Sclera Segmentation using Spatial Kernel Fuzzy Clustering Methods

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Abstract: Biometrics is one of the domain that is gaining lot of importance in the present digital industry. Biometrics are getting integrated in different devices and reaching the end users at a very affordable cost. Among various biometric traits, Sclera is one such trait that is getting popular in the research community for its distinct nature of authenticating and identification of individuals. The recognition system using sclera trait purely depends on efficient segmentation of sclera image. Segmentation process is considered to be significant in image processing system because of better visualization. The segmentation can be done using region based, edge based, threshold based and also clustering based techniques. This paper concentrates on clustering based technique by proposing a variant of conventional Fuzzy C Means (FCM) algorithm. Though the Fuzzy C Means presents outstanding results in many applications, unfortunately it is sensitive to noise and ignore neighbourhood information. Thus to alleviate these limitations this paper presents Generalized Spatial Kernel Fuzzy C Means (GSK-FCM) clustering algorithms for sclera segmentation. To evaluate the proposed methods, experimentation are conducted on Sclera Segmentation and Recognition Benchmarking Competition (SSRBC 2015) dataset. The result of the experiments reveals that the proposed methods outperform the other variants of FCM.

1 INTRODUCTION

In today's mobile based tech industry, biometric based technological platforms are the front runners in applying technologies to various devices. Biometric has lately received a lot of attraction in popular media including commercial applications. The requirement to validate ourselves to machines is always increasing in today's networked society, which in turn helps in closing the gap between the humans and the machines to secure the transactions and networks. Biometric deals with identification of persons based on their biological or behavioural distinctiveness (Jain et al., 2000). Amongst the various biometric traits available, this paper presents about sclera segmentation. Sclera which is the white part of the eye that surrounds the cornea, occupies more than 80% of the surface area of the eyeball. This trait when compared to other traditional traits is hard to spoof as the optic nerves of the sclera region are very unique and random including the identical twins. In addition the patterns of these nerves remain factual till the life-time of a person (Joussen, 2001). Sclera segmentation is a significant procedure in sclera recognition process. Segmentation partition the image into its constituent's parts and groups the uniform pixels into clusters. Segmentation techniques have been used in wide range of medical image processing such as thresholding (Otsu, 1979), region growing (Adams et al., 1994; Beveridge et al., 1989) and clustering (Ng et al., 2006; Chen et al., 1998; Wang el al., 2006; Hadjahmadi et al., 2008). Clustering has been extensively applied in numerous fields' such as geology, taxonomy, medical image processing, engineering systems. Among various clustering techniques the most widely used techniques include the k-means, fuzzy c-means (Wang el al., 2006) and their variants. The traditional fuzzy c-means clustering algorithm is found to comprise the pixel attributes. This process was found to fail in providing efficient results in the presence of corrupted noise in the image. Therefore, from the existing research it is

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observed that the significance to improve the performance of the standard FCM is essential.

Recently, several researchers have developed diverse methods by modifying the objective function or membership function of standard FCM method (Liew et al., 2001; Ahmed et al., 2001). Also, it was seen that traditional FCM, which uses Euclidean distance is used to determine the distance between cluster center and data. The above algorithm was found to be limited in revealing non-Euclidean structure of the input data. To overcome this problem, researchers modified the existing approaches in such a way that it improves the performance. Further, several researchers developed a novel FCM method where kernel function is employed to determine the distance between center of the cluster and data pixel (Chen et al., 2002). For better result, a hybrid technique is proposed which provide new robust clustering algorithm. In this technique, kernelized fuzzy logic is incorporated with spatial constraint which results in new clustering method called SKFCM. By introducing the higher and lower elimination of non-required data belonging to one cluster can be removed. Since FCM failed to handle the small differences between clusters and as it is sensitive to noise, FCM algorithm was derived into KFCM which is based on kernel method. Due to the limitations of this algorithm a robust generalized spatial kernel fuzzy C-Means clustering method is introduced in this research work.

2 BACKGROUND STUDY

Fuzzy C-Means (FCM), a method of clustering technique which maps each data point to two or more clusters and showcases very good results in many applications in the field of medicine, engineering, economics, psychology and many other disciplines (Ben-Dor et., 1999).

