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MODIFIED APPROACH OF MULTIMODAL IMAGE FUSION USING DAUBECHIES WAVELET TRANSFORM AND HYBRID FUSION RULE

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Abstract: There are many image fusion methods that can be used to produce high-resolution mutli-spectral images from a high-resolution panchromatic image and low-resolution multispectral images. There are various methods of image fusion. They might be based on the various transforms i.e. discrete cosine transform, discrete wavelet transform, complex wavelet transform. Further the different strategies can be followed to combine the elements of two images. The different rules for the fusion of 2 elements of images are: averaging, maximum coefficient selection, maximum absolute coefficient selection, maximum energy coefficient selection etc. This paper presents a new approach of fusion of two multimodal images, using Daubechies Wavelet transform, which is based on hybrid fusion rule. The Daubechies wavelets give better performance for the fusion. Further improvisation is obtained by the hybrid fusion rule, which uses two or more fusion rule in combination.

I. INTRODUCTION

The term fusion means in general an approach to extraction of information acquired in several domains. The goal of image fusion (IF) is to integrate complementary multisensor, multitemporal and/or multiview information into one new image containing information the quality of which cannot be achieved otherwise. Image fusion is a powerful tool used to increase the quality of image. Image fusion increases reliability, decreases uncertainty and storage cost by a single informative image than storing multiple images. The fast development of digital image processing leads to the growth of feature extraction of images which leads to the development of Image Fusion[1-2]. In the process of image fusion, two or more images are combined together into a single image retaining the important features from each of the original images. The images acquired from different instrument modalities or capture techniques of the same scene or objects often requires fusion of images. Important applications of the fusion of images include medical imaging, microscopic imaging, remote sensing, computer vision, and robotics[3-4]. For the image fusion the generalized approach follows the following steps: Transformation, Feature extraction or Component extraction, Selection or construction of the resultant component on the basis of the predefined technique. Here we have described the image fusion techniques based on the different transforms i.e. discrete cosine transform, discrete wavelet transform, complex wavelet transform. In our work, we have used the Daubechies wavelets, which gives better performance for the fusion purpose. The different rules for the fusion of 2 elements of images are: averaging, maximum coefficient selection, maximum absolute coefficient selection, maximum energy coefficient selection, maximum variance coefficient selection, maximum standard deviation based coefficient selection etc. In the hybrid approach we apply the combination of two or more rules in a predefine manner. There are various possibilities in hybrid approach. The each band of the decomposed images can be fused according to different-different rules. In our technique, we have used maximum absolute coefficient rule for the lower sub-band and maximum deviation fusion rule for the higher sub bands.

II. DWT AND IMAGE FUSION

The discrete wavelet transform (DWT) of image signal produces image representations which provides better spatial and spectral localization of image formation compared with other multi scale representations such as Gaussian and Laplacian pyramid.

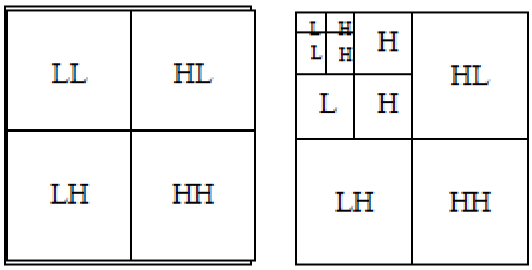

Fig.1 The pyramidal decomposition shown up to two levels

In the case of wavelet transform fusion all respective wavelet coefficients from the input images are combined using the fusion rule. Since wavelet coefficients having large absolute values contain the information about the salient features of the images such as edges and lines, a good fusion rule is to take the maximum of the corresponding wavelet coefficients. The maximum absolute value within a window is used as an activity measure of the central pixel of the window. A binary decision map of the same size as the DWT is constructed to record the selection results based on a maximum selection rule. The discrete wavelet transform (DWT) uses filter banks to perform the wavelet analysis.

