

Segmentation of Brain MR Images for Tumor Extraction by Combining Kmeans Clustering and Perona-Malik Anisotropic Diffusion Model

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Abstract

Segmentation of images holds an important position in the area of image processing. It becomes more important while typically dealing with medical images where pre-surgery and post surgery decisions are required for the purpose of initiating and speeding up the recovery process [5] Computer aided detection of abnormal growth of tissues is primarily motivated by the necessity of achieving maximum possible accuracy. Manual segmentation of these abnormal tissues cannot be compared with modern day's high speed computing machines which enable us to visually observe the volume and location of unwanted tissues. A well known segmentation problem within MRI is the task of labeling voxels according to their tissue type which include White Matter (WM), Grey Matter (GM) , Cerebrospinal Fluid (CSF) and sometimes pathological tissues like tumor etc. This paper describes an efficient method for automatic brain tumor segmentation for the extraction of tumor tissues from MR images. It combines Perona and Malik anisotropic diffusion model for image enhancement and Kmeans clustering technique for grouping tissues belonging to a specific group. The proposed method uses T1, T2 and PD weighted gray level intensity images. The proposed technique produced appreciative results

Keywords: White Matter (WM), Gray Matter (GM), Cerebrospinal Fluid (CSF)

1. INTRODUCTION

The developments in the application of information technology have completely changed the world. The obvious reason for the introduction of computer systems is: reliability, accuracy, simplicity and ease of use. Besides, the customization and optimization features of a computer system stand among the major driving forces in adopting and subsequently strengthening the computer aided systems. In medical imaging, an image is captured, digitized and processed for doing segmentation and for extracting important information. Manual segmentation is an alternate method for segmenting an image. This method is not only tedious and time consuming, but also

produces inaccurate results. Segmentation by experts is variable [16]. Therefore, there is a strong need to have some efficient computer based system that accurately defines the boundaries of brain tissues along with minimizing the chances of user interaction with the system [3]. Additionally, manual segmentation process require at least three hours to complete [1] According to [2] the traditional methods for measuring tumor volumes are not reliable and are error sensitive.

2. PREVIOUS WORK

Various segmentation methods have been cited in the literature for improving the segmentation processes and for introducing maximum possible reliability, for example:

2.1 Segmentation by Thresholding

Thresholding method is frequently used for image segmentation. This is simple and effective segmentation method for images with different intensities. [6] The technique basically attempts for finding a threshold value, which enables the classification of pixels into different categories. A major weakness of this segmentation mode is that: it generates only two classes. Therefore, this method fails to deal with multichannel images. Beside, it also ignores the spatial characteristics due to which an image becomes noise sensitive and undergoes intensity in-homogeneity problem, which are expected to be found in MRI. Both these features create the possibility for corrupting the histogram of the image. For overcoming these problems various versions of thresholding technique have been introduced that segments medical images by using the information based on local intensities and connectivity [7]. Though this is a simple technique, still there are some factors that can complicate the thresholding operation, for example, non-stationary and correlated noise, ambient illumination, busyness of gray levels within the object and its background, inadequate contrast, and object size not commensurate with the scene. [8]. [9] introduced a new image thresholding method based on the divergence function. In this method, the objective function is constructed using the divergence function between the classes, the object and the background . The required threshold is found where this divergence function shows a global minimum.

2.2 Region Growing Method

According to [10] Due to high reliability and accurate measurement of the dimensions and location of tumor, MRI is frequently used for observing brain pathologies. Previously, region growing and shape based methods were heavily relied upon for observing the brain pathologies. [11] Proposed a Bayes-based region growing algorithm that estimates parameters by studying characteristics in local regions and constructs the Bayes factor as a classifying criterion. The technique is not fully automatic, i.e. it requires user interaction for the selection of a seed and secondly the method fails in producing acceptable results in a natural image. It only works in homogeneous areas. Since this technique is noise sensitive, therefore, the extracted regions might have holes or even some discontinuities [7] Shape based method provides an alternative approach for the segmentation of brain tumor. But the degree of freedom for application of this method is limited too. The algorithm demands an initial contour plan for extracting the region of interest. Therefore, like region growing approach, this method is also semi automatic. Both of these methods are error sensitive because, an improper or false description of initial plan and wrong selection of the seed image will lead to disastrous results. Statistical methods and fuzzy logic approaches seems to be reliable and are the best candidates for the replacement of the above mentioned techniques.

