Chapter 3

Multimodal Medical Image Fusion

3.1 Introduction

With the rapid and significant development in technologies and modern instrumentations, medical imaging is taking on an increasingly critical and vital role in a large number of health-care applications including diagnosis, research, treatment etc. To provide support to the physicians on their clinical diagnosis and treatment, an increasing number of medical image modalities have become available [84–86]. We have seen in the previous chapters that various pre and post processing (enhancement) techniques are required to improve the visual quality of these diverse modalities of medical images. Enhancing the visual quality of the medical images results in higher information content and improves the interpretability, but, as the image formation principles of various medical imaging technologies and instrumentations are different [88,90–92], they reflect different information of human organs and tissues, and have their respective application ranges. As a consequence, it is often not possible for a single modality of medical image to provide comprehensive and accurate information. For instance, structural images like MRI, CT, USG, magnetic resonance angiography etc. provide high-resolution images containing anatomical information. On the other hand, functional images such as PET, SPECT and functional MRI (fMRI) etc., provide low-spatial resolution images with functional information. While X-ray, CT is the primary modality for most image-based treatment planning, other modalities such as MRI, PET and
SPECT and USG can provide important data that may improve overall patient management [87–89, 107]. As a result, combining multimodal medical images to provide much more useful information through image fusion has become the focus of imaging research and processing [88]. Multiple imaging modalities can complement each other to provide more information for understanding the real world of objects than the use of a single modality. Image fusion aims to generate a single fused image, which contains more precise and reliable visualization of the objects than any one of its source images. Such a fused image should provide extended information and better perception for human vision or computerized vision tasks [83–86].

In recent years, many IF and MIF techniques have been proposed by various researchers. It has been found that the pixel-level spatial domain methods usually lead to contrast reduction. Approaches based on IHS, PCA, and the Brovey transform offer better results, but suffer from spectral degradations. Pyramidal IF schemes fail to introduce any spatial orientation selectivity in the decomposition process, and hence often cause blocking effects [104]. The problem with widely used WT is that it can preserve spectral information efficiently but cannot express spatial characteristics well [105, 123, 124]. As a result, WT based fusion schemes fail to preserve the salient features of the source images efficiently and introduce artifacts and inconsistencies in the fused results [127]. Recently, to overcome these problems, many improved IF/MIF methods based on MGA tools (like curvelet, contourlet, ripplet etc.) are proposed [107, 127]. However, measuring the importance/contribution of individual source image in the fused image, and finding effective way of combining them is still an open problem. Most of the above mentioned schemes are modality specific with their own limitations [114]. The field of MIF is quite different from that of multifocus and visible/infrared IF. Most of the times, there are very subtle differences between the features of
the source medical images. Special care has to be taken during the fusion process of these fine details. Therefore, we need a MIF scheme that can simultaneously handle the problems of contrast reduction, loss of image details and unwanted image degradations. It has been observed that PCNN based IF schemes outperform the conventional IF methods [111,356–360]. Even though there exists several IF schemes based on transform domain and PCNN, most of these methods suffer from various problems. In [114] Z. Wang, et al. have proposed a fast MIF scheme based on a multi-channel PCNN (m-PCNN) model with easy extensibility capability, producing fused images with high information content, but suffering from the problems of contrast reduction and loss of image fine details. Q. X.-Bo et al. have developed an IF method based on spatial frequency (SF) motivated PCNN in NSCT domain [361]. It works well for multifocus IF and visible/infrared IF, but the absence of directional information in SF and the use of same fusion rule for both the subbands cause contrast reduction and loss of image details. The IF technique proposed by G. Xin et al. based on dual-layer PCNN model with a negative feedback control mechanism in the NSCT domain has shown promising results in multifocus IF [362]. In [359] M. M. Deepika et al. have proposed a combined method of MIF and edge deduction based on NSCT and PCNN. This scheme also suffers from the problems of contrast reduction and unwanted image degradations. The technique proposed by K. Feng et al. in [111] based on bi-dimensional empirical mode decomposition and m-PCNN, shows good result in preserving the source images fine details in the fused image, but suffers from contrast reduction. In most of the existing IF methods based on PCNN the value of a single pixel (coefficient) in spatial or transform domain is used to motivate one neuron [114,359,362]. But this simple use of pixels (coefficients) in spatial or transform domain is not effective enough, because humans are sensitive to edges and directional features. In this chapter, two novel MIF techniques (‘Scheme
and ‘Scheme 2’) are presented as possible solutions to the above mentioned information (image) integration problem.

The rest of the chapter is organized as follows: Section 3.2 first introduces the MIF method of ‘Scheme 1’. Subsection 3.2.1 contains the description of modified spatial frequency, which is used as the saliency measure in ‘Scheme 1’. The MIF technique of ‘Scheme 1’ is described in Subsection 3.2.2. In Subsection 3.2.3, the experimental and comparative results of ‘Scheme 1’ are included. Section 3.3, introduces the second MIF technique (‘Scheme 2’). In Subsection 3.3.1, a simplified PCNN model is described and the working principles of ‘Scheme 2’ is explained in Subsection 3.3.2. The Subsection 3.3.3 contains the experimental results and discussion of ‘Scheme 2’.

3.2 Scheme 1: NSCT-based Multimodal MIF using PCNN and MSF

To overcome from the above mentioned shortcomings of the existing MIF schemes, in the next section a novel MIF method (‘Scheme 1’) is described. The main contribution of ‘Scheme 1’ is the use of shift-invariance, multiscale and multidirectional properties of NSCT along with the modified spatial frequency (capable of capturing the fine details present in the image) motivated PCNN in such a way that can capture the subtle differences and the fine details present in the source medical images that result in fused images with high contrast, clarity and information content.

