CHAPTER 6

IMAGE FUSION BASED ON ENERGY OF THE PIXEL-A VARIATION FRAME WORK

This chapter presents a new method based on energy for fusing multiexposure, multifocal, multimodal, multispectral images. The proposed method presents a framework for combining multiple images based on energy.

6.1 INTRODUCTION

Given a set of multiple images, fusion is the process of getting a single image representative that has improved information from all the images. In particular, the final fused image has good quality in sense of every part of the image.

The primary objective of image fusion is getting a single image which has an improved quality with respect to every input image. Let \( I = \{I_1, I_2, \ldots, I_n\} \) be the set of multiple input images. Based on the attribute value (attribute is light effect on objects in the capturing scenario, without loss of generality) every image \( I_j \) for \( j \in \{1, n\} \) has at least a single object or portion, which is comparatively better than the other input images.

For every image \( I' \in I \), the featured portion is extracted to get the best pixels. At the end of feature extraction, the extracted features from every input image are combined. Unfortunately, there is no guarantee that every
portion of the captured scene would be contained in extracted features. To overcome the drawback, the notion of pixel wise feature extraction and energy boosting is introduced.

Local contrast enhancement can be achieved by enhancing the fundamental measures of an image such as color, saturation, exposure, and energy and so on. A variational method for exposure fusion proposed by David & Weickert (2015) formed the basis for designing an improved energy formulation to achieve perceptually inspired enhancement. The focus of this work is to formulate an energy function for local contrast enhancement. In this work, energy is formulated by extracting pixel information such as color difference, mean, and standard deviation. The quality of the work is demonstrated by carrying out several experiments to prove its excellence against the existing works. This method is simple and efficient and the energy function used to fuse the images directly, reduces the time and computational cost.

6.2 THE PROPOSED METHOD

The proposed method concentrates on enhancing the fusion in terms of simplicity and accuracy. The proposed work does not utilize any decomposition techniques for the input images. The pipeline of the work is shown in Figure 6.1. Let I be a set of N multi-exposure input images. All the input images should be of the same size. Red, green, and blue color information is extracted from the pixels of all the input images. The pixels at a particular position are taken from all the input images and mean and standard deviation are computed. From these statistical values, the fused image is constructed. On the other hand, the energy is calculated for all the pixels as explained in section 6.3.1. The energy of a pixel is calculated to maintain the importance of the corresponding pixel factors, such as color, focus, and so on. The energy value of a pixel lies in the range 0 to 255. The
pixel density or the energy is more when a pixel is surrounded by fully black or fully white pixels. The pixels in the fused image are boosted based on the energy values computed so as to increase the visibility of the fused image.

6.2.1 Energy Formulation

The main goal of the proposed work is to fuse n different exposure images \( I_1, I_2, I_3, I_4, \ldots, I_n \) into a single image, which is contributed by well exposed pixels. Basically, in pixel-based methods, the weighted average of a fused image is defined by

\[
FU(x, y) = \sum_{i=1}^{n} W_i(x, y) \cdot I_i(x, y)
\]  

(7.1)

where \((x, y)^T\) represents the position on the rectangular domain \( \Omega \subset \mathbb{R}^2 \), and \( W_i \) is the weight of an input image. All the previous methods in the literature
compute the weights of the pixels based on color, saturation and exposedness. In contrast, the proposed work computes the weight of an image from the statistical properties such as mean, variance and standard deviation of the RGB color in the pixels. The energy is calculated from the color components of a pixel.

Let I denote N multiexposure input images.

\[
\text{Let } I \in \{I_1, I_2, I_3, I_4, \ldots, I_n\}
\]  

(7.2)

Consider a 3x3 window of pixels. Let \((x, y)\) be the spatial position of the pixel under consideration and the neighboring pixels as shown in the matrix.

\[
\begin{bmatrix}
    x-1, y+1 & x, y+1 & x+1, y+1 \\
    x-1, y & x, y & x+1, y \\
    x-1, y-1 & x, y-1 & x+1, y-1
\end{bmatrix}
\]  

(7.3)

In the existing method, the energy of the pixel \((x, y)\) is calculated as

\[
E(x, y) = \text{Diff}[(x - 1, y), (x + 1, y)] + \text{Diff}[(x, y + 1), (x, y - 1)]
\]  

(7.4)

This energy calculation is shown below for simplicity.

\[
I_E = \begin{bmatrix}
    1 & 2 & 3 \\
    4 & 5 & 6 \\
    7 & 8 & 0
\end{bmatrix}
\]  

(7.5)

Energy of pixel number 5 is computed as follows:

But, in the proposed method, energy is calculated as shown below:

\[
ProposedE = Diff[(x - 1, y + 1)(x - 1, y - 1)] \\
+ Diff[(x, y + 1)(x, y - 1)] \\
+ Diff[(x + 1, y + 1)(x + 1, y - 1)] \\
+ Diff[(x - 1, y + 1)(x + 1, y + 1)] \\
+ Diff[(x - 1, y)(x + 1, y)] \\
+ Diff[(x - 1, y - 1)(x + 1, y - 1)] \\
- Diff[(x - 1, y - 1)(x + 1, y + 1)] \\
- Diff[(x - 1, y - 1)(x + 1, y - 1)]
\]  \hspace{1cm} (7.7)

\[
I_E = \begin{bmatrix}
1 & 2 & 3 \\
4 & 5 & 6 \\
7 & 8 & 9
\end{bmatrix} + \begin{bmatrix}
1 & 2 & 3 \\
4 & 5 & 6 \\
7 & 8 & 9
\end{bmatrix}
\]  \hspace{1cm} (7.8)

\[I_E = \text{Energy of pixel (5)}\]

\[= \text{Diff (1,7) + Diff (2,8) + Diff (3,9)}\]

\[+ \text{Diff (1,3) + Diff(4,6) + Diff(7,9)} \hspace{1cm} (7.6)\]

\[- \text{Diff (1,9) + Diff (3,7)}\]

The pixel’s energy is calculated by using the contrast of the input pixel ‘a’, with respect to the color coordinate values. Thus, the energy E can be calculated for every pixel in the image by means of the below given generalized standard formula

\[
\forall x, y E(x, y) = \sqrt{\Delta x^2 + \Delta y^2 - \Delta xy} \\
\Delta x^2 = Rx^2 + Gx^2 + Bx^2 \\
\Delta y^2 = Ry^2 + Gy^2 + By^2
\]  \hspace{1cm} (7.9)
For simplicity, the computations for red component are given in detail.

