CONCLUSION AND FUTURE WORK

This research work is focused on the approach of hybrid fuzzy clustering techniques for segmentation of cerebral tissues from human MRI brain images to improve the performance of segmentation method with more accuracy. The research work contributes largely in segmenting the optimized cerebral tissues from MRI brain images. Proposed methods and algorithms have greatly met the objectives of the research work. Considering the MRI brain images, segmenting the non-cerebral and cerebral tissues such as GM, WM and CSF is complex in nature. Above all, a dynamic image processing methodology has been formalized from 256 image slices with axial and coronal angles on MRI brain images. Although manual segmentation by qualified professionals remains superior in quality to automatic methods, it has two drawbacks. The first drawback is that producing manual segmentations or semi-automatic segmentations is extremely time consuming. The second problem with manual and semiautomatic segmentations is that the segmentation is subject to variations both between observers and within the same observer. This problem is solved by using the automatic segmentation methods. Nevertheless, automatic brain segmentation is still a difficult problem for two key reasons:

1. There is a large number of tissue types which differ greatly in size, shape, location, tissue composition and tissue homogeneity. In some cases, their border with normal tissues cannot be very well defined on images; therefore, they are even difficult for radiology experts to delineate, and

2. The consequence of the phenomenon of partial volume effect (PVE), where one pixel/voxel may belong to multiple tissue types, in addition to noise due to the MRI acquisition system.

In order to overcome these problems, soft computing approach based on fuzzy logic concept has been used in this research work. This fuzzy approach provides several advantages. First, it inherently has the attractive property of the soft classification model, where each point can belong to more than one class. Another key advantage of the fuzzy
approach is that it can segment several tissues at the same time. Therefore, this approach can be used to segment non-cerebral tissues of interest, such as skull, scalp and meninges and cerebral tissues such as WM, GM, and CSF. This thesis contributes largely in optimizing the segmentation process with higher accuracy rate for separating the MRI brain cerebral tissues by using computational intelligence with image processing techniques. The principal contributions of this thesis consists of four stages such as preprocessing stage, clustering segmentation techniques implemented using K-Means and FCM, Optimized clustering segmentation techniques such as Genetic Algorithm and Firefly Algorithm with FCM, and Random based Optimized clustering techniques such as Chaotic Firefly algorithm and Levy Flights Firefly Algorithm integrated with FCM which is described as follows. In the preprocessing stage, the skull stripping algorithm and proposed denoising algorithm remove the non-cerebral tissues and image artifacts of brain. The proposed OTVF filter removes the additive white Gaussian noise without disturbing the edges and has achieved higher PSNR value when compared with other existing methods. The same has been evaluated in each phase of the entire task by comparing the results of noisy and denoised images.

The clustering segmentation techniques are implemented using K-Means and FCM method for segmenting the brain cerebral tissues. Compared with K-Means, FCM reduces the segmentation metrics such as OvS, InS and UnS rate in GM, WM and CSF tissues. Optimized clustering segmentation is integrated with FCM for improving the segmentation of cerebral tissues from noisy and denoised MRI brain images. When compared with Genetic Algorithm, Firefly Algorithm has reduced the segmentation metrics in GM, WM and CSF tissues. Random based optimized clustering segmentation integrated with FCM is proposed to improve the segmentation of cerebral tissues from noisy and denoised MRI brain images. When compared with CFAFCM, LFFAFCM greatly reduced the evaluation metrics in GM, WM and CSF tissues. Standard benchmark test functions are used to test the efficiency of optimization and random based optimization algorithms. Firstly, the proposed CFA-FCM method reached global minimum value in 2 test functions, namely, Michalewicz and Egg holder test function. Secondly, the proposed LFFA-FCM method reached global minimum value in 4 test functions, namely, like Michalewicz, Rastrigin, Gold-Stein and Price, and Egg holder.
From the experimental results, it is observed that, the percentage of negative false segmentation attained from GA-FCM approach for GM, WM and CSF in noisy images is 0.58, 0.80 and 0.89 respectively. Similarly, for positive false segmentation, the results obtained for GA-FCM for Gray Matter, White Matter and Cerebrospinal Fluid in noisy images is 0.33, 0.50, and 0.51 respectively. The total percentage of false segmentation obtained for GA-FCM is 0.26, 0.30 and 0.50 for GM, WM and CSF in noisy images respectively.

However, the percentage of negative false segmentation obtained for the proposed FA-FCM for GM, WM and CSF in noisy images is 0.42, 0.80 and 0.50 respectively which is less when compared with GA-FCM approach. Similarly, the percentage of positive false segmentation attained for the proposed FA-FCM approach for GM, WM and CSF in noisy images is 0.33, 0.32 and 0.39 respectively which is less when compared with the GA-FCM approach. The total percentage of positive false segmentation attained for GM, WM and CSF in noisy images is 0.26, 0.10 and 0.39 respectively which is observed to be significant. GA-FCM and FA-FCM method provides above 80-95% accuracy with 8 test functions for noisy images. Benchmark test functions from FA-FCM method gives 90% accuracy for most of the test functions. This is mainly due to the fact that, GA-FCM approach has local optimal problem, which reduces the segmentation results whereas FA-FCM clustering approach overcomes the local optimal problem.

The percentage of negative false segmentation obtained for the second proposed CFA-FCM approach is 0.33, 0.80 and 0.39 for GM, WM and CSF respectively. Similarly, positive false segmentation and total percentage of false segmentation results are observed to be significant for GM, WM and CSF.

From the experimental results, the percentage of negative false segmentation obtained by the proposed LFFA-FCM is 0.09, 0.31 and 0.36 in noisy images for GM, WM and CSF respectively. Similarly, the results attained for the positive false segmentation and total percentage of false segmentation are observed to be significant and less when compared with the other approaches taken for comparison. Thus, the proposed CFA-FCM and LFFA-FCM method provides almost 100% accuracy with 2 and 4 test functions. This performance improvisation is due to the fact that, in FA algorithm, ‘randomness’ affects
the behavior of firefly. This problem is solved by using Chebyshev Chaotic map and Levy distribution for optimizing the attraction and randomization behavior of firefly algorithm.

**Future Enhancement**

In future, volume can be calculated in cerebral tissues for identifying the brain abnormalities using image processing techniques. Based on the volume and quantity of GM, WM and CSF, the normal and abnormal brain image can be classified. 3D MRI images can be processed and analyzed.

The current research is directed towards further improving the proposed algorithm by taking into account intensity non-uniformity in MRI data, which is often referred to as bias field. This inherent artifact in MRI is produced due to imperfection in radio frequency coil and also patient electrodynamics interactions. The bias field causes smooth variations in tissue intensities across MRI datasets. Although the bias field has little effect on visual interpretation, it may affect the accuracy of automatic processing tools, such as segmentation and registration. Therefore, reformulating the algorithm proposed here to account for bias field will further improve the MRI segmentation accuracy. In addition, the number of classes, into which a given dataset is segmented, is determined in the proposed algorithm in a supervised manner based on the expertise of the user (typically the radiologist).