1Details can be found in [340]
2Details can be found in [341]
3.2.1 Modified Spatial Frequency

Spatial frequency (SF) proposed by Eskicioglu et al. is calculated by row and column frequencies [363]. It reflects the whole activity level of an image which means: the larger the SF the higher the image resolution. A modified version of SF is used in ‘Scheme 1’. The MSF consists of row frequency (RF), column frequency (CF) and diagonal frequency (DF). The original SF lacks the directional information present in the image which results in the loss of important fine details of the image. Whereas, MSF incorporates this directional information and this results in an image clarity/activity level measure capable of capturing the fine details present in the image [364]. For an $M \times N$ pixel image $X$ the MSF is defined as

$$MSF = \sqrt{RF^2 + CF^2 + DF^2}, \quad (3.1)$$

where,

$$RF = \sqrt{\frac{1}{M(N-1)} \sum_{m=1}^{M} \sum_{n=2}^{N} [X(m, n) - X(m, n-1)]^2}, \quad (3.2)$$

$$CF = \sqrt{\frac{1}{(M-1)N} \sum_{m=2}^{M} \sum_{n=1}^{N} [X(m, n) - X(m-1, n)]^2}, \quad (3.3)$$

and,

$$DF = P + Q, \quad (3.4)$$

where,

$$P = \sqrt{\frac{1}{(M-1)(N-1)} \sum_{m=2}^{M} \sum_{n=2}^{N} [X(m, n) - X(m-1, n-1)]^2}, \quad (3.5)$$

and,

$$Q = \sqrt{\frac{1}{(M-1)(N-1)} \sum_{m=2}^{M} \sum_{n=2}^{N} [X(m-1, n) - X(m, n-1)]^2}, \quad (3.6)$$
3.2.2 Proposed Method

The notations used in this section are as follows: $X$, $Y$, $Z$ represent the two source images and the resultant fused image, respectively. $I = (X,Y,Z)$. $L^I_G$ indicates the low-frequency subband (LFS) of the image $I$ at the coarsest scale $G$. $D^{I}_{g,h}$ represents the high-frequency subband (HFS) of the image $I$ at scale $g$, $(g = 1, ..., G)$ and direction $h$. $(m,n)$ denotes the spatial location of each coefficient. The method can be easily extended to more than two images.

3.2.2.1 Fusing Low Frequency Subbands

The LFSs coefficients are fused using ‘max selection’ rule. According to this fusion rule, select the frequency coefficients from $L^X_G$ or $L^Y_G$ with greater absolute value as the fused coefficients:

$$L^Z_G(m,n) = \begin{cases} L^X_G(m,n), & |L^X_G(m,n)| \geq |L^Y_G(m,n)|, \\ L^Y_G(m,n), & \text{otherwise}, \end{cases} \quad (3.7)$$

3.2.2.2 Fusing High Frequency Subbands

The HFSs of the source images are fused using PCNN. As humans are sensitive to features such as edges, contours etc., so instead of using PCNN in NSCT domain directly (i.e., using individual coefficients), MSF in NSCT domain is considered as the image feature to motivate the PCNN. Let, $MSF_{g,h,I}^{g,h,I}_{m,n}$ be the modified spatial frequency corresponding to a coefficient $D^{I}_{g,h}(m,n)$, measured by using an overlapping window around the concerned coefficient where $I = (X,Y)$. In order to reduce the computational complexity, we use a simplified PCNN:

$$F^{g,h,I}_{m,n}[t] = MSF^{g,h,I}_{m,n}, \quad (3.8)$$
\[ L_{m,n}^{g,h,I}[t] = e^{-\alpha L} L_{m,n}^{g,h,I}[t-1] + V_L \sum_{k,l} W_{m,n,k,l}^{g,h,I} Y_{m,n,k,l}^{g,h,I}[t-1], \quad (3.9) \]

\[ U_{m,n}^{g,h,I}[t] = F_{m,n}^{g,h,I}[t](1 + \beta L_{m,n}^{g,h,I}[t]), \quad (3.10) \]

\[ Y_{m,n}^{g,h,I}[t] = \begin{cases} 1, & U_{m,n}^{g,h,I}[t] > \theta_{m,n}^{g,h,I} \vspace{0.2cm} \\ 0, & \text{otherwise}, \end{cases} \quad (3.11) \]

\[ \theta_{m,n}^{g,h,I}[t] = e^{-\alpha \theta_{m,n}^{g,h,I}[t-1]} + V_L Y_{m,n}^{g,h,I}[t], \quad (3.12) \]

where, the feeding input \( F_{m,n}^{g,h,I} \) is equal to the modified spatial frequency \( MSF_{m,n}^{g,h,I} \).

The linking input \( L_{m,n}^{g,h,I} \) is equal to the sum of neurons firing times in linking range. \( W_{m,n,k,l}^{g,h,I} \) is the synaptic gain strength and subscripts \( k \) and \( l \) are the size of linking range in the PCNN. \( \alpha_L \) is the decay constant. \( \beta \) is the linking strength, \( V_L \) and \( V_\theta \) are the amplitude gains. \( U_{m,n}^{g,h,I} \) is the total internal activity and \( \theta_{m,n}^{g,h,I} \) is the threshold. If \( U_{m,n}^{g,h,I} \) is larger than \( \theta_{m,n}^{g,h,I} \), then the neuron will generate a pulse \( Y_{m,n}^{g,h,I} = 1 \), also called one firing time. The sum of \( Y_{m,n}^{g,h,I} = 1 \) in \( t \) iteration (namely the firing times), is used to represent the image information. Here, rather than \( Y_{m,n}^{g,h,I}[t] \), the time matrix \( (G_{G}^{g,h}(m,n)) \) information is analyzed, since neighboring coefficients with similar features represent similar firing times in a given iteration time, and it is calculated by the following equation:

\[ G_{G}^{g,h}(m,n) = \sum_{t=1}^{T} Y_{m,n}^{g,h,I}[t], \quad (3.13) \]

### 3.2.2.3 Algorithm

The medical images to be fused must be registered to assure that the corresponding pixels are aligned. The block diagram of the proposed MIF scheme is shown in Fig. 3.1. Here the salient steps of ‘Scheme 1’ is outlined here:

1. Decompose the registered source medical images \( A \) and \( B \) by NSCT to get
the LFSs and HFSs.

2. Fused the coefficients of LFSs using the ‘max selection’ rule described in Section 3.2.2.1, to get the fused LFS.

3. Compute the MSF as described in Section 3.2.1, using overlapping window on the coefficients in HFSs.

4. Input MSF of each HFS to motivate the PCNN and generate pulse of neurons with Eqs.(3.8)–(3.12), and compute the firing times $G_{m,n}^{g,h,I}[t]$ by Eq.(3.13).