The $R_x$ value for a pixel at position $(x,y)$ is computed as

$$
R_x = \left[ \frac{\text{abs} \left( R_{(x+1,y+1)} - R_{(x-1,y-1)} \right) + \text{abs} \left( R_{(x,y+1)} - R_{(x,y-1)} \right) + \text{abs} \left( R_{(x+1,y+1)} - R_{(x+1,y-1)} \right)}{3} \right] 
$$

(7.10)

The generalized $R_x$ computation for a pixel at position $(x,y)$ is

$$
R_x = \sum_{i=x-1}^{x+1} \frac{\text{abs} \left( R_{(i,y+1)} - R_{(i,y-1)} \right)}{3} 
$$

(7.11)

The generalized $R_y$ computation for a pixel at position $(x,y)$ is

$$
R_y = \sum_{j=y-1}^{y+1} \frac{\text{abs} \left( R_{(x+1,j)} - R_{(x-1,j)} \right)}{3} 
$$

(7.12)

The same computation can be extended for green and blue components also.

The difference $\Delta_x^2$ and $\Delta_y^2$ can be calculated as

$$
\Delta^2 = R_y^2 + Gy^2 + By^2 
$$

(7.13)

$$
\Delta^2 = R_x^2 + Gy^2 + Bx^2 
$$

(7.14)
The computation of $R_x, R_y, G_x, G_y, B_x, B_y$ can be generalized for all the pixels as given as.

\[
T_x = \sum_{i=x-1}^{x+1} \frac{\text{abs}[T(i+y, y) - T(i, y-1)]}{3} T \in \{R, G, B\}
\] (7.15)

\[
T_y = \sum_{j=y-1}^{y+1} \frac{\text{abs}[T(i, j+1) - T(i, j-1)]}{3} T \in \{R, G, B\}
\] (7.16)

The generalized forms of $\Delta_x^2$ and $\Delta_y^2$ are shown as:

\[
\Delta_x^2 = \sum T_x^2
\] (7.17)

\[
\Delta_y^2 = \sum T_y^2
\] (7.18)

\[
\Delta_{xy} = R_{xy}^2 + G_{xy}^2 + B_{xy}^2
\]

\[
R_{xy} = \text{abs}[R_{(x+1, y+1)} - R_{(x-1, y-1)}] + \text{abs}[R_{(x+1, y-1)} - R_{(x-1, y+1)}]
\] (7.19)

Generalizing the values

\[
T_{xy} = \text{abs}[T_{(x+1, y+1)} - T_{(x-1, y-1)}] + \text{abs}[T_{(x-1, y+1)} - T_{(x+1, y-1)}] T \in \{R, G, B\}
\] (7.20)

Finally, the energy of the pixel can be calculated as

\[
\text{Energy} (E_{xy}) = \sqrt{\Delta_x^2 + \Delta_y^2 - \Delta_{xy}}
\]

\[
\forall x, y \in \text{Pixel of Image}
\]
\[ \forall [x, y] \in (\text{Row x col}) \]

### 6.2.2 Statistical-based Pixel Weight Calculation

Every image has its own pixel information. The values such as mean \( \mu \), standard deviation \( \sigma \) and Variance \( \sigma^2 \) are extracted from the color information as shown below. Equations (7.21), (7.22) and (7.23) gives the mean calculation for red, green and blue components respectively.

\[
\mu_{xy}^{[R]} = \frac{\sum_{I_1} R_x(I_1)}{|I|} \quad (7.21)
\]

Similarly, G and B can be calculated as

\[
\mu_{xy}^{[G]} = \frac{\sum_{I_1} G_x(I_1)}{|I|} \quad (7.22)
\]

\[
\mu_{xy}^{[B]} = \frac{\sum_{I_1} B_x(I_1)}{|I|} \quad (7.23)
\]

The calculation of mean for all the color components can be generalized as

\[
\mu_{xy}^{[R,G,B]} = \frac{\sum_{I_1} T_x(I_1)}{|I|} \quad |T \in (R, G, B)\]

(7.24)

The variance is computed for the red, green and blue color components are given in Equations (7.25), (7.26) and (7.27) respectively.
\[ \sigma_{xy}^2[R] = \frac{\sum_{l=1}^{I} \text{abs} \left| \mu_{xy} - R_{xy}^{(l')i} \right|}{|I|} \]  
(7.25)

\[ \sigma_{xy}^2[G] = \frac{\sum_{l=1}^{I} \text{abs} \left| \mu_{xy} - G_{xy}^{(l')i} \right|}{|I|} \]  
(7.26)

\[ \sigma_{xy}^2[B] = \frac{\sum_{l=1}^{I} \text{abs} \left| \mu_{xy} - B_{xy}^{(l')i} \right|}{|I|} \]  
(7.27)

Generalizing the variance,

\[ \sigma_{xy}^2[RGB] = \frac{\sum_{l=1}^{I} \text{abs} \left| \mu_{xy} - T_{xy}^{(l')i} \right|}{|I|} \]  
\( T \in R, G, B \)  
(7.28)

From the variance, standard deviation can be computed easily by taking square root.

\[ \sigma = \sum (\mu - x_i)^2 \]  
(7.29)

