HYBRID METHOD OF MRI BRAIN SEGMENTATION USING FUZZY K-MEANS

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ABSTRACT
In this paper, a proposed hybrid algorithm using K-means and Fuzzy logic for brain segmentation, is developed, simulated and evaluated. The system identifies the white matter, gray matter and Cerebrospinal Fluid (CSF). The proposed system was tested using Magnetic Resonance Imaging (MRI), and evaluated in terms of the misclassification rate and percentage of clustering. The misclassification rate was found to be lesser in the proposed system as compared to the existing systems using K-means and Fuzzy logic. Further, the percentage of clustering is improved by the proposed system as compared to the existing algorithms. This work paves the way for future development of Neuro Fuzzy K-means algorithm in order to reduce the misclassification rate further in clustering the white matter, gray matter and CSF.
Keywords: - Segmentation, MRI, K-means, Fuzzy, Brain.

INTRODUCTION

In the last decades, it can be seen that there has been vast contributions in the medical image processing field towards the development of various medical technologies, including X-ray, Computerized Tomography (CT), and Magnetic Resonance Imaging (MRI), and so on. X-ray is the most popular technique used in medical investigation and it uses short wavelength high energy electromagnetic waves, while CT is an X-ray oriented medical technique used to examine the internal organs. MRI is the newer imaging technique that provides information of the inner structures by using magnetic features as its working principle [1].

The most important part of image processing is the image segmentation [2], which can be defined as the procedure for extracting the Region Of Interest (ROI) through automatic or semi-automatic process. There are many image segmentation methods used in medical applications, for example in brain tumour detection purpose. In medical research, segmentation can be used in to differentiate between different tissues in the image, by extraction and classification of features [3]. The selection of the technique or algorithm and classification is dependent on the type of image and anatomical structure, and therefore, is different for brain, thorax or heart segmentation. Hence, selection of an algorithm and segmentation technique plays an important role to achieve precise outputs.

Brain MRI acquisition always contains inherent noise, caused by environmental (ambient noise), equipment (movement of the magnets) or patient (breathing artifact), which challenges the segmentation accuracy [4]. Hence, a robust efficient Brain MRI segmentation is still a challenge [5]. Since each type of tissue has its own significance, segmentation of these must be done accurately in order to diagnose the disease and to locate the pathological condition. Thus, there is a need to develop a robust Brain MRI segmentation method [6].

Brain Segmentation

Image segmentation algorithms are the most prominent approach in diagnosing as well as analyzing the MRI brain images [7-8]. The segmentation goal is basically to split the brain image into three major regions, namely, Cerebrospinal Fluid (CSF), gray and white matter. There have been several popular methods used for the segmentation of the MRI Brain images over decades, but it is still very challenging due to noise [9-12]. Some of the methods depend on the edge detection to determine the boundaries of segments. The drawback of the edge detection method includes false or fake edge detection, which leads to unpredicted performance [13,27]. On the other hand, area-dependent segmentation methods depend on extracting similar areas based on certain predefined criteria, which does include texture similarity, brightness level similarity or sharpness similarity [13]. Further, the brightness based similarity is the core principle for pixel based segmentation techniques, which includes thresholding [14], *K*-means [15] and Fuzzy clustering techniques [16-18]. Statistical properties of images form the basis for image statistical segmentation techniques, in which segmentation is done based on the estimated brightness function and the Markov random models are examples of this method [6].

Amongst the various segmentation methods, *K*-means, key technique in pixel based segmentation, is one of the simplest form [25, 31] of unsupervised algorithm for automatic learning, in order to solve the clustering problem with relatively low accuracy. Further, the *K*-means algorithm may not give an optimum value even for large data sets and iterations [26]. If the number of clusters chosen is the same as the actual number of clusters present in the image, it might produce the correct segmentation, otherwise, it may lead to faulty results and needs to be improved for better accuracy. Further, its efficiency is negatively affected in noisy MRI images [19-20].

