Improved MR Brain Image Segmentation Using Adaptive Gabor Filtering Scheme with Fuzzy C-Means Algorithm

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Abstract—Image segmentation is the foremost process in medical image processing. It aids the diagnostic and clinical analysis of MRI (Magnetic Resonance Imaging) images that were acquired through the most complex procedures of medical diagnostics. The earliest soft computing techniques in segmenting images were carried out through Fuzzy C-Means (FCM) and similar extensions of various clustering algorithms. In this paper, we introduced an innovative method that uses Gabor energy filter with adaptive features to pre-extract the information of various regions of a brain image, obtained either from a MRI or CT scanner. The noise-reduced image with blurred features was then made to undergo modifications by applying unsupervised learning methods such as FCM technique, whose output has efficient exclusion of certain strength of noise elements resulting in better classified pixels.

Keywords-Magnetic Resonance Imaging, Image segmentation, Fuzzy c-means, Gabor energy filters, pixels.

I. INTRODUCTION

Medical image segmentation was one among the challenging areas of Image processing technology. MRI images were comparatively better solution in terms of clear, high-resolution and increased contrast in medical diagnostic systems [3]. A human brain consists primarily of three regions namely Cerebrum, Cerebellum and Cerebrospinal fluids, each of which has distinct colour features. MRI plays a pivotal role in the human brain scanning rather than any other systems like computer tomography (CT), ultra-sound (US), etc. As the MRI imaging systems were having soft tissue contrast coupled with minimal invasiveness had placed it as the forerunner in clinical applications. Analysis of internal physiology of brain image is widely used to diagnose various brain diseases such as schizophrenia, multiple sclerosis, epilepsy and alcoholism. The significance of better segmentation methods of MR images is nurtured from the requirement of quantitative statistics of the possible affected regions displayed in the image. Earlier techniques such as region growing [16], thresholding, edge detection [9], fast greedy algorithm, Fuzzy C-mean clustering (FCM) [1], [13], watershed segmentation [17], statistical models [8] and active contours model have been proposed for medical image segmentation [10] .

Although earlier segmentation techniques relied on many supervised and unsupervised learning methods, especially k-means clustering [7] algorithm and FCM algorithm proposed by Bezdek [1], proved to be better than the above image segmentation approaches in terms of computation time and reduced noise levels. The structure of a brain image is always complicated structure and it always contains artefacts such as noise, intensity in-homogeneity and partial volume effect. In one or the other way the hard K-means algorithm was unable to yield the output as of FCM. The discrete nature of the hard partitioning also causes difficulties with algorithms based on analytic functional, since these functional are not differentiable. Unlike the crisp k-means clustering algorithm, which forces pixels to belong exclusively to one class, FCM allows pixels to belong to multiple clusters with varying degrees of membership values.

Unfortunately, in a standard FCM clustering algorithm, there is no consideration for spatial context [12] between pixels, since the clustering was done solely in the feature space. Customary medical images include considerable uncertainty and unknown noises caused by operator performance, equipment and the environment. Standard FCM algorithm was not able to completely overcome the above issues. Gabor filters were highly selective in both position and frequency, thus resulting in sharper texture boundary detection. They have been applied successfully to a broad range of image processing tasks and are efficient for extracting texture features based on localized spatial frequency information [5]. Specifically, various approaches have been proposed to deal with the task of segmenting brain tumours in MR images. The performance of these approaches usually depends on the accuracy of the spatial probabilistic information collected by domain experts. In this proposal, we are able to combine the salient features of the segmenting approaches by innovatively applying Gabor filter with adaptive strategy before applying the soft clustering algorithm. The above approach was actually able to address largely on spatial and the noise reduction issues.

