

Multimodality Medical Image Fusion Based on Hybrid Fusion Techniques

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Abstract -- Multimodal medical image fusion technique is one of the current researches in the field of medical imaging and radiation medicine and is widely recognized by medical and engineering fields. A multimodality medical image fusion technique plays a vital role in biomedical research and medical disease analysis. This paper, proposed an efficient multimodal therapeutic image fusion approach based on both traditional and hybrid fusion techniques are evaluated using several quality metrics. Computed Tomography (CT), Magnetic Resonance Imaging (MRI) and Single Photon Emission Computed Tomography (SPECT) are the input source images. Compared with other existing techniques the experimental results demonstrate the better processing performance in both subjective and objective evaluation criteria.

Keywords: Multimodal medical image fusion, CT, MRI, SPECT, PCA, DWT and PCNN.

1. Introduction

Image fusion is the mixture of two or more different images to form a novel image by using certain techniques [15]. It is extracting information from multi-source images. It improves the spatial resolution for the original multi-spectral image and preserves the spectral information. Image fusion can be done in three levels: Pixel level fusion, Feature level fusion and Decision level fusion. Pixel-level fusion having a large portion of the remarkable data is protected in the merged image. Feature-level fusion performs on feature-by-feature origin, such as edges, textures. Decision-level fusion refers to make a final merged decision. The image fusion decrease quantity of information and hold vital data. It make new output image that is more appropriate for the reasons for human/machine recognition or for further processing tasks [13]. Image fusion is classified into two types Single Sensor and Multi sensor picture combination consolidating the pictures from a few sensors to shape a composite picture and their individual pictures are converged to acquire an intertwined image Ex: Multi focus and Multi Exposure fusion. Multi sensor image fusion merging the images from several sensors to form a composite image and their individual images are merged to obtain a fused image .Ex: Medical Imaging, Military Area. Image fusion having several applications like Medical Imaging, Biometrics, Automatic Change Detection, Machine Vision, Navigation Aid, Military Applications, Remote Sensing, Digital Imaging, Aerial and Satellite Imaging, Robot Vision, Multi Focus Imaging, Microscopic Imaging, Digital Photography

and Concealed Weapon Detection. Multimodal medical imaging plays a vital role in a large number of healthcare applications including diagnosis and treatment. Medical image fusion combining multiple images into form a single fused modalities. Medical image fusion methods involve the fields of image processing, computer vision, pattern recognition, machine learning and artificial intelligence [15]. Multi-modality medical images categorised into several types which include Computed Tomography (CT),Magnetic Resonance Angiography (MRA), Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET), Ultra Sonography (USG), Nuclear Magnetic Resonance(NMR) spectroscopy, Single Photon Emission Computed Tomography (SPECT), X-Rays, Visible, Infrared and Ultraviolet[7]. MRI, CT, USG and MRA images are the structural therapeutic images which afford lofty resolution images. PET, SPECT and functional MRI (fMRI) images are functional therapeutic images which afford low-spatial resolution images with functional information. Anatomical and Functional therapeutic images can be incorporated to obtain more constructive information about the same object. Medicinal image fusion reduces storage cost by storing the single fused image instead of multiple-input images [7]. Different imaging modalities can only provide limited information. Computed Tomography (CT) image can display accurate bone structures. Magnetic Resonance Imaging (MRI) image can reveal normal and pathological soft tissues. The fusion of CT and MRI images can integrate complementary information to minimize redundancy and improve diagnostic accuracy. Combined PET/MRI imaging can extract both functional information and structural information for clinical diagnosis and treatment [13]. Multimodel medical image fusion uses the pixel level fusion [11].

