CHAPTER 4
AN IMPROVED BLOCK BASED FEATURE LEVEL IMAGE FUSION TECHNIQUE USING MULTIWAVELET TRANSFORM WITH NEURAL NETWORK

4.1 INTRODUCTION

Chapter 3 derived ‘An efficient block based feature level image fusion technique using discrete wavelet transform with neural network’ (BFWN) method which integrates Discrete Wavelet Transforms (DWT) with Neural Networks (NN) to fuse Panchromatic (PAN) and Multispectral (MS) images. The image fusion methods based on DWT suffers from structural distortions, lack of poor directionality, and lack of shift invariance. These methods contain less spatial information. To address these problems, this chapter extends upon the previous approach and derives ‘An improved block based feature level image fusion technique using multiwavelet transform with neural network’ (BFMN) method for fusing PAN and MS images. This proposed BFMN method integrates ‘Multiwavelet Transform’ (MWT) with the block based concepts of feed forward back propagation neural network for fusing Indian Remote Sensing Satellites (IRS-1D), Landsat-7, QuickBird images. The present study critically compares the fusion results of BFMN method with other existing methods for fusing PAN and MS images.
4.2 MULTIWAVELET TRANSFORM FOR IMAGE FUSION

Multiwavelet transforms are extensions of discrete wavelet transforms. Discrete wavelets are also called scalar wavelets. Multiwavelets are almost similar to scalar wavelets but have few key differences. Multiwavelets have two or more scaling functions and two or more mother wavelet functions used for signal representation. The analysis of multiwavelet transform is the new development in the area of wavelet transform.

The fusion process using multiwavelet fusion technique takes place in multiwavelet space with different frequencies. For this, more number of defined features is incorporated in the fused image. MWT offers simultaneous orthogonality, symmetry, compact support and vanishing moments which are not possible with scalar wavelet transforms.

In particular, multiwavelets are a generalization of scalar wavelets. The scalar wavelets have a single scaling function \( \phi (t) \) and a single wavelet function \( \Psi (t) \) whereas multiwavelets have two or more scaling functions and two or more wavelet functions. Multiwavelets have new features that arise from the structure of dilation equation. A function \( \phi (t) \) is scalable if it satisfies a dilation equation \( \phi(t) = \sum_k c_k \phi(2t - k) \). A scaling function generates a multi-resolution Analysis (MRA) if the following conditions are satisfied.

- Translates \( \phi (t - k) \) are linearly independent and produce a basis of the subspace \( V_0 \).
• Dilates \( \phi (2^j t - k) \) generate subspaces \( V_j \), \( j \in \mathbb{Z} \), as given in Equations (4.1) and (4.2)

\[
\ldots \subset V_{-1} \subset V_0 \subset V_1 \subset \ldots \subset V_j \subset \ldots \quad (4.1)
\]

\[
\bigcup_{j=\infty}^{\infty} V_j = L^2(\mathbb{R}) \quad \cap \bigcap_{j=\infty}^{\infty} V_j = 0 \quad (4.2)
\]

• There is a wavelet \( \Psi (t) \), such that its translates i.e., \( \Psi (t - k) \) are linearly independent and produce a basis of the subspace \( W_0 \) as given in Equation (4.3)

\[
V_1 = V_0 \oplus W_0 \quad (4.3)
\]

By subtracting Equation (4.3) from Equation (4.1) the following Equations are derived.

\[
L^2(\mathbb{R}) = \sum_{\infty} W_j \quad \text{and}
\]

\[
\{ w_{kj} : w_{kj} = w(2^j - k), \quad k, j \in \mathbb{Z} \} \quad \text{as a basis of } L^2.
\]

A several scaling functions \( \phi_0 \)(t)... \( \phi_{r-1} \)(t) are considered to generate a basis of \( V_0 \). The set of scaling functions can be denoted by using the vector notation \( \phi (t) \), such that \( \phi (t) \equiv [\phi_1(t) \quad \phi_2(t) \quad \ldots \quad \phi_r(t)]^T \)

where \( \phi(t) \) is called the multi-scaling function. The multi-scaling function satisfies a dilation equation with matrix coefficients \( C_k \). Since \( \phi (t) \in V_0 \) and \( V_0 \subset V_1 \), \( \phi (t) \) must be a linear combination of dilated translates of itself and is called a dilation equation as given in Equation (4.4).

