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Hybrid Multimodality Medical Image Fusion Technique for Feature Enhancement in Medical Diagnosis

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Abstract: *Multimodal medical image fusion is one the most important and useful disease diagnostic techniques. This research paper proposed a novel neuro-fuzzy hybrid multimodal medical image fusion technique to improve the quality of fused multimodality medical image. Computed Tomography (CT), Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET) and Single Photon Emission Computed Tomography (SPECT) are the input multimodal therapeutic images used for fusion process. An experimental result of proposed hybrid fusion techniques provides the best fused multimodal medical images of highest quality, highest details, shortest processing time, and best visualization. Both traditional and hybrid multimodal medical image fusion algorithms are evaluated using several quality metrics. Compared with other existing techniques the proposed technique experimental results demonstrate the better processing performance and results in both subjective and objective evaluation criteria.*

Keywords: *Multimodal medical image fusion, MRI, PET, SPECT, PCNN, Neuro-Fuzzy*

I. Introduction

The continual development of multi modal medical imaging and information processing technologies provides many types of multimodality medical images for clinical disease diagnosis. The medical images are broadly used in disease analysis, treatment centre, and radiation treatment. However, the obtained sensor responses of different modalities of medical images express different information about the human body, organs, and cells, and have their personal utilize. Image fusion is the mixture of two or more different images to form a novel image by using certain techniques. To preserve and improve the information of the original multi spectral images of the spatial resolution information is extracted from the multi-source image. Image fusion can be done in three levels: Pixel level fusion, Feature level fusion and Decision level fusion. The fused image retains the huge portion of the significant data in the pixel-level fusion. 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 fusions merge 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 categorized 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. The functional medical images are the fMRI, PET, SPECT images give the low-spatial resolution images with functional information. Anatomical and functional therapeutic images can be incorporated to obtain more constructive information about the same object. The fused multimodality medical image reduces the storage cost by single merged image instead of n number of input images. Multimodal medical image fusion uses the pixel level fusion. 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. Positron emission tomography (PET) images can provide functional eloquent brain regions such as motor or speech regions by using specific activation tasks. In addition, single-photon emission computed tomography (SPECT) images reveal clinically significant metabolic change. Therefore, single multimodal image often cannot provide enough information to doctors in actual clinical situations. It is usually necessary to combine the multimodal images of different modalities to obtain more comprehensive information on diseased tissue or organs. An effective combining method is to use image fusion technologies, which can automatically combine multimodal medical images. The fused multimodal medical image not only obtains a more accurate and complete description of a target, but also reduces randomness and redundancies produced by the sensor in the medical image. Multimodal medical Image fusion increases the effectiveness of image-guided disease analysis, diagnoses and the assessment of medical problems. 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 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. Sec. 4 performance evaluation metrics is briefly reviewed. Sec. 5 describes the implemented medical image fusion experimental results and performance comparative analysis. Finally, Sec. 6 concludes the paper.

