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Development of Image Fusion Algorithms by Integrating PCA, Wavelet and Curvelet Transforms

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ABSTRACT*:* Image fusion is the process of combining the relevant information from two or more images into a single highly informative image. The resulting fused image contains more information than the input images. In this paper, different methods namely Averaging method, Principal Component Analysis, Different Wavelet Transforms and Curvelet Transform were used to fuse different modality of images [e.g., MRI, CT; MULTI-SPECTRAL, PANCHROMATIC etc.] and all the fused images were compared using different comparison techniques namely Mean, Standard Deviation, Entropy (H) , Correlation Coefficient(CC), Co-Variance, Root Mean Square Error(RMSE), Peak Signal To Noise Ratio(PSNR). In addition to this, different wavelet transforms were integrated with PCA to improve performance evaluation. The wavelet Transform methods used here are Haar wavelet, daubechis wavelet, Bi-Orthogonal wavelet, discrete Meyer wavelet methods etc.

KEYWORDS: Image Fusion, PCA, Wavelet Transform, Curvelet Transform, Panchromatic, Multispectral, Root Mean Square Error (RMSE), Peak Signal To Noise Ratio (PSNR)

I. INTRODUCTION

Image fusion is a useful technique for merging similar sensor and multi-sensor images to enhance the information content present in the images. Image fusion techniques have been developed for fusing the complementary information of multi-source input images in order to create a new image that is more suitable for human visual or machine perception. Image fusion has several applications in various areas such as Medical Imaging, Satellite Imaging, Remote sensing, Robotics, Military applications and so on [1-4]. Computer Tomography (CT) and Magnetic Resonance (MR) are the most important modalities in Medical Imaging, used for clinical diagnosis and computer-aided surgery. CT provides more information about Bone structures and less information about soft tissues. Magnetic Resonance (MR) imaging provides more information about the Soft tissues and less information about the bone structures. A single modality of medical image cannot provide comprehensive and accurate information. As a result, combining anatomical and functional medical images to provide much more useful information through image fusion has become the focus of imaging research and processing in the recent years [7-11]. Moreover the fused image obtained is suitable for human visual and machine perception and analyzing tasks. Image fusion also improves reliability, decreases uncertainty and storage cost by storing a single informative image than storing multiple images.

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II. FUSION SCHEMES

In average method, simple averaging of all the pixels of the input images is taken to produce averaged pixels so that from these averaged pixels we can get fused image of the input images. The basic idea of all wavelet-based fusions schemes is to combine all respective wavelet coefficients from the input images. The combination is performed according to a specific fusion rule. The wavelet decomposition of each source image is performed leading to a multiresolution representation. The actual fusion process is performed as a combination of the corresponding wavelet decomposition coefficients of all input images, to build a single wavelet decomposition image. This combination takes place on all decomposition levels k (k = 1, 2…L) where L is the maximum wavelet decomposition level. Two different fusion rules are applied to combine the most important features of the input images. A basic fusion rule is applied to the Lth level approximation sub bands. The three detail sub bands (horizontal, vertical, and diagonal) are combined using a more sophisticated fusion algorithm [10].Principal Component Analysis [PCA] is a vector space transform used for reducing the multidimensional data sets to lower dimensions. In this we calculate Eigen values and Eigen vectors and then these Eigen vectors are sorted in decreasing order of Eigen values and then choose the best Eigen vector to perform Fusion. To improve Fusion we can integrate any two methods. The basic limitation of the wavelet fusion algorithm is in fusion of curved shapes and this can be rectified by the application of the Curvelet transform, would result in the better fusion efficiency. Curvelet transform involves the segmentation of the whole image into small overlapping tiles. Then the ridge let transform is applied on the Radon transform of each tile, which itself is a shape detection tool. The purpose of the segmentation process is to approximate curved lines by small straight lines. The overlapping of tiles aims at avoiding edge effects. Initially, Curve let transform was proposed for image denoising [5,6]. It is expected that the Curvelet transform would produce better fusion results than those obtained using the Multi-Wavelet transform.

