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APPLICATION OF WAVELET TRANSFORM FOR THE DETECTION OF BRAIN TUMOR FROM MAGNETIC RESONANCE IMAGES

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Abstract: In medical image processing Segmentation of anatomical regions of brain is the fundamental problem. As the brain structure is very complex involving white matter (WM), gray matter (GM), and cerebrospinal fluid (CSF) this makes feature extraction of brain images as a basic work. Recently MR images are handled manually for the diagnosis of brain tumor which involves errors and consumed time as due to large variation of the various images indicating varied brain structure. Tumor segmentation from magnetic resonance (MR) images may aid in tumor treatment by tracking the progress of tumor growth and shrinkage. There are a number of techniques to segment an image into homogeneous regions. As the structure of MR image or any medical images is nonhomogeneous and complex, these techniques are not suitable for their analysis. In this report, a new approach for segmentation of MR images has been proposed by incorporating the advantages of the undecimated wavelet transform and Gabor wavelets. The proposed method worked on T1, T2 weighted images to produce an appreciative result though the image is noisy. Undecimated wavelet transform decomposed an image into four sub-bands (LL, LH, HL, HH). Original image get superimposed on detailed component of decomposed image. Gabor filters are then applied to the resultant image at that level to obtained characteristic features. Finally, the brain tumor is detected with area, centroid and bounding box parameters.

Keywords: Magnetic Resonance Imaging (MRI), Computed Tomography, UDWT, Gabor Wavelets, Segmentation

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INTRODUCTION

Brain tumor is very hazardous disease that may lead to death. In the field of medical engineering brain tumor segmentation and detection from MR images has been interesting area of research [1]. Most of the researchers from biomedical field have shown their interest to develop an

automatic brain tumor segmentation and detection system. Brain diseases and disorders have been commonly studied using magnetic resonance imaging (MRI) technique [4]. For automatic detection of brain tumors, Magnetic resonance Imaging provides better results than computed tomography (CT) since greater contrast between different soft tissues of human body has been provided MRI. Hence MRI widely used in detection of brain and cancerous tumors.

Automatic image segmentation is most important process in medical imaging for analyzing different types of pathological and healthy tissues. In MRI segmentation problem is to label voxels according to their tissue types which includes white matter (WM), grey matter (GM), cerebrospinal fluid (CSF) and pathological tissues (tumor), etc [3]. Radiologist can diagnose and find location of lesions based on visual diagnosis with help of available software. While performing visual diagnosis, error may be introduced in finding location of tumor. To remove this problem there is need to develop a computer based automatic technique for detecting tumor from brain MR images [4].

For different surgical evaluations, Fluid Attenuated Inversion Recovery (FLAIR) magnetic resonance images are most widely used from different kind of MR images. FLAIR images are widely used in study and analysis of brain maturation, acute hemorrhage and in diagnosis of intra cranial tumor, periventricular lesions, head injury, multiple sclerosis, etc. A FLAIR sequence produces heavily T2 weighted MR images in which cerebrospinal fluid does not appear. In FLAIR images, subtle lesions near CSF appear against a background of attenuated CSF which looks dark and lesions, tumors and edematous tissues looks bright [4].

Automated tumor segmentation becomes difficult since it is tedious job to create a pre designed model of expected size, shape, location or image intensity [3]. Brain tumors are of different sizes, locations and positions. They also have overlapping intensities with normal tissues [3].

Accurate brain tissue segmentation and detection is a very vital issue for the diagnosis of brain tumors and study of brain diseases. Brain tumor detection is a time consuming process since tumor location and size is manually detected by expert because of which, it is more prone to human errors. Therefore, it is necessary to develop fully automated brain tumor segmentation and detection tools [2].

There are some techniques available such as classical, fuzzy, neural network, etc. for automatic brain tumor segmentation and detections. Classical techniques uses thresholding (part below threshold becomes bright otherwise dark), edge and region based methods which are known as standard image processing. In region based technique the region with similar pixel values are extracted. The brain tumor from MR images consist of similar pixel values. The edges consist of high frequency information of an image. Due to the lack of information, final segmentation using classical methods are highly sensitive to noise and usually do not result in continuous regions. Fuzzy segmentation technique applied for multichannel images but not for single channel images. Neural network techniques are applied only for some types of images [3].

