MRI Brain Image segmentation using Adaptive Thresholding and K-means Algorithm

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ABSTRACT
Segmentation of human brain from MRI without human interference is a major challenge in the field of medical image processing. Brain segmentation is used to extract different features of the image for analyzing, interpretation and understanding of images. The objective of brain MRI segmentation is to precisely identify the major tissue structures in these image volumes. There are a number of methods exist to segment the brain. In this paper, we have implemented a new approach based on adaptive thresholding and K-means clustering algorithm, which is used to get cerebrospinal fluid (CSF), Gray Matter (GM), White Matter (WM) and others. In order to segment an image thresholding method is adopted but a fixed threshold is not appropriate for segmentation, if the background is rough, hence adaptive thresholding method is more suitable for segmentation and K-means clustering algorithm is also used for segmenting MR brain image into K different tissue types, which include gray matter, white matter, and CSF. The efficiency and accuracy of the algorithm are proven by the experiments on the MR brain images.

General Terms
MRI, Segmentation, medical image processing, brain.

Keywords
Adaptive thresholding, K-means clustering algorithm, cerebrospinal fluid (CSF), Gray Matter (GM), White Matter (WM).

1. INTRODUCTION
Magnetic resonance imaging (MRI) is an important analytical imaging technique to obtain high quality brain images in both clinical and research areas [1], [2]. MRI scan creates pictures of tissues, organs and other structures inside your body using a strong magnetic field and radio waves. Magnetic resonance imaging (MRI) provides comprehensive images of living tissues. MR images are widely used for detecting tissue abnormalities such as cancers and injuries as well as for monitoring patients with neurodegenerative diseases such as Parkinson’s disease, Alzheimer’s disease (AD), epilepsy, schizophrenia and multiple sclerosis (MS) [2] – [5]. MRI is also used for studying brain pathology which gives useful and accurate clinical information. Brain tissue segmentation typically classifies voxels into grey matter (GM), white matter (WM), and Cerebrospinal fluid (CSF). Segmentation of MR brain images into different classes of tissue is a significant task for improving the understanding of many neurological disorders [2].

Image segmentation splits an image into its basic regions or objects. The level to which the subdivision is carried depends on the problem being solved. Segmentation of nontrivial images is the most difficult tasks in image processing. Segmentation accuracy decides the subsequent success or failure of the computerized analysis procedures [6]. Image segmentation is the essential step in image analysis, understanding, and interpretation and recognition tasks. Segmentation is the most important step in automated recognition system which has several applications in the field of medical imaging, satellite imaging, movement detection, security, surveillance etc. [7]. The segmentation of brain tissues into gray matter, white matter, and tumor on medical images is gaining tremendous acceptance with the advance of image guided approaches of surgery [8]. The aim of segmentation is to simplify and change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is frequently used to find objects and boundaries (lines, curves, etc.) in images [9]. The segmentation algorithm is based on the properties of gray level values of pixels. The different types of segmentation techniques are: (a) Edge based segmentation (b) Threshold Based Segmentation (c) Region Based Segmentation (d) Clustering (e) Matching [10].

2. SEGMENTATION TECHNIQUE
In this paper, we are using adaptive thresholding and K-means clustering algorithm for MRI brain image segmentation.

Thresholding is one of the commonly used methods for image segmentation [11]. Thresholding techniques detect a region based on the pixels with similar intensity values. This technique offers boundaries in images that contain solid objects on a contrasting background [10]. Thresholding technique gives a binary output image from a gray scale image. Using this method, the image is subdivided directly into different regions based on these intensity values of the pixels [12]. At present, threshold-based methods are classified into global and local thresholdings. If an image contains objects with homogeneous intensity or the contrast between the objects and the background is high, global thresholding is the best option to segment the objects and the backgrounds. When the contrast of an image is low, threshold selection will become difficult. Local thresholding can be determined by estimating a threshold value for the different regions from the intensity histogram [13].

Mathematically thresholding is defined as Eq. (1). Let f(x,y) be the input image and ‘T’ be the threshold value then the segmented image g(x,y) is given by,

$$g(x,y) = \begin{cases} 1, if\ f(x,y) > T \\ 0, if\ f(x,y) \le T \end{cases} \qquad (1)$$

Using the above Eq. (1), the image can be segmented into two groups. If we want to segment the given image into multi groups then we should have multi threshold point [15].

If we have two threshold values, then the above equation becomes as Eq. (2) and this equation segments the image into three groups

$$g(x,y) = \begin{cases} a, if\ f(x,y) > T_2 \\ b, if\ T_1 < f(x,y) \leq T_2 \\ c, if\ f(x,y) \leq T_1 \end{cases} \qquad (2)$$

The significant parameter in image segmentation using thresholding technique is the choice of selecting threshold value T. In manual thresholding technique, the threshold value T can be selected by the user with the help of image histogram. In automatic threshold selection method, the value of T can be selected based on histogram, clustering, variance, means etc [10].

