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Image Fusion of CT/MRI using DWT , PCA Methods and Analog DSP Processor

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ABSTRACT
Medical image fusion is a technique in which useful information from two or more recorded medical images is integrated into a new image to offer as much details as possible for diagnosis. The fusion of different modality images are Computer Tomography (CT) and Magnetic Resonance Imaging (MRI) by integrating the DWT & PCA methods. The decomposed coefficients of Discrete Wavelet Transformation (DWT) are applied with the Principal Component Analysis (PCA) to get fused image information. Choose decomposed coefficients by fusion rule and using inverse DWT to get the fussed image of two modalities CT and MRI. The RMSE and PSNR analysis shows better improvement on results. For the proposed fusion enhancement technique going to implement on the processor based kit or will show the hardware support.
Keywords – Image fusion, DWT, PCA, DSP Processor

I. INTRODUCTION

Combining anatomical and functional medical images to provide much more useful information through image fusion has become the focus of imaging research and processing. To get a high-resolution image with as much details as possible for the correct diagnosis is the main objective of medical imaging. CT gives best information about denser tissue and MRI provides better information on soft tissue [2, 10, and 4]. Both the techniques give special refined characteristics of the organ to be imaged. So, it is looked-for that fusion of MRI and CT images of the same organ would result in an integrated image with detail information [1,2,3,4].

Image fusion is a device to integrate multimodal medical images by using image processing techniques. Precisely it aims at the integration of disparate and complementary data in order to enhance the information visible in the images. It also upturns the reliability of the interpretation consequently leads to more accurate data and increased efficacy. Besides, it has been stated that fused data gives for robust operational performance such as increased confidence, reduced ambiguity, improved reliability and improved classification [1, 2, 3, 4]. Image Fusion applied in every field where images are should be analyzed. For example, medical image analysis, microscopic imaging, analysis of images from satellite, remote sensing Application, computer vision, robotics etc .

Different techniques are used for image fusion through the evolution. On this many approaches are used. They are of Spatial-domain like IHS, PCA, averaging, brovey transformation, etc and other type is Transformation-domain is like pyramid, wavelet, curvelet transformation, etc. The disadvantage of spatial domain approaches is that they create spatial distortion in the fused image. Spectral distortion becomes a negative factor while we go for further processing such as classification problem [5,7,9]. Spatial distortion can be very well handled by frequency domain approaches on image fusion. The multi resolution analysis has become a very useful tool for analyzing remote sensing images. The discrete wavelet transform has become a very useful tool for fusion. This paper presents method using pixel level and used a data set of two modalities CT/MRI images to fuse to get a relevant and redundant information by using the DWT & PCA [2,6,8,10] techniques. And then compare the two methods with analytical values and qualitative matrices like MSE, PSNR.

The DSP Processors such as ADSP-BF533/32/31 processors are enriched members of the Blackfin processor family. While retaining their ease-of-use and code compatibility benefits, they provide significantly higher performance and lower power than previous Blackfin processors. The processors are totally code and pin-compatible, differing only with respect to their performance and on-chip memory [11, 12].

This paper is organized as section II explains the DWT. In section III, PCA is dealt. Section IV involves the proposed algorithm steps. Section V gives Hardware support. Section VI presents experimental results and section VII gives conclusion.

II. DISCRETE WAVELET TRANSFORM (DWT)

Discrete Wavelet Transform (DWT) is a mathematical tool for hierarchically decomposing an image. With strong spatial support, the DWT provides a compact representation of a signal's frequency component. DWT decomposes a image into frequency sub-band at different scale from which it can be perfectly reconstructed. The signal into high and low frequency parts is split by the DWT. The low frequency part contains coarse information of signal whereas high frequency part contains information about the edge components.

Two dimensional Discrete Wavelet Transform implements image fusion. The resolution of an image, which is a evaluate amount of detail information in the image, is changed by filtering operations of wavelet transform. And the scale is changed by sampling. The DWT analyses the image at different frequency bands with different resolutions by decomposing the image into approximation and detail coefficients (Gonzalez and Woods, 1998).