Consider $X = \{x_1, x_2, ...x_i, ...x_n\}$ e the n data points and $V = \{v_1, v_2, ...v_j, ...v_c\}$ be the set of c cluster centers. The objective of FCM is to partition the data points into c group such that the data points present in the same group have similar characteristics when compared to the data points present in the other groups by reducing the objective function as shown in equation 1.

$$J = \sum_{j=1}^{n}\sum_{i=1}^{c} u_{ij}^{m} \left\| x_j - v_i \right\|^2 \quad (1)$$

where m refers to fuzzifier value, v_i refers to i^{th} cluster center, $u_{ij} \in [0,1]$ is the membership of the data point x_j to the i^{th} cluster center and $\|.\|$ is the distance measure used to compute the distance between data point (x_j) and cluster center (v_i). Fuzzy C-Means is an iterative algorithm which updates the membership (u_{ij}) and cluster centers using following equations.

$$u_{ij} = \frac{1}{\sum_{k=1}^{c}\left(\left\|\frac{x_j - v_i}{x_j - v_k}\right\|\right)^{\frac{1}{m-1}}} \quad (2)$$

$$v_i = \frac{\sum_{j=1}^{n} u_{ij}^{m}\, x_j}{\sum_{j=1}^{n} u_{ij}^{m}} \quad (3)$$

The Fuzzy C-Means process starts by randomly picking the c number of data points as initial cluster centers. Furthermore, the membership value is computed based on the distance of the data point x_j to the cluster center v_i using equation 2. In the following step, the objective function value is computed based on previously evaluated membership values using equation 1. The cluster centers are then updated based on the membership values of each data points using equation 3. This iterative process is stopped when the difference of successive iterations objective function value is less than the user specified stopping criterion value. Although Fuzzy C-Means is found to be an important tool for image processing by producing outstanding results it has its own limitations, such as sensitivity to noise and ignorance of neighborhood information (Bezdek, 1994). The use of euclidian distance metric in FCM inturn degrades the clustering results (Koza, 1994). Kernal FCM (KFCM) an alternative method was introduced to overcome the noise sensitivity problem in the traditional Fuzzy C-Means (Despotović et al., 2015). Unlike the traditional FCM which makes use of euclidian distance metric, the kernal FCM uses kernel distance function which minimizes the impact of noise. However, the limitation in the Kernal FCM is that it do not utilize the neighbourhood information. To overcome this problem, researchers propsed a variant of FCM known as Spatial Kernel FCM (SKFCM) (Timmis et al., 2008; Roy et al., 2014). This technique incorporates neighbourhood information into objective function of FCM. To certain extent the above techniques overcome the drawbacks of Fuzzy C-Means. However they still suffer from single feature inputs and high computational time. To address these limitations, a Robust Spatial Kernel FCM (RSKFCM) algorithm was proposed in (Kumar et al., 2015). Robust Spatial Kernel FCM (RSKFCM) consists of spatial information to the conventional FCM function. Similar to FCM, the main aim of the RSKFCM is to minimize the objective function shown in equation 4.

$$J = \sum_{i=1}^{c}\sum_{j=1}^{n} w_{ij}^{m} \left\| \Phi(x_j) - \Phi(v_i) \right\|^2 \tag{4}$$

Where c is the number of clusters, n is the number of data points, m is a constant, which controls the fuzziness of the resulting partition, w_{ij} is the RSKFCM membership degree of x_j in i^{th} cluster. v_i is the i th cluster center, Φ is an implicit non linear map which is computed as:

$$\left\| \Phi(x_j) - \Phi(v_i) \right\|^2 = K(x_j, x_j) + K(v_j, v_j) - 2K(x_j, v_i) \tag{5}$$

where K is the inner product of kernel function i.e., $K(x,y) = \Phi(x)^T \Phi(y)$.

$$K(x,y) = \exp\left(-\| x-y \|^2 / \sigma^2 \right) \tag{6}$$

In Gaussian kernel $K(x,x)=1$ and $K(v,v)=1$, hence the kernel function becomes:

$$\left\| \Phi(x_j) - \Phi(v_i) \right\|^2 = 2(1 - K(x_j, v_i)) \tag{7}$$

Substituting equation 7 in equation 4, the objective function becomes:

$$J = 2\sum_{i=1}^{c}\sum_{j=1}^{n} w_{ij}^{m} \,(1 - K(x_j, v_i)) \tag{8}$$

RSKFCM membership function w_{ij} is the combination of kernel membership function u_{ij} and neighbourhood function s_{ij} and it is computed as:

$$w_{ij} = \frac{u_{ij}^{p} s_{ij}^{q}}{\sum_{k=1}^{c} u_{kj}^{p} s_{kj}^{q}} \tag{9}$$

where p and q are parameter to control the relative importance of kernel membership and neighbourhood membership functions.The kernel and neighbourhood membership functions are computed using equation 10 and 11.

