



ISSN: 0975-833X

## RESEARCH ARTICLE

### A HYBRID CLUSTERING METHOD FOR COMPRESSING IRIS IMAGES

\*Mary Shanthi Rani, M.

Department of Computer Science and Applications, Gandhigram Rural Institute – Deemed University,  
Gandhigram-624302, India

#### ARTICLE INFO

##### Article History:

Received 13<sup>th</sup> September, 2013  
Received in revised form  
24<sup>th</sup> October, 2013  
Accepted 23<sup>rd</sup> November, 2013  
Published online 25<sup>th</sup> December, 2013

##### Key words:

Iris, Biometric Recognition,  
Image Compression,  
Subtractive Clustering,  
Fuzzy C-means, K-means

Copyright © Mary Shanthi Rani, M. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

#### ABSTRACT

The growing popularity of iris based biometric system has motivated rigorous research in iris image compression techniques, considering the need for effective storage and transmission of iris images. In this paper, a new method has been proposed for compressing iris images using a hybrid of two robust clustering methods for generating a codebook thereby achieving compression. Experimental results show that the proposed method outperforms similar compression methods by producing good quality images at high compression rate.

#### INTRODUCTION

The rapid growth and development of electronic imaging in the recent years has led to large scale digital media archives. These are increasingly becoming popular as more and more digital media contents are created and deployed online every day. One such application is the biometric system which handles vast amount of sensor acquired biometric data. A critical issue is how to store and handle the acquired sensor data effectively. Uncompressed data requires more storage and huge bandwidth for transmission. Though the cost of storage is rapidly dropping, compression still remains as a challenging issue due to the growing number of distributed biometric applications. Recently, iris has become one of the most secure biometric modalities in biometric recognition systems exhibiting 0% False Acceptance Rate (FAR). Aadhar, India's UID project assigns a Unique Identification Number (UID) to every Indian citizen by uniquely identifying them using iris scan along with fingerprints ((Bowyer K.M *et al.*, 2008). Sometimes, transmission of the captured iris images is necessary for authentication with master database located elsewhere in a distributed biometric system over a narrow-bandwidth communication channel This necessitates the design of highly efficient iris image compression systems for effective storage and transmission of iris images . Several novel methods have been proposed for compressing iris images and yet rigorous research is going on in developing robust algorithms in terms of compression rate and reconstructed image quality.

In order to maximize the benefit in terms of data reduction, lossy compression techniques have to be applied. As the quality of the decompressed image plays a vital role in iris recognition systems, research in iris image compression focus mainly on developing new methods that achieves good balance between compression rate and image quality as well. Daugman and Downing (2008) made a pioneering work on iris image compression and they proposed a region of interest (ROI) isolation method. This method isolates iris region from non-iris regions (eyelids and sclera) which are substituted using two different gray levels. It is also found that this method of ROI isolation leads to a two-fold reduction in file size and easy localization of eyelid boundaries in later stages as well.

The impact of using different lossy compression algorithms on the accuracy of recognition systems is investigated in (Matschitsch *et al.*, 2007) which concluded that JPEG 2000 and SPIHT are well suited iris compression algorithms. Furthermore, the study also revealed that Predictive Residual Vector Quantization (PRVQ) was equally competitive with the above two methods producing high quality images, thereby resulting in good recognition rates. As per the ISO/IEC 19794 standard on Biometric Data Interchange Formats”, JPEG 2000 has only been included as the standard for lossy compression and recommended for standardized Iris Exchange (IREX) records initiated by National Institute for Standards and Technology (NIST ). Still, the high computation complexity of JPEG 2000 triggers research in new lossy compression methods with less computation complexity. In this paper, a novel lossy compression method is proposed for compressing iris images combining the popular clustering methods Fuzzy C-means, K-means and Subtractive Clustering. Clustering is

\*Corresponding author: Mary Shanthi Rani, M.  
Department of Computer Science and Applications, Gandhigram  
Rural Institute – Deemed University, Gandhigram-624302, India

an important partitioning technique which organizes information in the form of clusters such that patterns within a cluster are more similar to each other than the patterns belonging to different clusters. Clustering algorithms partition the given dataset into subsets (clusters) based on some distance measure. Traditionally, clustering techniques are broadly divided into hierarchical and partitioning. Hierarchical algorithms build clusters hierarchically, whereas partitioning algorithms determine all clusters at once. The partitioning methods generally result in a set of  $K$  clusters, each object belonging to one cluster. Each cluster may be represented by a centroid or a cluster representative which is some sort of summary description of all the objects contained in a cluster.

