WATERSHED OVER-SEGMENTATION MINIMIZATION IN BRAIN TUMOR DETECTION

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ABSTRACT— *Medical image processing is an emanating and most challenging field nowadays. Segmentation of an image is one of the most important techniques in digital image processing. It separates different regions in an image and thus allows for removing unwanted areas along with enhancing features of interest. Segmentation of MRI of brain regions is a challenging task. This paper investigates a pre-processing centric approach to segment the tumor region using watershed algorithm in an MRI image. Image enhancement and noise reduction techniques are used in pre-processing to enhance the quality of image. Focus lies on the effects of altering pre-processing stages to avoid over-segmentation, a usual limitation of watershed algorithms. The algorithm is geared towards successful extraction of the tumor region without any over-segmentation and tested on axial, sagittal and coronal slices of human brain image. The results exhibit an intriguing variety of numbers when studying the distribution of information within an image and help tune the overall performance of the process*.

Keywords— brain, filtering, image processing, MRI, segmentation, tumor, watershed

I- INTRODUCTION

Segmentation of an image using watershed algorithm leads to over-segmentation of the brain regions. Two techniques have been used in recent past along with watershed to avoid over-segmentation, but there still remains a difficulty in avoiding this problem completely.

Brain tumor should be detected accurately during early stages. The major concern of the researchers from past few decades is to provide a solution for curing brain tumors. Researchers have proposed different techniques for the segmentation of brain tumor in Magnetic Resonance Imaging (MRI) [1, 2]. Medical science is yet trying to find all the main causes of the tumors and then developing the methods to cure them before their development starts.

Segmentation is an important technique in image processing. It is needed to facilitate the manipulation and visualization of data with a computer. It improves the analysis of the image when there is no direct correlation between the image pixels and the type of tissues. It finds the boundaries between different regions in an image and removes unwanted regions. The development of an efficient segmentation technique has become an important area of research in medical image processing. In past few decades, brain MRI segmentation has enjoyed extensive research focus [3-5]. Figure 1 shows the rate of tumor diagnosis each year in some countries [4].

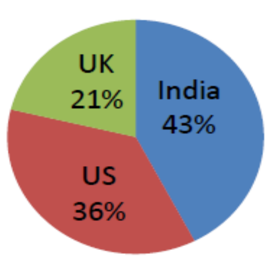

Figure 1-Rate of tumor diagnosis per year [4]

MRI is a high quality medical imaging, particularly used for the disease investigation of brain. Among all imaging techniques, MRI is most efficient for brain analysis. In most of the hospitals, the radiologists perform the diagnosis on MR images manually. This can be an error prone and time consuming process because large number of image slices of single patient have to be examined diligently. There are many image processing techniques for brain tumor detection using MRI. Some of these techniques are threshold detection, edge detection, region-growing, clustering, neural network, model based, and many other methods [5]. Every technique has its own advantages and disadvantages.

In Region growing, a seed point is to be selected. It is easy to implement but it is difficult to set growing criteria and stopping criteria [2]. Threshold detection depends on different intensity levels in an image but it is difficult to set a threshold value [1]. Clustering is an unsupervised method and it separates the different regions in the image but it needs human involvement in defining the seed points [5]. Edge detection is used to detect the boundaries in an image [1]. Model based method is applicable only if the exact shape of the objects in an image is known [1]. Neural network involves image segmentation and feature extraction [1, 5].

Watershed algorithms for segmenting medical images have gained lot of research interest in recent years [6, 7]. This is an efficient and cost effective approach for radiologists to get better and accurate results. However, the use of watershed technique for segmentation is limited in MRI because of over-segmentation. Watershed algorithm has been used along with high pass filter and median filter for segmenting the image [7]. Fig 2(a) shows input MRI and 2(b) shows over-segmentation of image when watershed algorithm was applied on input MRI.

