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A FRAMEWORK FOR COMPARISON OF DIFFERENT CT AND MRI MEDICAL IMAGES USING FUSION TECHNIQUES

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Abstract: A fusion of medical images can be used to enhance the medical diagnosis and treatment of brain pathology. Image fusion has become a popular tool in medical applications to improve image quality. In applications involving medical imaging, image fusion is essential. By assisting radiologists in identifying abnormalities in CT and MR brain images. On many fused images with greater information, a comparison analysis was performed.Medical image fusion in multimodality images like MRI and CT images will enhance the exactness of the image for identifying tumour cells in the brain, as well as provide doctors and clinical treatment designing systems with more information. This paper reviews the comparative analysis of medical image fusion techniques for fusing MRI and CT images to clearly determine brain tumours and help the physician make a better diagnosis. All performance metrics taken into consideration here. The experimental findings showed that the suggested strategies produce better viewing of fused images and produce superior outcomes to a number of currently used conventional algorithms.

Keywords: Magnetic Resonance Imaging (MRI), Computed Tomography (CT), Haar Wavelet Transform and Weighted Poison Solver (WPS).

1. INTRODUCTION

In order to improve clinical effectiveness and enable more informed decision-making, medical image fusion combines the essential elements of several medical images into a single image [1].

The integration of images derived from several modalities, including Positron Emission Tomography (PET), CT and MRI images, and others, is known as multimodal medical image fusion. MRI offers the best soft tissue information [2], while CT provides hard tissue information. Doctors are now able to diagnose patients and develop more precise treatment plans for them as a result of the combination of these images.

Fusion of images is done at three levels, i.e, level of pixels, level of features and level of fusion decisions. At the pixel level, pixel-based fusion rules are applied and at the feature level, the characteristics such as texture, brightness, contrast are extracted and utilized to create a feature vector. For image fusion at the decision level, the appropriate choice method is employed. The classifications of image fusion approaches are spatial domain fusion and transform domain fusion. The techniques are based on spatial domain fusion, including the Brovey process, Principal Component Analysis (PCA), and High Pass Filtering. The Wavelet Transform-based transform domain fusion techniques demonstrate greater efficacy than other fusion techniques. The two primary benefits of image fusion are first, which provides a thorough and accurate description of the object. Second, it reduces costs and storage.

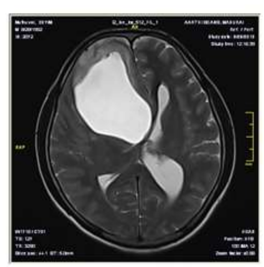
This paper is structured according to the following: In Sect. 2, a description of the CT and MRI images is given. Section 3 offers an overview of approaches for image fusion and hybrid multimodality proposed. Then the performance assessment metric of our approach and other methods of fusion is provided in Sect. 4. Finally, in Section 5, the concluding remarks are provided.

2 MATERIALS (CT AND MRI IMAGES)

Computed tomography (CT) and plain radiographs (X-rays) are used to visualize bony structures and hard tissues. The brain image scanned by CT is shown in Figure 1(a). The skull bone and other hard tissues can be seen clearly in the CT image, but soft tissues like the membranes that protect the brain are less visible.

MRI is a non-invasive method used for the diagnosis of a medical condition. A wide range of diseases, including broken ligaments and tumours, are often diagnosed using MRI scans. For examining the brain and spinal cord, MRIs are extremely useful. The appearance of air and bone are black during an MRI scan, while soft tissues appear white. The image of the same brain scanned for the MRI is shown in Figure 1(b) from the MRI image below. It is discovered that while the hard tissue, such as the bones of the skull, cannot be seen clearly, the soft tissue, such as the membranes protecting the brain, can.

(a)



(b)

Figure 1 (a) CT image Original, (b) MRI image Original

MRI and CT give information about hard and soft tissue respectively. CT gives structural information whereas MRI gives functional information. It is possible to integrate the scanned images from the CT and MRI using the fusion image. As a result, brain CT and MRI scans are combined to gain more information. When CT and MRI scans of the brain are combined, the resulting image include both soft and hard tissues, including the membranes that protect the brain. So, fused image gives better solution than CT alone or MRI alone.

3 IMAGE FUSION METHODS

Space domain fusion and Transform domain fusion techniques are known as image fusion methods [3]. Spatial domain technique focuses mainly on the pixels of the image. In order to get the required effects during image processing, pixel values are crucial. Such techniques are focused on gray level mapping. The mapping function depends on the requirements that the user selects for enhancement. The disadvantage of spatial domain methods is that they introduce spatial distortion into the merged image.

Techniques for transformation or frequency domain are based on converting the image from one domain to another, instead focusing on the image as a whole. Techniques for transformation of the domain are mainly used to process the image according to the frequency information.

