Mutual Information, Structure Similarity Index Measure and Edge Similarity Index Measure.

CHAPTER 5

ANATOMIC AND FUNCTIONAL IMAGE FUSION

5.1 INTRODUCTION

Medical Image Fusion (MIF) is defined as, ‘incorporates the complementary and redundant information from two or more multimodality images to get the fused image’. The fused image contains the precise and relevant information of the similar object and helps the memory reduction by storing the fused image. Fusion of images acquired several modality systems such as, CT image shows the dense structure (bone tissue) but it is not for showing the soft tissues. Hence it is not possible to identify the changes of living function, MRI image provides the soft tissues and used for brain tumor detection, PET and SPECT images are provides blood flow information and movements in the body, but it endure very low resolution than CT and MRI. All type of images plays a vital role in medical diagnosis and some other clinical applications like feature extraction, edge preserves, image analysis
etc. In a particular medical modality image does not retrieve the essential information as a result of it has own limit and difference within the geometry, scale, time consuming and space resolutions. So, Most of the physicians want both anatomic and functional information of the brain images for more accurate diagnosis of the brain tumor. The main motivation of this work is to fuse, both categories of the images using the multimodal medical image fusion approach to get sufficient and more important information.

This part of work, presents the anatomic image and the functional image are combined by the novel multimodal medical image fusion approach called mLOT and ICV based on DTCWT and IHS transforms. The DTCWT transform is used for decomposing the functional image and the particular component of intensity (I) in the anatomic image (color image). Because, The Color image (PET or SPECT) is consists of three components (RGB Signal) like Intensity (I), Hue (H) and Saturation (S). So, the color image is decomposed by the IHS transform. The new proposed approach, gives a fine results which are shown and proved that the results are high superior than the existing techniques. Based on the objective and subjective analysis, this work is compared and illustrated by some quality metrics such as SD, NMI, SSIM and ESIM.

5.2 IHS

The transform of IHS is applied to the anatomic images with RGB signal (Red, Green and Blue). After decomposing the image gives three certain color components namely, Spatial Characteristics like Intensity (I) and spectral characteristics such as Hue (H) and Saturation (S). Here, I stand for light intensity (brightness), H represents the wavelength and S is the purity level. Substituting the intensity component with the high-resolution image and combine to this with the H and S. finally, IHS inverse transform is carried out to enhanced resolution within the new substituted IHS components into
the RGB color space. The process of decomposes and reconstruct in the IHS transform can be summarized as follows (Gang Hong et al. 2013).

\[
I = \frac{(R + G + B)}{3} \quad (5.1)
\]

\[
H = \begin{cases} 
\frac{G-B}{3(I-B)}, & \text{if } B < R, G \\
\frac{B-R}{3(I-R)}, & \text{if } R < B, G \\
\frac{R-G}{3(I-G)}, & \text{if } G < R, B 
\end{cases} \quad (5.2)
\]

\[
S = \begin{cases} 
\frac{I-B}{I}, & \text{if } B < R, G \\
\frac{I-R}{I}, & \text{if } R < B, G \\
\frac{I-G}{I}, & \text{if } G < R, B 
\end{cases} \quad (5.3)
\]

The corresponding inverse IHS transformation is,

when B is the minimum,

\[
\begin{cases} 
R = \frac{1}{3} I' (1 + 2S - 3SH) \\
G = \frac{1}{3} I' (1 - S + 3SH) \\
B = \frac{1}{2} I' (1 - S) 
\end{cases} \quad (5.4)
\]

when R is the minimum,

\[
\begin{cases} 
R = \frac{1}{3} I' (1 - S) \\
G = \frac{1}{3} I' (1 + 5S - 3SH) \\
B = \frac{1}{3} I' (1 - 4S + 3SH) 
\end{cases} \quad (5.5)
\]

when G is the minimum,
PROPOSED FUSION FRAMEWORK

The proposed fusion approaches is broadly explained in this section by considering the two registered images, namely, anatomic (Grey Scale image) ‘A’ (CT/MRI) and functional (Color image) ‘B’ (PET/SPECT).

Step 1: Decomposition Process: Assume the input image has to be registered and then transformed to the anatomic image A using the DTCWT (Lewis et.al. 2007) method within the given n level to acquire the low frequency sub-bands and high frequency sub-bands at each level and these sub-bands are defined as,

\[
\begin{align*}
R &= \frac{1}{3} I'(1 + 7S - 3SH) \\
G &= \frac{1}{3} I'(1 - S) \\
B &= \frac{1}{3} I'(1 + 8S - 3SH)
\end{align*}
\]  

(5.6)

5.3 PROPOSED FUSION FRAMEWORK

...
Step 2: Segmentation Process: Based on literature, there are different segmentation algorithms studied and obtainable by various models (RuiXu and Donald Wunsch 2005). This algorithm usually makes undesired segmented regions. In segmented part, the algorithm of ‘normalized cut’ is used to segment the low pass frequency coefficients and shows the process of segmentation as in Figure 4.6 (Shi, J and Malik, J. 2000).