2.3 Supervised and Un-Supervised Segmentation Methods.

Supervised and un-supervised methods for image processing are frequently applied [3] [14]. [12] Presents a technically detailed review of these techniques. [13] Attempted to segment the volume as a whole using KNN and both hard and fuzzy c-means clustering. Results showed, however, that there appears to be enough data non-uniformity between slices to prevent satisfactory

segmentation. Supervised classification enables us to have sufficient known pixels to generate representative parameters for each class of interest. In an un-supervised classification pre hand knowledge of classes is not required. It usually employs some clustering algorithm for classifying an image data. According to [14] KNN, ML and Parzen window classifiers are supervised classification algorithms. Whereas, un-supervised classification algorithms include: K-Means, minimum distance, maximum distance and hierarchical clustering etc.

3 METHODOLOGY

A brain image consists of four regions i.e. gray matter (GM), white matter (WM), cerebrospinal fluid (CSF) and background. These regions can be considered as four different classes. Therefore, an input image needs to be divided into these four classes. In order to avoid the chances of misclassification, the outer elliptical shaped object should be removed. By removing this object we will get rid of non brain tissues and will be left with only soft tissues. In this experiment we have used T1, T2 and PD weighted brain MRIs. These images possess the same size and same pixel intensity values. The pixels from the image under consideration are supposed to be grouped in any one of the aforementioned classes. Finally, by applying certain post processing operations, the tumorous region can be extracted. Figure 1 shows the methodology of this work. The process uses Kmeans algorithm for solving clustering problem. This algorithm aims at minimizing an *objective function*, in this case a squared error function. Mathematically, this objective function can be represented as:

$$J = \sum_{j=1}^k \sum_{i=1}^x P x_i^{(j)} - c_j P^2$$

where $P x_i^{(j)} - c_j P^2$ is a chosen distance measure between a data point $x_i^{(j)}$ and the cluster centre c_j , is an indicator of the distance of the n data points from their respective cluster centres. Image is read from database. The image contains the skull tissues. These tissues are non brain elements. Therefore, they should be removed in the preprocessing step. The presence of these tissues might lead to misclassification.

Figure 2 shows an image of the brain with skull seen as an outer elliptical ring. In figure 3 this elliptical ring is removed and we are left with only soft tissues. This is done by employing the following morphological function, i.e. erosion and dilation. Mathematically, these functions can be expressed as:

$$A \ominus B = \{ w : B_w \subseteq A \}$$

$$A \oplus B = \bigcup_{x \in B} A_x$$

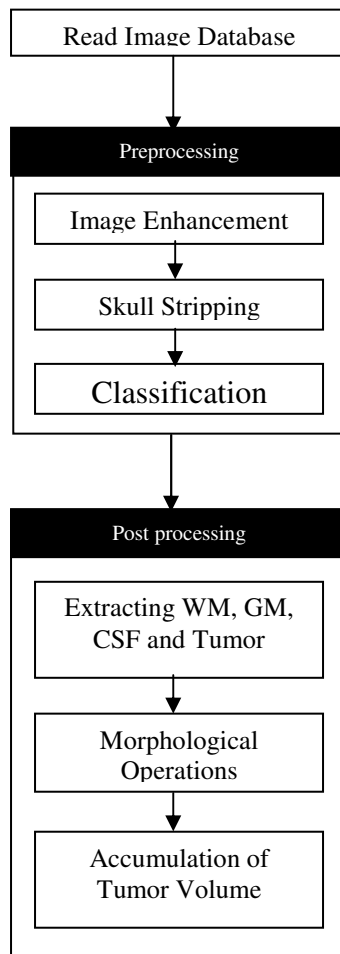
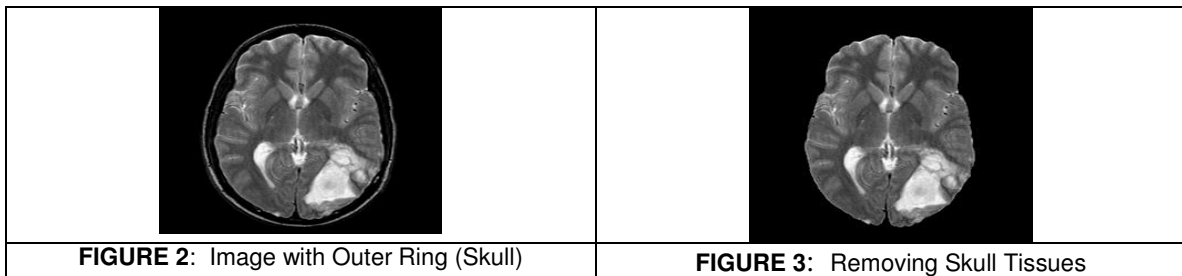


FIGURE 1: Methodology.