5. If $t = T$, then iteration stops. Then fuse the coefficients of the HFSs by the following fusion rule:

$$D_{g,h}^{Z}(m, n) = \begin{cases} 
D_{g,h}(m, n), & G_{X}^{g,h}(m, n) \geq G_{Y}^{g,h}(m, n), \\
D_{g,h}(m, n), & \text{otherwise,}
\end{cases}$$

(3.14)

6. Apply inverse NSCT (INSCT) on the fused LFS and HFSs to get the final fused medical image.
3.2.3 Results and Discussion

To evaluate the performance of ‘Scheme 1’, extensive experiments have been carried out on various modalities of medical images. Both objective as well as subjective analysis have been conducted to show the effectiveness of the proposed MIF technique.

3.2.3.1 Experimental Setup

In the experiments regarding the performance evaluation of ‘Scheme 1’, the decomposition parameter of NSCT has been set to levels = [1, 2, 4]. The ‘pyrexc’ and ‘vk’ are used as the pyramid filter and orientation filter, respectively. Parameters of PCNN have been set as $k \times l = 3 \times 3$, $\alpha_L = 0.06931$, $\alpha_0 = 0.2$, $\beta = 0.2$, $V_L = 1.0$, $V_0 = 20$, $W = [0.707 \ 1 \ 0.707, \ 1 \ 0 \ 1, \ 0.707 \ 1 \ 0.707]$, and $T = 200$. The quantitative measures used in the experiments are $STD$ (Eq.(1.38)), $EN$ (Eq.(1.40)), $SF$ (Eq.(1.41)), $MI$ (Eq.(1.45)), $Q^{XY/Z}$ (Eq.(1.46)) and $Q_0$ (Eq.(1.48)). To support our choice of MSF over SF, an experiment has been performed, where all the other configurations of ‘Scheme 1’ are kept same, only SF has been used instead of MSF (named NSCT_PCNN_SF for convenience).

The Fig. 3.2, shows five pairs of source medical images\(^3\) of different modalities used in the experiments along with the corresponding fused results obtained by ‘Scheme 1’. In Fig. 3.2, $C_i$ ($i = 1, 2, ..., 5$) indicates the image combinations: $C_i = (x_i, y_i, z_i)$, $x_i$ and $y_i$ are the two groups of source images and $z_i$ represents the fused results. The CT image in Fig. 3.2(x1) shows the bones and the MRI image in Fig. 3.2(y1) displays the soft tissue information. The T1-weighted MR image in Fig. 3.2(x2) contains the soft tissues and it also shows a lesion in the brain, but the vascular nature of the lesion is not clear. The vascular nature of the lesion

\(^3\)Source images are downloaded from http://www.imagefusion.org/; http://www.med.harvard.edu/aanlib/home.html.
Figure 3.2: Source images (top two rows) with fusion results of ‘Scheme 1’ (last row): $x_1 = \text{CT}$, $y_1 = \text{MRI}$, $x_2 = \text{T1-weighted MR}$, $y_2 = \text{MR Angiography}$, $x_3 = \text{CT}$, $y_3 = \text{T1-weighted MR-GAD}$, $x_4 = \text{T1-weighted MR}$, $y_4 = \text{T2-weighted MR}$, $x_5 = \text{CT}$, $y_5 = \text{Proton Density (PD) weighted MR}$.
is evident in MR Angiography of Fig. 3.2(y2), but the tissue information is low. In
Fig. 3.2(x3) and Fig. 3.2(y3), CT image demonstrates the calcification and the MR
image reveals several focal lesions involving basal ganglia with some surrounding
edema, respectively. Both the MR images of Fig. 3.2(x4) and Fig. 3.2(y4) show
a lesion in the frontal lobe. The CT image in Fig. 3.2(x5) indicates a medial left
occipital infarct involving the left side of the splenium of the corpus callosum and
the MR image in Fig. 3.2(y5) reveals only mild narrowing of the left posterior
cerebral artery.

For the five source medical images of Fig. 3.2, the detail quantitative evalu-
ation is given in Table 3.1. The Table 3.2 shows the performance comparisons
of ‘Scheme 1’ against some of the existing MIF schemes using the images of the
image combinations C1 and C5 as the source images. Fused images for the im-
age combinations C1 and C5 obtained by the compared methods of Table 3.2 are
shown in Fig. 3.3.

