Comparative Analysis of Wavelets for Fusion Application

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ABSTRACT
The Successful fusion of images acquired from different modalities is of great important in many applications such as microscopic imaging, remote sensing, robots and medical imaging. Medical image fusion is a technique in which useful information from two or more registered medical images is integrated into a new image that can be used to make clinical diagnosis and treatment more accurate. This paper proposes fusion of magnetic resonance and computed tomography medical images using Haar wavelet and principal component analysis (PCA).The wavelet transform is applied to decimate the each source image. The obtained decimated coefficients of source images are evaluated using principal component analysis. The resulting Coefficients are fused and reconstructed using inverse wavelet transforms. we applied number wavelets for the fusion process. The comparative analysis is made based on MSE & PSNR.

Keywords
Fusion, Haar wavelet, PCA.

1. INTRODUCTION
Image fusion is a tool to combine multimodal images by using image processing techniques. Specifically it aims at the integration of disparate and complementary data in order to enhance the information apparent in the images, as well as to increase the reliability of the interpretation. This leads to more accurate data and increased utility. In addition, it has been stated that fused data provides for robust operational performance such as increased confidence, reduced ambiguity, improved reliability and improved classification [1, 2, 3, 4, 5].Due to the advent of new diseases complementary information are required from different modalities. When sensitive organs like brain are scanned, both magnetic resonance imaging and computed tomography scans are preferred. CT provides best information about denser tissue and MR offers better information on soft tissue [2, 10, and 5]. These complementarities have led to idea that combining images acquired with different medical devices will generate an image that can offer more information than individual image. So, it is expected that fusion of MR and CT images of the same organ would result in an integrated image of much more details. Wavelet transform fusion is defined as considering wavelet transforms of the two registered input images together with the fusion rule. Then the inverse wavelet transform is computed and the fused image is reconstructed. This paper proposes principal component analysis integrated with wavelet transform for image fusion. The purpose of employing PCA is to obtain optimization for achieving better fusion results [1]. The work proposed in this paper uses Haar wavelet. Haar wavelets are fastest to compute and simplest to implement. The main advantages of Haar wavelet are, it is memory efficient, since it can be calculated in place without a temporary array and it is exactly reversible without the edge effects that are a problem with other wavelet transforms.

This paper is organized as follows. In section 2, Haar wavelet and discrete wavelet transform are explained. In section 3, principal component analysis is dealt. Section 4, provides the steps involved in the proposed method. In section 5, experimental results are presented. Finally, section 6, submits a conclusion of this paper.

2. WAVELET TRANSFORM
Wavelet transforms are linear transforms whose basis functions are called wavelets. The wavelets used in image fusion can be classified into many categories such as orthogonal, bi-orthogonal and A'trous wavelet etc. Although these wavelets share some common properties, each wavelet has a unique image decompression and reconstruction characteristics that lead to different fusion results. They are not shift invariants and consequently the fusion methods using dwt lead to unstable and flickering results. For the case of image sequences 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. To make the DWT shift invariant we use haar wavelet transform. Haar wavelets are real, orthogonal and symmetric. The Haar wavelet's mother wavelet function $\psi(t)$ can be described as,

$$\varphi(t) = \begin{cases} 1 & 0 \le t < \frac{1}{2}, \\ -1 & \frac{1}{2} \le t < 1, \\ 0 & otherwise \end{cases}$$

and its scaling function described as,

$$\emptyset(t) = \begin{cases} 1 & 0 \le t < 1, \\ 0 & otherwise \end{cases}$$

The Discrete Wavelet Transform (DWT) of image signals produces a non-redundant image representation, which provides better spatial and spectral localization of image formation, compared with other multi scale representations such as Gaussian and Laplacian pyramid. Recently, Discrete Wavelet Transform has attracted more and more interest in image processing. The DWT can be interpreted as signal decomposition in a set of independent, spatially oriented frequency channels. The signal S is passed through two complementary filters and emerges as two signals, approximation and Details. This is called decomposition or analysis. The components can be assembled back into the original signal without loss of information. This process is called reconstruction or synthesis. The mathematical manipulation, which implies analysis and synthesis, is called discrete wavelet transform and inverse discrete wavelet transform. Different spatial resolution images using DWT. In case of a 2D image, an N level decomposition can be performed resulting in 3N+1 different frequency bands namely, LL, LH, HL and HH. These are also known by other names, the sub- bands may be respectively called a1 or the first average image, h1 called horizontal fluctuation, v1 called vertical fluctuation and d1 called the first diagonal fluctuation. . The sub-image a1 is formed by computing the trends along rows of the image followed by computing trends along its columns. In the same manner, fluctuations are also created by computing trends along rows followed by trends along columns. The next level of wavelet transform is applied to the low frequency sub band image LL only. The Gaussian noise will nearly be averaged out in low frequency wavelet coefficients. Therefore, only the wavelet coefficients in the high frequency levels need to be thresholded.