To test the algorithm, white gaussian noise is added to the input image. This image is then processed for enhancement. Perona and Malik [17] model is used for this purpose. This model uses partial differential equation for image denoising and enhancement. The model smooths the image without losing important details with the help of following mathematical relation [15].

$$It = \nabla \cdot [f(x, y, t) \nabla I] = \text{div}(f(x, y, t) \nabla I)$$

$I(x, y, t)$ is the intensity value of a pixel at sampling position (x, y) and scale t and $f(x, y, t)$ is the diffusivity acting on the system. The diffusivity function in Perona and Malik mode is given by the following mathematical relation

$$f(x, y, t) = f(P \nabla P^2) = \frac{1}{1 + P \nabla P^2 / k^2}$$

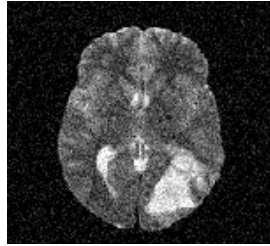


FIGURE 4: Noisy Image

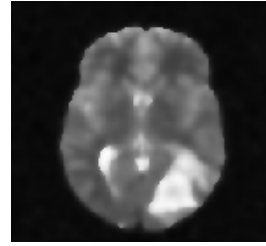
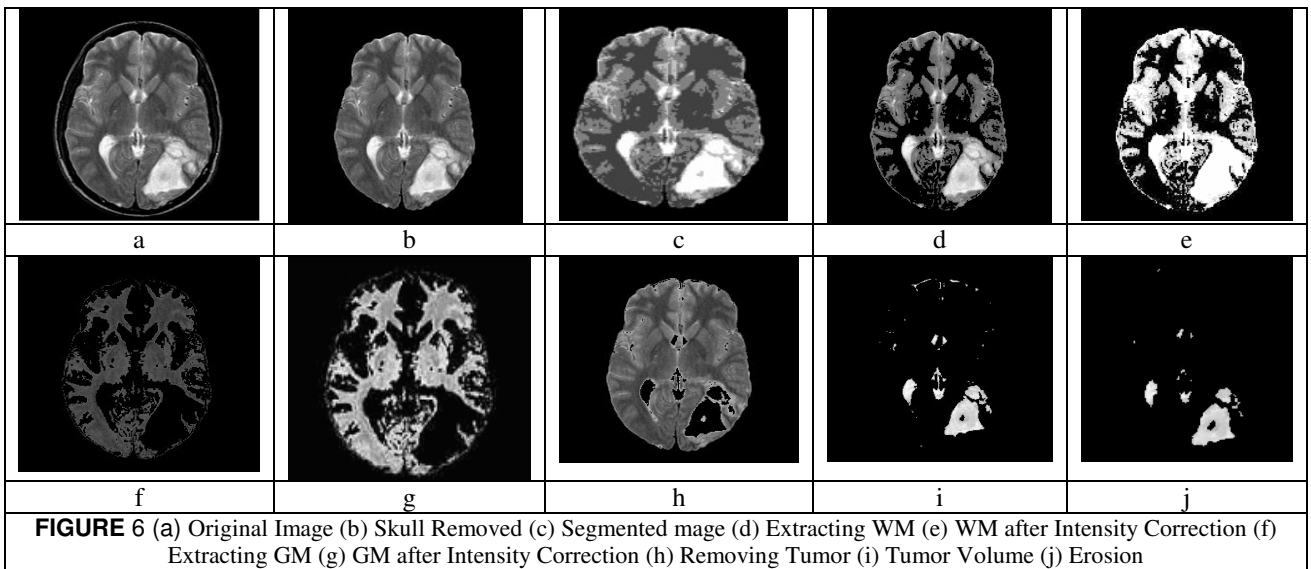


FIGURE 5: Enhanced Image

4 RESULTS AND CONCLUSION

It has been observed that when Perona and Malik model is combined with Kmeans algorithm, it produces reliable results. Due to un-supervised nature of the approach, the proposed system is efficient and is less error sensitive.



It can be deduced from the results that un-supervised segmentation methods are better than the supervised segmentation methods. Because for using supervised segmentation method a lot of pre-processing is needed. More importantly, the supervised segmentation method requires considerable amount of training and testing data which comparatively complicates the process. Whereas, this study can be applied to the minimal amount of data with reliable results. However, it may be noted that, the use of K-Means clustering method is fairly simple when compared with

frequently used fuzzy clustering methods. Efficiency and providing simple output are fundamental features of K-Means clustering method [18]. To check the accuracy of the proposed method, mean and standard deviations of clean image, noisy image containing white gaussian noise and enhanced image is drawn in Figure 7.

