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Combining Multi-Modality Medical Image Fusion Based on Hybrid Intelligence for Disease Identification

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Abstract: A multimodality medical image fusion technique plays an important role in biomedical research and clinical disease diagnosis. This paper, proposed an efficient hybrid multimodal medical image fusion approach based on combining the Transform technique with pulse coupled neural network fusion rule. The proposed work combines the discrete cosine harmonic wavelet transform (DCHWT) and pulse coupled neural network (PCNN) for fusion process. Experimental results demonstrate that the proposed method can obtain magnetic resonance imaging, positron emission tomography and single photon emission computed tomography are the source images. Hybrid fusion algorithms are evaluated using several performance metrics. Compared with other existing techniques the proposed experimental results demonstrate the superior processing performance in both subjective and objective evaluation criteria.

Keywords: Multimodal medical image fusion, DWT, DCHWT, MRI, PET, SPECT and PCNN.

1. INTRODUCTION

Image fusion is the mixture of two or more different images to form a novel image by using certain techniques. It is extracting information from multi-source images and 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 conclusion. 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. 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. multimodality 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. 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. Multimodal medical image fusion uses the pixel level fusion. Different imaging modalities can only provide limited information. Computed Tomography image can display accurate bone structures. Magnetic Resonance Imaging 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. Image fusion

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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 medical 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.

The research paper is organized as follows. Sec. 2 describes the literature survey on related works. Sec. 3 discusses the proposed research work method both traditional and hybrid multimodal medical image fusion techniques, performance evaluation metrics is briefly reviewed. Sec. 4 describes the implemented medical image fusion experimental results and performance comparative analysis. Finally, Sec. 5 contains the conclusion.

2. RELATED WORKS

B.Rajalingam, Dr. R.Priya [1] proposed an efficient multimodal therapeutic image fusion approach based on both traditional and hybrid fusion techniques are evaluated using several quality metrics. B.Rajalingam, Dr. R.Priya [2] Proposed a novel multimodal medicinal image fusion approach based on hybrid fusion techniques. Magnetic resonance imaging, positron emission tomography and single photon emission computed tomography are the input multimodal therapeutic brain images and the curvelet transform with neural network techniques are applied to fuse the multimodal medical image. B.Rajalingam, Dr. R.Priya [3] proposed a novel neuro-fuzzy hybrid multimodal medical image fusion technique to improve the quality of fused multimodality medical image. Jiao Du, Weisheng Li, Ke Lu.[4] proposed method in the field of multimodal medicinal image f/usion is image disintegration and image restoration, image mixture rules, image excellence assessments and experiments on the standard dataset. Therapeutic image fusion has been broadly used in medical assessments for disease diagnose. Xiaojun Xua, Youren Wang, et al. [5] proposed a multimodality medicinal image mixture algorithm based on discrete fractional wavelet transform. The input therapeutic images are decomposed using discrete fractional wavelet transform. The sparsity character of the mode coefficients in subband images changes. Xingbin Liu, Wenbo Mei, et al.[6] proposed a new technique namely Structure tensor and non subsampled shearlet transform to extract geometric features. A novel unified optimization model is proposed for fusing computed Tomography (CT) and Magnetic Resonance Imagin images. K.N. Narasimha Murthy and J. Kusuma[7] proposed Shearlet Transform (ST) to fuse two different images Positron Emission Tomography and Magnetic Resonance Imaging image by using the Singular Value Decomposition (SVD) to improve the information content of the images. Satishkumar S. Chavan, Abhishek Mahajan,et al.[8] 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 neurocysticercosis. S. Chavan, A. Pawar, et al.[9] innovated a feature based fusion technique Rotated Wavelet Transform and it is used for extraction of edge-related features from both the source modalities. Heba M. El-Hoseny, El-Sayed M.El.Rabaie,et al.[10] proposed a hybrid technique that enhance the fused image quality using both traditional and hybrid fusion algorithms(Additive Wavelet Transform and Dual Tree complex wavelet transform. Udhaya Suriya TS, Rangarajan P [11] implemented an innovative image fusion system for the detection of brain tumours by fusing MRI and PET images using Discrete Wavelet Transform. Jingming Yang, YanyanWu,et al.[12] described an Image fusion technique Non-Subsampled Contourlet Transform to decompose the images into lowpass and highpass subbands. C.Karthikeyan, B. Ramadoss[13] proposed the fusion of medical images using dual tree complex wavelet transform and self organizing feature map for better disease diagnosis. Xinzheng Xu,Dong Shana,et al.[14] introduced an adaptive pulse-coupled neural networks, which was optimized by the quantum-behaved particle swarm optimization algorithm to improve the efficiency and quality of QPSO. Three performance evaluation metrics is used. Jyoti Agarwaland Sarabjeet Singh Bedi, et al.[15] innovate the hybrid technique using curvelet and wavelet transform for the medical diagnosis by combining the Computed Tomography image and Magnetic Resonance Imaging. Jing-jing Zonga and Tian-shuang Qiua[16] proposed a new fusion scheme for medical images based on sparse representation of classified image patches In this method, first, the registered input images are separated into confidential patches according to the patch geometrical route, from which the corresponding sub-dictionary is trained via the online dictionary learning algorithm and the least angle regression 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[17] proposed a