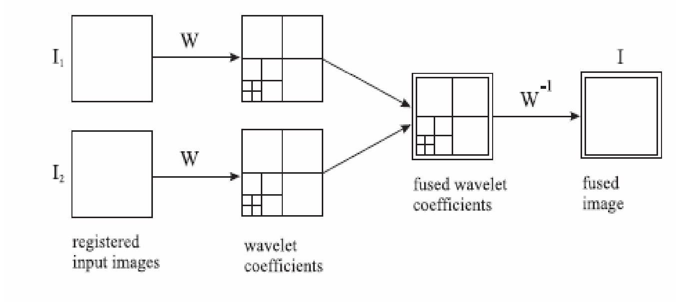

Fig. 2 Wavelet Based Image Fusion

III. FUSION RULES

There are following rules can be adopt for the DWT based image fusion:

Average coefficient: All the four sub bands of the fused image F is simply acquired by averaging the wavelet coefficients of source images A and B.

Maximum absolute values coefficient: Since larger absolute transform coefficients correspond to sharper brightness changes, the good integration rule is to select, at every point in the transform domain, the coefficients whose absolute values are higher.

Maximum energy coefficient: The coefficients correspond to the frequency band having largest energy is chosen in the fused image.

Maximum deviation coefficient: The coefficients correspond to the frequency band having largest standard deviation is selected in the fused image.

IV. DAUBECHIES CONTINUOUS WAVELET TRANSFORM

The Daubechies wavelets, based on the work of Ingrid Daubechies, are a family of orthogonal wavelets defining a discrete wavelet transform and characterized by a maximal number of vanishing moments for some given support. With each wavelet type of this class, there is a scaling function (called the father wavelet) which generates an orthogonal multiresolution analysis. In general the Daubechies wavelets are chosen to have the highest number A of vanishing moments, (this does not imply the best smoothness) for given support width N=2A. There are two naming schemes in use, DN using the length or number of taps, and dbA referring to the number of vanishing moments. So D4 and db2 are the same wavelet transform. Among the 2A−1 possible solutions of the algebraic equations for the moment and orthogonality conditions, the one is chosen whose scaling filter has extremal phase. The wavelet transform is also easy to put into practice using the fast wavelet transform. Daubechies wavelets are widely used in solving a broad range of problems, e.g. self-similarity properties of a signal or fractal problems, signal discontinuities, etc. The Daubechies wavelets are not defined in terms of the resulting scaling and wavelet functions; in fact, they are not possible to write down in closed form. The graphs below are generated using the cascade algorithm, a numeric technique consisting of simply inverse-transforming [1 0 0 0 0 ...] an appropriate number of times.

The basic equation of multiresolution theory is the scaling equation.

$$\phi(x) = 2\sum_k a_k \phi(2x-k) \qquad (1)$$

The construction of complex Daubechies wavelet transform is as in [11]. The generating wavelet w(t) is given by:-

$$\psi(t) = 2\sum_n (-1)^{\wedge} n.\bar{a}(1-n)\phi(2t-n) \qquad (2)$$

Here and /(t) share the same compact support[N,N+1].

Any function f(t) can be decomposed into complex scaling function and mother wavelet as:

$$f(t) = \sum_k c_k^{j0} \phi_{j0,k}(t) \sum_{j=j0}^{j\max-1} d_k^j \psi_{j,k(t)} \qquad (3)$$

where j0 is a given resolution level. Where ak are the coefficients [4]. The ak can be real as well as complex valued and $\Sigma a_k = 1$.

V. IMAGE FUSION USING DAUBECHIES COMPLEX WAVELET TRANSFORM

The Daubechies complex wavelet transform has the following advantages:

(i) It has perfect reconstruction property.

(ii) No redundancy.

(iii) It is symmetric.

This property makes it easy to handle edge points during the signal reconstruction. However there are some other important properties of the Daubechies complex wavelet transform that directly influence the performance of image fusion. Standard wavelet transform and its extensions mainly consist of the following limitations: shift variance, aliasing, lack of directionality, absence of phase information. Due to these limitations standard DWT may not be preferred to use in some applications of image and signal processing [4-6,9-10].