3.1 Wavelet Transformation (WT) Based Image Fusion

Discrete wavelet transforms, which offer spectral and directional information, are the most often employed wavelet transforms for image fusion. This transformation divides the input image into coarse and fine components with vertical, horizontal, and diagonal spatial directions in the frequency domain[4]. It provides multi-resolution analysis of an image. The Wavelet Transform (WT) is the optimal fusion process for the decomposition of multiple scales. But the disadvantage of wavelet is that it is not good at edges and textured regions and the spatial resolution of the output image is less.

A wavelet-based multi-resolution approach is a mathematical technique that adopts a number of new images for data fusion, each of which also has a different degree of resolution. This technique uses wavelet transform to add low frequency and high frequency coefficients to the transformed image from the original source images. The maximum selection fusion rule fuses these coefficients. An inverse wavelet transform is employed to produce a final fused image. Figure 3 displays the wavelet-based input images of (a) an MRI, (b) a CT scan, and (c) the fused output image.

3.2 Curvelet Transform (CvT) Based Image Fusion

Recently, image fusion has used the curvelet's transformation. The transformation of the curvelet is conceptually represented as a multi-scale pyramid with different directions and positions at each stage. The image is broken down into several frequency scales using the curvelet transform [5]. At the largest size, the fundamental functions are isotropic wavelets. The position is taken over by curvelets at the largest scales. The extraction accuracy has increased using the curvelet transform. When compared with other methods, it leads to accuracy that is noticeably improved and the extraction of the most information possible. The human visual system is more likened by the Curvelet Transform; hence, compared to other methods, it results in improved visualization and interpretation.

The curvelet transform has greater PSNR, Entropy, and Correlation than the wavelet transform, so the visual quality of the image is better than the wavelet transform. The initial two multimodal medical images that are used as input for the curvelet transform are taken, and both images are then scaled down to 512*512 dimensions. Next, the Basic Average Fusion, Minimum Selection, and Maximum Selection procedures are applied to a set of Curvelet coefficients. Finally, to reconstruct the multimodal source image, apply the Inverse Curvelet transform. Image reconstruction and fusion to provide the final multimodal medical image. Figure 3 shows input (a) MRI image, (b) CT image and (d) fused output image based on curvelet transform. Figure 3 displays the curvelet-based input images of (a) an MRI, (b) a CT scan, and (c) the fused output image.

3.3 Medical image fusion using Ridgelet Transform (RgT)

The ridgelet transform belongs to the class of discrete transformations that use basic functions. It can be presented in the Radon domain as a wavelet analysis to promote its mathematical representation [6]. In this study, CT and MR images are transformed using the Ridgelet Transform. Then, using a maximum frequency fusion rule to extract the coefficients with absolute maximum values, the Ridgelet coefficients are fused. The fused ridgelet coefficients are then subjected to the Inverse Ridgelet Transform to produce the final image.

In order to combine MR and CT images, the Ridgelet fusion technique was assessed and matched with the traditional wavelet fusion algorithm. The visual consistency of the fused image and the quantitative analysis are used with wavelet and ridgelet transforms for testing the fusion algorithm. The results indicated that the results of the ridgelet fusion have lower entropy values and higher PSNR values than the result of the wavelet fusion. It demonstrates that the ridgelet transform outperforms the wavelet transform when brain images from CT and MR are combined. Furthermore, compared to wavelet fusion, ridgelet fusion produces images with greater visual quality. Figure 3 displays the ridgelet-based input images of (a) an MRI, (b) a CT scan, and (c) the fused output image.

3.4 Medical image fusion using Contourlet Transform (CnT)

A multiscale, multidirectional, and really two-dimensional transform is the contourlet transform (CnT) [7]. It is intended to address both the wavelet and curvelet transform issues. In comparison to wavelets, contourlets are multi-directional, anisotropic and constructed from non-separable filter banks. Contourlets are described directly in the discrete domain with reduced redundancy, as opposed to curvelets.

Based on the above benefits, a lot of work has been done on contourlet transform-based image fusion. In the fusion of medical images, CnT is frequently used. The two photos are first divided into two parts. The decomposition involves two stages. Transformation and sub-band decomposition are the first and second, respectively. A Laplacian pyramid is used in the first stage to divide the input into several scales, and directional filter banks are used in the second stage to provide subband decomposition. Directional filter banks with a low pass and high pass filter are used for multiscale decomposition. After eliminating the DC components, all the frequencies are merged to get the resultant fused image. Figure 3 displays the contourlet-based input images of (a) an MRI, (b) a CT scan, and (c) the fused output image.

3.5 Ripplet Transform (RT)

Image discontinuities like edges and contours cause problems for traditional FT and WT transforms [8]. The RT is a Curvelet Transform (CVT) generalisation of higher dimensions, capable of displaying images in various directions and scales. In this technique, the LF-subband and HF-subbands are obtained by decomposing the source medical images, such as CT and MRI, using the Ripplet transform. After that, various arrangements of fusion rules are utilised to fuse the HF and LF subbands. The last step is to apply the inverse ripplet transform to obtain the combined medical image.

