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Implementation and qualitative analysis of image fusion methods using wavelets.

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***Abstract*—Image fusion is a process of blending the complementary as well as the common features of a set of images, to generate a final image with superior information content in terms of subjective as well as objective analysis point of view. The objective of this paper is to develop some novel image fusion algorithms and their applications in various fields such as edge detection, multi spectra sensor image fusion, medical image fusion. Here, an improved hybrid DWT and PCA based image fusion technique has been developed to compose a resultant image with better perceptual as well as quantitative image quality indices in terms of lower RMSE higher PSNR. .**

***Index Terms*—DWT,PCA, RMSE, PSNR.**

I. INTRODUCTION

The most fundamental debate concerning image fusion is to choose how to consolidate the sensor images. In recent years, a number of image fusion methods have been projected . One of the primitive fusion schemes is pixel-by-pixel gray level average of the source images. This simplistic method often has severe side effects such as dropping the contrast. Enhanced outcomes were gotten with image fusion, performed in the transfer domain. The pyramid change fathoms this reason in the transform domain.. The basic idea is to perform a multiresolution decomposition on each source image, then coordinate all these decompositions to develop a composite depiction and finally reconstruct the fused image by performing an inverse multi-resolution transform. A number of pyramidal decompositionmethods have been developed for image fusion, such as, Laplacian Pyramid, Ratio or low-pass Pyramid, Morphological Pyramid, and Gradient Pyramid[1]. Most recently, with the evolution of wavelet based multi resolution analysis concepts, the multi-scale wavelet decomposition has begun to take the place of pyramid decomposition for an image. The image fusion method can be classified in two categories i.e fusion in spatial domain and fusion in transform domain . spatial domain methods related to pixel-to-pixel operation like maximum selection, principal component analysis[2] etc. transform domain method like wavelets[3] and curvlet transform[4]operates in transform domain and resultant image can be obtained by performing its inverse operations.

II. SPATIAL FUSION METHODS

(a)Maximum selection method

The sample of two multi-focus images is taken and the maximum of the pixel intensities at every position (i,j) is selected as the (i,j) pixel of the fused image. The max Selection method uses the simple maximum value selection principle in which the first pixel of the two input image are compared and the maximum of the pixel value obtained is the first pixel of the resultant Fused image. Now the second pixels of the input image are compared and it's maximum value is stored as the second pixel of the output image. Similarly the same procedure is applied to all the pixels and the resultant Fused image is the maximum valued pixels of input images. The resultant image have higher intensity level or brightness features.

(b) PCA Method

The PCA [2] principal component analysis image fusion method uses the pixel values of source images at each pixel location, adds a weightage factor to each pixel value, and takes an average of the weighted pixel values to produce the resultant pixel for the fused image at the same pixel location. The optimal weighted factors are determined by the PCA method. The PCA image fusion method reduces the redundancy of the image data set. PCA, the data is projected from its original space to its Eigen space to increase the variance and reduce the covariance so as to identify patterns in the data. The flow chart of original PCA is shown in Figure.1.PCA is the simplest true eigenvector-based multivariate analysis. It involves ways for identifying and to show patterns in data, in such a way as to highlight their similarities and differences, and thus reduce dimension without loss of data. In this method first the column vectors are extracted, from respective input image matrices. Then covariance matrix is calculated. Diagonal elements of covariance vector will contain variance of each column vector. The Eigen values and the vectors of covariance matrix are calculated and the PCA fusion is implemented by neglecting the lower order components i.e. whose variance is very less to the resultant image. The PCA method provides better spatial resolution but suffers with degraded spectra response.

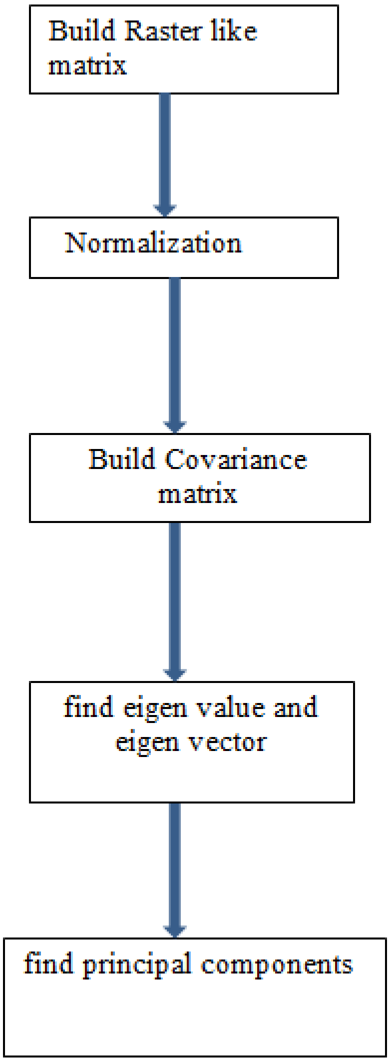

Fig.1flow chart of the PCA.