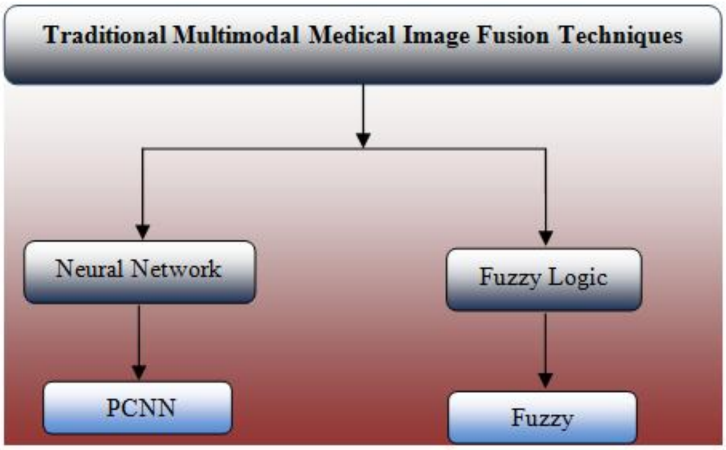
II. Related Works

B. Rajalingam, Dr. R. Priya. [1] Proposed a multimodal medicinal image fusion approach based on traditional and hybrid fusion techniques and performance are evaluated using quality metrics. B. Rajalingam, Dr. R. Priya.[2] Proposed a novel multimodal medicinal image fusion approach based on hybrid fusion techniques. Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET) and Single Photon Emission Computed Tomography (SPECT) are the input multimodal therapeutic brain images and the curvelet transform with neural network techniques are applied to fuse the multimodal medical image. Srinivasa Rao D, Seetha, et al[3] proposed image fusion using fuzzy and neuro fuzzy logic approaches utilized to fuse images from different sensors, in order to enhance visualization and further explores comparison between fuzzy based image fusion and neuro fuzzy fusion technique along with quality evaluation indices. Saad M. Darwish[4] proposed an contourlet transform and multi-level fuzzy reasoning technique for image fusion system based on medical engineering in which useful information from two spatially registered medical images is integrated into a new image that can be used to make clinical diagnosis and treatment more accurate. Sudeb Das, Malay Kumar Kundu[5] introduce a novel approach to the multimodal medical image fusion (MIF) problem, employing multiscale geometric analysis of the nonsubsampled contourlet transform and fuzzy-adaptive reduced pulse-coupled neural network (RPCNN). C. T. Kavitha, C.Chellamuthu [6] proposes image fusion based on Integer Wavelet Transform (IWT) and Neuro- Fuzzy. The anatomical and functional images are decomposed using Integer Wavelet Transform. The wavelet coefficients are then fused using neuro-fuzzy algorithm. Meenu Manchanda, Rajiv Sharma [7] proposed a novel method of multimodal medical image fusion using fuzzy-transform (FTR). FTR based fusion helps in preservation as well as effective transfer of detailed information present in input images into a fused image. Yong Yang, Yue Que, et al [8] proposed a novel multimodal medical image fusion method that adopts a multi scale geometric analysis of the non sub sampled contourlet transform (NSCT) with type-2 fuzzy logic techniques. Jiao Du, Weisheng Li, Ke Lu.[9] proposed the multimodal medicinal image fusion for the image disintegration, image restoration, image mixture rules and image excellence assessments. Therapeutic image fusion has been broadly used in medical assessments for disease diagnose. Xiaojun Xua, Youren Wang, et al. [10] 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.[11] 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[12] 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.[13] 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.[14] 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.[15] proposed a hybrid technique 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 [16] implemented an innovative image fusion system for the detection of brain tumors by fusing MRI and PET images using Discrete Wavelet Transform (DWT). Jingming Yang, Yanyan Wu, et al.[17] described an Image fusion technique Non-Subsampled Contourlet Transform (NSCT) to decompose the images into low pass and high pass subbands. C.Karthikeyan, B. Ramadoss[18] proposed an multimodal medical fusion using dual tree complex wavelet transform (DTCWT) and self-organizing feature map (SOFM) for enhanced disease analysis. Xinzheng Xu,Dong Shana,et al.[19] 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. Zhaobin Wang, Shuai Wang,Ying Zhu,et al.[20] described the statistical analysis PCNN and some modified models are introduced and reviewed the PCNN's applications in the field of image fusion.

III. 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 Fig. 1.



3.1.1 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 Image Fusion Process of PCNN demonstrated in the Fig. 2.

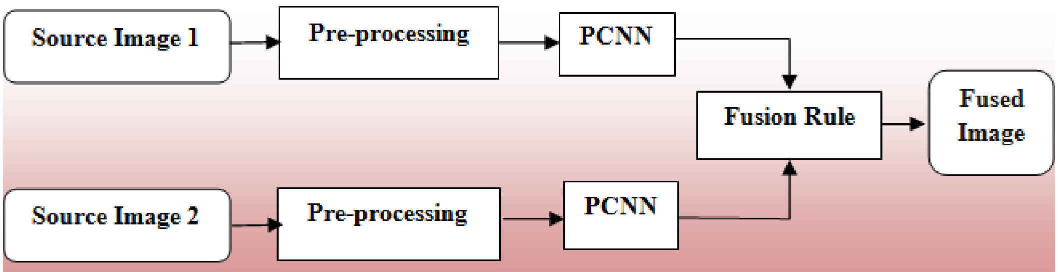


Fig. 2: Image Fusion Process of PCNN

3.1.1.1 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.