When compared to a standard wavelet transform, an RT offers superior benefits for directionality, localisation, multiscale, and anisotropy. The outcomes of the experiment demonstrated that RT is highly efficient. RT is examined numerically and graphically. The outcomes show that the RT-based method is able to maintain a greater spatial resolution and more valuable data in the fused medical image. Figure 3 displays the ripplet-based input images of (a) an MRI, (b) a CT scan, and (c) the fused output image.

3.6 Non Subsampled Contourlet Transform-Based Medical Image Fusion

In this work, NSCT Transformation decomposes original images into proper levels [12]. Both low frequency and high frequency image coefficients are produced by it. Low frequency image coefficients are fused using the Phase Congruency approach. High frequency coefficients of an image are fused using the directive contrast approach. Finally, to obtain the combined medical image, an inverse transformation is performed. Comparing the proposed method to existing traditional fusion methods reveals an advantage. The proposed algorithm is evaluated with various qualitative analytical measurements. It showed that it provided better results than some traditional methods. Figure 3 displays the non-subsampled contourlet-based input images of (a) an MRI, (b) a CT scan, and (c) the fused output image.

3.7 Hybrid multimodal image fusion algorithm (CVT-PCNN)

Traditional approaches to therapeutic image fusion cannot produce images of superior quality.

Therefore, to achieve that goal , it is necessary to use hybrid fusion techniques. The fundamental idea behind the hybrid technique is to fuse neural network fusion techniques with fuzzy logic to increase the efficiency of a single process. Another option is to apply two-stage changes to the input images before the fusion process. Better input image categorization, improved curved form handling, and improved quality for fused data are all benefits of these operations. The general advantages of hybrid techniques are an increase in visual quality and a decrease in noise and errors in images.

For this study, CT and MRI were the two inputs that were fused into multimodal medical images. For appropriate medical image fusion, the curvelet transform is first used, followed by the generation of a number of curvelet coefficients, and finally the neural network fusion rule combined with pulse The fused final product is then displayed as a multimodal medical image. Figure 3 displays the CVT-PCNN-based input images of (a) an MRI, (b) a CT scan, and (c) the fused output image.

3.8 Image Fusion Using a Wavelet-Curvelet (WT-CT) Hybrid

Curvelet-based image fusion successfully handles curved shapes, and when used in the medical industry, it produces superior fusion outcomes to the wavelet transform alone. The wavelet transform, on the other hand, performs well with multifocus, multi-spectral images, unlike any other fusion law. It increases the image's frequency resolution by decomposing it again and again into various bands until it obtains different frequencies and resolutions. Therefore, a wavelet and curvelet hybrid [9] will produce better results than a single transformation alone.

In the hybrid method, input image decomposition is carried out initially up to level N without running the image via a series of low-pass and high-pass filters. The low pass band and high pass band are then transformed into curvelets and merged using the wavelet transform, then the inverse wavelet transform is employed to obtain full size images. This is done by further breaking them up into tiny tiles. The quality of the image produced by the hybrid approach has been confirmed using a variety of quality criteria. Clearly, the suggested fusion strategy outperformed a number of alternative strategies. Figure 3 displays the Wavelet-Curvelet based input images of (a) an MRI, (b) a CT scan, and (c) the fused output image.

3.9 Fuzzy Logic and the Discrete Wavelet Transform (FL+DWT) were used to focus on CT and MRI Fusion Images

The method [10] for combining CT and MR images is a hybrid one. The discrete wavelet transform is first used in this work to transform CT and MRI images. The approximation coefficients of the DWT are then fused using the fuzzy logic technique. The fused images are then obtained by applying an inverse discrete wavelet transform. The outcomes are evaluated using a variety of performance metrics. The results showed that it produced superior performance than other approaches. Figure 3 displays the Fuzzy Logic and the Discrete Wavelet-based input images of (a) an MRI, (b) a CT scan, and (c) the fused output image.

3.10 Hybrid Multimodality Medical Image Fusion based on Guided Image Filter with Pulse Coupled Neural Network (GIF+PCNN)

A quick and effective way of fusion is the multimodal medical image fusion approach, which is designed to merge highly integrative and detailed medical images of the same organism. In biomedical research and clinical illness diagnosis, a multimodal digital picture fusion technique is crucial. In this work, the neural network and pulses are connected with directed image filtering for the fusion process (GIF-PCNN) [11]. In this study, multimodal medical pictures from the CT and MRI input sources are subjected to applications of both GIF and PCNN.