2. Related Works

Xingbin Liu, Wenbo Mei,et al.[1] proposed a new technique namely Structure tensor and non subsampled shearlet transform (NSST) to extract geometric features. A novel unified optimization model is proposed for fusing computed Tomography (CT) and Magnetic Resonance Imaging (MRI) images. K.N. Narasimha Murthy and J. Kusuma[2] proposed Shearlet Transform (ST) to fuse two different images Positron Emission Tomography (PET) and Magnetic Resonance Imaging (MRI) image by using the Singular Value Decomposition (SVD) to improve the information content of the images. Satishkumar S. Chavan, Abhishek Mahajan,et al.[3] introduced the technique called Nonsubsampled Rotated Complex Wavelet Transform

(NSRCxWT) combining CT and MRI images of the same patient. It is used for the diagnostic purpose and post treatment review of NCC. S. Chavan, A. Pawar, et al.[4] innovated a feature based fusion technique Rotated Wavelet Transform (RWT) and it is used for extraction of edge-related features from both the source modalities (CT/MRI). Heba M. El-Hoseny, El-Sayed M.El.Rabaie, et al.[5] proposed a hybrid techniques that enhance the fused image quality using Both traditional and hybrid fusion algorithms(Additive Wavelet Transform (AWT) and Dual Tree complex wavelet transform (DT-CWT)). Udhaya Suriya TS, Rangarajan P[6] implemented an innovative image fusion system for the detection of brain tumours by fusing MRI and PET images using Discrete Wavelet Transform (DWT). Jingming Yang, YanyanWu, et al.[7] described an Image fusion technique is Non-Subsampled Contourlet Transform (NSCT) to decompose the images into lowpass and highpass subbands. C.Karthikeyan, B. Ramadoss[8] proposed the fusion of medical images using dual tree complex wavelet transform (DTCWT) and self-organizing feature map (SOFM) for better disease diagnosis. Xinzheng Xu, Dong Shana, et al.[9] introduced an adaptive pulse-coupled neural networks (PCNN), which was optimized by the quantum-behaved particle swarm optimization (QPSO) algorithm to improve the efficiency and quality of QPSO. Three performance evaluation metrics is used. Jyoti Agarwal and Sarabjeet Singh Bedi, et al.[10] innovate the hybrid technique using curvelet and wavelet transform for the medical diagnosis by combining the Computed Tomography (CT) image and Magnetic Resonance Imaging (MRI) image. Jing-jing Zonga, Tian-shuang Qiu [11] proposed a new fusion scheme for medical images based on sparse representation of classified image patches In this method, first, the registered source images are divided into classified patches according to the patch geometrical direction, from which the corresponding sub-dictionary is trained via the online dictionary learning (ODL) algorithm, and the least angle regression (LARS) algorithm to sparsely code each patch; second, the sparse coefficients are combined with the “choose-max” fusion rule; Finally, the fused image is reconstructed from the combined sparse coefficients and the corresponding sub-dictionary. Richa Gautam and Shilpa Datar [12] proposed a method for fusing CT (Computed Tomography) and MRI (Medical Resonance Imaging) images based on second generation curvelet transform. Proposed method is compared with the results obtained after applying the other methods based on Discrete Wavelet Transform (DWT), Principal Component Analysis (PCA) and Discrete Cosine Transform (DCT). Jiao Du, Weisheng Li, Bin Xiao, et al [13] proposed an approach union Laplacian pyramid with multiple features for accurately transferring salient features from the input medical images into a single fused image. Xiaojun Xua,, Youren Wang, et al. [14] proposed a multimodal medical image fusion method based on discrete fractional wavelet (DFRWT). The source medical images are decomposed by DFRWT indifferent p order. The sparsity character of the mode coefficients in subband images changes. Jiao Du, Weisheng Li, Ke Lu. [15] proposed methods in the field of

medical image fusion namely (1) image decomposition and image reconstruction, (2) image fusion rules, (3) image quality assessments and (4) experiments on the benchmark dataset. Medical image fusion has been widely used in clinical assessments for physicians to comprehend the lesion by the fusion of different modalities medical images. Zhaobin Wang, Shuai Wang, Ying Zhu, et al.[16] described the statistical analysis PCNN and some modified models are introduced and review the PCNN’s applications in the field of image fusion.

