A Multimodal Medical Image Fusion Using a Hybrid Technique Based On Wavelets

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Abstract — *Image fusion is the process of combining relevant information from two or more images into a single image without the introduction of distortion or loss of information. The image description of the scene in this new image is more comprehensive, more accurate and more reliable than any single image. Although an increasing number of high-resolution images are available along with sensor technology development, the process of image fusion is still a popular and important method to interpret the image data for obtaining a more suitable image for a variety of applications. To get the complete information from the single image we need to have a method to fuse the images. In the current paper we are going to propose a method that uses hybrid of wavelets for Image fusion.*

Keywords: *Image fusion, Wavelet Transform, MFHWT, BIOR Wavelet.*

I. INTRODUCTION

The objective of image fusion is to combine complementary as well as redundant information from many images to have a fused resultant image. Thus, the resultant image produced must contain a more accurate details of the scene than any of the individual sources image and is more beneficial for human visual and for machine perception or even further image processing and analysis tasks[2]. Depending on the applications, fusion problems can occur in different situations, in which the types of information elements are not the same. The main fusion situations in image processing are the following:-

A. Several images from the same sensor:-

This consists, for example, of several channels on the same satellite, or multi-echo images in MRI, or also of image sequences for scenes in motion. The data in those cases is relatively homogenous because it corresponds to similar physical measurements.

B. Several images from different sensors:-

This is the most common case, in which the different physical principles of each sensor allow the user to have complementary perspectives of the scene [4]. They can consist of ERS and SPOT images, MRI or ultrasound images, etc. The heterogeneity is then much greater, since the various sensors do not deal with the same aspects of the phenomenon. Each image gives a partial image with no information on the characteristics they are not meant to observe (for example, an anatomical MRI yields no functional information and the resolution of a PET scan is too low for a precise view of the anatomy).

C. Several elements of information extracted from a same image:-

In this situation, different types of information are extracted from an image using several sensors, operators, classifiers, etc., that rely on different characteristics of the data and attempt to extract different objects, often leading to very heterogeneous elements of information to fuse. The extracted information can involve the same object (fusion of contour detectors, for example) or different objects and the goal is then to find an overall interpretation of the scene and consistency between the objects. The elements of information can be on different levels (very local, or more structural when studying spatial relations between objects).

D. Images and another source of information:-

By another source of information, we mean, for example, a model, which may be particular like a map, or generic like an anatomical atlas, a knowledge base, rules, information provided by experts, etc [13]. The elements of information are again in very different forms, both in nature and in their initial representation (images in the

ISSN: 2229-6913 (Print), ISSN: 2320-0332 (Online) -, Web Presence: http://www.ijoes.vidyapublications.com

case of a map or a digital atlas, but also linguistic descriptions, databases, etc.).

II. WAVELET METHODS FOR IMAGE FUSION

In the wavelet domain, high-frequency detail coefficients have large absolute values correspond to sharp intensity changes and present salient features in the image whereas edges, lines and region boundary present. Low-frequency approximation coefficients are coarse representations of the original image and may have inherited some properties such as the mean intensity or texture information of our original image. As an approximation sub-image and detail sub-images have different physical meaning, they are treated differently in the fusion process. In this, low-frequency detail of the sub-images, and denotes the approximate components of input images; and we use image energy as weight coefficient to fuse them. The principle of image fusion using the DWT is similar to that for signals. For image, DWT is extended to two dimensions and fusion of an image is done using 2-D wavelet analysis. An image here is represented by M×N matrix, where M is the number of rows and N is the number of columns in the matrix. The Wavelet decomposition generates four components of an image. HL(high-low), LH(low high) and HH(high-high) are the highest resolution horizontal, vertical and diagonal details as shown in fig:1. The LL sub-band (low-low) is in the upper left hand corner and come from low pass filtering in both directions. It consists of low frequency components and will be split at higher level of decomposition. Out of the four components, it is the more like the original picture and is called approximation component. The remaining three components are called detail components. The upper right corner comes from the high pass filtering in the horizontal direction (low) and low pass filtering in the vertical direction (columns) and so labeled as HL. The visible detail in this subimage, for instance, edge, have an overall vertical orientation since there alignment is perpendicular to the direction of the high pass filtering. Therefore these are called vertical details. The diagonal component (high-high) is obtained by from high pass filtering in both the directions. In the proposed technique, we are applying two level wavelet decomposition on the source images using RMFHWT and Bior wavelets.

