels. These results are a direct consequence of the new algorithm being capable of controlling the over scaling problem highlighting in Section 1. The analytical results in Table 1 again confirm that the average error of 2.7% for the OSF algorithm is lower than all other clustering algorithms, with this particular example also highlighting the potential of the OSF algorithm to be extended into the domain of object-based video segmentation and coding applications.

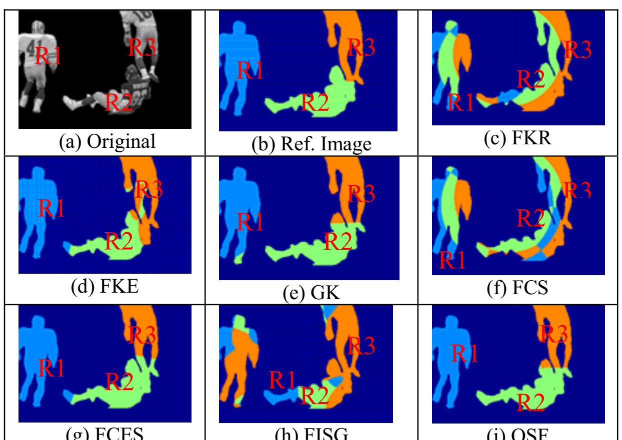

Figure 2: (a) Original *football* image, (b) Manually segmented reference of (a). Figures (c) – (h) the segmented results of (a) using FKR, FKE, GK, FCS, FCES and FISG respectively. (i) Segmented results for OSF.

4. CONCLUSIONS

This paper has presented a shape-based image segmentation algorithm called *object based segmentation using fuzzy clustering* (OSF) which incorporates generic shape information and specifically addresses the limitations of previous shape-based algorithms in respect of obtaining an appropriate initial shape representation, avoiding cluster overlapping and controlling over scaling during iterations. A qualitative and quantitative analysis compared the performance against existing shape-based algorithms including, fuzzy k-rings, fuzzy k-ellipse, Gustafson-Kessel, fuzzy c-circular shell, fuzzy c-elliptical shell and FISG for a variety of images comprising multiple objects having different shapes and orientations, with segmentation results consistently proving the superiority of the new OSF algorithm.

Table 1: Percentage errors for the *X-ray* and *football* reference test images in Figure 1 and Figure 2.

Algorithm	**Error**			
	X-ray			***Football***
	Type I	**Type II**	**Mean**	**Mean**
FKR	31	37.4	34.2	43.3
FKE	43.8	0	21.9	6.9
GK	5.2	10.3	7.7	3.8
FCS	0	12.4	6.2	42.7
FCES	0	12.4	6.2	4.9
FISG	46.8	51.7	49.3	37.9
OSF	0.4	6.2	3.3	2.4

5. REFERENCES

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