Step 3: Fusion of Low Frequency Sub Images: Fusion of the low frequency coefficients using the WA fusion rule based on Equation (4.2), the weights are optimized by the proposed ‘mLOT’ approach (described in the chapter 3) to get the composite fused low coefficients.

Step4: Fusion of High Frequency Sub Images: The MS rule is used for high frequency sub-bands; this rule is preferred to construct the composite bands; however this rule doesn't take any thought of the surrounding pixels. Therefore, a complete unique approach is proposed by Intensity Co-variance Verification (ICV) to obtain the composite fused high frequency coefficients. This rule is employed to elaborate the information from the high frequency sub images.

Step 5: The composite frequency sub-bands on both low and high are performed by the IDTCWT up to reach the given level and to get the new image (intensity).

Step 6: The H and S components of the image B (color) are combined with the new intensity image followed by the inverse IHS transform is applied to reconstruct the image to get a fused image. The fused image contains superior information of spatial and spectral which shows the flow of information of the proposed fusion algorithm as Figure 5.1.
Figure 5.1  Block diagram of information flow of proposed Multimodal Medical Image Fusion Framework.

The input image on CT/ MRI is decomposed by the DT-CWT to get the low and high frequency coefficients. Another input image on PET/ SPECT is decomposed by the IHS transform to obtain three components like I, H and S. Now, the intensity (I) is further decomposed by the DT-CWT to get the low and high frequency components. The low frequency coefficients of both images are segmented by the region and fuse the region coefficients using WA fusion rule, the weights are optimized by the proposed mLOT to obtain the composite low frequency coefficients. Now, the high frequency coefficients are fused by the new fusion rule on ICV to get composite high frequency coefficients. After reconstructing the low and high composite coefficients using inverse DT-CWT to get the obtained inversed coefficients, then it is combined with the H and S components to get the combined coefficients. Finally, to reconstruct the combined image using the inverse IHS will get the resultant fused image.

5.4 EXPERIMENTAL RESULTS AND DISCUSSIONS
Generally, CT image can provide the anatomic information with higher degree of resolution whereas PET image can produce significant information of tissue features and MRI image can provide the soft tissue information with high resolution. Based on this observation, no other modality can provide for all, because individual imaging modalities have its own merits and demerits. However, those modalities could provide high superior results when one or more medical image modalities are fused in the way of fusion technique. At present, the PET scanner will deliver more enough information for the diagnosis. However, the clinical assessment by the doctors needs to analyze more supplementary information to preferred and gathered from some other image like CT or MRI (Vogel et.al. 2004). Those types of images are not shown in appropriate information so, the doctors are not able to get and view exact fusion of the patient details. Therefore, two or more images are fused (anatomic and functional) to get more sufficient information which helps the doctor for the patient disease analysis, assessment and preparation for the treatment.

The one set of CT-SPECT, one set of MRI-SPECT, one set of CT-PET and one set of MRI-PET images are assumed for perfect registration in the image combinations $A_i=(X_i, Y_i)$ is show the Figure 5.2 $X_i$ and $Y_i$ are the two groups of input images.
Figure 5.2  Input and output images from different image combinations of Ai=(A1-A4): X1 is CT and Y1 is SPECTI of A1; X2 is MRI and Y2 is SPECT of A2; X3 is CT AND Y3 is PET of A3; X4 is MRI and Y4 is PET of A4; Fused images from (a1 –a2) PCA based technique; (b1-b2) DWT based technique; (c1-c2) SWT based technique; (d1-d2) DTCWT based technique; (e1-e2) Curvelet based technique; (f1-f2) DTCWT-PSO based technique; (g1-g2) NSCT-PCNN based technique; (h1-h2) Proposed Technique (SCHEME 2).

The input images are tested by variety of different fusion techniques and applied to the given datasets by numerous existing and proposed algorithms delivered from the entire brain image database. This
The proposed approach gives enhanced information and also it will be useful for medical applications like medical diagnosis for doctors.

The state and ideology opinion by the different image and based on review, only some modalities of source images have complementary information. Based on various acceptable existing and present approaches, the proposed fusion results are superior visual quality and acquire the complementary information. The assessment of statistical parameters for the fused images is absolutely varied from the fusion algorithms and it is shown within the tables, visually in Figure 5.3.

The proposed technique is understandable and additionally improves the spatial detail information to the overall existing algorithm, which might be easily observed to obtain the most values of evaluation indices of SD, NMI, SSIM and ESIM. Based on the values of evaluation indices are shows in the Table 5.1 to 5.4.

Table 5.1 Evaluation Performance for Fused Medical Images by Standard Deviation Quality Metrics.