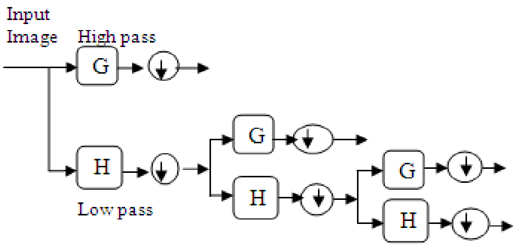


Fig 1:2-D DWT for image

3. PRINCIPAL COMPONENT ANALYSIS

Principal component analysis is carried out which aims at reducing a large set of variables into a small set that still containing most of the information that was available in the large set. The technique of principal component analysis enables us to create and use a reduced set of variables, which are called principal factors. A reduced set is much easier to analyze and interpret. The most straight forward way to build a fused image of several input images is performing the fusion as a weighted superposition of all input images. The optimal weighting coefficients, with respect to information content and redundancy removal, can be determined by a principal component analysis (PCA) of all input intensities. By performing PCA of the covariance matrix of input intensities, the weightings for each input image are obtained from the eigenvector corresponding to the largest Eigen value. PCA is the simplest of the true eigenvector-based multivariate analysis. Often, its operation can be thought of as revealing the internal structure of the data in a way which best explains the variance in the data. If a multivariate dataset is visualized as a set of coordinates in a high-dimensional data space (1 axis per variable), PCA can supply the user with a lower- dimensional picture, a "shadow" of this object when viewed from its most informative viewpoint. This is done by using only the first few principal components so that the dimensionality of the transformed data is reduced. The number of principal components is less than or equal to the number of original variables. This transformation is defined in such a way that the first principal component has as high a variance as possible (that is, accounts for as much of the variability in the data as possible), and each succeeding component in turn has the highest variance possible under the constraint that it be orthogonal to (uncorrelated with) the preceding components. Principal components are guaranteed to be independent only if the data set is jointly normally distributed. PCA is sensitive to the relative scaling of the original variables. Depending on the field of application, it is also named the discrete Karhunen–loève transform (KLT), the Hotelling transform or proper orthogonal decomposition.

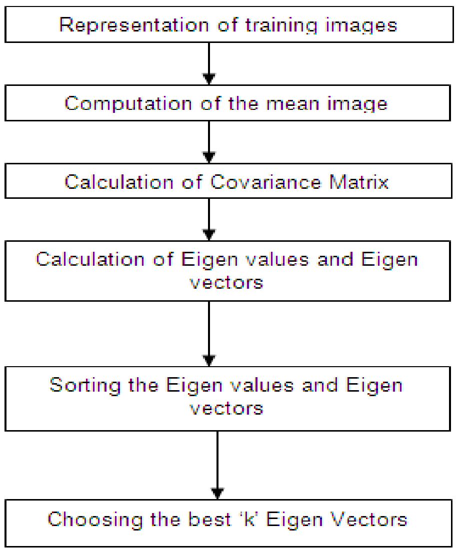
3.1 PCA ALGORITHM

Organize the data into column vectors. The resulting matrix Z is of dimension 2 x n.
Compute the empirical mean along each column.
The empirical mean vector Me has a dimension of 1 x 2.
Subtract the empirical mean vector M_e from each column of the data matrix Z. The resulting matrix X is of dimension 2 x n.

