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A Novel Wavelet Based Image Fusion for Brain Tumor Detection

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Abstract

Accurate detection of size and location of brain tumor plays a vital role in the diagnosis of tumor. In this paper, we propose an efficient wavelet based algorithm for tumor detection which utilizes the complementary and redundant information from the Computed Tomography (CT) image and Magnetic Resonance Imaging (MRI) images. Hence this algorithm effectively uses the information provided by the CT image and MRI images there by providing a resultant fused image which increases the efficiency of tumor detection. We also evaluate the effectiveness of proposed algorithm on varying the wavelet fusion parameters like number of decompositions, type of wavelet used for the decomposition. The experimental results of the simulation on MRI and CT images show the performance efficiency of the proposed approach.

Keywords: computed tomography image, image fusion, magnetic resonance image, segmentation, tumor detection

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1. INTRODUCTION

Medical science has seen a radical development [1] in the field of biomedical imaging in the last two decades. The advancements in the field of artificial intelligence and computer vision technologies [2] have been effectively put into practice for medical applications such as diagnosis of various diseases like cancer [3], biomedical imaging for 3D tissue harmonics [4] and 3D vessel lumen segmentation techniques [5]. A tumor can be defined as a mass which grows without any control of normal forces [1]. The National Brain Tumor Foundation (NBTF) for research in United States estimates the death of 13000 patients while29,000 undergo primary brain tumor diagnosis. This high mortality rate of brain tumor greatly increases the importance of Brain Tumor detection. Real time diagnosis of tumors by using more reliable algorithms has been the main focus of the latest developments in medical imaging and detection of brain tumor in MR images and CT scan images has been an active research area [2]. The separation of the cells and their nuclei from the rest of the image content is one of the main problems faced by most of the medical imagery diagnosis systems. The process of separation i.e. segmentation, is paid at most importance in the construction of a robust and effective diagnosis system. Image segmentation is performed on the input images. This enables easier analysis of the image thereby leading to better tumor detection efficiency. Hence image segmentation is the fundamental problem in tumor detection. A number of methods have been proposed in the past for brain tumor detection. Chunyan et al. [6] designed a method for 3D variational segmentation for processes because of the high diversity in appearance of tumor from various patients. Schendra et al [7] proposed a method based on multi scale image segmen-

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tation using hierarchical self-organizing map for the segmentation of brain tumor. It uses high speed parallel fuzzy c-mean algorithm. Another improved algorithm based on Neuro fuzzy technique [8]. Image fusion is one of the most commonly used methods in medical diagnosis. It merges or overlays the multimodal images to provide additional information. In medical imaging image fusion, usually involves combining information of multi modalities such as magnetic resonance image (MRI), computed tomography (CT), positron emission tomography (PET), and single photon emission computed tomography (SPECT). Image fusion is more general solution to a number of applications in image processing where high spatial and spectral information are required in a single image, especially in the fields of medical imaging and remote sensing. Image fusion is used to overcome the observational constraints, which account for the disability to build such instruments to provide such information. Wavelets were first mentioned in 1909 in a thesis by Alfred Haar [9]. Wavelet transforms is a new area of technology, replacing the Fourier transform in various fields of application like image processing, heart-rate and ECG analysis [10], DNA analysis [11], protein analysis [12], climatology [13], speech recognition [14], computer graphics [15] and Multi fractal analysis [16]. The paper utilizes wavelet analysis based image fusion to enhance the efficiency of brain tumor detection. Fourier Transform fails to analyze a non-stationary signal whereas wavelet transform allows the components of a non-stationary signal to be analyzed. Wavelets allow complex information such as speech signals, images and patterns to be decomposed in to elementary forms at different positions and scales and subsequently reconstructed with high precision. In this paper, the MRI and CT image and are processed using wavelet analyses. Image enhancement techniques such as point operations, mask operations, and global operations [17], which sharpen image features and eliminate noise for efficient analysis, are used on the source images. The proposed algorithm uses spatial low-pass filter operation, which improve the efficiency of the image fusion algorithm through elimination of ambient elements from the source images. Low-pass filter operations emphasize on large homogenous areas of similar tones, and eliminate the smaller details resulting in a smoother appearance in the image. The paper discusses the variation in results of the wavelet based image fusion on changing the parameters in wavelet analysis like type of wavelet used for decomposition and the level of decomposition used.

