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Image Fusion Using DWT & PCA

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Abstract - Image fusion is of great importance in defence and information from multiple images of same scene. The result of fusion is a new image which is more suitable for human and machine perception. Pixel level image fusion using wavelets and principal component analysis has been implemented and demonstrated. different performance metrics with and without reference image are implemented to evaluate the performance of mage fusion algorithms. It has been concluded that image fusion using wavelets with higher level of decomposition showed better performance in some metrics and in other metrics PCA showed better performance.

Keywords: Wavelet transform, Principal component analysis, entropy, deviation, mean square error

I. INTRODUCTION

Multi-sensor image fusion (MIF) is a technique to combine the registered image to increase the spatial resolution of acquired low detail multi-sensor images and preserving their spectral information. The problem that multi-sensor image fusion tries to solve is to merge the information content from several images taken from the same scene and provide a fused image that have the finest information. So fused image provide superior image than the original source images. MIF could be performed at three different levels: pixel level, feature level and decision level[1].

The simple fusion method take the average of the gray level source mages pixel by pixel and produce some undesired effects gives poor performance. To overcome this problem, multi scale transforms such as wavelets, laplacian pyramids and gradient pyramid. Discrete wavelet transform (DWT) would provide directional information in decomposition levels and contain unique information at different resolutions Principal component analysis (PCA) is a mathematical tool which transforms a number of correlated variables into a number of uncorrelated variables. The PCA is used in image compression and image classification. Image fusion algorithms that uses PCA is explained in this paper. The fused image is achieved by weighted average of source images. The weights for each source image are obtained from the eigen vector corresponding to the largest eigen value of the covariance metrices of each source.

II. FUSION ALGORITHMS

In this section the details of wavelets and PCA algorithm and their use in image fusion are described.

A. Wavelet Transform

Wavelet theory is an extension of Fourier theory and it is introduced as an alternative to the short time fourier transform. In Fourier theory the signal is decomposed into sines and cosines but in wavelets the signal is projected on a set of wavelet functions. Fourier transform would provide good resolution in frequency domain but wavelet would provide good resolution in frequency domain as well as time domain. 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 etc. Although these wavelets share some common properties, each wavelet has a unique image decompression and reconstruction characteristics that lead different fusion results. The Discrete Wavelet Transform (DWT) of image signals produces a non-redundant image representation, which provides better spatial and spectral localization of image information, compared with other multi scale representations. 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.

1. Image Decomposition: The information flow in one level of 2-D image decomposition is illustrated in figure 1. 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 $I_H(x,y)$.

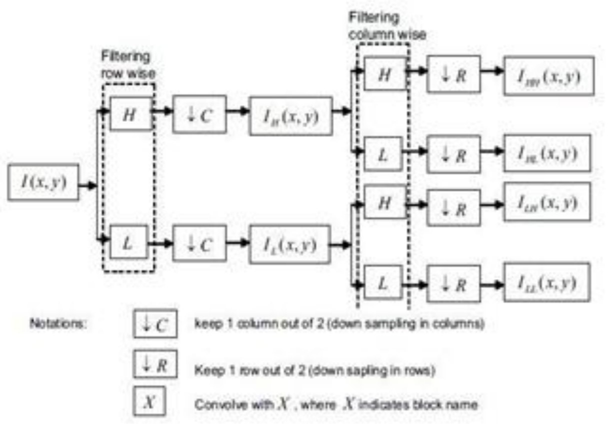


Figure 1: One Level Of 2-D Image Decomposition[7]

