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Enhancing Medical Image Fusion: A Three-Stage Hybrid Methodology Integrating Laplacian-Gaussian Decomposition and Convolutional Neural Network

Kalpana K[1], Kandukuri Srinivas[1], Dr. Somasekhar[2]

[1]Assistant Professor, [2]Professor, [1,2]Department of Electronics and Communication Engineering
[1,2]Malla Reddy Engineering College and Management Sciences, Kistapur, Medchal, Hyderabad, 501401, Telangana, India

Abstract

In the current era of technological advancement, medical imaging assumes a substantial role in various applications of medical diagnosis and therapy. Medical image fusion is a potentially influential method for integrating many modalities of medical pictures through the application of image processing techniques. However, traditional methods have been unsuccessful in delivering satisfactory image quality evaluations and ensuring the durability of fused images. In order to address these limitations, the present study proposes a three-stage hybrid fusion methodology. This strategy involves the utilization of both Laplacian and Gaussian pyramid decomposition techniques on the source picture as an initial step. Subsequently, a weight-based convolutional neural network (CNN) approach is employed for generating the fusion results. The fusion of frequency bands is achieved through the application of pyramid reconstruction, employing the probabilistic fusion bands. The method described in this study was implemented in the MATLAB R2018a environment and has demonstrated superior quantitative and qualitative analysis capabilities when compared to conventional methodologies.

Keywords: MR imaging, image fusion, pyramid decomposition, and deep learning.

1. INTRODUCTION

Medical imaging provides a vital contribution to the overall diagnosis of a patient. It includes various radiological imaging techniques such as X-Ray, Magnetic Resonance Imaging (MRI), Computed Tomography (CT), Positron Emission Tomography (PET)[1] etc. Imaging modalities provide better anatomical visualization and analysis of the patient body and hence produces improved survival rates. Within the current clinical setting, medical imaging is a vital component in many applications. Medical imaging tests are non-invasive test procedures which help the doctors to diagnose diseases or injuries for treatment planning. Since the information (info) retrieved from couple of images adopted is generally of a free nature, it is frequently demanded that efficient merging of the utile data from the images is necessary. The basic stage in this procedure of merging is to sum the modes necessitated into spatial alignment, which is cited as ‘Registration’. Later, a procedure of Fusion is needed for the unified perception of the demanded data. In the designing of radiotherapy diagnosis, an instance of the utilization of registering distinctive modes can be discovered, whereas at present CT is employed almost entirely. The usage of compounding of both CT and MR would provide enhancing results as the earlier is more beneficially accommodated for characterization of tumour tissue (and is in natural more beneficial to gentle tissue counterpoint), while the second is necessitated for exact dose of radiation reckoning. Novel Methods[2] to Improve Diagnostic Details in Medical Images through Registration and Fusion Techniques Human beings possess wonderful sense to appreciate visuals. Eye plays a key role in supporting various human activities. Human beings have five sensing capabilities (systems). They are eyes, ears, nose, tongue and

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skin. These sensors can acquire independent information. Eyes can visualize a scene. Ears can sense the data by listening to the sounds. Nose can smell the odour of an object. The tongue can sense the object's taste. Skin can sense the texture and size of the object. All the five sensing systems act as sensors and human brain collects data from these individual sensors and fuses or combines it for compact representation or better description about a scenario. This compact data is useful for decision making and task execution. The definition of image fusion is as follows, "Image Fusion is the process of merging or combining or integrating useful or complementary information of several source images so that the resultant image provides more accurate description about the scene than any one of the individual source images". Image is a two-dimensional quantity. It can be viewed as the combination of illumination and reflectance. Illumination stands for light from the source falling on the object and reflectance corresponds to the amount of light that is reflected back from the same object. The visual information present in a scene can be captured as a digital image (x, y) using a sensor array[3]. All the elements in the sensor array will be of same modality. Hence image capture using a sensor array is simply referred to as single sensor image capture. One may be interested in the details of a scene using multiple sensor arrays, each operating in a different wavelength range. This is simply termed as multi sensor image capture. In the following discussion, it can be noted that, the term sensor is used simply in place of a sensor array. Acquiring pictures by employing single sensor may not extract entire info every time regarding a directed scene. In certain cases, one or more images would be Novel Methods to Improve Diagnostic Details in Medical Images through Registration and Fusion Techniques required for enhanced visual understanding of the scene, which is acquired by enforcing a single sensor of similar mode or by employing numerous sensors of distinctive modes, based on the application. These pictures render appropriate complementary or optical discrete info. Effective or complementary info of these pictures should be unified into a single image to render precise description regarding the scene, than any one of the separated input images.