II. RELATED WORKS

A. Fuzzy C Means (FCM) Algorithm

The FCM algorithm is one of the most widely used methods in fuzzy clustering [14]. Fuzzy clustering is an approach operating towards fuzzy logic and it provides the flexible method of assigning the data points to the clusters. This method allows the objects to belong to several clusters simultaneously, assigning different degrees of membership. In many situations, fuzzy clustering is more practical than the hard clustering. Objects on the boundaries between several classes are not forced to fully belong to one of the classes, but rather were assigned membership degrees between 0 and 1 indicating their partial membership. These indicate the strength of the association between that data element and a particular cluster. The data points are given partial degree of membership in multiple nearby clusters. The central point in fuzzy clustering is always number of unique partitioning of the data in a collection of clusters. In this membership value is assigned to each cluster. Sometimes this membership has been used to decide whether the data points belong to cluster or not. The objective of the FCM algorithm is to converge to an optimal fuzzy c-partition and corresponding prototypes minimizing the given objective function (equation no.1).

$$J_m = \sum_{n=1}^{C} \sum_{i=1}^{N} \mu_{ni}^m \| X_i - C_n \|^2 \quad \text{for } 1 \le m < \infty \tag{1}$$

$$\text{where } \sum_{n=1}^{C} \mu_{ni} = 1$$

Where μ_{ni} is a fuzzy membership qualification indicating the membership of sample i to the j cluster. The fuzzification parameter (m) in the range [1,n] was introduced, which determines the degree of fuzziness in the clusters and it is greater than 1. x_i is the i^{th} data point. C_n is the cluster centre. $\| x_i - c_n \|$ is the distance matrix from a point x_i to each cluster centre to with taking the Euclidean distance between the point and the cluster centre. Although FCM is considered good clustering algorithm, the algorithm has some disadvantages also. The foremost is that the objective function does not take into account of the spatial dependence, but deal with images as the same as separate points [3], [19]. Due to this factor, the FCM algorithm is sensitive to noise and outliers in the image and a noisy pixel is always misclassified because of this abnormal feature. Also for an FCM algorithm the computational time is more and is sensitivity to the initial guess. In order to enhance the outcome of the FCM, the algorithm is optimized using Gabor filtering.

B. Gabor Filtering

Gabor filters [6] are linear filters whose impulse response is defined by a harmonic function multiplied by a Gaussian function [4]. Gabor filter responses have been successfully used in various image processing techniques such as in face detection, texture segmentation [2], [9] and iris pattern description [5]. One of the foremost advantages of these filters is that they satisfy the minimum space-bandwidth product per the uncertainty principle. Hence they provide simultaneous optimal resolution in both the space and spatial-frequency domains. Gabor filters are used to solve segmentation problems involving complicated images comprised of textured regions. It is evident that Gabor filters have many advantageous or even superior properties for feature extraction [5], Since Gabor filters correspond to any linear filters the most straightforward technique to perform the filtering operation is via the convolution in the spatial domain. [17]. The Distinct features were obtained by convolving an image with the Gabor elementary functions. A 2-D Gabor function is an oriented complex sinusoidal grating modulated by a 2-D Gaussian function [11].

The implementation of Gabor filtering scheme is as shown in Fig. 1. The 2-D Gabor function is given as follows

$$g(x,y) = \frac{1}{2\pi\omega^2} \exp\left\{-\frac{(x^2+y^2)}{2\omega^2}\right\} \exp\left[j2\pi\left(u_x + v_y\right)\right] \tag{2}$$

for $\omega_x = \omega_{y,} = \omega$ the parameters ω_x and ω_y are the space constants of the Gaussian envelop along *x* and *y* axes, respectively.

Gabor Filtered image as O_h is given as

$$O_h\,(i(x,y)) = |\, i(x,y) \otimes h(x,y)\, | \tag{3}$$

where $i(x,y)$ is the input image and The function $h(x,y)$ is the impulse-response of the *2-D* Gaussian function, given as below

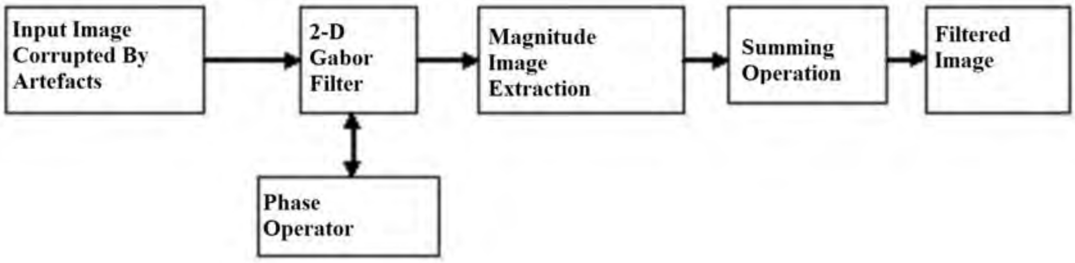

Fig. 1. Block representation of generalized Gabor filtering for feature extraction

