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Image Fusion Based On Wavelet Transform For Medical Diagnosis

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ABSTRACT
In the image fusion scheme presented in this paper, the wavelet transforms of the input images are appropriately combined, the new image is obtained by taking the inverse wavelet transform of the fused wavelet co-efficients. The idea is to improve the image content by fusing images like computer tomography (CT) and magnetic resonance imaging (MRI) images, so as to provide more information to the doctor and clinical treatment planning system. This paper aims to demonstrate the application of wavelet transformation to multi- modality medical image fusion. This work covers the selection of wavelet function, the use of wavelet based fusion algorithms on medical image fusion of CT and MRI, implementation of fusion rules and the fusion image quality evaluation. The fusion performance is evaluated on the basis of the root mean square error (RMSE).
***Keywords* -** Medical image fusion, Multimodality images, Wavelet transforms, Fusion rules.

I. INTRODUCTION

1.1 About Image fusion

Image fusion is the process of combining relevant information from two or more images into a single image. The resulting image will be more informative than any of the input images. Image fusion involves two or more images to attain the most useful features for some specific applications. For Instance, doctors can annually combine the CT and MRI medical images of a patient with a tumour to make a more accurate diagnosis, but it is inconvenient and tedious to finish this job. And more importantly, using the same images, doctors with different experiences make inconsistent decisions. Thus, it is necessary to develop the efficiently automatic image fusion system to decrease doctor's workload and improve the consistence of diagnosis. Image fusion has wide application domain in Medicinal diagnosis. Medical images have difference species such as CT, MRI, PET, ECT, and SPECT. These different images have their respective application ranges. For instance, functional information can be obtained by PET, SPECT. They contain relative low spatial resolution, but they can provide information about visceral metabolism and blood circulation. And that anatomical image contains high spatial resolution such as CT, MRI, B-mode ultrasonic, etc. Medical fusion image is to combine functional image and anatomical image together into one image. This image can provide abundance information to doctor to diagnose clinical disease.

1.2 Methods involved in Image Fusion:

The simplest way of image fusion is to take the average of the two images pixel by pixel. However, this method usually leads to undesirable side effect such as reduced contrast. Other methods based on intensity-hue saturation (IHS), principal component analysis (PCA), synthetic variable ratio (SVR) etc. have also been developed. Due to the multiresolution transform can contribute a good mathematical model of human visual system and can provide information on the contrast changes, the multiresolution techniques have then attracted more and more interest in image fusion. The multiresolution techniques involve two types, viz. pyramidal transform and wavelet transform. The pyramid method was firstly introduced by Burt and Adelson and then was extended by Toet. However, for the reason of the pyramid method fails to introduce any spatial orientation selectivity in the decomposition process and usually contains blocking effects in the fusion results, the wavelet transform has then been used more widely than other methods. In this paper, a novel approach for the fusion of computed tomography (CT) and magnetic resonance images (MR) images based on wavelet transform has been presented. Different fusion rules are then performed on the wavelet coefficients of low and high frequency portions. The registered computer tomography (CT) and magnetic resonance imaging (MRI) images of the same people and same spatial parts have been used for the analysis.

II. IMAGE FUSION BASED ON WAVELET TRANSFORM

The original concept and theory of wavelet-based multiresolution analysis came from Mallat. The wavelet transform is a mathematical tool that can detect local features in a signal process. It also can be used to decompose two- dimensional (2D) signals such as 2D gray-scale image signals into different resolution levels for multiresolution analysis Wavelet transform has been greatly used in many areas, such as texture analysis, data compression, feature detection, and image fusion. In this section, we briefly review and analyze the wavelet-based image fusion technique

2.1. Discrete Wavelet Transform (DWT)

The discrete wavelet transform (DWT) is a spatial-frequency decomposition that provides a flexible multiresolution analysis of an image. In one dimension the aim of the wavelet transform is to represent the signal as a superposition of wavelets. The Discrete Wavelet Transform (DWT), which is based on sub-band coding, is found to yield a fast computation of Wavelet Transform. It is easy to implement and reduces the computation time and resources required. The foundations of DWT go back to 1976 when techniques to decompose discrete time signals were devised. Similar work was done in speech signal coding which was named as sub-band coding. In 1983, a technique similar to sub-band coding was developed which was named pyramidal coding. Later many improvements were made to these coding schemes which resulted in efficient multi-resolution analysis schemes.