K-means (Linde *et al.*, 1980) is one of the most popular partitioning techniques which has great number of applications in the fields of image and video compression (Gersho and Gray, 1992), image segmentation (Ng *et al.*, 2006), pattern recognition and data mining (Duda and Hart, 1973). It is simple and easy to implement and the computation time mainly depends on the amount of training data, codebook size, vector dimension, and distortion measure for convergence. It clusters the given objects, based on their attributes into  $K$  partitions. K-means comprises of four steps: initialization, classification, computational and convergence criteria. The objective is to minimize the total intra-cluster variance, or the squared error function. There are two issues in creating a K-means clustering model:

- Determining the optimal number of clusters to create
- Determining the center of each cluster

Determining the number of clusters ( $K$ ) is specific to the problem domain. The K-means algorithm is significantly sensitive to the initial randomly selected cluster centers. Poor selection of initial seeds has great impact on its performance yielding sub-optimal clusters and increase in convergence time. Several methods have been proposed on seed initialization in order to improve K means convergence (Somasundaram and Mary, 2011). The proposed method explores the formation of initial cluster centers based on Fuzzy C-means (FCM) and Subtractive Clustering. Fuzzy C-means clustering is a soft computing partitioning method proposed by Bezdek (Bezdek, 1973). The method employs fuzzy partitioning such that a given data point can belong to several clusters with the degree of belongingness specified by membership grades between 0 and 1. However, FCM uses a cost function which is to be minimized while partitioning the data set. The values of the membership matrix  $U$  will vary between 0 and 1. The subtractive clustering approach is a hierarchical clustering method which discovers clusters  $r$  centers based on a density measure and can be used as a preprocessor for other sophisticated clustering methods (Jang *et al.*, 1997). It starts with assuming each data point as a potential cluster center and calculates a measure of the likelihood of each data point to be the cluster center, based on the density of surrounding data points. The algorithm does the following:

- Selects the data point with the highest potential to be the first cluster center
- Removes all data points in the vicinity of the first cluster center as determined by radii, in order to determine the next data cluster and its center location

- Iterates on this process until all of the data is within radii of a cluster center

Thus the proposed method is a hybrid method of both hierarchical and partitioning clustering methods. The rest of the paper is organized as follows: Section II briefly describes the proposed method, Section III presents the results and discussion of the performance of HCM and Section IV concludes by highlighting the merits and demerits of the proposed method.

## MATERIALS AND METHODS

The proposed method Hybrid Clustering Method (HCM) is a novel method of seed initialization of K-means Clustering algorithm blending the nice features of subtractive clustering and fuzziness of fuzzy c-means. The algorithm works in two phases. The first phase extracts the iris region from the given eye image. The output of this phase is a rectilinear image perfectly covering the iris. The second phase is the seed initialization phase which forms the initial seeds for clustering process. First, the extracted iris region is divided into  $4 \times 4$  blocks and each block is converted into a 16-vector which collectively forms the training set of vectors for clustering process. Next, subtractive clustering is carried out on the training set which yields a set of cluster centres. The resulting number of cluster centres can be varied by changing the radius parameter supplied to the subtractive clustering. Smaller radii values result in more number of clusters. The best values of radii are usually between 0.2 and 0.5. Let ' $K$ ' be the desired number of clusters and ' $S$ ' the number of cluster centres returned by subtractive clustering. The iris region is clustered further using Fuzzy C-means clustering to generate ( $K$ - $S$ ) seeds. This soft computing approach employs fuzzy measures as the basis for membership matrix calculation and for identifying cluster centres. Thus the proposed method employs two clustering algorithms exploiting them to get the best combination of initial cluster centres (seeds). The third phase performs K-means Clustering with the initial cluster centres generated in the seed initialization phase. The resulting cluster centres or the centroids form the master codebook which represents the compressed version of the iris image.

### Algorithm

#### Phase One

Extract the iris region from the input eye image by manual segmentation.

#### Phase Two

**Step 1:** Partition the iris region into blocks of size  $4 \times 4$  (16-vector) forming the training set ' $T$ ' of vectors.