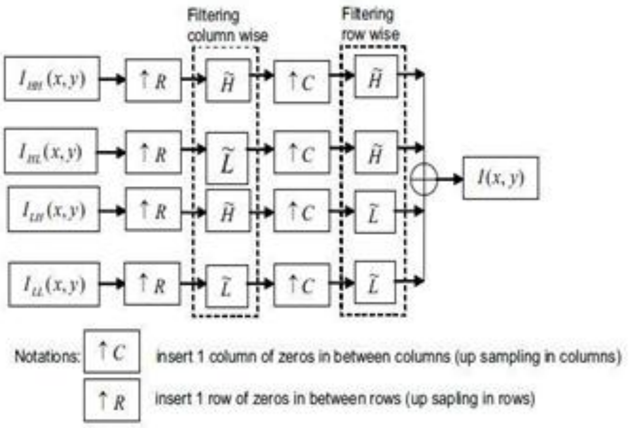


Figure 2: One Level Of 2-D Image Reconstruction[7]

The coefficient matrix 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), I_{HH}(x,y)[7]. Direction characteristics of the sub-signals after wavelet transformation. Its frequency division characteristic is equal to high-and low dual-band filter The signal can be decomposed Images can be decomposed into a number of images with different spatial resolution, frequency characteristics and the flexibility in the choice of wavelets. The I_{LL}(x,y), contains the average image information corresponding to low frequency band of multi scale decomposition. It could be considered as smoothed and sub sampled version of the source image I(x,y). It represents t_{LH}he approximation of source image I(x,y). I (x,y), I_{HL}(x,y) ,and I_{HH}(x,y) are detailed sub images which contains directional (vertical, horizontal and diagonal) information of the source image I(x,y). Multi-resolution could be achieved by recursively are detailed sub images which contain directional information, applying the same algorithm to low pass coefficients from the previous decomposition.

2. Image Reconstruction :

The information flow in one level of 2-D image reconstruction is illustrated in figure 2. 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), L_{HL}(x,y), and L_{HH}(x,y). This involves column up sampling (inserting zeros between samples) and filtering using low pass L and high pass filter H for each sub images. Row up sampling and filtering with low pass filter L and high pass filter H of the resulting image and summation of all matrices would construct the image I(x, y).

3. Block Diagram Of DWT : The figure 3 shows the main blocks and flow of fusion process using DWT. First consider two registered input image I_1 and I_2 which are too be fused. Then apply DWT to both I_1 and I_2, and their coefficients in pixel p are $D_{I1}(p)$ and $D_{I2}(p)$, respectively. The output DWT coefficient in pixel p is D_{I3} (p) given by using "choose-max" selection rule i.e. choosing maximum DWT coefficient. After that Perform Inverse DWT to *DI3*. Finally, the fused image is displayed. The fusion rule used in this paper is simply averages the approximation coefficients and picks the detailed coefficients in each sub band with the largest magnitude.

B. Principal Component Analysis

PCA transformation [3] is a statistical method. It transforms a group of related variables into a group of the original variables. The aim is to compress multi-band image information into an image and information can perform maximum in the new image. During the fusion process, it first carries on PCA transformation so that the gray scale mean and variance are consistent with PCA component of the image.

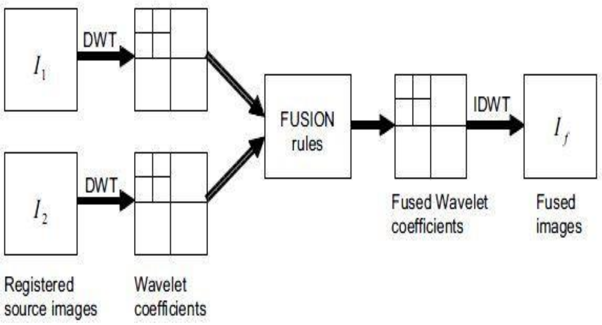


Figure 3: Information Flow Of DWT

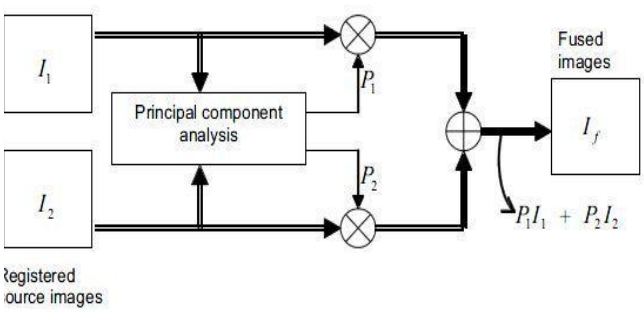


Figure 4 : Information Flow Diagram Of PCA

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. The 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.