In CWT, the signals are analyzed using a set of basic functions which relate to each other by simple scaling and translation. In the case of DWT, a time-scale representation of the digital signal is obtained using digital filtering techniques. The signal to be analyzed is passed through filters with different cut-off frequencies at different scales If a discrete signal is represented by f(t), its wavelet decomposition is then

$$f(t)=\sum_{m,n} C_{m,n}\, \varphi_{m,n}(t) \qquad \text{……………………..(2.1)}$$

where φ is the dilated and or translated version of the mother wavelet φ given by the equation

$$\varphi_{m,n}(t) = 2^{-m/2}\varphi[2^{-m}t - n] \qquad \text{……………….(2.2)}$$

where m and n are integers. This ensures that the signal is decomposed into normalised wavelets at octave scales. For an iterated wavelet transform additional coefficients $a_{m,n}$ are required at each scale. At each scale $a_{m,n}$ and $a_{m-1,n}$ describe the approximations of the function f at resolution 2^m and at the coarser resolution 2^{m-1} respectively, while the coefficients $c_{m,n}$ describe the difference between one approximation and the other. In order to obtain the coefficients $c_{m,n}$ and $a_{m,n}$ at each scale and position, a scaling function is needed that is similarly defined to equation 2.3 The convolution of the scaling function with the signal is implemented at each scale through the iterative filtering of the signal with a low pass FIR filter h_n .The approximation coefficients $a_{m,n}$ at each scale can be obtained using the following recursive relation

$$a_{m,n} = \sum_k h_{2n-k}\, a_{m-1,k} \qquad \text{……………………..(2.3)}$$

where the top level $a_{0,n}$ is the sampled signal itself. In addition, by using a related high pass FIR filter g_n the wavelet coefficients can be obtained

$$c_{m,n} = \sum_k g_{2n-k}\, a_{m-1,k} \qquad \text{………………………(2.4)}$$

To reconstruct the original signal the analysis filters can be selected from a biorthogonal set which have related set of synthesis filters. These synthesis filters $\hat{h}$ and $\hat{g}$ can be used to perfectly reconstruct the signal using reconstruction formula.

$$a_{m-1,l}(f) = \sum_n [\hat{h}_{2n-l}\, a_{m,n}(f) + \hat{g}_{2n-l} c_{m,n}(f)] \qquad \text{……………………………(2.5)}$$

Equations 2.3 and 2.4 are implemented by filtering and subsequent down sampling. Conversely equation 2.5 is implemented by an initial up sampling and a subsequent filtering.

2.2 Filter Banks

Filters are one of the most widely used signal processing functions. Wavelets can be realized by iteration of filters with rescaling. The resolution of the signal, which is a measure of the amount of detail information in the signal, is determined by the filtering operations, and the scale is determined by upsampling and downsampling (subsampling) operations.

The DWT is computed by successive lowpass and highpass filtering of the discrete time-domain signal as shown in below figure . This is called the Mallat algorithm or Mallat-tree decomposition. Its significance is in the manner it connects the continuous-time muti resolution to discrete-time filters. In the figure, the signal is denoted by the sequence x[n], where n is an integer. The low pass filter is denoted by G0 while the high pass filter is denoted by H0. At each level, the high pass filter produces detail information, d[n], while the low pass filter associated with scaling function produces coarse approximations, a[n].

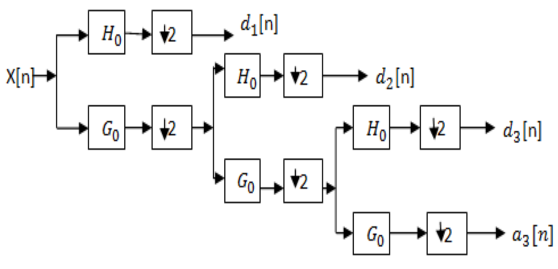

Fig 2.1 : Three-level wavelet decomposition tree

At each decomposition level, the half band filters produce signals spanning only half the frequency band. This doubles the frequency resolution as the uncertainty in frequency is reduced by half. In accordance with Nyquist's rule if the original signal has a highest frequency of ω, which requires a sampling frequency of 2ω radians, then it now has a highest frequency of ω/2 radians. It can now be sampled at a frequency of ω radians thus discarding half the samples with no loss of information. This decimation by 2 halves the time resolution as the entire signal is now represented by only half the number of samples. Thus, while the half band low pass filtering removes half of the frequencies and thus halves the resolution, the decimation by 2 doubles the scale.

With this approach, the time resolution becomes arbitrarily good at high frequencies, while the frequency resolution becomes arbitrarily good at low frequencies. The time-frequency plane is thus resolved as shown in figure. The filtering and decimation process is continued until the desired level is reached. The maximum number of levels depends on the length of the signal. The DWT of the original signal is then obtained by concatenating all the coefficients, a[n] and d[n], starting from the last level of decomposition.

