An Efficient Modified Fuzzy Possibilistic C-Means Algorithm for MRI Brain Image Segmentation

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Abstract--- Image processing plays an important role in medical field because of its capability. Particularly, image segmentation offer several guides in medical field for analyzing the captured image. Usually, the medical images are captured via different medical image acquisition techniques. The captured image may be affected by noise because of some faults in the capturing devise; this will leads to false diagnosis. This paper focuses on enhancing the captured brain image by using image segmentation technique. Usually, brain image is captured using Magnetic Resonance Imaging (MRI) technique. The captured brain image will have high amount of noise or distortion, this noise must be removed before it is used for diagnosis purpose. Brain segmentation is widely applied for removing those noises to produce the clear image. The segmentation can be achieved with the help of clustering techniques. The widely used clustering technique for brain image segmentation technique is Fuzzy C-Means (FCM) clustering. But FCM will result in poor segmentation when more edge regions are involved. To overcome this problem, Fuzzy Possibilistic C-Means Algorithm (FPCM) is introduces. Even FPCM will result in poor segmentation when more noise are involved. To overcome all these problems, a Modified Fuzzy Possibilistic C-Means Algorithm (MFPCM) is proposed in this paper. The experimental result show that the segmentation resulted for the proposed technique is better when compared to the existing methods.

Keywords--- Brain Image Segmentation, Fuzzy C-Means, Fuzzy Possibilistic C-Means, Modified Fuzzy Possibilistic C-Means

I. INTRODUCTION

THE huge increase in the development of information technology have completely modified the world. The most important reasons for the establishment of computer systems are reliability, accuracy, simplicity and user-friendliness. Additionally, the customization and optimization merits of a computer system stand with the key driving forces in implementing and subsequently strengthening the computer aided systems. When medical imaging is considered, an image is captured, digitized and processed for performing segmentation [6] and for obtaining useful data. Manual segmentation is another method for segmenting an image. This method is not only complex and time consuming, but also results in inaccurate results. Therefore, there is a need to have some proficient computer based system that efficiently identifies the edges of brain tissues along with decreasing the probability of user involvement with the system.

There are various medical image acquisition methods in present days such as Magnetic Resonance Imaging (MRI), Ultra-Sound (US), X-ray Computer Tomography (CT), Single Photon Emission Tomography (SPET), Positron Emission Tomography (PET), etc. Moreover, with the increasing size and number of medical images, the usage of computers in providing their processing and examination has grown to be essential. Magnetic resonance imaging is an advanced [11], widely used medical imaging technique. It offers better contrast resolution for different tissues and has advantages over Computerized Tomography (CT) for brain tissue analysis. Because of the merits of MRI over other diagnostic imaging technique, the most of researches in image segmentation concern to its use for MRI images.

There are various methods available for MRI brain image segmentation [12, 13]. But all those techniques possesses some disadvantages like lack of accuracy, misclassification in noise affected image, etc., To overcome these demerits, this paper uses Modified Fuzzy Possibilistic C-Means algorithm [5, 7, 15] for segmentation of MRI brain images.

II. RELATED WORKS

This section provides some of the existing technique available for MRI image segmentation [8].

Mrigank *et al.,* [1] proposed a fuzzy system based approach in segmentation of MRI Brain tumor. Segmentation of 3-D tumor structures from MRI is a very challenging problem due to the variability of tumor geometry and intensity patterns. Level set development combining global smoothness with the flexibility of topology changes offers significant advantages over the conventional statistical classification followed by mathematical morphology. Level set development with constant propagation needs to be initialized either completely inside or outside the tumor and can leak through weak or missing boundary parts. Replacing the invariable propagation term by a statistical force overcomes these limitations and results in a convergence to a stable solution. Using MRI presenting tumors, probabilities for background and tumor regions are calculated from a pre- and post-contrast difference image and mixture modeling fit of the histogram. The whole image is used for the initialization of level set evolution to segment the tumor boundaries.