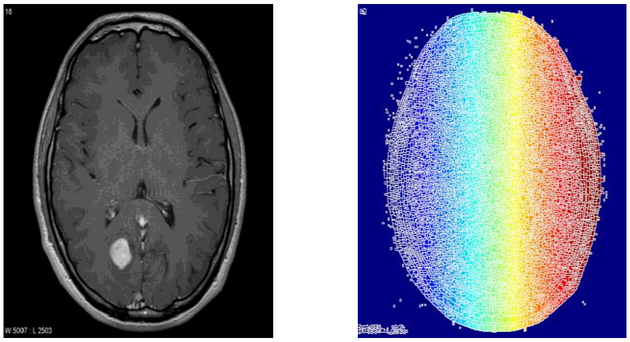

Figure 2-(a) input image (b) over-segmentation after applying watershed algorithm

To avoid over-segmentation, Marker Controlled method [6] or Meyer's Flooding method [7] along with watershed algorithm have been used in the recent past. In Marker Controlled method, segmentation works better if you can mark the background location along with foreground objects. In Meyer's Flooding method, set of markers are chosen where the flooding starts. This can be complex as well as a time consuming process.

Segmentation by watershed transform is a fast and robust method. It is simple instinctive method and it produces a complete division of image in separate regions even if the image has poor contrast. This paper proposes a simple strategy to avoid over-segmentation problem without going into complex methods. The pre-processing steps are developed in such a way that there is no over-segmentation when watershed algorithm is used.

The proposed study makes use of various filtering techniques at the pre-processing stage and investigates their impact on the whole algorithm. Input MRI is converted to grayscale followed by filtering. After filtering, Contrast Limited Adaptive Histogram Equalization (CLAHE) is performed and then threshold detection and watershed transform helps in segmenting the tumor regions. Performance of each filtering variation is probed to weigh down their pros and cons.

II- PROPOSED METHODOLOGY

The algorithm has three stages. First is the pre-processing of given MRI data. Second is threshold detection along with some morphological operations and finally the watershed algorithm for segmentation of brain MRI is performed. The flow chart of algorithm is shown in figure 3.

The explanation of the above steps is given below.

A- Grayscale conversion

Grayscale conversion is done to make further processing easier. Grayscale image has the range of different shades of gray without apparent color. The darkest possible shade is black and lightest possible shade is white.

B- Filtering

In image processing, filtering is important and it is used to achieve many things like interpolation, noise reduction, sampling, etc. The choice of filter depends on the nature of the task and the behavior of the data we are dealing with. In cases where the image contains a small amount of noise but high magnitude, a median filter may be suitable. If the image has a large amount of noise but low magnitude, then a

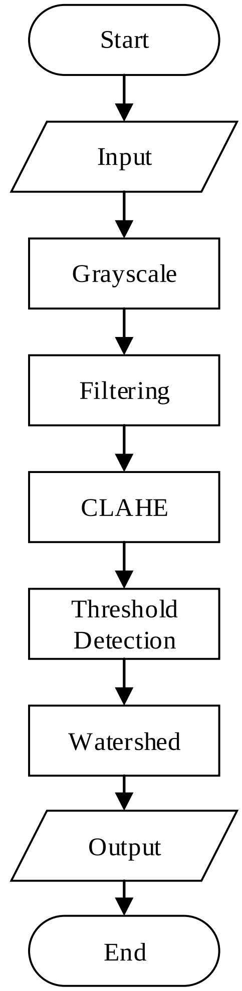

Figure 3-Flow Chart of Algorithm

low pass filter may be more appropriate. In either case, overall frequency content of the image is changed after filtering is done. Different pre-processing filters like high pass filter, sobel filter, median filter, low pass filter, etc were tested on grayscale images and the results were compared on the basis of entropy, standard deviation, homogeneity correlation and other factors.

