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Analysis of Mri Image Segmentation Based on Modified Clustering Schemes

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***Abstract*-This paper proposes a novel fuzzy learning vector quantization algorithm for the image segmentation. In the design process, the challenges are computational costs, initialization. So, a hybrid FLVQ method based on k means, fuzzy c-means and competitive agglomeration is proposed in this paper. This algorithm utilizes a specialized objective function, which involves k means, fuzzy c-means and CA. The competitive agglomeration term creates large clusters, and also migrate the small clusters close to large clusters, rending more competitive. The joint process reduces the computational costs and number of cluster centers affected by the training samples is also reducing. Thus the codeword migration process reduces the dependence on initialization by using the competitive agglomeration. This algorithm is a fast process and maintains high quality for the reconstructed images.**

Keywords: Competitive Agglomeration, K means, Fuzzy c-means, Fuzzy learning Vector Quantization (FLVQ).

I INTRODUCTION

Image segmentation is the process of partitioning a digital image into multiple segments. Image segmentation is used to locate objects and boundaries in images. It is the process of assigning a label to every pixel in an image such that pixels with the same label share certain characteristics. The result of image segmentation is a set of segments that collectively cover the entire image, or a set contours extracted from the image [1]. Each of the pixels in a region are similar with respect to some characteristics such as color, intensity, texture. Clustering algorithms groups the samples of a set such that two samples in the same cluster are more similar to one another than two samples from different clusters. Clustering methods can be categorized into two broad classes: non-parametric and parametric methods. Non-parametric clustering involves finding natural groupings (clusters) in a dataset using an assessment of the degree of difference (such as Euclidean distance) between the samples of the dataset. It requires the measure of similarity between samples, defining a criterion function for clustering, and defining an algorithm to minimize (or maximize) the criterion function. Popular non-parametric clustering algorithms include k-means, Hierarchical clustering algorithms and Spectral clustering. A widespread classification of clustering-based VQ methods distinguishes them into crisp and fuzzy. Crisp VQ is mainly based on the c- means method. The c-means is very sensitive on initialization. Fuzzy techniques are mainly based on the fuzzy c-means algorithm. Fuzzy Learning Vector Quantization (FLVQ) manipulates the fuzziness parameter from large to small values. FLVQ also results in high computational cost. The second tries to accomplish the transition from fuzzy to crisp mode by incorporating special mechanisms to reduce the number of distance calculations, while keeping the fuzziness parameter constant. Finally the third constitutes a combination fuzzy c-means and CA term. The implementation of vector quantization (VQ) is based on code words and codebook [2]

II SEGMENTATION BASED ON CLUSTERING

Image segmentation is used to locate objects and boundaries in images. It is the process of assigning a label to every pixel in an image such that pixels with the same label share certain characteristics. The result of image segmentation is a set of segments that collectively cover the entire image, or a set contours extracted from the image each of the pixels in a region are similar with respect to some characteristics such as color, intensity, texture [4]. The disadvantage of the segmentation based on conventional techniques such as region growing, thresholding is stated as follows. In region growing, the choice of different seeds leads to different segmentation results. The seed lies at the edge of the image were the major problem in the segmentation result. The drawback of watershed transform technique was to fix the threshold value. The choice of different thresholding values leads to different segmented results. The disadvantage of these methods leads to the development of segmentation based on clustering techniques. Image segmentation process is very close to the clustering problem. Clustering methods [3] have been successfully used to segment an image into a number of clusters (segments). Clustering-based segmentation techniques [5] have used several control parameters, e.g., the predefined number of clusters to be found or some tunable thresholds. These parameters are adjusted to obtain the best image segmentation. The parameters value is a nontrivial task.

II PROPOSED WORK

The proposed work is the hybridization of c means, fuzzy c- means and competitive agglomeration for image segmentation. It is fuzzy clustering-based vector quantization algorithm. Fuzzy clustering vector quantizer which linearly combined the fuzzy c- means and CA term as described in section III.

This algorithm utilizes a specialized objective function, which involves the c-means, fuzzy c-means along with a competitive agglomeration term. The images are taken and converted into blocks. The vectors are formed

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from the blocks of images. Then the clustering process is carried out. Then the blocks form the feature vectors and designing a codebook that minimizes the distortion measure. Then the code vectors again are reconstructed into blocks. Then the corresponding reconstructed image is obtained.