2.1 Representation of 2D-DWT Image

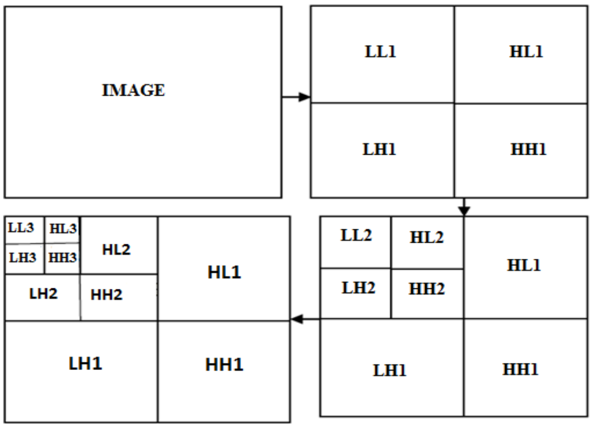


Fig 1. Image Decomposition using 2D DWT

Image representation using DWT, On the previously registered images a transform is applied. Coefficients for images are generated by This operation. A fusion rule has to be established and applied on these coefficients. The fused image is obtained using inverse transform. At every level are obtained two sets of coefficients, approximation (LL) and detail (HL, LH and HH). First perform the DWT in the vertical direction, followed by the DWT in the horizontal direction. After the first level of decomposition, there are 4 sub-bands: LL1, LH1, HL1, and HH1. For each successive level of decomposition, the LL sub band of the previous level is used as the input. To perform DWT on 2 level applied DWT on LL1 & for 3Level decomposition applied DWT on LL2 & finally get 4 sub-band of 3 level that are LL3, LH3, HH3, HL3 shown in Fig. 1. At many different resolutions, a single image is represented simultaneously (1x1, 2x2, 4x4, …, 2Nx2N). At every level create 4 new images of size (2N-1)x(2N-1).

2.2 FliterBanks

Wavelet separately filters and down samples the 2-D data (image) in the vertical and horizontal directions (separable filter bank). The input (source) image is $I\,(x, y)$ filtered by low pass filter L and high pass filter H in horizontal direction and then down sampled by a factor of two (keeping the alternative sample) to create the coefficient matrices $I_L\,(x, y)$ and $I_H(x, y)$ .The coefficient matrices $I_L\,(x, y)$ and $I_H(x, y)$ are both low pass and high pass filtered in vertical direction and down sampled by a factor of two to create sub bands (sub images) $I_{LL}\,(x, y)$, $I_{LH}(x, y)$, $I_{HL}\,(x, y)$ and $I_{HH}(x, y)$.

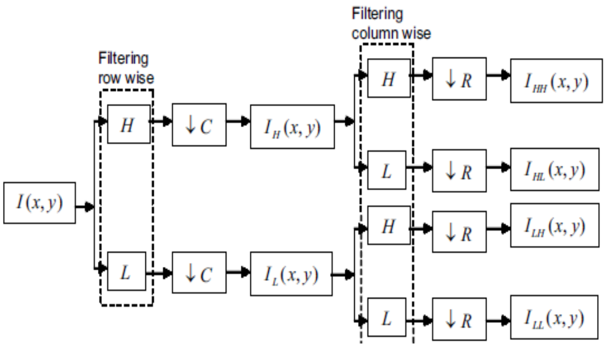


Fig 2. One level of 2-D image decomposition.

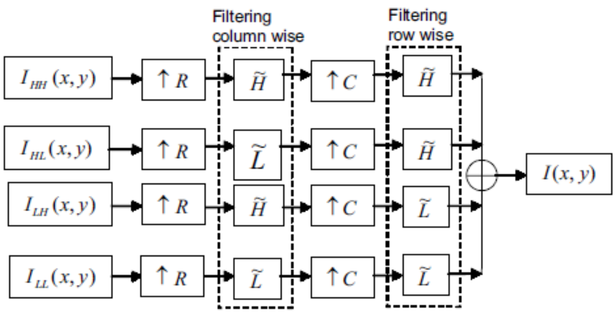


Fig 3. One level of 2-D image reconstruction.

The $I_{LL}\,(x, y)$, comprises the average image information corresponding to low frequency band of multi scale decomposition. It could be measured as smoothed and sub sampled version of the source image $I\,(x, y)$. It represents the approximation of source image. $I\,(x, y)$, $I_{LH}\,(x, y)$, $I_{HL}\,(x, y)$, and $I_{HH}\,(x, y)$, are detailed sub images which contain directional (horizontal, vertical and diagonal) information of the source image $I\,(x, y)$, due to spatial orientation. Multi-resolution could be achieved by recursively applying the same algorithm to low pass coefficients from the previous decomposition.