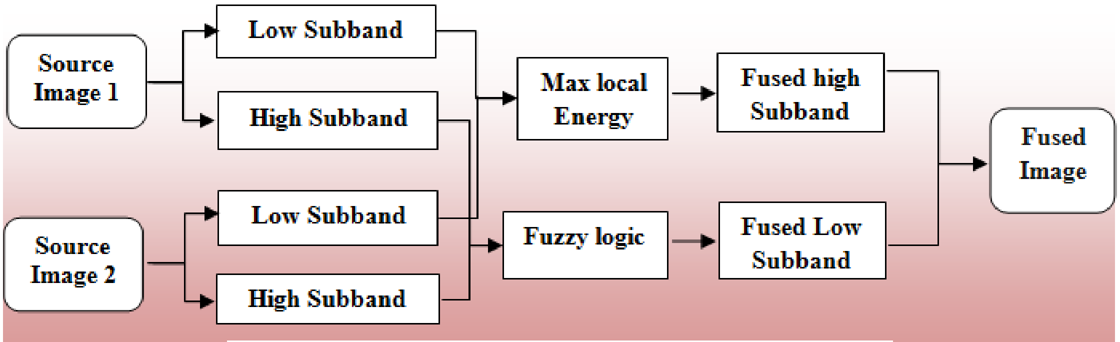


Fig. 3: Image Fusion Process of Fuzzy Logic

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

3.1.2 Fuzzy Logic

Fuzzy image processing is not a unique theory. The collection of segments and features of fuzzy sets represent the process of fuzzy image processing. The representation and processing depend on the selected fuzzy technique and on the problem to be solved. It has three main stages:Image fuzzification (Using membership functions to graphically describe a situation)

1. Modification of membership values ((Application of fuzzy rules)
2. Image defuzzification (Obtaining the crisp or actual results)The coding of image data (fuzzification) and decoding of the results (defuzzification) are steps that make possible to process images with fuzzy techniques. The membership values of the middle step modification are the major power of the fuzzy image processing. After the image data are transformed from gray-level plane to the membership plane (fuzzification), appropriate fuzzy techniques modify the membership values. The approach of the fuzzy integration and fuzzy rule is based on fuzzy clustering.The original multimodal medical image in the gray level plane is subjected to fuzzification and the modification of membership functions is carried out in the membership plane. The final output result is the fused multimodality medical image obtained after the defuzzification process. The algorithm for pixel-level medical image fusion using fuzzy logic is given as follows.

3.1.2.1 Procedural steps for image fusion using Fuzzy Logic.

1. Take the two input multimodal medical images I1 and I2.
2. Resize both images into 512 x 512 dimensions
3. Variables I1 and I2 are multimodal images in matrix form where each pixel gray level value is in the range from 0 to 255.
4. Compare rows and columns of both input multimodal medical images.
5. Convert the multimodality images in column form which has $C = r1 \times c1$ entries.
6. Make a fuzzy inference system file, which has two input medical images.
7. Decide number and type of membership functions for both the input multimodal medical images by tuning the membership functions.
8. Input images in antecedent are resolved to a degree of membership ranging 0 to 255.
9. Make fuzzy if-then rules for input medical images, which resolve those two antecedents to a single number from 0 to 255.
10. For num = 1 to C in steps of 1, apply fuzzification using the rules developed above on the corresponding pixel gray level values of the input multimodality medical images, which gives fuzzy sets represented by membership functions and results in output medical image in column format.
11. Convert the column form to matrix form and display the fused final multimodal medical image. Membership functions and rules used in the fuzzy system

3.2 Hybrid Multimodal Medical Image Fusion Techniques

The traditional therapeutic image fusion methods lack the ability to get superior-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 fuzzy logic 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. Fig. 4a, 4b shows dataset 1 of original MRI and PET images. Each image size is 512*512 dimensions. Fig. 5 illustrates the schematic diagram of the proposed hybrid multimodal medical image fusion techniques.