Entire work is around the automatic brain tumor detection from MR images using wavelet transform. Wavelet transform can provide multi resolution approach. Multiscale image analysis and image segmentation provide an indication of where visually sensible objects in an image are located and also information about their relative size or interest. In this work undecimated wavelet transform is applied to an input MR image. Wavelet has property to decompose an image into 4 sub images each having sub-frequency bands. Wavelet can study each component with a resolution matched to its scale. In this case it study decomposed images. Gabor filter is then applied to resultant image. Region based segmentation is possible using multichannel filtering technique. Local parameters of each suspicious region called patch or the blob of resultant Gabor filtered image is calculated. Area, perimeter, height, length etc. are local parameters. Area of the brain tumor image is most vital parameter among all parameters. Algorithm works on an area parameter of each blob. It selects 3 major area regions from each patch or blob. It checks for area value with bounded range. If founded in the range, algorithm checks vertical height and horizontal length with bounded range. Finally evaluate the area value and location value (x, y), else skip the process. If MR image of the brain tumor consist of brain tumor then tumor part is efficiently detected with area value and location of the tumor otherwise area value is not calculated in the absence of tumor.

2. SYSTEM DEVELOPMENT

Brain tumor detection and segmentation in magnetic resonance images is important in medical diagnosis because it provide information associated to anatomical structures as well as potential abnormal tissues necessary to treatment planning and patient follow-up. The segmentation of brain tumors can also be helpful for general modeling of pathological brains and the construction of pathological brain atlases. Segmentation and characterization of abnormalities are still a challenging and difficult task because of the variety of the possible shapes, locations and image intensities of various types of tumors. Existing methods leave significant platform for increased automation, applicability and accuracy. [5]

The general characteristics of tumors which make it difficult to segment the tumor from the surrounding brain tissue. Brain tumors vary greatly in size and position. They may have uncertain intensities with normal tissue. Some time original tumor size may vary that they show up in MRI. They may enhance completely, partially or not at all with contrast agent. Tumor may be accompanied by surrounding edema, which is a swelling of normal tissue surrounding the tumor, and which changes the tissue properties in that area. The amount and regional extent of edema that accompanies a tumor is variable. Because of the large number of MR scans in a single brain, the segmentation and detection should be automated and should be done in a reasonable amount of time.

