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Implementation and Comparison of Image Fusion using Discrete Wavelet Transform and Principal Component Analysis

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Abstract— Nowadays with rapid development in high technology and modern instrumentation image fusion has become a vital component of a large number of applications. On the basis of three categories Pixel, Feature and decision a no of methods and algorithms have proposed for Image Fusion. This would be an interesting task to take some best recently used methods and analyze which one is better and effective. This Paper considers two fusion techniques Discrete Wavelet Transform (DWT) and Principal Component Analysis, fusion methods for these two techniques has been proposed and also the effectiveness is compared.

In DWT the two images to be fused are decomposed at different levels and their approximation and detail co-efficient are calculated, a fusion scheme is used to combine these co-efficient and then Inverse of DWT is taken to reconstruct the image. In PCA the principal components of the two images are extracted and a fusion scheme is proposed to fuse these principal components to reconstruct the image.

Finally comparison of these two techniques is performed on the basis of some evaluation criteria and the decision has drawn that which technique is better.

Keywords/Index Term—Image Fusion, Wavelets, DWT, PCA.

I. INTRODUCTION

Image Fusion is the process of combining relevant information from two or more images into a single image. The resulting image will be more informative than any of the input images. The aim of image fusion is to integrate complementary as well as redundant information from multiple images to create a fused image output. Therefore the new image generated is more informative and accurate than any of the individual source.

Multisensor data fusion has become a discipline which demands more general formal solutions to a number of application cases. Several situations in image processing require both high spatial and high spectral information in a single image. This is important in remote sensing. However, the instruments are not capable of providing such information either by design or because of observational constraints. One possible solution for this is data fusion.

Image fusion can be broadly defined as the process of combing multiple input images or some of their features into a single image without the introduction of distortion or loss of information. The aim of image fusion is to integrate complementary as well as redundant information from multiple images to create a fused image output. Therefore, the new image generated should contain a more accurate description of the scene than any of the individual source images and is more suitable for human visual and machine perception or further image processing and analysis tasks. For medical image fusion, the fusion of images can often lead to additional clinical information not apparent in the separate images. Another advantage is that it can reduce the storage cost by storing just the single fused image instead of multisource images.

II. IMAGE FUSION USING DISCRETE WAVELET TRANSFORM (DWT)

Introduction should lead the reader to the importance of the DWT fusion is based on multiresolution [1] or multiscale techniques [1]. Usually the real world object contains structures at different scales and resolution so objects can also be process at different scales and resolutions this is called as multiresolution theory (Mallat) [1], so Mallat is concerned with the representation an analysis of signals(or image) at more than one resolution. Image Pyramid [1], Sub-band coding and the Haar transform are the examples of multiresolution analysis. Multiresolution technique involves two kinds one is Pyramid Transform [1] and other is Wavelet Transform [2].

A. *Pyramid Transform*

In the pyramid fusion the input images are first transformed into their multiresoution pyramid representation. The fusion process then creates a new fused pyramid from the input image pyramids in a certain fusion rule. The fused image is finally reconstructed by performing an inverse multiresolution transform [1].

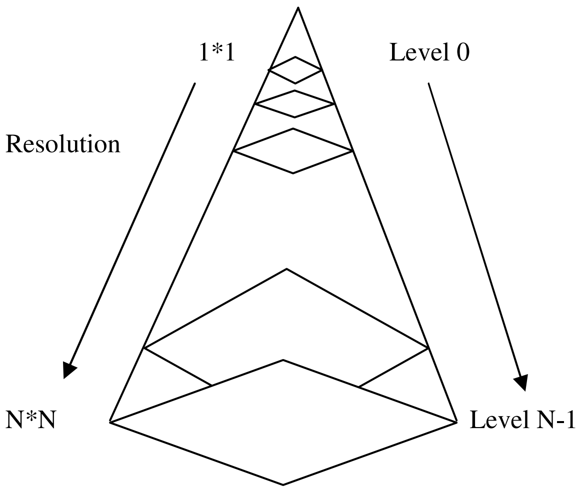

Figure1 An Image Pyramid

B. Wavelet Transform

Another family of the multiresolution fusion technique is the wavelet based method. Which generally uses discrete wavelet transform (WT) in fusion. The WT is a spatial-frequency decomposition that provides a flexible multiresolution analysis of an image. In one dimension (1D) the basic idea of the WT is to represent the signal as a superposition of wavelets. Wavelet Transform are base on small waves, called wavelets.