After computing the mean and standard deviation, initialize a dummy matrix filled with zeros to store the final pixel values. From every input image, the pixel values that lie between the range \((\mu + \sigma)\) and \((\mu - \sigma)\), are copied to the final pixel matrix. The final pixel matrix thus obtained may have some pixel values as zero if the pixels from the input images in those positions do not fall in the specified range. These positions are filled by the average value of pixels from all the input images. Thus, a resultant image is constructed with pixels restored from different images. This procedure is given in the Algorithm shown below:
6.1 Statistical based pixel weight calculation

Input: Images $I_1, I_2, \ldots, I_n$ of size height x width
Output: Pixel Matrix

\begin{algorithm}
\begin{algorithmic}
\STATE \textbf{begin}
\FOR{$x, y \in [\text{height x width}]$} 
\STATE \quad List $\leftarrow \{ P_{xy}[RGB] \} \ \forall I^l \in I_1, I_2, \ldots, I_n$
\STATE \quad $\mu_{xy}[RGB] \leftarrow \text{find}_\text{mean} \ (\text{List})$
\STATE \quad $\sigma_{xy}[RGB] \leftarrow \text{find}_\text{dev} \ (\mu_{xy}[RGB], \text{List})$
\STATE \quad value_{xy}[RGB] $\leftarrow 0$;
\STATE \quad count_{xy}[RGB] $\leftarrow 0$.
\FOR{$I^l \in I_1, I_2, \ldots, I_n$}
\IF{$P_{xy}[RGB] \leq \mu_{xy}[RGB] + \sigma_{xy}[RGB] \ \&\& \ P_{xy}[RGB] \geq \mu_{xy}[RGB] - \sigma_{xy}[RGB]$}
\STATE \quad value_{xy}[RGB] $\leftarrow$ value_{xy}[RGB] + $P_{xy}[RGB]$
\STATE \quad count_{xy}[RGB] $\leftarrow$ count_{xy}[RGB] $+$;
\ENDIF
\ENDFOR
\IF{value_{xy}[RGB] $=$ 0}
\FOR{all $I^l \in I_1, I_2, \ldots, I_n$}
\STATE \quad value_{xy}[RGB] $\leftarrow$ value_{xy}[RGB] + $P_{xy}[RGB]$
\ENDFOR
\STATE \quad count_{xy}[RGB] $\leftarrow$ n;
\ENDIF
\STATE \quad value_{xy}[RGB] $\leftarrow$ value_{xy}[RGB] / count_{xy}[RGB]
\STATE \quad set value_{xy}[RGB] into pixel position (x, y)
\ENDFOR
\textbf{end};
\end{algorithmic}
\end{algorithm}

6.2.3 Blending of Pixel Information and Energy-based Weight

This is the final step of the fusion process. The Pixel weight calculation discussed in section 6.3.2 results in a pixel matrix with the same size as that of the input images. The energy formulation proposed in section 6.3.1 gives an energy matrix which is also of the same size. The fusion process is yet to go with energy blending which is given in the Algorithm 6.2. Energy blending is the process of binding pixels of fused image up to energy levels. That is, based on the energy matrix, the pixel matrix is boosted. The pixel matrix which represents the fused image has Red, Green and Blue color.
components. For every pixel, first a preliminary condition is checked. The condition is that at least one of the color components of the pixel should be above the corresponding energy level. If this condition is not satisfied for a pixel, energy blending is done by picking the color component that is closer to the energy component value and by computing the difference between that color component and the energy component. Now all the color components are boosted by adding this difference with them to result in a final fused image with improved energy levels. Thus an enhanced image is obtained by fusing the input images using the new energy formulation. The pixel weight modification combined with energy computation strengthens the clarity of the reconstructed image which makes it suitable for fusing different kinds of images.

Algorithm(6.2) Energy Blending
Input: Energy Blending(Image I, Matrix[ ][ ] E):
Output: Fused image

begin
I' ← I
for each pixel p=I[x][y] in I do
    e ← E[x][y];
    if ( p.RED < e && p.GREEN < e && p.BLUE < e) then
        max ← p.RED;
    end if
    if(p.GREEN > max) then
        max ← p.GREEN;
    end if
    if(p.BLUE > max) then
        max ← p.BLUE;
    end if
    diff ← e - max;
    p.RED ← p.RED + diff;
    p.GREEN ← p.GREEN + diff;
    p.BLUE ← p.BLUE + diff;
    update p into I';
end for
return I';
end
6.3 EXPERIMENTAL RESULTS

The proposed energy based fusion (EBF) method is applied for fusing multiexposure, multifocal, multimodal, multispectral images and the results are analyzed. To examine the effectiveness of the EBF technique, different kinds of analysis are done with the obtained results. Then the results of the proposed method are compared with those of those seven existing methods. Finally, the qualitative and quantitative analyses are performed and the results are analyzed.

6.3.1 Experimental Results of Multiexposure Images

Exposure fusion is performed based on the energy of the pixel. The energy-based method is compared with the existing methods. Experiments are carried out with different sets of input images and the results are examined.

![Multiple exposure image of Kulki House](image1.png)

(a) Multiple exposure image of Kulki House

![The color informations taken from the pixel](image2.png)

(b) The color informations taken from the pixel

![Merten’s Raman’s proposed Method](image3.png)

(c) Merten’s Raman’s proposed Method

Figure 6.2 Multiexposure image fusion with the proposed EBF (a) multiple exposure images. (b) Extraction of colour information (c) fused images with EBF
Figure 6.2 the three multiexposure input image of kulki house is taken for experiment and the fused image is compared with mertens and ramans method.

Multiple exposure images are combined with the proposed energy-based method as shown in Figure 6.2. The energy is calculated with the color information obtained from the pixel and the mean and variance help to restore the pixels which contribute to the final image.