Find the covariance matrix C of X i.e. $=XX^T$ mean of expectation = covariance(X).
Compute the eigenvectors V and Eigen value D of C and sort them by decreasing Eigen value. Both V and D are of dimension 2x2.
Consider the first column of V which corresponds to larger Eigen value to compute P1 and P2 as

$P_1=V(1)/\sum V$, $P_2=V(2)/\sum V$

Fig 2:Steps involved in PCA



4. PROPOSED ALGORITHM

The proposed algorithm is as follows. In this paper CT and MR images are considered as input images for image fusion.
Each source image is resambled i.e., preprocessing is done at first. Resampling changes the pixel dimensions of an image. This process does not alter the gray level value, a nearest neighbor interpolation is preferred if variations in the gray levels need to be retained.
This method is considered as the most efficient in terms of computation time since Haar wavelet is used Haar wavelet transform is applied on the each source image to obtain the decimated coefficients and the source images are subjected to 8-level decomposition and the resulting coefficients are evaluated using PCA for both dimension reduction as well as to obtain best coefficients for fusion.
The fusion is performed by applying fusion rule and the fused image is obtained.

The fusion rule involves multiplication of each principal component with each decimated wavelet coefficient and adding them to obtain the fused image.
The fusion rule is,
imf = pca(1)*I_W1 + pca(2)*I_W2
This fused image is reconstructed using inverse transform and quality metrics are calculated and analyzed.
The proposed algorithm is shown in the following figure3

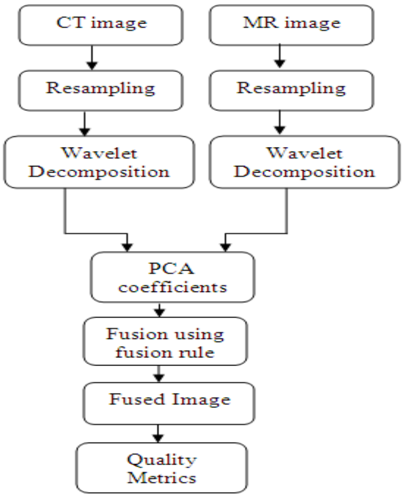


Fig 3:Proposed algorithm

For the comparative analysis, we applied different wavelets for the same input images. Table1 shows the result obtain by using various wavelets.

5. RESULTS

In the MRI image the inner contour 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. Figure4 and figure5 represents the CT and MR images of brain of same person respectively

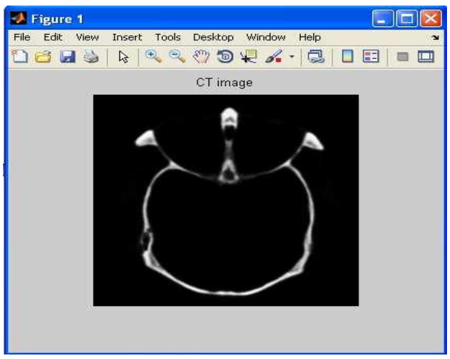


Fig 4: CT image of brain

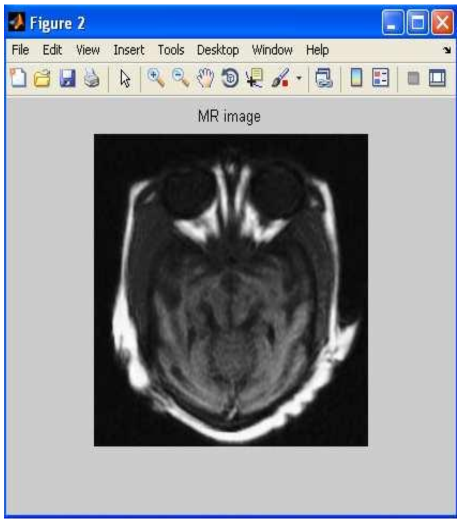


Fig 5: MR image of brain

Figure 6 represents 8-level decomposition of fused image in our proposed method.

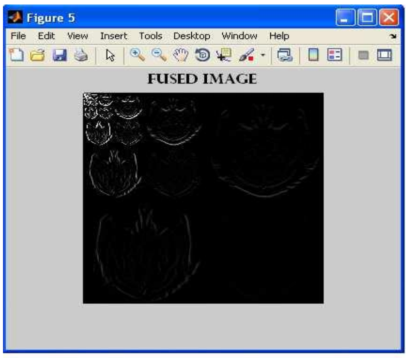


Fig 6: 8-level decomposition of fused image

Figure 7 represents the reconstructed image after applying wavelet transform.