III .WEIGHED AVERAGE METHOD

Firstly, input images must be of the same scene, i.e. the fields of view of the sensors must contain a spatial overlap. Furthermore, inputs are assumed to be spatially registered and of equal size and spatial resolution. In practice, size and resolution constraints are often satisfied by re-sampling one of the input images. Another important consideration in pixel-level fusion is the number of input images and the color characteristics of the input and output images.

Step 1: Read the set of multifocus images i.e. here in our proposed algorithm we have consider two images which are of same size (registered images).

Step 2: Alpha Factor can be varied to vary the proportion of mixing of each image.

With Alpha Factor = 0.5, the two images are mixed equally.

With Alpha Factor < 0.5, the contribution of background image will be more.

With Alpha Factor > 0.5, the contribution of foreground image will be more.

So, in our proposed algorithm we have consider alpha factor= 0.5

Step 3: Perform element by element multiplication of image array with alpha factor for foreground image and multiply complement of alpha factor with image array of background image.

Step 4: Now perform pixel by pixel intensity value comparison and find the maximum intensity value.

Step 5: This value is consider for the final output image.

Step 6: Finally display the fused image contains all the huge intensity value of the pixel.

IV.WAVELET TRANSFORM METHODS

A wavelet means a small wave (the sinusoids used in Fourier analysis are big waves) and in brief, a wavelet is an oscillation that decays quickly. Equivalent mathematical conditions for wavelet are:

$$\int_{-\infty}^{\infty} |\,\psi(t)|^2\, dt < \infty \quad \int_{-\infty}^{\infty} |\,\psi(t)|^2\, dt = 0 \quad \int_{-\infty}^{\infty} \frac{|\tilde{\psi}(\omega)|^2}{|\psi(\omega)|} d\omega < \infty$$

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Where $\tilde{\psi}(\omega)$ is the Fourier Transform of $\psi(t)$. Equation [4] is called the admissibility condition. The wavelet transform is a mathematical tool that can detect local features in a signal process. It also can be used to decompose two-dimensional (2D) signals such as 2D gray-scale image signals into different resolution levels for multi-resolution analysis. Wavelet transform is given by following equation.

$$\psi_{a,b}(t) = \frac{1}{\sqrt{|a|}}\psi\left(\frac{t-b}{a}\right),\ a, b \in R,\ a \neq 0$$

The parameter a is the scaling parameter or scale, and it measures the degree of compression. The parameter b is the translation parameter which determines the time location of the wavelet. If $|a| < 1$, then the wavelet [5] is the compressed version (smaller support in time- domain) of the mother wavelet and corresponds mainly to higher frequencies. On the other hand, when $|a| > 1$, then $\psi_{a, b}(t)$ has a larger time-width than $\phi(t)$ and corresponds to lower frequencies. Thus, wavelets have time-widths adapted to their frequencies. Wavelet transform has been greatly used in many areas, such as texture analysis, data compression, feature detection, and image fusion. In this section, we briefly review and analyze the wavelet-based image fusion technique.

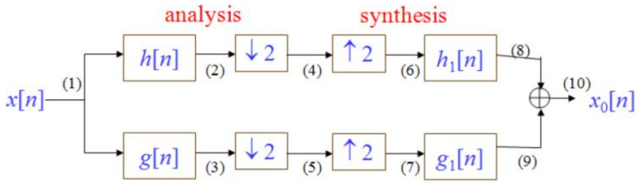
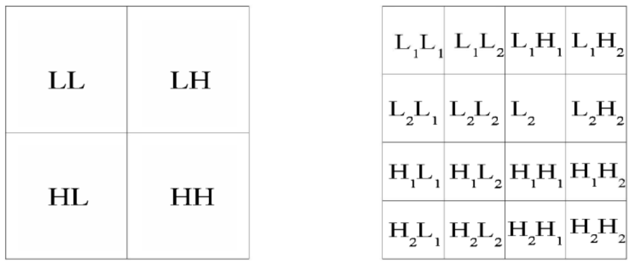


Fig.4.1.Process of Wavelet Transform

An image can be decomposed into a sequence of 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. Wavelet based techniques for fusion of 2-D images is described here.



