Enhanced Brain Tumor Detection using Segmentation based on Discrete Wavelet Transform

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Abstract- Digital Image Processing is rapidly growing and demanding research domain in the field of Medicine. Internal state of organs can be described significantly with help of MRI images. They denote the infected region along with the healthy one. The process of dividing the infected region from the MRI image is known as Digital Image Segmentation. It is important to classify the infected region correctly because the raw form of the MRI image may contain unwanted noise which can lead to unsuccessful treatment. This paper presents a technique for de-noising the image to get better results after segmentation. To de-noise the image effectively, it is necessary to have the higher level details of image which can be easily obtained by the application of Discrete Wavelet Transform. After processing the results of DWT, we get the preprocessed image that is sharpened. Further, for segmentation purpose, various methods can be applied.

Keywords- Segmentation, discrete wavelet transform(DWT), enhancement, magnetic resonance imaging, preprocessing.

1. INTRODUCTION

Brain is the vital organ of human body. If it gets infected by the disease like tumor, it becomes a serious issue. Based upon some of the basic factors like patients age, location of tumor, its size, and the type of tumor, the medication and treatment is decided. To detect the Tumor, technology of Magnetic Resonance Imaging is used. MRI technique is used to generate the MRI images that help the doctor to visualize the condition of the brain. Tumor region (known as white matter and has whitish shade) can be distinguished from the healthy region (known as Gray Matter and has darker shade than tumor region). If the tumor region is detected manually, there exists the possibility of some human errors. Hence, segmentation methods are being researched and developed in Medical Image Processing.

For the determination of Tumor in MRI image with greater efficiency and accuracy, either the image can be segmented with robust and elegant segmentation algorithm with less focus on enhancement, or the image can be enhanced in a robust manner and the segmentation algorithm can be applied. This paper is concerned about the enhancement of the MRI image, so that the Tumor region is distinguished by any segmentation algorithm with greater efficiency.

Enhancement of MRI images can be done in several ways. Paper [13] gives a review about most of the popular enhancement or the denoising methods. One of the methods is the enhancement of Resolution of the MRI image. No doubt, when this method is applied, the resolution of original image gets enhanced, but it makes the algorithm computationally complex. This paper gives information about one more interesting method known as Normalization. Normalization is pretty effective and fast method that can be used for enhancement as well as segmentation. But as it contains several mathematical computations, the implementation requires more time. Normalization involves modification of intensity values of pixel. Hence, in several cases, it can be found that Normalization results in poor contrast.

Papers [14] and [18] discuss the Histogram approach for the enhancement. This method specifically focuses on the improvisation of sharpness and the feature details so that the process of extraction of information becomes easier. According to [14], if sharpening or histogram stretching is done manually on trial and error basis, more time is required. Hence, an algorithm called Adaptive Histogram Equalization is presented in [18] which is more effective than the one in [14].

Morphological approach is discussed in [16]. This approach suggests the use of morphological filters that are to be applied on each pixel to get the transformed image that is enhanced. These approaches definitely works for most of the MRI images effectively, but as the amount of calculations are more, the overall speed of algorithm is slow and hence time required for enhancement is more.

We have used a simple Wavelet based approach. Our main objective is to get an image in which the contrast of image is enhanced in such a way that the tumor part and non-tumor part easily gets distinguished i.e. the lighter shade of tumor part gets more whitish color and the dark shade of non-tumor part gets darker. Due to this, the result of segmentation becomes more robust.

The rest of this paper is ordered as follows: Section 2 discusses related literature of Image Segmentation Techniques. Section 3 provides the Methodology. Section 4 shows the Experimental results and Analysis based on the Methodology proposed in Section 3. Section 5 discusses the Concluding remarks along with the possible modification.