C. Wavelets

Wavelets [1] are small waves of varying frequency and limited duration. This allows them to provide the equivalent of a musical score of an image, revealing not only what notes to play but also when to play them. Fourier transform on the other hand, provide only the notes or frequency information while temporal information is lost during transformation process. In 1987, wavelets were first shown to be the foundation of powerful approach to signal processing and analysis called Mallat or multiresolution theory.

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D. *Wavelet Transform Types*

Wavelet transform provide a framework in which a signal is decomposed, with each level corresponding to a coarser resolution or lower-frequency band and higher-frequency bands. The wavelet transform is similar to the Fourier transform (or much more to the windowed Fourier transform) with a completely different merit function. The main difference is this: Fourier transform decomposes the signal into sines and cosines, i.e. the functions localized in Fourier space; in contrary the wavelet transform uses functions that are localized in both the real and Fourier space. Generally, the wavelet transform can be expressed by the following equation:

$$F_{(\mathrm{a,b})} = \int_{-\infty}^{\infty} f(x)\psi_{(a,b)}{}^{*}(\mathrm{x})dx$$

where the * is the complex conjugate symbol and function ψ is some function. This function can be chosen arbitrarily provided that obeys certain rules.

D.1 *Discrete Wavelet Transform*

The discrete wavelet transform (DWT) is an implementation of the wavelet transform using a discrete set of the wavelet scales and translations obeying some defined rules. In other words, this transform decomposes the signal into mutually orthogonal set of wavelets, which is the main difference from the continuous wavelet transform (CWT) [2].

The wavelet can be constructed from a scaling function which describes its scaling properties. The restriction that the scaling functions must be orthogonal to its discrete translations implies some mathematical conditions on them which are mentioned everywhere, e.g. the dilation equation

$$\emptyset(x) = \sum_{k=-\infty}^{\infty}(a_k\emptyset(S_x - \mathrm{k}))$$

Where S is a scaling factors\(usually chosen as 2). Moreover, the area between the function must be normalized and scaling function must be orthogonal to its integer translations, i.e.

$$\int_{-\infty}^{\infty}\emptyset(x)\emptyset(x+l)\,dx=\delta_{0,l}$$

After introducing some more conditions (as the restrictions above does not produce unique solution) we can obtain results of all these equations, i.e. the finite set of coefficients a_k that define the scaling function and also the wavelet. The wavelet is obtained from the scaling function as N where N is an even integer. The set of wavelets then forms an orthonormal basis which we use to decompose the signal. Note that usually only few of the coefficients a_k are non-zero, which simplifies the calculations [2].

D.2 Continuous Wavelet Transform

Continuous wavelet transform (CWT) [2][7] is an implementation of the wavelet transform using arbitrary scales and almost arbitrary wavelets. The wavelets used are not orthogonal and the data obtained by this transform are highly correlated. For the discrete time series we can use this transform as well, with the limitation that the smallest wavelet translations must be equal to the data sampling.
In principle the continuous wavelet transform works by using directly the definition of the wavelet transform, i.e. we are computing a convolution of the signal with the scaled wavelet. For each scale we obtain by this way an array of the same length N as the signal has. By using M arbitrarily chosen scales we obtain a field N×M that represents the time-frequency plane directly. The algorithm used for this computation can be based on a direct convolution or on a convolution by means of multiplication in Fourier space (this is sometimes called Fast Wavelet Transform) [2].

E. PROPOSED FUSION RULE

DWT decomposes the image and computes approximation coefficient CA and detail coefficient CH, CV, CD (horizontal, vertical, and diagonal, respectively) and these coefficients for two different images are compute and then fused to form the single image. The fusion is performed in following steps:

Step I:
Perform 2-level decomposition of both the images by means of wavelet transform.

Step II:
Compute approximation coefficient CA and detail coefficient CH, CV, CD (horizontal, vertical, and diagonal, respectively) for each pixel of both the images.

Step III:
Fuse these coefficients (high frequency component) of both images for corresponding pixel at each level as:

CA(new)= max(CA1, CA2)

CH(new)=max(CH1, CH2)

CV(new)=max(CV1, CV2)

CD(new)=max(CD1, CD2)

Step IV:
Perform 2-level inverse wavelet transform to construct the image.