Figure 6.4 Fusion of multiexposure images with the proposed EBF(a), (b), (c) are the inputs (d) fused output with EBF
The data set of landscape, Venice and the office images are used for fusion. The results ultimately prove that the proposed method is comparatively better than the other two proposed.

6.3.1.1 Comparison of the proposed fusion method with the existing methods

Table 6.1 presents results of the proposed method compared with the existing methods. Eight multiexposure image sequences are utilized in the experiments.

**Table 6.1 Quality metrics Comparison of the Proposed method with different methods**

<table>
<thead>
<tr>
<th>Image</th>
<th>Indexes</th>
<th>Methods</th>
<th>Rein hard</th>
<th>iCAM06</th>
<th>Photomatix</th>
<th>Median filter</th>
<th>Proposed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Park</td>
<td>$Q_0$</td>
<td></td>
<td>0.577</td>
<td>0.664</td>
<td>0.586</td>
<td>0.723</td>
<td>0.782</td>
</tr>
<tr>
<td></td>
<td>$Q_{AB/F}$</td>
<td>$Q$</td>
<td>0.571</td>
<td>0.651</td>
<td>0.619</td>
<td>0.684</td>
<td>0.681</td>
</tr>
<tr>
<td></td>
<td></td>
<td>VIF</td>
<td>0.592</td>
<td>0.642</td>
<td>0.624</td>
<td>0.676</td>
<td>0.673</td>
</tr>
<tr>
<td>Forest</td>
<td>$Q_0$</td>
<td></td>
<td>0.493</td>
<td>0.543</td>
<td>0.514</td>
<td>0.570</td>
<td>0.661</td>
</tr>
<tr>
<td></td>
<td>$Q_{AB/F}$</td>
<td>$Q$</td>
<td>0.384</td>
<td>0.407</td>
<td>0.374</td>
<td>0.519</td>
<td>0.628</td>
</tr>
<tr>
<td></td>
<td></td>
<td>VIF</td>
<td>0.234</td>
<td>0.235</td>
<td>0.224</td>
<td>0.368</td>
<td>0.374</td>
</tr>
<tr>
<td>Via</td>
<td>$Q_0$</td>
<td></td>
<td>0.805</td>
<td>0.696</td>
<td>0.643</td>
<td>0.942</td>
<td>0.984</td>
</tr>
<tr>
<td></td>
<td>$Q_{AB/F}$</td>
<td>$Q$</td>
<td>0.750</td>
<td>0.694</td>
<td>0.691</td>
<td>0.838</td>
<td>0.930</td>
</tr>
<tr>
<td></td>
<td></td>
<td>VIF</td>
<td>0.987</td>
<td>0.979</td>
<td>0.911</td>
<td>1.105</td>
<td>1.201</td>
</tr>
<tr>
<td>Garage</td>
<td>$Q_0$</td>
<td></td>
<td>0.555</td>
<td>0.576</td>
<td>0.469</td>
<td>0.675</td>
<td>0.855</td>
</tr>
<tr>
<td></td>
<td>$Q_{AB/F}$</td>
<td>$Q$</td>
<td>0.520</td>
<td>0.561</td>
<td>0.441</td>
<td>0.674</td>
<td>0.691</td>
</tr>
<tr>
<td></td>
<td></td>
<td>VIF</td>
<td>0.467</td>
<td>0.443</td>
<td>0.377</td>
<td>0.522</td>
<td>0.546</td>
</tr>
</tbody>
</table>

The comparisons can be performed with (Reinhard et al. 2002), iCAM06 which is proposed by Kuang et al. (2005), Photomatix (Joffre et al. 2009) is employed for measuring the fusion performance. Three objective
quality matrices like index $Q_0$ (Ramanet al. 2009), visual fidelity (Drago et al. 2009), $Q^{AB/F}$ (Reinhardtet al. 2005) are analyzed. The index $Q_0$ are designed as the combination of three factors correlation loss, distortion in luminance and contrast. $Q^{AB/F}$ valuates the information that has been preserved in edges from the source to the fused output. VIF is derived from a statistical model for natural scene, which can accurately quantify the distortion and improvement in visual quality. Higher values indicate that the fusion is considered to be perfectly conducted with proper edge preservation.

Table 6.1 shows the Quality metrics for the multiexposure images. Four datasets such as Park, Forest, Via, Garage are considered for the experiment and the results are tabulated. From the table it is understood that the proposed method is compared with the existing methods such as Reinhard tone mapping operator, icam06, the readymade package of Photomatix, and median filter methods. The proposed method of fusion gives comparatively better results. This quality assessment results are shown in the Table 6.1 Visual information fidelity (VIF) shows that the proposed method holds significant results for the multiexposure images.

![Quantitative Analysis(Qo)](image)

**Figure 6.4 Graphical representation of Quantitative Analysis(Qo) for Multiexposure Images**
Figures 6.4, 6.5 and 6.6 show the pictorial representation grouped by the quality metrics and the dataset. The proposed method gives better results when compared with the other methods mentioned in the literature.
6.3.1.3 Comparison of the proposed fusion method with the existing methods based on energy

Figure 6.5 shows the results of the proposed method EBF compared with other methods proposed in the literature which are also based on the energy.

![Comparison of the Proposed method with different methods](image)

**Figure 6.7 Comparison of the Proposed method with different methods**

Figure 6.7 shows the results of the other energy-based method compared with the proposed EBF. Hafner et al. (2015) have proposed a method for formulating the energy. Singh et al. (2015) presented an energy based method using the texture property of the image and Wang et al. (2015) have proposed a color-based energy formation and these methods are compared with the proposed method. As shown in Table 6.2 various images such as park, memorial, forest, garage, via has been compared with the existing known methods and quality measures are tabulated. Figure 6.5 infers that the result of the proposed method is visually equivalent to the other methods.

