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Fully Automatic Segmentation of Different Brain Tissue from MR Image

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ABSTRACT

In last few decades Medical Image Processing became one of the most popular and challenging research field due to its non-invasive nature for viewing internal body organs. Medical imaging modalities such as MRI, CT scan mostly depend on computer imaging technology to generate or display digital images of the internal organs of the human body which helps the medical practitioners to visualize the inner portions of the body. MRI of brain provides best resolution images for visualizing brain tissue without any surgical interventions. We propose a multimodal histogram thresholding method to separate brain MR images into different tissue components and also dissociation of skull from brain. We are processing the histogram of MRI brain in such a way that, number of cluster and cluster center are automatically detected and we are passing this data to a clustering algorithm. In this technique no prior knowledge about the number of cluster is needed. The coordinates of cluster centers and their number can be passed to the clustering algorithm. In our work we used Fuzzy C-Means (FCM) for the clustering the gray levels. Each cluster gives us different gray levels for each tissue type in the MR brain image. Main Objective of our work is to dissociate the skull from a brain MRI and automatically segment different parts of brain tissue types e.g. white matter (WM), gray matter (GM), and Cerebra-Spinal Fluid (CSF).

Key words: Fuzzy C Means Clustering, Fourier Descriptor, Skewness, Thresholding

INTRODUCTION

Magnetic Resonance Imaging (MRI) provides detailed images of living tissues, and is used both for studying brain and other human organs. Data obtained from MR images is used for detecting tissue deformities such as tumors and injuries. MR is also used extensively in studies of brain pathology, where regions of interest (ROI's) are often examined in detail, for example in Multiple Sclerosis (MS) studies [4]. MRI images are used to produce accurate and detailed pictures of organs from different angles to diagnosis any abnormalities. There are two types of MRI high field for producing high quality images and low field MRI for smallest diagnosis condition. MRI images allow the physician to visualize even hair line cracks and tears in injuries to ligaments, muscles and other soft tissues. MRI is based on the principle of absorption and emission of energy in radio free range of electromagnetic spectrum. Magnetic resonance imaging (MRI) is excellent for showing abnormalities of the brain such as stroke, hemorrhage, tumour multiple sclerosis or lesions. Accurate anatomical three-dimensional (3D) models derived from 2D MRI. Medical image data helps in providing precise and accurate diagnostic information about spatial relationship between critical anatomical structures such as eloquent cortical areas, vascular structures etc and other pathological findings which were otherwise indistinguishable by the naked eye [4].

Automatic segmentation of MRI volumes of the human brain is a complex task. Manual segmentation is time consuming task and be prone to errors, especially due to fatigue. Manual segmentation also gives inter and intra expert variability in results. In this scenario reliable algorithms are essential for the delineation of anatomical structures and other Regions of Interest (ROI) to assist and automate the radiological tasks. In order to perform good quantitative studies, ROI's within the brain must be well defined. After considerable review of literature [7-9] on the various methods on MRI segmentation, we found that non-parametric methods are by far the best when it comes to MRI segmentation weighing on the fact that they are used in an ambiance (i.e. clinical) where requirements on least intra- and inter-operator variations are high.

In this paper we propose a multi-level thresholding algorithm for segmenting brain from skull and dissociating other tissue types i.e. Cerebro-Spinal Fluid (CSF), White Matter (WM), Gray Matter (GM), in high resolution brain MR images. Initially, we used smoothed histogram of the MRI for assessment of number of modes. Since, automatic detection of number of clusters is a difficult task and performance of clustering algorithm greatly depends on initial estimation of cluster centers, a novel skewness based statistical technique is used for detecting the cluster centers and number of clusters. These cluster centers are passed to the fuzzy C-means clustering algorithm for accurate detection of the parameters of various tissue types.

