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MEDICAL IMAGE FUSION USING STATIONARY WAVELET TRANSFORM WITH DIFFERENT WAVELET FAMILIES

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ABSTRACT

The Medical image fusion restrain the complementary and significant information from multiple source images that used for identify the diseases and better treatment. Image fusion has become vital part of medical diagnosis. This paper presents a comparative study of wavelet families along with its performance analysis. Magnetic Resonance Imaging (MRI) is used to fuse which form a contemporary image so as to improve the complementary and redundant information for diagnosis function. The proposed method of Stationary Wavelet Transform (SWT) with Fusion using Principle Component Analysis (PCA)are employed along with its analysis both Qualitative and Quantitative Analysis methods. Quantitative Analysis of experimental results are evaluated by way of performance metrics like peak signal to noise ratio (PSNR), Entropy (E), Standard deviation(SD)and Image Quality Assessment(Q).Assessment of different wavelet family techniques concludes the better approach for its upcoming research.

Keywords: *Wavelet families; SWT; PCA; Qualitative Analysis; Quantitative Analysis.*

I. INTRODUCTION

According to the stage at which image information is incorporated, image fusion algorithms can be categorized into pixel [1], feature [2] and decision levels [3]. Pixel-level fusion generates a fused image in which information content related with every pixel is determined from a set of pixels in source images. Feature-level fusion [4] requires the extraction of special features which are depending on pixel intensities, edges or textures. The next basic requirement for image fusion is human organs likes Brain, Lungs, Liver, Stomach, Spleen, Pancreas, Breast, Kidneys, bone marrow, head, neck ect. Normally these algorithms can be categorized into two, spatial domain fusion [5] and transform domain fusion [6]. There are Discrete Wavelet Transform (DWT), Stationary Wavelet Transform (SWT) type transform techniques. So, the majority of fusion using simple minimum, simple maximum and simple average type and PCA [7] , which is using in spatial domain techniques. Whilst the transform domain used[8], then we have to use parameters like, Peak Signal to Noise Ratio (PSNR), Entropy (E), Standard Deviation (SD),Universal Image Quality Index(Q). The Medical image fusion methodology involving anatomical image. It can be explain the Human body information [9], which concludes the Magnetic Resonance Imaging (MRI),Computed Tomography (CT),X ray imaging and Ultrasound (US).A detailed understanding of different medical imaging modalities can be obtained from [9][10]. For example Magnetic resonance imaging is primarily a medical imaging technique used in radiology to envision complete internal structure and limited function of the body. MRI provides greatly better contrast between the different soft tissues of the body and making it especially useful in brain imaging. Some vital Categories are present in the image fusion method along with the data entering and the fusion purpose. 1) Multiview fusion of images from same modality and taken by the same time but from different viewpoints. 2) Multimodal fusion of images coming from different sensors (like CT, MRI, PET, ect). 3) Multi temporal fusion of images taken at diverse times in order to detect changes between them. 4) Multifocus fusion of images of a 3D scene taken repeatedly with various focal length. In this paper fully focused on Multiview fusion method. Therefore fusion of images obtained from same modalities is desirable to extract enough information for clinical diagnosis and treatment. This information includes the size of tumors and its location, which enable better detection when compared to the source images.

II. IMAGE FUSION TECHNIQUES

Image fusion can be classified into two domains namely, spatial and transform domains.

The spatial domain method, straightly deals with the pixels of the input image. Fusion techniques like averaging, maximum selection rule, Brovey transform, Intensity Hue Saturation (IHS) perform under this category. The major advantage of this domain lies in the preservation of the pixels' originality that depicts the shape more clearly. The only limitation of this domain is that it introduces the spatial and spectral distortion in the finally fused image. On the other hand, fusion in transform domain involves the decomposition of the source image into sub-bands which are then selectively processed using appropriate fusion algorithm [11]. Wavelet Transform based image fusion has three methods namely, Discrete Wavelet Transform (DWT), Stationary Wavelet Transform (SWT) and Multi Wavelet Transform (MWT). DWT plays a fundamental role in image fusion because it minimizes structural distortions beside with the various other transforms. The drawbacks of DWTs are deficiency of shift invariance, meager directional selectivity and non presence of segment information. These drawbacks are conquering by Stationary Wavelet Transform.