2. LITERATURE REVIEW

An identified and powerful tool that is very practicable for the application of fusion and many other image processing is referred as Multi Scale (MS) transform. The procedure of image fusion that utilizes MS transform is as follows: Initially, MS Novel Methods to Improve Diagnostic Details in Medical Images through Registration and Fusion Techniques representations of source image are retrieved by employing the MS transform, where the characteristics of an image are represented using a frequency transform. Next, a particular rule for fusing these MS representations is utilized to get a fused outcome where the specified rule assumes the coefficients activity level, and the correlations of neighboring pixels and distinctive scale's coefficients. In the recent days, various efforts are made to resolve these couple of issues, which are explained as follows:

In earlier works, transforms such as Pyramids and Wavelets are the largely employed MSD approaches for fusing the images, where the Pyramid and Wavelets include Laplacian Pyramid (LP) [4], Discrete Wavelet Transform (DWT) [5], and Stationary Wavelet Transform (SWT).

An approach for image fusion using MATLAB is presented in [6] where LP decomposition and reconstruction is utilized for fusing the images. However, the LP is believed as being unable to represent outline and contrast of the images well. To undertake these jobs, in [7] authors proposed an approach based on union LP with numerous characteristics for exactly channelizing the prominent characteristics from the source medical images into a solitary fused outcome. Initially, source medical image is mapped into their theatrics of MS by employing LP. Afterwards, the feature maps of contrast and outline are evoked from the source images at every scale, and then an efficacious scheme of fusion was implemented

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to unify coefficients of Novel Methods to Improve Diagnostic Details in Medical Images through Registration and Fusion Techniques pyramid. At last, the inverse pyramid reconstruction procedure is utilized to get a fused image. However, the image fusion metrics utilized in this, only assess the fused image quality from a restricted view, and it is quite complicate to differentiate which non-subjective metric is importantly amended.The DWT is most popular MS fusion approach. It provides much better fusion results as compared to the pyramid transforms due to its better simultaneous representation of spatial and spectral information.

in [8] authors proposed a fusion strategy of medical images with Global Energy Method (GEM) based on the DWT , in which the match measures are calculated to select the wavelet coefficients coming from different sub images of the same scale. In [9] authors proposed a new approach for fusing PET- MRI images by utilizing DWT and Spatial Frequency (SF) method, in which influence of image imbalance and blurred phenomenon of fusion image is eliminated and further enhanced the clarity. In [10] authors presented a multimodal medical image fusion method based on Wavelet Transform (WT) and Human Visual System (HVS), which unify both the WT and HVS advantages and obtained better fusion performance. First, WT is utilized to decompose the input medical images to be fused, and then the HVS is utilized for the coefficient selection. Finally, inverse WT is applied to obtain the fused medical image. In [11] authors presented a novel approach for MRI and PET image enhancement and fusion using DWT. First, the source medical images which are degraded and nonreadable due to several factors are pre-processed to enhance the quality of the input images using Gaussian filters. These enhanced images are then fused by utilizing DWT for brain regions with different activity levels. It showed around 80-90% more accurate outcomes with mitigated color distortion and without losing any anatomical information in comparison with the existing medical fusion techniques. However, the DWT based fusion algorithms suffers from shift variance, aliasing, and lack of directionality.