(a) (b)

Fig.4.2. Image sub-band after a single level decomposition, for (a) Scalar wavelets and (b) Multi wavelets

In all wavelet based image fusion techniques the wavelet transforms W of the two registered input images I1(x, y) and I2(x, y) are computed and these transforms are combined using some kind of fusion rule ∅ as show in below equation

I(x,y) = W-1 (Ø (W(I1(x,y)), W(I2(x,y)))

Steps of our proposed method of the wavelet based image fusion are explained below:

Step 1: Read the set of multifocus images i.e. here in our proposed algorithm we have consider two images which are of same size (registered images).
Step 2: Apply wavelet decomposition on both the Images with the use of Daubechies filter.
Step 3: Extracts from the wavelet decomposition structure [C, S] the horizontal, vertical, or diagonal detail.
Step 4: Perform average of approximation coefficients of both decomposed images
.**Step 5:** Compare horizontal, vertical and diagonal coefficient of both the images and apply maximum selection Scheme to select the maximum coefficient value by comparing the coefficient of the two images. Perform this for all the pixel values of image i.e. m x n.
Step 6: Now Apply wavelet decomposition on both the Images with the use of different wavelet filters (namely Haar wavelet, daubechis wavelet, Bi-Orthogonal wavelet, discrete Meyer wavelet filters etc.)
.**Step 7:** Display the final fused image.

V. PRINCIPAL COMPONENT ANALYSIS (PCA) METHOD

PCA is a vector space transform used for reducing the Multidimensional data sets to lower dimensions [22-24]. The PCA algorithm for the fusion of images is discussed as Follows.
Step1: Generate the column vectors, respectively, from the input image matrices.
Step2; Calculate the covariance matrix of the two column vectors formed.
Step 3: The diagonal elements of the 2x2 covariance matrix would contain the variance of each column vector with itself, respectively.
Step 4: Calculate the Eigen values and the Eigen vectors of the covariance matrix.
Step5: Normalize the column vector corresponding to the larger Eigen value by dividing each element with mean of the Eigen vector.
Step 6: The values of the normalized Eigen vector act as the Weight values which are respectively multiplied with each pixel of the input images.
Step 7: Sum of the two scaled matrices calculated in the previous step will be the fused image matrix [25].

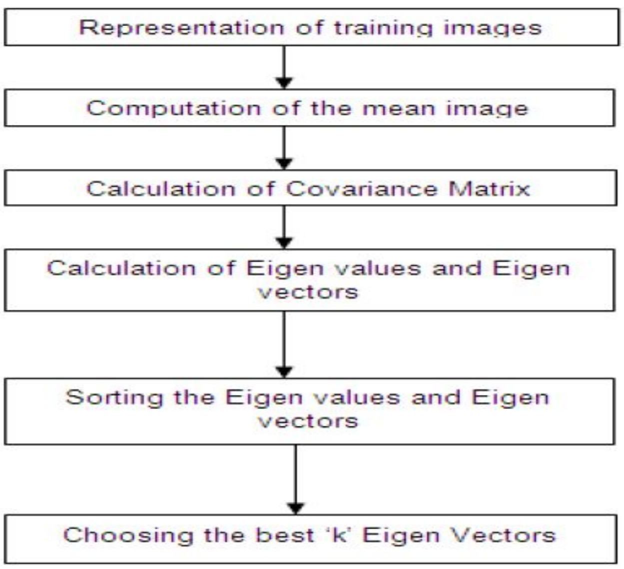


Fig.5.1 Process of Principle Component Analysis

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The above Eigen Vectors are used for fusing the Input images

VI. CURVELET TRANSFORM

The Curvelet transform is suited for objects which are smooth away from discontinuities across curves. Fourier Transform does not handle point's discontinuities well because a discontinuity point affects all the Fourier Coefficients in the domain. Moreover, Wavelet transform handles point discontinuities well and doesn't handle curve discontinuities well. Curvelet transform handles curve discontinuities well as they are designed to handle curves using only a small number of coefficients.