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method for fusing CT and MRI 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, Principal Component Analysis and Discrete Cosine Transform. Jiao Du, Weisheng Li, Bin Xiao,et.al.[18] proposed an approach union Laplacian pyramid with multiple features for accurately transferring salient features from the input medical images into a single fused image. Zhaobin Wang, Shuai Wang,Ying Zhu,et al.[19] described the statistical analysis PCNN and some modified models are introduced and reviewed the PCNN's applications in the field of image fusion. Zhaobin Wang, Shuai Wang, et al.[20] Proposed a novel guided filtering based weighted average technique to make full use of spatial consistency for fusion of the base and detail layers. B. K. Shreyamsha Kumar [21] proposed a discrete cosine harmonic wavelet transform based image fusion to retain the visual quality and performance of the merged image with reduced computations.

3. PROPOSED RESEARCH WORK

3.1 Traditional Multimodal Medical Image Fusion Techniques

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

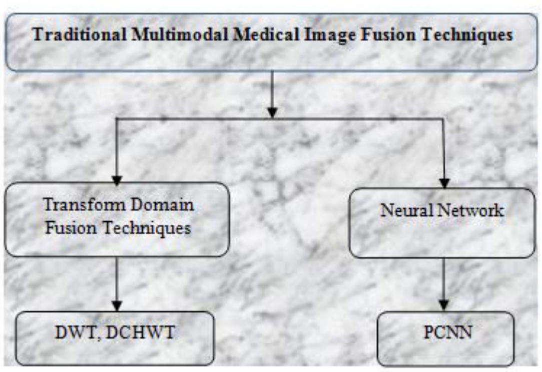

Figure 1: Traditional medical image fusion techniques

3.1.1 Discrete Wavelet Transform (DWT)

Wavelet transform is applied in two domains namely 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

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

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.

$$X[n] * h[n] = \sum_{k=-\infty}^{\infty} X[k] . h[n-k] \qquad (2)$$

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.

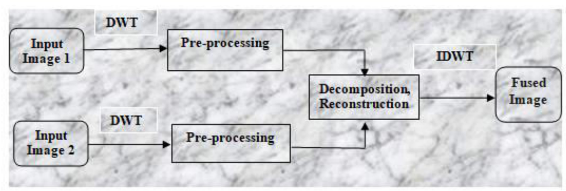

Figure 2: Image Fusion Process of DWT

3.1.1.1 Procedural steps for image fusion using DWT algorithm

1) Take the two input multimodal medical images.
2) Resize both images into 512 x 512 dimensions.
3) Convert both the images into gray scale if required.
4) Apply 2D-DWT on both the images and obtain its four components.
5) Now apply the fusion rule as per the requirement.
a) Most extreme pixel determination governs (all maximum): By choosing every single greatest coefficient of both the input images and merging them.
b) Mean: By taking the normal of the coefficients of both the images.
c) 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.
6) Now apply IDWT to obtain the fused output image.

3.1.2 Discrete cosine harmonic wavelet transforms (DCHWT)

A DCT expresses a predetermined order of data indicated in terms of a sum of cosine functions alternate at different frequencies. The discrete cosine transform generate the signal in the symmetric cyclic order and remove the

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discontinuity symmetric signal to move from one step to next step efficiently. The extension of the symmetric signal make the length into double for the original signal and giving better frequency resolution for factor of two.