Table 6.2 gives the values of subjective quality assessment of the other methods with the proposed method. Four methods are taken for assessment and the methods referred to are based on the weight of the
The Guided filter (Li et al. 2013) is one of the popular edge preserving filters used in the fusion method. He et al. (2015) presented a weighted guided filter which is popularly used in fusion. Mertens et al. (2003) presented a method which is the foremost method used in fusion. The results for five multiexposure image is compared in terms of quality, naturalness and structural fidelity. Analyzing the results it is understood that the proposed method gives better results.

Table 6.2 Subjective Quality metrics Comparison of the Proposed method with different methods

<table>
<thead>
<tr>
<th>Input data set</th>
<th>Park</th>
<th>memorial</th>
<th>Forest</th>
<th>garage</th>
<th>Via</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proposed Method</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>FBS Q</td>
<td>0.9532</td>
<td>0.9783</td>
<td>0.9621</td>
<td>0.9532</td>
<td>0.9331</td>
</tr>
<tr>
<td></td>
<td>0.8732</td>
<td>0.8431</td>
<td>0.8560</td>
<td>0.9562</td>
<td>0.9432</td>
</tr>
<tr>
<td></td>
<td>0.8361</td>
<td>0.9811</td>
<td>0.9870</td>
<td>0.9880</td>
<td>0.9707</td>
</tr>
<tr>
<td>Proposed Method</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>FBS Q</td>
<td>0.9435</td>
<td>0.9756</td>
<td>0.9551</td>
<td>0.9435</td>
<td>0.9234</td>
</tr>
<tr>
<td></td>
<td>0.8657</td>
<td>0.8761</td>
<td>0.9592</td>
<td>0.9134</td>
<td>0.9135</td>
</tr>
<tr>
<td></td>
<td>0.7667</td>
<td>0.9876</td>
<td>0.9884</td>
<td>0.9894</td>
<td>0.9698</td>
</tr>
<tr>
<td>Proposed Method</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DRAW Q</td>
<td>0.9320</td>
<td>0.9638</td>
<td>0.9507</td>
<td>0.9240</td>
<td>0.9085</td>
</tr>
<tr>
<td></td>
<td>0.8690</td>
<td>0.8690</td>
<td>0.9490</td>
<td>0.8743</td>
<td>0.8674</td>
</tr>
<tr>
<td></td>
<td>0.7641</td>
<td>0.9878</td>
<td>0.9836</td>
<td>0.9885</td>
<td>0.9533</td>
</tr>
<tr>
<td>GFF Method</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Q</td>
<td>0.8561</td>
<td>0.9549</td>
<td>0.9793</td>
<td>0.9421</td>
<td>0.9157</td>
</tr>
<tr>
<td>S</td>
<td>0.8264</td>
<td>0.8347</td>
<td>0.9346</td>
<td>0.8045</td>
<td>0.8509</td>
</tr>
<tr>
<td>N</td>
<td>0.3797</td>
<td>0.9844</td>
<td>0.9694</td>
<td>0.9537</td>
<td>0.9537</td>
</tr>
<tr>
<td>Weighted GF</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Q</td>
<td>0.8667</td>
<td>0.9576</td>
<td>0.9763</td>
<td>0.9567</td>
<td>0.912</td>
</tr>
<tr>
<td>S</td>
<td>0.813</td>
<td>0.8222</td>
<td>0.832</td>
<td>0.834</td>
<td>0.845</td>
</tr>
<tr>
<td>N</td>
<td>0.623</td>
<td>0.843</td>
<td>0.934</td>
<td>0.954</td>
<td>0.956</td>
</tr>
<tr>
<td>Merten’s</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Q</td>
<td>0.886</td>
<td>0.8792</td>
<td>0.8762</td>
<td>0.8897</td>
<td>0.9213</td>
</tr>
<tr>
<td>S</td>
<td>0.882</td>
<td>0.854</td>
<td>0.864</td>
<td>0.843</td>
<td>0.845</td>
</tr>
<tr>
<td>N</td>
<td>0.634</td>
<td>0.921</td>
<td>0.965</td>
<td>0.952</td>
<td>0.912</td>
</tr>
</tbody>
</table>

6.3.1.3 Comparison of fusion metrics with EBF and the other methods

Table 6.3 gives the values of various fusion metrics which facilitate validating the fusion methods. The table contains the other methods discussed.
in the literature. SA is the simple averaging method where the weight of the pixel is considered by averaging. LP is the Laplacian pyramid method used for decomposition. SWT is the simple wavelet method used for decomposition of the input image. PCA is one of the probability component method which is used in fusion taken as referred in the literature. EBF is the proposed method. The RMSE value gives a significantly reduced value from the other methods. The PSNR value is comparatively good when compared with the other methods. Coefficient of correlation is comparatively good for the proposed method. Entropy as well as the mutual information shows the information or the details that have been preserved in the fused image comparing the input image. While comparing the other methods, the proposed method also equivalently good in multiexposure images.