The Curvelet transform includes four stages and is implemented as follows.

A. Sub-band Decomposition

The image is first decomposed into log_2^M (M is the size of the image) wavelet sub-bands and then Curve let Sub-bands are formed by performing partial reconstruction from these wavelet sub-bands at various levels. The sub band decomposition is denoted as

$$f \rightarrow (P_0 f, \Delta_1 f, \Delta_2 f, \ldots)$$

where Po ---Low-pass filter.

The image is divided into resolution layers Po.Each layer contains the details of different frequencies.

B. Smooth Partitioning

Each subband is smoothly windowed in to 'squares' of an appropriate scale. A grid of dyadic squares is defined as:

$$Q_{(s,k_1,k_2)} = \left[\frac{k_1}{2^s}, \frac{k_1+1}{2^s}\right] \times \left[\frac{k_2}{2^s}, \frac{k_2+1}{2^s}\right] \in Q_s$$

Let w be a smooth windowing function. For each square, W_Q is a displacement of W localized near Q. Multiplying L1sf with W produces a smooth dissection of the function into 'squares'

C. Renormalization

Each resulting square is renormalized to unit scale. For a dyadic square Q, let

$$(T_Q f)(x_1, x_2) = 2^s f(2^s x_1 - k_1, 2^s x_2 - k_2)$$

denote the operator which transports and renormalizes f so that the part of the input supported near Q becomes the part of the output supported near the unit square [0, 1] x [0, 1]. In this stage each 'square' resulting in the previous stage is renormalized to unit scale.

D. Ridgelet Analysis

Ridgelet transform is performed on each square resulting from the previous stage. To facilitate its representation mathematically, it can be viewed as a wavelet analysis in the Radon domain. The Radon transform itself is a tool for shape detection. So, the Ridgelet transform was primarily a tool for ridge detection or shape detection of the objects in an image. The Ridgelet transform deals effectively with line singularities in 2-D. The basic idea is to map a line singularity in the twodimensional (2-D) domain into a point by means of the Radon transform. Then, a one-dimensional (I-D) wavelet is performed to deal with the point singularity in the Radon domain. The Ridgelet basis function is given by

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$$\psi_{a,b,\theta} = a^{-1/2}\psi\left(\frac{(x_1\cos\theta + x_2\sin\theta - b)}{a}\right)$$

The Ridgelet coefficients are represented by

$$R_f(a,b,\theta) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty}\psi_{a,b,\theta}(x_1,x_2)f(x_1,x_2)dx_1dx_2$$

Ridgelet transform is invertible and the reconstruction formula is denoted by

$$f(x_1,x_2) = \int_0^{2\pi}\int_{-\infty}^{\infty}\int_0^{\infty}R_f(a,b,\theta)\psi_{a,b,\theta}(x_1,x_2)\frac{da}{a^3}db\frac{d\theta}{4\pi}$$

VII. PROPOSED WORK

Many of these image fusion techniques proposed aim at improving the fusion rate and not concentrating on enhancing the information content on the images.So,,to improve the information content much more here, proposing integration of wavelet method with PCA method.

The whole process consists of following steps.

Step1: Transform the multispectral image into the IHS or PCA components.

Step2: Apply histogram match between panchromatic image and intensity component and obtain new panchromatic image.

Step3: Decompose the histogram matched panchromatic image and intensity component to wavelet planes respectively.