\[
\phi(t) = \sum_k C_k \phi(2^j t - k) \quad (4.4)
\]

Then a basis \( \{ w_{jk} : w_{jk} = w(2^j t - k) \}, j,k \in \mathbb{Z} \) of \( L^2(\mathbb{R}) \) is generated by a wavelet function \( \Psi (t) \), whose translates \( \Psi (t - k) \) form a basis of \( W_{0,V1} = \ldots \subset W_{-1} \subset W_0 \subset W_1 \subset \ldots \subset W_j \subset \ldots \subset W_{\infty} \subset L^2(\mathbb{R}) \).
$V_0 \ominus W_0$. Similarly, $\Psi(t)$ must satisfy a wavelet equation as given in Equation (4.5).

$$\Psi(t) = \sum_k D_k \phi(2t - k) \tag{4.5}$$

Similarly, the multiwavelet function is defined from the set of wavelet functions as $\Psi(t) = [\Psi_1(t) \; \Psi_2(t) \; \ldots \; \Psi_r(t)]^T$ where $\Psi(t)$ is called the multiwavelet function. When $r = 1$, $\Psi(t)$ becomes a scalar wavelet. The scaling and wavelet functions have finite support if and only if the number of coefficients $C_k$ and $D_k$ are finite. The Haar scaling and wavelet functions are supported on $[0, 1]$ and satisfy two-scale relations with two coefficients:

$$\phi(t) = \phi(2t) + \phi(2t - 1)$$

$$\Psi(t) = \phi(2t) - \phi(2t - 1)$$

The advantages of multiwavelets to scalar wavelets are - it provides a combination of orthogonality, symmetry, compact support and vanishing moments which cannot be achieved by any scalar wavelets except by Haar wavelet and possess all these properties at the same time [17]. The multiwavelet filters are given by GHM (Geronimo-Hardin-Massopust), CL (Chu-Lian), and SA (Shen-Tan-Tham). Among these filters, [27] and [21] proposed that GHM filter is famous. Each decomposition level of multiwavelets consists of 16 subbands i.e., the low-pass subband consists of 4 blocks and the high-pass subband consists of remaining 12 blocks as illustrated in Figure 4.1. The horizontal, vertical and diagonal subbands which are called as detail subbands consist of blocks having similar spectral content. The low-
pass subband is an approximation of the input image while the detail subbands convey information about the detail parts in horizontal, vertical and diagonal directions. Hence, the $i^{th}$ level decomposition using discrete multiwavelets look like $(i+1)^{th}$ level decomposition using discrete scalar wavelets [46]. The transform values for the subbands other than low-pass fluctuate around zero [83]. Any fusion algorithm can be applied to approximation and detail subbands to get the better fused image. Due to the above advantages and properties, the present thesis used multiwavelet transforms for image denoising.

![Figure 4.1: The decomposition level consists of 16 subbands.](image)

To implement MWT, new filter bank structures are used where the low-pass and high-pass filter banks are matrices rather than the scalars i.e., the two scaling and two wavelet functions satisfy the following two-scale dilation equations [30]. Since GHM filter has two scaling and two wavelet functions, it has two low-pass subbands and two high-pass subbands in the transform domain as mentioned in Equations (4.6) and (4.7).

$$
\begin{bmatrix}
\phi_1(t) \\
\phi_2(t)
\end{bmatrix} = \sqrt{2} \sum_k H_k \begin{bmatrix}
\phi_1(2t - k) \\
\phi_2(2t - k)
\end{bmatrix} \quad (4.6)
$$
and
\[
\begin{bmatrix}
\psi_1(t) \\
\psi_2(t)
\end{bmatrix} = \sqrt{2} \sum_k G_k \begin{bmatrix}
\psi_1(2t - k) \\
\psi_2(2t - k)
\end{bmatrix}
\]

