A Hybrid Method for Block-Based Feature Level Image Fusion Technique of PAN and MS Image Using Contour let Transform with Neural Network

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Abstract- Multisensor image fusion is one of the widely researched areas in the field of image processing. The highest spatial content can be achieved while preserving the spectral resolution of an image with spatial information of a high resolution panchromatic (PAN) image combines with spectral information of a low resolution multispectral image (MS). This paper derived and renovates block-based feature level contourlet transform with neural network (BFCN) mannequin for image fusion. The proposed BFCN mannequin combines Contourlet Transform (CT) with neural network (NN), which performs a vital role in feature extraction and detection in machine learning applications. In the designed BFCN mannequin, the two fusion techniques, Contourlet Transform (CT) and neural network (NN) discussed for fusing the IRS-1D images using LISS III scanner about the places Patancheru, Mahaboobnagar Hyderabad and Vishakhapatnam in Andhra Pradesh, India. Also, Landsat 7 image data and QuickBird image data are used to carry out experiments on The designed BFCN mannequin. The features like contrast visibility, spatial frequency, the energy of gradient, variance, and edge information are studied. Since the learning capability of NN makes it feasible, Feedforward back propagation neural network is trained and tested for classification. The trained NN is then used to fuse the pair of PAN and MS images. The designed BFCN mannequin is analogized with other techniques to evaluate the quality of the fused image. The designed BFCN mannequin is an efficient and feasible algorithm for image fusion, and It is clearly shown that from the experimental results.***Key words – Contourlet Transform(CT), Neural Network (NN), block based , performance measures Image fusion,***

1. Introduction

Many researchers worked on pixel level image fusion. Thus excess of pixel level fusion algorithms have been developed [1], [2] with different performance and complexity characteristics. Siddiqui et al. [3] described an algorithm for block-based feature-level multi-focus image fusion. A region-based multi-resolution image fusion algorithm which combines the aspects of region and pixel-based fusion by G. Piella[4]. An algorithm for image fusion by a ratio of low pass pyramid proposed by A. Toet [5]. The performance of all the levels of multi-focused images using different wavelet transforms evaluated by K. Kannan et al. [6]. Various advances in multi-sensor data fusion discussed by Dong et al. [7]. Riazifar et al. [8] proposed a compression scheme in transform domain and compared the performance of both DWT and CT.

In this paper a new method derived based on Discrete Wavelet Transform (DWT) with Neural Networks (NN) [9] and another method based on Multiwavelet Transform (MWT) with Neural Networks to fuse Panchromatic (PAN) and Multispectral (MS) images[10]. As the fused image using DWT and MWT have less spatial information, Present paper derives "A Hybrid method for Block Based Feature Level Image Fusion Technique of PAN and MS Image Using Contourlet Transform With Neural Network". The PAN image obtained by satellites is transmitted with the maximum resolution available and the MS data is transmitted with coarser resolution. The proposed BFCN method addresses this problem efficiently. The proposed BFCN method integrates Contourlet Transform (CT) with the block based concept of feed forward back propagation neural network. The present study critically compares the fusion results of BFCN with other existing fusion techniques for fusing PAN and MS images about the Places Hyderabad, Vishakhapatnam, Mahaboobnagar, Patancheru, Landsat 7 and QuickBird images.

2. Image fusion Based On Contourlet Transform

After an in-depth literature survey, the present study found that to overcome the deficiencies of the wavelet transforms, multi-scale and directional representations such as complex wavelets [11], curvelets [12], contourlets [13], etc were proposed in the literature. These wavelets can capture the intrinsic geometrical structures such as smooth contours that exist in the images. One of the major disadvantages of wavelets is they do not give proper results when contours are present in the images. After a vast research in directional transforms and to address this, a new geometrical transform called contourlet transform is introduced in the present study, which represents images containing contours and textures. A directional extension of multidimensional wavelet transform is a CT that aims to capture curves instead of points and provides for directionality and anisotropy.

The Contourlet Transform was introduced by Do M N and Vetterli M [14]. It has the property of capturing contours and fine details in the images. CT is computationally efficient as it has an approximation property for smooth 2D functions and finds a direct discrete-space construction. Its advantages are multi-scale localization, directionality and anisotropy. It is a multi-resolution and directional decomposition of a signal which uses a combination of Laplacian Pyramid (LP) and a Directional Filter Bank (DFB). The LP decomposes images into subbands and DFB analyzes each detail image. Hence, contourlet transform is a double filter bank structure.