Later, in [12] authors presented SWT based medical image fusion approach to overcome the shift variance restriction. Recently, Rotated Wavelet Transform (RWT) for medical image fusion is presented, which extracts more spectral features in different orientations other than DWT and SWT. However, it also suffers from the lack of directionality. To avoid these limitations, productive fusion of images is employed by Dual Tree - Complex Wavelet Transforms (DT-CWT). Shift invariance and directional selectivity are the central benefits of DT-CWT over other wavelet transform variants like DWT and SWT, which mitigates the artifacts innovated by these two variants. In [13] authors focused on feature level image fusion based on DT-CWT, which is utilized to produce region maps by segmenting the features of registered source images with watershed transform either jointly or separately. Then the calculated region characteristics are utilized to fuse the images. In [14] authors implemented a fusion approach in which first the input images were decomposed by employing DT-CWT and afterwards, the max and local energy fusion laws were employed to integrate the obtained coefficients at low and high frequencies severally. At last, inverse DT-CWT is applied to get the fused outcome. In [15] authors also presented DT-CWT based fusion scheme for 3D medical images based on two stage process. First re-slicing and co-registration is done for source images and in the second stage, fusion of those co-registered images is done using DT-CWT. The approximate shift-invariance property of DT-CWT, which is vital for fusion of sub bands, is used. This makes it to obviate the information loss at the multi-level process. On the other hand, phase information availability is also utilized in encoding more fused image coherent structures.

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3. Preliminaries

3.1 Gaussian Pyramid decomposition

A very highly efficient algorithm is required for processing of image fusion using multilevel decomposition. Consider that bottom level of the Gaussian Pyramid $G1$ is equivalent to the source image. This is decomposed again by a factor of 2 and also low passes filtered to from the next level of the pyramid $G2$. This process is repeated in order to get to the next level in a pyramid. This can be represented in terms of equation from 0 < 1 < N:

$$G(i,j) = \sum_m \sum_n w(m,n) G_j - (2i+m, 2j+n) \tag{1}$$

$$G = REDUCED[G_j - i] \tag{2}$$

The w (m,n) waiting function named as generating kernel using the small and attain the promising efficiency. Generally, a five tap filter is used to generate a pyramid. The pyramid construction is considered as equivalent to convolving the original image with a set of Gaussian like weighting function. It should be considered that at each level of the pyramid, the function width always increases to double always. It is also considered that convolution acts as a low pass filter. A band limit of the low pass filter is reduced correspondingly by one octave with each level. In many cases, there is a requirement of the band pass rather than low pass filtered image. In order to achieve this requirement for gaining subtract each Gaussian (low pass) level from the next level which is lower in the pyramid. In terms of the sample density these levels are not the same. Therefore it is considered very important that these new levels should be interpolated between those at a given level and after that level it is subtracted from the next level which is low. This whole process could be formed by reversing the REDUCE process and so called EXPAND process. Thus, if $G_{l,k}$ is the expanded output which is generated by expanding the G to k number of times as follows

$$G_{l,k} = EXPAND[G\ G_{l,k-1}] \tag{3}$$

Precisely

$$G_{l,j}(i,j) = 4 \sum_m \sum_n G_{l,k-1}\left(\frac{2i+m}{2}, \frac{2j+n}{2}\right) \tag{4}$$

In the case of the expand operation, double the size of the image with each iteration, so that Gl,1 is the size of same as that of the original image.

Band pass level or the Pyramid L0,L1, ...LN, may now be specified in terms of low pass pyramid level as below.

$$L_l = G - EXPAND[\ G_{l+1}] \tag{5}$$

$$L_1 = G_1 - G_{l+1,1} \tag{6}$$

The value at each node in Gaussian Pyramid could be obtained by convolving a Gaussian like equivalent weighting function with the original image. The difference with its original image convolution each value of band pass pyramid could be obtained. These operations have a close resemblance with the other Pyramid model, which is called a Laplacian pyramid, as described next section.