A. C-Means Clustering

It is a partitioning method which finds mutual exclusive clusters of spherical shape. It generates a specific number of disjoint, flat (non-hierarchical) clusters. Statiscal method can be used to cluster to assign rank values to the cluster categorical data. Here, categorical data had been converted into numeric by assigning rank value. K-Means algorithm organizes vectors into k – partitions where each partition represents a cluster. The set of means was initialized and classify cases based on their distances to their centers. Next the cluster means are once again computed, using the cases that are assigned to the clusters. Then based on the new set of means all cases are reclassified. The steps are repeated until cluster means did not change between successive steps. Then [6] the means of clusters are calculated once again and assigned the cases to their permanent clusters.

The dataset is partitioned into K clusters and the vectors are randomly assigned to the clusters resulting in clusters that have roughly the same number of vectors. For each vector, the distance is calculated from the vector to each cluster. The vector is unchanged if it is closest to its own cluster. If the data vector is not closest to its own cluster, move it into the closest cluster. The above step is repeated until a complete pass through all the vectors results in no vector moving from one cluster to another. At this point the clusters are stable and the clustering process is ended. The choice of initial parameters of this clustering technique affects the final clusters that result, in terms of inter-cluster and intra cluster distances [10].

B. Fuzzy C means

Fuzzy algorithm [5] allows gradual memberships of data vectors to clusters measured as degrees in [0, 1]. This algorithm is used for analysis based on distance between various input data vectors. The clusters are formed according to the distance between data vectors and the cluster centers are formed for each cluster. The degree of membership of each input vector to the cluster is calculated which decides the cluster belonging to the corresponding input vector. For each input vector, the membership degree cluster is specified as follows:

$$u_{ij} = \sum_{k=1}^{N} \left(\frac{d_{ij}}{d_{ik}} \right)^{\left(\frac{2}{m-1}\right)} \qquad (1)$$

where,
d_{ij} denotes distance of ith item from jth cluster,
d_{ik} denotes distance of ith item from kth cluster,
m is the fuzzification factor.

The main problem in this algorithm is to select the number of clusters. Another major problem in this method is the selection of objective function. The selection of fuzziness coefficient is the important step in this algorithm. The higher the value of fuzziness coefficient, a larger number of data vectors will fall inside a `fuzzy' band where the degree of membership is neither 0 nor 1, but somewhere in between. Therefore, the selections of appropriate cluster centers, optimization of objective function and identify the appropriate fuzziness coefficient are considered to be the major issues of FCM [2]. So, a combination of fuzzy c-means along with competitive agglomeration is proposed in this section.

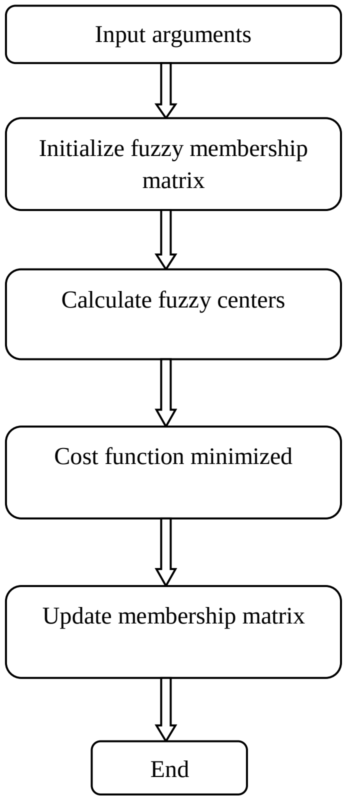

Fig.1. represents the process of clustering techniques using FCM algorithm

C. Modified C-Means and Fuzzy C-Means Along With Competitive Agglomeration

The competitive agglomeration (CA) algorithm is a powerful technique that refines good from spurious and badly delineated clusters by minimizing the following objective function.

$$J(U,V,X) = \sum_{k=1}^{n}\sum_{i=1}^{c}(u_{ik})^2 \|x_k - v_i\|^2 - \gamma \sum_{i=1}^{c}\left(\sum_{k=1}^{n} u_{ik}\right)^2 \qquad (2)$$

subject to the constraint

$$\sum_{j=1}^{c} u_{jk} = 1 \qquad \forall k \qquad (3)$$

where
u_{ik} denotes the membership degree of the kth training vector to the ith cluster.

The membership degrees and the cluster centers are calculated based on the equations (4) and (5).