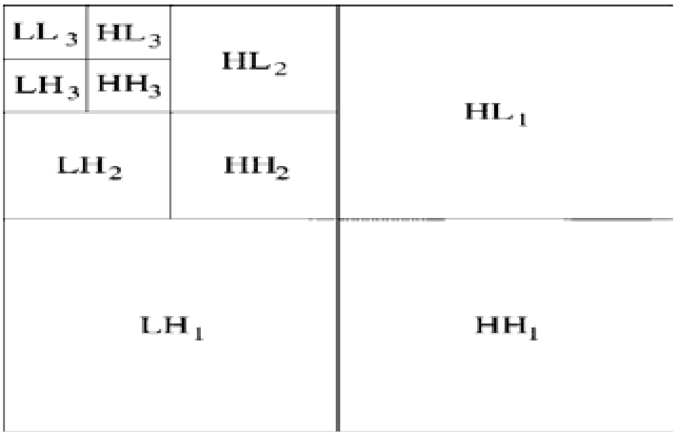


Fig.1 2-DWavelet Decomposition

Decompose the image using wavelet (Sub band) with MFHWT: Modified Fast Haar Wavelet Transform: In MFHWT, first average the sub signal (a' =a1,a2, a3… $a_{n/2}$), at one level for a signal of length N i.e. f =(f1, f2,f3,f4…fn) is

$$a_m = \frac{f_{4m-3} + f_{4m-2} + f_{4m-1} + f_{4m}}{4}, \quad m = 1,2,3,\dots,N/4,$$

[2]

and first detail sub-signal(d'= $d_1,d_2,d_3\dots d_n$), at the same level is given as :

$$d_m = \begin{cases} \frac{(f_{4m-3} + f_{4m-2}) - (f_{4m-1} + f_{4m})}{4}, & m = 1,2,3,\dots,N/4, \\ 0, & m = N/2,\dots,N. \end{cases}$$

For the orthogonal wavelets the reconstruction formula and the decomposition Formula coincides. A biorthogonal wavelets system consists of two sets of wavelets generated by a mother wavelet ψ and a dual wavelet $\psi\tilde{}$, for which

(ψ˜k,_,ψm,n) = δk,mδ_,n, for all integer values *k, _,m* en *n*.

We assume that *(ψk,_)* constitute a so called Riesz basis (numerically stable) of *L*2(IR*)*, i.e. *A (f, f)* ≤ *__k,_ ξk,__*2 ≤ *B (f, f)*

for positive constants *A* en *B*, where *f* = *_k,_ ξk,_ψk,_*.

The reconstruction formula now reads *f =_k,_(f,ψk,_)ψ˜k,_*

III. RDWT

The redundant discrete wavelet transform (RDWT) is specific redundant frame expansion which is essentially an undecimated version of the discrete wavelet transform (DWT).With redundancy, greater functionality often becomes possible. For instance, redundant transforms provide greater robustness to added noise and quantization as well as increased numerical stability. in the RDWT domain, we can determine exactly the variance (i.e.,expected distortion energy per sample) in the original signal domain of noise added in the RDWT domain. In addition, the redundancy can produce shift invariance, which can facilitate, among other tasks, feature detection and motion estimation.

IV. Proposed Technique

The methodology of work will start with the overview of image fusion algorithms. The results of various algorithms will be interpreted on the basis of different quality measures. Thus, the methodology for implementing the objectives can be summarized as follows:-

1 To focus on the feature detection so that we decide which algorithm to be applied.
2 Based on the Detection we will apply the hybrid wavelet transform based on RMFHWT and Bior transform for Image Fusion.
3 This will increase the efficiency of the fusion method and quality in the Image.

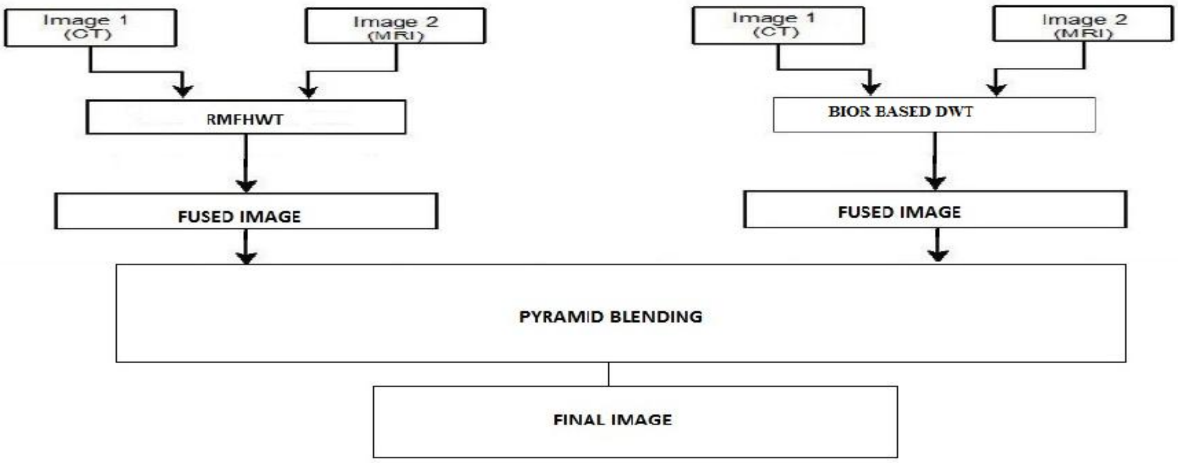


Fig.2. Overview of Hybrid Technology of Image Fusion Consists of RMFHWT and Bior Based Dwt