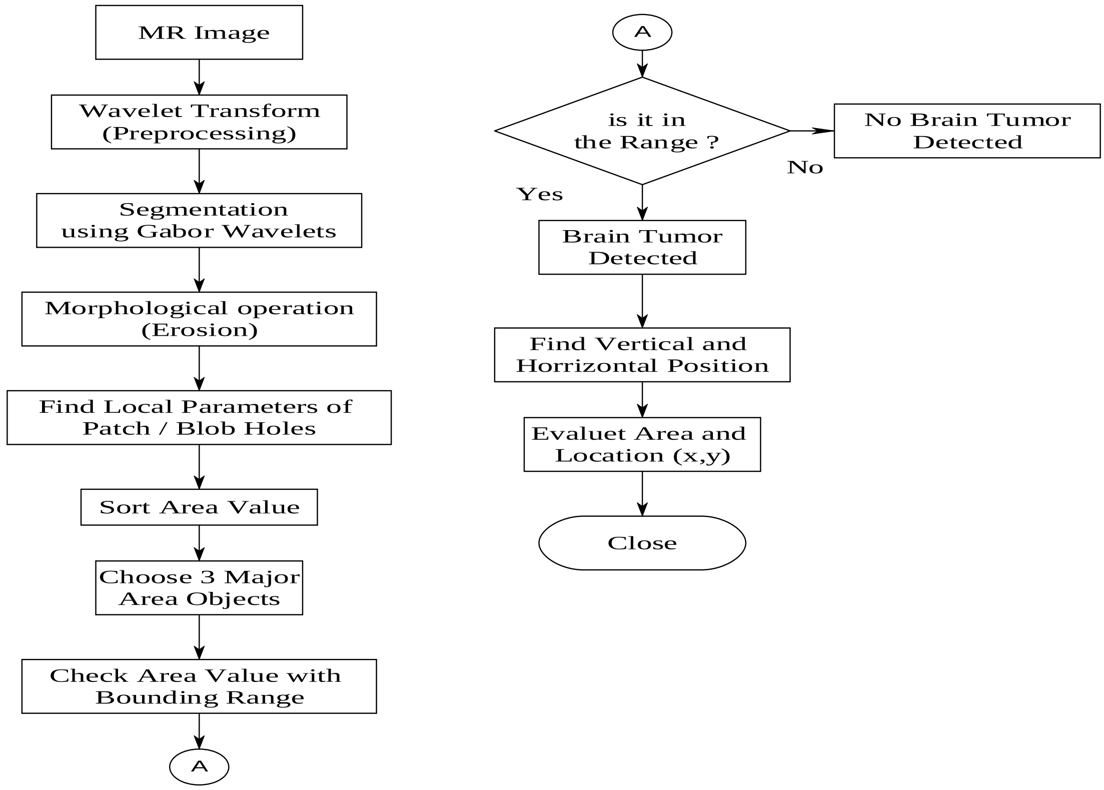

Figure 2.1 flow chart of automatic brain tumor detection using wavelet transform

MR image is required as an input to the proposed system. Different kinds of MRI images are present such as T1 weighted, T2 Weighted, FLAIR MR Image, etc. Preprocessing is the first step of the automatic brain tumor detection. Here preprocessing is done with the help of undecimated wavelet transform. The edges of the MRI images are not so sharp. Preprocessing can make the MR image sharp. The wavelet transform can decomposed an image into the 4 sub images (one approximation and three detailed components). These images are of different frequency sub-bands. Original MR image edges can be make sharp by adding all the detained components of the decomposed image. All the detailed components have the information of high frequency and hence the edges. Preprocessing can enhance the MR image. Next process is image segmentation. Segmentation is done by applying Gabor filter to the enhanced image. Gabor filter generally filter out dc components from image. In image processing Gabor filter is a linear filter used for edge detection. Frequency and orientation representations of Gabor filters are similar to those of the human visual system, and they have been found to be particularly appropriate for texture representation and discrimination. It filters out dc components of an image showing only the edges in the brain MR images. Now apply morphological operation such as erosion. Then algorithm finds local parameters such as area, centroid, perimeter, bounding box. It works on area parameter of the blob to sort area values. From number of area regions 3 major area regions can be selected in descending order. If the area region found in the bounded range then the tumor is detected and area, location (x, y) values and boundingbox parameters can be calculated. Otherwise tumor not detected.

2.2 Wavelet Transform

Wavelets are mathematical functions that cut up data into different frequency components, and then study each component with a resolution matched to its scale. They have advantages over traditional Fourier methods in analyzing physical situations where the signal contains discontinuities and sharp spikes. During the last ten years have led to many new wavelet applications such as image compression, turbulence, human vision, radar, and earthquake prediction. Wavelet analysis was developed to perform signal analysis in the time-frequency domain. Prior to the development of wavelet theory, signals were commonly analyzed within the frequency domain using the Fourier transform (FT). Fourier analysis uses waves (sinusoids) as deterministic basis functions for the expansion of functions (signals) that are assumed to be time invariant or stationary. In reality most naturally occurring signals, of which images are an example, cannot be considered stationary. Therefore, assuming stationarity and performing analysis in only the frequency domain has serious limitations. So even though the FT gives an accurate representation of the frequency content of a signal, it cannot offer both the time and frequency localization necessary for most naturally occurring (non-stationary) signals [9].

Consider a real or complex-value continuous-time function $\psi(t)$with the following properties:

1. The function integrates to zero:

$$\int_{-\infty}^{\infty} \psi(t)dt = 0 \qquad (1)$$

2. It is square integral or, equivalently, has finite energy:

$$\int_{-\infty}^{\infty} |\psi(t)|^2 dt < \infty \qquad (2)$$

The function $\psi(t)$is a mother wavelet or wavelet if it satisfies these two properties as well as the admissibility condition.