Table 6.3 Fusion metrics for set of Multiexposure Images

<table>
<thead>
<tr>
<th>Images</th>
<th>Method</th>
<th>Metrics</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Park</td>
<td>SA</td>
<td>RMSE</td>
<td>8.17</td>
<td>38.45</td>
<td>0.899</td>
<td>0.734</td>
</tr>
<tr>
<td></td>
<td>LP</td>
<td>RMSE</td>
<td>8.19</td>
<td>36.67</td>
<td>0.879</td>
<td>0.772</td>
</tr>
<tr>
<td></td>
<td>SWT</td>
<td>RMSE</td>
<td>7.98</td>
<td>37.90</td>
<td>0.893</td>
<td>0.735</td>
</tr>
<tr>
<td></td>
<td>DWT</td>
<td>RMSE</td>
<td>7.23</td>
<td>36.49</td>
<td>0.994</td>
<td>0.734</td>
</tr>
<tr>
<td></td>
<td>PCA</td>
<td>RMSE</td>
<td>6.56</td>
<td>37.29</td>
<td>0.993</td>
<td>0.754</td>
</tr>
<tr>
<td></td>
<td>DRAW</td>
<td>RMSE</td>
<td>6.29</td>
<td>39.34</td>
<td>0.847</td>
<td>0.782</td>
</tr>
<tr>
<td></td>
<td>FBF</td>
<td>RMSE</td>
<td>6.31</td>
<td>40.21</td>
<td>0.883</td>
<td>0.786</td>
</tr>
<tr>
<td></td>
<td>EBF</td>
<td>RMSE</td>
<td>5.65</td>
<td>42.13</td>
<td>0.872</td>
<td>0.811</td>
</tr>
<tr>
<td>Memorial</td>
<td>SA</td>
<td>RMSE</td>
<td>9.12</td>
<td>37.34</td>
<td>1.022</td>
<td>0.757</td>
</tr>
<tr>
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<td>RMSE</td>
<td>8.13</td>
<td>35.56</td>
<td>1.031</td>
<td>0.735</td>
</tr>
<tr>
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<td>SWT</td>
<td>RMSE</td>
<td>8.98</td>
<td>37.45</td>
<td>0.998</td>
<td>0.786</td>
</tr>
<tr>
<td></td>
<td>DWT</td>
<td>RMSE</td>
<td>8.23</td>
<td>36.78</td>
<td>0.993</td>
<td>0.787</td>
</tr>
<tr>
<td></td>
<td>PCA</td>
<td>RMSE</td>
<td>7.99</td>
<td>37.56</td>
<td>0.879</td>
<td>0.779</td>
</tr>
<tr>
<td></td>
<td>DRAW</td>
<td>RMSE</td>
<td>7.45</td>
<td>41.21</td>
<td>0.889</td>
<td>0.791</td>
</tr>
<tr>
<td></td>
<td>FBF</td>
<td>RMSE</td>
<td>7.03</td>
<td>41.06</td>
<td>0.891</td>
<td>0.795</td>
</tr>
<tr>
<td></td>
<td>EBF</td>
<td>RMSE</td>
<td>6.08</td>
<td>42.2</td>
<td>0.889</td>
<td>0.797</td>
</tr>
</tbody>
</table>
6.3.2 Experimental Results of Multi Focal Images

The proposed method is employed for multifocal images where the images are captured at different focal lengths. Standard multifocal images are taken for the experiment. The proposed EBF method is applied and the results are shown in Figure 6.8. Experiments are done with left focused and right focused images and also images with near and distant focus. Standard datasets having the ground truth have also been used for assessment.

The flower on the left is focused more and the hanging pot on the right is less focused. The switch box is also not clear.

(a) Left focused Image

The hanging pot on the right is more focused and the flower on the left is less focused.

(b) Right focused image

This is the fused image. The red square shows that both the pot and the switch are focused and are visible.

(c) Fused Image with proposed EBF

Figure 6.8 Multifocal image fusion with EBF
Figure 6.8 show a multifocal image fusion using the proposed method. The red square boxes drawn show the clarity of the less focused regions in the resultant image.

Figure 6.9 Multi focal images fused with EBF (a) Image A (b) Image B (c) Fused Image

Figure 6.9 shows the fused output of the multifocal images. Image A and image B are the differently focused images and the fused image shows considerable improvement in preserving both the focuses on single image. The Quality metrics for the image fusion is tabulated to prove the significance of EBF.
Table 6.4 Quality metrics for multifocal image fusion with EBF

<table>
<thead>
<tr>
<th>Images</th>
<th>RMSE</th>
<th>PSNR</th>
<th>NCC</th>
<th>C.Entropy</th>
<th>MSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pot</td>
<td>4.89</td>
<td>34.33</td>
<td>1.23</td>
<td>5.42</td>
<td>1327.34</td>
</tr>
<tr>
<td>leaf</td>
<td>4.43</td>
<td>33.98</td>
<td>1.62</td>
<td>5.18</td>
<td>1456.55</td>
</tr>
<tr>
<td>Newspaper</td>
<td>3.83</td>
<td>33.89</td>
<td>1.71</td>
<td>5.09</td>
<td>1478.89</td>
</tr>
<tr>
<td>lizard</td>
<td>3.91</td>
<td>33.88</td>
<td>1.58</td>
<td>5.08</td>
<td>1587.35</td>
</tr>
<tr>
<td>clock</td>
<td>4.02</td>
<td>33.45</td>
<td>1.66</td>
<td>5.46</td>
<td>1492.34</td>
</tr>
</tbody>
</table>

Table 6.4 presents the metrics like RMSE, PSNR, NCC, cross entropy, mean square error which are some of the evaluation metrics to justify the clarity of the image and fusion efficiency. From the above examples it is clear that the output of the fused images give good results.

Table 6.5 Metrics for multifocal image fusion with EBF with varying decomposition method

<table>
<thead>
<tr>
<th>Images</th>
<th>Method</th>
<th>Metrics</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Edge Intensity</td>
</tr>
<tr>
<td>Clock</td>
<td>SA</td>
<td>35.33</td>
</tr>
<tr>
<td></td>
<td>LP</td>
<td>35.36</td>
</tr>
<tr>
<td></td>
<td>SWT</td>
<td>37.43</td>
</tr>
<tr>
<td></td>
<td>DWT</td>
<td>36.65</td>
</tr>
<tr>
<td></td>
<td>PCA</td>
<td>35.77</td>
</tr>
<tr>
<td></td>
<td>DRAW</td>
<td>37.52</td>
</tr>
<tr>
<td></td>
<td>FBS</td>
<td>37.49</td>
</tr>
<tr>
<td></td>
<td>EBF</td>
<td>38.56</td>
</tr>
<tr>
<td>Leaf</td>
<td>SA</td>
<td>35.67</td>
</tr>
<tr>
<td></td>
<td>LP</td>
<td>36.22</td>
</tr>
<tr>
<td></td>
<td>SWT</td>
<td>36.56</td>
</tr>
<tr>
<td></td>
<td>DWT</td>
<td>36.27</td>
</tr>
<tr>
<td></td>
<td>PCA</td>
<td>35.55</td>
</tr>
<tr>
<td></td>
<td>DRAW</td>
<td>36.66</td>
</tr>
<tr>
<td></td>
<td>FBS</td>
<td>37.55</td>
</tr>
<tr>
<td></td>
<td>EBF</td>
<td>39.45</td>
</tr>
</tbody>
</table>
Table 6.5 presents the objective metrics of fusion which proves the efficiency of the proposed method. The proposed energy-based fusion (EBF) is compared with some of the popular methods available in pixel-based fusion. The results of proposed method are favorably high while comparing with the other methods.

