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HYBRIDIZATION OF FUZZY C-MEANS AND COMPETITIVE AGGLOMERATION FOR IMAGE SEGMENTATION

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ABSTRACT

Image segmentation is the process of partitioning a digital image into multiple segments. Different methodologies have been proposed for the segmentation based on normal techniques such as region growing, threshold technique, watershed transform. The disadvantage of these methods leads to the development of segmentation based on clustering techniques. The main concept of data clustering is to use the centroid to represent each cluster. Also it is based on the similarity between the input vectors to that of the centroid to represent each cluster. Parametric and Non-parametric methods are the broad classes of the clustering methods. Non-parametric method involves finding natural groupings in a dataset using a Euclidean distance between the samples of the dataset. Non-parametric clustering includes k-means, hierarchical, spectral clustering. The disadvantages of these methods are lack of sufficient robustness to image noise. So, a fuzzy segmentation methodology has been widely applied in image clustering and segmentation. The important problem in fuzzy c-means is to specify the number of clusters and selection of objective function. So, a fuzzy clustering-based vector quantization algorithm is used. This algorithm utilizes a specialized objective function, which involves the fuzzy c-means along with a competitive agglomeration term. This algorithm is a fast process and the reconstructed images maintain high quality.

Keywords: competitive agglomeration, fuzzy c-means, fuzzy learning vector quantization (FLVQ).

1. 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 set contours extracted from the image. Each of the pixels in a region is 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 [1].

Image segmentation process is 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 [9] 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. This section provides a basic idea for the segmentation based on clustering technique.

2. PROPOSED WORK

The proposed work is the hybridization of 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 fuzzy c-means along with a competitive agglomeration term. 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. The images are taken and converted into blocks. The vectors are formed from the blocks of images. Then the clustering process is carried out. The blocks form the feature vectors and designing a codebook that minimizes the distortion measure as given in Equation (1). Then the code vectors again are reconstructed into blocks. Then the corresponding

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reconstructed image is obtained. The distortion measure is calculated as follows:

$$D = \frac{1}{n} \sum_{k=1}^{n} \min \left\{ \left\| x_k - v_i \right\|^2 \right\} \qquad (1)$$

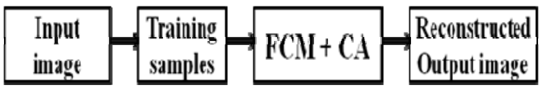

Figure-1. Block diagram for the proposed system.

3. MATHEMATICAL DESCRIPTION

A. Fuzzy c-means algorithm

In fuzzy clustering, the data vectors are associated with membership grades which indicate the degree to which the data vectors belong to the different clusters. The main objective of fuzzy clustering algorithm is to partition the data vectors into clusters so that the similarity of data vectors within each cluster is maximized and the similarity of data vectors in different clusters is minimized. Their fuzzy nature makes the clustering procedure able to retain more original image information than the crisp or hard clustering methodologies. Fuzzy algorithm allows gradual memberships of data vectors to clusters measured as degrees in [0, 1]. This gives the flexibility to express that data vectors belong to more than one cluster.

From the image database, the images are taken and converted into blocks. The vectors are formed from the blocks of images. Then the clustering process is carried out. The cluster centers are input arguments from the vectors. Then the input vector and the cluster centers are compared based on the Euclidian distance function. The minimum distance between the input vector and cluster center is chosen and the corresponding label of the cluster center value is assigned as index to the corresponding input vector. This process is iteratively done until for all the iterations will be over. Then the minimum distance of input vector corresponding to which cluster center is taken for reconstructing the images as given in Eq. (2). Then the code vectors again are reconstructed into blocks. Then the corresponding reconstructed image is obtained.

Iterations: In each iteration of the FCM algorithm, the following objective function J is minimized.

$$J = \sum_{i=1}^{N} \sum_{j=1}^{N} u_{ij}^{m} \left\| x_i - c_j \right\|^2 \qquad (2)$$

where

N = number of vectors,

c = number of clusters,

c_j = centre vector for cluster j,

u_{ij} = degree of membership for the ith data vector x_i in cluster j.

$\|*\|$ The norm, measures the similarity (or closeness) of the data vector x_i to the centre vector c_j of cluster j.

In the iteration, a centre vector for each of the clusters is maintained. These vectors are calculated as the weighted average of the data vectors, where the weights are given by the degrees of membership.

Degree of membership for a given data vector u_{ij}, the degree of its membership to cluster c_j calculated as follows:

$$u_{ij} = \frac{1}{\left(\frac{\left\| x_i - c_j \right\|}{\left\| x_i - c_j \right\|} \right)^2} \qquad (3)$$

where

m denotes the fuzziness coefficient.

The centre vector c_j is calculated as follows.

$$c_j = \left(\frac{\sum_{i=1}^{N} u_{ij}^{m} * x_i}{\sum_{j=1}^{N} u_{ij}^{m}} \right) \qquad (4)$$

Fuzziness coefficient in the above equations the fuzziness coefficient m, where 1 < m < 1, measured the tolerance of the required clustering. The clusters are overlapped with one another is determined by the value of m.The overlapping between clusters is larger for large values of m. 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.

Termination condition the required accuracy of the degree of membership is determined by the number of iterations completed by the FCM algorithm. This measure of accuracy is calculated using the degree of membership from one iteration to the next, taking the largest of these values across all vectors considering all of the clusters.