**Step 2:** Generate  $S$  cluster centres from the training set ( $T$ ) for iris region by using Subtractive clustering

**Step 3:** Apply Fuzzy C-means algorithm on the same training set  $T$  and generate ( $K$ - $S$ ) cluster centres.

#### Phase Three

Perform K-means Clustering on the training set  $T$  and get the final set of cluster centres which forms the master codebook.

**Encoding**

The output of Phase three is the master codebook. Compression is achieved by encoding each training vector to its matching code vector based on euclidean distance.

**Decoding**

Retrieve the corresponding code vector for each training vector in the iris region using its code index from the master codebook.

**RESULTS AND DISCUSSION**

Experiments were conducted on sample left-eye iris images of IIT Delhi Iris database v1 with resolution 320x240 pixels and 256 gray levels to evaluate the compression performance of the proposed method. The performance is assessed based on reconstructed image quality, compression ratio and computing time. The most widely used image quality metric is the Mean Square Error (MSE), computed by averaging the squared intensity differences of original and reconstructed image pixels, along with the related quantity of Peak Signal-to-Noise Ratio (PSNR).

The MSE is calculated as

$$MSE = \frac{1}{n} \sum (P_i - Q_i)^2$$

where  $P_i$  denote the pixels of the original image and  $Q_i$ , the pixels of the reconstructed image,  $1 \leq i \leq n$  and  $n$  is the total number of pixels.

The root mean square error (RMSE) is defined as square root of the MSE, and the PSNR is defined as

$$PSNR = \frac{20 \log_{10} \text{Max}|P|}{RMSE}$$

High PSNR values indicate high quality, implying close similarity between the reconstructed and the original images. An universal image quality index for gray scale images, Q was proposed by Wang (Wang *et al.*, 2004) which models any distortion as a combination of three different factors: loss of correlation, mean distortion, and variance distortion. The dynamic range of Q is [-1,1] with the best value of 1 achieved when original image is exactly equal to the reconstructed image. Table 1 shows the results of experiments and the performance comparison of the proposed method with Fuzzy C-means and K-means with random initialization of seeds.

BPP represents bits per pixel expressing the rate of compression. Experimental results clearly indicate that the proposed method produces high quality reconstructed image in terms of both PSNR and structural quality index (Q). It is evident from Table 1 that the proposed method outperforms K-means and FCM by producing high quality images with high PSNR and structural quality index as well with the compressed file size reduced to 10% of the size of the original file. Though the computing time is little higher, it can be argued that quality is the most significant parameter in biometric recognition systems. Poor quality of reconstructed image may lead to increase in False Recognition Rate (FRR) and False Acceptance Rate (FAR) as well.

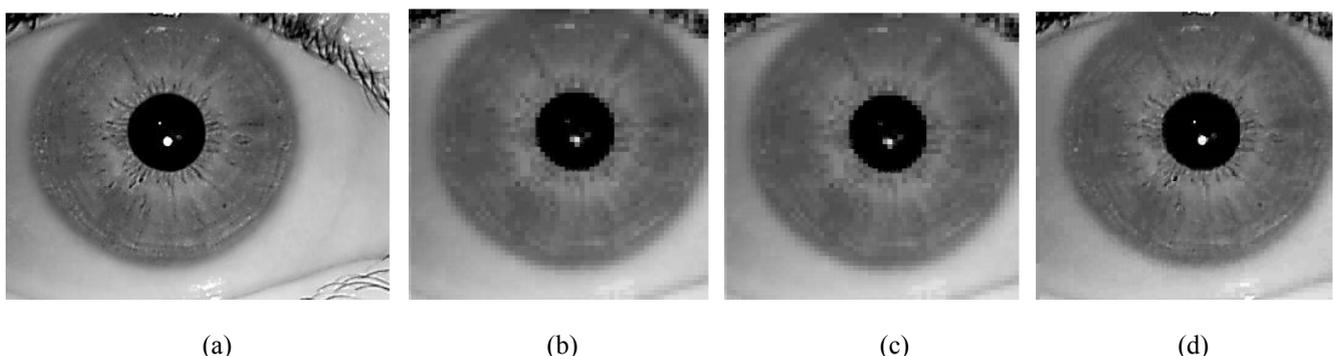
**Table 1. Performance Comparison of Proposed (HCM) and other methods**