6.3.3 Experimental Results for Multimodal Images

The proposed fusion technique is applied for multi modal medical images like Positron Emission Tomography (PET), Magnetic Resonance Image (MRI), Computer Tomography (CT), Single-Photon emission computed tomography (SPECT) images. CT images are suitable for imaging the bone structures and the MRI images are superior in soft tissues and the fusion of these two images enhances and emphasizes the qualities of each other and helps the doctors to diagnose the diseases.

![CT MRI Fused image using EBF](image)

Figure 6.10 Fusion of CT and MRI fusion for Multimodal image fusion using EBF

Figure 6.10 shows the input images of CT brain and MRI brain and the fused image. The fused image contains the information in both the input images. In medical images edge discontinuous may appear across the curves while fusing the different structures of the image. So, multimodal image fusion concentrates on such aspects but this energy based fusion is highly
informative to the physicians in the diagnosis of diseases by overcoming such property.

Figure 6.11 presents the fusion of different modality images such as CT, MRI, SPECT and PET images. The results apparently show the significance of EBF method.

(a) Fusion of a CT image and an MRI image lateral view of brain

(b) Fusion of a SPE CT image and an MRI image

Figure 6.11 (Continued)
Figure 6.11  Multimodal image Fusion using the proposed EBF

Figure 6.11 (a) represents the fusion of a CT image and an MRI image. Figure 6.11 (b) show the fusion of a SPECT image and an MRI image. Figure 6.11(c) presents the fusion of a T1-weighted MRI and original MRI.

Table 6.6 Quality Assessment of image fusion of Multimodal Images

<table>
<thead>
<tr>
<th>Metrics</th>
<th>LP</th>
<th>DWT</th>
<th>SWT</th>
<th>AVG</th>
<th>EBF</th>
</tr>
</thead>
<tbody>
<tr>
<td>EI</td>
<td>32.34</td>
<td>33.12</td>
<td>34.17</td>
<td>33.18</td>
<td>34.76</td>
</tr>
<tr>
<td>EN</td>
<td>4.31</td>
<td>3.98</td>
<td>3.97</td>
<td>4.12</td>
<td>4.51</td>
</tr>
<tr>
<td>AG</td>
<td>5.39</td>
<td>5.09</td>
<td>5.44</td>
<td>5.30</td>
<td>5.611</td>
</tr>
<tr>
<td>SF</td>
<td>5.891</td>
<td>5.761</td>
<td>5.883</td>
<td>5.893</td>
<td>5.921</td>
</tr>
</tbody>
</table>
Table 6.6 exhibits the quality assessment comparison of the proposed method EBF with that of four existing methods. Average gradient of the medical images helps in justifying the fusion approach. Larger average gradient indicates richer detailed information. Larger mutual information proves that bandlet-based fused image is strongly correlated with the source images, and more image features are preserved in the fusion. Larger standard deviation and entropy indicate that more information is contained in the fused images. Table 6.7 presents the results which prove that the other methods are comparatively better than the proposed method for the medical images. Since the fusion of medical images helps the early diagnosis for the physicians, this method proves to be highly informative based on the analytical assessments. The energy-based fusion presents very clear picture while transferring the useful information from each source image to the target image.

Table 6.7 Assessment of Quality metrics for various dataset with Multi modal Images using EBF

<table>
<thead>
<tr>
<th>Metrics</th>
<th>Dataset1</th>
<th>Dataset2</th>
<th>Dataset3</th>
<th>Dataset4</th>
<th>Dataset5</th>
</tr>
</thead>
<tbody>
<tr>
<td>SD</td>
<td>23.12</td>
<td>22.16</td>
<td>21.11</td>
<td>24.11</td>
<td>24.12</td>
</tr>
<tr>
<td>EN</td>
<td>5.13</td>
<td>4.891</td>
<td>4.671</td>
<td>4.324</td>
<td>4.412</td>
</tr>
<tr>
<td>MI</td>
<td>5.45</td>
<td>5.14</td>
<td>5.34</td>
<td>5.412</td>
<td>5.106</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Metrics</th>
<th>Dataset6</th>
<th>Dataset7</th>
<th>Dataset8</th>
<th>Dataset9</th>
<th>Dataset10</th>
</tr>
</thead>
<tbody>
<tr>
<td>EN</td>
<td>5.23</td>
<td>5.17</td>
<td>4.23</td>
<td>5.12</td>
<td>5.41</td>
</tr>
<tr>
<td>MI</td>
<td>5.572</td>
<td>5.862</td>
<td>5.891</td>
<td>5.921</td>
<td>5.412</td>
</tr>
</tbody>
</table>

Standard deviation (SD), Entropy (E) and Mutual Information (MI) for 10 different datasets are tabulated in Table 6.7. From the table, it can be inferred that, all the images give approximately equivalent values for a particular metric.
Figure 6.12 Analysis of Standard deviation for fused Multimodal images for different data sets using EBF

Figure 6.13 Analysis of Entropy for fused Multimodal images with different datasets using EBF
Figure 6.14 Analysis of Mutual information for fused Multmodal images with different data sets using EBF

Figures 6.12, 6.13 and 6.14 pictorially represent standard deviation, entropy and mutual information respectively for 10 different datasets.