III Wavelet based fusion method

Algorithm A Discrete Wavelet Transform (DWT)[3][5] is any wavelet transform for which the wavelets are discretely sampled. The first DWT was invented by the Hungarian mathematician Alfrd Haar.Application of wavelet transform in image processing is one of the active areas in wavelet studies.Two dimensional wavelet transform can be considered as an extension of 1D wavelet transform. M dimensional wavelet transform is a natural extension of 2D wavelet transform. It is applied in problems such as system modeling used in control systems and construction of autoregressive models.

For 2D wavelet transform, we consider separable wavelet basis to decompose the image as follows. A separable wavelet basis of $L^2(R^2)$ space is constructed using tensor product of a scaling function ϕ and a wavelet function ψ. Consider ϕ, ψ and $\tilde{\phi}$ and $\tilde{\psi}$ as two dual pairs of scaling and wavelet functions in a biorthogonal wavelet transform in $L^2(R)$. Accordingly, three wavelet functions can be defined for the decomposition stage as the product of scaling and wavelet functions ϕ, ψ as follows:

$$\psi^1(x,y)=\varphi(x)\psi(y), \quad \psi^2(x,y)=\psi(x)\varphi(y)$$

and

$$\psi^3(x,y)=\psi(x)\psi(y)$$

Similarly the dual wavelets of ψ^1, ψ^2 and ψ^3 for a biorthogonal analysis of the image acan be written as:

$$\tilde{\psi}^1(x,y)=\tilde{\varphi}(x)\tilde{\psi}(y), \quad \tilde{\psi}^2(x,y)=\tilde{\psi}(x)\tilde{\varphi}(y)$$

and

$$\tilde{\psi}^3(x,y)=\tilde{\psi}(x)\tilde{\psi}(y)$$

One can verify that in a general case when basis functions are indexed according to scale j, translation m and frequency band n (as done in wavelet packet), orthogonality is maintained between the bases. For example the basis function as given below

$$\left\{\psi^1_{j,n,m}(x,y),\psi^2_{j,n,m}(x,y),\psi^3_{j,n,m}(x,y),\right\}_{(j,n,m)\in Z^3}$$

and

$$\left\{\tilde{\psi}^1_{j,n,m}(x,y),\tilde{\psi}^2_{j,n,m}(x,y),\tilde{\psi}^3_{j,n,m}(x,y),\right\}_{(j,n,m)\in Z^3}$$

are biorthogonal bases of $L^2(R^2)$.

In case of orthonormal bases, it is easy to see that two-dimensional separable orthonormal basis, can be considered as a special case of biorthogonal basis if we start with orthonormal one dimensional bases i.e. scaling function ϕ and wavelet function ψ.

The reason biorthogonal wavelets are often used in image analysis is due to human visual system where they are more tolerant of symmetric errors than asymmetric ones, it is desirable that wavelet and scaling functions be symmetric. However, unfortunately, orthogonality and symmetry conflicts with each other in the design of filter banks. Note in symmetric biorthogonal wavelets scaling function is symmetric, wavelet function is anti-symmetric.

For a 2D biorthogonal discrete wavelet transform (DWT), a real-valued image is represented in terms of translation and dilations of a scaling function and a wavelet functions, the same as in 1D DWT. The scaling and wavelet coefficients can be easily computed using a 2D filter bank composed of lowpass and highpass filters and decimators (downsampling). The 2D wavelet and scaling functions provide an orthogonal basis for 2D images. Therefore, every image has a unique representation in the wavelet-domain.

At each scale, an image f(x,y) is decomposed[6] into an approximation image a_j of a lowpass band, and three detail images d_j^x, d_j^y, d_j^{xy} corresponding to a horizontal highpass band d_j^x, a vertical highpass band d_j^y ,and a highpass band d_j^{xy} as given below

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$$a_j(x,y) = \langle f\ (x,y), \phi_j(x)\phi_j(y)\ \rangle$$
$$d_j^x(x,y) = \langle f\ (x,y), \psi_j(x)\phi_j(y) \rangle$$
$$d_j^y(x,y) = \langle f\ (x,y), \phi_j(x)\psi_j(y) \rangle$$
$$d_j^{xy}(x,y) = \langle f\ (x,y), \psi_j(x)\psi_j(y) \rangle$$

Due to down sampling of the coefficients, the size of the image at lower level is half of that of the higher level.