3.2.3.2 Subjective Analysis and Discussion

An expert radiologist has been asked to subjectively evaluate the effectiveness of
the proposed MIF method. After careful manual inspection of the images of the
Fig. 3.2, the radiologist has conformed to the effectiveness of ‘Scheme 1’. He has
found that the fused images obtained by ‘Scheme 1’ are more clear, informative
and have higher contrast than the source medical images that is helpful in vi-
sualization as well as interpretation. The fused image of image combination C1
contains both the bone structure (from Fig. 3.2(x1)) and the soft tissue informa-
tion (from Fig. 3.2(y2)). Both the lesion and its vascular nature along with the
soft tissue information are evident in the fused image (Fig. 3.2(z2)) of the image
combination C2. Similarly, the fused images of the other image combinations (C3,
C4 and C5) contain information from both the corresponding source images. The
Figure 3.3: Fusion results of ‘Scheme 1’ on image combinations $C_1$ and $C_5$: (a)(g) Method NSCT_PCNN_SF, (b)(h) Method of [361], (c)(i) Method of [114], (d)(j) Method of [124], (e)(k) Method of [127] and (f)(l) Method of [123].
resultant fused images of Fig. 3.3 obtained by the compared methods of Table 3.2 have been also shown to the radiologist. The resultant fused images obtained by NSCT_PCNN_SF are visually very much similar to the fused images obtained by ‘Scheme 1’ (as can be seen from the fused images of Figs. 3.2(z1),(z5) and Figs. 3.3(a)(g)). But during the quantitative analysis, it has been found that the fused images obtained by ‘Scheme 1’ have higher quantitative results than the method of NSCT_PCNN_SF. All the compared methods of Fig. 3.3 except the schemes of [123] and NSCT_PCNN_SF suffer from the problem of contrast reduction. It is clear from the images of Fig. 3.3 that the methods of [361], [124] and [127] (Figs. 3.3(b)(h),(d)(j) and (e)(k)) have lost large amount of image details. As can be easily seen from the images of Figs. 3.3(d)(j) and Figs. 3.3(f)(l), the methods of [124] and [123] suffer from the problems of blocking effects (as evident from the lower portions of the images) and contain unwanted image degradations. It is also clear from the resultant images given in Fig. 3.2 and Fig. 3.3 that ‘Scheme 1’ results in low contrast reduction, high clarity and high information content. The ‘Scheme 1’ also causes less unwanted degradations in the fused images, as well as is free from the problem of blocking effects. Therefore, it is clear from the subjective analysis of the fused images that ‘Scheme 1’ is very effective in fusing multi-modality medical images and superior than many state-of-the-art MIF techniques.

3.2.3.3 Objective Analysis and Discussion

In Table 3.1, columns 3 to 5 show the spatial frequencies, entropies and standard deviations of the source medical images, and columns 6 to 11 give the values of the different quantitative measures of the fused images obtained by ‘Scheme 1’. The ‘bold’ values indicate the highest values in the Table 3.1 for that quantitative measure. The higher values of SF for the image combinations C1 to C4 indicate
that the fused images obtained by ‘Scheme 1’ have more activity and clarity level than the source images (Fig. 3.2(z5)). Only the proton density weighted MR image (Fig. 3.2(y5)) of image combination C5 has higher value of SF than the fused image (Fig. 3.2(z5)). The reason behind it may be that the CT image (Fig. 3.2(x5)) of the image combination C5 contains a thick whitish outer-boundary which become predominant in the fused result. Similarly the higher values of \( EN \) for the fused images show that the fused images obtained by ‘Scheme 1’ have more information content than the source images. We can also see from the Table 3.1 that the standard deviation’s values of the resultant images for 4 out of 5 source image combinations are higher than their corresponding source images, which indicates that the fused images obtained by our proposed MIF method have higher contrast than the corresponding source images. Only in case of image combination C2 the \( STD \) value of one of the source image Fig. 3.2(x2) (T1-weighted MR) is greater than the fused image (Fig. 3.2(z2)). It may be because of the fact that the other source image Fig. 3.2(y2) (MR Angiograph) of the image combination C2 has very low contrast (indicated by low \( STD \) value) causing the fused image (Fig. 3.2(z2)) to have a lower \( STD \) value (lower by very

<table>
<thead>
<tr>
<th>Comb. Name</th>
<th>SF</th>
<th>EN</th>
<th>STD</th>
<th>MI</th>
<th>SF</th>
<th>EN</th>
<th>STD</th>
<th>( Q_{AB/F} )</th>
<th>( Q_0 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>C1</td>
<td>a1</td>
<td>4.4316</td>
<td>1.7126</td>
<td>44.7519</td>
<td>4.8300</td>
<td>6.9434</td>
<td>6.7724</td>
<td>65.8646</td>
<td>0.7771</td>
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<td>5.0067</td>
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<tr>
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<td>6.0659</td>
<td>68.9896</td>
<td>0.6699</td>
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<tr>
<td></td>
<td>b3</td>
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<td>3.4385</td>
<td>61.7932</td>
<td>5.0067</td>
<td>7.8946</td>
<td>6.0659</td>
<td>68.9896</td>
<td>0.6699</td>
</tr>
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<td>3.3046</td>
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<td>5.6013</td>
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Table 3.2: Performance comparison of ‘Scheme 1’ using image combinations C1 and C5

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<tr>
<th>Scheme</th>
<th>Comb.</th>
<th>MI</th>
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<th>EN</th>
<th>STD</th>
<th>Q^{AB/F}</th>
<th>Q_0</th>
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<td></td>
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<td></td>
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<td>4.1933</td>
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<tr>
<td></td>
<td>c5</td>
<td>2.9788</td>
<td>6.2938</td>
<td>4.3528</td>
<td>81.9448</td>
<td>0.5007</td>
<td>0.8751</td>
</tr>
<tr>
<td>‘Scheme 1’</td>
<td>c1</td>
<td>4.8300</td>
<td>6.9434</td>
<td>6.7724</td>
<td>65.8646</td>
<td>0.7771</td>
<td>0.5286</td>
</tr>
<tr>
<td></td>
<td>c5</td>
<td>3.0593</td>
<td>6.3261</td>
<td>4.3645</td>
<td>83.7037</td>
<td>0.5338</td>
<td>0.8796</td>
</tr>
</tbody>
</table>

small amount). Therefore, it is clear from Table 3.1 that the fused images obtained by ‘Scheme 1’ are more clear, informative and have higher contrast which is helpful in visualization and interpretation.