Step4: Replace the LL^P in the panchromatic decomposition with the LL^1 of the intensity decomposition, add the detail images in the panchromatic decomposition to the corresponding detail image of the intensity and obtain LL^1, LH^P, HH^P and HL^P. Perform an inverse wavelet transform and generate a new intensity.

Step5: Transform the new intensity together with hue, saturation components or PC1, PC2, PC3 back into RGB space [4].

VIII. PERFORMANCE MEASURES FOR IMAGE FUSION

Assessment of image fusion performance can be divided into two categories: one with and one without reference images. In reference-based assessment, a fused image is evaluated against the reference image which serves as a ground truth. In second case only fused image is taken. In the present work, we have used some Performance measures to evaluate the performance of the Image fusion algorithms.

A. Entropy (H)

The Entropy (H) is the measure of information content in an image. The maximum value of entropy can be produced when each gray level of the whole range has the same frequency. If entropy of fused image is higher than parent image then it indicates that the fused image contains more information.

$$H = -\sum_{g=0}^{L-1} P(g)\log_2 P(g)$$

B.MEAN (M)

M = mean (A) returns the mean values of the elements along different dimensions of an array.

If A is a vector, mean (A) returns the mean value of A.

If A is a matrix, mean (A) treats the columns of A as vectors, returning a row vector of mean values.

If A is a multidimensional array, mean (A) treats the values along the first non-singleton dimension as vectors, returning an array of mean values.

M = mean (A, dim) returns the mean values for elements along the dimension of A specified by scalar dim. For matrices, mean (A, 2) is a column vector containing the mean value of each row.

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C. STANDARD DEVIATION

A measure of how the data values are spread out around the mean. It can also define as the square root of the variance. It can be calculated using below formula

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2}$$

Here, x_i is the input, μ is the Mean value

D.CO-VARIANCE

Co-Variance is a measure of how much two random variables change together. If the greater values of one variable mainly correspond with the greater values of the other variable, and the same holds for the smaller values, i.e., the variables tend to show similar behavior, the covariance is positive. In the opposite case, when the greater values of one variable mainly correspond to the smaller values of the other, i.e., the variables tend to show opposite behavior, the covariance is negative. The sign of the covariance therefore shows the tendency in the linear relationship between the variables.

$$COV(X,Y) = \sum_{i=1}^{N} p_{x_i y_i}(X_i - E(X))(Y_i - E(Y))$$

X_i ,Y_i are Inputs(X), E(Y) are means of X, Y

E.CORRELATION CO-EFFICIENT (CC)

The correlation coefficient is the measure of the closeness or similarity in small size structures between the original and the fused images. It can vary between -1 and +l Values closer to + 1 indicate that the reference and fused images are highly similar while the values closer to -1 indicate that the images are highly dissimilar.

$$CC=\frac{2c_{rf}}{c_r+c_f}$$

Where, $\mathbf{c_r}$ is the reference image and $\mathbf{c_f}$ is the fused image respectively.

$$c_r=\sum_{i=1}^{M}\sum_{j=1}^{N} I_r(i,j)^2$$

$$c_f=\sum_{i=1}^{M}\sum_{j=1}^{N} I_f(i,j)^2$$

$$c_{rf}=\sum_{i=1}^{M}\sum_{j=1}^{N} I_f(i,j)I_r(i,j)$$

F. Root Mean Square Error (RMSE)

A commonly used reference based assessment metric is the Root Mean Square Error (RMSE). The RMSE between a reference image, R, and a fused image, F, is given by the following equation:

$$RMSE=\sqrt{\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(R(i,j) - F(i,j))^2}$$

Where R (I, j) and F (i, j) are the reference and fused images, respectively, and M and N are image dimensions. Smaller the value of the RMSE, better the performance of the fusion algorithm.