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$$v_i = \frac{\sum_{k=1}^{n}\left(\theta u_{ik} + (1-\theta)\left(u_{ik}^2\right)\right)\chi_k}{\sum_{k=1}^{n}\left(\theta u_{ik} + (1-\theta)(u_{ik}^2)\right)} \quad (4)$$

$$u_{ik} = \left(\frac{2+\left(N(\Im_k)-2\right)\theta}{2(1-\theta)}\right)\frac{1}{\sum_{v_j\in\Im_k}\left(\|x_k-v_i\|/\|x_k-v_j\|\right)^2} + \frac{\gamma}{1-\theta}\frac{1}{\|x_k-v_i\|^2}\left(N(C_i)-\tilde{N}(\chi_k)\right)-\frac{\theta}{2(1-\theta)} \quad (5)$$

$$\gamma^t = \eta^t \frac{\sum_{k=1}^{n}\sum_{i=1}^{c}\hat{u}_{ik}\|x_k-v_i\|^2+(1-\theta)\sum_{k=1}^{n}\sum_{i=1}^{c}\left(\hat{u}_{ik}^2\right)\|x_k-v_i\|^2}{\sum_{i=1}^{c}\left(\sum_{k=1}^{n}\hat{u}_{ik}\right)^2} \quad (6)$$

where

$$N(C_i) = \sum_{k=1}^{n} u_{ik} \quad (7)$$

$$\tilde{N}(x_k) = \sum_{v_j\notin\Im_k}\frac{N(C_i)}{\|x_k-v_j\|^2} \Big/ \sum_{v_j\in\Im_k}\frac{1}{\|x_k-v_j\|}^2 \quad (8)$$

The codewords distant to x_k may be assigned negative or zero membership degree values and they are not affected by x_k. For the ith iteration, the set $\Im_k^{(t)}$ is the collection of codewords affected by x_k.

$$\Im_k = \{v_i \in \Im_k^{(t-1)} : u_{ik} \rangle \ 0 \quad (9)$$

As the learning process proceeds, each set is ssgradually reducing its size by excluding its codewords that are assigned zero membership degrees. Then after some iterations, it is possible for the set $\Im_k$ to satisfy the condition $N(\Im_k) = 1$.So that the vector x_k transferred in crisp mode. If $N(\Im_k) \rangle 1$ the vector x_k remains in fuzzy mode. For reach training vector x_k that remains in fuzzy mode, calculate the membership degrees based on Eq. (6).

The Competitive Agglomeration term creates large clusters while continuously shrinking the small clusters until their size becomes less than a predefined threshold. In the migration process, a codeword migration strategy is used. The code words of small clusters are detected and they are relocated in specific positions close to large clusters. Due to the competition to achieve an increasing size between the clusters is increased. The competitive agglomeration creates the large clusters, while the low cardinality clusters become smaller as the iteration number increases and are, ultimately discarded.

(i) Codeword migration process

The algorithm utilizes a specialized objective function, which involves the c-means and the fuzzy c-means along with a competitive agglomeration term. The joint effect is a learning process where the number of code words (i.e. cluster centers) affected by a specific training sample is gradually reducing and therefore, the number of distance calculations is also reducing. Thus, the computational cost becomes smaller. In addition, the partition is smoothly transferred from fuzzy to crisp conditions and there is no need to employ any aggressive interpretation of fuzzy clustering.

The competitive agglomeration term refines large clusters from small and spurious ones. Then, contrary to the classical competitive agglomeration method, we do not discard the small clusters but instead migrate them close to large clusters, rendering more competitive. Thus, the codeword migration process uses the net effect of the competitive agglomeration and acts to further reduce the dependence on initialization in order to obtain a better local minimum. The algorithm is applied to grayscale image compression. The main simulation findings can be summarized as follows:

(a) a comparison between the proposed method and other related approaches shows its statistically significant superiority,
(b) the algorithm is a fast process,
(c) the algorithm is insensitive with respect to its design parameters, and
(d) the reconstructed images maintain high quality, which is quantified in terms of the distortion measure