<table>
<thead>
<tr>
<th>Image Combi.</th>
<th>Standard Deviation (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>PCA</td>
</tr>
<tr>
<td>A1</td>
<td>62.506</td>
</tr>
<tr>
<td>A2</td>
<td>54.672</td>
</tr>
<tr>
<td>A3</td>
<td>59.6754</td>
</tr>
<tr>
<td>A4</td>
<td>40.3456</td>
</tr>
</tbody>
</table>

Table 5.2 Evaluation Performance for Fused Medical Images by Normalized Mutual Information Quality Metrics.
### Table 5.3 Evaluation Performance for Fused Medical Images by Structure Similarity Index Metric Quality Metrics.

<table>
<thead>
<tr>
<th>Image Combi.</th>
<th>Structural Similarity Index Metric (SSIM)</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>PCA</td>
<td>DWT</td>
<td>SWT</td>
<td>DTCWT</td>
<td>Curvelet</td>
<td>DTCWT</td>
<td>PSO</td>
<td>NSCT</td>
</tr>
<tr>
<td>A1</td>
<td>0.933</td>
<td>0.9354</td>
<td>0.87</td>
<td>0.8075</td>
<td>0.8242</td>
<td>0.8904</td>
<td>0.9089</td>
<td></td>
</tr>
<tr>
<td>A2</td>
<td>0.91</td>
<td>0.9296</td>
<td>0.873</td>
<td>0.8867</td>
<td>0.8657</td>
<td>0.9116</td>
<td>0.9185</td>
<td></td>
</tr>
<tr>
<td>A3</td>
<td>0.8214</td>
<td>0.8892</td>
<td>0.805</td>
<td>0.85</td>
<td>0.9395</td>
<td>0.8395</td>
<td>0.8871</td>
<td></td>
</tr>
<tr>
<td>A4</td>
<td>0.8345</td>
<td>0.8854</td>
<td>0.77</td>
<td>0.7899</td>
<td>0.8134</td>
<td>0.8133</td>
<td>0.6865</td>
<td></td>
</tr>
</tbody>
</table>

### Table 5.4 Evaluation Performance for Fused Medical Images by Edge Similarity Index Measures Quality Metrics.

<table>
<thead>
<tr>
<th>Image Combi.</th>
<th>Edge Similarity Index Measures (ESIM)</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>PCA</td>
<td>DWT</td>
<td>SWT</td>
<td>DTCWT</td>
<td>Curvelet</td>
<td>DTCWT</td>
<td>PSO</td>
<td>NSCT</td>
</tr>
<tr>
<td>A1</td>
<td>0.594</td>
<td>0.6495</td>
<td>0.503</td>
<td>0.5862</td>
<td>0.5938</td>
<td>0.7551</td>
<td>0.8174</td>
<td></td>
</tr>
<tr>
<td>A2</td>
<td>0.542</td>
<td>0.6244</td>
<td>0.495</td>
<td>0.6091</td>
<td>0.5762</td>
<td>0.7774</td>
<td>0.7805</td>
<td></td>
</tr>
<tr>
<td>A3</td>
<td>0.7435</td>
<td>0.6288</td>
<td>0.469</td>
<td>0.6228</td>
<td>0.695</td>
<td>0.623</td>
<td>0.6315</td>
<td></td>
</tr>
<tr>
<td>A4</td>
<td>0.7291</td>
<td>0.6161</td>
<td>0.393</td>
<td>0.4955</td>
<td>0.5012</td>
<td>0.5046</td>
<td>0.4464</td>
<td></td>
</tr>
</tbody>
</table>

Based on the above tables to create the graphical representation with existing as well as mLOT in terms of SD, NMI, SSIM and ESIM quality metrics are shown in Figure 5.3. The new technique is showed and proved.
with higher value and superior quality by the way of work is done by the existing and the new method.

Figure 5.3  Variation of performance parameters with different Fusion Methods along with mLOT: a) Standard Deviation b) Normalized Mutual Information c) Structural Similarity Index Metric and d) Edge Similarity Index Measure.

Based on this table value, every value is close to one another and the value of NSCT-PCNN is higher than the others except the proposed
methods. Each and every algorithm is delivered by the good quality on fused image. But, those fused results are undergoing for the visual quality, higher time complexity and also lack of significant information due to the process on the low level decomposition. In Curvelet based fused image could provide more contrast and brightness. So, the relevant information could not be view by the doctors, as results on difficulty for assessment to the patient treatment. In optimization (PSO) based approach offers fine fused image that contains more significant information. However, it is time consuming due to the process of finding the optimal value and some edge and corner are misplaced. By appearing in the fused image of NSCT-PCNN-SF, inner edge (weak edge) are lost or blurred and the processing time is very long during the decomposition process and reconstruction process. So, the key idea of this proposed work is to give the good performance results on the basis of image visual quality, time, and statistical assessment and retrieves the significant information of the resultant fused image.