Image	Metrics	Method		
		Fuzzy C-means	K-means	HCM (Proposed method)
Image1	PSNR	27.460	31.689	31.830
	Q	0.617	0.698	0.706
	BPP	0.75	0.75	0.75
	Time (in sec.)	39.8	22.02	66.5
Image2	PSNR	22.81	25.966	26.2
	Q	0.598	0.651	0.650
	BPP	0.75	0.75	0.75
	Time	33.875	42.15	65.15
Image3	PSNR	30.92	36.329	36.975
	Q	0.799	0.780	0.775
	BPP	0.75	0.75	0.75
	Time (in sec.)	42.56	14.78	61.12
Image4	PSNR	25.522	29.451	29.544
	Q	0.615	0.646	0.707
	BPP	0.75	0.75	0.75
	Time	43.53	28.08	54.45
Image5	PSNR	27.568	32.639	32.744
	Q	0.689	0.735	0.763
	BPP	0.75	0.75	0.75
	Time (in sec.)	30.12	29.18	52.18

For visual comparison, the original and reconstructed images of test iris image are shown in Fig.1. As far as the memory requirements are considered, the proposed method requires storage for the master codebook, as well as for storing code indices. As the master codebook contains K code vectors, the size M in bits of the master codebook is given by

$$M = K \times 16 \times 8 \text{ bits}$$

If 'N' is the total number training vectors in the input image, a total of N code indices will be required to retrieve code vectors from the master code book. The key feature of the proposed method is that it is simple and easy to implement and requires



**Figure 1. (a) Original iris image; Reconstructed image using (b) Fuzzy C-means (c) K-means and (d) HCM(Proposed method)**

no special hardware for implementation as required by JPEG and JPEG 2000.

## Conclusions

In this paper, we have proposed an innovative approach for selection of initial seeds for K-means which has great impact on its performance. The proposed method HCM has contributed to enhancement in image quality at comparable bit rate and computing time and hence it is an ideal choice for biometric applications where quality is given the highest priority. Furthermore, the reduced complexity and easy implementation of HCM with high image quality makes it a perfect option for medical image compression.

## REFERENCES

- Bezdek JC, "Fuzzy mathematics in pattern classification", Ph.D thesis, Cornell University, 1973.
- Bowyer, K.W., Hollingsworth, K. and Flynn, P. J. 2008. "Image understanding for iris biometrics: A survey," *Comp. Vis. Image Underst.*, Vol. 110, no. 2, pp. 281 – 307.
- Daugman J. and Downing C. 2008. "Effect of severe image compression on iris recognition performance," *IEEE Trans. Inf. Forensics and Sec.*, Vol. 3, pp. 52–61.
- Jang, J.-S. R., Sun, C.-T., Mizutani, E., "Neuro-Fuzzy and Soft Computing – A Computational Approach to Learning and Machine Intelligence," *Prentice Hall*.
- Linde Y., Buzo A., and Gray R.M., "An Algorithm for Vector Quantizer Design", *IEEE Transactions on Communication*, Vol. 28, pp. 84–95, 1980
- Matschitsch S., Tschinder, M. and Uhl, A. 2007. "Comparison of compression algorithms' impact on iris recognition accuracy," in *Proc. of the 2nd Int'l Conf. on Biometrics (ICB 2007)*, LNCS, 4642, pp. 232–241.
- Gersho A. and Gray R.M. 1992. "Vector Quantization and Signal compression", Kluwer Academic Publishers, New York, pp. 761.
- Ng H.P., Ong S.H., Foong K.W.C, Goh P.S , and Nowinski W.L. 2006. "Medical image segmentation using k-means clustering and improved watershed algorithm", *IEEE Southwest Symposium on Image Analysis and Interpretation*, Denver, pp. 61-65.
- Duda, R.O. and Hart P.E. 1973. "Pattern Classification and Scene Analysis", John Wiley Sons, New York, pp. 482.
- Somasundaram K. and Mary Shanthi Rani M. 2011. "Novel K-means Algorithm for Compressing Images", *International Journal of Computer Applications*, Volume 18– No.8, pp.9-13.
- Zhou Wang, Alan C. Bovik, Hamid R. Sheikh, and Eero P. Simoncelli, 2004. "Image Quality Assessment: From error visibility to structural similarity", *IEEE Transactions on Image processing*, Vol.13, No. 4, pp. 600-612.

\*\*\*\*\*