Fuzzy C-Means (FCM) is a popular clustering technique and is an iterative algorithm [21]. It uses fuzzy partitioning of data points with various membership values ranging from 0 to 1 [29]. FCM iteratively updates the cluster centres and the membership values of each data point. It moves the centre cluster to the right location within the given data set. Although it gives accurate edge detection, produces better results than *K*-means and is more robust to noisy images, the time taken for edge detection by FCM is longer than many other methods [28].

Fuzzy Logic systems, when applied to problems that are appropriate, produce responses that are typically faster as well as smoother than the traditional methods [22] Further, Fuzzy systems save energy, by reducing the number of iterations, thereby reducing the system maintenance and simplifies control with fewer rules [22]. Thus, the system is much faster than traditional methods.

PROPOSED METHODOLOGY

Hybrid methods [23-24], which are a combination of multiple algorithms, have become popular as they integrate the advantages of the individual techniques to produce a robust efficient method of segmentation. In this paper, the hybrid system developed for the MRI brain image segmentation is robust against noise. The proposed method integrates *K*-means and Fuzzy logic instead of FCM that has been widely used in the literature. The proposed methodology, as shown in Fig.1 overcomes the drawbacks of these individual algorithms.

The proposed hybrid algorithm is given as follows:

Step 1. Read the given input image
Step 2. Arbitrarily choose *K* objects as initial centroids
Step 3. Update the centroids
Step 4. Develop the Fuzzy Interference System (FIS)
Step 5. Finalize the number and the type of the Membership function
Step 6. Create and validate the Fuzzy Rules for fuzzification
Step 7. Apply the Fuzzy Rules on the input image
Step 8. Output the segmented image

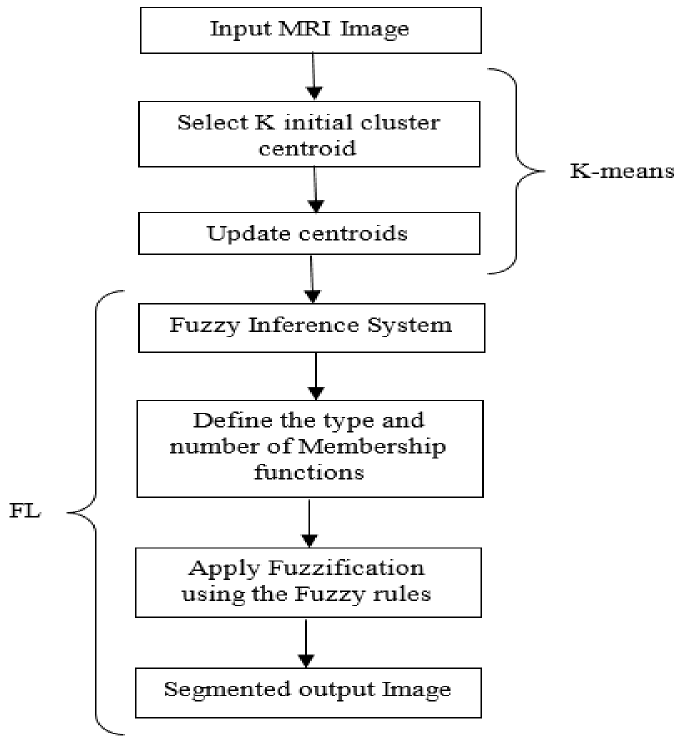

Figure 1. Proposed Hybrid method flow diagram

K-means Component

In Fig.1 first the input image is converted to gray scale image, resized and then the *K*-means algorithm is applied. The procedure classifies a given data set through a certain number of clusters (assume *K* clusters) fixed a priori. The main idea is to define *K* centroids, one for each cluster. These centroids should be placed strategically because different locations can lead to different results. For better coverage, the better choice is to place them away from each other. The next step is to take each point belonging to a given data set and associate it to the nearest centroid. When there are no more pending points, the first step is completed and an early clustering is done. At this point, re-calculate the *K* new centroids as barycenters of the clusters resulting from the previous step. With these *K* new centroids, a new binding has to be done between the same data set points and the nearest new centroid. We may notice that the *K* centroids change their location step by step at each iteration until there are no more changes to the centroid. Finally, this algorithm minimizes an *objective function*, in this case a squared error function.