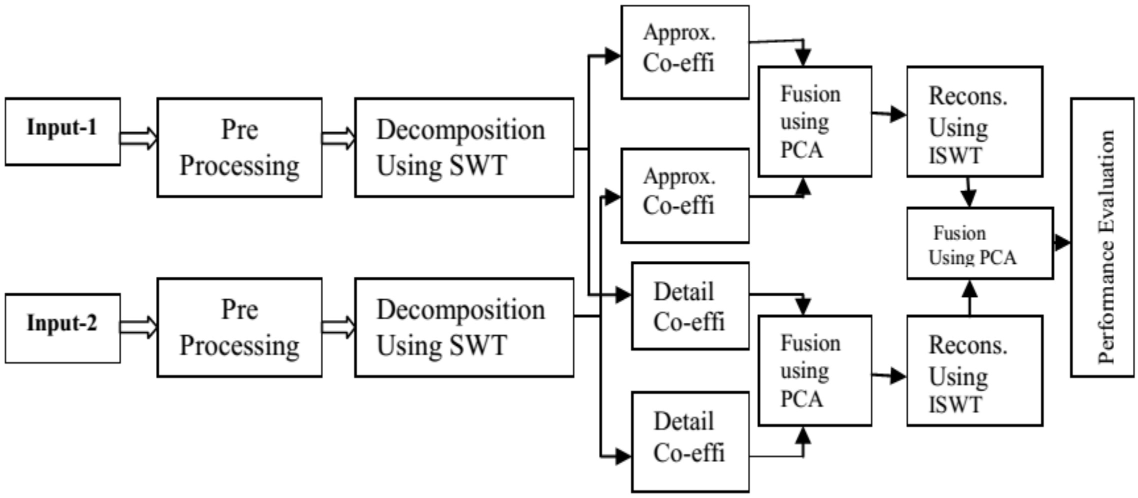


Fig.1. Block diagram of the proposed fusion methodology Using SWT with PCA.

SWT provide good time and frequency localization and phase information.But with Shift variant. Shift Variant means if its input and output characteristic does change with Time.

The Wavelet transforms are based on multi-resolution approaches dealing with the image analysis at different resolution levels, so that the characteristic missing at one level can be easily acquired at another. In work of Yang [12],wavelets were combined with maximum energy based selection rule. The algorithm by authors' employed different fusion rules for high level and low level coefficients separately; which constrained the detection of border line in fused images. Choi [13] in their work used HIS rule with the wavelet transform as fusion approach. However, the combo of wavelets and IHS contributed for the spatial distortion in the fused image. Xhao and Wu [14] implemented fusion method using lifting wavelets, but limited to facilitate the shift invariance and phase information. Singh and Khare [15] employed the Redundant Discrete Wavelet Transform (RDWT, also referred to as Stationary Wavelet Transform-SWT) along with the maximum selection rule for the fusion. However, the fused image contained a lot of redundant information.

III. PROPOSED METHOD

This section discusses the sub-band decomposition approaches along with fusion algorithms employed in the proposed methodology for collection of the useful information from MRI medical images. In this paper, an improved medical image fusion methodology involving a Stationary Wavelet Transform (SWT) with fusion using PCA. The block diagram presenting the image fusion frame for medical images is given in Fig. 1. The proposed methodology is initiated with pre-processing of the source images (from same modalities). This involves conversion of the RGB components of the image into the gray scale and it is also ensured during this step that the source images are appropriately registered [16]. This is followed by the first decomposition stage using SWT.