3. Proposed Research Work

3.1. Traditional Multimodal Medical Image Fusion Techniques

This research paper implements different traditional image fusion algorithms for different types of multimodality medical images as shown in Fig. 1

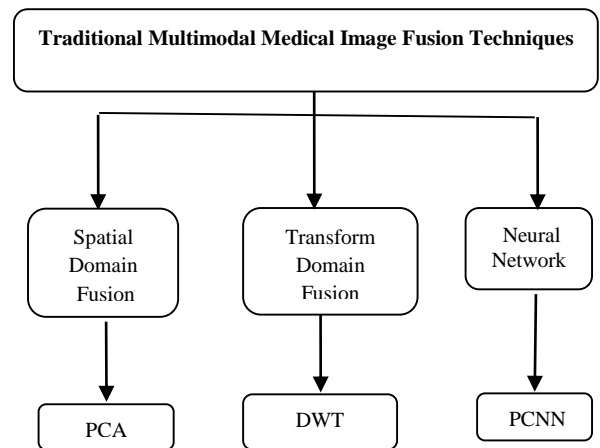


Fig. 1: Traditional multi-modal medical image fusion techniques

Well-known techniques used for measurement decrease, feature removal and data revelation. In general, PCA is defined by the conversion of an elevated dimensional vector space into a near to the ground dimensional vector space. This property of principal component analysis is helpful in reducing the size of medical image data which is of large size without losing essential information. In this method a number of simultaneous variables are altered into uncorrelated variables called principal components. Each principal component is taken in the route of highest variance and lie in the subspace at right angles to one another.

3.1.1. Procedural steps for image fusion using PCA algorithm

- (a) Convert the two input images into column vectors and make a matrix 'B' using these two column vectors.
- (b) Calculate the empirical mean vector along each column and subtract it from each of the columns of the matrix.

- (c) Calculate the covariance matrix 'R' of the resulting matrix.
- (d) Calculate the eigen values K and eigen vectors E of the covariance matrix.
- (e) Select the eigenvector equivalent to well-built eigen value and divide its each element by mean of that eigenvector. This will give us first principal component P1. Repeat the same procedure with eigenvector corresponding to smaller eigen value to get second principal component P2.

$$P_1 = \frac{R(1)}{\sum R} \quad P_2 = \frac{R(2)}{\sum R}$$

- (f) Fused image is obtained by

$$I_f(x, y) = P_1 I_1(x, y) + P_2 I_2(x, y) \quad (1)$$

3.1.2. Discrete Wavelet Transform (DWT)

Wavelet is a waveform of limited duration having zero average value and nonzero. Wavelet transform applied on a signal decomposes the signal into scale (dilate or extended) and shift (translate) version of the elected protect wavelet. The term protect wavelet implies that the other window functions are derived from this function. Wavelet transform is applied in two domains viz continuous and discrete. CWT (Continuous Wavelet Transform) is the correlation between the wavelet at different scales (inverse of frequency) and the signal and is figured by changing the size of the investigation window each time, moving it, increasing it by the flag. Scientific condition is given by

$$\varphi_x(\tau, R) = \frac{1}{\sqrt{R}} \int X(t) \cdot \varphi * \left(t - \frac{\tau}{R}\right) dt \quad (2)$$

In the above expression τ (translation) and R (scale) are variables required for transforming the signal $x(t)$. Psi (Ψ) is the transforming function known as mother wavelet. In DWT (Discrete Wavelet Transform) a 2D signal (image) $I(x, y)$ is first filtered through low pass and high pass finite impulse response filters (FIR), having impulse response $h[n]$ in horizontal direction and then decimated by factor of 2. This gives first level decomposition. Further the low pass filtered image is again filtered through low pass and high pass FIR filters in vertical direction and then again decimated by 2 to obtain second level decomposition. Filtering operation is given by the convolution of the signal and impulse response of signal.

$$X[n] * h[n] = \sum_{k=-\infty}^{\infty} X[k] \cdot h[n - k] \quad (3)$$

Now to perform inverse wavelet transform, first up sample the sub band images by factor of 2 column wise and then filter them through low pass and high pass FIR filters. Repeat the same process in next step row wise. Now add all the images to get the original image.

Procedural steps for image fusion using DWT algorithm

We have two input images $R1(x, y)$ and $R2(x, y)$ obtained from CT and MRI scan of brain respectively.

- (a) Take two input images.
- (b) Resize both of them to 256 x 256.