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3.2 Laplacian Pyramid decomposition

Image pyramid decomposes images into various information and various scales t extracts various region of interest, features like edges. Laplacian pyramid decomposes low pass and high pass group recursively. The band found in Laplacian pyramid is the difference of two adjacent of low pass images. The Laplacian pyramid is a sequence of error images L0, L1, L2, · · · , Lp. Each is the difference between two levels of the Gaussian pyramid

$$L_l = \begin{cases} g_l - g_{l+1}, \ if \ l = 0,1,2, \dots \dots .., p-1 \\ g_p, \ if \ l = p \end{cases} \quad (7)$$

The reconstruction of image from Laplacian pyramid is a inverse process of decomposition, and in the reverse direction, from the top to the bottom level with the definition as follows. The original image, g0, can be obtained by expanding then summing all the levels of LP. The original image, g0, can be obtained by expanding then summing all the levels of LP:

$$g_p = \begin{cases} L_l + g_{l+1}, \ if \ l = 0,1,2, \dots \dots .., p-1 \\ L_p, \ if \ l = p \end{cases} \quad (8)$$

Predicted values will be higher for compression rates when the values are around zero. G0, G1 levels of laplician pyramid prediction level Gl is derived from Gl+1 then Gl is obtained by expanding Gl+1, multi scale is used to expand its color feature. Features are extracted from two images are needed to fuse by decision making level fusion. When performing decision making level fusion, the image is extracted and well classified, with credibility to have a specific objective. When using decision making, redundancy is reduced and uncertain information, retains important information to have a good work. When performing image fusion the characteristic information should be retained, should not include any artificial or contractor information, and should reduce unforgettable characteristics of the input and database images as possible. When comparing both images consider the max value of the pixel which results in good focus of the image.

4. PROPOSED HYBRID FUSION METHOD

The proposed Fusion method can merging information obtained from two or more multimodal images such as CT and MR combinations into a single image which would be more informative than the any of the input images applied. The proposed fusion approach is represented in figure 3. The detailed operation is as follows:

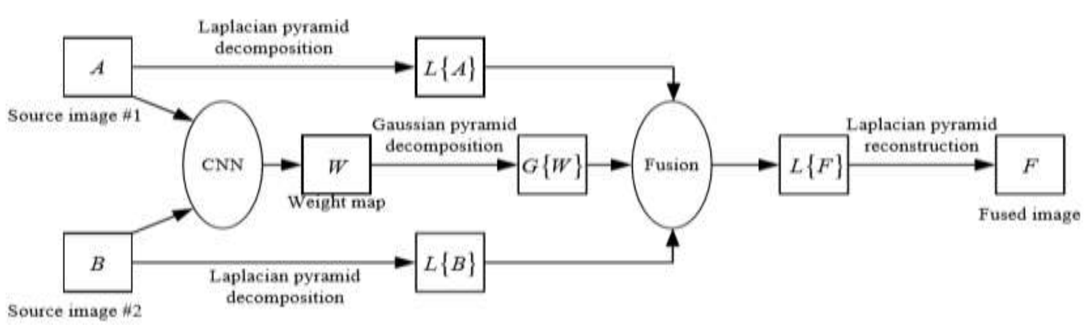

Figure. 2 Proposed medical image fusion

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Step 1: apply the Laplacian pyramid decomposition operation on $A\ and\ B$ input source images individually. The Laplacian pyramid decomposition operation is effectively used to denoise and enhance the images as well as it also performs the decomposition of image pixels by applying the low pass and high pass filters.