Vasuda *et al.*, [2] puts forth a novel technique for MR Brain Image segmentation. Fuzzy clustering with the use of Fuzzy C- Means (FCM) algorithm [4] proved to be superior over the other clustering approaches in terms of segmentation efficiency. But the most important drawback of the FCM algorithm is the huge computational time required for convergence. The efficiency of the FCM algorithm [10] in terms of computational rate is improved by modifying the cluster center and membership value updation criterion. In his research, convergence rate is compared between the conventional FCM and the Improved FCM.

Krishnapuram *et al.*, [3] proposed a new clustering model named Possibilistic C-Means (PCM), which relaxes the column sum constraint so that the sum of each column satisfies the looser constraint $0 < \sum_{i=1}^{c} u_{ik} \leq c$. In other words, each element of the k-th column can be any number between 0 and 1, as long as at least one of them is positive. They suggested that in this case the value should be interpreted as the typicality of relative to cluster i (rather than its membership in the cluster). They interpreted each row of U as a possibility distribution over X. The PCM algorithm they suggested for optimization of the PCM objective function sometimes helps to identify outliers (noise points).

III. Methodology

The methodology used in this paper for MRI brain image segmentation is the modified fuzzy possibilistic c-means algorithm. This technique combines the advantages of Possibilistic C-Means Algorithm [16] and logic with some modification in its membership function for removal on noise from the MRI brain images.

Possibilistic C-Means Algorithm (PCM)

The Possibilistic C-Means method uses a Possibilistic type of membership function to demonstrate the degree of similarity. It is beneficial that the memberships for representative feature points are very high and unrepresentative points have low membership. The intention function, which suits the necessities, is as follows,

$$min\left\{J_m(x,\mu,c) = \sum_{i=1}^{c}\sum_{j=1}^{N}\mu_{ij}^{m}\, d_{ij}^{2} + \sum_{i=1}^{c}\eta_i\sum_{j=1}^{N}(1-\mu_{ij})^m\right\}$$

where, d_{ij} indicates the distance between the j^{th} data and the i^{th} cluster center, μ_{ij} represents the degree of belonging, m indicates the degree of fuzziness, η_i represents the appropriate positive number, c represents the number of clusters, and N represents the number of pixels. μ_{ij} can be found with the help of the following equation,

$$\mu_{ij} = \frac{1}{1+\left(\frac{d_{ij}^2}{\eta_i}\right)^{\frac{1}{m-1}}}$$

The value of η_i finds the distance at which the membership values of a point in a cluster happen to be 0.5. The major merit of this Possibilistic C-Means method is that the value of η_i can be set or modified based on every iteration. This can be achieved by modifying the values of d_{ij} and μ_{ij}. The Possibilistic C-Means technique is highly robust in the occurrence of noise, in determining suitable clusters, and in providing a robust approximation of the centers.

Updating the membership values are based on the distance measurements. The Euclidean and Mahalanobis distance are two general distance measurements. The Euclidean distance performs better when a data set is dense or isolated and Mahalanobis distance considers the correlation in the data with the help of inverse of the variance-covariance matrix of data set which is described as below,

$$D = \sum_{i,j=1}^{i,j=p} A_{ij}(x_i - y_i)(x_j - y_j)$$

$$A_{ij} = \rho_{ij}\sigma_i\sigma_j$$

where, x_i and y_i represents the mean values of two different sets of parameters, X and Y. σ_i^2 represents the corresponding variances, and ρ_{ij} indicates the coefficient of correlation between i^{th} and j^{th} variants.