- (c) Convert both the images into gray scale if required.
- (d) Apply 2D- DWT on both the images and obtain its four components viz: one approximation and three detail ones.
- (e) Now apply the fusion rule as per the requirement. Here we have experimented with different fusion rules viz:
 - (i) Most extreme pixel determination govern (all maximum): By choosing every single greatest coefficient of both the input images and merging them.
 - (ii) Mean: By taking the normal of the coefficients of both the images.
 - (iii) Blend: By taking the normal of the estimated coefficients of both the input images and choosing the most extreme pixels from detail coefficients of both the input data.
 - (iv) Now apply IDWT to obtain the fused output image.

3.1.3. PCNN Model

Pulse coupled neural network system (PCNN) is a novel visual cortex roused neural system portrayed by the worldwide coupling and heartbeat synchronization of neurons. The basic PCNN demonstrate is appeared in Fig. 2, which incorporates three sections: open field, modulation field and heartbeat generator. The equation for streamlined PCNN can be communicated as

$$F_{ij}(r) = S_{ij} \quad (4)$$

$$L_{ij}(r) = e^{-\alpha L} L_{ij}(r-1) + V^L \sum_{k,j} W_{kj} Y_{ijkl}(r-1) \quad (5)$$

$$U_{ij}(r) = F_{ij}(r) [1 + \beta L_{ij}(r)] \quad (6)$$

$$\theta_{ij}(r) = e^{-\alpha \theta} \theta_{ij}(r-1) + V_{ij}^{\theta} Y_{ij}(r-1) \quad (7)$$

$$Y_{ij}(r) = \text{step}(U_{ij}(r) - \theta_{ij}(r)) = \begin{cases} 1, & U_{ij}(r) > \theta_{ij}(r) \\ 0, & \text{otherwise} \end{cases} \quad (8)$$

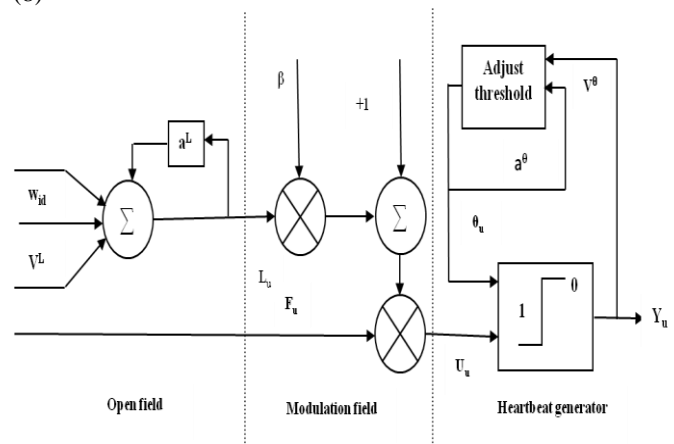


Fig. 2 Simplified PCNN model

In Fig. 2, the open field contains two input compartment: the feeding F_{ij} and the connecting L_{ij} (see (1) and (2)). Each neuron receives the output Y_{ij} of neighborhood neurons and

the peripheral stimuli S_{ij} , where S_{ij} represent the gray value of the input image. In the modulation field, the domestic state signal U_{ij} is created by connecting input signal L_{ij} and the feeding input F_{ij} via connecting coefficient β . Then, if U_{ij} is superior to the threshold value θ_{ij} of the neuron, the heartbeat generator will produce a pulse, namely, it is called a fire. After the neuron outputs a pulse, the threshold of the neuron will get higher rapidly by feedback. If θ_{ij} is superior to U_{ij} , the heartbeat generator stops generating the pulse, the threshold starts to reduce until θ_{ij} is less than U_{ij} again. W_{kl} denotes the connecting weight, the decay coefficients a^L , a^0 and potentials coefficients V^L , V^0 undertaking the periodicity of the pulse output of the PCNN model.