SWT poses certain advantages over conventional DWT. Firstly, SWT is translation invariant and therefore can be extended to dyadic inputs. SWT decomposes the source image into its respective approximation and detailed coefficients. These sub-bands coefficients are generally the low frequency and the high frequency sub-bands of the image. The approximation coefficients are the low frequency components while the detailed coefficients lie in the high frequency band. SWT is the member of wavelet family.

Wavelets are finite interval oscillatory functions through zero average value. The irregularity and good localization properties generate them better basis for analysis of signals with discontinuities. Wavelets [17] can be described by using two functions. The scaling function *f(t)*also called 'father wavelet' and the wavelet function 'mother wavelet'. The 'Mother' wavelet $\Psi(t)$undergoes translation and scaling operations [18] to give self similar wavelet families as in (1)

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \quad \textit{for } (a,b \in R),\ a>0 \rightarrow (1)$$

Where, a and b are the dilation and the translation factor as given by Eq. (2).

$$a = a_0^{\ j}, b = ma_0^{\ j}b_0 \quad \textit{for } (j,m \in Z) \rightarrow (2)$$

Thus, the wavelet family can be defined as:

$$j,m \in Z \rightarrow (3)\ \psi_{j,m}(t) = a_0^{-j/2}\psi(a_0^{-j}t - mb_0) \quad (3)$$

And, SWT can be mathematically expressed as a dyadicdiscretisation of continuous wavelet transform as in Eq.(4).

$$\sqrt{C_\psi}F(a,b) = \frac{1}{\sqrt{2\pi a}}\int_R ft\,\tilde{\psi}\left(\frac{t-b}{a}\right)dt \rightarrow (4)$$

The wavelet family plays a extensive role in defining the output image. Different wavelet families have separate features that advocates for different attributes in the fused image. In addition, the level of decomposition [19] to be applied is also an important feature; as there is loss of features or changes in the degree of reconstruction as the level of decomposition changes. In this paper, the decomposed approximation and the detailed coefficients from each of the source images are fused by PCA. The number of correlated variables are transformed into number of uncorrelated variables known as principal components. PCAis a vector spacetransform often used to reduce multidimensional data setsto lower dimensions for analysis. PCA is the easiest andmost valuable of the true eigenvector-based multivariateanalyses, because its operation is to expose the internal construction of data in an unbiased way. After finishing Fusion using PCA are reconstructed using the inverse SWT (in both the cases).Again fused the ISWT images using PCA function. The entire processing carried out in this stage serves to provide significant localization leading to a better preservation of features in the fused image.

IV. RESULTS AND DISCUSSIONS

The performance measures used in this paper provide various qualitative and quantitative analysis comparison among different wavelet families. The Qualitative analysis is called Visual analysis. It observe the edge of fused image which is very useful for correct diagnosis as shown in Fig.2. Quantitative Analysis[20][25]is called a Mathematical analysis. For evaluating the outcome various performance metrics were like Peak Signal to Noise Ratio (PSNR), Entropy(E), Standard Deviation (SD), Universal Image Quality Index (Q). It is used to how much information carry from input images to fused image.

a) Performance Metrics

Peak Signal To Noise Ratio (PSNR):

PSNR is the ratio between the maximum possible power of a single and the power of corrupting noise that affects the fidelity of its representation. The PSNR is given by,

$$PSNR(dB) = 10\log_{10}(R^2 / MSE)$$

Mean Square Error (MSE):

MSE is a frequently used measure of the difference between original image and fused image pixels. MSE is defined as Image with size of given by below equation,

$$MSE = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n}[I_{1(i,j)} - I_{2(i,j)}]^2}{m.n}$$

R- Maximum fluctuation in input images,$I_{1(i,j)}$- original image,$I_{2(i,j)}$- Fused image, *n,m* – Row & Column dimension of the image pixels.