For HPF, the entropy is decreased to 4.6, that means the original image has lost some information because the entropy of original image after grayscale conversion came out to be near 5. If the entropy is more, then image has more information. So, in this case the higher value of entropy is desirable. The entropy of sobel filter is also decreased, it is 2.6. The entropy of median filter and LPF is greater as compared to HPF and SF. LPF has maximum entropy among all other filters mentioned before. The entropy of LPF is 5.04 and MF has entropy of 4.96. So, LPF is suitable in this case because maximum entropy is desirable. The standard deviation is generally a measure of spread. A high value of SD shows that the data is widely spread and low value of SD shows that data is clustered closely. LPF has maximum value of SD as compared to other filters. HPF and SF have low values of SD. A high value of homogeneity shows rich gray level contents in the image. Both MF and LPF have almost same value of homogeneity correlation.

Table 1-Comparsion of different filters

IMAGE	ENTROPY	SD	[HOMOGEINETY] [CORRELATION]
HPF	4.62	28.27	[0.95 0.95] [0.90 0.88]
SF	2.60	20.84	[0.94 0.96] [0.58 0.78]
MF	4.96	44.28	[0.95 0.94] [0.95 0.94]
LPF	5.04	44.87	[0.95 0.94] [0.95 0.95]

The histograms of these filters were also compared. The histogram of HPF shows that some information is lost. Histogram of SF shows that a lot of information is lost. Histograms of MF and LPF show that no information is lost. The results were also compared after applying watershed to these filters and it was observed that HPF and SF are not appropriate for this approach. So, a low pass filter should be chosen among high pass filter, sobel filter and median filter. Figure 4 shows histograms of different filters.

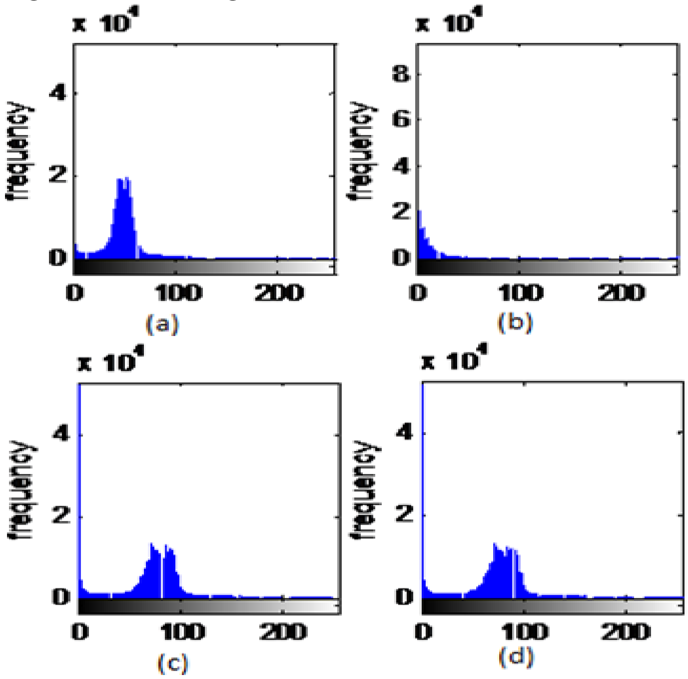

Figure 2-Histogram comparison of different filters (a) HPF (b) SF (c) MF (d) LPF

C- CLAHE

In order to enhance the contrast of the image, CLAHE is used. It works in such a way that image is divided into small tiles and then CLAHE is applied on each tile separately. A clip limit is chosen and histogram above that limit is clipped. Then the neighboring tiles are combined using bilinear interpolation in order to eliminate artificially induced boundaries. It makes hidden features of the image more visible. Figure 5 shows histogram of the image when CLAHE is performed.