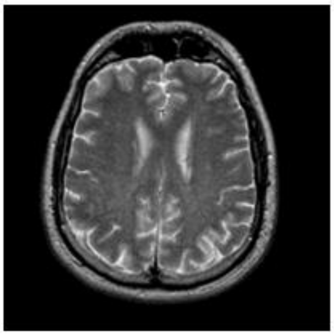


Fig. 4(a): Original MRI image

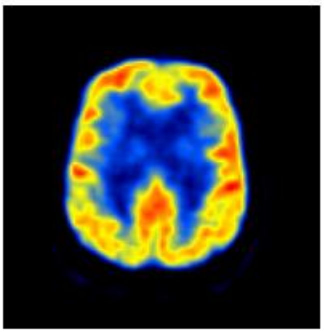


Fig. 4(b): Original PET image

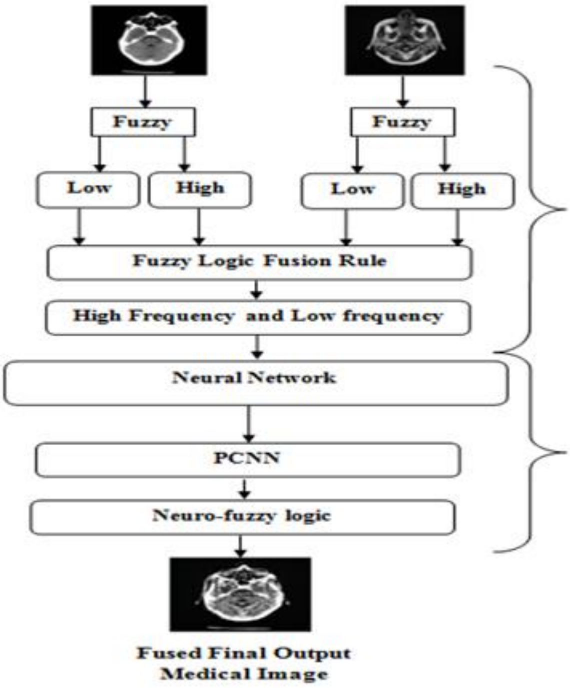


Fig. 5: Proposed structure of hybrid fusion algorithm (Neuro-Fuzzy)

3.2.6 Proposed hybrid multimodal image fusion Algorithm for (Neuro Fuzzy logic)

In this work both Fuzzy Logic and PCNN are applied on the input multimodal medical images.

Input: I1 and I2 are the two inputs of multimodal medical images which need to be processed.

Output: Multimodality medical image which is getting fused.

Step 1 : Take the two input multimodal medical images I1 and I2.

Step 2 : Resize both images into 512 x 512 dimensions

Step3 : Variables I1 and I2 are multimodal images in matrix form where each pixel gray level value is in the range from 0 to 255.

Step4 : Compare rows and columns of both input multimodal medical images.

Step5 : Convert the multimodality images in column form which has C = r1×c1 entries.

Step6 : Make a fuzzy inference system file, which has two input medical images.

Step7 : Decide number and type of membership functions for both the input multimodal medical images by tuning the membership functions.

Step 8 : Input images in antecedent are resolved to a degree of membership ranging 0 to 255.

Step 9 : Make fuzzy if-then rules for input medical images, which resolve those two antecedents to a single number from 0 to 255.
Step 10 : For num = 1 to C in steps of 1, apply fuzzification using the rules developed above on the corresponding pixel gray level values of the input multimodality medical images, which gives fuzzy sets represented by membership functions and results in output medical image in column format.
Step11: Apply the pulse coupled neural network fusion rule with fuzzy logic for the accurate medical image fusion.
Step 12: Convert the column form to matrix form and display the fused final multimodal medical image. Membership functions and rules used in the Neuro-fuzzy system

IV. Evaluation Metrics

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

4.1 Average Gradient (g)

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

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

(1)

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

4.2 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:

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

(2)

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

4.3 Local Contrast (C_{local})

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

$$C_{local} = \frac{|\mu_{target} - \mu_{background}|}{\mu_{target} + \mu_{background}}$$

(3)

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.

4.4 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*.

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

(4)

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.

4.5 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

$$Q^{AB/F} = \frac{\sum_{m=1}^{M} \sum_{n=1}^{N} (Q_{(m,n)}^{AF} W_{(m,n)}^{AF} + Q_{(m,n)}^{BF} W_{(m,n)}^{BF})}{\sum_{m=1}^{M} \sum_{n=1}^{N} W_{(m,n)}^{AF} + W_{(m,n)}^{BF}} \quad (5)$$

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

4.6 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:

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

(6)

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.

$$MI(r,s,f) = \frac{I(r,s)+I(r,f)}{H(r)+H(s)}$$
(7)

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

4.7 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

$$FSIM = \frac{\sum_{x\in\Omega} S_L(x).PC_m(x)}{\sum_{x\in\Omega} PC_m(x)}$$
(8)

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.