2.1 Adaptive Threshold

Thresholding is called adaptive threshold when a different type of threshold is used for different regions in the image. This is known as local or dynamic thresholding [16]. Thresholding assumes that the image has pixel values generally different from the background [17]. This technique allows the threshold value T to change based on the slowly varying function of position in the image or on local neighboring hood statistics. Threshold T depends on the spatial coordinated (x, y) themselves.

We adapt this technique with some optimization. Following is the outline of adaptive thresholding:

1) Binarize the image with a single threshold T

2) Thin the thresholded image

3) Remove all branchpoints in the thinned image

4) All remaining endpoints are placed in the probe queue and used as a starting point for tracking

5) Track the region with threshold T

6) If the region passed testing, T=T-1, go to 5

The adaptive thresholding algorithm calculated the local weighted mean just along the row, or pairs of rows, in the image using a recursive filter. Here, we use symmetrical 2D Gaussian smoothing to calculate the local mean. This is slower but more general. Median filtering is an alternative to the mean and offers the option of using a fixed threshold relative to the mean/median. Although the potential advantage of median filtering being more robust the output is generated by using Gaussian filtering [18].

In this algorithm consider p_n represent the value of a pixel at point n in the image being thresholded. For the moment consider the image a single row of pixels composed of all the rows in the image lined up next to each other.

Let $f_s(n)$ be the sum of the values of the s pixels at point n.

$$f_s(n) = \sum_{i=0}^{s-1} p_{n-1} \qquad (3)$$

The value of the resulting image T(n) is either 1 (for black) or 0 (for white) depending on whether it is t percent darker than the average value of the previous s pixels.

$$T(n) = \begin{cases} 1\ if\ p_n < \left(\frac{f_s\,(n)}{s}\right)\left(\frac{100-t}{100}\right) \\ 0\ \ otherwise \end{cases} \qquad (4)$$

2.2 K-means clustering algorithm

A Clustering is very useful techniques in MRI Segmentation, where it divides pixels into classes, without knowing prior information or training [19]. It classifies pixels with the highest probability of the same class. In the clustering technique, the training is done by using the pixel characteristics with properties of each class [15].

K-Means is the simple unsupervised learning algorithm for clusters. Clustering the image is grouping the pixels according to some features [20]. In K-means 'K' centers are defined, one for each cluster. These clusters must be placed far away from each other. The next step is to take a point fit in to a given data set and associates it to the nearest center. When no point is pending, the first step is completed and early grouping is done. In the second step, recalculate 'k' new centroids as barycenter of the clusters resulting from the previous step. After having 'K' new centroids a new binding has to be done between the same data set points and the nearest new center. A loop has been generated. Due to this loop, the k centers change their location step by step until centers do not move any more [15]. Finally, this algorithm aims at minimizing an objective function known as squared error function given by,

$$J(V) = \sum_{i=1}^{c} \sum_{j=1}^{c_i} \left\| x_1 - v_j \right\|^2 \qquad (5)$$

Where,

$\left\| x_1 - v_j \right\|^2$ is the Euclidean distance between x_i and v_j

'C_i' is the number of data points in the i^{th} cluster.

'C' is the number of cluster centers.

Algorithmic steps for K-means clustering:

Let X = {x_1, x_2, x_3, ...x_n}be the set of data points and V = { v_1, v_2, v_3, ...v_c }be the set of centers.

Step1: Randomly select 'c' cluster centers

Step2: Calculate the distance between each data point and cluster centers.

$$D(i) = \arg min\ \|x_i - M_c\|^2, i = 1 \ldots N \qquad (6)$$

Step3: Allocate the data point to the cluster center whose distance from the cluster center is a minimum of all the cluster centers.

Step4: Recalculate the new cluster center using

$$v_i = \left(\frac{1}{c_i}\right) \sum_{j=1}^{c_i} x_i \qquad (7)$$

Where 'Ci' denotes the number of data points in the ith cluster.

Step5: Recalculate the distance between each data point and newly obtained cluster centers.

Step6: If no data point was reallocated then stop, otherwise repeat from step 3.

K-means algorithm is fast, robust and easier to understand. It also gives a better result when data set are well separated from each other. The following figure shows the flowchart of K-means algorithm.