2. RELATED LITERATURE

It is known that the raw image contains noise. Segmentation algorithms should be applied only after reducing the noise i.e. pre-processing. The methods of denoising and segmentation for MRI images are developed by many researchers. Some of the simple methods of segmentation are Fuzzy C-Means, Watershed segmentation, Region Growing method, Canny Segmentation (this is an algorithm for edge detection), Thresholding, Soft Computing based segmentation, Probabilistic Neural Network approach, Morphological Image Processing, etc. The most commonly used method is Thresholding because it is the simplest. Segmentation algorithms work efficiently if and only if the image is clear enough to interpret. For proper segmentation, the details of image must be very clear. For this, the image should have less noise i.e. the image must be sharpened. For the sharpening or noise reduction, the commonly used procedures are Histogram stretching, Fast Fourier Transform, Walsh-Hadamard Transform, Discrete Cosine Transform (DCT), Haar Transform, Wavelet Transform, etc. According to the paper [1] by Gurmeet Kaur and Rupinder Kaur, Noise can be reduced by application of various filters like Gaussian Filter, Wiener Filter, Average Filter and the Wavelet Transform. Most of the methods that are used for sharpening the image make use of a High Pass Filter. Some of the papers that give an idea about the pre-processing and segmentation are mentioned below:

Combination of Probabilistic Neural Network and DCT is suggested by authors D. Shridhar and Murali Krishna in [5]. They have used DCT for preprocessing and dimensionality reduction. The results were satisfactory, but more accuracy could be obtained if DWT was used instead of DCT[21].

Morphological approach is used by Amlan Jyoti, Pradeep Kumar Mallick and Mihir Marayan Mohanty in [7]. After cleansing/preprocessing, the author suggests to use the smoothing filters like Butterworth Filter, Bessel Filter, Chebyshev Filter and Gaussian Filter according to the requirement of Image.

Authors Logeswari and M. Karnan [4] have used the Soft Computing approach. They have used the Self Organizing Feature Map. This is an example of ANN for the unsupervised learning. SOM operates in two modes: Training (Vector Quantization) and Mapping. It works in similar way like the perceptrons in the Neural Network.

According to Aung Soe Khaing and Swe Zin Oo in [10], a gradient based segmentation technique known as Watershed Technique can be used for segmentation. Authors of this paper have combined the Watershed Segmentation Technique with the Morphological Segmentation Technique. In Watershed method, the concept explained is, the image can be compared with the dams in real life. The gradient map of the image is considered as dam. The regions that are segmented are known as catchment basins. Edge of dam separating two regions is to be defined. For this, Sobel operator is used. As this technique separates any image based on different intensity proportions. As the Tumor cells have high intensity in comparison with non-tumor part, Watershed method can prove to be effective method for segmentation.

3. METHODOLOGY

The procedure followed in this paper is subject to two phases, namely, image pre-processing (Noise Reduction Phase) and image-segmentation (Segmentation Phase).

3.1. *Image processing*

To acquire better segmentation results, the image needs to be pre-processed. Firstly, it is ensured that the MRI image that is to be operated is in grayscale. If image is not in grayscale, it must be converted to gray scale. For the analysis of the performance of our algorithm, it was necessary to compare it with other methods. We did choose FFT for the comparison. We pre-processed the image with FFT before using DWT. After pre-processing with FFT, the performance evaluation was done. For evaluation, the metrics that we considered are Mean, Standard Deviation, Structural Similarity Index (SSIM) and Entropy. After the application of FFT and its performance evaluation, the algorithm specified in this paper is to be applied.

The block diagram of the propounded method is shown in Fig. 1.

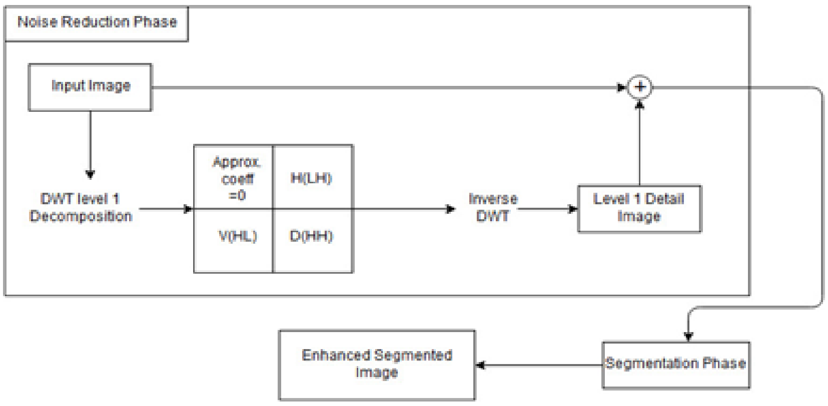


Fig. 1. The Proposed Method

The blocks in the diagram are briefly described below:

(1) Original i.e. the input image is subjected to the application of DWT.
(2) 4 sub-bands are formed after the first level of decomposition. They are HH, HL, LH and LL. LL contains the low level details whereas the remaining sub-bands contain the high level details.Now the image half processed image needs to be reconstructed. For so, set the approximation coefficient in LL image to 0. Then simply apply the IDWT in order to obtain the high pass image from HH, LH and HL sub-band. The result of this step is the Level 1 Detail Image
(3) Now, add the result of Step 3 to the original image. After the addition, a sharpened image is obtained.
(4) Apply the Segmentation in order to get the enhanced segmented image.

3.2. *Fast fourier transform*

FFT is extensively used to analyze sounds as well as images. In case of images, FFT can be used for reducing blurry effect and noise. In this paper, FFT is used for the sharpening of image for segmentation phase. In this process, initially, the FFT is applied on the original image and the corresponding Fourier Spectrum is obtained. The inverse FFT (IFFT) is applied on this spectrum to get a sharpened image. According to the traditional practice, the output of inverse FFT is to be added to the initial (original) image to obtain the pre-processed image. Instead of adding, we have multiplied the IFFT result to original image so that the tumor features can easily be easily distinguished because of the contrast difference between tumor and non-tumor regions. But the size of transformed image after multiplication is larger than the original image. Hence it needs to be resized to the original dimensions before passing it to the segmentation phase. After the successful pre-processing, the image is subjected to the segmentation phase.

3.3. *Discrete wavelet transform*

Discrete Wavelet Transform is mainly used for coding a signal or data compression. Hence the applications of DWT are found in digital communications, signal processing as well as image processing. DWT is highly efficient in decomposing the signals. When it comes to Image Processing, we either process the Frequency information or the Spatial information and cannot process both at same time. This statement is analogous to the Heisenberg's Uncertainty Principle. But the Discrete Wavelet Transform provisions to process the Spatial and Frequency information at single instant. This is the reason why DWT gives better results than any traditional method for image pre-processing. The DWT makes use of Fourier Transform, Low Pass Filter (Smoothing Filter) and the High Pass Filter (Sharpening Filter).

DWT breaks the image in 4 sub-sampled or decimated images as shown in Fig. 2. They can be described as follows:

(1) LL - Obtained by the application of low-pass filter in vertical as well as horizontal directions.
(2) HL – Obtained by the application of low-pass filter in the horizontal direction and high-pass filter in vertical direction.
(3) LH – Obtained by application of high-pass filter in horizontal direction and low-pass filter in the vertical direction.
(4) HH - Obtained by the application of high-pass filter in both the directions.

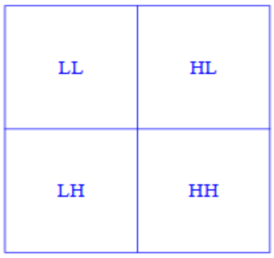


Fig. 2. Four sub-sampled image of DWT

For greater details, the sub-sampled image can be sub-sampled multiple times. The scheme in which the image is decomposed multiple times is known as multi-scale representation or multi-resolution scheme.
Algorithm of Discrete Wavelet Transform:
Step 1 - Convolve low pass filter with rows and save the results.
Step 2 - Convolve low pass filter with columns of the results of Step 1 and sub-sample this result by taking every other value. This gives the Low pass – Low pass (LL) version of image.
Step 3 - Convolve the result from Step 1, the low pass filtered rows, with the high pass filter on the columns. Sub-sample by taking every other value to produce low pass - high pass (LH) version of image and is known as the Horizontal Component of the result.
Step 4 - Convolve the original image with high pass filter on the rows and save the result.
Step 5 - Convolve the result of Step 4 with low pass filter on columns and then sub-sample to form the high pass – low pass (HL) version of the image which is known as the Vertical Component of the result.
Step 6 - In order to obtain the high pass - high pass (HH) version of the image which is the Diagonal Component, convolve the columns of result from Step 4 with the high pass filter.
Mathematically, Discrete Wavelet Transform can be expressed as follows:

$$W(j,k) = (M)^{-1/2} \sum_{x=0}^{M-1} f(x) \cdot \phi_{j,k}(x) \qquad (1)$$

In equation (1), f(x) and $\varphi_{j,k}(x)$ represent the functions of discrete variables 'x' and x = 0, 1, 2, …(M-1). This equation is used for the calculation of approximation coefficients.