MULTIMODAL GRAY LEVEL HISTOGRAM ANALYSIS

Let I be a *p* x *q* gray scale MR image with G represents the set of possible gray levels and I(x,y) be the gray value of pixel co-ordinate (x,y) with x=1,2,… p, and y=1,2,…q. Then the gray-level histogram H of image I is of the form H={h(j) | j ∈ [1,G]}. Normalized version of h(1) to h(G) represent the histogram probabilities of the observed gray values from 1 to G and h(g)=#{I(x,y) = g | g ∈ G} [1]. Usually histograms are not flat. Peaks and valley parts are observed. The peaks can correspond to meaningful groups which forms objects in an image and valley intervals corresponds to separations between them. We will call the peaks *modes of histogram.* Generally, there will exit a number of “modes” in the histogram if it is multimodal histogram and each mode in the histogram will in general map to an object in the image. Fig 1 shows an example of five distinctive modes in a gray level histogram. For any gray level histogram with ‘n’ distributions (modes), represents ‘n’ over-lapping distributions. The multi-level thresholding techniques can [5] be applied in this case for segmenting objects. Accurate threshold values required to be determined to separate this multimodal histogram into n non over-lapping distributions.

WINDOW BASED CLUSTER DETECTION

For deciding automatic multiple thresholds (Fig. 1), we need to find the local minima’s in the histogram. But a random fluctuation in the histogram prevents us to find actual local minima. To avoid this we used *Fourier descriptor* for initial smoothing. Then genuine local minimums are extracted following rule: $\forall i \in [1, G]$, *h*(i) is in a *valley* if following happens; *h*(i-3)>*h* (i-2) , *h* (i-2)>*h* (i-1) and *h*(i-1)>*h* (i) and *h*(i)<*h* (i+1) and *h*(i+1)< *h*(i+2) and *h*(i+2)<*h* (i+3). For any two consecutive local minima, a gray level cluster (mode) is present. To get the cluster centre we used a moving window over the histogram between two consecutive minima and found the skewness in each window. The size of the window r_i is taken as half the size of two consecutive minima. The window which gives minimum skewness gives us the optimal symmetric distribution (here we are assuming the distributions in the histogram are symmetric distribution e.g Gaussian). For any cluster in the histogram, there exists only one estimation interval nearing the cluster center with the smallest absolute skewness value. Initial cluster centers are determined from each smallest fitted window as described below.

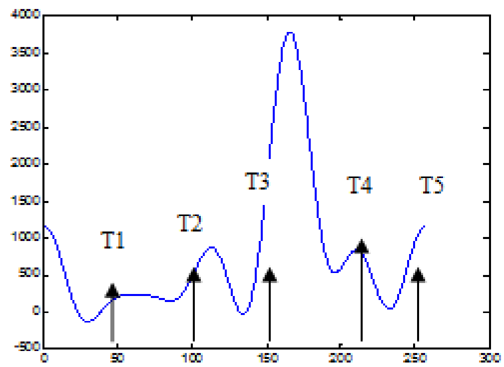


Fig. 1 Five distinctive distributed histogram. They must have five threshold value,T1,T2,T3,T4,T5 which separate this histogram into five non over-lapping distribution

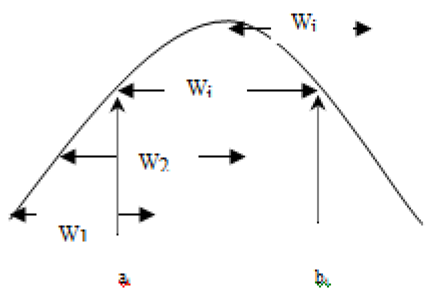


Fig. 3 Ooptimal intervals for parameter estimation. For each cluster in the histogram distribution ,the searching window w with fixed length r slides from the leftmost point towards the right end of the cluster .The interval with minimum absolute skewness value will become the optimal interval w*