In Table 3.2, the ‘bold’ values indicate the highest values. It is clear from the Table 3.2 that ‘Scheme 1’ has all the highest quantitative results except for MI. The method of [114] has the highest value for the MI measure. It may be because of the fact that the method of [114] is based on m-PCNN in the spatial (pixel) domain. It preserves the information from both the source images better than ‘Scheme 1’. But since ‘Scheme 1’ is based on modified spatial frequency motivated PCNN in NSCT domain, hence it is superior in capturing the fine details of the source images into the fused image. The highest value of SF indicates that the fused image obtained by ‘Scheme 1’ has more activity and clarity level than the source images. Similarly the highest values of EN and STD for the fused images show that the fused images obtained by the proposed scheme have more information as well as higher contrast than the source images. It is also clear
from the Table 3.2 that the fused image obtained by NSCT_PCNN_SF has lower quantitative results than the results obtained by ‘Scheme 1’ MIF technique. For the other image combinations used in the experiments similar kind of results are obtained.

Although, PCNN based IF/MIF methods outperform other conventional schemes, these approaches have one main shortcoming: PCNN has several parameters with complex structures, and optimal estimation of these parameters is a major limitation for automation and generalization of PCNN based IF/MIF methods. Moreover, from literature it is known that IF/MIF techniques based on HVS response provide better fused results. Incorporating the advantages of PCNN and HVS response, in the next section, a novel MIF scheme (‘Scheme 2’) is described based on a novel parameter estimation technique for PCNN.

3.3 Scheme 2: A Neuro-Fuzzy Approach for Medical Image Fusion

In most of the PCNN based IF/MIF techniques, the parameters of PCNN model are kept same and set as a constant. But, according to HVS, the responses to a region with notable features are stronger than a region with non-notable features. Thus, the parameters of PCNN’s neurons should be related to the importance (significance) of the features of either the corresponding pixel (in spatial domain) or coefficient (in transform domain) of the image [365–367]. But, the problem remains: how to measure the importance (significance) of the pixel (coefficient) in the corresponding image. Therefore, we not only need a way to adaptively and automatically set the values of the parameters of the PCNN, but also to make the fusion scheme free from the common problems faced by the existing
techniques [368]. In the next section, fuzzy logic is used for building a simultaneous fusion and enhancement technique based on the HVS model to address these above mentioned problems. In this regard, the main contributions of ‘Scheme 2’ are as follows: (1) A novel MIF scheme employing NSCT and reduced PCNN (RPCNN) with adaptive linking strengths based on the corresponding image’s local features. (2) Following the subjectivity of HVS, fuzzy logic is used to enable the proposed scheme to produce high quality fused images with higher contrast, more clarity and more useful subtle detail information. (3) Without involving any prior training and trials the less complex RPCNN having less number of parameters leads to computational efficiency, which is suitable for real time image processing applications (like point-of-care (POC) health care technologies).

### 3.3.1 Reduced Pulse Coupled Neural Network

Considering the applications of multimodal MIF, and in order to improve the computational efficiency (in terms of reducing the number of optimizable parameters), in ‘Scheme 2’, a simplified model of PCNN known as RPCNN is adapted slightly from [369]:

\[
F_{m,n}[t] = S_{m,n}, \quad (3.15)
\]

\[
L_{m,n}[t] = \sum_{k,l} W_{m,n,k,l} Y_{m,n}[t - 1], \quad (3.16)
\]

\[
U_{m,n}[t] = F_{m,n}[t](1 + \beta L_{m,n}[t]), \quad (3.17)
\]

\[
Y_{m,n}[t] = \begin{cases} 
1, & U_{m,n}[t] > \theta_{m,n}[t], \\
0, & \text{otherwise}, 
\end{cases} \quad (3.18)
\]

\[
\theta_{m,n}[t] = e^{-a_\theta} \theta_{m,n}[t - 1] + V_\theta Y_{m,n}[t], \quad (3.19)
\]
where, the symbols used in Eqs.(3.15)-(3.19) have usual meaning as described in Section 1.3.2.

Compared to the 9 parameters of the standard PCNN model, the RPCNN contains only 4 key parameters: \( W_{m,n,k,l} \), \( \beta_{m,n} \), \( V \) and \( \alpha \) [322,325,369]. Moreover, \( W_{m,n,k,l} \) is usually kept unchanged and we set these to the reciprocal of square distance between two pixels (coefficients). Among the remaining three parameters, the linking coefficient \( \beta \) can vary the weighting of the linking channel in the internal activity, and hence is application dependant. Keeping this in mind, the values of the linking strengths (\( \beta \)) are adaptively set based on fuzzy logic approach, and set the values of the other two parameters, heuristically.

3.3.2 Proposed Method

In ‘Scheme 2’, coefficients of both LFSs and HFSs are fused in a similar way using RPCNNs with fuzzy-adaptive linking strengths. The notations used are as follows: \( I = (X,Y,Z) \) where \( X, Y, Z \) represents the two source images and the resultant fused image, respectively. The value \( B_{g,h}^{I}(m,n) \) indicates a coefficient of the subband \( B \) of the image \( I \) at the scale \( g (= 1,...,G) \) and direction \( h \), where \( S \) is the coarsest scale, and \( (m,n) \) denotes the spatial location of the coefficient in the subband. The method can be easily extended to more than two images.

3.3.2.1 Fuzzy Adaptive Linking Strength

From PCNN related literature it is known that the linking strength (\( \beta \)) reflects the pixel’s (coefficient) characteristics, and should be adaptive to the importance (significance) of the corresponding pixel (coefficient). Moreover, from the HVS model related literature, it has been found that the contrast enhancement mechanism and incremental visual threshold can be effectively model as a non-linear
system, which following the HVS decide visually significant or insignificant pixels with respect to its neighbors [366,370,371]. The uncertainty exists in deciding the visual quality (significance) of the image’s pixel (coefficient) and the subjectivity of the HVS response is successfully handled by fuzzy logic approaches [367,372].