$$u_{ij} = \frac{\left(1 - K\left(x_j, v_i\right)\right)^{-1/(m-1)}}{\sum_{k=1}^{c}\left(1 - K\left(x_j, v_k\right)\right)^{-1/(m-1)}}; \tag{10}$$

$$s_{ij} = \sum_{k \in NK(x_j)} u_{ik} \tag{11}$$

where $N_k(x_j)$ represents a neighbourhood data points of x_j . This neighbourhood function represents the probability that data point x_j belongs to i^{th} cluster.

Similar to FCM, RSKFCM also work in iterative process by updating the membership and cluster center values. The cluster centers are updated using equation 12

$$v_i = \frac{\sum_{j=1}^{n} w_{ij}^{m} K(x_j, v_i) x_j}{\sum_{j=1}^{n} w_{ij}^{m} K(x_j, v_i)} \tag{12}$$

This iterative of RSKFCM will stop when stopping criteria is satisfied i.e., the difference of successive iterations objective function value is less than the user specified stopping criteria value. Though RSKFCM solved the problems of single feature inputs and high computational time, it still holds few limitations:

- Firstly, incorporating neighborhood information only to the objective function.
- Secondly, the current methods assume that, all features have equal importance. However, in real world cases all the features may not be equally important.

To alleviate these drawbacks, Generalized Spatial Kernel Fuzzy C-Means (GSKFCM) is proposed in this article.

3 PROPOSED METHOD

Generalized Spatial Kernel Fuzzy C-Means (GSK-FCM) incorporates the weighted neighborhood information into distance function and uses Gaussian kernel as distance metric.

The aim of the GSK-FCM is to minimize the objective function shown in equation 13

$$J = 2\sum_{i=1}^{c}\sum_{j=1}^{n} z_{ij}^{m} d_{new}^{2}\left(x_j, v_k\right) \tag{13}$$

where z_{ij} is the GSK-FCM membership function and it is computed as:

$$z_{ij} = \frac{1}{\sum_{k=1}^{c}\left(\frac{d_{new}^2\left(x_j,v_i\right)}{d_{new}^2\left(x_j,v_k\right)}\right)^{\frac{1}{(m-1)}}} \quad (14)$$

Where d_{new} is the GSK-FCM distance function which incorporates the neighbourhood function into distance function and it is computed as:

$$d_{new}^2\left(x_j,v_i\right) = d^2\left(x_j,v_i\right) f\left(p_{ij}\right) \quad (15)$$

where, $d^2\left(x_j,v_i\right)$ is the Gaussian Kernel distance function shown in equation 7 and $f(p_{ij}) = \frac{1}{p_{ij}}$ is the neighborhood function.

GSK-FCM considers neighbourhood information and computes membership value associated with each data point as weighted sum of traditional FCM membership value and the membership value of the N_k neighbour points. The neighbourhood function (p_{ij}) is defined as

$$p_{ij} = \sum_{k=0}^{N_k} h\left(x_j,x_k\right) g\left(u_{ik}\right) \quad (16)$$

Where N_k is the number of neighbourhood data points, $g(u_{ik}) = u_{ik}$ is the membership function (equation 10), $h(x_j, x_k)$ is the distance function which is computed as:

$$h\left(x_j,x_k\right) = \left(\sum_{l=0}^{N_k}\frac{d^2\left(x_j,x_k\right)}{d^2\left(x_j,x_l\right)}\right)^{-1} \quad (17)$$

Substituting equation 17 in 16 the neighbourhood function becomes:

$$p_{ij} = \sum_{k=0}^{N_k} g\left(u_{ik}\right)\left(\sum_{l=0}^{N_k}\frac{d^2\left(x_j,x_k\right)}{d^2\left(x_j,x_l\right)}\right)^{-1} \quad (18)$$