$A_E(t)$ and $\psi_E(t)$ are denoted as real symmetric signal and real symmetric wavelet function respectively.

$$R_c(x,y) = \frac{|x|^{\frac{1}{2}}}{2\pi} \int_{-\infty}^{\infty} A_E(\sigma)\, \Psi_E(x\sigma)\, \cos(\sigma y)\, d\sigma \qquad (3)$$

Where the cosine transforms are represented by $A_E(\sigma)$ and $e(\sigma)$ of wavelet functions $A_E(t)$ and $\psi_E(t)$, respectively. The wavelet transform $R_c(x,y)$ used in the cosine domain moderately than the Fourier domain. Consequently, Eq. 13 can be modified as

$$R_c(x,y) = |x|^{\frac{1}{2}} \quad {}^{-1}[R_E(\sigma)\Psi_E(x\sigma)] \qquad (4)$$

In Eq.4 cosine transform functions $A_E(\sigma)$ and $e(\sigma)$ are used to compute the cosine wavelet coefficients $R_c(x,y)$ for a particular scale *x*. The harmonic wavelet function is denoted as $\Psi(\sigma)$ in harmonic wavelet transform, the cosine harmonic wavelet function $s(\sigma)$ is easy and it is zero for all frequencies apart from the small frequency band where it is stable, It is referred by.

$$\Psi_E(\sigma) = \begin{cases} 1, \sigma_c - \sigma_0 < \sigma < \sigma_c + \sigma_0, \\ -\sigma_c - \sigma_0 < \sigma - \sigma_c + \sigma_0, \\ 0, \qquad \text{elsewhere} \end{cases} \qquad (5)$$

The equivalent wavelet $\varphi_E(t)$ in time domain is converted into.

$$\Psi(t) = \frac{\sigma_0}{\pi} \frac{\sin \sigma_0 t}{\sigma_0 t} \cos(\sigma_c t)$$

$$= \frac{\sigma_0}{\pi} \sin c(\sigma_0 t) \cos(\sigma_c t) \qquad (6)$$

The Shannon scaling function is a cosine modulated edition of the protect wavelet. The symmetric rectangular function and for a discrete signal, it is zero apart from on symmetric finite bands [π/c, π/d] and [−π/c, −π/d] where c, d can be real numbers for the spectral weighing in cosine harmonic transform. The cosine harmonic transform too suffers from the difficulty of poor time localization and the result of spectral weighing to restrict in time period by wavelet functions other than rectangular outputs in non orthogonal wavelets due to spectral overlap similar to the Fourier based harmonic wavelet transform. In discrete cosine harmonic wavelet transform the multimodal medical image is decomposed by cluster the discrete cosine transform coefficients in a method similar to that of discrete Fourier transform coefficients except for the conjugate procedure in inserting the coefficients symmetrically. The inverse discrete cosines transform of these collection results in discrete cosine harmonic wavelet coefficients. The discrete cosine transform of these progression subbands results in subband DCT coefficients, which are relocated in their equivalent spot to recover the overall DCT range at the unique sampling rate.

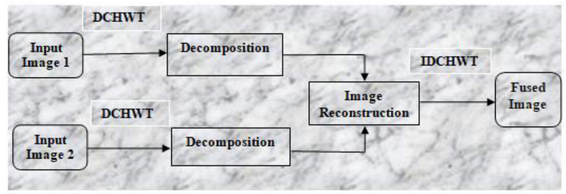

Figure 3: Image Fusion Process of DCHWT

3.1.2.1 Procedural steps for image fusion using DCHWT algorithm

1) Take the two source multimodal medical images.
2) Resize both images into 512 x 512 dimensions
3) Divide the first 2D image into rows and link them together in a chain form to have a 1D row vector R.
4) Divide the second 2D image into columns and link them together in a chain form to have a 1D column vector C.
5) Apply DCHWT on both R and C separately and then apply averaging operation on the vectors.
6) Apply inverse DCHWT on the resulting vector.
7) Convert 1D vector into 2D image to obtain the fused output medical 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. Basic Image Fusion Process of PCNN demonstrated in the Figure 4.