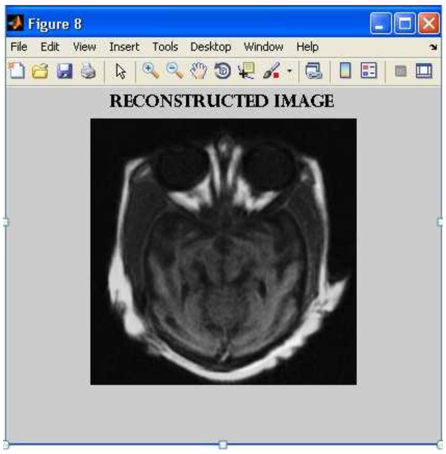


Fig 7: Reconstructed Image

The following table shows the statistical parameters of reconstructed images obtained by using various wavelets with PCA.

Table1. Statistical Parameters

Parameter / Wavelet Type	MSE	PSNR
Biorthogonal	89.3112	28.6217
Reverse Biorthogonal	87.7467	28.6985
Daubechies	35.2386	32.6606
Symlet	28.5260	33.5784
Coiflet	12.7239	37.0846
Discrete Meyer	11.0325	37.7041
Haar	8.1567	39.0157

The statistical parameters are Mean Square Error, Signal to Noise Ratio. The table shows that the proposed technique outperforms the other wavelet approaches. The worst performance is yielded by Biorthogonal wavelet approach.

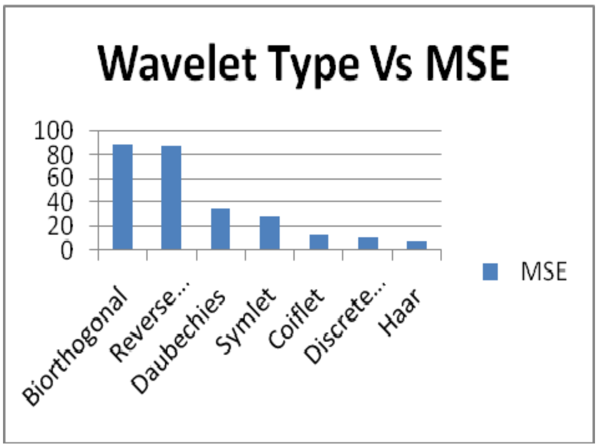


Fig 8: Wavelet Type Vs MSE

Figure 8 explains the variation in Mean Square Error for different wavelets. Figure 9 represents the variation in Signal to Noise Ratio for various wavelets. From the figures 8 and 9,we can observe that the proposed method has less Mean Square Error and high Signal to Noise Ratio compared to other methods

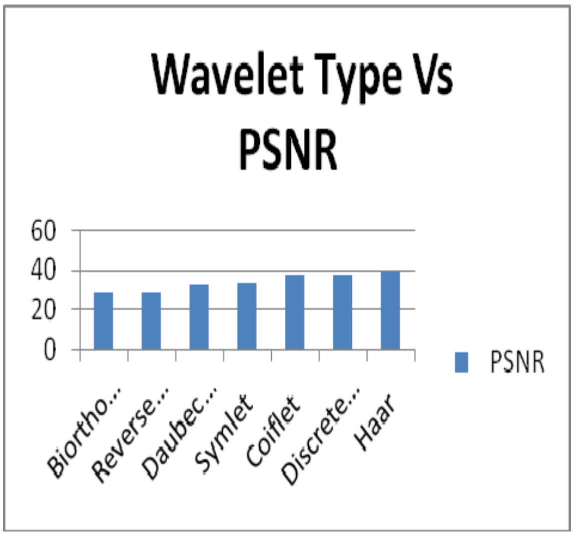


Fig 9: Wavelet Type Vs PSNR

6. CONCLUSION

Fusion imaging is one of the most modern, accurate and useful diagnostic techniques in medical imaging today. In this paper the integration of wavelets and PCA for the fusion of magnetic resonance and computed tomography image has been proposed. We compared the performance of the fused images obtained from the wavelets, Biorthogonal, Reverse Biorthogonal, Daubechies ,Symlet, Coiflet, Discrete Meyer with Mean Square Error and Signal to Noise Ratio(PSNR).From our qualitative analysis Haar wavelet produces less error and free from noise thus suitable for medical image fusions.

7. REFERENCES

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