Substituting equation 15 in equation 14, the membership function z_{ij} becomes,

$$z_{ij} = \left(\sum_{k=1}^{c}\left(\frac{d^2\left(x_j,v_i\right) f\left(p_{ij}\right)}{d^2\left(x_j,v_k\right) f\left(p_{jk}\right)}\right)^{\frac{1}{(m-1)}}\right)^{-1} \quad (19)$$

$$= \frac{\left(\sum_{k=1}^{c}\left(\frac{d^2\left(x_j,v_i\right)}{d^2\left(x_j,v_k\right)}\right)^{\frac{1}{m-1}}\right)^{-1} f^{\frac{1}{1-m}}\left(p_{ij}\right)}{\sum_{k=1}^{c}\left(\sum_{l=1}^{c}\left(\frac{d^2\left(x_j,v_i\right)}{d^2\left(x_j,v_l\right)}\right)^{\frac{1}{m-1}}\right)^{-1} f^{\frac{1}{1-m}}\left(p_{jk}\right)} \quad (20)$$

where, $\left(\sum_{k=1}^{c}\left(\frac{d^2\left(x_j,v_i\right)}{d^2\left(x_j,v_k\right)}\right)^{\frac{1}{m-1}}\right)^{-1} = u_{ij}$

Then the membership function z_{ij} becomes

$$z_{ij} = \frac{u_{ij} f^{\frac{1}{1-m}}\left(p_{ij}\right)}{\sum_{k=1}^{c} u_{jk} f^{\frac{1}{1-m}}\left(p_{jk}\right)} \quad (21)$$

Similar to FCM and RSKFCM, GSKFCM operates in iterative process by updating membership and cluster center value. The cluster centers are updated using equation 22

$$v_i = \frac{\sum_{j=1}^{n} z_{ij}^m K\left(x_j,v_i\right) x_j}{\sum_{j=1}^{n} z_{ij}^m K\left(x_j,v_i\right)} \quad (22)$$

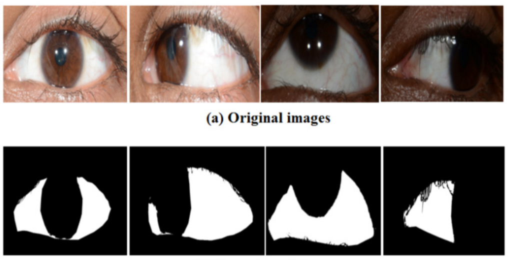
GSK-FCM decides the label based on the maximum membership value.

4 DATASET AND RESULT ANALYSIS

This section presents the result evaluated of the proposed GSK-FCM clustering algorithm. To evaluate the proposed method, experimentations are conducted using Sclera Segmentation and Recognition Benchmarking Competition (SSRBC2015) dataset (Das et al., 2016). Table 1 presents the characteristics of the dataset. The dataset contains 30 individuals eye image with different cases such as blinked eye, closed eye, blurred eye. For every individual eye, the images are captured in different angles like looking at the center, left, right and up. Thus the dataset in total consists of 120 eye images with ground truth images.

Table 1: Characteristics of SSRBC2015 dataset.

Number of individuals	30
Number of samples per individuals	4
Captured Angle	Center,left, right and up
Image resolution	1489 X 1105
Total number of samples	120



(a) Original images

(b) Ground truth images

Figure 1: Sample sclera images and ground truth of SSRBC2015 dataset.

To test the effectiveness of the proposed model, the performance of the GSK-FCM method is compared with other versions of FCM and RSKFCM. To find the optimal value of the parameters, four well known cluster validity indices: Partition Coefficient (V_{pc}), Partition Entropy (V_{pe}), Fukuyama-Sugeno function (V_{fs}), Xie-Beni function (V_{xb}) are used as an evaluation metrics. For all the experiments, we have set the fuzzifier m value to 2 and stopping criteria ε to 0.00001 empirically. For sclera segmentation, cluster number c is set to 3 (sclera, iris and outer region). Figure 2 and Figure 3 presents the cluster validity results of the existing RSKFCM and proposed GSK-FCM method for different p and q values.

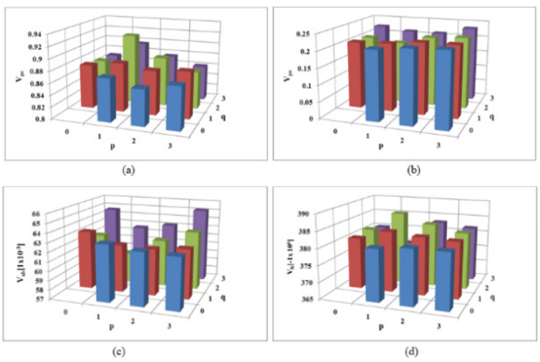


Figure 2: Cluster validity indices for different p and q values of RSKFCM on sclera segmentation (a) V_{pc}, (b) V_{pe}, (c) V_{xb}, (d) V_{fs}.