V. Quality metrics

The performance, experimental results or comparison of the proposed scheme is evaluated by various quantitative measures like:

A. Entropy:

Entropy is one of the quantitative measures in digital image processing. Claude Shannon introduced the entropy concept in quantification of information content of the messages. Although he used entropy in communication, it can be also used as a measure and also quantifying the information content of the digital images. Any digital image consists of the pixels arranged in several rows and many columns [9]. Every pixel is defined by its position and also by its grey scale levels. For an image which is having L grey levels, the entropy can be defined as: $H = -\sum_{i=1}^{L} P(i) \log_2 P(i)$

H-Pixel entropy;
L-image's total grayscale;
Where $P_i = N_i/N_p = \{p_0, p_1 \cdots p_{i......} p_{l-1}\}$ reflects the probability distribution which has different gray values in the image. The diagram of $i - N_i$ is the Image's gray histogram. The entropy of fusion image is larger which is respected that the amount information of fused images is increased, the Information which is contained in fusion images is richer and fusion quality is better. Where is the probability (here frequency) of each grey scale level.

For images with high information content the entropy will be large. The larger alternations and changes in an image give larger entropy and the sharp and focused images have more changes than blurred and miss focused images.[1] Hence, the entropy is a measure to assess the quality of different aligned images from the same scene.

B. *Quality:*

The overall quality of images can be measured by using the brightness μ, contrast σand sharpness S. The following criteria are used for brightness, contrast and the sharpness [3].

i. Let μ_n be the normalized brightness parameter, such that

$$\mu_n = \begin{cases} \mu/225 & \mu < 154 \\ 1 - \mu/225 & otherwise \end{cases}$$

eq(1.2) [14]

A region is considered to have sufficient brightness when $0.4 \leq \mu_n \leq 0.6$

ii. Let σ_n be the normalized contrast parameter, such that

$$\sigma_n = \begin{cases} \sigma/128 & \mu \leq 64 \\ 1 - \sigma/128 & otherwise \end{cases}$$

A region is considered to have sufficient contrast when $0.25 \leq \sigma_n \leq 0.5$. When $\sigma_n \leq 0.25$, the region has poor contrast, and when $\sigma_n > 0.5$, the region has too much contrast.

Let S_n be the normalized sharpness parameter, such that S= *min* (2.0, *S*/100). When$S_n > 0.8$, the region has sufficient sharpness. The image quality is assessed using

$$Q = 0.5\mu_n + \sigma_n + 0.1S_n$$

eq(1.4)

Where 0 <*Q* <1.0 is the quality factor. A region is classified as good when *Q* > 0.55, and poor when $\sigma_n \leq 0.5$[11]. An image I classified as good when the total number of regions that are classified as good exceeds.

C. *Standard Deviation:*

Standard deviation is usually used to represent the deviation degree of the estimation and the average of the random variable. The standard deviation mainly reflects the discrete degree between the pixel gray and the mean value. The more is the standard deviation, the more discrete will be the distribution of gray levels. It estimates the activity level as follows:

$$A_l(p) = \sum_{s\epsilon S, t\epsilon T} \left(\frac{|D_l(m+s,n+t,j,k) - D_l(m+s,n+t,j,k)|^2}{S \times T} \right)^{\frac{1}{2}}$$

[6]

Where, S and *T*are sets of the current window.

D. *Peak Signal to Noise Ratio (PSNR) & Mean Square Error (MSE): -*

Image quality assessment is an important issue in image fusion. MSE used to measure the degree of image distortion because they can represent the overall gray-value error contained in the whole image, and is mathematically tractable as well[3]. In many applications, it is usually straightforward to design systems that minimize MSE. MSE works satisfactorily when the distortion is mainly caused by contamination of additive noise.

The PSNR computes the peak signal-to-noise ratio between two images (in decibels). This computed ratio is often used as a measure of quality between the original and the compressed image. The higher the PSNR, higher will be the quality of reconstructed image.