G. PEAK SIGNAL TO NOISE RATIO (PSNR)

PSNR is the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. The PSNR of the fusion result is defined as follows:

$$PSNR= 10 \log[\frac{(f_{max})^2}{RMSE^2}]$$

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Where f_{max} is the maximum gray scale value of the pixels in the fused image. Higher the value of the PSNR, better the Performance of the fusion algorithm.

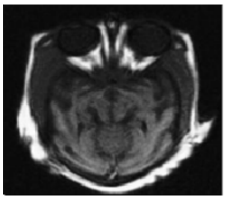
IX. EXPERIMENTAL RESULTS AND COMPARISONS

Different images are taken as the source images. Different Fusion methods are applied to fuse the input images. The corresponding outputs of the source images are shown in the below Figs.

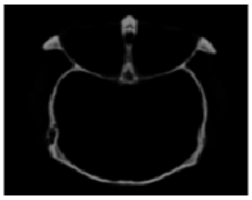
(A)Experimental Results

(I)Take MRI, CT scanned images as input images

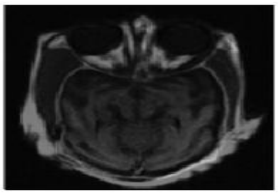
(A)MRI image



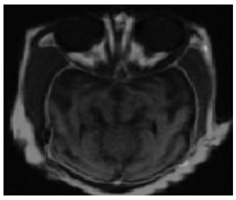
(B) CT Image



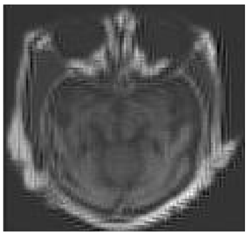
(i) weighted average method



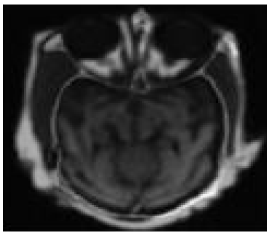
(ii) PCA Method



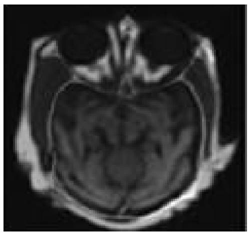
(iii)Haar wavelets



(iv)Haar wavelet with PCA



(v)Curvelet Transform



IV) Results for Hoed Images

(A)Middle side blurred image

(B) Corner side blurred image

(i) weighted average method

(ii) PCA Method

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(iii) Haar Wavelet

(iv) Haar wavelet with PCA

(v) Curvelet Transform

(B)Comparison

i) Statistical Results For CT, MRI Images

Metrics	Fusion Methods				
	Weighted Average Method	PCA	Haar Wavelet	Haar With PCA	Curvelet Transform
Entropy	5.9562	6.4647	6.2154	5.9961	6.0293
Mean	32.844	50.087	32.666	32.723	30.7234
Standard Deviation	36.403	52.598	26.637	26.449	20.6613
Co-Variance	1.1920	3.4727	5.2360	5.3130	4.3130
Correlation Coefficient	0.1570	0.1570	0.3778	0.6196	0.5801
RMSE	3.2996	3.5362	0.2925	0.1579	0.3562
PSNR	16.265	11.398	58.842	69.855	59.8557

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(ii)Statistical Results for Hued Images

Metrics	Fusion Methods				
	Weighted Average Method	PCA Method	HAAR WAVELETS	HAAR WITH PCA	Curvelet Transform
Entropy	7.6156	7.6171	7.596	7.6515	7.6500
Mean	98.5008	98.161	98.5866	98.100	98.5866
Standard Deviation	57.4893	57.552	44.6777	45.664	55.4321
Covariance	3.5358	3.6575	5.4994	5.6241	6.6241
Correlation Coefficient	0.8379	0.9509	0.8618	0.8680	0.9636
RMSE	6.6755	6.976	0.4468	0.0788	0.1740
PSNR	23.801	22.827	55.1845	85.305	92.3053

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