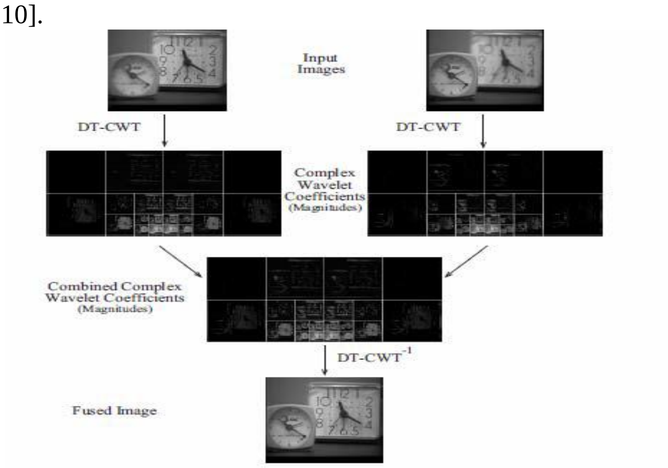

Fig 3 Image fusion process using DTDCWT

Fig 3. demonstrates the fusion of two images using the complex wavelet transform. The areas of the images more in focus give rise to larger magnitude coefficients within that region. A simple choose maximum scheme is used to produce the combined coefficient map (we may also use the other rules of image fusion that use for the image fusion using 2DDWT. DCWT does not makes any difference we only changed the wavelet transform type). The resulting fused image is then produced by transforming the combined coefficient map using the inverse complex wavelet transform. The wavelet coefficient images show the orientated nature of the complex wavelet sub bands. Each of the clocks hands which are pointing in different directions are picked out by the differently orientated sub bands. All of the coefficient fusion rules implemented with the discrete wavelet transform can also be implemented with the complex wavelet transform. In this case, however, they must be applied to the magnitude of the DT-DCWT coefficients as they are complex.

VI. PROPOSED METHODOLOGY

Proposed method uses Daubechies complex wavelet transform and Hybrid fusion rule for multimodal image fusion [5]. A general image fusion scheme using proposed method is shown in Figure 1.

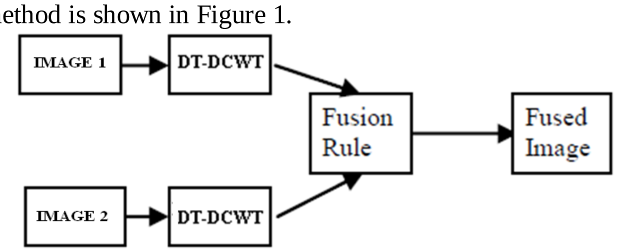

Fig 4: Image fusion using proposed methodology

There are following steps are followed in the methodology:
Step1: The multimodal images A and B are decomposed into different levels using Daubechies complex wavelet transform [7] to obtain the low frequency (LLA, LLB) and high frequency (LHA, HLA, HHA, LHB, HLB, HHB) coefficients.

Step2: Divide the each sub band coefficients into K small blocks. For each pair of corresponding blocks the standard deviations SDA(k) and SDB(k) are computed for k=1,2…..K.

Step3: Thus, the block with a larger standard deviation value is chosen to construct the fused image coefficients for the higher sub-bands. For the lower sub-band the Maximum absolute values coefficient rule is applied and coefficient having the maximum value is chosen for the lower subbands.

Step4: Apply inverse Daubechies transform to obtain fused image.

VII. PARAMETER

There are so many parameter have been prescribed for the quality assessment of the fussed image, common papameters are RMSE, Correlation, SNR, PSNR, SSIM, entropy of fused image(EN), standard deviation of fused image(STD). Other parameters are Persentage fit error (PFE), Mean absolute error (MAE), Quality index (QI), Mutual information (MI) and Fusion Factor (FF) . But on the basis of these parameter better assessment cannot be obtain because these parameters compare the fused image in respect to the first or the second image. So there is an another parameter that can be used for the proper analysis of the fused image. It is called by Mutual information[7]. Fusion Factor (FF) essentially computes how much information from each of the original images is transferred to the fused image. The larger the FF value, the better the fused result is.

$$FF = MI_{FA} + MI_{FB}$$

Where $MI_{FA} and\ MI_{FB}$ is the mutual information (MI) fused image w.r.t. first and seconds image.