Keeping these in mind, a novel fuzzy based technique is described to adaptively set the value of $\beta$, by estimating each coefficient’s significance (importance) in the corresponding image. If a coefficient’s ‘local average energy’ is large or its ‘local information entropy’ is large, then the coefficient has more importance in the image. In ‘Scheme 2’, $\text{LAE}_{g,h}^I(m,n)$ and $\text{LIE}_{g,h}^I(m,n)$ are considered as the representations of a coefficient’s ‘local average energy’ and its ‘local information entropy’, respectively. LAE gives information about the existence of edges, contours and textures in an image. Similarly, LIE indicates the complexity or unpredictability of a local region. Regions corresponding to high signal complexity tend to have flatter distributions hence higher entropy and these regions are considered to be the important regions (edges, contours and texture information) of the image [373]. Two fuzzy membership values are computed corresponding to each coefficient $B_{g,h}^I(m,n)$ using the ‘S-type’ membership function. Considering, $\mu_1(B_{g,h}^I(m,n))$ and $\mu_2(B_{g,h}^I(m,n))$ as the fuzzy membership values associated with $\text{LAE}_{g,h}^I(m,n)$ and $\text{LIE}_{g,h}^I(m,n)$, respectively, $\mu(B_{g,h}^I(m,n))$ is computed as the membership value associated with the coefficient’s larger ‘local average energy’ or larger ‘local information entropy’. This $\mu(B_{g,h}^I(m,n))$, reflecting the importance of the coefficient $B_{g,h}^I(m,n)$ in the corresponding image $I$, is used as the linking strength $\beta_{g,h}^I$.

For a coefficient $B_{g,h}^I(m,n)$, $\text{LAE}_{g,h}^I(m,n)$ and $\text{LIE}_{g,h}^I(m,n)$ are computed according to the Eq. (3.20) and Eq. (3.21), respectively, considering a window of size
\[ M \times N \text{ centered around the coefficient:} \]

\[
LAE^{f}_{g,h}(m,n) = \frac{1}{M \times N} \sum_{m=1}^{M} \sum_{n=1}^{N} B^{f}_{g,h}(m,n)^2, \quad (3.20)
\]

\[
LIE(B^{f}_{g,h}(m,n)) = -\sum p(B^{f}_{g,h}(m,n)) \log_2 p(B^{f}_{g,h}(m,n)), \quad (3.21)
\]

where, \( p(B^{f}_{g,h}(m,n)) \) is the probability of occurrence of the coefficient \( B^{f}_{g,h}(m,n) \).

The fuzzy membership values \( \mu_1(B^{f}_{g,h}(m,n)) \) and \( \mu_2(B^{f}_{g,h}(m,n)) \) are computed as follows:

\[
\mu_1(B^{f}_{g,h}(m,n)) = \begin{cases} 
0, & LAE^{f}_{g,h}(m,n) \leq a_1, \\
2\left(\frac{LAE^{f}_{g,h}(m,n) - a_1}{c_1 - a_1}\right)^2, & a_1 \leq LAE^{f}_{g,h}(m,n) \leq b_1, \\
1 - 2\left(\frac{LAE^{f}_{g,h}(m,n) - a_1}{c_1 - a_1}\right)^2, & b_1 \leq LAE^{f}_{g,h}(m,n) \leq c_1, \\
1, & LAE^{f}_{g,h}(m,n) \geq c_1,
\end{cases} \quad (3.22)
\]

and

\[
\mu_2(B^{f}_{g,h}(m,n)) = \begin{cases} 
0, & LIE^{f}_{g,h}(m,n) \leq a_2, \\
2\left(\frac{LIE^{f}_{g,h}(m,n) - a_2}{c_2 - a_2}\right)^2, & a_2 \leq LIE^{f}_{g,h}(m,n) \leq b_2, \\
1 - 2\left(\frac{LIE^{f}_{g,h}(m,n) - a_2}{c_2 - a_2}\right)^2, & b_2 \leq LIE^{f}_{g,h}(m,n) \leq c_2, \\
1, & LIE^{f}_{g,h}(m,n) \geq c_2,
\end{cases} \quad (3.23)
\]

where,

\[
b_1 = \text{average}(LAE^{f}_{g,h}) \quad (3.24)
\]

\[
c_1 = b_1 + \max(\max(b_1 - \max(LAE^{f}_{g,h})), \min(b_1 - \min(LAE^{f}_{g,h})) \) \quad (3.25)
\]

\[
a_1 = 2b_1 - c_1 \quad (3.26)
\]

and similarly,

\[
b_2 = \text{average}(LIE^{f}_{g,h}) \quad (3.27)
\]
\[ c_2 = b_2 + \max(|b_2 - \max(LIE_{Ig;h}|, |b_2 - \min(LIE_{Ig;h})|) \quad (3.28) \]

\[ a_2 = 2b_2 - c_2 \quad (3.29) \]

where \( b_i \) is the cross-over point, \( c_i \) is the shoulder point and \( a_i \) is the feet point of \( S \) type membership curve, \( i = 1, 2 \) (considering two source images).

The linking strength \( \beta_{m,n}^{g,h,I} \) corresponding to the coefficient \( B_{g,h}^I(m,n) \) is then computed as follows:

\[ \beta_{m,n}^{g,h,I} = \max(\mu_1(B_{g,h}^I(m,n)), \mu_2(B_{g,h}^I(m,n))) \quad (3.30) \]

### 3.3.2.2 Algorithm

The block diagram of ‘Scheme 2’ is shown in Fig. 3.4. Assuming that the medical images to be fused are co-registered to ensure that the corresponding pixels are aligned, the salient steps of the ‘Scheme 2’ is outlined here:
1. Decompose the registered source medical images $P$ and $Q$ by NSCT to get the LFSs and HFSs.

2. Compute the linking strengths $\beta_{m,n}^{g,h,I}$, $I = (X,Y)$ as described in Section 3.2.2.1.

3. Input the coefficients of the subbands to motivate the RPCNNs and generate pulse of neurons using Eqs. (3.15)–(3.19), and compute the firing times $G^I_{g,h}(m,n)$ by Eq. 1.19.