6.3.4 Experimental Results for Multi Spectral Images

The proposed method is experimented with multispectral images like IR image and visible image. The standard dataset is used for testing the algorithm and the results are discussed. Figure 6.13 shows four sets of visible image and infrared image, and the background of the image is clear in the visible band, and the foreground are highlighted in the infrared band. Obviously, the fused image presents all the details combined together.
Figure 6.15  Fusion of Visible band image and infrared band image using the proposed EBF
Table 6.8 Quality Assessment of image fusion Multispectral Images

<table>
<thead>
<tr>
<th>Metrics</th>
<th>LP</th>
<th>DWT</th>
<th>SWT</th>
<th>AVG</th>
<th>FBF</th>
</tr>
</thead>
<tbody>
<tr>
<td>EI</td>
<td>31.25</td>
<td>33.24</td>
<td>32.17</td>
<td>31.14</td>
<td>33.04</td>
</tr>
<tr>
<td>EN</td>
<td>6.03</td>
<td>6.532</td>
<td>6.79</td>
<td>6.37</td>
<td>6.92</td>
</tr>
<tr>
<td>AG</td>
<td>2.621</td>
<td>2.594</td>
<td>2.958</td>
<td>2.884</td>
<td>2.822</td>
</tr>
<tr>
<td>SF</td>
<td>6.74</td>
<td>6.584</td>
<td>6.784</td>
<td>6.721</td>
<td>6.894</td>
</tr>
</tbody>
</table>

Table 6.8 tabulates the quality assessment in terms of edge intensity EI, entropy EN, average gradient AG, and spatial frequency SF for the proposed method and 4 existing methods. The proposed method exhibits better value for all the metrics. Figure 6.8 presents quality assessment in terms of RMSE, PSNR, CC, Cross entropy CE for the three fused images.

Table 6.9 Quality Assessment of image fusion Multispectral Images for different datasets

<table>
<thead>
<tr>
<th>Images</th>
<th>RMSE</th>
<th>PSNR</th>
<th>CC</th>
<th>C Entropy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Garden</td>
<td>13.34</td>
<td>27.33</td>
<td>1.03</td>
<td>4.43</td>
</tr>
<tr>
<td>Road</td>
<td>12.36</td>
<td>25.24</td>
<td>0.99</td>
<td>4.45</td>
</tr>
<tr>
<td>UN Camp</td>
<td>11.36</td>
<td>23.28</td>
<td>0.88</td>
<td>4.35</td>
</tr>
<tr>
<td>Airport</td>
<td>12.13</td>
<td>27.24</td>
<td>0.89</td>
<td>4.21</td>
</tr>
</tbody>
</table>

Table 6.9 shows the comparison of the proposed method with the 5 existing methods in terms of Edge intensity (EI), Cross correlation (cc), entropy(EN), mutual information (MI) compared with the proposed method DRAW. The results are compared with the methods discussed in the literature Laplacian Pyramid (LP), Discrete wavelet transform (DWT), Simple wavelet transform (SWT), Averaging (AVG), Simple Averaging (SA) and PCA.
Table 6.10  Comparison of Multispectral fusion with the existing fusion methods

<table>
<thead>
<tr>
<th>Images</th>
<th>Method</th>
<th>Edge Intensity</th>
<th>CC</th>
<th>Entropy</th>
<th>MI</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Metrics</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Image 1</td>
<td>SA</td>
<td>36.52</td>
<td>0.861</td>
<td>0.731</td>
<td>4.67</td>
</tr>
<tr>
<td></td>
<td>LP</td>
<td>36.42</td>
<td>0.848</td>
<td>0.761</td>
<td>4.97</td>
</tr>
<tr>
<td></td>
<td>SWT</td>
<td>36.55</td>
<td>0.867</td>
<td>0.724</td>
<td>4.94</td>
</tr>
<tr>
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<td>0.895</td>
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<td>5.13</td>
</tr>
<tr>
<td></td>
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<td>0.891</td>
<td>0.743</td>
<td>5.34</td>
</tr>
<tr>
<td></td>
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<td>0.752</td>
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<td>0.966</td>
<td>0.748</td>
<td>5.58</td>
</tr>
<tr>
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</tr>
<tr>
<td></td>
<td>DWT</td>
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<td>0.992</td>
<td>0.761</td>
<td>6.21</td>
</tr>
<tr>
<td></td>
<td>PCA</td>
<td>35.55</td>
<td>0.889</td>
<td>0.763</td>
<td>5.82</td>
</tr>
<tr>
<td></td>
<td>FBF</td>
<td>36.66</td>
<td>0.992</td>
<td>0.773</td>
<td>6.23</td>
</tr>
<tr>
<td></td>
<td>EBF</td>
<td>37.68</td>
<td>0.993</td>
<td>0.783</td>
<td>6.39</td>
</tr>
</tbody>
</table>

Standard deviation represents the gray values of the pixels and the average of the fused image with the proposed method. SD is directly proportional to the fusion effect. Mutual information shows the amount of data transferred from the source images to the fused image.

6.4 SUMMARY

Image fusion has been a constructive research topic in the past decade and the need for the significant algorithm is still a growing trust. Energy plays a vital role in estimating the weight with color information. Salient information from the source image is extracted and fused into a single
image with high visibility. Energy-based fusion method has very apparently proved its significance with the results shown in the chapter. This method is very efficient for multifocal images than the other two proposed methods. This method holds good even for multimodality images. From the tabulations of objective performance analysis, it can be deduced that the proposed EBF approach is better than the existing approaches. In future, this work can be extended with sub-banding to give best results.