2.3 Undecimated wavelet transform

Multiscale image analysis and image segmentation provide an indication of where visually sensible objects in an image are located and also information about their relative size or importance [3]. With this information, it is possible to perform quantitative measurements of object properties such as size, shape, position, and orientation, and to accomplish higher level vision tasks such as object recognition [3]. Wavelets are mathematical functions that decompose data into different frequency components and then study each component with a resolution matched to its scale. The wavelet analysis decomposes a signal into a hierarchy of scales ranging from the coarsest scale to the finest scale. Hence, the wavelet transform, is a better tool for feature extraction from images. [3]

There are several possible modifications of the DWT each corresponding to a different choice of basis. One such simple modification is the Stationary Wavelet Transform (SWT) also known as Undecimated or Redundant or Translation Invariant transform that no longer depends on the origin. The absence of a decimator leads to a redundant input signal representation. This makes a denser approximation to the continuous wavelet transform than that of the DWT. One level UDWT is shown in figure 3.2.

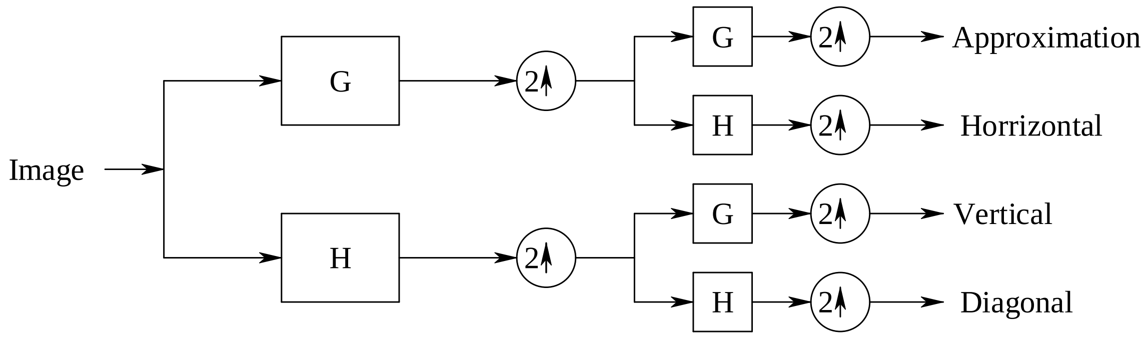

Figure 3.2 Undecimated Wavelet Transform - one level decomposition

Where G and H are H are low pass and high pass filter banks respectively. The basic idea of UDWT is simply to apply appropriate low and high pass filters to that data at each level to produce two sequences to the next level. The resultants are not decimated and two new sequences have the same length as the original sequence. The multi resolution is achieved by modifying (up sampling) the filter at each level. [3]

2.4 Gabor Wavelets

For the efficient segmentation of the tumor mass from the MRI images, a multi-channel filtering approach of texture analysis is required. This approach is inspired by a multi-channel filtering theory for processing visual information in the early stages of the human visual system. According to this theory, the human visual system decomposes the retinal image into a number of filtered images, each of which contains intensity variations over a narrow range of frequency (size) and orientation. These mechanisms in the visual cortex of mammals that are 'tuned' to combinations of frequency and orientation in a narrow range are referred to as 'channels' and are appropriately interpreted as band-pass filters. The characteristics of the tumor tissue can be efficiently captured by such band-pass filters. [3]

In a two-dimensional case, the absolute square of a correlation between an image and the two-dimensional Gabor function provides a local spectral energy density concentrated around a given position and frequency in a certain direction. A two-dimensional convolution with a circular (non-elliptical) Gabor function is separable to series of one-dimensional ones. [3]

Some texture segmentation algorithms produce region based segmentations, where regions with "uniform" texture are identified and given different labels. Others produce edge-based segmentations by detecting the boundaries between differently textured regions. Here multi-channel filtering techniques employ to obtain region-based segmentations. [3]