Entropy (E): The fusion quality entropy is, the more abundant of information the fusion image contains. The entropy is defined as follows,

$$E = -\sum_{l=0}^{L-1} P_l \log_2 P_l$$

P_l - probability of fused image pixels, l = 0 to 255

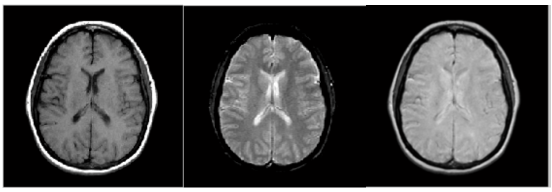
Standard Deviation (SD): The Standard deviation is a measure that is used to quantify the amount of variation of a fused image values. SD mathematical expressed as,

$$SD = \{\frac{1}{m.n}\sum_{1}^{m}\sum_{1}^{n}(f(n,m) - \mu)^2\}^{1/2}$$

f(n, m)- distribution function of fused image pixels, *n,m* – Row & Column dimension of the fused image pixels.

Universal Image Quality Index (Q): Universal Image Quality Index (Q) is depends on edge strength. The higher value indicates higher degree of edge preservation. It is defined as,

$$Q_{AB}^{F} = \frac{\sum_{n=1}^{N}\sum_{m=1}^{M} Q^{AF}(n,m)w^{A}(n,m) + Q^{BF}(n,m)w^{B}(n,m)}{\sum_{i=1}^{N}\sum_{j=1}^{M}(w^{A}(i,j) + w^{B}(i,j))}$$



(a) (b) (c)

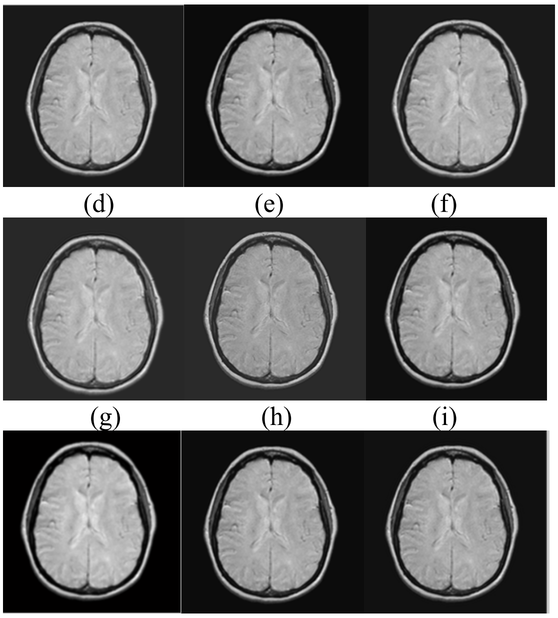


Fig. 2. Input image[21] (a)MRI-1(representing fatty tissues),(b)MRI-2 (depicting information of fluids), Qualitative analysis of fused images with different wavelet families:(c)Haar wavelet,(d)symlet wavelet, (e)coiflet wavelet, (f) daubechies complex wavelet(db3), (g)daubechies complex wavelet(db10), (h)biorthogonal wavelet(bior 3.1), (i)biorthogonal wavelet(bior 6.8), (j)Reverse Biorthogonal (rbio3.1), (k) Reverse Biorthogonal (rbio 6.8), (l)Dmeyer(dmey)

TABLE.1. PERFORMANCE METRICS FOR DIFFERENT WAVELET FAMILIES

WAVELET FAMILIES	ENTROPY	SD	PSNR	EDGE STRENGTH
Haar (haar)	1.0128	114.91	10.2186	0.3721
Symlet (sym3)	1.1592	115.54	9.8823	0.3650
Coiflet (coif1)	1.1246	115.44	10.3253	0.3657
Daubechies (db3)	1.1592	115.54	9.8823	0.3712
Daubechies (db10)	1.3620	115.64	7.9724	0.3623
Biorthogonal (bior3.1)	1.0536	118.87	10.0259	0.3658
Biorthogonal (bior6.8)	1.3864	115.88	10.3104	0.3796
Reverse Biorthogonal (rbio3.1)	1.0912	113.64	10.2310	0.3762
Reverse Biorthogonal (rbio6.8)	1.3306	115.38	10.3190	0.3744
Dmeyer (dmey)	1.7988	115.66	10.3071	0.3894