4. At $t = T$ (total number of iterations), determine the fused coefficient $B^Z_{g,h}(m,n)$ following the fusion rule:

$$B^Z_{g,h}(m,n) = \begin{cases} 
B^X_{g,h}(m,n), & G^X_{g,h}(m,n) \geq G^Y_{g,h}(m,n), \\
B^Y_{g,h}(m,n), & \text{otherwise}
\end{cases} \quad (3.31)$$

5. Apply inverse NSCT on the fused coefficients to get the final fused medical image $Z$.

### 3.3.3 Results and Discussion

To evaluate the performance of ‘Scheme 2’, extensive experiments have been carried out on various modalities of medical images. Both objective as well as subjective analysis have performed to show the effectiveness of ‘Scheme 2’.

#### 3.3.3.1 Experimental Setup

Parameters of PCNN $k \times l$, $\alpha_T$, $V_T$, $W$ and $T$ have been set to the values described in ‘Scheme 1’. The size of the window for computing the local average energy and the local information entropy, has been set as $3 \times 3$. The quantitative measures used in these experiments are same as that of the ‘Scheme 1’.
Figure 3.5: Visual results for the five pairs $(a_k, b_k)$ of source images, $(k = 1, 2, 3, 4, 5)$. Fused images obtained: $c_1$-$c_5$ by scheme [124], $d_1$-$d_5$ by scheme [114], $e_1$-$e_5$ by scheme [361], $f_1$-$f_5$ by scheme [127], $g_1$-$g_5$ by scheme [123], $h_1$-$h_5$ by NFHF-CNT, $i_1$-$i_5$ by NFHF-CVT, $j_1$-$j_5$ by ‘Scheme 2’.
The visual and quantitative results for 5 pairs of source images from 5 different combinations are given in this section. For simplicity, the five pairs of source medical images are termed as ‘Group 1’ to ‘Group 5’, and these are shown in the first two columns of Fig. 3.5. In ‘Group 1’ the CT image in Fig. 3.5(a1) shows the bone structure, and the MRI image in Fig. 3.5(b1) displays the soft tissue information. The T1-weighted MR image in Fig. 3.5(a2) contains the soft tissues, and a lesion in the brain, but the vascular nature of the lesion is not clear. The vascular nature of the lesion is evident in MR Angiography of Fig. 3.5(b2), but the tissue information is low. The fluid attenuated inversion recovery (FLAIR) MR image of Fig. 3.5(a3) shows symmetrical signal hyper-intensity of the occipitoparietal cortical ribbon, and the diffusion-weighted (DW) image of Fig. 3.5(b3) shows increased signal in the areas of the FLAIR abnormality. In Fig. 3.5(a4) the coronal F-18 fluorodeoxyglucose (FDG)-PET image provides the metabolic information, whereas, the coronal MR-T1 image of Fig. 3.5(b4) shows the structural information. The FDG-PET image of Fig. 3.5(a5) shows a lesion in the right lung that indicates increased FDG uptake, and the CT image of Fig. 3.5(b5) shows the structural information with exact location of the lesion within the right lung.

The ‘Scheme 2’ has been compared with five state-of-the-art MIF schemes both subjectively and objectively. The performance of ‘Scheme 2’ is also compared with the effectiveness of other MGA-tools such as CNT and CVT. Keeping all the other configurations same NSCT is replaced from ‘Scheme 2’ by CNT and CVT for this purpose. In the following discussion, these two MIF techniques are termed as NFHF-CNT and NFHF-CVT, respectively. Even though the visual and quantitative results are provided only for 5 pairs of medical images, for the other source images similar results are obtained.
3.3.3.2 Subjective Analysis and Discussion

An expert radiologist has been asked to subjectively evaluate the effectiveness of ‘Scheme 2’. Both the fused images obtained by ‘Scheme 2’, and the fused images obtained by the compared schemes are shown to the radiologist. According to the clinician opinion, it can be seen from the given results of Fig. 3.5, that apart from ‘Scheme 2’ (Fig. 3.5: j1-j5) and the schemes of [123] (Fig. 3.5: g1-g5) and [361] (Fig. 3.5: e1-e5), all the other compared techniques suffer from the problem of contrast reduction. Moreover, he has found that the fused images obtained by the schemes of [124] (Fig. 3.5: c1-c5), [361] (Fig. 3.5: e1-e5), [127] (Fig. 3.5: f1-f5) and [123] (Fig. 3.5: g1-g5) have lost large amount of image details. Furthermore, he observed that the methods of [127] (Fig. 3.5: f1-f5) and [123] (Fig. 3.5: g1-g5) suffer from the problem of blocking effect (as evident from the lower portions of the images) and contain unwanted image degradations. Whereas, in his opinion, the fused image Fig. 3.5(j1) obtained ‘Scheme 2’ for ‘Group 1’ source images, contains both the bone structure (from the CT image of Fig. 3.5(a1)) and the soft tissue information (from the MRI image of Fig. 3.5(b1)). The lesion and its vascular nature along with the soft tissue information are evident in the fused image Fig. 3.5(j2) of ‘Group 2’. Both the complementary information from the source images of ‘Group 3’ can be clearly seen in the fused image Fig. 3.5(j3). For ‘Group 4’, the fused image shown in Fig. 3.5(j4) contains the metabolic information from the FDG-PET image of Fig. 3.5(a4) and the structural information from the T1-weighted MR image of Fig. 3.5(b4). The fused image Fig. 3.5(j5) of ‘Group 5’ shows both the structural information (exact location) and the metabolic activity of the lesion in the same image. Finally, after careful inspection of all the resultant images, the clinician has conformed to the effectiveness of ‘Scheme 2’. He has found that the fused images obtained by ‘Scheme 2’, are clearer, informative and have higher
Figure 3.6: Performance comparison of CNT, CVT and NSCT. Zoomed in versions of ‘Group 1’ fused images of Fig. 3.5: (a) $h_1$ for CNT, (b) $i_1$ for CVT and (c) $j_1$ for NSCT.