Fuzzy Possibilistic C-Means Algorithm (FPCM)

Fuzzy Possibilistic C-Means algorithm comprises both possibility and membership values. FPCM model can be seen as below:

$$\underset{(U,T,V)}{min}\{J_{m,\eta}(U,T,V;X)\} = \sum_{i=1}\sum_{k=1}(u_{ik}^{m} + t_{ik}^{\eta})D_{ikA}^{2}$$

subject to the constraints

$$m > 1, \eta > 1, 0 \leq u_{ik}, t_{ik} \leq 1, D_{ikA} = \|x_k - v_i\|A, \quad and$$
$$\sum_{i=1}^{c} u_{ik} = 1\forall k, \ \ i.e., \ \ U \in M_{f\ cn}$$

and

$$\sum_{k=1}^{n} t_{ik} = 1\forall i, \ \ i.e., \ T^t \in M_{f\ nc}$$

Where U represents the membership matrix, T represents the possibilistic matrix, and V represents the obtained cluster centers, c and n indicates the cluster number and data point number. The first order essential conditions for extreme of $J_{m,\eta}$ are: If $D_{ikA} = \|x_k - v_i\|A > 0$ for all i and k,m,η > 1 and X contains at least c distinct data points, then

$$(U, T^t, V) \in M_{fcn} \times M_{fcn} \times R^p$$

may minimize $J_{m,\eta}$ only if

$$u_{ik} = \left(\sum_{j=1}^{c}\left(\frac{D_{ikA}}{D_{jkA}}\right)^{2/(m-1)}\right)^{-1}$$

$$1 \leq i \leq c; 1 \leq k \leq n$$

$$t_{ik} = \left(\sum_{j=1}^{n} \left(\frac{D_{ikA}}{D_{ijA}} \right)^{2/(\eta-1)} \right)^{-1}$$

$1 \le i \le c; 1 \le k \le n$

$$v_i = \frac{\sum_{k=1}^{n} (u_{ik}^m + t_{ik}^\eta) x_k}{\sum_{k=1}^{n} (u_{ik}^m + t_{ik}^\eta)}, 1 \le i \le c$$

The above equations indicate that membership u_{ik} is influenced by every c cluster centers, while possibility t_{ik} is influenced just by the i-th cluster center c_i. The possibilistic term distributes the t_{ik} with respect to every n data points, but not by means of every c clusters. Thus, membership can be described as relative typicality, it determines the degree to which a data fit in to cluster accordance with other clusters and is helpful in correctly label a data point. And possibility can be observed as absolute typicality, it determines the degree to which a data point belongs to cluster correctly to every other data points, it can decreases the consequence of noise. Joining both membership and possibility can afford to good clustering result. In PCM, the similarity is about 92.50, which is comparatively better than FCM and Modified FCM. The False Positive Rate is 12.80 and False Negative Ratio is 3.40, this false positive and negative ratio is lesser when compared to FCM and Modified FCM. As False Negative and Positive value is lesser when compared to the method of FCM. It is understandable that PCM is better in performance when compared to FCM and modified FCM.

Modified Fuzzy Possibilistic C-Means Algorithm

The selection of suitable objective function is the major factor for the success of the cluster technique and to achieve enhanced clustering [17]. Hence the clustering optimization is based on objective function to be used for clustering. To obtain an appropriate objective function, the following set of necessities is considered:

- The distance between clusters and the data points allocated to them must be reduced
- The distance between clusters must to be reduced

The desirability between data and clusters is modeled by the objective function. Also Wen-Liang Hung provides a new technique called Modified Suppressed Fuzzy C-Means, which considerably improves the function of FCM because of a prototype-driven learning of parameter α. The learning procedure of α is dependent on an exponential separation strength between clusters and is updated at every iteration. The α is described as:

$$\alpha = exp\left(- \min_{i \ne k} \frac{\|v_i - v_k\|^2}{\beta} \right)$$

where β represents a normalized term so that β is taken as a sample variance. That is, β is described as:

$$\beta = \frac{\sum_{j=1}^{n} \|x_j - \bar{x}\|^2}{n} \quad where\ \bar{x} = \frac{\sum_{j=n}^{n} x_j}{n}.$$