$$W_{\psi}(j,k) = (M)^{-1/2} \sum_{x=0}^{M-1} f(x)\ .\ \psi_{j,k}(x) \qquad (2)$$

In equation (2), j' >= j. f(x) and $\psi_{j',k}(x)$ represent the functions of discrete variables. This equation is used for the calculation of detail coefficients.
The size of sub-sampled image is always less than the original one. Inverse Discrete Wavelet Transform is used to reconstruct the image dimensions which later match with the dimensions of the original image.

3.4. *Segmentation*

Segmentation methods are classified on the basis of Similarity or Discontinuity. Segmentation methods discussed in this paper are based on the discontinuity approach. There are several methods for segmentation available. We have used two simple methods of segmentation as mentioned below:

3.4.1 *Auto single threshold(AST)*

Output of this method is always a binary image. In the single threshold method, the threshold value is chosen manually by inspecting the histogram of image. Auto Single Thresholding method doesn't need manual inspection. It automates the process. AST algorithm chooses the average gray-level value of image as threshold. Then after applying this threshold, the image gets divided in two halves. The same process is applied on each halves until a threshold value is obtained that does not change further. At the end, when the final threshold value is obtained, it is applied on the pre-processed to get binary segmented image as result.

3.4.2 *Fuzzy C-means(FCM)*

FCM is an efficient method for the formation of clusters as one data point can constitute its existence to more than one clusters at same time. This method is mostly used in the pattern recognition. To apply this algorithm, a cost function or the objective function is applied on the image and then it is subjected to minimization. Using this method, the pixels are assigned to each category by making use of fuzzy membership function. The algorithm works in iterative basis.

4. EXPERIMENTAL RESULT AND ANALYSIS

As mentioned in Section 3, grayscale image is used for the experimentation. This section is organized as follows: Section 4.1 and Section 4.2 depicts the results of FFT, Section 4.3 and Section 4.4 shows the results of DWT, Section 4.5 shows the analysis of the experimental results.

4.1. *Preprocessing using FFT*

Following images represent the stepwise formation of the final pre-processed image using Fast Fourier Transform. Fig. 4-a represents the original image. FFT with block size 8 is applied on original Fig. to obtain the result shown in Fig. 3(b). As shown in Fig. 3(c), the inverse FFT is applied on Fig. 3(b) and reconstructed image is obtained. It can be seen that Fig. 3(c) and Fig. 3(a) look analogous. Fig. 3(d) proves that they look similar but they are not. Fig. 3(e) and 3(f) represent the pre-processed images obtained my addition and multiplication of Fig. 3(c) with Fig. 3(a) respectively. Fig. 3(c) is enhanced but the region surrounding the tumor part seems to be bright. It would complicate the segmentation process. Hence, to get a good contrast difference in tumor and non tumor region, Fig. 3(c) is multiplied with Fig. 3(a) and Fig. 3(f) is obtained in which the tumor region can be distinguished effectively. So, it can be said that instead of adding the inverse of the transform to original image, multiplication operation should be performed.