The paper is further divided into the following sections. Section II explains the MRI and CT analysis, Wavelet analysis to detect the brain tumor. Section III presents the implementation of proposed algorithm, preprocessing used to detect the brain tumor. Section IV elaborates the Wavelet Based Fusion algorithm. In Section V, the results obtained by the using the proposed algorithm on MR Image and CT scan Image are summarized for performance analysis and Section VI, briefs the conclusions drawn from the observations.

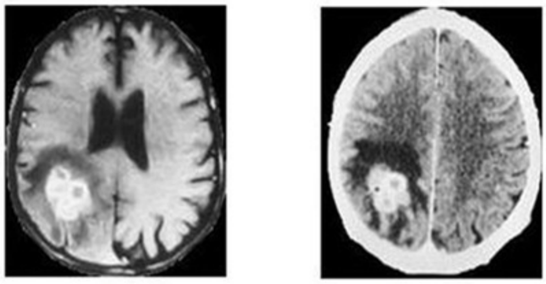

Figure 1: MR Image and CT Scan Image.

2. Basic Algorithms

2.1. MRI and CT Analysis

In this paper fused images from CT and MRI imagers are used for detection of tumor. The fused images are obtained from multiple modality images like Computed Tomography (CT) and Magnetic Resonance Image (MRI) [4] as shown in Fig1. (a) and (b). These multiple modality images play a key role in medical image processing; CT images which are used to ascertain the difference in tissue density and MRI provide an excellent contrast between various tissues of the body. CT images signify the difference in tissue density depending upon the tissues ability to reflect the X-rays, while MRI images provide contrast between different soft tissues. The above features make CT and MRI more suitable for the detection of tumor [17]. The complementary and redundant information of both the source images are retained in the fused image, these information including the tumor size and location, which enable better detection of tumor, when compared to the source images.

2.2. Wavelet Analysis

Wavelet analysis is an effective methodology capable of revealing aspects of data which other signal analysis techniques overlook like trends, breakdown points, discontinuities in higher derivatives, and self-similarity. In addition, wavelet analysis is capable of compressing or de-noising a signal without appreciable degradation. Hence, wavelet analysis is of at most importance in case of delicate informations, such as in case of medical imaging. The basic idea of the algorithm is to divide the input images into respective decomposed sub-images using the forward wavelet transform as shown in Fig.2.

In case of wavelet transform which each image has different resolution at different levels of decomposition. The decomposition process of the 2D image signals is carried out layer by layer which results in four frequency bands, i.e. (A) Low-Low (B) Low-High (C) High-Low (D) high-High at first level of decomposition. After the first level

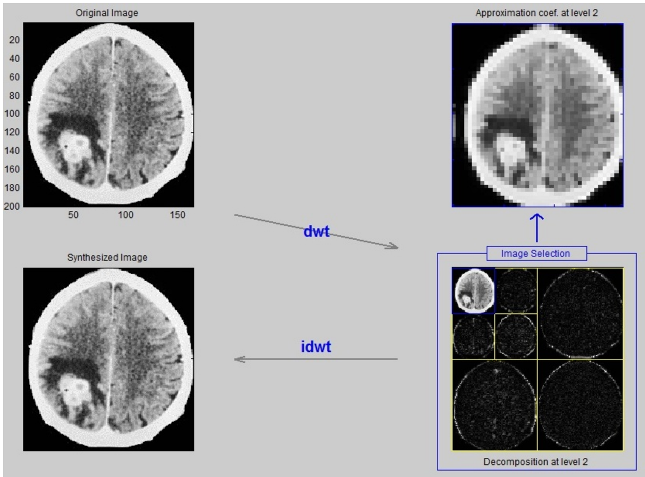

Figure 2: Two Level Wavelet Decomposition of CT image.

of decomposition, a recursive higher order decomposition procedure is applied to the Low-Low band of the present decomposition level. Similarly, in case of N-level decomposition will result in 3N+1 different frequency bands, which includes 3N high frequency bands and one Low-Low frequency band. In this paper the performance evaluation of the various image fusion algorithms is analyzed under various levels of decomposition in Section IV. Fig.2 shows the structures of 2-D DWT with 2 decomposition levels.