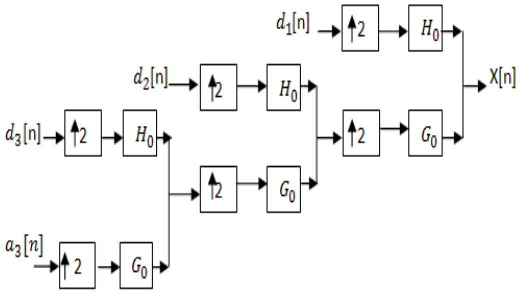

Fig 2.2 : Three-level wavelet reconstruction tree

The above figure shows the reconstruction of the original signal from the wavelet coefficients. Basically, the reconstruction is the reverse process of decomposition. The approximation and detail coefficients at every level are upsampled by two, passed through the low pass and high pass synthesis filters and then added.

This process is continued through the same number of levels as in the decomposition process to obtain the original signal. The Mallat algorithm works equally well if the analysis filters, G0 and H0, are exchanged with the synthesis filters, G1 and H1.

2.3 Wavelet Transform for Fusing Images

In this subsection, to better understand the concept and procedure of the wavelet based fusion technique, a schematic diagram is first given in Figure 2.3.

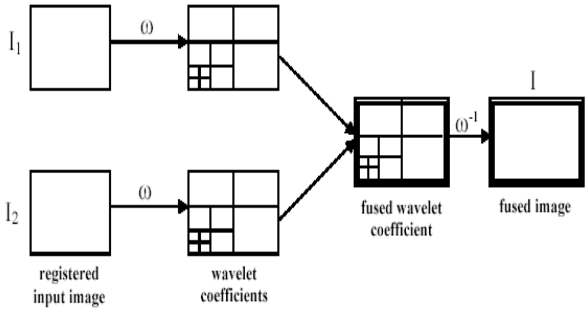

Fig 2.3 The scheme for image fusion using the wavelet transform

In general, the basic idea of image fusion based on wavelet transform is to perform a multiresolution decomposition on each source image; the coefficients of both the low-frequency band and high-frequency bands are then performed with a certain fusion rule as displayed in the middle block of Figure1. The widely used fusion rule is maximum selection scheme. This simple scheme just selects the largest absolute wavelet coefficient at each location from the input images as the coefficient at the location in the fused image. After that, the fused image is obtained by performing the inverse DWT (IDWT) for the corresponding combined wavelet coefficients.

2.4 Image Fusion steps

Step 1. The images to be fused must be registered to assure that the corresponding pixels are aligned.

Step 2. These images are decomposed into wavelet transformed images, respectively, based on wavelet transformation. The transformed images with *K*-level decomposition will include one low-frequency portion (low- low band) and 3*K* high-frequency portions (low-high bands, high-low bands, and high-high bands).

Step 3. The transform coefficients of different portions or bands are performed with a certain fusion rule.

Step 4. The fused image is constructed by performing an inverse wavelet transform based on the combined transform coefficients from Step 3.

2.4 Image Fusion Performance

In order to measure the fusion performance, we calculate the root mean square error (RMSE) between the reconstructed image and the original image for every fusion performed, and present this error as a percentage of the mean intensity of the original image. The RMSE is given by

$$RMSE=\sqrt{(1/(M*N))\sum x\sum y(I_{true}(x,y)-I_{fused}(x,y))2]}$$

Where *Itrue(x, y)* is the reference image, *Ifused(x, y)* is the fusion image and M & N are the dimensions of the images. For each level of reconstruction, RMSE is measured and compared.

III. EXPERIMENTAL RESULTS

We considered five wavelet families namely Haar, Daubechies (db), Symlets, Coiflets and Biorsplines for fusing CT and MRI medical images. The filter Daubechies (db) - which produced the smallest RMSE was chosen for further analysis. Different fusion rules were tested, including the mean rule, maximum rule, minimum rule and random rule. Here maximum rule gives better result, so maximum rule is selected. Here we applied maximum fusion rule to three CT and MRI pair images, (1) brain CT and MRI images shown in Figure 2(a) and 2(b) respectively. Figure 2(c) shows the resultant fusion image (2) head CT and MRI images shown in Figure 3(a) and 3(b) respectively. Figure 3(c) shows the resultant fusion image (3) abdomen CT and MRI images shown in Figure 4(a) and4 (b) respectively. Figure 4(c) shows the resultant fusion image using the above mentioned fusion algorithm. For fusing simulated images, our observation was that the smallest RMSE at the higher decomposition levels.