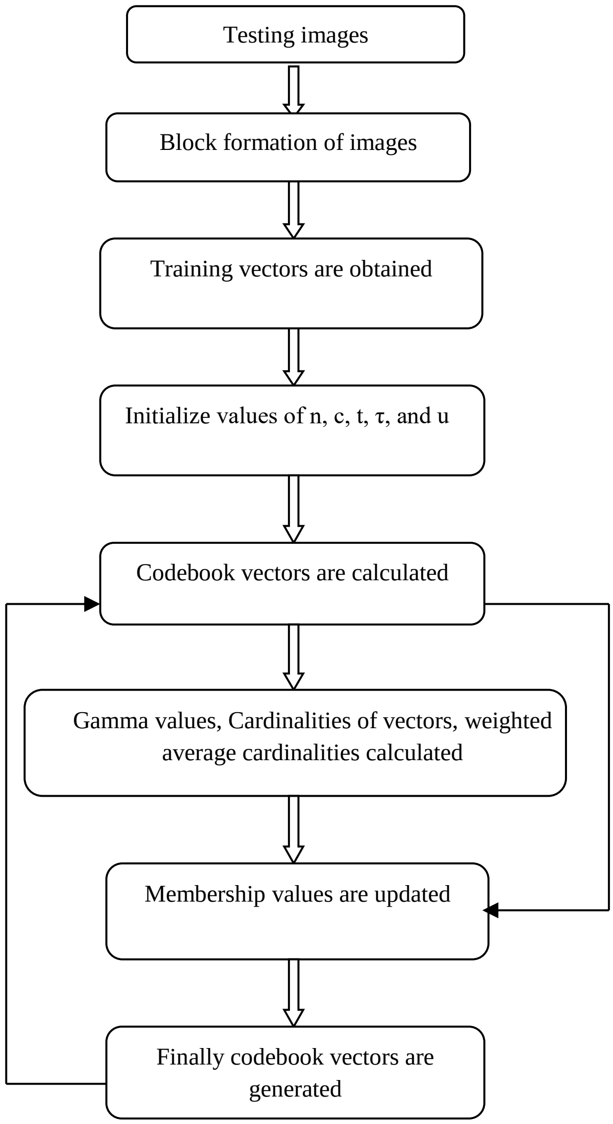

Fig.2. illustrates the codebook generation using the competitive agglomeration techniques.

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D. Fuzzy Vector Quantization Method

Vector quantization is used in image processing. The set of prototypes are called code words and the set is referred as codebook. The VQ is used in grayscale image compression. The images are decomposed into number of rectangular blocks. The feature vectors are formed from these blocks and finally, the codebook is designed. The distortion measure is calculated. Then the image is reconstructed by replacing each feature vector by its closest codeword.

The proposed work is fuzzy clustering-based vector quantization algorithm. This algorithm utilized a specialized objective function, which involves the c-means, fuzzy c-means along with a competitive agglomeration term. A widespread classification of clustering-based VQ methods distinguished them into crisp and fuzzy. Crisp VQ is mainly based on the c means method. The c-means is very sensitive on initialization. Fuzzy techniques are mainly based on the fuzzy c-means algorithm.

Fuzzy Learning Vector Quantization (FLVQ) manipulates the fuzziness parameter from large to small values. FLVQ also results in high computational cost. The second tried to accomplish the transition from fuzzy to crisp mode by incorporating special mechanisms. The number of distance calculations is reduced. Finally the third constitutes a combination c-means, fuzzy c-means and CA term. The implementation of vector quantization (VQ) is based on code words and codebook.