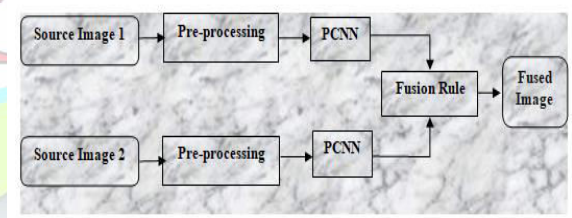

Figure 4: Image Fusion Process of PCNN

3.1.3.1 Procedural steps for image fusion using PCNN

1) Take the two input multimodal medical images.
2) Resize both images into 512 x 512 dimensions.
3) Each input multimodal medical image is then analyzed and performing pre-processing operations based on neural network fusion rule.
4) Perform segmentation operation on the pre-processed multimodality medical image with the PCNN.
5) Finally reconstruct the multimodal medical source imageand then the segmented feature objects and the original image are fused to improve the rate of object identification.

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6) Perform the image reconstruction and get the final fused multimodal medical image.

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 technique is to combine the transform technique with neural network 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. Each image size is 512*512 dimensions. Figure 5 illustrates the schematic diagram of the proposed hybrid multimodal medical image fusion techniques.

3.2.1 Proposed hybrid multimodal image fusion algorithm (DCHWT-PCNN)

In this work both transform domain and neural network are applied on the multimodal medical images.

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

Output: Multimodality medical image which is getting fused.

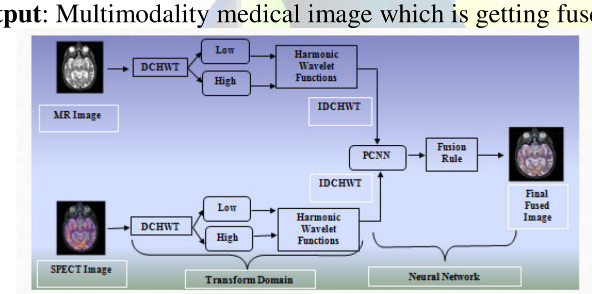

Figure 5: Schematic diagram for the proposed hybrid multimodal medical image fusion

Step 1: Obtain the wavelet coefficients of the two input multimodal medical 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: Divide the first 2D image into rows and link them together in a chain form to have a 1D row vector R.

Step 6: Divide the second 2D image into columns and link them together in a chain form to have a 1D column vector C.

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

Step 8: Apply inverse DCHWT on both source images separately and then apply averaging operation on the vectors.

Step 8: Now apply the PCNN pre-processing steps on the guided filter processed source images.

Step 9: Apply the pulse coupled neural network fusion rule for the accurate medical image fusion.

Step 10: Fused final 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:

3.3.1 Average Gradient (g)

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

$$g = \frac{1}{(R-1)(S-1)} \sum_{i=1}^{(R-1)(S-1)} \frac{\sqrt{(\frac{\partial f}{\partial x})^2 + (\frac{\partial f}{\partial x})^2}}{2} \qquad (7)$$

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

3.3.2 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:

$$STD = \frac{\sqrt{\sum_{i=1}^{R}\sum_{j=1}^{S} |f(i,j)-\mu|^2}}{RS} \qquad (8)$$

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

3.3.3 Local Contrast (C_{local})

It is an index for the image quality and purity of view. It is calculated using the equation:

$$C_{local} = \frac{|\mu_{target}-\mu_{background}|}{\mu_{target}+\mu_{background}} \qquad (9)$$

Where μ_{target} is the mean gray-level of the target image in the local region of interest and $\mu_{background}$ is the mean of the background in the same region. The larger value of C indicates more purity of the image.

3.3.4 Structural Similarity Index Metric (SSIM)

It is a measure of the similarity between two regions w_x and w_y of two images *x* and *y*.

$$SSIM(x,y|w) = \frac{(2\bar{w}_x\bar{w}_y + C_1)(2\sigma w_x w_y + c_2)}{(\bar{w}_x^2 + \bar{w}_y^2 + C_1)(\sigma^2 w_x + \sigma^2 w_y + c_2)} \qquad (10)$$

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Where C_1 *and* C_2 *are* small constants. $\bar{w}_x$, $\bar{w}_y$ are the mean values of w_x and w_y. $\sigma^2 w_x$, $\sigma^2 w_y$ are the variance of w_x and w_y. $\sigma w_x w_y$ is the covariance between the two regions