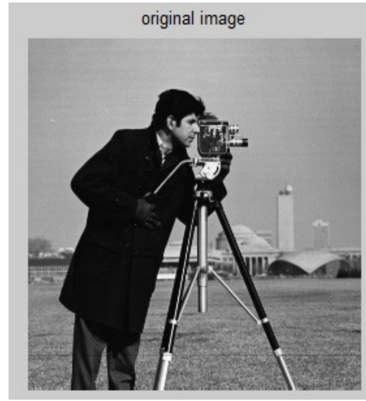

Figure2 (a) Original Sample image for DWT

Figure2 (b) Source image A

Figure2(c) Source image B

Figure2(d) 2-level fused image from decomposed coefficient of image A and image B using DWT

Figure2(e) Reconstructed Image using IDWT

Table1. Quantitative evaluation results of the DWT fusion method

	PSNR	STD	RMSE	MEAN
DWT	25.122	2.5717	14.139	9.4885

III. IMAGE FUSION USING PRINCIPALCOMPONENT ANALYSIS

Principal component analysis is a statistical analysis for dimension reduction. It basically projects data from its original space to its eigenspace to increase the variance and reduce the covariance by retaining the components corresponding to the largest eigen values and discarding other components. PCA [3] helps to reduce redundant information and highlight the components with biggest influence. Some facts about PCA are as follows:-

- PCA is a powerful and widely used linear technique in statistics, signal processing, image processing, and elsewhere.
- Several names: the (discrete) Karhunen-Loève transform (KLT, after Kari Karhunen and Michael Loève) or the Hotelling transform (after Harold Hotelling) [3].
- In statistics, PCA is a method for simplifying a multidimensional dataset to lower dimensions for analysis, visualization or data compression.
- PCA represents the data in a new coordinate system in which basis vectors follow modes of greatest variance in the data. Thus, new basis vectors are calculated for the particular data set.
- The price to be paid for PCA's flexibility is in higher computational requirements as compared to, e.g., the fast Fourier transform .

A. *PROPOSED FUSION RULES WITH PCA*

During fusion through 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 [3]. The flow chart of proposed PCA is shown in figure 3-

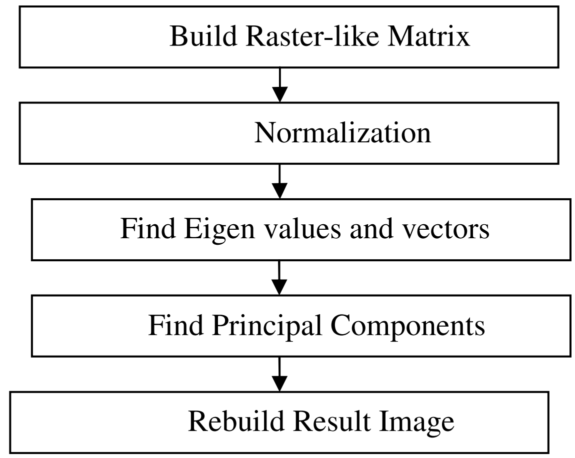

Figure3 Flow chart of Proposed PCA based fusion

Steps in Fusion
The fusion has carried out in following steps:-

Step I:
Calculate the eigen vectors for image A and image B and say $(x, y)^T$ is set of eigen vectors of image A and image B.

Step II:
Ccalculate the weight value of image A and image B using Equation

$$w_A = \frac{x}{x+y} \qquad w_B = \frac{y}{x+y}$$

Step III:
The low frequency coefficients are fused using Equation:

$$\mathrm{I}_{FL} = w_A I_A + w_B I_B$$

Step IV:
The high frequency coefficients are fused using Equation as:

$$I_{FH} = \max(\mathrm{abs}(I_A), \mathrm{abs}(I_B))$$

Step V:
I_{FL} and I_{FH} are fused to find the reconstructed image.