In 2002, Do M N and Vetterli M proposed that CT represents images using basis elements having a variety of elongated shapes with different aspect ratios. It is suitable for applications including edge detection with high curve content. An algorithm for multi-focus image fusion using wavelet based contourlet transform and region proposed In 2009, [15]

Directional filter banks (DFB) decompose frequency space into wedge-shaped partitions as illustrated in Figure 5.1. In the example, eight directions are used, where directional subbands of 1, 2, 3, and 4 express horizontal directions (directions between -45° and +45°) and the rest represnt for the vertical directions (directions between 45° and 135°). The DFB is realized using iterated quincunx filter banks. Vertical DFB (VDFB) and Horizontal DFB (HDFB) are use to achieve vertical or horizontal directional decomposition, particularly. Figure 2 depicts the frequency space partitioned by the VDFB and HDFB. The implementation of these schemes is straight forward to use the iterated tree-structured filter banks [22] to realize the DFB.

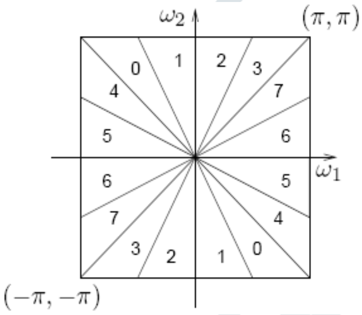


Figure .1: Directional filter bank frequency partitioning where l = 3 and there are 2^3 = 8 real wedge-shaped frequency bands.

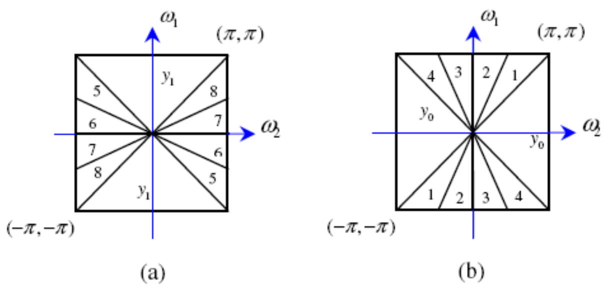


Figure .2: (a) An example of the vertical directional filter banks (b) An example of the horizontal directional filter banks.

As CT implements LP and DFB it is a double filter bank structure. The low frequency content is poorly handled since DFB was designed to capture high frequency which represents directionality. In fact, low frequency would "leak" into several directional subbands and hence DFB alone does not provide a sparse representation for images. This fact provides another reason to combine DFB with a multi-scale decomposition, where low frequencies of input image are removed before applying the DFB. The Figure 3 depicts a multi-scale and directional decomposition using a combination of LP and DFB. Bandpass images from the LP are fed into a DFB in such a way that the directional information can be captured. The scheme can be iterated on the coarse image. The combined result is a double iterated filter bank structure which decomposes images into directional subbands at multiple scales. Hence, it is named as contourlet filter bank.

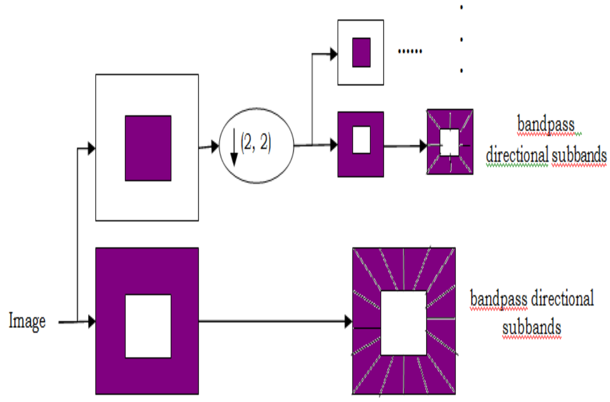


Figure 3: Decomposition of Contourlet Transform.

3 The Proposed BFCN method For Image Fusion

The background information of each image belongs to low frequency subband whereas edge and texture information belongs to high frequency subband and this contains abundant detail information of objects. This can be described more accurately by Contourlet transform [16, 17]. For this, the proposed method decomposed source images into low frequency subband and high frequency subband and then the fusion algorithm using the concepts of feed forward back propagation neural networks is applied.

The block diagram of the proposed BFCN method is shown below in Figure 4.