3.3.5 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

$$Q^{AB/F} = \frac{\sum_{m=1}^{M}\sum_{n=1}^{N}(Q_{(m,n)}^{AF}W_{(m,n)}^{AF}+Q_{(m,n)}^{BF}W_{(m,n)}^{BF})}{\sum_{m=1}^{M}\sum_{n=1}^{N}W_{(m,n)}^{AF}+W_{(m,n)}^{BF}} \quad (11)$$

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

3.3.6 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:

$$I(r,s) = \sum_{y\epsilon R}\sum_{r\epsilon R} p(r,s)\log\left(\frac{p(r,s)}{p(r)p(s)}\right) \quad (12)$$

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.

$$MI(r,s,f) = \frac{I(r,s)+I(r,f)}{H(r)+H(s)} \quad (13)$$

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

3.3.7 Feature Similarity Index Metric (FSIM)

It represents edge similarity between input images and the fused image, and it can be calculated from the following equation:

$$FSIM = \frac{\sum_{x\epsilon\Omega} S_L(x).PC_m(x)}{\sum_{x\epsilon\Omega} PC_m(x)} \quad (14)$$

Where, Ω is the image spatial domain, S_L (x) is the total similarity between the two images, and $PC_m(x)$ is the phase congruency value.

3.3.8 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 four set of source images and the proposed technique is compared with existing techniques i.e. DWT, DCHWT and PCNN. The implementation is executed in MATLAB R2015b 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 (22) and radiopedia.org (23) medical image online database. The size of the image is 512 × 512 for execution process.

4.1 Dataset 1

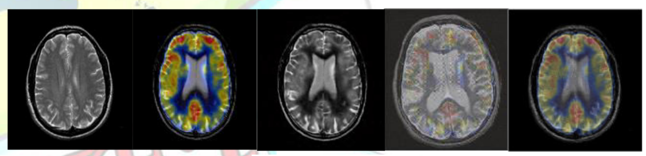
The MRI and PET are the input source images as shown in Figure-6A, B respectively. Figure-6E is the fused final output image of the proposed technique. The Existing techniques are DCHWT and PCNN outputs as shown in Figure-6C, D respectively.

4.2 Dataset 2

The MRI and SPECT are the input source images as shown in Figure-7A, B respectively. Figure 7E is the fused final output image of the proposed technique. The Existing techniques are DCHWT and PCNN outputs as shown in Figure-7C, D respectively.

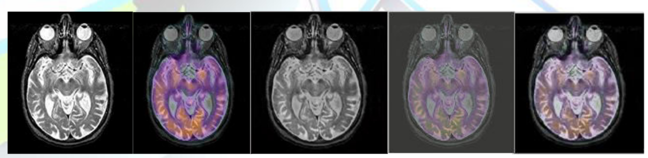
4.3 Dataset 3

The MRI and SPECT are the input source images as shown in Figure-8A, B respectively. Figure 8E is the fused final output image of the proposed technique. The Existing techniques are DCHWT and PCNN outputs as shown in Figure-8C, D respectively.



(A) MRI **(B) PET** **(C) DCHWT** **(D) PCNN** **(E) Proposed Method**

Figure 6: output of Dataset 1



(A) MRI **(B) SPECT** **(C) DCHWT** **(D) PCNN** **(E) Proposed Method**

Figure 7: Output of Dataset 2

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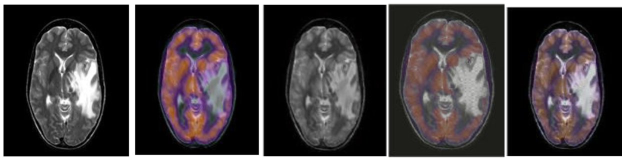


(A) MRI (B) SPECT (D) DCHWT (F) PCNN (G) Proposed Method

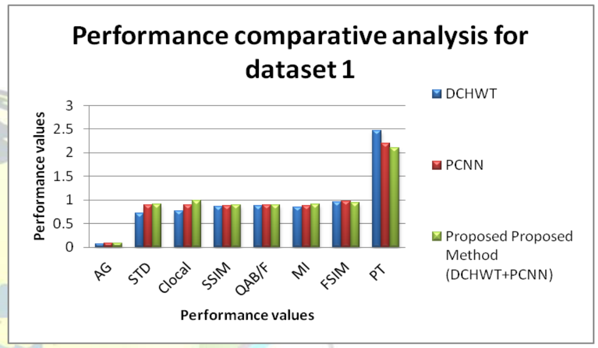
Figure 8: Output of Dataset 3

Table1: Performance Metrics values obtained from different multimodal medical image fusion techniques