The above mentioned features imply that Gabor filters can be highly selective in terms of position and frequency parameters, thus resulting in sharper image boundary detection; this is very much evident from the equations no. 2 and 3, which gives the impulse response of a 2-D Gabor function. But at the same time if the computational complexity cannot be improved, their application areas will remain limited. Besides the large computational burden imposed by a large bank of filters, it produces an output feature vector with high dimensionality and therefore, requires a complicated classifier [7], [15] for texture discrimination.

III. PROPOSED METHOD

It is very clear from the above discussions, each of the above earlier existing methods have short falls in one way or the other in achieving a better segmentation of the MRI images. In the proposed method we utilize the 2-D Gabor feature extraction [5], [8] to separate out the desired features based on magnitude parameters and remove the noisy pixels algorithm is implemented to regroup into three clusters or regions namely White matter (WM), Grey Matter (GM) and cerebrospinal fluid (CSF). The tumour region is usually identified with range of pixels as that of CSF.

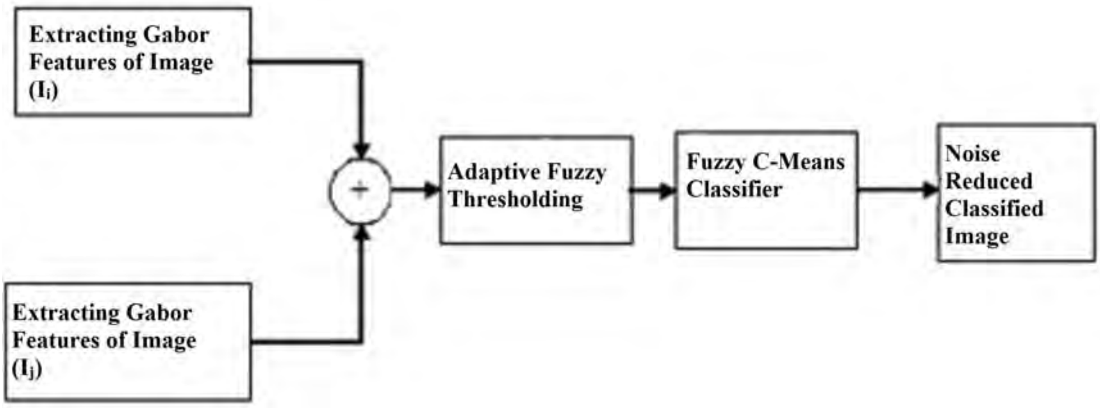

Fig. 2. Overall block representation of the proposed work

In our proposed work the we consider a simple 2-D Gabor filter design after assuming values for f, which is the central frequency of the filter and θ is the rotation angle of both the Gaussian major axis and the plane wave, and find intermediate output from the input raw images.

(i) The first step consists of applying the noisy (after adding a known value of noise strength, for determining the noise efficiency accurately) MRI image in to input of Gabor filter banks. Taking the two cases for $h(x,y)$ as discussed above the following two algorithms are developed. For this purpose it is assumed that, a bipartite texture image $I(x,y)$ is given as input for the fuzzy based thresholding section as referred in figure no. 2. The algorithm implemented in the above block distinctively segregates the noisy pixel by performing a qualitative iteration with neighboring pixels of a given desired sized window.