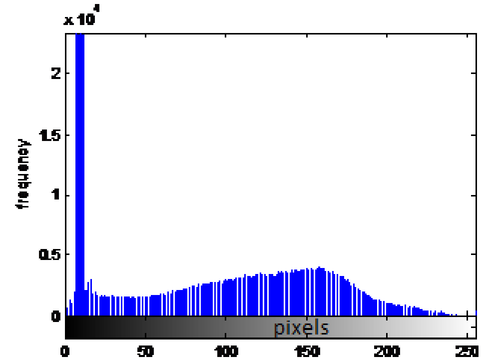

Figure 3-histogram of CLAHE

D- Threshold detection

Threshold detection is used to convert grayscale image to binary image. This technique works in such a way that a specific threshold value is chosen. We have chosen threshold value of 128 because it yields best background elimination of unwanted regions of interest. All pixels above 128 were converted to white levels and all pixels below 128 were converted to black levels. The value of white pixels is 1 and value of black pixels is 0. Figure 6 shows result of threshold detection performed on the image. 6(a) shows MRI slice after using CLAHE and then threshold detection is performed as shown in 6(b).

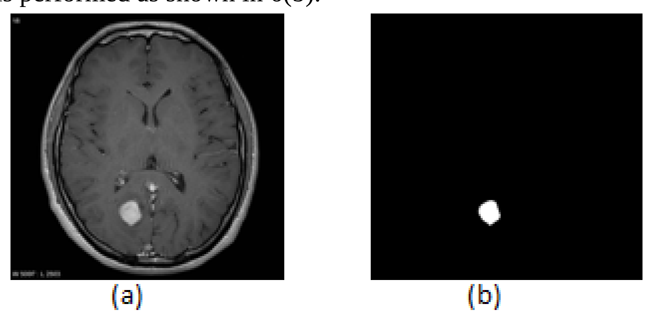

Figure 4- (a) brain MRI (b) threshold detection

E- Watershed segmentation

Finally the watershed segmentation is applied on the image after threshold detection. As there is no over-segmentation observed, so we have achieved the results using simple watershed segmentation technique. First the gradient magnitude is calculated then watershed is applied on gradient magnitude to detect the tumor. Fig 7(b) shows result when gradient magnitude is applied on 7(a).

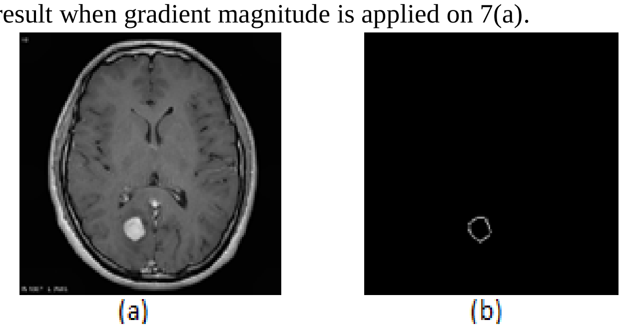

Figure 5-(a) brain MRI (b) gradient magnitude

III- RESULTS

Following are the results achieved after applying watershed algorithm. Results show that only low pass filter and median filter are suitable for detecting tumor using watershed algorithm. Fig 8(a) shows input MRI of brain, in 8(b) results of threshold detection are shown, 8(c) shows result of watershed segmentation and in 8(d) detection of tumor is shown.

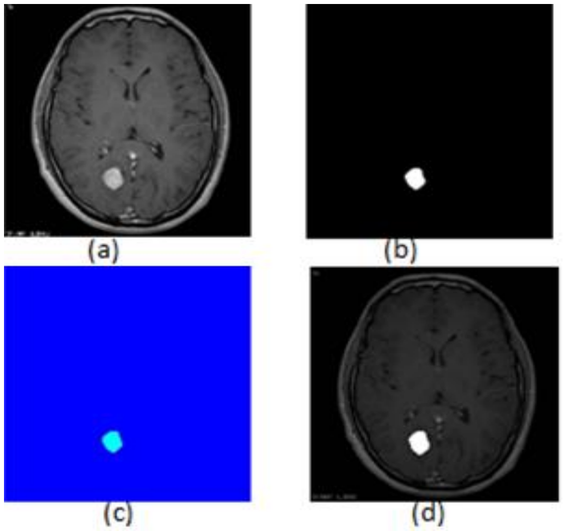

Figure 8-(a) input axial slice (b) threshold detection applied on axial slice (c) watershed transform (d) tumor detected in axial slice