Inverse 2-D wavelet transform is used to reconstruct the image $I\ (x,\ y)$, from sub images $I_{LL}\ (x,\ y)$, $I_{LH}\ (x,\ y)$, $I_{HL}\ (x,\ y)$, and $I_{HH}\ (x,\ y)$ as shown in Fig. 2. This involves column up sampling (inserting zeros between samples) and filtering using low pass L and high pass filter H for each sub images. The image $I\ (x,\ y)$ would be constructed by row up sampling and filtering with low pass filter L and high pass filter H of the resulting image and summation of all matrices.

2.3 Haar Wavelet Transform

Wavelets share some common properties. Each wavelet has a unique image decompression and reconstruction characteristics which lead to different fusion results. They are not shift invariants and subsequently the fusion methods using DWT lead to unstable and flickering results. The fusion process should not be dependent on the location of an object in the image and fusion output should be stable and consistent with the original input sequence for the case of image sequences. Haar Wavelet Transform is used to make the DWT shift invariant. Haar wavelets are real, orthogonal and symmetric.

The Haar transform functions as a square matrix of length N = some integral power of 2. Implementing the discrete Haar transform consists of acting on a matrix row-wise finding the sums and differences of consecutive elements. If the matrix is split in half from top to bottom, the sums are stored in one side and the differences in the other. Next operation occurs column-wise, splitting the image in half from left to right. It stores the sums on one half and the differences in the other. The process is repeated on the smaller square, power-of-two matrix resulting in sums of sums. The number of times this process occurs can be thought of as the depth of the transform.

Properties of Haar wavelet transform:

1. Haar Transform is real and orthogonal. Therefore

$$Hr = Hr^* \qquad (1)$$

$$Hr = Hr \qquad (2)$$

Haar Transform is a very fast transform.

2. The basis vectors of the Haar matrix are sequence ordered.

3. Haar Transform has poor energy compaction for images.

4. Orthogonality: The original signal is split into a low and a high frequency part and filters enabling the splitting without duplicating information are said to be orthogonal.

5. Linear Phase: Symmetric filters would have to be used to obtain linear phase.

6. Compact support: The magnitude response of the filter should be exactly zero outside the frequency range covered by the transform. The transform is energy invariant if this property is algebra satisfied.

7. Perfect reconstruction: If the input signal is transformed and inversely transformed using a set of weighted basis functions and the reproduced sample values are identical to those of the input signal, the transform is said to have the perfect reconstruction property. If, in addition no information redundancy is present in the sampled signal, the wavelet transform is, as stated above, ortho normal.

III. Principle Component Analysis

The PCA involves a mathematical procedure that transforms a number of correlated variables into a number of uncorrelated variables. It computes a compact and optimal description of the data set. The first principal component accounts for as much of the variance in the data as possible and each succeeding component accounts for as much of the remaining variance as possible. First principal component is taken to be along the direction with the maximum variance. The second principal component is constrained to lie in the subspace perpendicular of the first. This component points the direction of maximum variance within this subspace. The third principal component is taken in the maximum variance direction in the subspace perpendicular to the first two and so on. The PCA is also called as Karhunen-Loève transform or the Hotelling transform.The PCA does not have a fixed set of basis vectors like FFT, DCT and wavelet etc. Its basis vectors depend on the data set.

PCA is also a linear transformation that is easy to be implemented for applications in which huge amount of data is to be analyzed. PCA is widely used in data compression and pattern matching by expressing the data in a way to highlight the similarities and differences without much loss of information.

3.1 PCA Algorithm

Let the source images (to be fused) of size m x n matrix, the steps for PCA are:

1. Organise the data into column matrix. The resulting matrix Z is of dimension 2 x n.

2. Calculate the empirical mean along each column. Assing The empirical mean matrix M of 1 x 2.

3. Subtract the empirical mean vector M from each column of the data matrix Z. The resulting matrix X is of dimension 2 x n i.e variance.

4. Find the covariance matrix C of X i.e.C=XX_T mean of expectation = cov(X)

5. Compute the eigenvectors V and eigenvalue D of C and sort them by decreasing eigenvalue. Both V and D are of dimension 2 x 2.