3. Implementation

Fig.3 represents the flow chart of the proposed algorithm; Input Images can suffer from artifacts due to different factors. However the recent advances in acquisition protocol make it possible to acquire images with very limited artifacts. Indeed, there is a trade-off between acquiring more images for accurate guidance and not increasing the time for imaging. Images of a patient obtained by MRI and CT scan is displayed as an array of pixels in two dimensional matrix, stored and displayed in MATLAB 7.0a. The grayscale or intensity images are displayed of default size 128 128, these images can be specified by giving a large matrix whose entries are numbers between 0 and 255, with 0 corresponding, say, to black, and 255 to white. A black and white image can also be specified by giving a large matrix with integer entries. The noise in the input image can reduce the performance of the algorithm. Image processing techniques are applied on the source images i.e. MR image and CT scan image to increase the contrast, brightness, reduce the artifacts due to noise and other factors. The input image is given to enhancement stage for the removing high intensity component, which helps to enhance the smoothness towards piecewise- homogeneous region and reduces the edge blurring effects. This proposed system describes the information of enhancement using weighted median filter for removing high frequency component which characterize the noise. These filters have the robustness and edge preserving capabilities with noise attenuation characteristics. After the pre processing operations the input images are subjected to wavelet analysis followed by fusion which is described in the following section.

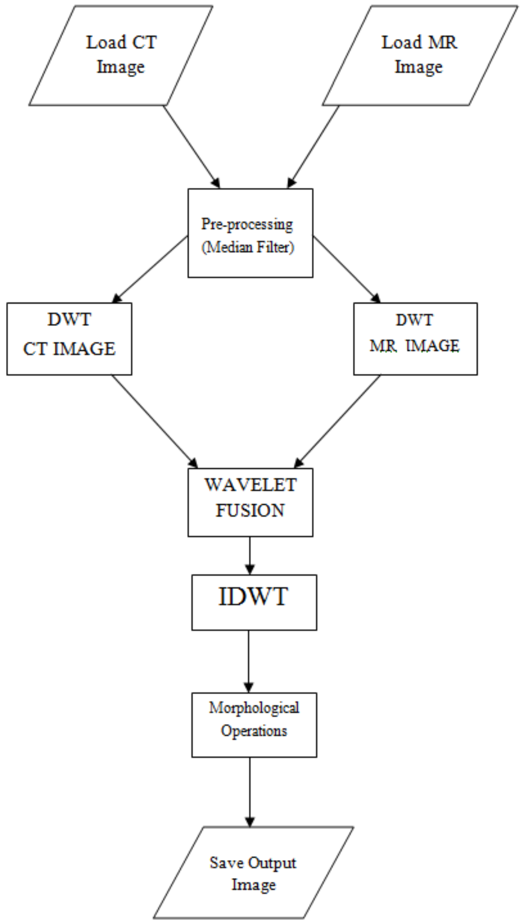

Figure 3: Flow chart of the algorithm.

4. WAVELET FUSION ALGORITHM

In the next step, wavelet transform is further applied on these images by passing the processed images through the respective wavelet filters. The wavelet transform is applied on the source images with different wavelets such as Daubechies, Symlets, and Coiflets in order to try and obtain optimum results. Fusion can be performed either by taking the average of the coefficients either the minimum of the coefficients or maximum of the coefficients.

In this paper, fusion is performed by taking the absolute maximum of the coefficients as the larger coefficients correspond to sharper brightness changes thus making the salient features visible. In MST initially the source images are subjected to multi-scale transform or multi resolution analysis, which involves decomposition of the origi-

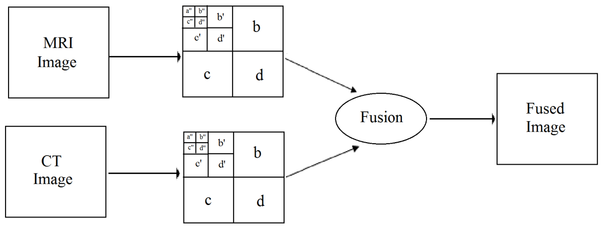

Figure 4: Block diagram depicting basic image fusion using multi resolution analysis.