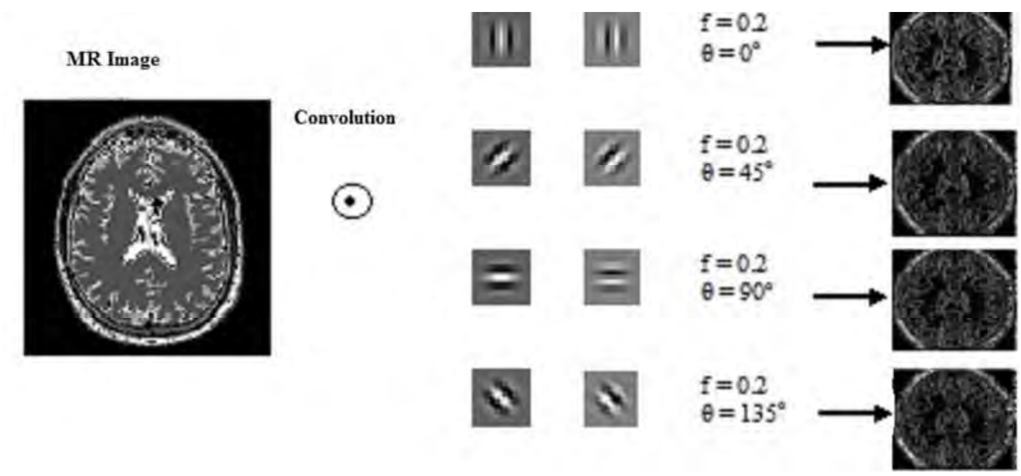

Fig. 3. Application of Gabor Filtering of the input noisy image for different θ orientations (θ = 0, 45, 90 & 135 degrees)

(ii) For the adaptive-fuzzy [18] thresholding section, assigned to perform segregation on the basis of the desired pixel values within a window of pixels, size of the window assigned (desirably 3 X 3 is taken) to it during the iteration. When two textures differ from each other, then a Gabor filter produces a step change in *m(x,y)* at the texture boundary. There is a case where the two textures A and B may be the same but offset to each other. In such a case the properly selected Gabor filter will produce a valley discontinuity at the texture boundary. Such an output is referred as a valley signature. Primarily it is focused on the case where two textures differ. Hence the proposed filter design algorithm strives to give Gabor filters that produce step change in *m(x,y)*.

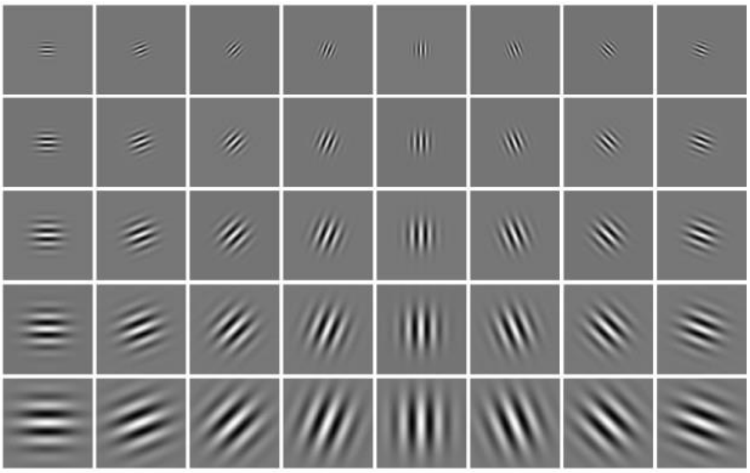

Fig. 4. the Real Part of the Gabor Kernels in 5 Scales and 8 Orientations

Theoretically a Gabor filter is determined by the parameters U, V, ω. The above depicted figure (fig. 4) shows the Gabor filtering scheme implementation for a kernel in 5 scales and 8 orientations. By carefully selecting the values of these three parameters, the optimal Gabor filter is designed. After the completion of the first stage as shown in Fig. 3, the FCM clustering image for each case. Here we consider to resolve the output image for the θ values or 0^0, 45^0, 90^0, 135^0 at the central frequency f =0.2. The resultant intermediate output image as shown in Fig. 3 is fed as the input image of the FCM algorithm. The Fig. 3 shows the block schema of the Gabor filtering, which is nothing but a convolution of the sample noisy image with Gabor filter for various values of θ (Ref. Fig.3). As displayed in Fig. 2, the output of Gabor filter is the combination of a complex valued function of the given image. The intermediate output image is then fed to the FCM clustering algorithm. The FCM algorithm is specified to work for a number of cluster center value c, for this present case of brain image we assign value for c, c = 3 in order to accommodate the three regions of human brain (referred in earlier part). The FCM algorithm is converged after performing required number of iterations. The final output image is tilarity index by comparing with the initial image (which is almost free from noise).