6. Consider the first column of *V* which corresponds to larger eigenvalue to compute P_1 and P_2 as:

$$P_1 = \frac{V(1)}{\sum V} \quad \text{and} \quad P_2 = \frac{V(2)}{\sum V}$$

3.2 Image Fusion by PCA

The information flow diagram of PCA-based image fusion algorithm is shown in Fig. 4. The input images (images to be fused) $I_1\ (x, y)$ and $I_2(x, y)$ are arranged in two column vectors and their empirical means are subtracted. The resulting vector has a dimension of n x 2, where n is length of the each image vector. The eigenvector and eigenvalues for this resulting vector are computed and the eigenvectors corresponding to the larger eigenvalue achieved. The normalized components P1 and P2 (i.e., P1 + P2 = 1) are computed from the obtained eigenvector. The fused image is:

$$I_f\,(x, y) = P_1 I_1\,(x, y) + P_2 I_2\,(x, y)$$

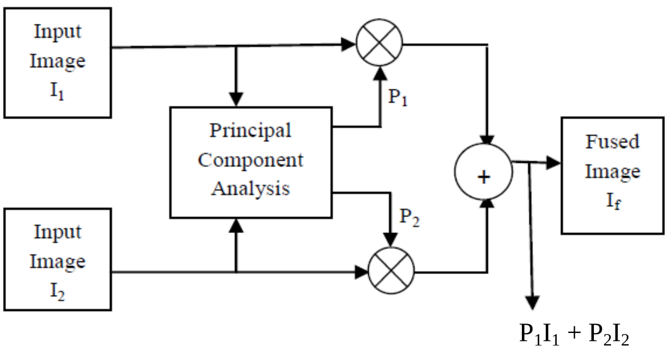


Fig 4. Image Fusion by PCA

IV. PROPOSED METHOD

In this paper, image fusion of two modality images i.e. CT and MRI. Consider image I_1 as CT and image I_2 as MRI. The following steps are the proposed methods, as shown in figure 4.

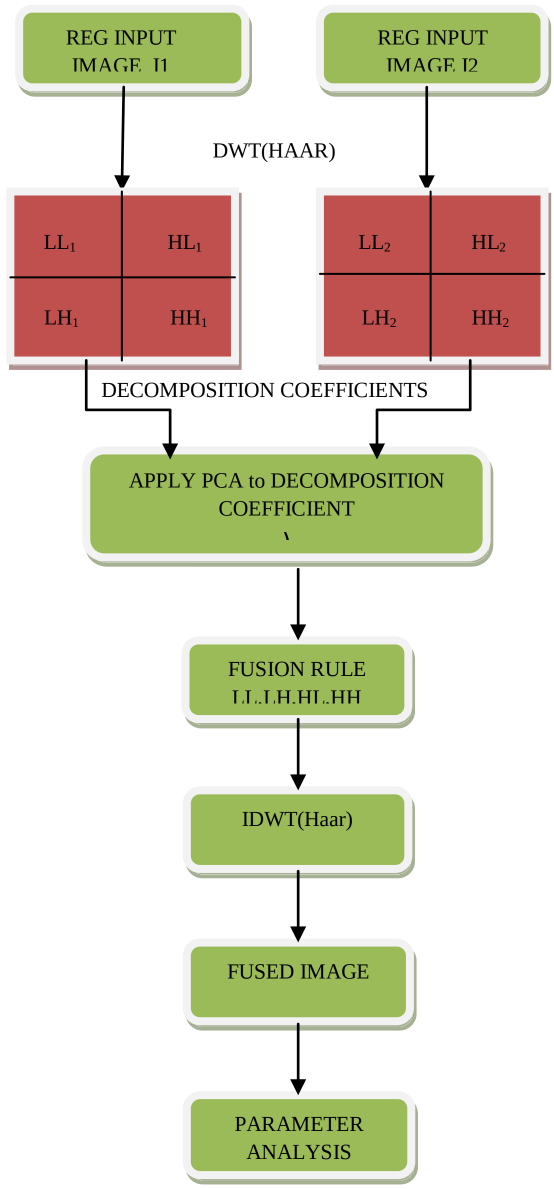


Fig 5. The proposed method

- The images to be fused must be registered to assure the corresponding pixels are aligned together i.e. registered image I_1 and I_2.
- This method is considered as the most efficient in terms of computation time since Haar wavelet is used. By applying DWT (haar), the reg image I_1 and I_2 are decomposed i.e. {LL1, LH1, HL1, HH1}= DWT {reg image I_1} and {LL2, LH2, HL2, HH2}= DWT {reg image I_2} to obtain the coefficients and the reg images are subjected to 3-level decomposition.
- The resulting coefficients are evaluated using PCA for both dimension reduction as well as to obtain best coefficients for fusion. Now, using each coefficients of reg image I_1 and I_2 and applying PCA by taking respective coefficients.