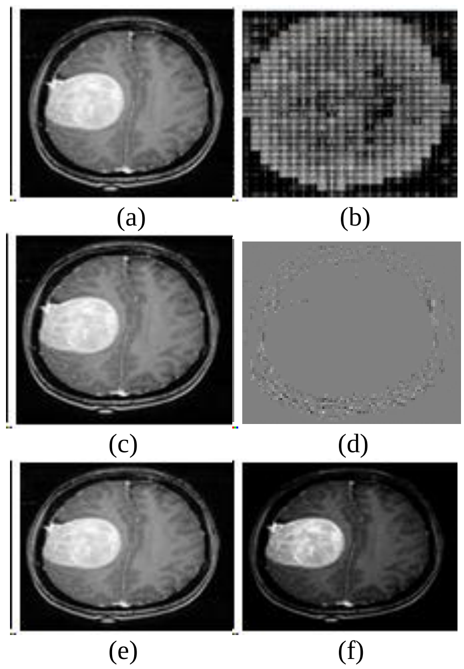
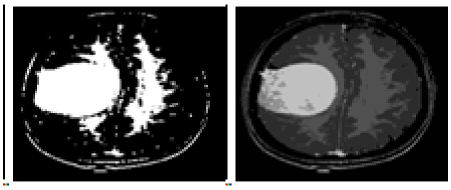


Fig. 3. Pre-processing using FFT: (a) Original image; (b) FFT(block size-8) of original image; (c) Inverse FFT of Fig. 3(b); (d) Subtraction of Fig. 3(a) from Fig. 3(c); (e) Addition of Fig. 3(a) and Fig. 3(c); (f) Pre-processed image obtained by multiplication of Fig. 3(a) and Fig. 3(c)

4.2. *Segmentation of FFT preprocessed image*

The image depicted in Fig. 3(f) is used for the segmentation. Fig. 4 shows the images that are segmented using Auto Single Thresholding method and Fuzzy C-Means method respectively.

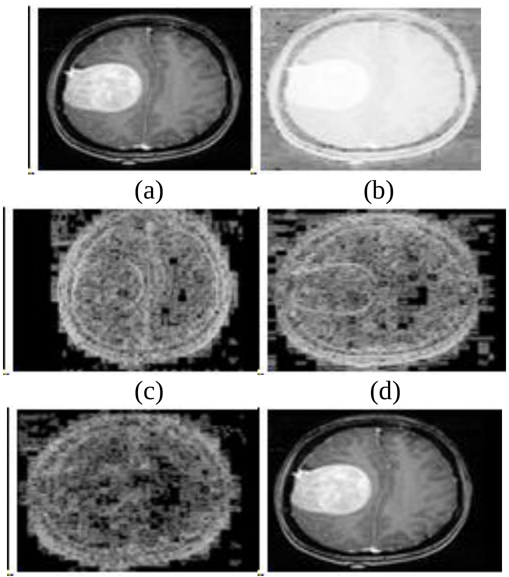


(a) (b)

Fig. 4. Segmentation results of FFT pre-processed images: (a) Segmentation of Fig. 3(f) using Auto Single Threshold Method; (b) Segmentation of Fig. 3(f) using FCM

4.3. *Preprocessing using DWT*

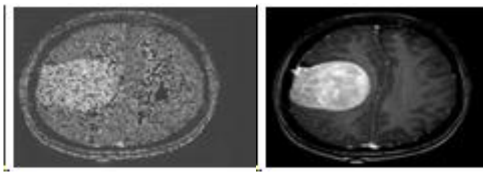
Following images represent the stepwise formation of the final pre-processed image using Discrete Wavelet Transform. Fig. 5(a) represents the initial (original) image. DWT with 1 level Decomposition is applied on original Fig. to obtain the result shown in Fig. 5(b), Fig. 5(c), Fig. 5(d) and Fig. 5(e). These four Fig.s represent the LL, HL, LH and HH sub-bands of DWT. When these four figures are combined as shown in Fig. 2, the actual DWT image can be obtained. Inverse DWT is applied on the combination of Fig. 5(b), Fig. 5(c), Fig. 5(d) and Fig. 5(e) to obtain Fig. 5(f). Fig. 5(f) and Fig. 5(a) look alike but they are not the same. This can be seen in Fig. 5(g) where the original image is subtracted from result of Inverse DWT i.e. Fig. 5(f). The final pre-processed image is formed after multiplication of Fig. 5(f) and Fig. 5(a).