contrast than the source medical images. For evaluating the efficiency of NSCT over CNT and CVT (NFHF-CNT and NFHF-CVT, respectively), the zoomed in versions of the fused images produced by these MIF schemes are shown to the clinician. The zoomed in version resultant images of ‘Group 1’ images, obtained by NFHF-CNT, NFHF-CVT and NFHF-NSCT are shown in ‘Scheme 2’. The clinician has conformed that even though, the fused images obtained by NFHF-CNT and NFHF-CVT look similar to the fused images produced by ‘Scheme 2’. But, both of these image (CNT and CVT) transforms result in blurring of edges and unwanted image degradations as shown in Fig. 3.6. It can be seen from the resultant images given in Fig. 3.5 and Fig. 3.6 that ‘Scheme 2’ results in low contrast reduction, high clarity and high information content. The ‘Scheme 2’ also causes less unwanted degradations in the fused images, as well as is free from the problem of blocking effects.

3.3.3.3 Objective Analysis and Discussion

For the five pairs of source medical images the detailed quantitative evaluations are given in Table 3.3. Columns 3 to 5 in the Table 3.3, show the SF, EN and STD of the source medical images, respectively. The values of these quantitative measures of the fused images obtained by ‘Scheme 2’ are given in columns 6 to 8 of Table 3.3. The ‘bold’ values indicate the highest values in Table 3.3, for that
Table 3.3: Performance evaluation of ‘Scheme 2’ MIF method

| Group No. | Source Image | Fused Image | | |
|-----------|--------------|-------------| | |
|           | SF           | EN          | STD         | SF          | EN          | STD       |
| 1         | a1 4.4316    | 1.7126      | 44.7519     | 7.2512      | 6.7918      | 64.6989   |
|           | b1 6.2600    | 5.6013      | 58.8283     | 7.9600      | 6.3514      | 69.1150   |
| 2         | a2 7.7005    | 4.1524      | 69.1972     | 10.5607     | 5.8155      | 64.4903   |
|           | b2 6.4901    | 4.3310      | 25.5812     | 12.7502     | 2.6375      | 49.6101   |
| 3         | a3 10.4970   | 2.4263      | 59.7992     | 10.5607     | 5.8155      | 64.4903   |
|           | b3 **12.7502** | 2.6375 | 49.6101     |             |             |           |
| 4         | a4 5.1728    | 3.2840      | 67.1263     | 9.5685      | 6.6329      | 74.2056   |
|           | b4 9.3992    | 5.3682      | 64.4280     |             |             |           |
| 5         | a5 2.8705    | 1.9766      | 19.8552     | 5.8448      | 4.9837      | 56.5273   |
|           | b5 5.6831    | 5.0498      | 56.8748     |             |             |           |

The quantitative measure. The highest values of $SF$ for the images of Groups 1, 2, 4, and 5 indicate that the fused images obtained by ‘Scheme 2’ have more activity and clarity level than the source images. Similarly the highest values of $EN$ for the fused images indicate that the fused images obtained by ‘Scheme 2’, have more information content than the source images. It can be observed from Table 3.3 that the STD values of the fused images for 3 out of 5 source image combinations are higher than their corresponding source images. This shows that the ‘Scheme 2’ produces higher contrast fused images. Only in case of image groups 2 and 5, the $STD$ values of one of the corresponding source images (Fig. 3.5(a2) and Fig. 3.5((b5)) are greater than the fused images. It may be because of the fact that the other source images (Fig. 3.5(b2) and Fig. 3.5(a5)) of the image groups 2 and 5, have very low contrast (indicated by low $STD$ values), causing the fused images to have lower STD values (lower by very small amount). Therefore, it is evident from Table 3.3, that the fused images obtained by ‘Scheme 2’ are more clear, informative and have higher contrast which is helpful in visualization and interpretation.

The quantitative performance comparisons of ‘Scheme 2’ against some of the
Figure 3.7: Objective performance comparisons of ‘Scheme 2.’
existing MIF schemes are given in the Fig. 3.7 in the form of “error bar” plots. Fig. 3.7 shows the average and the standard deviation values of the different measures used in the experiments for all the 7 pairs of source images for all the 5 different groups. It can be seen from Fig. 3.7 that ‘Scheme 2’ has all the largest objective measures (5 out of 6), which is obviously better than the other methods. The highest values of $SF$ indicate that the fused images obtained by ‘Scheme 2’, have more activity and clarity level than the other schemes. Similarly the highest values of $EN$ and $STD$ for the fused images show that the fused images obtained by ‘Scheme 2’, have more information, as well as higher contrast than the other compared methods. It is also clear that the method [114] is better than ‘Scheme 2’ in respect of the quantitative measure MI. It may be because that the method of [114] is based on a multi-channel PCNN in spatial domain, which can retain the source image information in the fused image better than ‘Scheme 2’. But, ‘Scheme 2’ is superior for all other quantitative measures. Moreover, the RPCNN used in ‘Scheme 2’ having less complex structure and parameters is computationally efficient than the original PCNN. This helps in reducing the computational cost of the overall system. Specifically, ‘Scheme 2’ requires approximately 45 to 55 seconds to fuse a pair of source medical images of size $512 \times 512$, irrespective of their modalities. Therefore, it is obvious from Table 3.3 and Fig. 3.7, that the fused images obtained by ‘Scheme 2’ MIF method based on hybrid neuro-fuzzy technique and NSCT, are more clear, informative and have higher contrast than the existing mentioned MIF methods.

Even though, the visual quality of the different modalities of medical images are enhanced by some enhancement techniques (denoising, contrast improvement, bias correction, fusion etc.), because of the huge amount of digital medical images (growing every hours), it is often not possible for a medical expert to quickly and correctly search and retrieve relevant information from these vast information
repositories. Development of automated diagnostic tools to draw quicker and easier inferences from these huge databases has become an important area of research in biomedical engineering. In the next chapter, this ‘effective information retrieval’ paradigm in medical domain is explored.