Normalize column vector corresponding to larger Eigen value by dividing each element with mean of Eigen vector. Those normalized Eigen vector values act as the weight values and are multiplied with each pixel of input image. Sum of the two scaled matrices are calculated and it will be the fused image matrix.

The information flow diagram of PCA-based image fusion algorithm is shown in figure 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. Compute the eigenvector and eigen values for this resulting vector are computed and the eigenvectors corresponding to the larger eigen value obtained[7].The fused image is:

$I_f(x,y) = P_1I_1(x,y) + P_2I_2(x,y)$

...(1)

1. Major Steps in PCA Algorithm : Following steps should be followed for using PCA algorithms for fusion of images. Let the source images (images to be fused) be arranged in two-column vectors. The steps followed to project this data into 2-D subspaces are [7]. Organize the data into column vectors. The resulting matrix Z is of dimension 2 x n. Then compute the empirical mean along each column. The empirical mean vector Me has a dimension of 1 x 2. Subtract the empirical mean vector Me 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. $C=XX_T$ mean of expectation = cov(X). Compute the eigenvectors V and eigen value D of C and sort them by decreasing Eigen-value. V and D are of dimension 2 x 2. Consider the first column of V which corresponds to larger eigen value to compute P1 and P2 as: $\rho_1 = \frac{V(1)}{\sum V}$; $\rho_2 = \frac{V(2)}{\sum V}$

...(2)

III. PERFORMANCE EVALUATION

Performance evaluation is an essential part of Image fusion processing so one can further adjust the algorithm parameter through analyzing, testing and evaluating the effects of the fusion algorithm and performance so that the whole fusion process can be optimized. Performance parameters are of two types: with reference image and without reference image.

A. Without Reference Image

When the reference image is not available then the performance of the image fusion algorithms cab be evaluated using following metrics.

1. Information Entropy: Entropy is used to evaluate the information quantity contained in an image. If entropy of fused image is high, it indicates that the fused image contains more information. Entropy is defined as

$$E = -\sum_{i=0}^{l-1} p_i \, log_2 \, p_i$$

...(3)

Where L is the number of pixel levels in the fused image. Pi is probability of occurrence of a particular gray level i. Entropy can directly reflect the average information content of an image.

2. Standard Deviation: Degree of dispersion between the value Of each Pixel and the average value of image. Standard Deviation can be find using following formula:

$$\sigma = \sqrt{\sum_{i=0}^{L}(i-\bar{i})^2 h_{I_f}(i)}, \ \bar{i} = \sum_{i=0}^{L} i h_{I_f}$$

...(4)

Maximum the standard deviation gives better resultant image.

3. Mean : The mean value of an image with the size of m×n is defined as

$$\hat{\mu} = \frac{1}{n\times n}\sum_{j=1}^{n}\sum_{i=1}^{m} x_{i,j}$$

...(5)

where $x_{i,j}$ denotes the gray level of a pixel with coordinate (i, j). The mean value represents the average intensity of an image. Higher the mean value better the image quality.

B. With Reference Image

When the reference image is not available then the performance of the image fusion algorithms cab be evaluated using following metrics.