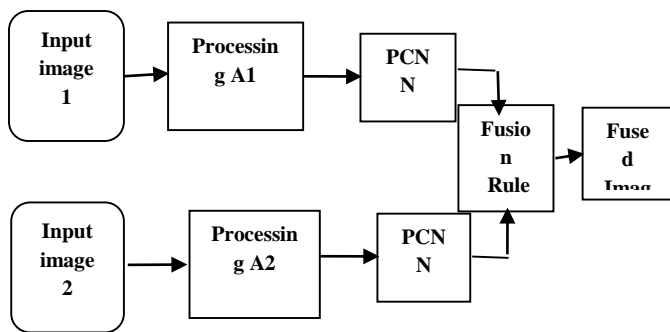
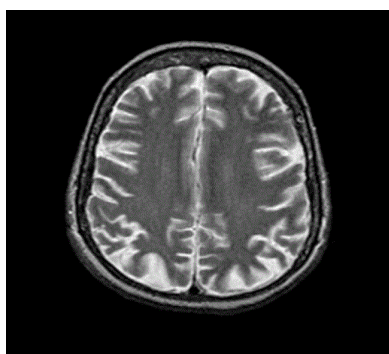


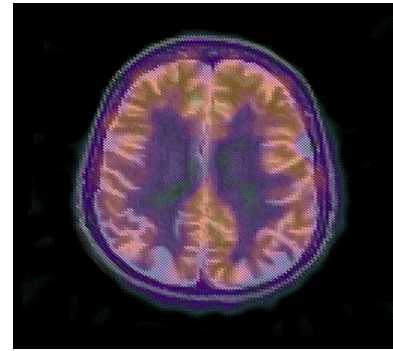
Fig. 3 Image Fusion Process of PCNN

3.2. Hybrid Multimodal Medical Image Fusion Techniques

Traditional medical image fusion techniques lack the ability to get high-quality images. So, there is a bad need to use hybrid fusion techniques to achieve this objective. The basic idea of the hybrid techniques is to combine spatial domain with transform domain fusion techniques to improve the performance and increase fused image quality. Another possibility is applying two stage transformations on input images before fusion process. These transformations provide better characterization of input images, better handling of curved shapes and higher quality for fused details. The overall advantages of the hybrid techniques are improving the visual quality of the images, and decreasing image artifacts and noise. Figure 4 shows data set 2 of original MRI and SPECT brain images. Each image is 256*256 of size. Figure 5 illustrates the block diagram of the proposed hybrid multimodal medical image fusion techniques.



(a)



(b)

Fig. 4: (a) MRI (data set 2), (b) SPECT (data set 2)

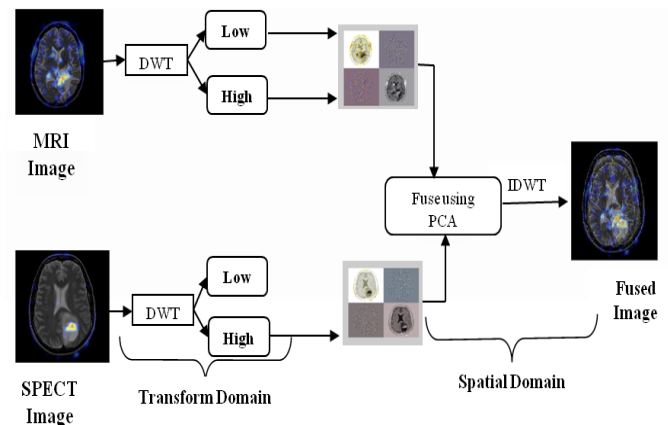


Fig.5 Proposed Hybrid Multimodal Medical Image Fusion Techniques

Algorithm (DWT-PCA)

In this work both DWT and PCA are applied on the source images.

Input: R and E are the two inputs of multimodal medical images which need to be processed.

Output: Multimodality medical Image which is getting merged.

Step 1: Obtain the wavelet coefficients of the two source images.

Step 2: Alter the wavelet coefficient matrices into column vectors.

Step 3: Compute the covariance matrix using these vectors such that each matrix has first column vector obtained through first image and second column vector obtained through second image will give us four sets of covariance matrices.

Step 4: Form the eigen values K and eigen vectors E of the covariance matrices.

Step 5: Select the eigen vector equivalent to well-built eigen value and divide its each component by mean of that eigen vector. This will give us first principal component P1. Repeat the same procedure with eigenvector corresponding to smaller eigen value to get second principal component P2. Do this for all four sets of covariance matrices.

Step 6: Multiply the normalised eigen vector values with the suitable wavelet coefficient matrix (P1 with approximate coefficient matrix

of first image and P2 with approximate coefficient matrix of second image)

Step 7: Do this for both approximate and detail coefficients of both the images.