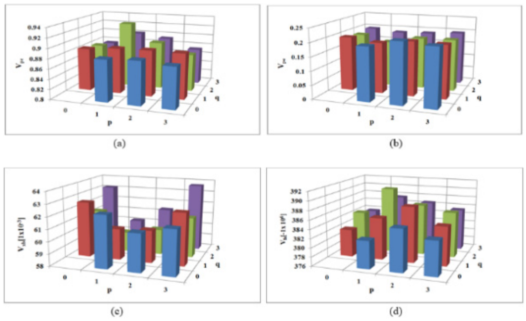


Figure 3: Cluster validity indices for different p and q values of GSKFCM on sclera segmentation (a) V_{pc}, (b) V_{pe}, (c) V_{xb}, (d) V_{fs}.

Figure 4 and Figure 5 presents the comparison of four cluster validity indices values of the proposed methods for different window size on sclera segmentation. From empirical evaluation, it is found $p=1$, $q=2$, $\sigma=150$ and window size=5 are optimal values for sclera segmentation. Table 2 and Table 3 shows the cluster validity indices value, precision and recall values of the proposed methods.

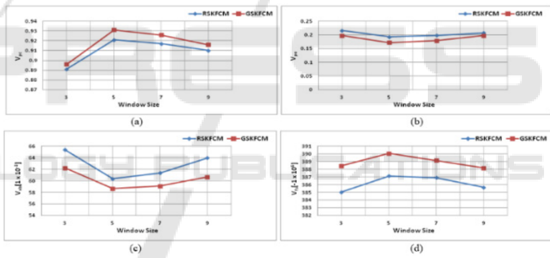


Figure 4: Cluster validity indices for different window size of the existing RSKFCM and proposed GSK-FCM methods on sclera segmentation (a) V_{pc}, (b) V_{pe}, (c) V_{xb}, (d) V_{fs}.

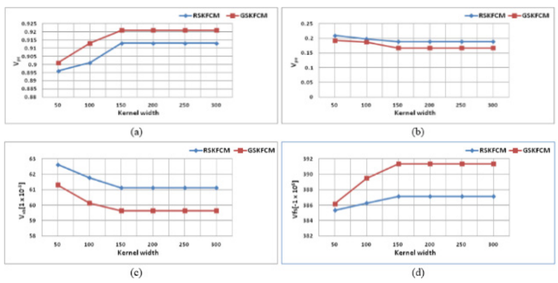


Figure 5: Cluster validity indices for different kernel width σ of the existing RSKFCM and proposed GSK-FCM methods on sclera segmentation (a) V_{pc}, (b) V_{pe}, (c) V_{xb}, (d) V_{fs}.

Table 2: Performance comparision in terms of cluster validity indices on sclera traits.

Method	Precision	Recall
FCM	65.98	65.12
KFCM	67.43	66.96
SFCM	69.72	68.79
SKFCM	72.93	73.08
RSKFCM	85.21	80.21
GSK-FCM	**85.89**	**80.23**

Table 3: Performance comparision in terms of segmentation on sclera traits.

Method	V_{pc}	V_{pe}	$V_{xb}[1x10^{-3}]$	$V_{fs}[-1x10^{6}]$
FCM	0.832	0.236	74.68	350.64
KFCM	0.848	0.225	72.19	353.68
SFCM	0.866	0.220	70.68	361.31
SKFCM	0.884	0.213	67.84	365.38
RSKFCM	0.921	0.192	60.34	387.13
GSK-FCM	**0.931**	**0.167**	**59.65**	**390.67**

5 CONCLUSION

This paper presents the Generalized Spatial Kernel-Fuzzy C Means (GSK-FCM) clustering algorithm which is capable of segmenting sclera images. The proposed algorithm have overcome the drawbacks of traditional FCM method by considering neighbourhood information and using Gaussian kernel distance measure. The inclusion of neighbourhood information and use of kernel function reduces the impact of noise which in turn increases the results. This paper work has been applied to sclera segmentation images, where in the segmentation plays a crucial role for recognition/identification purpose for future researchers who deal in authentication of users using sclera biometric trait. From the observations of the results and its comparison with other methods the proposed GSK-FCM performs better than the other methods.

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