Figure4 (a) Original sample Image for PCA)

Figure4 (b) Source Image A

Figure4 (c) Source Image B

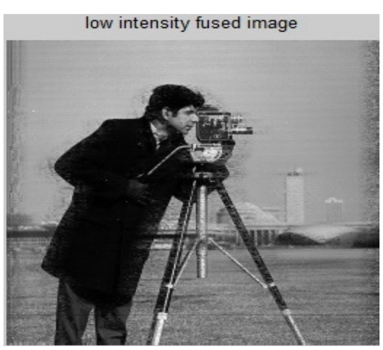

Figure4(d) High frequencies of image A and Image B are fused

Figure4 (e) Low frequencies of image A and Image B are fused

Figure4(f) Reconstructed image using PCA

Table2. Quantitative evaluation results of the PCA fusion method

	PSNR	STD	RMSE	MEAN
PCA	25.213	19.5599	13.99	116.6809

IV. EXPERIMENTAL RESULT AND ANALYSIS

In this section both the proposed techniques i.e. DWT and PCA are compared to analyze that which technique among the two gives the better result. For this we have used some parameters which evaluate the fusion method. The selected parameters are sufficient to describe the quality of reconstructed image. The parameters used are as follows:

1) Peak Signal to Noise ratio (PSNR)
2) Standard Deviation (STD) [4] [6].
3) Root Mean Squared Error (RMSE) [5].

In DWT the two images to be fused are decomposed up-to 2- levels and their approximation and detail co-efficient are calculated, a fusion scheme is used to combine these co-efficient and then Inverse of DWT is taken to reconstruct the image.

In PCA the principal components of the two images are extracted and a fusion scheme is proposed to fuse these principal components to reconstruct the image.
With the help of these two techniques we have fused the two images image A which is blurred from the top and the image B which is blurred from the bottom. The following figure represents the two images and the resultant output from DWT and PCA.

Figure5 (a) original image

Figure5 (b) Image A

Figure5(c) image B

Figure5(d) image A and image B fused with DWT

Figure5 (e) image A and image B fused with PCA

Table3 Quantitative evaluation results of the PCA fusion method

	PSNR	MEAN	STD	RMSE
PCA	25.213	116.6809	19.5599	13.99
DWT	25.122	9.4885	2.5717	14.139

V. CONCLUSION

As the result comparison table represents that PSNR for PCA is greater than DWT and greater value leads to more correctness, standard deviation STD is also better for PCA and RMSE for PCA is smaller than DWT and smaller the RMSE better the result. So PCA gives better Result than DWT.

VI. FUTURE SCOPE

The principles of the merger have been around for many years, and the application of this technique is not limited to medical imaging. The military has used the fusion of infrared images from visible light to detect camouflaged targets. The daily weather report includes a satellite image merged with a geographic map. Fusion Software is like glue, bringing together images from multiple devices, including dual-mode scanners and PACS systems and now even planning systems for radiation therapy. The relationship between the software and hardware of the merger will become more intertwined in the future, and radiological practices only benefit from it.
There are , of course, the limits of what is possible with any fusion methodology . The extreme differences between the imaging studies will always create problems. The use of (non-linear) deformable techniques introduce a degree of flexibility and expand the range of possibilities, but the fact is that the quality of the images fusion depends on the quality of the data being merged. We must remember that image fusion is not foolproof , as are also the modalities underlying images.

- However, this is an interesting tool for the diagnostician and researcher . As more realize the role of PET as the method of molecular imaging in vivo, we probably have more chance of image fusion are discovered. The following are some possible given practical advances in the project: - Multi Image fusion based Wavelets can be done to achieve a better quality of image fusion efficiency of multiple wavelets on DWT usual methods merging the images involved in remote sensing is explained. The same can be applied in this project and can also be verified on the basis of quality indicators developed image.

- The quality of image fusion was evaluated on the basis of sets of optical images with perfect image . The efficiency of the project can better assess whether it was possible in multivariate images. The same could not be done due to the absence of proof test sample multivariate images. The same issue has been discussed with ADE and agreed to provide a set of multivariate images to test the project at a later stage, as many of the steps are involved in it from their side.
- The assessment of image fusion algorithms classifying is performed based on the metrics of image quality readings . An important point to note here is that all quality metrics are assigned equal weighting , regardless of their accepted efficacy. The metrics could be given weightage for a best list assessment.
- A learning algorithm such as neural networks and, more specifically, Support Vector Machine can be designed in the assignment of weighting indicators of image quality in order to evaluate them. A larger number of image sets could be considered the beginning of a learning process using SVM, based on indicators which could be fitted with weighted ranks.
- Image Registration has not been incorporated in the project. Line Registration / Image certainly enhance efficiency vast set of images not yet registered can be considered as a set of input images project. It would also help in possibility of several sets of test images shows / Perfect made available for the assessment of image fusion algorithms.

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