- The fusion rule involves multiplication of each principle component with each decimated wavelet coefficient adding them to obtained fused image.
- The fused image is constructed by performing the IDWT (Haar) based on the combined transform coefficients from previous step.

V. HARDWARE SUPPORT

Analog Devices Blackfin® processors offer best-in-class performance for the given power and cost, allowing developers to create intelligently aware systems that communicate via wireless or wired connections and are not limited to a specific package or standard. A set of image processing primitives designed to enable faster development of complex image or video processing solutions on Blackfin is called Blackfin Image Processing Toolbox. Primitive functions have been highly optimized to run on Analog Devices' Blackfin BF-5xx and BF-60x processor family. It is a self-contained software module.

All the ease of use and architectural attributes of the Blackfin processor are offered by Analog Devices initial product family, the ADSP-BF531, ADSP-BF532, and ADSP-BF533. These three processors are all completely pin compatible - differing solely with respect to their performance and on-chip memory. Thus reduces risk and offering the ability to scale up or down depending upon the end application needs. All three processors offer low power consumption with scaleable performance from low-cost to very high performance.

The ADSP-BF532 offers excellent performance, large on-chip memories, and an array of application-tuned peripherals. The Blackfin Evaluation Board is specially devised for developers in DSP field as well as beginners. The BF532 kit is devised in such way that all the possible features of the DSP will be easily used by everyone. The kit supports in VisualDsp++5.0 and later.

The followings are playing a major role in our hardware support:

- BF532 KIT with 128Mbit SDRAM, 1Mbyte FLASH & UART
- Visual Dsp++
- MATLAB

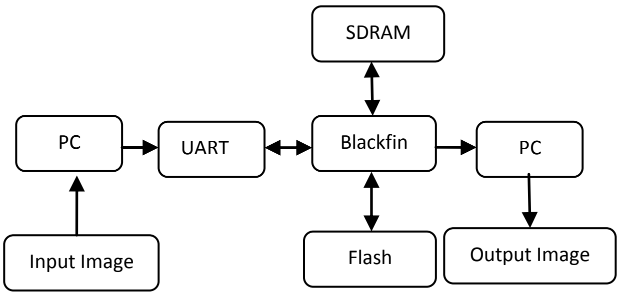


Fig. 6 The flow diagram of proposed system

Step1. The Blackfin Evaluation Board has 128 Mbit SDRAM interfaced in BF532 kit. To store a huge data (pixel), this interface will be used.

Step2. The RS2329 pin serial communication is interfaced through UART Serial Interface peripheral. This interface is used to communicate kit with the Matlab.

Step3. The Visual Dsp++ will help to do the source code for Blackfin 532 to implement the Image Fusion algorithm and to debug.

Step4. The MatLab will help to see images on GUI Window from processor UART through pc.

VI. PERFORMANCE EVALUATION

The two modality CT and MRI images are fused by proposed method i.e integrating of DWT and PCA methods. By using platform of MatLab, the implementation of this project is done The GUI model of this project implementation is shown below in fig 7. The fused image is analyzed with MSE, PSNR, Entropy, the values of these over proposed method gives better results.

Fig. 7 The GUI implementation of project

In the MRI image, the inner contour is missing but it provides better information on soft tissue. In the CT image, it provides the best information on denser tissue with less distortion, but it misses the soft tissue information.