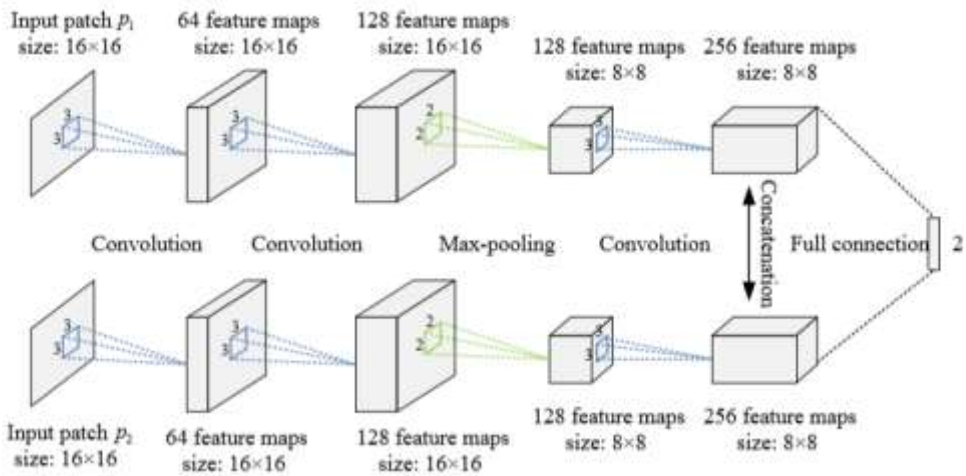

Figure 2: Architecture for CNN training

Step 2: apply the both input images to the CNN network. The CNN training operation is presented in the figure 2 using the multiple layers respectively. This approach preserves the texture information of fused images most effectively where CNN is utilized to decompose the source images into approximation and detail layers then final detail and approximation layers are computed with the support of CNN. Finally, generation of fused image is done with the linear combination of final detail and approximation layers. Further, CNN process smoothens the given image at homogeneous regions while preserving the nonhomogeneous regions (edges) using PDE. It overcomes the drawbacks of non-linear isotropic filtering, which uses inter-region smoothing. So, edge information is lost. In contrast, PCA uses intraregional smoothing to generate coarser resolution images. At each coarser resolution edges are sharp and meaningful. Most of the state-of-art methods extract the spatial information from the MR images by utilizing the upsampling approach. But, the output obtained by this process is quite blurry and is not Novel Methods to Improve Diagnostic Details in Medical Images. Thus the proposed CNN Technique much accurate in fusion performance. And this method has been employed over a great extent in numerous practical applications of image procedures like denoising, de-blurring and reconstruction of images when there is no reference image.

Step 3: Then, apply the Gaussian pyramid decomposition on CNN fused image. Gaussian pyramid decomposition is the process of image division into categories or regions, which correspond to parts of an object sampling. Initially, a measure of sampling coefficient of a definite pattern is used. Considering the medical images with large size, there is a necessity of defining stable similarity measure without introducing high computational complexity. Hence, to uphold the spatial info; in which there will be an enhancement in the meagerness of threshold pulses if any misalignment occurs in the source images. In general the slopes of medical images are often piecewise smooth and tend to have meagerness and the non-zeros represent the edges. Further, such edge positions should be similar as those on the image when

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proper alignment is done on these images. Superficial resolutions would concede a huge adequate shift which leads to the overlapping of images to fuse at the same time as function of decompositions.

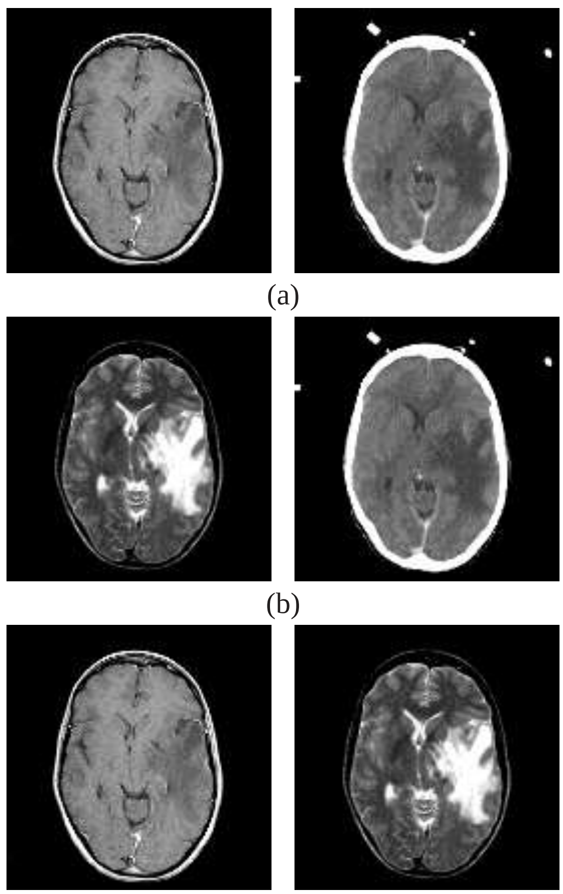
Step 4: perform the band fusion rule on source images using optimized CNN coefficients as follows