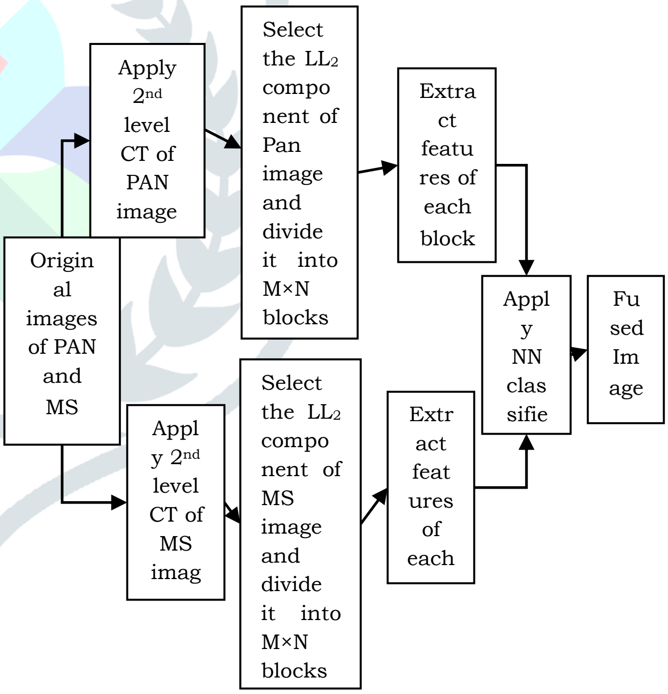


Figure4: Block diagram of the proposed BFCN method.

The stepwise working of the proposed BFMN algorithm is described below.

1. Read PAN and MS images.
2. Apply CT at second level decomposition to both the images.
3. Consider the LL_2 component of PAN and MS images.
4. Partition LL_2 component of each image into non-overlapped blocks of size 4×4 or 8×8.
5. Extract statistical features (such as contrast visibility, spatial frequency, energy of gradient, variance and edge information) from each block of PAN and MS images. These features are treated as

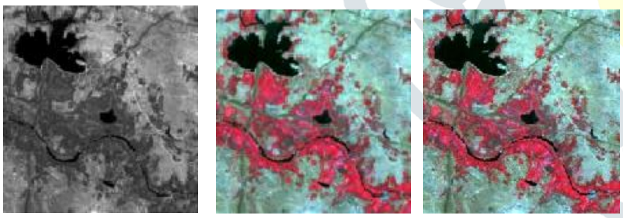
feature vector F_1 of PAN image and feature vector F_2 of MS image.

6. Subtract feature values of F_1 from F_2 of each block.If difference is 0 then denote it as 1 else-1. Then construct an index vector (i.e. the combination of 1's and -1's).
7. Index vector is given to the classifier for classification which will be given as an input for the NN.
8. Train the newly constructed NN randomly by simulating it.
9. If simulated output > 1 then consider corresponding block of PAN image else consider corresponding block of MS image.
10. Construct fused image by selecting appropriate block from step 9.

In the present work, the quality assessment is derived on fusing the source images using MWT and BFMN methods. To assess the quality of the fused images, few performance metrics such as standard deviation (SD), entropy, correlation coefficient (CC), mean squared error (MSE), peak signal to noise ratio (PSNR), root mean squared error (RMSE), mean absolute error (MAE), mutual information measure (MIM), fusion factor (FF), and the metric QAB/F. [10].

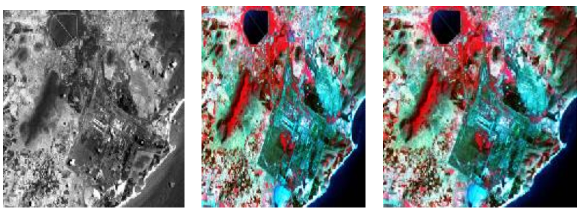
4 Results And Discussions

The proposed BFCN method is experimented on the PAN and MS images about the places Hyderabad, Vishakhapatnam, Mahaboobnagar and Patancheru in Andhra Pradesh, India of IRS-1D using LISS-III scanner. And Landsat-7 and QuickBird image datasets are also experimented using the proposed BFCN method.
The following Figures (5) to (10) demonstrate the fused images using the proposed BFCN method about the six locations.