Step 8: Now apply IDWT to these manipulated coefficient matrices to rebuild the image.

Step 9: merged output multimodal medical image is displayed.

3.3. Evaluation Metrics

Fusion quality metrics are utilized in this work to evaluate the efficiency of the fusion algorithms. These metrics are:

a) Average Gradient (g)

The average gradient represents the amount of texture variation in the image. It is calculated as:

$$g = \frac{1}{(R-1)(S-1)} \sum_{i=1}^{(R-1)(S-1)} \frac{\sqrt{(\frac{\partial f}{\partial x})^2 + (\frac{\partial f}{\partial y})^2}}{2} \quad (9)$$

Where R and S are the image dimensions of images x and y respectively.

b) Standard Deviation (STD)

It is used to establish how much difference of the data is from the average or mean value. The input data is said to be clearer if its STD value is bigger. STD is deliberate using the equation:

$$STD = \sqrt{\frac{\sum_{i=1}^R \sum_{j=1}^S |f(i,j) - \mu|^2}{RS}} \quad (10)$$

Where R and S represent the dimensions of the image f(i,j), and the mean value is represented by μ ..

c) Image Entropy (E)

It is a compute of the quantity of information contained in the input data and it takes values from 0 to 8 and it can be denoted as:

$$E = - \sum_{i=0}^S p(x_i) \log p(x_i) \quad (11)$$

Where x_i of the i^{th} point is its gray-scale value. The image is better if it has a large value of E.

d) Peak Signal-to-Noise Ratio (PSNR)

It is a quantitative evaluates based on the Root Mean Square Error (RMSE), and it is denoted as:

$$PSNR = 10 \times \log \left(\frac{(f_{max})^2}{RMSE^2} \right) \quad (12)$$

Where f_{max} represents the greatest pixel gray level value in the reconstructed picture

e) Mutual Information (MI)

MI is an index that calculates the quantity of dependency between two images (R, S), and it gives the joint distribution detachment between them using the subsequent equation:

$$I(r, s) = \sum_{y \in R} \sum_{r \in R} p(r, s) \log \left(\frac{p(r, s)}{p(r)p(s)} \right) \quad (13)$$

Where $p(r)$ and $p(s)$ are the marginal probability distribution functions of the both images, and $p(r, s)$ is the joint probability distribution function.

$$MI(r, s, f) = \frac{I(r, s) + I(r, f)}{H(r) + H(s)} \quad (14)$$

Where $H(r)$, $H(s)$ are the entropies of images r and s.

f) Xydeas and Petrovic Metric ($Q^{AB/F}$)

This metric is used to measure the transferred edge information amount from source images to the fused one. A normalized weighted performance form of that metric can be calculated as following

$$Q^{AB/F} = \frac{\sum_{m=1}^M \sum_{n=1}^N (Q_{(m,n)}^{AF} W_{(m,n)}^{AF} + Q_{(m,n)}^{BF} W_{(m,n)}^{BF})}{\sum_{m=1}^M \sum_{n=1}^N (W_{(m,n)}^{AF} + W_{(m,n)}^{BF})} \quad (15)$$

Where $Q_{(m,n)}^{AF}$, $Q_{(m,n)}^{BF}$ is the edge information preservation value and $W_{(m,n)}^{AF}$, $W_{(m,n)}^{BF}$ are their weights

g) Processing Time

It represents the time required for the fusion process in seconds according to the computer specifications.

4. Experimental Results and Discussions

The implementations are based on three set of source images and the proposed technique is compared with existing techniques i.e. DWT, PCA and PCNN. The implementation is executed in MATLAB R2013b on windows 7 laptop with Intel Core I5 Processor, 4.0 GB RAM and 500 GB Hard Disk. The processed multimodality therapeutic input images are gathered from harvard medical school and radiopedia.org medical image database. The size of the image is 256×256 for execution process.

4.1 Example 1

The CT and MRI input source images are shown in Figure-6i, j respectively. Figure-6n is the output image of the proposed technique. The Existing techniques PCA, DWT and PCNN outputs are shown in Figure-5k, l and m respectively.

4.2 Example 2

The MRI and SPECT input source images are shown in Figure-7i, j respectively. Figure 7n is the output image of the proposed technique. The Existing techniques PCA, DWT and PCNN outputs are shown in Figure-6k, l and m respectively.