(4.7)

where
\[
H_0 = \sqrt{2} \begin{bmatrix}
\frac{3}{10} & 2\sqrt{2} \\
-\frac{3\sqrt{2}}{40} & -\frac{3}{20}
\end{bmatrix} \quad H_1 = \sqrt{2} \begin{bmatrix}
\frac{3}{10} & 0 \\
\frac{9\sqrt{2}}{40} & 1
\end{bmatrix}
\]

\[
H_2 = \sqrt{2} \begin{bmatrix}
0 & 0 \\
\frac{9\sqrt{2}}{40} & -\frac{3}{20}
\end{bmatrix} \quad H_3 = \sqrt{2} \begin{bmatrix}
0 & 0 \\
\frac{9}{40} & \frac{1}{2}
\end{bmatrix}
\]

and
\[
G_0 = \sqrt{2} \begin{bmatrix}
\frac{\sqrt{2}}{40} & -\frac{3}{20} \\
-\frac{1}{20} & -\frac{3\sqrt{2}}{20}
\end{bmatrix} \quad G_1 = \sqrt{2} \begin{bmatrix}
\frac{9\sqrt{2}}{40} & -\frac{1}{2} \\
\frac{9}{20} & 0
\end{bmatrix}
\]

\[
G_2 = \sqrt{2} \begin{bmatrix}
\frac{9\sqrt{2}}{40} & -\frac{3}{20} \\
-\frac{9}{20} & \frac{3\sqrt{2}}{20}
\end{bmatrix} \quad G_3 = \sqrt{2} \begin{bmatrix}
-\frac{\sqrt{2}}{40} & 0 \\
\frac{1}{20} & 0
\end{bmatrix}
\]

By examining the transform matrices of scalar wavelet and multiwavelet of Equations (4.6) and (4.7) respectively, it is observed that in MWT domain there will be first and second low-pass coefficients followed by first and second high-pass filter coefficients rather than one low-pass coefficient followed by one high-pass coefficient. Therefore, if the four coefficients are separated there will be four subbands in the transform domain.

**4.3 PROPOSED BFMN ALGORITHM FOR IMAGE FUSION**

The proposed BFMN method uses a feed forward back propagation neural network, which is one of the classifier tools to take decisions during the execution of the process. It integrates multiwavelet transform with NN because NN based methods employ a nonlinear response function that iterates many times in a special network structure in order to learn the complex functional relationship between
input and output training data. NN based fusion method exploits the pattern recognition capabilities of NN. Many applications indicate that NN-based fusion methods have more advantages than traditional statistical methods, especially when input multiple sensor data were incomplete or with much noise.

The block diagram of the proposed BFMN method is shown in Figure 4.2.

Figure 4.2: Block diagram of the proposed BFMN method.

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

1. Read PAN and MS images.
2. Apply MWT at second level decomposition to both the images.
3. Consider the LL2 component of PAN and MS images.
4. Partition LL2 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 the feature values of \( F_1 \) and \( F_2 \) of each block. If the 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 to the NN.

8. Train the newly constructed NN randomly by simulating it.

9. If the simulated output > 1 then consider corresponding block of PAN image else consider corresponding block of MS image.

10. Construct the fused image by selecting the 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 \( Q^{AB/F} \) values are calculated. These quality metrics are discussed in Chapter 2 of Equations (2.14) to (2.24) which are used to compare the fused images.

**4.4 RESULTS AND DISCUSSIONS**

The proposed BFMN method is experimented on PAN and MS images about the locations 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 BFMN method.

Following Figures (4.3) to (4.8) demonstrate fused images using the proposed BFMN method about the six locations.

Figure 4.3: Location of Hyderabad (a) PAN image (b) MS image (c) Fused image of proposed BFMN method.

Figure 4.4: Location of Visakhapatnam (a) PAN image (b) MS image (c) Fused image of proposed BFMN method.

Figure 4.5: Location of Mahaboobnagar (a) PAN image (b) MS image (c) Fused image of proposed BFMN method.
Figure 4.6: Location of Patancheru (a) PAN image (b) MS image (c) Fused image of proposed BFMN method.

Figure 4.7: Location of Landsat-7 (a) PAN image (b) MS image (c) Fused image of proposed BFMN method.

Figure 4.8: Location of QuickBird (a) PAN image (b) MS image (c) Fused image of proposed BFMN method.