$$MI_{FA} = H_A + H_F - H_{FA}$$
$$MI_{FB} = H_B + H_F - H_{FB}$$

And
H_A = entropy of first image;
H_B = entropy of second image;
H_f = entropy of fused image;
H_{FA}= crossed entropy of first image and fused image;
H_{FB}= crossed entropy of second image and fused image;
PFE is given by:

$$PFE = 100 * norm(imt - imf)/norm(imt)$$

Where imt is true image and imf is fused image.
Mean absolute error is given by:

$$MAE = \frac{1}{N * M} \sum_{1}^{N} \sum_{1}^{M} |imt(x,y) - imf(x,y)|$$

VIII. CONCLUSION

In this paper, we have seen the Significance and requirement of the image fusion. We have also seen the generalized methodology of the image fusion. Then we have seen the overview of the different techniques of image fusion. We have discussed the image fusion using DWT in brief. Then we have seen the Daubchies wavelet transform and its advantages and applications in image fusion. Further we have seen, the image fusion using Daubechies complex wavelet transform. We have also described the different fusion rule and significance of hybrid fusion rule. In the proposed methodology, we have used the Daubechies complex wavelet transform and used the hybrid fusion rule, In which we have applied the Maximum deviation coefficient approach for the higher subband and for the lower subbands we have used the Maximum absolute values coefficient rule. The results obtained are compared with the Image fusion using Daubechies wavelet transform and Image fusion using Daubechies complex wavelet transform with the Maximum deviation coefficient approach used as the fusion rule. The results obtained are compared as per different parameters. The performance of proposed methodology is found much better as compare to the existing methods. In the future we may try to get much better fusion rule to get optimum performance in Image fusion.

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Appendix

Table 1: results for image fusion of the images: Saras91 Saras92

Parameters	**Image fusion using Daubechies wavelet transform**	**Image fusion using Daubechies complex wavelet transform**	**Image fusion using Daubechies wavelet transform using hybrid fusion rule**
RMSE	9.7698732	9.4133652	0.6915372
PFE	4.1908182	4.0378932	0.2966372
MAE	3.0887492	3.1256992	0.3790972
CORR	0.9991192	0.9991822	0.9999962
SNR	27.5540242	27.8769042	50.5554962
PSNR	38.2659102	38.4273502	49.7666462
QI	0.5073482	0.5062822	0.6292182
SSIM	0.9659152	0.9688722	0.9988442
MIFA	2.4533152	2.3724572	2.6214782
MIFB	2.0906292	2.3177462	1.8874552
FF	4.5439442	4.6902032	4.5089322
EN	4.0255692	4.0381272	3.9206472
STD	46.0401152	46.0247682	50.1098992

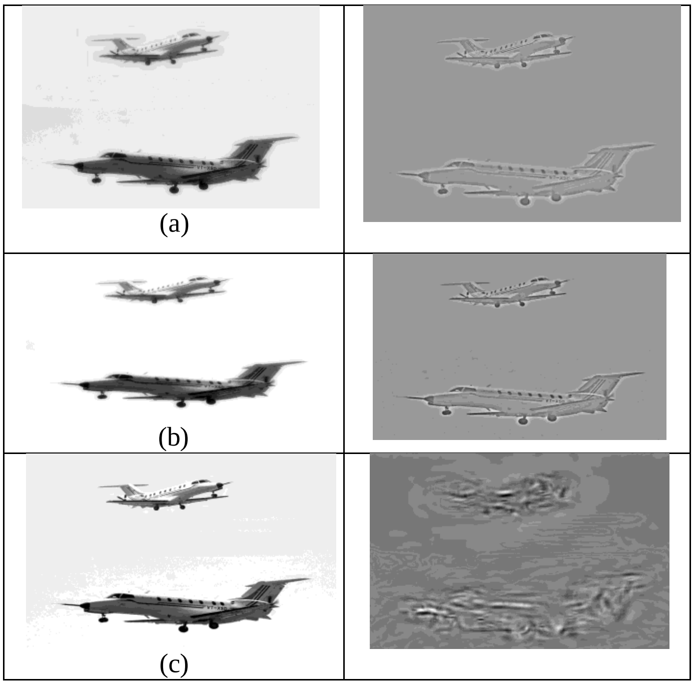

Fig:5 Original and difference for different for (a) Image fusion using Daubechies wavelet transform (b) Image fusion using Daubechies complex wavelet transform (c) Image fusion using Daubechies wavelet transform using hybrid fusion rule