(a) (b)

(c) (d)

(e) (f)

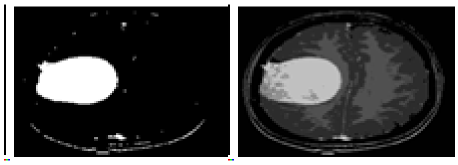


(g) (h)

Fig. 5. Pre-processing using DWT: (a) Original image; (b) LL sub-band of DWT; (c) HL sub-band of DWT; (d) LH sub-band of DWT; (e) HH sub-band of DWT; (f) Inverse DWT obtained from Fig. 5(b), Fig. 5(c), Fig. 5(d) and Fig. 5(e); (g) Subtraction of Fig. 5(a) from Fig. 5(b); (h) Pre-processed image obtained by multiplication of Fig. 5(f) and Fig. 5(a)

4.4. *Segmentation of DWT preprocessed image*

The image shown in Fig. 5(h) is used for the segmentation. Fig. 6 shows the images that are segmented using Auto Single Thresholding method and Fuzzy C-Means method respectively.



(a) (b)

Fig. 6. Segmentation results of DWT pre-processed images: (a) Segmentation of Fig. 5(h) using Auto Single Threshold Method; (b) Segmentation of Fig. 5(h) using FCM

4.5. *Analysis of results*

Following table describes the Original image(Fig. 5(a)), Pre-processed image obtained by applying Fast Fourier Transform (Figure 3(f)) and Pre-processed image obtained by application of Discrete Wavelet Transform (Figure 5(h)):

Table 1. Metrics for Fig. 5(a), Fig. 3(f) and Fig.6(h)

Image	**Mean**	**STD**	**SSIM**	**Entropy**
Original	76.293	69.446	1	4.924
FFT	39.686	53.633	0.2490	5.245
DWT	34.426	51.733	0.3553	4.716

4.5.1 *Mean*

It is simply the average of all the pixel values in an image and is denoted by greek letter 'μ'.

$$\mu = (x_0 + x_1 + \ldots + x_N) / N \quad (3)$$

In (3), x_i is the value of pixel at the index 'i' and N represents the number of pixels[20].

4.5.2 *Standard deviation*

It is the amount by which the individual pixel values deviate or differ from the mean of the image.

$$\sigma= ((x_0-\mu)^2 + (x_1-\mu)^2 + ... + (x_{N-1} -\mu)^2 / (N-1))^{1/2} \qquad (4)$$

In (4), x_i is the value of pixel at the index 'i' and N represents the number of pixels[20].

4.5.3 *Structural similarity index(SSIM)*

SSIM value indicates the similarity of structure of result image in comparison with the original image based upon three parameters namely the structure, contrast and luminance. The similarity index can be mathematically denoted as function of luminance (l), contrast (c) and structure (s) as mentioned below:

$$S(a, a') = f(l(a, a'), c(a, a'), s(a, a')) \qquad (5)$$

In (5), 'a' is the reconstructed image and x' is the reference image[7].
In this paper, the reference image is the original image (Figure 6-a). The similarity index ranges from 0 to 1. It can be clearly noticed that in the pre-processed images, non-tumor parts are darker than the original ones whereas the tumor parts are slightly light. Hence, when they are compared with the original image, the corresponding pixel values of pre-processed image differ from the original image. Hence, for the pre-processed images, SSIM is low. But still, DWT pre-processed image retains the original image more than the FFT pre-processed image.

4.5.4 *Entropy*

It statistically measures the randomness of pixel values and it can be used for characterization of the texture of the image. In simple words, it can be defined as the measure of 'disorder' in an image. If entropy value is more, then there is more disorder in the image. If disorder in the image is more, then the accuracy of segmentation is less. FFT and DWT definitely reduce the entropy of original image. But in their mutual comparison of entropy values, it can be seen that DWT is more effective than that of FFT as DWT has less entropy than the FFT. Mathematically, Entropy can be defined as,

$$Entropy = sum(p.*log2(p)) \qquad (6)$$

In (6), p contains the counts of normalized histogram [12].

5. CONCLUSION

This paper presents a simple strategy to reduce the noise of MRI image so that the results that we get after segmentation are better. As shown in the Experimental Results section, this pre-processing method is applicable with any segmentation algorithm. In future, this work can be extended to implementation of Curvlets so that the edges are enhanced. This may increase the efficiency of segmentation and yield better results.

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