nal image into different levels. Similarly in case of wavelet transform, the image is decomposed into various bands like low-low, high-low, low-high, and high-high. By increasing the number of decomposition levels [19], may result in overlap of neighboring features of the lower band signals. Hence, increasing the number of decomposition levels does not necessarily produce better results. The overlap of lower band features leads to discontinuities in composite representation and distortions are introduced, resulting in blocking effect or ringing artifacts into the composite image. Hence, selection of the appropriate decomposition level, allows combination of salient features of source images. Fig. 3 shows the basic block diagram of the image fusion algorithm. In case of pyramid analysis as the depth of the analysis increases, we may lose some part of information on small objects. This is the main drawback of MST, which is avoided in wavelet transform implemented in this paper by the use of absolute transform coefficients. Any sharp changes in intensity of the source images, will obtain the absolute transform coefficients. During integration, selection of the highest value of the absolute transform coefficients optimizes the relative resolution of the source images. This leads to multi resolution representation, while preserving the silent features of the each source image. The results of the above algorithm gives new and better composite image for the detection of brain tumor, which can be obtained by applying inverse wavelet transform. Thus fusion takes place in all resolution levels (as shown in Fig. 3) and the prominent features at each scale are preserved. The resultant image is formed by performing inverse wavelet transform. The wavelet transform technique of image fusion allows us to effectively extract the salient features of the input images due to the availability of directional information. Thus the wavelet techniques produce better results than Laplacian pyramid based methods. The reconstruction of the final image is also better in wavelet transform technique than in Laplacian Pyramid based methods as errors such as blocking effects are effectively removed. In this wavelet based image fusion algorithm, we propose a feature selection method for better efficiency of tumor detection. The fused image is converted in to binary form for computational ease and better efficiency of detection by applying appropriate threshold values. The optimum value of the threshold is determined experimentally, to have best result. The image can be seen as a 2D matrix consisting of 1s and 0s. The pixels having 1s are white and 0s are black. In the proposed feature selection algorithm, the value of each pixel in the output image is based on a comparison of the corresponding pixel in the binary image with its neighbors. This method may add or remove pixels from the boundaries of the objects in the image depending on the size and structuring element [20] used to process the image. This facilitates better detection of the tumor with minimum error. The output of the proposed image fusion algorithm is dependent on two main parameters: (a) the wavelet used for the image decomposition i.e. Haar(haar), Daubechies(db), Coiflets(coif) or symlets(sym) (b) the total number of decompositions of the image using the wavelets analysis. As number of decompositions increase we may lose some minute details of image in the image as these small regions can be of significant importance in the medical analysis. Hence, with the variation of decomposition levels we evaluate the performance of algorithm the errors are plotted with number of decompositions against the PSNR. The results are future illustrated by varying the wavelets for a given level of decomposition to give relative study the performance of the various wavelets in order to obtain optimum results.

Figure 5: Segmentation results after the algorithm .

5. RESULT AND ANALYSIS

This section elaborates and compares the results obtained for brain tumor detection using wavelet based image fusion. The results obtained enables us to investigate the capabilities of the image fusion algorithm applied to MR image and CT scan image (Fig 1(a) and 1(b) respectively).. The performance of the algorithm is evaluated on MATLAB (Version 7.10.0.499). This section further analyses the results upon variation of different wavelet parameters.

Table 1: Tabulated results depicting the variation of PSNR for the proposed algorithm.

Wavelet	PSNR at Decomposition Level			
	First	*Second*	*Third*	*Fourth*
Bior 2.2	10.562	10.5634	10.5632	10.5625
Coif	10.63	10.635	10.645	10.655
Db2	10.5631	10.563	10.5633	10.5634
Dmey	10.563	10.5635	10.5635	10.5625
Rbio 2.2	10.563	10.5628	10.5627	10.5625
Sym4	10.631	10.634	10.635	10.65
Haar	10.563	10.5636	10.5634	10.5655

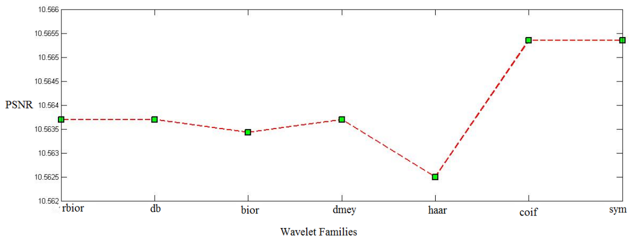

Figure 6: Variation of PSNR when the algorithm is applied on different wavelets at 4th decomposition level .

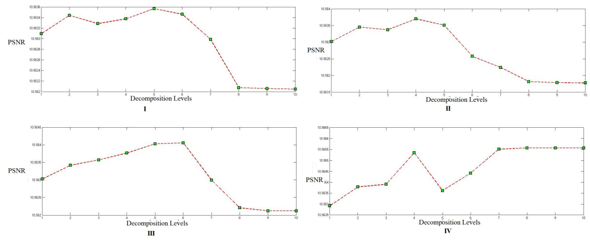

Figure 7: Variation of PSNR with varying decomposition levels for db2, coif2, sym2 and Haar wavelets respectively .