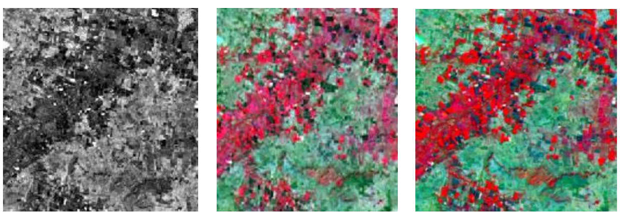
(a) (b) (c)

Figure 5: Location of Hyderabad (a) PAN image (b) MS image (c) Fused image of proposed BFCN method.



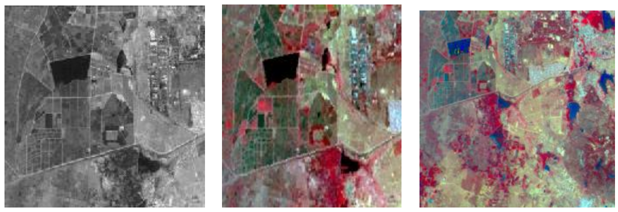
(a) (b) (c)

Figure 6: Location of Visakhapatnam (a) PAN image (b) MS image (c) Fused image of proposed BFCN method.



(a) (b) (c)

Figure 7: Location of Mahaboobnagar (a) PAN image (b) MS image (c) Fused image of proposed BFCN method.



(a) (b) (c)

Figure 8: Location of Patancheru (a) PAN image (b) MS image (c) Fused image of proposed BFCN method.

(a) (b) (c)

Figure 9: Location of Landsat-7 (a) PAN image (b) MS image. (c) Fused image of proposed BFCN method.

(a) (b) (c)

Figure 10: Location of QuickBird (a) PAN image (b) MS image. (c) Fused image of proposed BFCN method.

The Table 1 shows results of quality metrics using proposed BFCN method for all the above six locations. By observing results of Table 1 of the proposed BFCN method, the following observations are made.

- The average value of correlation coefficient (CC) is almost ≅1, which implies that the fused image is similar to the corresponding original MS image. The higher correlation between the high frequency components of the fusion panchromatic image represents that more spatial information from the PAN image is injected into the fusion result.
- The average value of Peak Signal to Noise Ratio (PSNR) is greater than 75, which implies that the spectral information of MS image and high signal is preserved most effectively.
- The average value of Entropy is above 7, which implies that the fused image contains rich information and better quality than either of the source images.
- The average value of Mutual Information Measure (MIM) is almost near to 2, which indicates that good amount of information of the source images is furnished in the fused image.
- The average value of Fusion Factor (FF) is above 3.6, which indicates that the similarity of image intensity distribution of the corresponding image pair is contained in the fused image.
- The average value of $Q^{AB/F}$ is greater than 0.5, which indicates that good amount of edge information is transferred from the source images to the fused image.

- The average value of Standard Deviation (SD) is less than 50, which implies that not much deviation is induced in the fused image.
- The average value of Mean Squared Error (MSE) is less than 0.1, which indicates that the spectral distortion in the fused image is comparatively less.
- The average value of Root Mean Squared Error (RMSE) is less than 0.1, which indicates that less standard error is contained in the fused image.
- The average value of Mean Absolute Error (MAE) is less than 0.1, which indicates that less average magnitude of the errors in a set of forecasts is induced in the fused image.

Table 1: Quality metrics using proposed BFCN method about the locations Hyderabad, Vishakhapatnam, Mahaboobnagar, Patancheru, Landsat-7 and QuickBird

Metrics	Hyderabad	Vishakhapatnam	Mahaboobnagar	Patancheru	Landsat-7	QuickBird	Average
SD	40.5190	62.3870	49.4436	35.4800	39.6270	77.5713	44.0196
ENT	7.1384	7.8438	7.6880	7.3715	7.4416	7.6809	7.5973
CC	0.9993	0.9980	0.9980	0.9566	0.9996	0.9980	0.9988
MSE	0.0004	0.0022	0.0013	0.0011	0.0009	0.0015	0.0012
PSNR	81.8370	74.6278	74.3011	76.6010	78.2501	75.9508	76.9279
RMSE	0.0350	0.0473	0.0609	0.0370	0.0540	0.0431	0.0362
MAE	0.0061	0.0209	0.0211	0.0101	0.0294	0.0174	0.0175
MIM	2.6289	2.1687	1.6426	1.6437	1.6845	1.9487	1.9528
FF	4.0597	4.3373	3.2851	3.2873	3.3686	3.6994	3.6729
$Q^{AB/F}$	0.6801	0.5864	0.3211	0.5893	0.3230	0.3019	0.5462