However the statement which must be presented here is the common value used for this parameter by every data at each iteration, which may provided in error. Thus the weight parameter is introduced for determining common value for α. Or each point of the data set contains a weight in association with each cluster. So the usage of weight allows providing good classification particularly in the case of noise data. So the weight is determined as given below:

$$w_{ji} = exp\left(- \frac{\|x_j - v_i\|^2}{\left(\sum_{j=1}^{n} \|x_j - \bar{v}\|^2\right) * c/n} \right)$$

where w_{ji} indicates the weight of the point j in accordance with the class i. This weight is used to alter the fuzzy and typical separation. All the techniques described previously are iterative in nature, since it is not likely to change any of the objective functions evaluated straightly. Otherwise to categorize a data point, cluster centroid has to be nearer to the data point, it is membership; and for determining the centroids, the typicality is used for reducing the undesirable cause of outliers. The objective function contains two expressions:

(i) Fuzzy function and use of fuzziness weighting exponent,
(ii) Possibililstic function and use of typical weighting exponent

But the two coefficients in the objective function are alone used as exhibitor of membership and typicality. A new relation, slightly unusual, offers a very fast reduction in the function and enhances the membership and the typicality when they inclined near 1 and reduce this degree when they are near 0. This relative is to provide Weighting exponent as exhibitor of distance in the two under objective functions. The objective function of the MFPCM can be described as below:

$$J_{MFPCM} = \sum_{i=1}^{c} \sum_{j=1}^{n} \left(\mu_{ij}^m w_{ji}^m d^{2m}(x_j, v) + t_{ij}^\eta w_{ji}^\eta d^{2\eta}(x_j, v_i) \right)$$

U = {μ_{ij}} indicates a fuzzy partition matrix, and is described as:

$$u_{ij} = \left[\sum_{k=1}^{c} \left(\frac{d?\, X_j, v_i}{d?\, X_j, v_k} \right)^{2m/(m-1)} \right]^{-1}$$

T = {t_{ij}} indicates a typical partition matrix, is represented as:

$$t_{ij} = \left[\sum_{k=1}^{n} \left(\frac{d?\, X_j, v_i}{d?\, X_j, v_k} \right)^{2\eta/(\eta-1)} \right]^{-1}$$

V = {v_i} indicates c centers of the clusters, is represented as:

$$v_i = \frac{\sum_{j=1}^{n} (\mu_{ij}^m w_{ji}^m + t_{ij}^\eta w_{ji}^\eta) * x_j}{\sum_{j=1}^{n} \left(\mu_{ij}^m w_{ji}^m + t_{ij}^\eta w_{ji}^\eta\right)}$$

With the help of this segmentation result of MRI brain image using the modified fuzzy possibilistic c-means algorithm, the noise pixels can be easily predicted with better accuracy.

IV. Experimental Results

The proposed MRI brain segmentation technique is evaluated using the real MRI data obtained from the Internet Brain Segmentation Repository. Figure 1 shows the segmentation result for the existing and proposed segmentation methods. Figure 1(a) represent the original MRI brain image with noise, figure 1(b) represent the segmentation result using FCM technique, figure 1(c) represents the segmentation result using the FPCM technique and figure 1(d) represents the segmentation result using the proposed MFPCM technique. It can be clearly observed from the figure that the segmentation result obtained by the proposed technique is better when compared to the existing segmentation method.

Figure 2 shows the similarity measure for the FPCM and proposed MFPCM with various noise levels. Initially the similarity measure is same for both methods, but when the noise level is increased, the similarity measure starts decreasing for both methods.