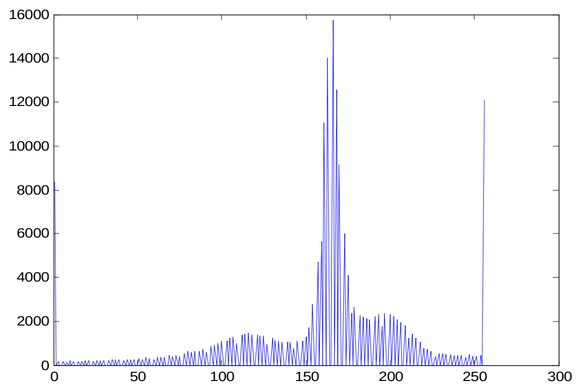


Fig. 2(a) Original Brain MR Image Histogram

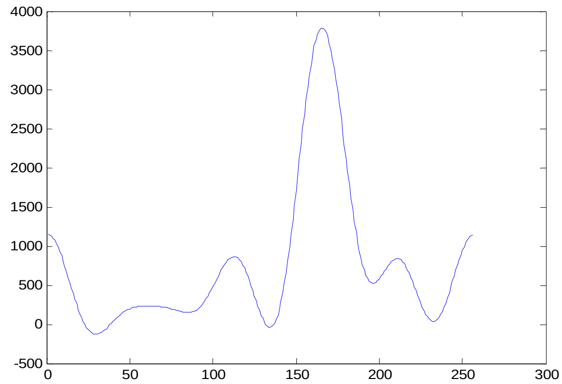


Fig. 2(b) Smoothed Histogram

Now let us define a searching window *w* with length r_i to search the location of optimal $_{\text{estimation}}$ interval of cluster C_i. Let v_k represent k^{th} valley (minima) in the smoothed histogram H determined in the previous step. The searching window w which starts by placing the leftmost point at $v_k(i-1)$ slides toward the end of cluster i.e. next valley $v_{k+1}(i)$ by moving one bin at a time. The searching process stops if the rightmost point reaches the end of cluster v (i)-1 .There will be $v_k(i)-v_{k-1}-1-r_i$ searching windows. Meanwhile, the skewness β_i is calculated for each searching window w_j where j=1,2,…v(i)-v(i-1)-1-r_i searching windows describe by $\beta_1(w_j)$. For our problem, the skewness of each searching window can be calculated as

$$\overline{m_{wj}} = \frac{\sum_{i\in w_j} ih(i)}{\sum_{i\in w_j} h(i)}, \quad \mu_n(w_j) = \frac{\sum_{i\in w_j} (i - m'_{wj})^n h(i)}{\sum_{i\in w_j} h(i)} \quad \text{and } \beta_1(w_j) = \frac{\mu_3(w_j)}{\sqrt{\mu_2^3(w_j)}} \tag{1-3}$$

Therefore, the optimal interval W* for estimating the centroid of each cluster is determine by the interval has minimum absolute skewness value, i.e. W*= $\min_j |\beta_1(w_j)|$

The optimal estimation interval w* of cluster C_i will be located at (a_i,b_i) as shown in Fig. 3(a). Which as an example shows the position of searching windows w and the location of optimal estimation interval w* for one distribution.

THRESHOLDING USING FUZZY C MEANS

The fuzzy clustering algorithm [5] provides possible solutions to accommodate the structural details in segmented description, since it identifies each of the clusters as a fuzzy set characterized by a membership distribution. The mechanism of fuzzy clustering is that partitioning the set of n sample points X={x_1, x_2,…,x_n} into c classes such that the membership distribution (μ) has the following properties: $\mu_i(x_j) \in [0,1]$

$$0 < \sum_{j=1}^{n} \mu_i(x_j) < n \qquad \text{and} \qquad \sum_{j=1}^{C} \mu_{ik} = 1, \qquad 1 \le i \le n \tag{4}$$

The fuzzy c means algorithm, a fuzzy extension of the k means algorithm, minimizes a least square objective function

$$J_m(U,V) = \sum_{i=1}^{n} \sum_{j=1}^{C} (\mu_{ij})^M (d_{ik})^2 \tag{5}$$

The parameter $M \ge 1$ controls the amount of fuzziness in the partition and when M=1, the equation (5) provides an equivalent classification as a k means algorithm.