Fig 9 shows the results of sagittal and coronal MRI slices. By using low pass filter with watershed, the algorithm helped in meticulous detection of tumor in different MRI slices of brain. 9(a) shows input sagittal slice and in 9(b) tumor is detected in sagittal slice. 9(d) shows detection of tumor after applying algorithm on coronal slice shown in 9(c).

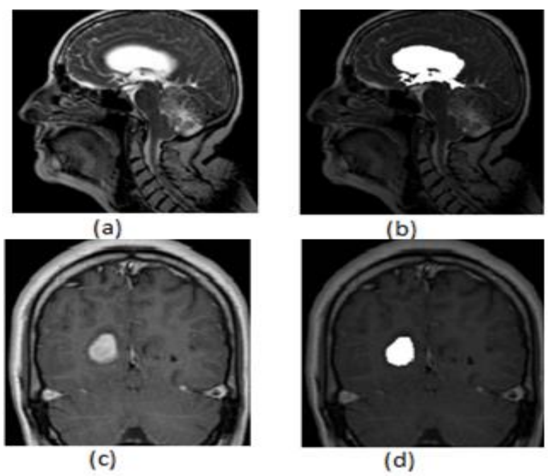

Figure 9 (a) input sagittal slice (b) tumor extracted in sagittal slice (c) input coronal slice (d) tumor extracted in coronal slice

Difference images of these filters were also compared and observed. High pass filter could not help in precise detection of tumor as it could only detect small area of tumor as shown in fig 10(a) whereas LPF helped in detecting complete tumor area as shown in 10(d). MF 10(c) can also be used here but LPF detects tumor more accurately as compared to that. Sobel filter leads to over-segmentation as shown in 10(b). So, LPF should be used here while detecting tumor using watershed algorithm. Figure 10 shows the comparison of different filters after applying watershed segmentation.

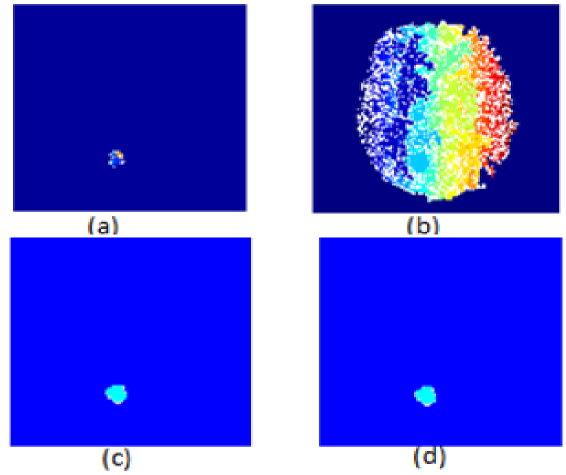

Figure 10-Comparsion of different filters after watershed (a) HPF (b) SF (c) MF (d) LPF

Figure 11 shows comparison of HPF and LPF in detection of tumor using watershed. It can be seen that HPF was not effective in accurate detection of tumor as shown in 11(a), whereas a LPF applied in 11(b) results in a more elaborate segmentation of the tumor region, 11(c) shows the difference image of LPF and HPF, exhibiting the tumor region missed by latter.