The performance is evaluated on the basis of PSNR (Peak signal to noise ratio).

It is given by Equation (1)

$$PSNR = 20 * log(\frac{256}{E}) \tag{1}$$

The root mean square error is given by Equation (2)

$$E = [\frac{\sum_i (r_i - d)^2}{m * n}]^{\frac{1}{2}} \tag{2}$$

Where E is the root-mean-square-error, mn is the number of pixels in the image, and r, d denotes the original and the fused image respectively. Fig. 4 shows the segmentation results which show the qualitative and quantitative tumor. A MR image and CT scan image are taken as the inputs to the algorithm. The method successfully determined the position of the tumor and the area of the tumor with slight error. An analysis of the PSNR has been made with respect to two important parameters which determine the efficiency of the algorithm. The results obtained from varying the parameters are compared on the basis of run-time analysis and the accuracy with which the tumor is detected. Wavelet analysis is performed using different wavelets. The results from the image fusion using different wavelets are compared on basis of the Signal to noise ratio in detection of the tumor as compared to the original MR image and CT scan image.

Another important factor which determines the performance of the algorithm is the decomposition level used for the wavelet transform. Increasing the analysis depth i.e. increasing the number of decomposition levels does not essentially produce better results as the neighboring features of lower band may overlap and distortions such as blocking effect may be introduced because of this distortion. Fig.5 shows the PSNR offered by the different wavelets in the wavelet family at the fourth decomposition level. Further, the performance analysis of the algorithms at various level of decomposition for different wavelets used is summarized in Table I.

It is clearly observed that the wavelets coif2 and sym4 produce a better efficiency i.e. a better PSNR of 10.655 at the fourth decomposition level. The high accuracy is attained as the method effectively extracts the complementary and redundant information from the MR image and CT scan image thereby producing a highly reliable fused output image for detection of tumor. The efficiency offered by different wavelets has also been tested at different decomposition levels as shown in Fig.7.

Fig.7 depicts the variation of the PSNR value with respect to various wavelets used for a given level of decomposition ,the sub image (I) Variation of PSNR with varying decomposition levels for db2 wavelet (II) Variation of PSNR with varying decomposition levels for coif2 wavelet (III) Variation of PSNR with varying decomposition levels for sym2 wavelet (IV) Variationa of PSNR with varying decomposition levels for haar wavelet respectively. which helps us select the level of decomposition which yield optimum results for a given wavelet and the further analysis can be of the each of the wavelets through the Fig.7 in which Variation of PSNR with varying decomposition lev-

Table 2: Comparative Study of performance Efficiency of Algorithms

Algorithm	Comparison of Performance	
	$PSNR$	$ExecutionTime(sec)$
GVF	9.4	7.2
Segmentation Algorithm	10.4	13.76
Wavelet Based Image Fusion	10.67	0.774

els for haar wavelet respectively, which have high PSNR value at higher levels of decomposition. This clearly affirms the theory that increasing the number of decomposition levels does not essentially produce better results. Hence an optimum decomposition level has to be selected for the best results. The method takes 0.774 seconds for the whole process when a 4th level decomposition is used. It takes 2.3 seconds, 1.06 seconds, 0.88 seconds for 1st level, 2nd level and 3rd level decomposition respectively. The best result i.e. detection of the tumor with a PSNR of 10.655 and run time of 0.774 seconds is achieved when the algorithm is used with coif2 wavelet with fourth level decomposition. The efficiency of the proposed algorithm as compared with GVF [21] and segmentation [22] algorithm can be seen in Table II. The PSNR is the lowest for GVF algorithm as the parameters in it are manually set by the user and hence is erroneous. The PSNR value obtained using segmentation algorithm is less than the PSNR value obtained using the proposed algorithm.

6. CONCLUSIONS

The efficiency of the proposed algorithm is compared with GVF [21] and segmentation algorithm [22]. From Table 2 it can be seen that the PSNR is lowest for GVF algorithm. PSNR for segmentation algorithm is better than that of GVF algorithm but it is lower than that of the proposed algorithm. The efficiency of the algorithm was tested using various wavelets for different decomposition levels. It can be seen that coif2 and sym4 wavelets give the best results with PSNR for the detection of brain tumor from Table 1. Run time of the algorithm is found to be 0.774 seconds. An efficient algorithm for brain tumor detection has been demonstrated through this paper.

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