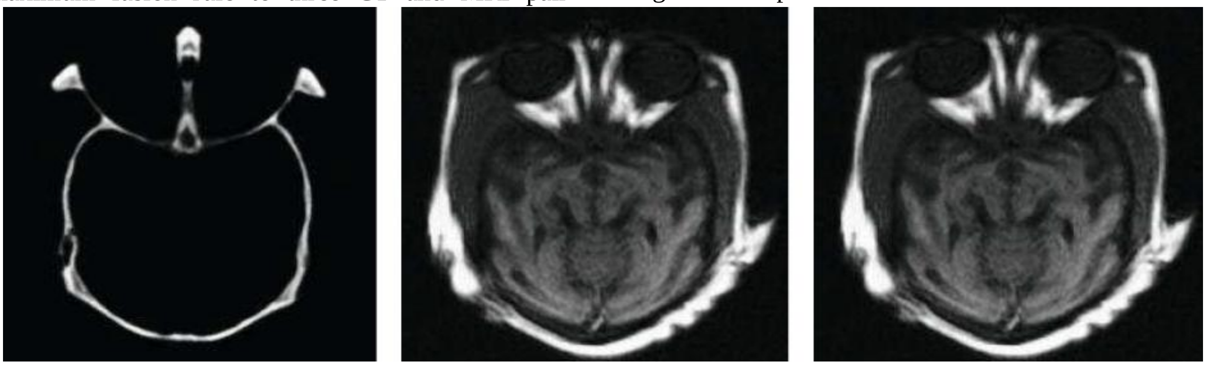

Figure. 2. (a) CT image (Brain), (b) MRI image (Brain) and (c) Resultant Fused image using maximum fusion rule

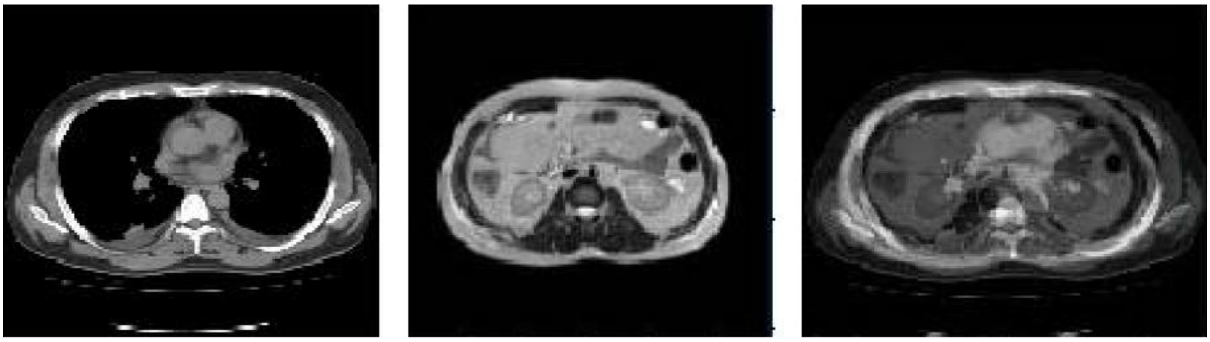

Figure.3. (a) CT image (abdomen), (b) MRI image (abdomen) (c) Resultant Fused image using maximum fusion rule

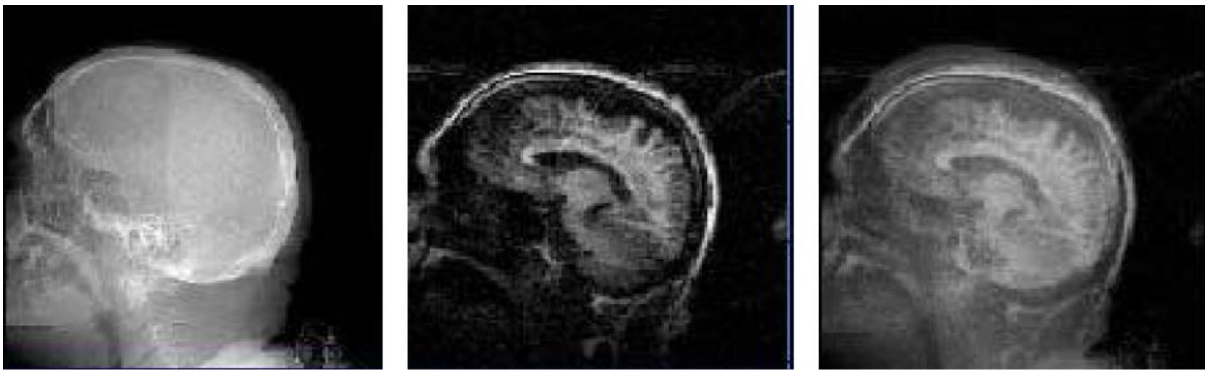

Figure. 4. (a) CT image (head), (b) MRI image (head), (c) Resultant Fused image using maximum fusion rule

IV. CONCLUSION AND FUTURE WORK

We have combined the wavelet transform and various fusion rules to fuse CT and MRI images. This method gives encouraging results in terms of smaller RMSE. Among all the fusion rules, the maximum fusion rule performs better as it achieved least MSE.s Using this method we have fused other head and abdomen images. The images used here are grayscale CT and MRI images. However, the images of other modalities (like PET, SPECT, X-ray etc) with their true color nature may also be fused using the same method.

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