K-means algorithm is given as follows:

Step 1. Choose *K* arbitrary Initial Centers:

$$Z_1(1), Z_2(2), \ldots, Zj(K).$$

Step 2. At the K^{th} Iterative Step, distribute the sample $\{X\}$ among the *K* Cluster Domain, using the relation

$$X \in S_j(k) \text{ if } \| X- z_j(k) \| < \| X-z_i(k) \|,$$

where $S_j(k)$ is the set of samples whose cluster center is $z_j(k)$.

Step 3. From the result of step 2, calculate the new clusters:

$z_j(k+1)$, where $j=1,2,\ldots,k$

$z_j(k+1)=1/n_j \sum X, X \in S_j(k)$

where, n_j is the number of samples in $S_j(k)$ and the cluster centers are sequentially updated.

Step 4. If $z_j(k+1)= z_j(k)$,then the algorithm is said to have converged and the procedure is terminated, otherwise go to step 2.

Fuzzy Logic Component

The output of the *K*-means algorithm is given as input to the Fuzzy Logic system, where the membership functions are defined and clusters are formed using fuzziness. As neighborhood attraction is considered to exist between neighboring pixels, this is considered as a feature for extraction. During clustering, each pixel attempts to attract its neighboring pixels toward its own cluster. This neighborhood attraction depends on two factors; the pixel intensities or feature attraction, and the spatial position of the neighbors or distance attraction, which also depends on the neighborhood structure. Consideration of these neighboring pixels greatly restrains the influence of noise.

The developed Fuzzy Rules are given below:

1. If the mean value is low and the standard deviation value is low, then it is **not** an edge pixel.
2. If the mean value is medium and the standard deviation value is low, then it **is** an edge pixel.

3. If the mean value is high and the standard deviation value is low, then it is **not** an edge pixel.
4. If the mean value is low and the standard deviation value is high, then it is **not** an edge pixel.

SIMULATION RESULTS

Database

For this research work, the images in the form of MRI imaging modalities were collected from several hospitals and medical research centres associated with public universities in Saudi Arabia [10]. The proposed integrated algorithm was tested on 500 clinical images acquired from 22 patients. Each image was resized to 256x256 pixels. Implementation was undertaken on an Intel CORE i5 processor, using MATLAB software.

Graphical User Interface

A Graphical User Interface (GUI) was created for segmentation analysis, allowing the user to select to analyse the impact of the existing (i.e., *K*-means and Fuzzy Logic) and proposed algorithms. Fig. 2 presents the developed GUI to show a sample input image selected for brain segmentation and the method selected for analysis. First the existing method of *K*-means is selected to segment the given input brain image. The output image is segmented into white matter, gray matter and CSF. Along with that, the percentage of clustering and misclassification rate is displayed. Fig. 3 shows the same image analysed using Fuzzy Logic, whilst Fig. 4 shows the segmentation using the proposed Hybrid Fuzzy *K*-means method.

As observed from the images, the *K*-means was able to highlight the gray matter of the segmented input brain image in which the edges are preserved well, while the algorithm fails to segment the white matter and CSF accurately and this is evident through the high misclassification rate for white matter and CSF, as shown in Fig. 2. Visually looking at Fig. 2, it is observed that the white matter is clearly not segmented and it is mingled with the other tissues of the brain and noisy. On the other hand, the Fuzzy Logic implementation was able to significantly segment the white matter and CSF where the edges of the white matter and CSF are well preserved and can be identified as seen visually in Fig. 3. Further, the misclassification rate has been reduced highly by 41% as compared to *K*-means, but the Gray matter is not well segmented and the misclassification rate is increased by 60%, as compared to *K*-means. This proves that although using Fuzzy logic the white matter and CSF are well segmented, gray matter is not accurately segmented. In comparison, the proposed technique developed was able to segment the white matter, gray matter and CSF more accurately, which is evident as seen visually in Fig. 4. Additionally, the visual images shows that the edges of the brain are well preserved and the white matter, gray matter and CSF are clearly segmented. Also, the proposed algorithm's misclassification rate has been reduced significantly by 48% and 12% for white matter, 17% and 50% for gray matter and 48% and 12% for CSF, as compared to *K*-means and Fuzzy Logic, respectively.