In two dimensional image analysis, the three wavelets $\psi^1(x,y) = \varphi(x)\psi(y)$, $\psi^2(x,y) = \psi(x)\phi(y)$ and $\psi^3(x,y) = \psi(x)\psi(y)$ extract image details at different scales and orientations(Fig.1). At each scale, we end up with three "detail" images:

One is low-pass filtered in the x-direction and high-pass filtered in the y direction $\psi^1(x,y) = \phi(x)\psi(y)$, yielding detail D^xone is low-pass filtered in the y direction and high-pass filtered in the x direction $\psi^2(x,y) = \psi(x)\phi(y)$ yielding detail D^y

and, finally

one is high-pass filtered in both x and y directions $\psi^3(x,y) = \psi(x)\psi(y)$ yielding detail D^{xy}.

So, we have three orientations for details horizontal, vertical and diagonalAfter one level of decomposition, there will be four frequency bands, namely Low- Low (LL), Low-High (LH), High-Low (HL) and High-High (HH). The next level de- composition is just applied to the LL band of the current decomposition stage as it contains the approximate image, which forms a recursive decomposition procedure. Thus, an N-level decomposition will finally have 3N+1 different frequency bands, which include 3N high frequency bands and just one LL frequency band. The 2-D DWT will have a pyramid structure shown in the above figure. The frequency bands in higher decomposition levels willhave smaller size.

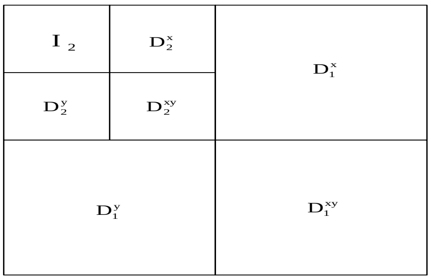
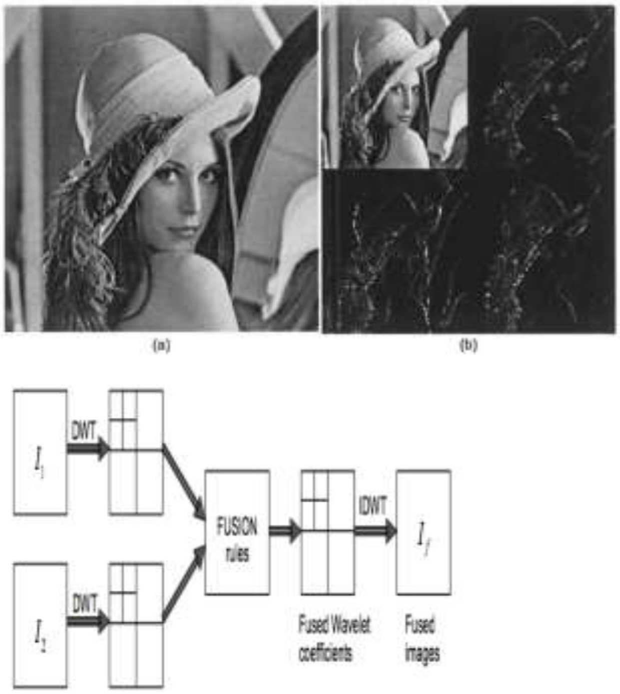


Fig.2 Components of decomposed image, three details and one approximation at each scale

as DWT operate in transform domain image intensity may degraded but it provide better spectral resolution compared to spatial methods.



(c)

Fig 3 a)lenna image b) 1-level haar wavelet decomposition of lenna imaga (c) DWT based fusion general flow chart[3].

Proposed image fusion method

As the resultant image from pixel wise fusion methods like PCA have good spatial resolution but degraded spectral response so combination with wavelet is used to provide better spatial as well as spectral response. The proposed method that combines the PCA method with wavelet transform provides outstanding outcomes compared to standard PCA or wavelet transform alone.

1 .Input two sample images
2. Rescale the images as per requirement.
3. Apply DWT technique on images.
4. Apply principle component analysis on approximation images.
5. High-spatial contents extracted from images using gradient based approach .
6. Apply inverse wavelet transform on resultant concatenated image.
7. Finally the fused image is obtained.

As most of the information is present in the approximation part hence we used spatial based PCA mechanism and for detail part we used gradient based approach to get better edge response.so the combined method achieves betterspatial as well as spectral response. By this method sample images are fused together and output result is shown in next chapter.

Fig 4. shows the complete flow chart of the given methology . From DWT we get approximation and detail part in first level after this PCA method is used for approximation part and Gradient based approach *i.e* the detail part is convolved with the gradient mask and finally maximum coefficient selection is done and at the last level inverse DWTis performed to get resultant fused image.The gradient[7] of an image is given by the formula:

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$$\nabla f = \begin{bmatrix} g_x \\ g_y \end{bmatrix} = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix}$$

where $\frac{\partial f}{\partial x}$ is the gradient in the x direction and $\frac{\partial f}{\partial y}$ is the gradient in the y direction.
The gradient direction can be calculated by the formula

$$\theta = \tan^{-1}\left(\frac{g_y}{g_x}\right)$$

After finding the gradient of the detail parts masking and addition is performed and their coefficients are concatenated with the PCA approximate image at last IDWT is performed to get the resultant fused image.