The complex Gabor function in space domain is represented as,

$$g(x,y) = s(x,y)w_r(x,y) \qquad (3)$$

Where,

$s(x,y)$ – complex sinusoid (carrier)

$w_r(x,y)$ – 2-D Gaussian shaped function (envelope)

3. PERFORMANCE ANALYSIS

3.1 An Approach for Evaluating Performance

For measuring the performance of improved image segmentation method, it is applied on various MR images and output of this algorithm at various stages is determined. Output of the system is affected by superimposing different Gabor filtered images with original image. Initially 30% of the resultant Gabor filtered images are superimposed with original image. Output brain tumor detected images are shown in Figure 3.1.

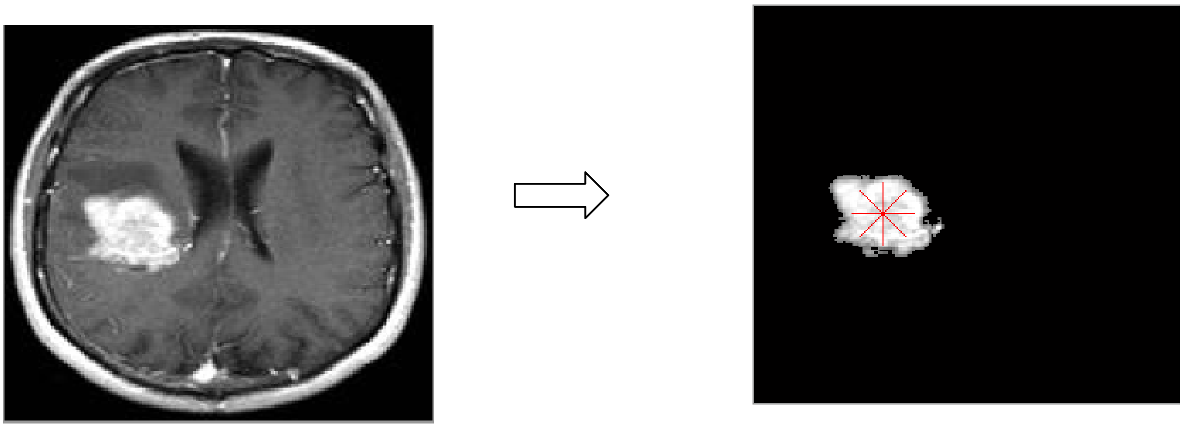

Figure 3.1 Brain tumor detection image 2

In above figure the input MR image consists of tumor shown by white patch. This tumor is detected by proposed algorithm. With tumor some extra part nearby suspicious region is also detected. The algorithm evaluates area value in pixels, centroid (x,y), Bounding box (Rect x, Rect y, Width, Height).

Brain tumor area value is 1459 pixels, centroid location is 61 pixel from x – axis and 97 pixels from Y – axis. Bounding box parameters are as follows: Rect x is 37 pixels, Rect y is 79 pixels, width is 54 pixels and height of 38 pixels.

If 10% of the Gabor filtered image is superimposed with original Brain tumor MR image then resultant output image with brain tumor of different area and bounding box parameters were found. Experimental result is shown in Figure 3.2.