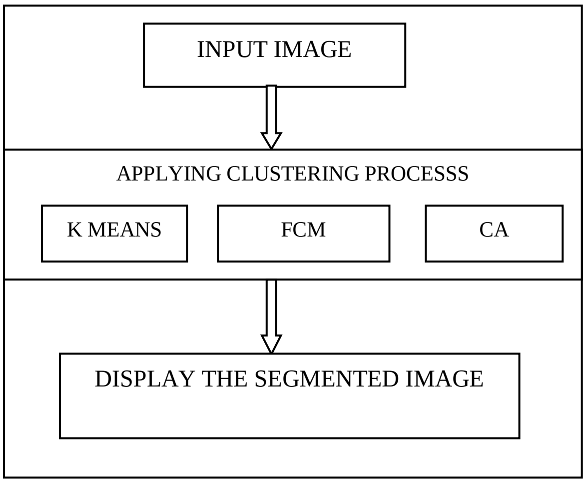


Fig.4. Overall representation of the proposed work

III FLOW CHART FOR THE PROPOSED ALGORITHM

1. Initialize values for n,c, θ, φ ,the partition matrix U.

2. Initialize v_i and the cardinality set $\mathfrak{I}_k$.

3. Calculate the distortion measure as in Eq. (1).

Let the set of training samples in fuzzy mode as

FM = {X$\mu(1)$, X$\mu(2)$ ... ... X$\mu(v)$}

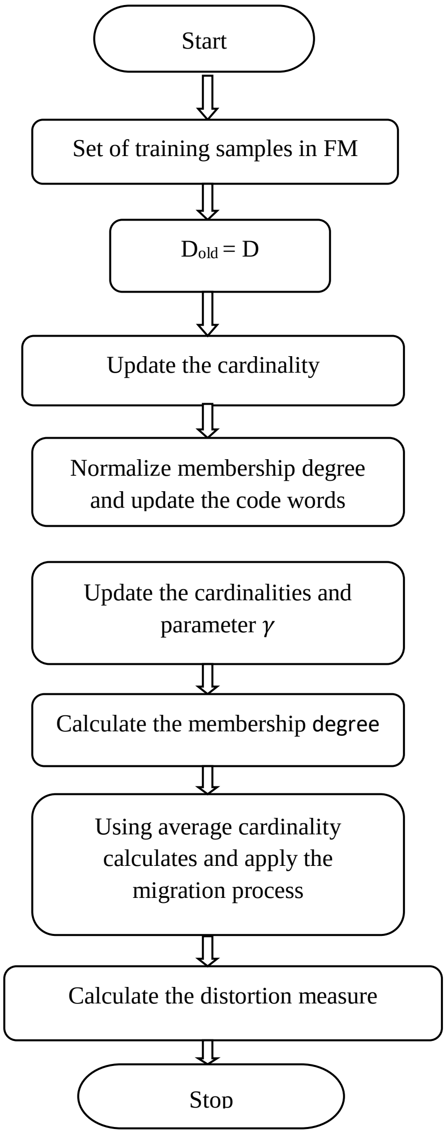
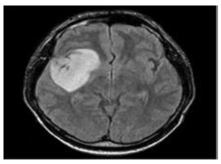


Fig.5. Flow chart for the modified fuzzy c means with competitive agglomeration

IV EXPERIMENTAL RESULTS AND DISCUSSION

In this section, we experimentally evaluate our proposed method for a set of images. The experiments have been developed in Mat lab R2009b, and are executed on an Intel Pentium Dual-Core 2.2 GHZ CPU, 2G RAM.

Fig. 6(i) Input images and preprocessing using median filter



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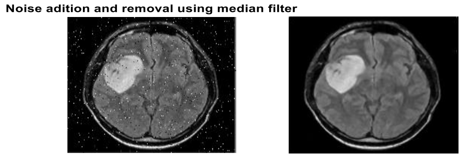
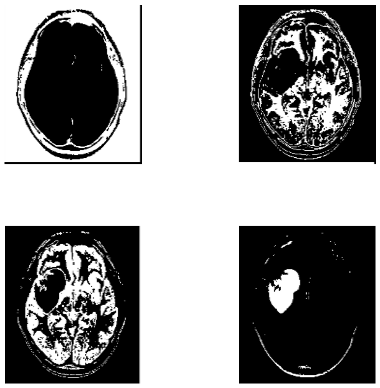


Fig. 6 (ii) Output images (i)kmeans, (ii)fcm, (iii)ca, (iv)modified fcm with ca



The input images are preprocessed using median filter. Then the preprocessed image is fed as input to the clustering process. The output shows the results for segmented image using k means, Fuzzy c means, competitive agglomeration, Modified FCM with CA.

V CONCLUSION

In this paper, we propose a new simple and effective Fuzzy clustering-based vector quantization using c means, fuzzy c-means along with CA term. The joint effect is a learning process where the number of code words affected by a specific training sample is gradually reducing and therefore, the number of distance calculations is also reducing. Thus, the computational cost becomes smaller. The proposed algorithm is a fast process and is insensitive with respect to its design parameters. The algorithm is based on distortion measure function. The reconstructed images maintain high quality, which is quantified in terms of the distortion measure.

VI FUTURE SCOPE

The future scope is to formulate a new objective function by combining different clustering techniques. The competitive agglomeration term incorporates in the new objective function for the transition strategy from fuzzy to crisp mode. The main aim of future work is to maintain high level of performance and high quality of reconstructed images.

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