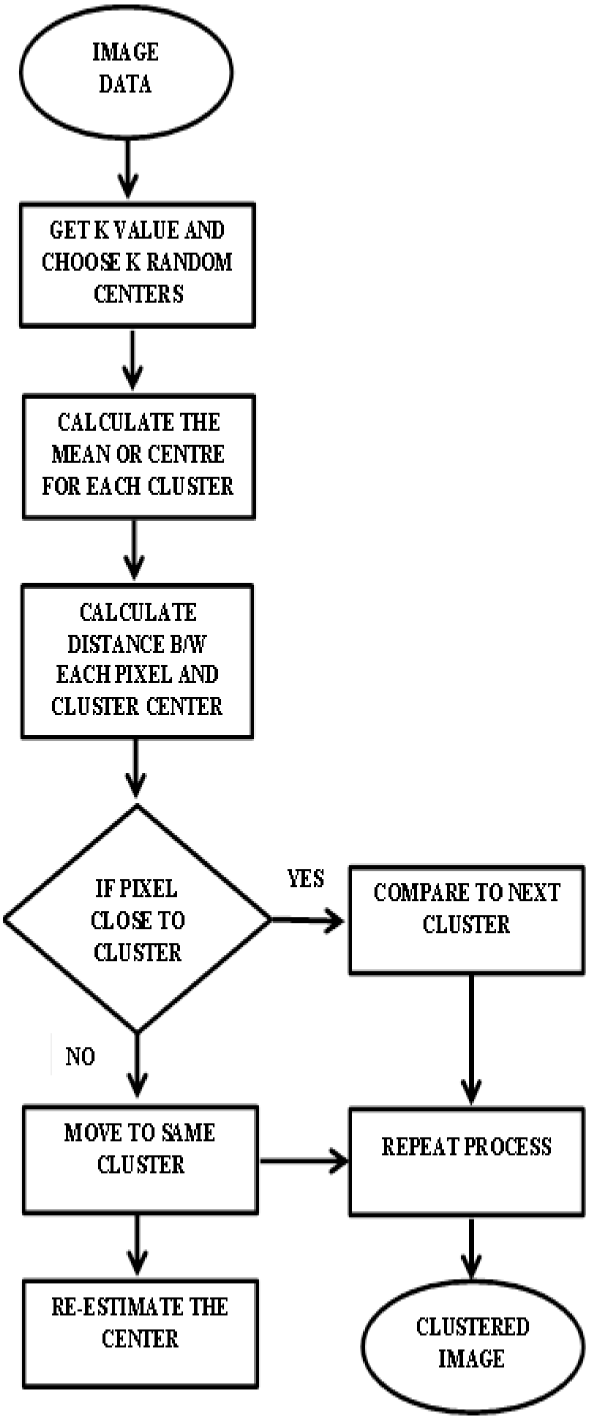

Fig.1 Flowchart of K-means clustering algorithm

3. EXPERIMENTAL WORK AND RESULTS

The flowchart shown in following Fig. 2 fully explains the overall procedure of the system. Firstly, the system starts with an MRI brain image as an input. Here, we pre-process the input image with the help of median filter algorithm and histogram equalization. Then we apply adaptive threshold method and K-means algorithm on produced image. This gives segmented images of brain GM, WM, and CF. Further MRI brain Images are divided into three classes C1, C2, and C3 and we calculated different statistical features.

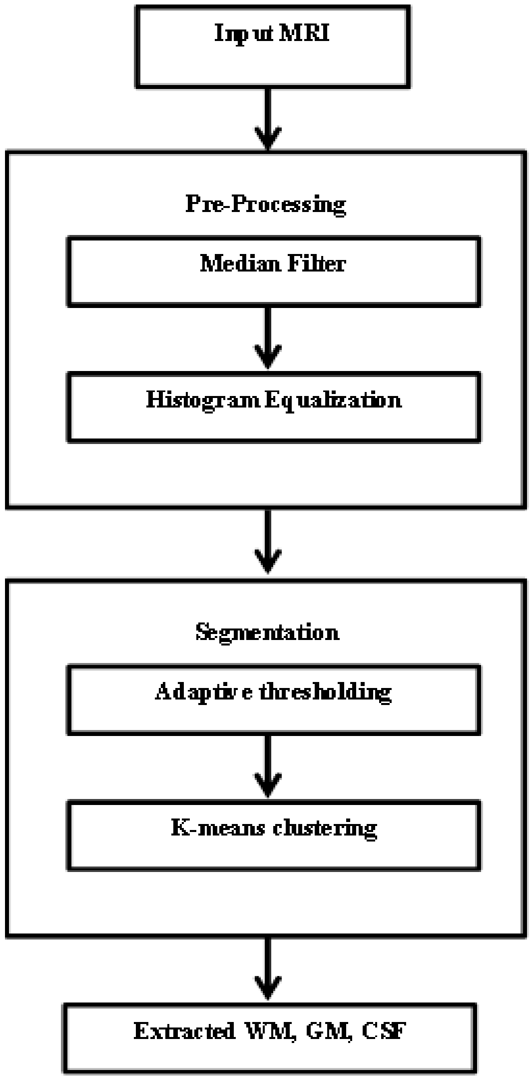

Fig.2 Block diagram of proposed method

In pre-processing phase, the input image is initially processed before it passes through any special purpose processing. Here the image quality is improved and noises are removed. It contains two sub-steps:

The median filter is often using to perform noise reduction in an image. Window slide entry by entry which is the main idea of the median filter, it slides over the entire image, the pixel at the center is the central pixel. The neighboring pixels are classified according to the intensity and the median value replaces the central pixel value Advantage of median filters algorithm is that it can perform an excellent operation of rejecting certain types of noise [21]. This filtering algorithm enhances the quality of the MRI brain images.

In order to have contrast adjustment of pixel Histogram equalization is used, so that intensities can be distributed among classes. The input image may be composed of an uneven distribution of intensity, which makes the image having weak contrast and low quality. The histogram equalization applied for enhancing the appearance of an image.

Finally, adaptive threshold method and K-means clustering algorithm are used for segmentation. The experimental work is performed in MATLAB on Brain web database images. Fig.1 and Fig. 2 depicts the result of these methods.

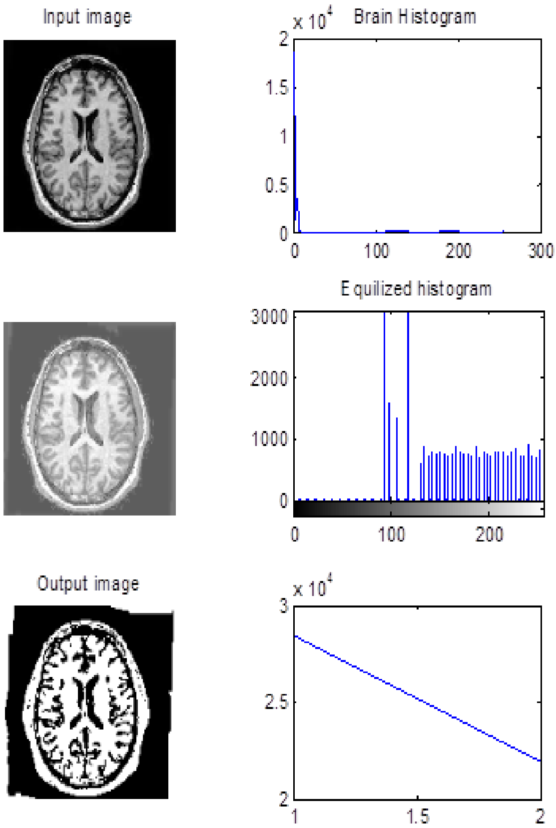

Fig.3 Segmentation after adaptive threshold

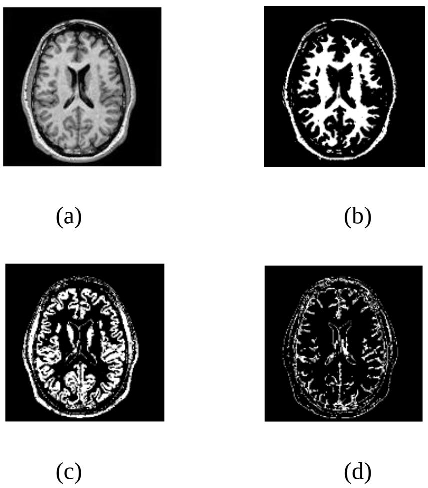

Fig.4 (a) Original Image (b) WM (c) GM (d) CSF

Table.1 Statistical values of WM, GM, and CSF

Statistical features	WM	GM	CSF
Area	125577	26236	23891
Perimeter	1888.32	4811.92	3730.25
Std Dev of Intensity	109.548	87.676	122.036
Coefficient of skewness	-1.0779	1.8075	-0.1821
Median Intensity	253	0	5

4. CONCLUSION

In this paper, we have implemented a new approach based on adaptive thresholding and K-means clustering algorithm, which is used to get cerebrospinal fluid (CSF), Gray Matter (GM), White Matter (WM) and others. In order to segment an image thresholding method is adopted but a fixed threshold is not appropriate for segmentation, if the background is rough, hence adaptive thresholding method is more suitable for segmentation and K-means clustering algorithm is also used for segmenting. Fig 1 and fig 2 shows experimental work on brain web database of MRI images and table 1. Shows Statistical values of three tissues WM, GM, and CSF. Hear adaptive thresholding and K-means clustering has performed best to generate different clusters of input MRI images.

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