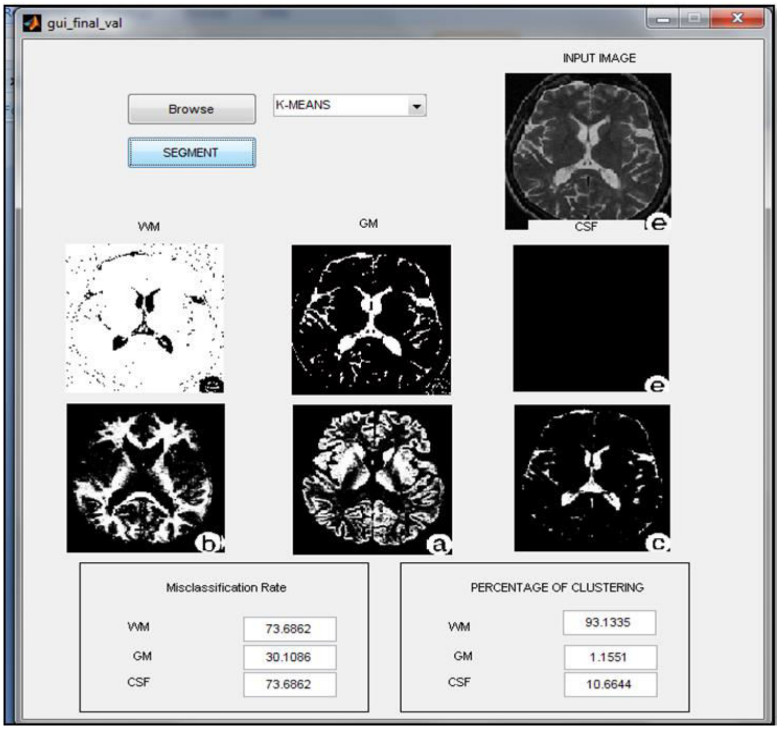

Figure 2. GUI for segmentation of brain using *K*-means for *k*=3

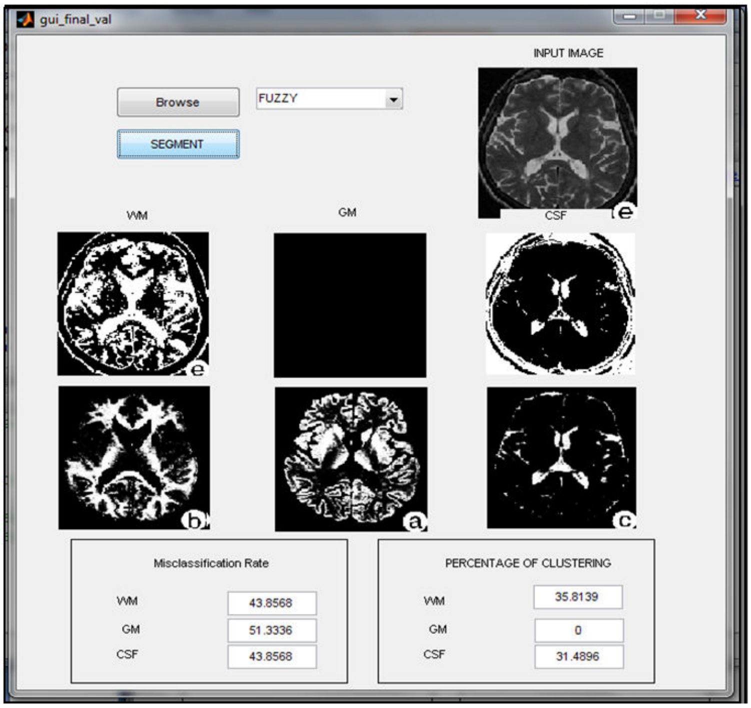

Figure 3. GUI for segmentation of brain using Fuzzy Logic

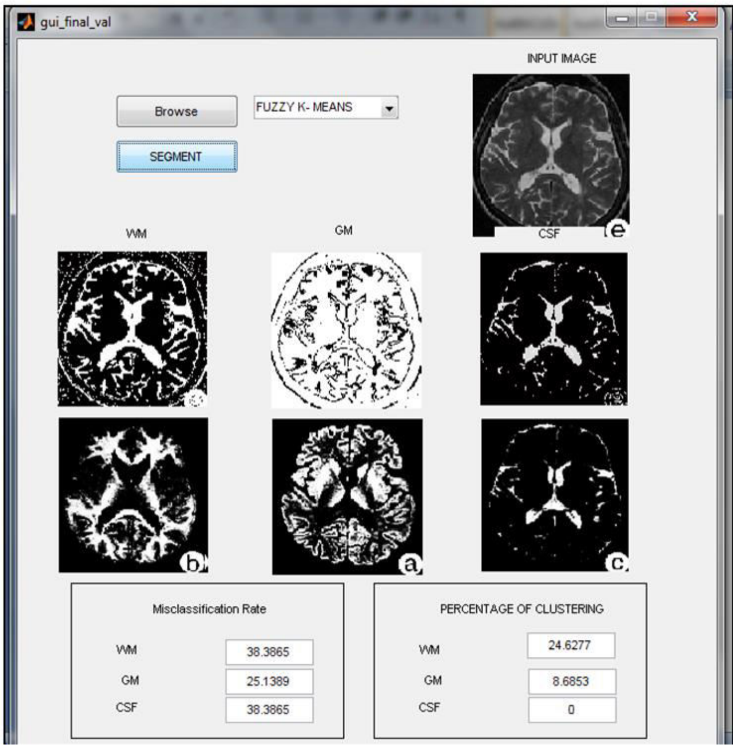

Figure 4. GUI for segmentation of brain using Hybrid Fuzzy *K*-means

Result Analysis

Fig. 5 shows the white matter of the brain segmented using *K*-means, Fuzzy and proposed algorithm. It can be seen from Fig. 5(a) that the white matter is not clearly distinguished using *K*-means and contains more white pixels and edges are not clearly detected, while in Fig. 5(b), although the white matter is well highlighted, there are also many misclassified pixels shown as white matter. However, noise is reduced as compared to Fig. 5(a). Fig 5(c) shows well detected edges of the white matter and noise inside the segmented brain is highly reduced although noises outside the segmented brain are evident. Comparatively, this proves that the proposed algorithm has segmented the white matter more accurately preserving the edges and reducing the noise and misclassification.

(a) (b) (c)

Figure 5. White Matter segmented by (a) *K*-means, (b) Fuzzy and (c) Hybrid approach