IV. EXPERIMENTAL RESULTS

The main objective of our work, i.e. reducing the noise values present in a scanned image which were not totally eliminated in case of working with a FCM algorithm. From the results which were displayed as below Fig. 5 a, b, c and d where a is the image with the combination of all possible types of noises already mentioned appears to display a vague image of the brain scan. Then image b is extracted by implementing the Fuzzy C-means to the above corrupted image which almost fails by wrongly classifying the noise pixels to any of the two extreme pixel value 0 or 1 resulting in grouping either to a black or white region of group of pixels. The image c displays the filtering based on the 2-D Gabor filtering concept. The above method was observed to be inefficient in terms of salt and pepper noises which were meagerly present in the image.

(a) (b) (c) (d)

Fig.5. Segmentation results on MRI image (a) Original MRI image (b) segmented MRI brain image using FCM (c) segmented MRI brain image using Gabor filtering (d) segmented MRI brain image using our method (adaptive Gabor-FCM combination)

After the application of the adative Gabor-FCM (our proposed method) the output image seems to be almost clear of nosies which were present initially and at the same time all the important informations in the test sample image had been preserved. This phenomenon is shown in the Fig. 6, which is a plot between the similarity values(correlation between original images and the resultant filtered images, corrupted with known noise strengths) against corresponding magnitudes of noise values. In that graph a comparison between our proposed method and the FCM method has been plotted.

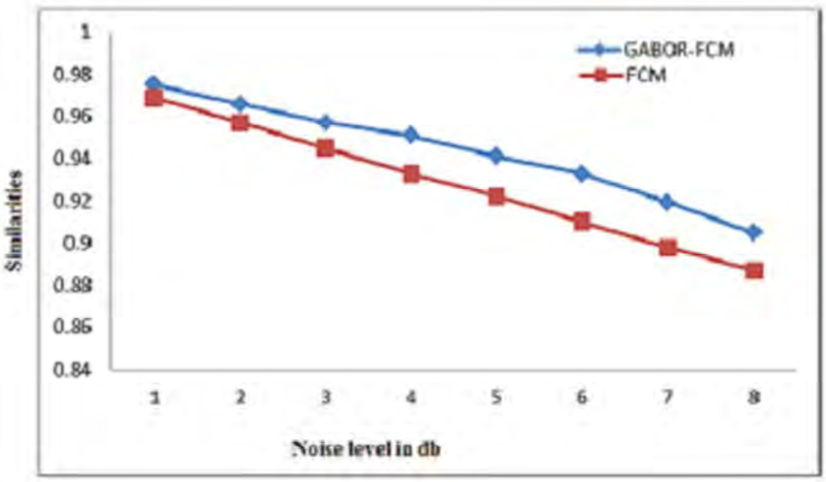

Fig.6. Plot between the different similarity values at various noise levels

From the plot, it could be inferred that when the noise level starts increasing, the difference will also start increasing. When initially a noise level of 1 in db scale is applied, the similarity measure is 0.968 for FCM and 0.979 for the proposed Adaptive Gabor FCM. For the maximum noise level of 8, the similarity measure is 0.884 for FCM, 0.916 for the proposed Adaptive Gabor FCM respectively. The observation implies that there is a gradual degradation of image quality upon increasing noise levels and from the compared above two methodologies our proposed method yields better result than the earlier methods like FCM and similar techniques.

V. Conclusion

MR image Segmentation in medical field is difficult to achieve the noiseless image because of the noise captured along with the image becomes inseparable and complex. Earlier methods like FCM proves to some extent in removing this menace but still lacked in certain regions of segmentation. Even when the noise removal quality is improved and almost the noise has been successfully removed, the image quality was degraded. The new proposed algorithm, which combines the power of Gabor filtering with adaptive nature, enhances the classification power of the already existing Fuzzy C-Means. After clinical examinations conducted by some doctors involved in diagnostic-based treatments had orally found to be satisfied and acknowledged the effectiveness of the new method when compared with some existing techniques.

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