4.8 Edge Intensity (S)

A higher edge intensity of an image represents a higher image quality and more clearness. Edge intensity for image f can be measured using Sobel operator (S).

$$Sx = f * \mathrm{h}x \, , Sy = f * \mathrm{hy} \quad (9)$$

$$\sqrt{(s_x{}^2 + s_y{}^2)} \quad (10)$$

Where $h_x = \begin{pmatrix} 1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{pmatrix} h_y = \begin{pmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{pmatrix}$

4.9 Universal Image Quality Index (UIQI)

UIQI is a quality based metric that measures the correlation between two images *x* and *y* using the following equation:

$$Q_0(x,y) = \frac{\delta xy}{\delta x \delta y} . \frac{2\bar{x}\bar{y}}{\bar{x}^2+\bar{y}^2} . \frac{2\delta x \delta y}{\delta x^2+\delta y^2} \quad (11)$$

Where $\bar{x}, \bar{y}$ is the mean value of an image *x*, *y*. δx^2, $\delta y^2 is$ the variance of image *x*, *y*. $\delta xy$is the covariance between *x* and *y*.

4.10 Processing Time

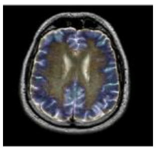
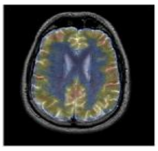
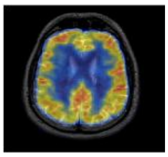
It represents the time required for the fusion process in seconds according to the computer specifications.

V. Experimental Results And Discussions

The implementations are based on two stages. Firstly, the traditional fusion algorithms are applied to datasets of MRI and PET images and evaluated using all metrics mentioned in the previous section. 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 [21] and radiopedia.org [22] medical image online database. The size of the image is 512 × 512 for execution process.

Table1. Performance Metrics obtained for different multimodal medical image fusion algorithms

Method	Metrics	PCNN	FUZZY	FUZZY+ PCNN
Dataset 1	**AG**	0.0782	0.0386	**0.0823**
	STD	0.3854	0.0019	**0.0042**
	C_{local}	0.6852	0.7015	**1.231**
	SSIM	0.9712	0.9589	**0.9963**
	$Q^{AB/F}$	0.4173	0.2312	**0.4532**
	MI	0.7957	0.5942	**0.8012**
	FSIM	0.9879	0.9478	**0.9915**
	EI	0.5321	0.3871	**0.715**
	UIQI	0.7954	0.6543	**0.5921**
	PT	2.412 sec	3.173 sec	**1.671 sec**

	Fused Image			

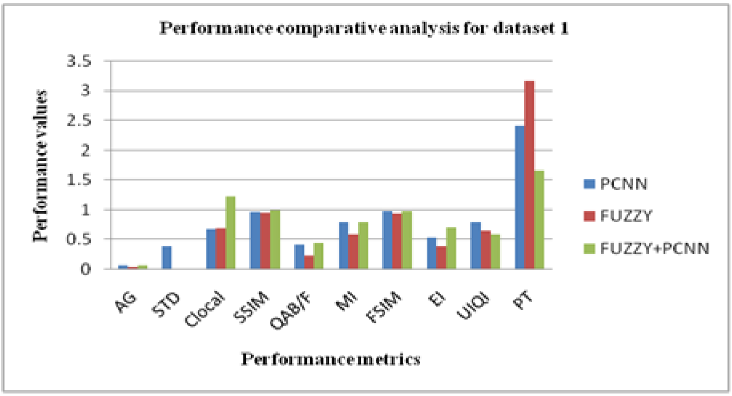


Fig. 6: Performance Comparative analysis for dataset-**1**

The evaluated performance metrics output results are shown in Table 1. 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 Fig. 6. From the Table 1 and Fig. 6, it is clear the proposed hybrid technique outperform the existing techniques for all the performance metrics.

VI. Conclusions

The performance of the traditional and hybrid multimodality medical image fusion algorithms using several evaluation metrics are implemented in this paper. The implemented hybrid technique (PCNN + Fuzzy Logic) produce the best result of the fused multimodal medical image. This hybrid method introduced a better performance compared to traditional algorithms. It gives much more imaged tails, 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 disease analysis for an accurate treatment. Compared with other existing techniques the proposed technique experimental results demonstrate the better processing performance and results in both subjective and objective evaluation criteria

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