Table 4.1 provided below shows the results of quality metrics using the proposed BFMN method for all the above six locations. By
observing the results of Table 4.1 of the proposed BFMN method, the following observations are made

- It is clear that the average value of correlation coefficient (CC) is almost $\cong 1$, 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 PAN image indicates 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 70, 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 greater than 1, 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 2.5, which indicates that the similarity of image intensity distribution of the corresponding image pair is induced in the fused image.

- The average value of $Q^{AB/F}$ is around 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 induced in the fused image.

• The average value of 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 4.1: Quality metrics using proposed BFMN method about locations Hyderabad, Vishakhapatnam, Mahaboobnagar, Patancheru, Landsat-7 and QuickBird

<table>
<thead>
<tr>
<th>Metrics</th>
<th>Hyderabad</th>
<th>Visakhapatnam</th>
<th>Mahaboobnagar</th>
<th>Patancheru</th>
<th>Landsat-7</th>
<th>QuickBird</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>SD</td>
<td>35.7098</td>
<td>55.1914</td>
<td>44.2487</td>
<td>31.1235</td>
<td>34.4128</td>
<td>66.4046</td>
<td>44.5151</td>
</tr>
<tr>
<td>ENT</td>
<td>6.9483</td>
<td>7.6323</td>
<td>7.509</td>
<td>7.6507</td>
<td>7.6354</td>
<td>7.973</td>
<td>7.5581</td>
</tr>
<tr>
<td>CC</td>
<td>0.9994</td>
<td>0.9993</td>
<td>0.9976</td>
<td>0.9991</td>
<td>0.9998</td>
<td>0.998</td>
<td>0.9901</td>
</tr>
<tr>
<td>MSE</td>
<td>0.001</td>
<td>0.0041</td>
<td>0.0029</td>
<td>0.0013</td>
<td>0.0004</td>
<td>0.0017</td>
<td>0.0019</td>
</tr>
<tr>
<td>PSNR</td>
<td>78.0004</td>
<td>72.0199</td>
<td>72.3152</td>
<td>76.0441</td>
<td>81.4575</td>
<td>75.9335</td>
<td>75.9618</td>
</tr>
<tr>
<td>RMSE</td>
<td>0.0556</td>
<td>0.0639</td>
<td>0.0615</td>
<td>0.0367</td>
<td>0.0216</td>
<td>0.0407</td>
<td>0.0467</td>
</tr>
<tr>
<td>MAE</td>
<td>0.0073</td>
<td>0.0287</td>
<td>0.0283</td>
<td>0.016</td>
<td>0.0248</td>
<td>0.0183</td>
<td>0.0206</td>
</tr>
<tr>
<td>MIM</td>
<td>2.4232</td>
<td>1.4223</td>
<td>1.0235</td>
<td>1.5254</td>
<td>1.1676</td>
<td>1.8657</td>
<td>1.5713</td>
</tr>
<tr>
<td>FF</td>
<td>2.8463</td>
<td>2.8446</td>
<td>2.0471</td>
<td>3.0507</td>
<td>2.3352</td>
<td>2.6114</td>
<td>2.9854</td>
</tr>
<tr>
<td>QAB/F</td>
<td>0.5276</td>
<td>0.6299</td>
<td>0.4095</td>
<td>0.5688</td>
<td>0.5287</td>
<td>0.3971</td>
<td>0.5103</td>
</tr>
</tbody>
</table>
4.4.1 Comparison of Proposed BFMN with other existing Fusion Techniques

Quality parameters of the proposed BFMN method are compared with MWT technique, Siddiqui et al. [1], Luo et al. [88], Yuhendra [95], Zheng et al. [35] methods on the images Hyderabad, Vishakhapatnam, Mahaboobnagar, Patancheru, Landsat-7 and QuickBird. The following Table 4.2 lists the average values of the each quality parameter on the above images.

The first column of Table 4.2 represents the names of the quality metrics evaluated for the present study. The seventh column represents the average values of the proposed BFMN method. The rest of the columns contain the average fusion values of other existing methods.