The cluster means for each class

$$v_i = (\sum_{k=1}^{n} (\mu_{ik})^M x_k) / (\sum_{k=1}^{n} (\mu_{ik})^M) \quad \forall \text{i} = 1,2,\ldots\text{c} \tag{6}$$

Characterize the background and object regions. The objective function equation (5) can be iteratively minimized by computing the means with equation (6) and updating the memberships as

$$\mu_{ik} = \frac{1}{\sum_{j=1}^{C} (d_{ik}/d_{jk})^{(2/M-1)}} \quad \forall \text{i, k} \;\; \text{if } d_{ik} = 0 \text{ then } \mu_{ik} = 1 \text{ and } \mu_{jk} = 0 \text{ and } j \ne i. \tag{7}$$

Table -1 List of Parameters

Parameter	Description
μ_{ik}	Membership value of k^{th} data and i^{th} centroid
d_{ik}	Distance between k^{th} data and i^{th} centroid value
μ_3	Third order central Movement
μ_2^3	Second Order Central Movement

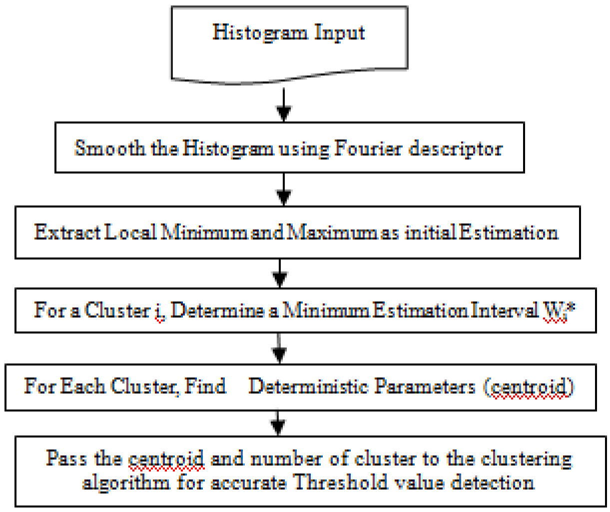


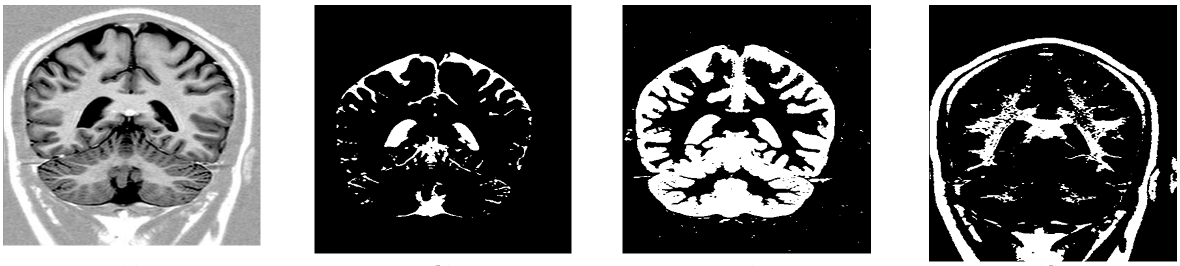
Fig. 5 Flow Diagram Window Based Automatic Multithresholding Selection Algorithm

EXPERIMENTAL RESULTS

Experimental results in our proposed method are showing in Fig. 5. For each tissue type found by our algorithm, we also conducted the experiment using Otsu Multithresholding method, results shown in Fig. 6. Fig 6. shows that Otsu Multithresholding cannot cluster the image correctly.

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

Fig. 5 (a) Original Brain MR Image, (b) Dissosiation of Skull,
(c) Cerebro Spinal Fluid(CSF), (d) Gray Matter(GM), (e) White Matter(WM)



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

Fig. 6 (a) Original Brain MR Image (b) Cerebro Spinal Fluid (c) Gray Matter (d) White Matter by Otsu Multithresholding method

CONCLUSION

Segmentation of Brain Image in different tissue parts is vital in surgical planning and treatment planning in the field of medicine. In this work, a computer aided system is proposed for automatic segmentation of regions containing Cerebra Spinal Fluid, Gray Matter and White Matter location using Fuzzy C Means Clustering. It is believe that this approach can also be applied to other modalities, by automatic estimation parameters. Experiment shows clearly that our method successfully works on brain MR images and gives very good result.

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