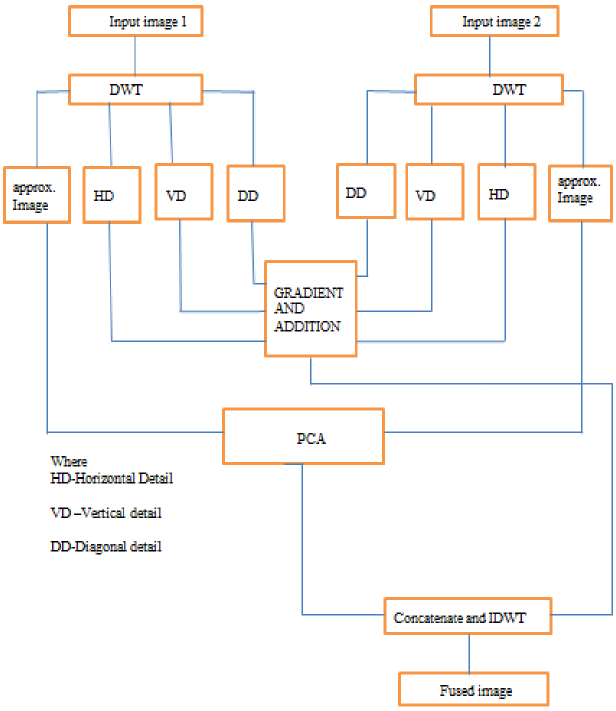

Fig.4 flow chart of proposed method .

3.6 performance analysis of an Image

image Quality[9][10] is a normal for a picture that measures the apparent image degradation (commonly, contrasted with a perfect or impeccable image). Imaging frameworks may present a few measures of twisting or antiques in the flag, so the quality evaluation is an imperative issue. There are a few systems and measurements that can be measured dispassionately and consequently assessed by a PC program. Subsequently, they can be named Full Reference Methods (FR) and No-Reference Methods (NR). In FR picture quality appraisal techniques, the nature of a test picture is assessed by contrasting it and a reference picture that is accepted to have culminate quality. NR measurements attempt to survey the nature of a picture with no reference to the first one. The picture quality records attempt to make sense of the a few or the mix of the different variables that decide the nature of the picture. A portion of the basic components that the picture quality measurements are

(a)RMSE
Rroot Meansquareerrorisoneofthemostcommonlyusederrorprojectionmethodwhere,theerrorvalueisthevaluedifferencebetweentheactualdataandtheresultantdata.Themeanofthesquareofthiserrorprovidestheerrorortheactualdifferencebetweentheexpected/idealresulttotheobtainedorcalculatedresult

$$\text{MSE}=\frac{\sum_{i=1}^{i=m}\sum_{j=1}^{j=n}\left(A_{ij}-B_{ij}\right)^2}{mn}$$

RMSE is given as the under root of the MSE.

(b) PSNR
PSNRisdefinedaslogoftheratiobetweenthesquareofthepeakvaluetotheMeanSquareErrormultipliedtothevalue10.Thisbasicallyprojectstheratioof thehighestpossiblevalueofthedatatotheerrorobtainedinthedata

$\text{PSNR}=10\times\log_{10}(\text{peak}^2/\text{MSE})$

Thehighestpossiblevalueis255.i.e.ina8bitgreyscaleimage,themaximumpossiblevalueishavingeverybitas1.i.e11111111;whichisequalto255.Theerrorbetweenthefusedimageandtheperfectimageiscalculatedasthe MeanSquareErrorandtheratiovalueifobtained.Ifboththefusedandtheperfectimagesareidentical,thentheMSEvaluewouldbe0.Inthatcase,thePSNRvaluewillremainundefined

Simulation Results
.

a)right focused image **b)left focused image**

c) Fused image using PCA d)Fused image using DWT

e) Max selection

f) proposed methodology

Fusion methology	RMSE	PSNR
Maximum selection method	9.8319	28.2781
PCA METHOD	9.7095	28.3868
DWT method	9.8160	28.2921
Proposed hybrid method	9.7086	28.3876

Table.1RMSE and PSNR comparison of different fusion methodologies

Conclusion

In this paper, attention was drawn towards the current trend of the use of multiresolution image fusion methods, especially approaches based on discrete wavelet transforms. The work started with the review of several image fusion algorithms.The proposed hybrid DWT and PCA based image fusion method provides a resultant image with better perceptual as well as quantitative image quality indices in terms of lower RMSE higher PSNR. At last different image fusion method compared with the proposed one and there comparative analysis is done

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