The customary requirements of an image fusion process include that all the reasonable and functional information from the source images should be safeguarded. In decomposition employs SWT; this calls for preliminary analysis for the selection of the optimal wavelet family for the implementation of proposed methodology[22].The Different wavelet families: Haar, Symlet, Coiflet, Daubechies, Biorthogonal, Dmeyer, Reverse Biorthogonal symmetrical wavelets are known for their diverse features like: symmetry, vanishing moments, familiarity of use, regularity and many more[23].SWT based decomposition has been initially simulated individually with each of the above mentioned wavelet families on Source image of MRI .The MRI medical image which represents soft tissue details. Additionally, different image[21] sets such as MRI-1 (representing fatty tissues) & MRI-2 (depicting information of fluids) have been also used. The responses for the same are shown in Fig.2.

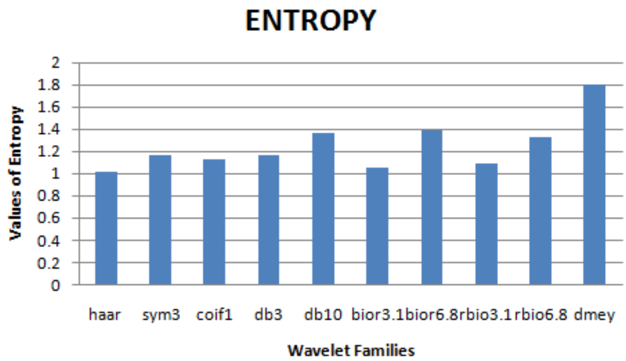


Fig.3(a).Graphical variation of Entropy(E) fusion metric using different wavelet families.

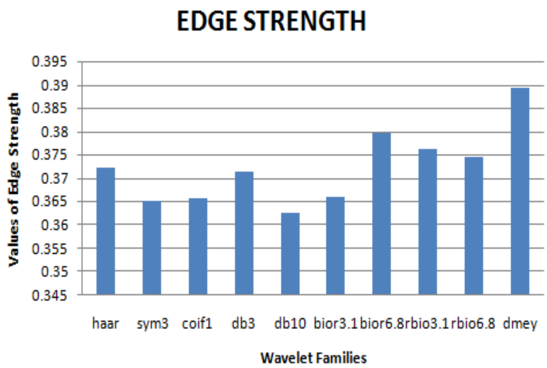


Fig.3(b). Graphical variation of Edge Strength(Q) fusion metric using different wavelet families.

In addition, the values of fusion metrics PSNR, E, SD and Qare also computed for each of the wavelet families on the same source images. From the various available IQA measures, only the above two (i.e. *E*& *Q*) are selected presently for tuning of parameters[25]. From the analysis of these wavelet families, the superiority of the Dmeyer wavelet on others has been ascertained. The values of fusion metrics like Entropy and edge strength obtained for fused image using Dmeyer wavelet have comparatively large values as shown in Fig. 3(a&

b)[26].Qualitatively, it can be also examined that in Fig. 2, that visually improved results are obtained using Dmeyer wavelet; i.e. the fused image provides a complete representation of complementary features from both the source images.

V. CONCLUSION

The results obtained illustrates that the proposed methodology has been compared to various wavelet families. The Dmeyer wavelet family gives better result compare to other wavelet family. The present work explores the key potential of SWT domains. The SWT fused image is increased frequency and time localization features of medical images supported with fusion of complementary structures. PCA rule adds to the performance of the fusion approach in terms of minimization of redundancy, better restoration of morphological details and improved contrast. The qualitative analysis of the fused image and the quantitative analysis obtained fusion metrics also shows coherence with the human perception. Hence, confirming the appropriateness of the proposed fusion method for precise and efficient clinical diagnosis.

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