$$IMF = PF1 * L\{A\} + PF2 * L\{B\} + PF2 * G\{W\}$$

Finally perform the laplacian pyramid reconstruction operation to get the final fused output image.

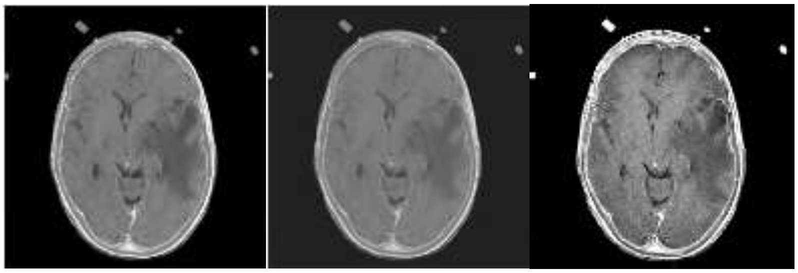
5. RESULTS AND DISCUSSION

All the experiments have been done in MATLAB 2016b version under the high-speed CPU conditions for faster running time with test images shown in figure 3. The fusion metric with best value is highlighted in bold letter. Visual quality of fused images obtained using state-of-art algorithms such as DWT, SWT and proposed method has demonstrated in figure 4, figure 5 and figure 6 with data set 1, data set 2 and dataset 3.



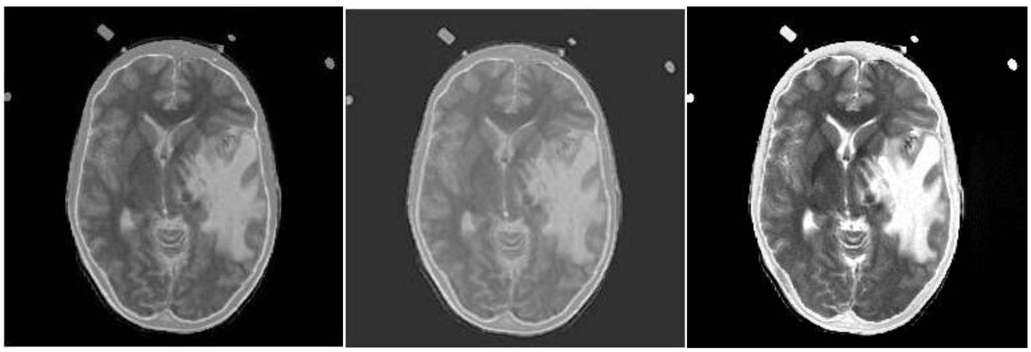
(a) (b) (c)

Fig. 3 Test images (a) dataset 1 (MR-Gad & CT) (b) dataset 2 (MR-T2 & CT) (c) dataset 3 (MR-Gad and MR-T2)



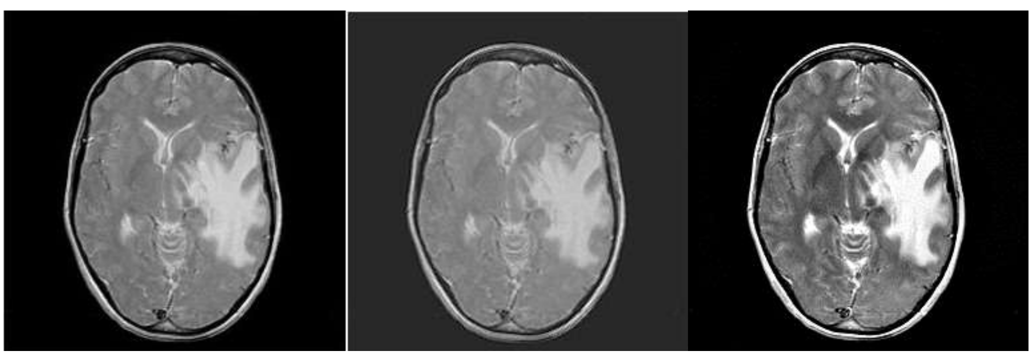
(a) (b) (c)