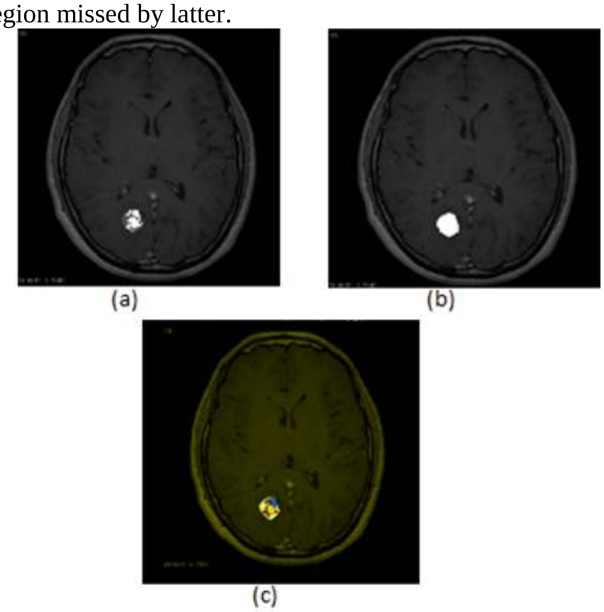

Figure 11-(a) HPF (b) LPF (c) difference image of LPF and HPF

Figure 12 shows tumor detected in axial slices using different filters. Again the LPF outperforms all other filters at the segmentation stage.

IV- CONCLUSION AND FUTURE WORK

The proposed algorithm was applied on number of datasets and better results were achieved employing the LPF in all the cases. The results also show that the major problem of over-segmentation in watershed algorithm can be minimized by planning the pre-processing steps intelligently. Figure 13 shows that the problem of over-segmentation is minimized completely by using watershed in conjunction with a low pass filter.

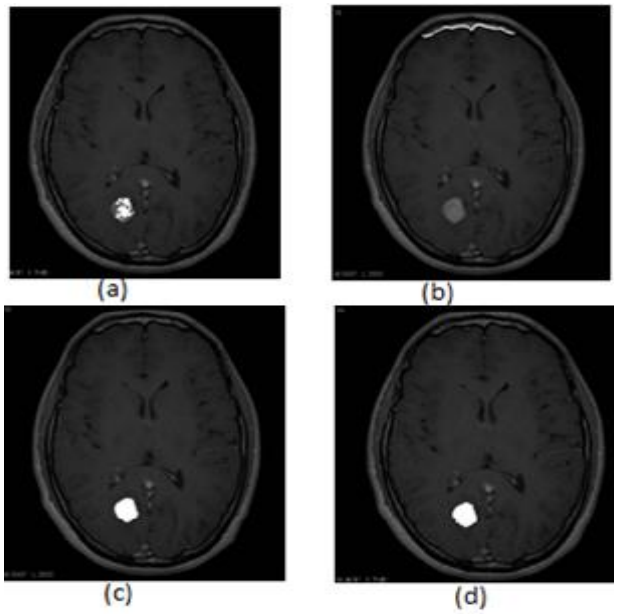

Figure 12-Tumor detection using (a) HPF (b) SF (c) MF (d) LPF

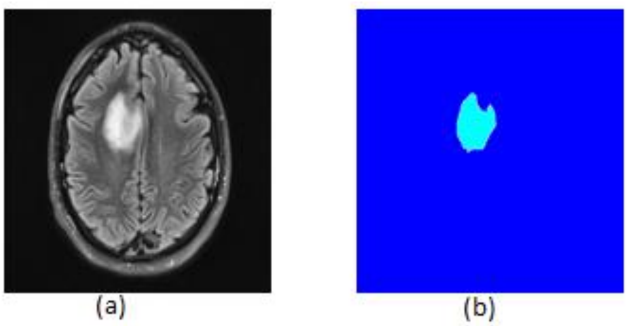

Figure 13-(a) input slice (b) over-segmentation minimized

The proposed algorithm demonstrates an effective approach for segmenting the brain tumors of 2D MR images. Future work can encompass 3D images by taking multiple slices as an input and visualizing the results in 3D. Also, the location and volume of tumor can be calculated to further elaborate the scope of the disease.

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