Fig. 6 shows the gray matter of the brain segmented using the three algorithms. It can be seen from the first image that the gray matter is visually present using *K*-means but some edges are not clearly detected, while in Fig. 6(b), the gray matter is not observable as the Fuzzy Logic fails to detect the gray matter. However, the proposed algorithm in Fig 6(c) shows well detected edges of the gray matter which is highly preserved as compared to the other two algorithms. Again comparatively, this proves that the proposed algorithm has segmented the gray matter more accurately preserving the edges and reducing the noise and misclassification as compared to the benchmark algorithms.

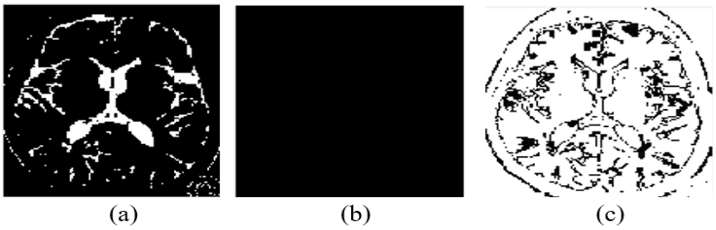

Figure 6. Gray Matter segmented by (a) *K*-means, (b) Fuzzy and (c) Hybrid approach

The segmentation results of the brain CSF is shown in Fig. 7. In Fig. 7(a), the CSF is undetectable, hence the *K*-means failed to segment the CSF. In Fig. 7(b), Fuzzy logic was able to segment the CSF but some edges were not clearly detected. On the other hand, as observed in Fig. 7(c), the proposed again successfully produced the best visual results in detecting the edges of the CSF while reducing the misclassifications.