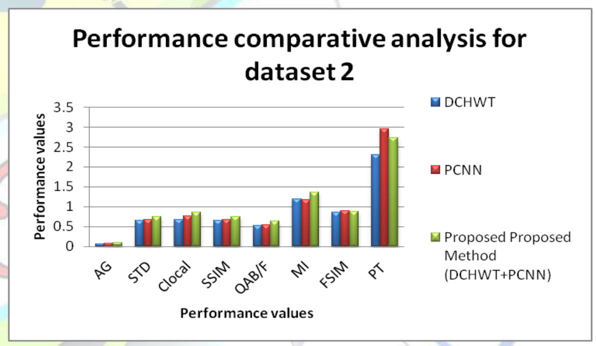
Method	Metrics	DCHWT	PCNN	Proposed Method
Dataset 1	AG	0.0735	0.0881	**0.0895**
	STD	0.7130	0.8993	**0.9013**
	C_{local}	0.7671	0.8982	**0.9811**
	SSIM	0.8593	0.8831	**0.8954**
	$Q^{AB/F}$	0.8691	0.8993	**0.8965**
	MI	0.8487	0.8816	**0.9013**
	FSIM	0.9487	0.9689	**0.9341**
	PT	2.473 sec	2.189 sec	**2.094 sec**
Dataset 2	AG	0.0675	0.0799	**0.0893**
	STD	0.6479	0.6787	**0.7452**
	C_{local}	0.6743	0.7645	**0.8521**
	SSIM	0.6589	0.6758	**0.7371**
	$Q^{AB/F}$	0.5279	0.5437	**0.6321**
	MI	1.1854	1.1763	**1.3513**
	FSIM	0.8483	0.8891	**0.8754**
	PT	2.297 sec	2.957 sec	**2.721 sec**
Dataset 3	AG	0.0731	0.0814	**0.0821**
	STD	0.8862	0.8942	**0.9982**
	C_{local}	0.673	0.7142	**0.7912**
	SSIM	0.7172	0.7869	**0.8012**
	$Q^{AB/F}$	0.6239	0.6878	**0.7142**
	MI	1.0177	1.4724	**1.9321**
	FSIM	0.9487	0.9689	**0.9421**
	PT	3.273 sec	2.889 sec	**2.523 sec**

The above table present the performance metrics of the evaluated results for experimental datasets. Table 1 demonstrates the experimental results of the traditional fusion algorithms and hybrid fusion algorithms on the dataset 1, 2, 3 and 4. To evaluate the performance of the proposed image fusion approach MRI, PET 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. The performance metrics are compared with the traditional methods like Discrete Wavelet Transform Discrete Cosine Harmonic Wavelet Transform (DCHWT) and Pulse Coupled Neural Network (PCNN) to the hybrid method (DCHWT-PCNN). The evaluations of performance metrics for techniques results are better than other existing al techniques as shown in Table 1. By means of criteria analysis, the proposed algorithm not only s edge information but also improves the spatial detail ion. Therefore, the proposed method of multimodal 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)



(C)

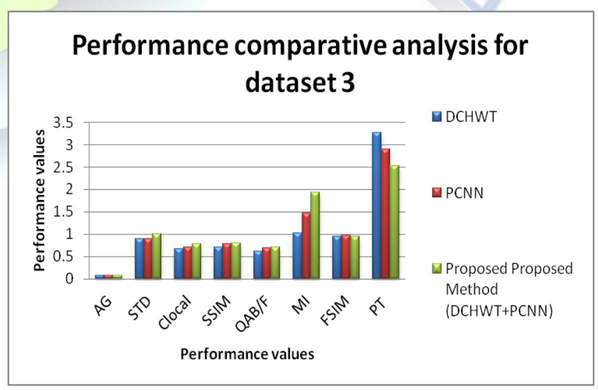


Figure 9: Performance Comparative analysis for 3 datasets (A, B and C)

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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 are shown in the Figure 9A, B and C. From the Table 1 and Figure 9, it is clear the proposed technique outperform the existing techniques for all the performance metrics.

5. CONCLUSIONS

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 hybrid technique. This hybrid technique (DCHWT - PCNN) 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 for assisting medical diagnosis for an accurate treatment.

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