The *Mean Square Error (MSE)* and the *Peak Signal to Noise Ratio (PSNR)* are the two metrics of error are used to compare quality of compressed image. The MSE also displays the cumulative squared error between the two images, compressed and the original image [15], on the other hand, the PSNR represents peak error. If value of MSE is low, the lower is the error.

To compute the PSNR, We must calculate the mean-squared error with the help of equation:

$$MSE = \frac{\sum_{M,N} [I_1(m,n) - I_2(m,n)]^2}{M * N}$$

In the above equation, M and N are the number of rows and columns in the images, respectively. Then the block will compute the PSNR using the equation:

$$PSNR = 10\log_{10}\left(\frac{R^2}{MSE}\right) \quad [5]$$

In the previous equation, R is the maximum fluctuation in our input image data type. We can say, if our input image is having a double-precision floating-point data type, then value of R is 1. And if it having an 8-bit unsigned integer data type that is, R is 255, etc.

VI. MODIFIED FAST HAAR WAVELET TRANSFORM

In MFHWT, first average sub signal (a' =a1,a2, a3… an/2), at one level for a signal of length N i.e. f =(f1, f2,f3,f4…fn) is

$$a_m = \frac{f_{4m-3} + f_{4m-2} + f_{4m-1} + f_{4m}}{4}, \quad m = 1, 2, 3, \ldots, N/4,$$

[12]

and first detail sub-signal(d= d1,d2,d3….dn), at the same level is given as:

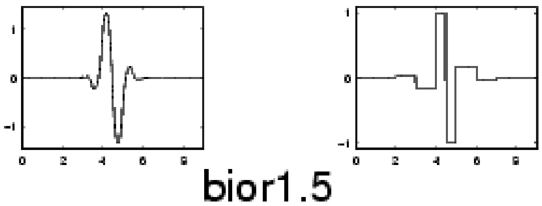
$$d_m = \begin{cases} \dfrac{(f_{4m-3} + f_{4m-2}) - (f_{4m-1} + f_{4m})}{4}, & m = 1, 2, 3, \ldots, N/4, \\ 0 & , \quad m = N/2, \ldots, N. \end{cases}$$

[12]

The MFHWT is faster in comparison to FHT and reduces the calculation work. In MFHWT, we get the values of approximation and detail coefficients one level ahead than the FHT and HT [1].

VII. BIORTHOGONAL WAVELET

Biorthogonal wavelets provide a pair of scaling functions and associated scaling filters, one for analysis and one for synthesis. Similarly, there is also a pair of wavelets and associated wavelet filters one for analysis and one for synthesis. This family of wavelets exhibits the property of linear phase, that is needed for signal and image reconstruction. There are different numbers of vanishing moments and regularity properties for the analysis and synthesis wavelets. In this, we can use the wavelet with the greater number of vanishing moments for analysis whiles the smoother wavelet for reconstruction [1]. Therefore, here we can use two wavelets, one for decomposition (on the left side) and the other for reconstruction (on the right side) instead of the same single one.



[1]

Fig 3. Bior Wavelet

VIII. RESULTS

To illustrate the effectiveness of algorithm proposed, we are taking four quality metrics and the outcome is compared with the previous algorithms. These are: Entropy, PSNR (peak to signal noise ratio), Standard Deviation and Quality.

TABLE I

Comparative Results Of Algorithm: Entropy, PSNR (Peak to Signal Noise Ratio), Quality And SD (Standard Deviation). The Focus Is Set On to have comparatively good measures of these parameters

IMAGE SET	Entropy		PSNR		S.D		Quality Index	
	Earlier Technique	Proposed Technique	Earlier Technique	Proposed Technique	Earlier Technique	Proposed Technique	Earlier Technique	Proposed Technique

MRI, MRI	5.2	6.8	11.9	51.02	11.5	43.6	26.9	166.9
CT,MRI	4.9	7.2	22.94	37.4	12.8	79.23	22.67	136.8
CT,MR1	5.06	6.9	19.5	45.4	9.3	69.5	27.5	167.3

IX. CONCLUSION AND FUTURE SCOPE

In the current paper we have given the comparison of hybrid wavelet MFHWT and BIOR, with a single wavelet i.e redundant discrete wavelet transformation. Quality Metrics have been used for computing results to compare quantitatively these techniques. Experimental results show that proposed method achieves well than the prior methods (RDWT) in terms of quality of images. The proposed method

improves the quality of image efficiently, while preserving the important details. This technique also gives the better results in terms of visual quality. For future work, the other hybrids of Curve let and contourlet transformation may be done to improve the results. This algorithm can be used in other type of images like Remote sensing images, Ultrasound images, SAR images etc. Other quality metrics can be used to judge the performance of this algorithm. Further improvements can also be done in the algorithm to improve the quality.

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