1. Mean Square Error: The MSE represent the cumulative squared error between the original image and reconstructed image. The lower the value of MSE, the error may be lower.

$$MSE = \sqrt{\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left(I_r(i,j) - I_f(i,j)\right)^2}$$

..(6)

2. Peak Signal To Noise Ratio : PSNR used for quality measurement ratio between original image and reconstructed image. The higher the PSNR, the better the quality of the reconstructed image.

$$PSNR = 20 \, log_{10}\left(\frac{L^2}{\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left(I_r(i,j)-I_f(i,j)\right)^2}\right)$$

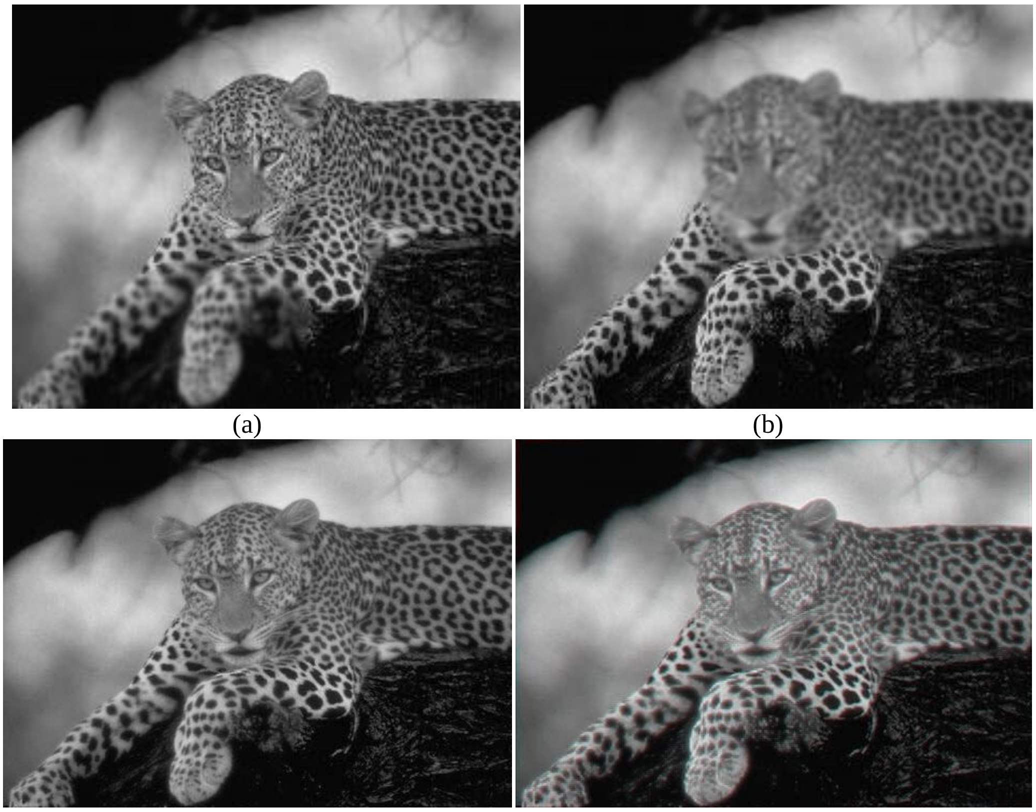
...(7)

C. Result And Comparative Analysis

In table 1, we have compared a variety of the parameters of fusion methods PCA and DWT .Figure 5 shows the fused images for various fusion algorithms.

Table 1: Comparison Of Performance Parameters

Fusion Methods	EN	SD	MEAN	PSNR
DWT	7.4086	64.6288	95.0575	7.0174
PCA	7.4072	63.9570	92.0713	7.2360



(a) (b) (c) (d)

Figure 5: (a) & (b) input images, (c) is fused image using PCA , (d) is Fused image using DWT

IV. CONCLUSION

Pixel level image fusion using wavelet transform and principal component analysis are implemented in PC MATLAB and different performance parameters with and without reference image have been evaluated and compared. On the basis of fused images shown in figure 5 and performance parameter values in table 1 all the parameters values are higher for DWT, In DWT higher entropy indicates more information in resultant image ; higher standard deviation gives better resultant image in terms of contrasr so by using DWT we can get fused image having higher contrast than any other fusion algorithms. Higher mean and peak signal to noise ratio indicates better quality of image so fused resultant image obtained by DWT have better quality of information than PCA. For DWT we get all parameters performs better than the PCA fusion algorithm so finally we can conclude that DWT is performs better than PCA .

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