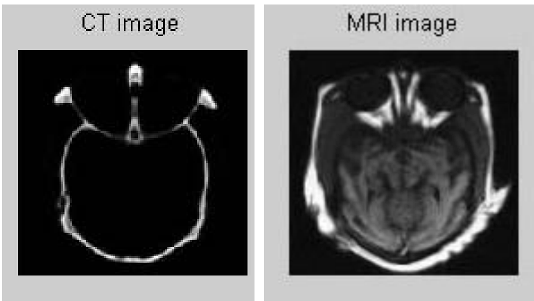
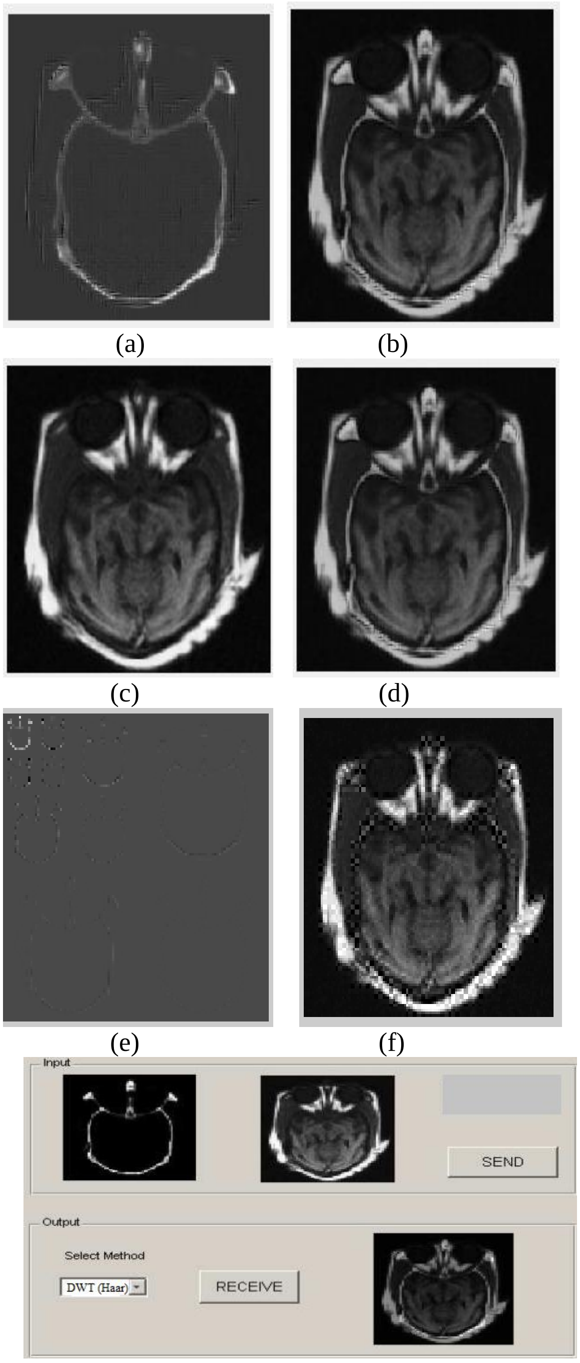


Fig 8. Input Image1 and input Image2 represents the CT and MRI images of Brain of same person respectively



(a) (b) (c) (d) (e) (f) (g)

Fig 9. Fused images by (a) Normal Min (b) Bi-orthogonal (c) PCA method (d) DWT(Haar) (e) 3-level of decomposition (f) the proposed method DWT-PCA and Analog BF532 support image fusion.

The results are compared and given in table of graphs and respective graphs of quantitative matrices are given. The following table shows the statistical parameters of reconstructed images.

Table1. Statistical Parameters

Parameter / fusiom Methode	RMES	PSNR
Normal Min	75.71	29.33
Bi-orthogonal	76.80	29.31
PCA	75.59	29.34
DWT(Haar)	25.86	34.00
DWT+PCA	13.70	36.76

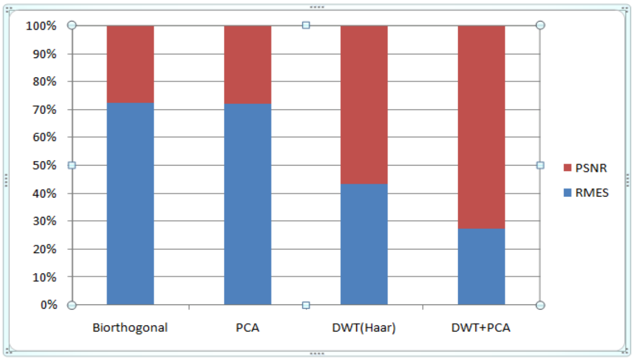


Figure 10. Fusion Method Vs RMES , PSNR

The statistical parameters are Mean Square Error, Signal to Noise Ratio and Entropy. The table shows that the proposed technique outperforms the other fusion method. From the above table, it can observe that the proposed method has less Mean Square Error and high Signal to Noise Ratio compared to other methods.

VII. CONCLUSION

The fusion of CT and MRI of two modality images improves the view of the images and adds information of both anatomical and physiological information in one image. The Wavelet transforms is the best technique for the image fusion which provides a high quality spectral content. But a good fused image has both quality so the combination of DWT & spatial domain fusion method (like PCA) fusion algorithm improves the performance as compared to use of individual DWT and PCA algorithm. Finally this review concludes that a image fusion algorithm based on combination of DWT and PCA with morphological processing will improve the image fusion quality and may be the future trend of research regarding image fusion.

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