For all the six image data sets, the average values of Entropy, CC, PSNR, MIM, FF and $Q^{AB/F}$ is less for other existing methods when compared with the proposed BFMN method. The average value of SD, MSE, RMSE and MAE is high for other existing methods when compared with the proposed BFMN method. The fused image has the capability of perfect signal representation and preserves spectral features while increasing spatial resolution of the fused image. Hence, it is ascertained that the proposed BFMN method has superior performance than other existing methods which are compared in Table 4.2. The Figure 4.9 represents the graph which gives the comparative analysis of the proposed BFMN method with other existing methods about the quality parameters.
Table 4.2: Comparison of proposed BFMN method’s quality metrics with other image fusion methods

<table>
<thead>
<tr>
<th>Metrics</th>
<th>MWT</th>
<th>Siddiqui et al.,</th>
<th>Luo et al.,</th>
<th>Yuhendra</th>
<th>Zheng et al.,</th>
<th>BFMN</th>
</tr>
</thead>
<tbody>
<tr>
<td>SD</td>
<td>54.751</td>
<td>45.571</td>
<td>51.332</td>
<td>52.3498</td>
<td>52.4356</td>
<td>44.5151</td>
</tr>
<tr>
<td>ENT</td>
<td>7.538</td>
<td>7.1234</td>
<td>7.503</td>
<td>7.2498</td>
<td>7.1584</td>
<td>7.5581</td>
</tr>
<tr>
<td>CC</td>
<td>0.9543</td>
<td>0.9023</td>
<td>0.9097</td>
<td>0.9117</td>
<td>0.9627</td>
<td>0.9901</td>
</tr>
<tr>
<td>MSE</td>
<td>0.0038</td>
<td>0.0041</td>
<td>0.0036</td>
<td>0.0081</td>
<td>0.0106</td>
<td>0.0019</td>
</tr>
<tr>
<td>PSNR</td>
<td>72.659</td>
<td>62.315</td>
<td>43.7836</td>
<td>71.3422</td>
<td>39.4065</td>
<td>75.9618</td>
</tr>
<tr>
<td>RMSE</td>
<td>0.0606</td>
<td>0.1967</td>
<td>4.2453</td>
<td>9.0498</td>
<td>2.859</td>
<td>0.0467</td>
</tr>
<tr>
<td>MAE</td>
<td>0.0281</td>
<td>1.0435</td>
<td>0.1839</td>
<td>6.93</td>
<td>0.059</td>
<td>0.0206</td>
</tr>
<tr>
<td>MIM</td>
<td>0.8758</td>
<td>0.98</td>
<td>0.564</td>
<td>0.983</td>
<td>0.9803</td>
<td>1.5713</td>
</tr>
<tr>
<td>FF</td>
<td>1.7515</td>
<td>1.3245</td>
<td>0.4397</td>
<td>0.3452</td>
<td>1.2342</td>
<td>2.9854</td>
</tr>
<tr>
<td>QA/B/F</td>
<td>0.4051</td>
<td>0.0234</td>
<td>0.134</td>
<td>0.4029</td>
<td>0.0118</td>
<td>0.5103</td>
</tr>
</tbody>
</table>

Figure 4.9: Comparative analysis of proposed BFMN method with other existing methods about the quality parameters

**SUMMARY**

The main purpose of this chapter is to develop a new algorithm which can overcome the disadvantages of DWT for better quality of the fused images. With this goal, the present chapter has proposed a BFMN algorithm, which integrates MWT with the learning capabilities of neural networks for better quality of the fused image.
The MWT, which is an extension of DWT, has the capability of perfect signal representation which helps in better fusion process. The properties of multiwavelets such as orthogonality, symmetry, and compact support help in preserving the spectral features while increasing the spatial resolution of the fused image.

The performance of the proposed BFMN technique is compared with other existing fusion techniques. The quality of the fused image is calculated by using few quality metrics and it is proved that the panchromatic fusion sharpening does not only improve the eye appraisal of the fused image, but also substantially improves the accuracy of the spectral reflectance values. Experimental results show that the proposed BFMN method performs better in preserving the image detail information than other existing methods. Hence, after conducting the experimental results, it is ascertained that the proposed BFMN method has superior performance than other existing methods compared in the Table 4.2.