4.3 Example 3

The MRI and SPECT input source images are shown in Figure-8a, b respectively. Figure 8n is the output image of the proposed technique. The Existing techniques PCA, DWT and PCNN outputs are shown in Figure 8k, l and m respectively.

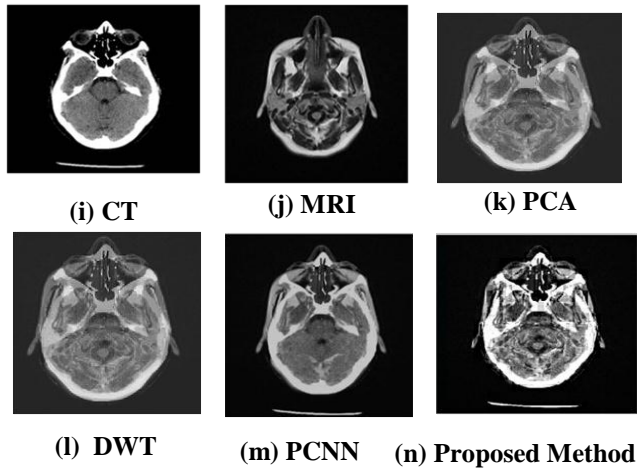


Fig. 6: Results of example 1

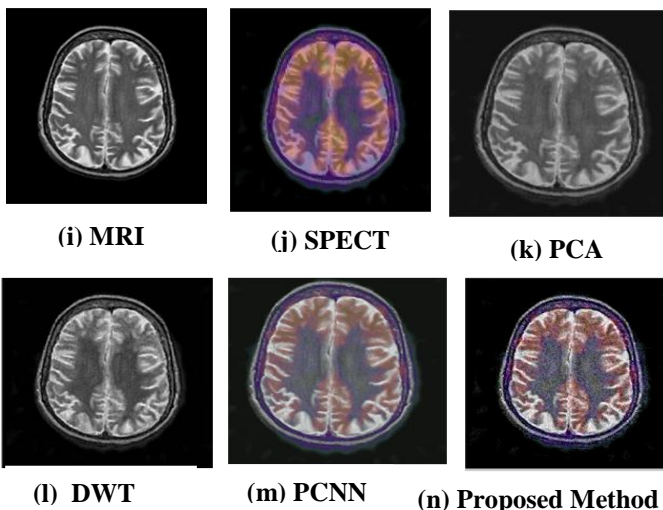


Fig. 7: Results of example 2

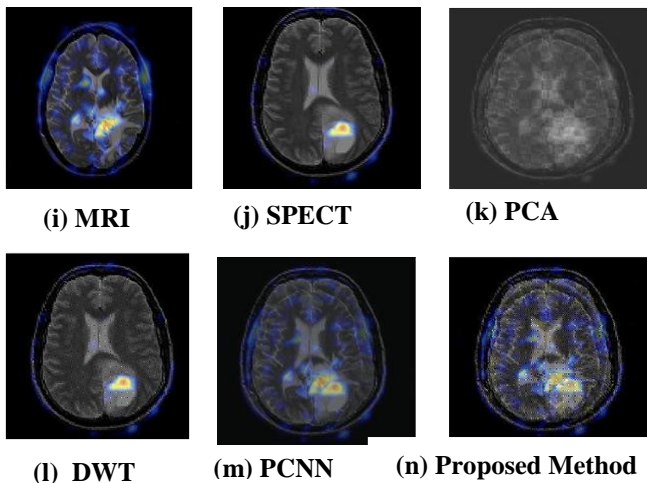
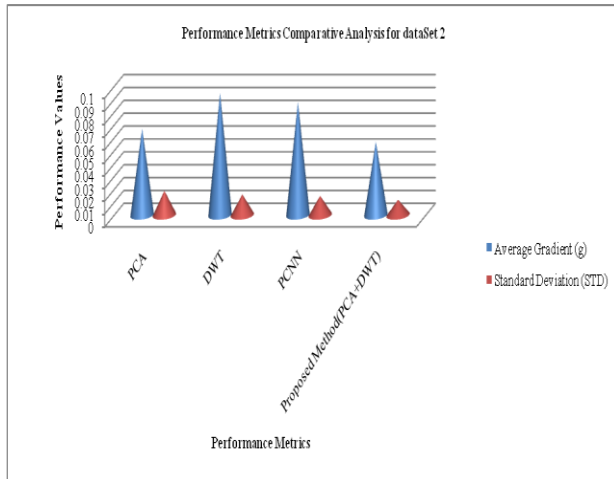