Table.1: Comparison Of Proposed BFCN Method With The Existing Fusion Techniques

The quality parameters of the proposed BFCN method are compared with Contourlet Transform (CT) and with other proposed methods by Siddiqui et al. [18], Luo et al. [19], Yuhendra [20], Zheng et al. [21] methods on the images Hyderabad, Vishakhapatnam, Mahaboobnagar, Patancheru, Landsat-7 and QuickBird. The Table 2 lists the average values of each quality parameter on the source images.

Table 2: Quality metrics of proposed BFCN method with other image fusion methods about all the six locations

Metrics	CT	Siddiqui et al.,	Luo et al.,	Yuhendra	Zheng et al.,	BFCN
SD	50.837	45.571	51.332	52.3498	52.435	44.0196
ENT	7.5274	7.1234	7.503	7.2498	7.1584	7.5973
CC	0.9916	0.9023	0.9097	0.9117	0.9627	0.9988
MSE	0.0012	0.0041	0.0036	0.0081	0.0106	0.0012
PSNR	76.928	62.315	43.783	71.3422	39.406	76.9279
RMSE	0.0462	0.1967	4.2453	9.0498	2.859	0.0362
MAE	0.0175	1.0435	0.1839	6.930	0.059	0.0175
MIM	1.9528	0.98	0.564	0.983	0.9803	1.9528
FF	3.6729	1.3245	0.4397	0.3452	1.2342	3.6729
$Q^{AB/F}$	0.4669	0.0234	0.134	0.4029	0.0118	0.5462

The proposed BFCN method is compared with CT and with the other methods proposed by Siddiqui et al. [18], Luo et al. [19], Yuhendra [20], Zheng et al. [21].

From the Table 2 it is clearly evident that for all the six image data sets, the average values of Entropy, CC, PSNR, MIM, FF and $Q^{AB/F}$ is higher for the proposed BFCN method when compared with other existing fusion techniques. Similarly, the average values of SD, MSE, RMSE and MAE is smaller for the proposed BFCN method when compared with other existing fusion techniques. The fused image has the capability of efficiently representing images containing contours and textures while capturing smooth curve edges. Hence, the proposed BFCN method performs better than existing methods which are compared in Table 2. Figure 11 represents the graph which gives comparative analysis of proposed BFCN method with other existing methods about the quality parameters.

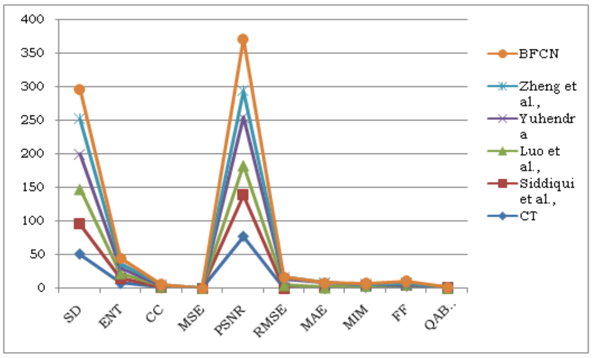


Figure 11: Comparative analysis of the proposed BFCN method with other existing methods about the quality parameters.

5. CONCLUSION

Image fusion using the proposed BFCN method provides an efficient way for extracting all the useful information related to smooth curve edges over the source images. . It is truly show that from the experimental results the proposed BFCN fusion algorithm gives encouraging results. The fused image has high spatial information, which leads to more clarity with minimum distortion i.e., the visual artefacts are eliminated. Thus, the fused image is more reliable and has robust performance and can be used for further interpretation.

With the proposed BFCN method is achieved the higher value for Entropy, CC, PSNR, MIM, FF and $Q^{AB/F}$ .For all the six image data sets.The smaller value of SD, MSE and RMSE is achieved for the proposed BFCN method. So, when contourlet transform, which is a multi-resolution analysis tool, is integrated with the learning capabilities of neural network proved that it performs well for image fusion purpose. that's why, it is ascertained that BFCN mannequin has superior performance than other existing methods. The proposed BFCN method has the ability to assess the quality of the fusion result.

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