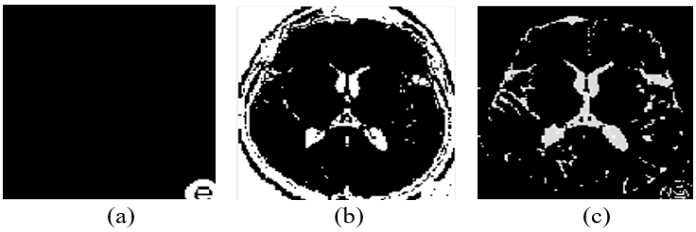

Figure 7. CSF segmented by (a) *K*-means, (b) Fuzzy and (c) Hybrid approach

Performance Measures

The performance of the proposed hybrid algorithm is evaluated based on the following parameters:

Misclassification Rate

This measure calculates the rate at which the algorithms wrongly classified the brain tissues. Table I shows the Misclassification Rate (MR) for the white matter, gray matter and CSF using the benchmark and proposed algorithms. K-means produced better MR than Fuzzy

Logic for gray matter, whilst Fuzzy Logic was better than K-means for white matter and CSF. However, as observed from the results, the MR of the proposed Hybrid Fuzzy K-means algorithm was consistently the lowest for all 3 tissue types. Hence, the proposed algorithm was better at brain classification as compared to the benchmark algorithms.

Table 1 Misclassification Rate

Algorithms Tested	**Misclassification Rate (MR)**		
	White Matter	***Gray Matter***	***CSF***
1. K-means	73.68	30.10	73.68
2. Fuzzy Logic	43.85	51.33	43.85
3. Hyrbid Fuzzy K-means	**38.38**	**25.13**	**38.38**

Percentage of Clustering

This measures grouping of pixels with respect to certain groups or in other words, it describes the classification rate of a particular group such as white matter, gray matter and CSF. The percentage of clustering must be higher for better classification. It must be higher so that the pixels within a group will be accurately grouped as clusters. It can be seen from the Table II that the percentage of clustering for white matter, gray matter and CSF was again the lowest for the proposed algorithm. Also, consistent to the MR, Fuzzy Logic performed better than K-means for white matter and CSF.

Table 2 Percentage of Clustering

Algorithms Tested	**Percentage of Clustering**		
	White Matter	***Gray Matter***	***CSF***
1. K-means	93.13	1.15	10.66
2. Fuzzy Logic	35.81	31.48	0
3. Hyrbid Fuzzy K-means	24.62	0	8.68

Overall, from both measures, it is clear that the proposed algorithm consistently performed the best in classifying the white, gray and CSF brain tissue. The improvement brought about by the proposed algorithm as compared to the two benchmark algorithms was relatively significant (approximately 11-50%) for the given MRI data set.

CONCLUSION

This paper proposed a hybrid algorithm uisng *K*-means and Fuzzy logic method, which was developed, simulated and evaluated. Segmentation of the brain was simulated using the MATLAB software, and the system proposed segments into white matter, gray matter and CSF.The algorithm was tested using clinical MRI images.

The performance of the proposed algorithm was evaluated in terms of the Misclassification Rate (MR) and percentage of clustering. The results showed that the proposed algortihm was able to consistently achieve the best results in the classification of the brain, when compared against the benchmark algorithms (i.e., *K*-means and Fuzzy logic). Further, the percentage of clustering was also improved by the proposed system as compared to the existing algorithms.

Future work may be carried out to further improve the MR. Possibilitied include incorporation with other intelligent algorithms and techniques, including optimising Neuro Fuzzy *K*-means algorithm for brain segmentation.

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