Fig. 8: Results of example 3

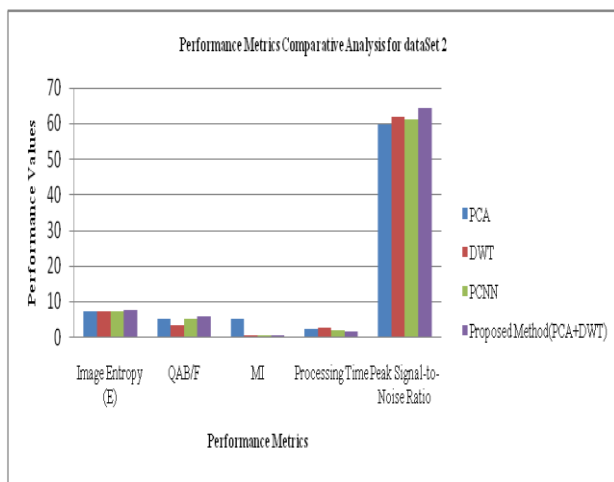
Table 1. Performance Metrics obtained for different medical image fusion algorithms

| Performance Metrics (Dataset 2) | PCA | DWT | PCNN | Proposed Method (PCA+DWT) |
|----------------------------------|-----------|-----------|-----------|---------------------------|
| Average Gradient (g) | 0.0673 | 0.0952 | 0.0882 | 0.0571 |
| Standard Deviation (STD) | 0.019 | 0.016 | 0.015 | 0.012 |
| Entropy (E) | 7.281 | 7.469 | 7.521 | 7.689 |
| PSNR | 59.69 | 62.01 | 61.02 | 64.46 |
| $Q^{AB/F}$ | 5.2781 | 3.6925 | 5.4406 | 5.8505 |
| MI | 5.2781 | 0.7361 | 0.7965 | 0.8202 |
| Processing Time | 2.396 sec | 2.673 sec | 2.189 sec | 1.918 sec |
| Visual inspection of fused image | | | | |

We present here examples of the evaluated results. Table 1 demonstrates the experimental results of the traditional fusion algorithms and hybrid fusion algorithms on example 2. To evaluate the performance of the proposed image fusion approach. CT, MRI and SPECT image are selected as the input source images. It can be seen that because of different imaging standards, the source images with various modalities contain integral data. Compared with the traditional principal component analysis (PCA), Discrete Wavelet Transform (DWT) and Pulse Coupled Neural Network (PCNN) to the Hybrid Algorithm (PCA-DWT). In addition, the evaluation of performance metrics for hybrid methods are better than other existing traditional methods as shown in Table 1. By means of objective criteria analysis, the proposed algorithm not only preserves edge information but also improves the spatial detail information. Therefore, the proposed method of medical image fusion is an effective method in both subjective and objective evaluation criterion. The experimental results are shown in Figure 6, 7, 8 and Table 1.



(a)



(b)

Fig. 9 Performance Comparative analysis of Set 2(a,b)

The evaluated performance metrics output results are shown in Table 1. Note that the superior performance value in each column of Table 1 is shown in bold. The graphs for all the values of Table 1 (Example 2) are displayed in the Figure-9a, b. From the Table 1 and Figure-9, it is clear the proposed techniques outperform the existing techniques for all the performance metrics.

5. Conclusion

This work investigated the performance of both the traditional and hybrid multimodal medical image fusion techniques using several evaluation metrics. It has been shown that the best medical image fusion technique was implemented using proposed PCA-DWT hybrid technique. This hybrid technique introduced a superior performance compared to all the other traditional techniques. It gives much more image details, higher image quality, the shortest processing time and a better visual inspection. All these advantages make it a good choice for several applications such as medical diagnosis for an accurate treatment.

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