B. Modified fuzzy c-means with competitive agglomeration algorithm

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

$$J(U, V, X) = \sum_{k=1}^{n} \sum_{i=1}^{c} (u_{ik})^2 \left\| x_k - v_i \right\|^2 - \gamma \sum_{i=1}^{c} \left(\sum_{k=1}^{n} u_{ik} \right)^2 \qquad (5)$$

subject to the constraint

$$\sum_{j=1}^{c} u_{jk} = 1 \qquad \forall k \qquad (6)$$

where

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

The first component in Eq. (5) is similar to the fuzzy c-means objective function with the fuzziness parameter. The second component is the CA term whose basic contribution is to control the number of clusters. The parameter is chosen properly, the final partition will minimize the sum of intra-cluster distances, while partitioning the available data set into the smallest number of clusters.

$$\gamma^t = \eta^t \frac{\sum_{k=1}^{n}\sum_{i=1}^{c} (u_{ik})^2 \|x_k - v_i\|^2}{\sum_{i=1}^{c}\left(\sum_{k=1}^{n} u_{ik}\right)^2} \tag{7}$$

$$\eta^t = \eta_0 \ell^{\frac{-t}{\tau}} \tag{8}$$

where

η_0 = initial value of η
τ = time constant of the learning process.

The membership degrees and the cluster centers are calculated as follows

$$v_i = \frac{\sum_{k=1}^{n} (u_{ik})^2 x_k}{\sum_{k=1}^{n} (u_{ik})^2} \tag{9}$$

$$u_{ik} = \frac{1}{\sum_{j=1}^{c}\left(\|x_k - v_i\| / x_k - v_j\right)^2} + \frac{\gamma}{\|x_k - v_i\|^2} \mathrm{N}((C_i) - \mathrm{N}(x_k)) \tag{10}$$

$$\mathrm{N}(c_i) = \sum_{k=1}^{n} u_{ik} \tag{11}$$

$$\tilde{\mathrm{N}}(x_k) = \sum_{j=1}^{c} \frac{\mathrm{N}(c_j)}{\|x_k - v_j\|^2} \Big/ \sum_{j=1}^{c} \frac{1}{\|x_k - v_j\|^2} \tag{12}$$

where
$\mathrm{N}(c_i)$ = fuzzy cardinality of the ith cluster.
$\mathrm{N}(x_k)$ = weighted average cardinality calculated with respect to the training vector.

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.

4. FLOW CHART FOR THE PROPOSED ALGORITHM

1. Initialize the partition matrix U, n, t, c, τ .
2. Initialize v_i .
3. Calculate the distortion measure as in Equation (1).

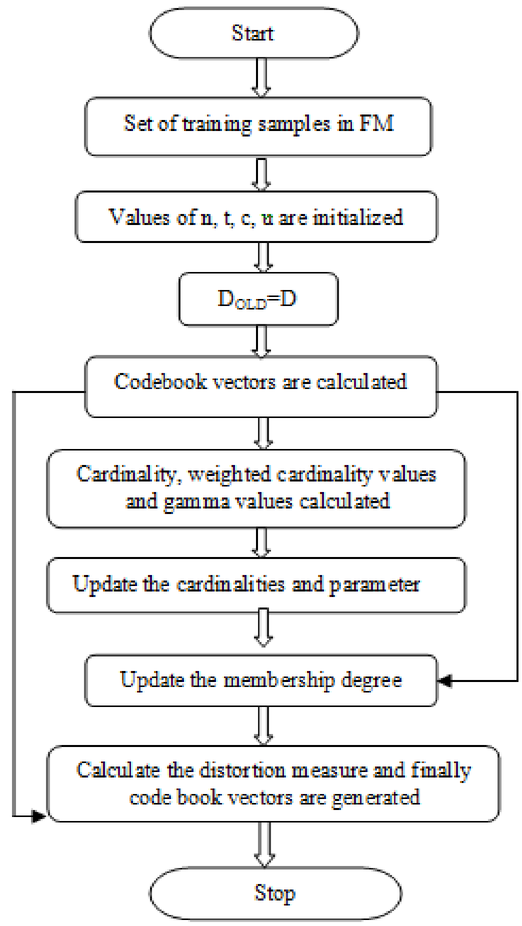
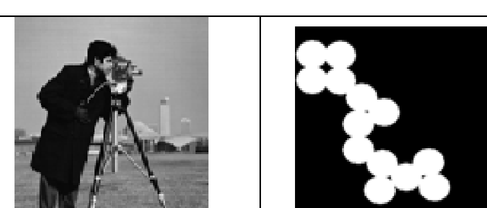


Figure-2. The flow chart illustrating the procedure for the competitive agglomeration algorithm.

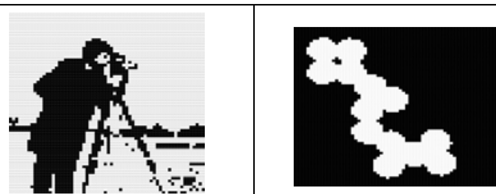
5. EXPERIMENTAL RESULTS AND DISCUSSIONS

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.



(a) (b)

Figure-3. (a) and (b) Original images.



(c) (d)

Figure-4. (c) and (d) Image segmentation results.

6. CONCLUSIONS

In this paper, we propose a new simple and effective Fuzzy clustering-based vector quantization using 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.

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