Fig. 4. Obtained fused images for dataset 1using (a) DWT (b) SWT (c) Proposed method



(a) (b) (c)

Fig. 5. Obtained fused images for dataset 2 using (a) DWT (b) SWT (c) Proposed method



(a) (b) (c)

Fig. 6. Obtained fused images for dataset 3 using (a) DWT (b) SWT (c) Proposed method

However, all the existing fusion methods outputs not good at visual perception, lack of contrast with edge information and texture preservation. Our proposed method with 3 different datasets which are presented in figure 4(c), figure 5(c) and figure 6(c) looks more quality in visualization, good contrast with proper edge information and excellent texture preservation as the value of entropy is much higher.

TABLE 1: QUANTITATIVE ANALYSIS OF FUSION METHODS FOR DATASET 1

Methodology	PSNR (in dB)	RMSE	CC	SSIM	Entropy
SWT[7]	68.95	0.0909	0.94	0.988	1.12

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DWT[9]	68.69	0.093	0.944	0.98	1.11
Proposed method	**90.51**	**0.00047**	**1**	**1**	**4.37**

TABLE 2: QUANTITATIVE ANALYSIS OF FUSION METHODS FOR DATASET 2

Methodology	PSNR (in dB)	RMSE	CC	SSIM	Entropy
SWT[7]	63.56	0.169	0.867	0.975	1.03
DWT[9]	63.60	0.16	0.871	0.975	1.02
Proposed method	**86.60**	**0.0007**	**1**	**1**	**4.76**

TABLE 3: QUANTITATIVE ANALYSIS OF FUSION METHODS FOR DATASET 3

Methodology	PSNR (in dB)	RMSE	CC	SSIM	Entropy
SWT[7]	65.05	0.142	0.885	0.979	1.009
DWT[9]	65.02	0.14	0.89	0.979	0.99
Proposed method	**88.19**	**0**	**1**	**1**	**4.90**

Quantitative analysis with IQA sown in table 1 for the test results presented in figure 4, which gives the analysis of dataset 1. Table 1 consists of various fusion metric parameters such as PSNR, RMSE, CC, SSIM and entropy. The best values are highlighted in bold letters. Our proposed method obtained far better values over all the existing fusion methods discussed in the literature. Similarly, table 2 and table 3 presents the qualitative analysis of dataset 2 and dataset 3 with the similar fusion metric parameters considered for dataset 1 respectively. From the results it is observed that the proposed method shows the better results than conventional approaches DWT and SWT image fusion approaches.

6. CONCLUSION

Novel implementations of medical image fusion are developed in this research work. A single medical imaging modality is not sufficient to analyze the patient’s disease. Hence doctors advise to go for different Non-Invasive methods based on the type of disease to visualize the internal parts of the body. With MR imaging modality gives soft tissue information whereas CT imaging modality gives hard tissue information. No imaging modality provides the entire desired information. Hence to produce a single image which can give soft tissue as well as hard tissue information registration and fusion methods are used. Fusion methods integrate the information of two more images applied to it to produce an image with the desired information. To achieve this, Hybrid fusion approach was developed by utilizing the laplacian and Gaussian pyramid decomposition with CNN fusion. And finally all the decomposed bands are fused using Band-fusion approach to achieve the final output fused image. The proposed provides the better quantitative and visual quality analysis compared to the conventional approaches. This research work can be extended to fusion of color images. Another possibility for future work is the fusion of multiple images. Effective fusion of 3-D images is yet another challenging problem. The extension of this analysis could also be attempted in real time applications.

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