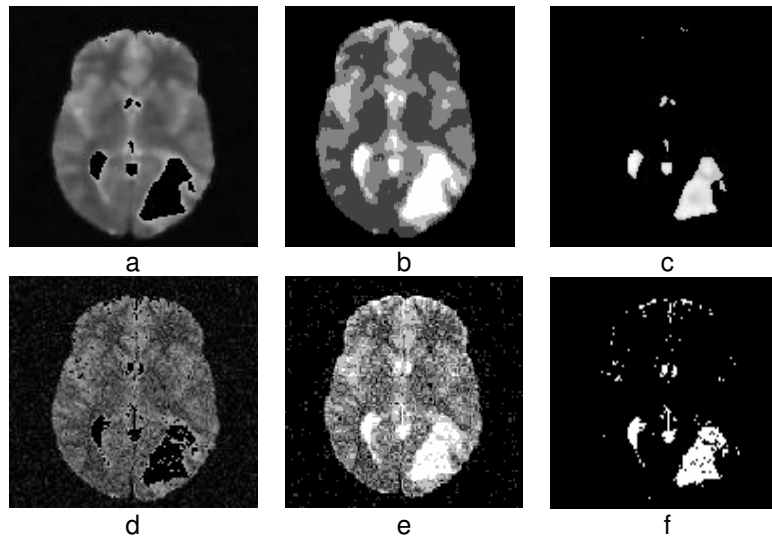


Figure 7: (a) Deleting normal tissues from enhanced MRI slice (b) Segmentation of enhanced MRI slice (c) Extraction of tumor (d) Noisy image showing only normal tissues (e) Segmentation of noisy image (f) Deleting normal tissues and retaining tumor cells.

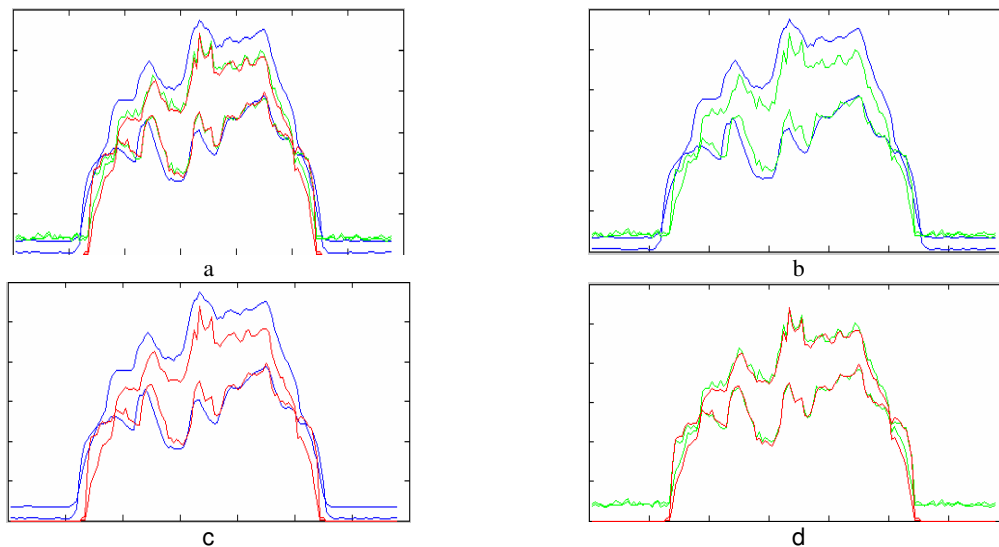


Figure 8: (a) Mean and Standard Deviations of Clean, Noisy and Enhanced Image (b) Mean and Standard Deviations of Noisy and Enhanced Image (c) Mean and Standard Deviations of clean and Enhanced Image (d) Mean and Standard Deviations of clean and Noisy Image

Figure 7 shows some results from an image enhanced by Perona-Malik anisotropic diffusion model and results from an image corrupted with with gaussian noise. There is a significant difference in both the results. Tumor extracted from a noisy image marks various portions of the MR slice which even contain the normal tissues. The results obtained from enhanced image and the clean image are almost similar. The accuracy of

the proposed method can be deduced from Figure 8 in which mean and standard deviations of MR image in various combinations is shown. Due to very less amount of noise, mean and standard deviations plotted in Figure 8 (d) shows almost the same range.

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6. REFERENCES

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