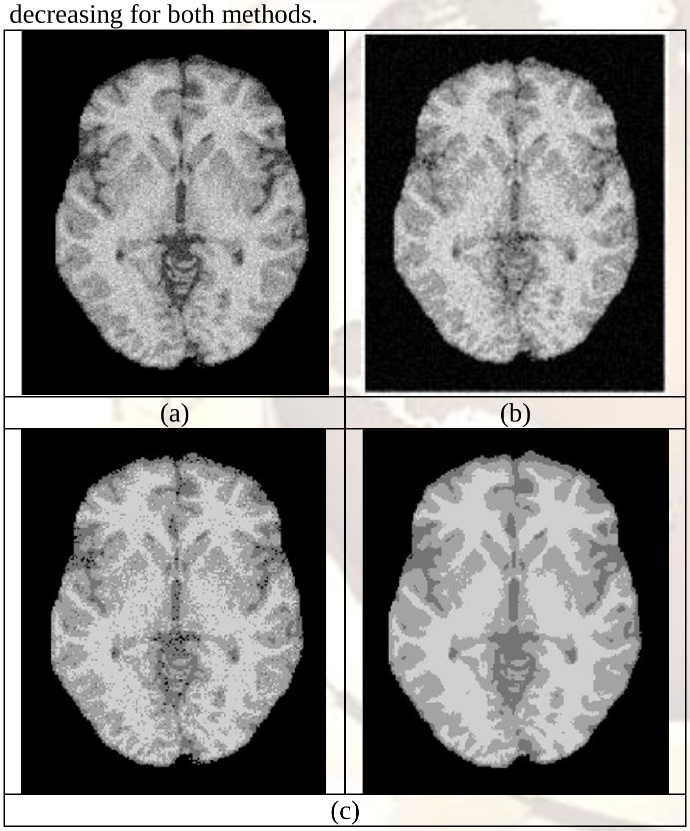

Figure 1. Comparison of Segmentation Result for MRI Brain Image (a) Original Image with Noise, (b) Segmentation using FCM, (c) Segmentation using FPCM, (d) Segmentation using MFPCM

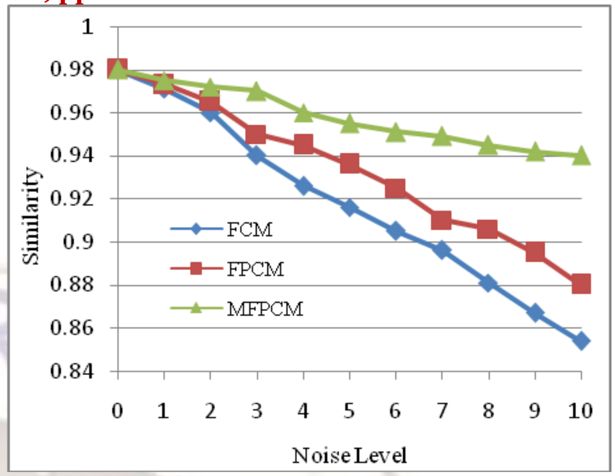

Figure 2. Similarity Measure for the Different Segmentation with Various Noise Level

When the noise level is 1, the similarity measure by using FCM is 0.971, FPCM is 0.973 and 0.975 for using MFPCM that us little higher than FCM and FPCM techniques. When the noise level starts increasing, the difference will also start increasing. When the noise level is 4, the similarity measure is 0.926 for FCM, 0.945 for FPCM and 0.96 for the proposed MFPCM. For the noise level of 8, the similarity measure is 0.881 for FCM, 0.906 for FPCM and 0.945 for the proposed MFPCM which much higher than the existing FCM and FPCM segmentation techniques. Overall, the segmentation result is better for the proposed segmentation technique than the existing techniques.

V. Conclusion

Image enhancement in medical field is a wide problem because of the noise occurrence in the captured image because of some faults in the capturing device. This will help the doctors to analyze the better image and for providing better diagnosis. This can be done with the help of image segmentation technique. This paper focuses on brain image enhancement with the help of image segmentation. Clustering is considered to be better segmentation technique because of its advantages. There are several techniques exist for this purpose, but those techniques fails when more edges and noise are involved. To overcome those problems, this paper proposed a Fuzzy Possibilistic C-Means algorithm for segmenting the MRI brain image. The experimental result shows that the proposed segmentation technique is very effective in enhancing the MRI brain image better than the existing techniques.

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