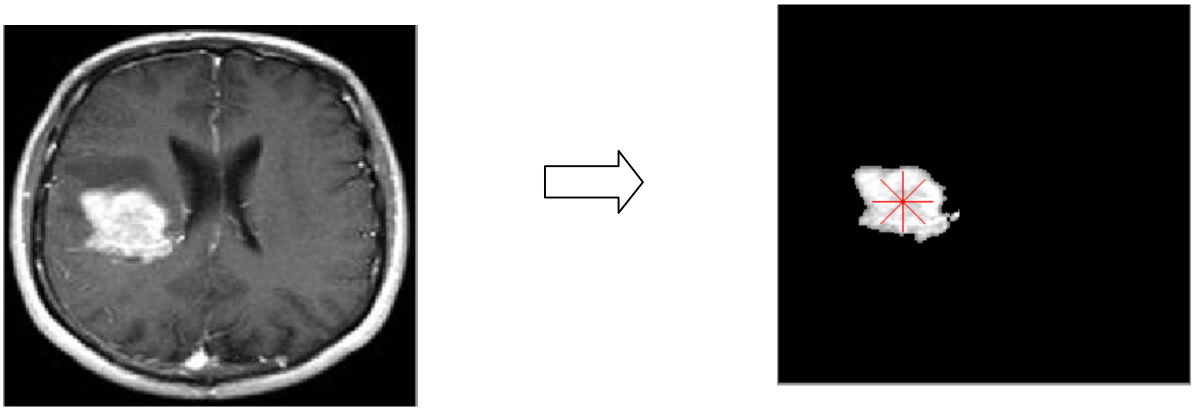

Figure 3.2 Brain tumor detection image 1

In above Figure 3.2 the input MR image consists of tumor shown by white patch. This tumor is detected by proposed algorithm. The algorithm evaluates area value in pixels, centroid (x, y), Bounding box (Rect x, Rect y, Width, Height).

Brain tumor area value is 1311, centroid location is 61 pixel from x – axis and 97 pixels from Y – axis. Bounding box parameters are as follows: Rect x is 37 pixels, Rect y is 80 pixels, width is 52 pixels and height of 37 pixels.

By comparing Figure 4.1 parameters with Figure 3.2, it is found that for former case Area value is 1459 pixels while for later case it is 1311 pixels. In later case pixel values are less as compared to former, also nearly exact tumor part is detected.

Similarly, experiment is performing on 10 different brain MR images. The result of this experiment is shown in the Table 3.1 and 3.2.

3.2 Results and Discussion

The tests of proposed technique are performed with respect to the brain tumor segmentation accuracy using 10 MR images of different patients. Images that we have used for testing contain brain tumor of different size, shape and intensity. Experimental results for different MR images are summarized in Table 3.1 and 3.2 containing area in pixel values, location on x axis, location on y axis and status of tumor detection.

Table 3.1 Brain tumor parameters for 30% Gabor filter output

Image	Area in pixels	Centroid		Bounding box parameters			
		Loc x	Loc y	Rect x	Rect y	Width	Height
Image 1	1459	61	97	36	79	54	38
Image 2	1684	115	105	94	76	45	62
Image 3	949	188	134	167	113	42	54
Image 4	773	95	201	81	181	28	43
Image 5	1351	62	82	38	60	47	44
Image 6	1457	75	113	53	90	50	48
Image 7	2944	69	67	39	32	61	69
Image 8	2625	81	146	56	115	54	66
Image 9	No Tumor Detected						
Image 10	No Tumor Detected						

Table 3.2 Brain tumor parameters for 10% Gabor filter output

Image	Area in pixels	Centroid		Bounding box parameters			
		Loc x	Loc y	Rect x	Rect y	Width	Height
Image 1	1311	61	97	37	80	52	37
Image 2	1475	113	105	95	77	40	54
Image 3	774	188	133	168	114	41	49
Image 4	630	96	199	82	182	26	39
Image 5	1197	62	82	39	60	45	44
Image 6	1282	74	113	54	90	49	47
Image 7	2700	69	68	40	33	59	66
Image 8	2484	81	146	56	116	53	64
Image 9	925	83	194	64	174	36	60
Image 10	No Tumor Detected						

CONCLUSION

The proposed algorithm was developed for segmentation of tumors from MR images. The brain tumor segmentation and detection was done using Magnetic Resonance images. The method used T1 and T2 weighted MR images. This method enhanced the MR images and segment tumor using wavelet transform. This used undecimated wavelet transform for enhancing MR images. Gabor wavelet was applied to an image and captured characteristic of tumor at 1st level of decomposition which segments tumor precisely. Working on area parameter, brain tumor was detected with area value in pixel, location from x and y axis. Table 3.1 and 3.2 contains the different parameters of brain tumor. If tumor is not present inside brain, algorithm does not find any parameters. Though tumor size and location inside skull are different, tumor is detected very precisely. As diagnosis tumor is a complicated and sensitive task; therefore, accuracy and reliability are always assigned much importance. The proposed algorithm provides accuracy, precision and reliability.

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