The input source images are first divided into multiple-level representations by average filtering, and then all of the images are resized to 512 * 512 dimensions. Comparing rows and columns of multimodal medical images from both inputs, the Gaussian Laplacian filter is then used to create a weight map. In biological research and the diagnosis of clinical diseases, a multimodal digital image fusion technique is important. The reconstruction procedure is then applied to the attribute layers and the bottom layer of the different input images.

On the guided filter processed source images, PCNN pre-processing steps are used. The precise medical image is then fused using the neural network fusion rule and pulse. It has been established that this hybrid strategy was used to build the best medical image fusion method. Compared with all other conventional techniques, this hybrid technique implemented superior performance. It provides the quickest processing times, the best image quality, more file data, and improved visual inspection. The experimental findings indicate better processing efficiency in both subjective and objective assessment parameters as opposed to other current techniques. All these benefits make it a popular option for many applications for effective care, such as assisting with medical diagnosis. Figure 3 displays the *GIF+PCNN* - based input images of (a) an MRI, (b) a CT scan, and (c) the fused output image

3.11 Hybrid Multimodality Medical Image Fusion Using Noise-Removal and Contrast Enhancement Scheme with Convolutional Neural Network

The basic objective of any medical image fusion technique is to extract all characteristics from multimodal sensors to produce a single fused image that accurately and precisely combines the information from both images without the addition of noise. The bottom-hat-top-hat strategy is suggested in this study as a morphological preprocessing method to deal with noise and non-uniform illumination. In this study, the bottom-hat-top-hat preprocessing method is used to remove noise and uneven illumination [14]. Then, the RGB image is converted to a grey image using grey-PCA, which keeps important features by boosting contrast in the image. The robust execution of this stage also eliminates the superfluous amount of data. Before the LSIST is utilised, the processed images are divided into the LP and HP sub-bands using the non-subsampled pyramid filters (NSPF) and shearing filters (SFs), which further enhance the image quality by preserving the significant features in numerous orientations and scales. The two branches of the Siamese CNNs are then used to form the HP sub-bands, which produce sharp edges and textures while removing the artefacts. The local energy fusion approach employing average and selection mode is then employed with the LP sub-bands that retrieve the energy information. A final inverse transformation is used to combine an image with enhanced details, significant features, and negligible artefacts. Figure 3 displays the Noise-Removal and Contrast Enhancement Scheme with Convolutional Neural Network - based input images of (a) an MRI, (b) a CT scan, and (c) the fused output image.

3.12 Medical Image Fusion Using Using Variational Mode Decomposition (VMD) and local energy maxima (LEM)

Using local energy maxima (LEM) and variational mode decomposition (VMD), we present a novel multimodal medical image fusion technique in this research [15]. In order to effectively recover edge features while avoiding boundary distortions, we used VMD to decompose source pictures into a variety of intrinsic mode functions (IMFs). LEM is required to properly combine the IMFs based on the local data. LEM plays a vital influence in the quality of the fused image by carefully preserving the required spatial information. Some of the source images' information may be preserved during this deconstruction process. These specifics, meanwhile, fall short of what radiologists need clinically. We used an LEM fusion rule to keep complementary data from IMFs, a critical criteria for diagnosing medical images. Figure 3 displays the VMD-LEM - based input images of (a) an MRI, (b) a CT imag, and (c) the fused output image.

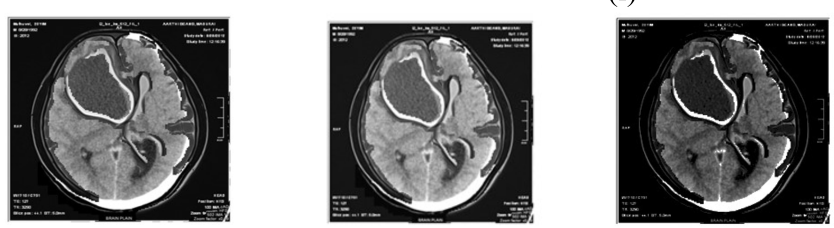
3.13 Proposed approach: Hybrid Multimodality Medical Image Fusion based on Haar wavelet and weighted poison solver

In this proposed work, the first RGB colour space is converted into YCbCr colour space in the brain image. The Y represents the luminance and Cb and Cr represent the chrominance of the brain image. The gradient value of the luminance (Y) channel of the CT image is calculated first; then the weighted sum of all Cb values and Cr values are fused separately. The Haar wavelet is used to reconstruct the information and the weighted poison solver [16] is used to remove cupping artefacts in the luminance channel. Finally, luminance (Y) and chrominance (Cb, Cr) are fused to make a fused CT output. The same procedure has been followed for the MR image. Then, finally, CT output and MR output are fused using an algorithm to make a high-quality hybrid image output. Figure 3 displays weighted poison solver (WPS) and Haar wavelet based input images of (a) an MRI image, (b) a CT image and (o) fused output image.

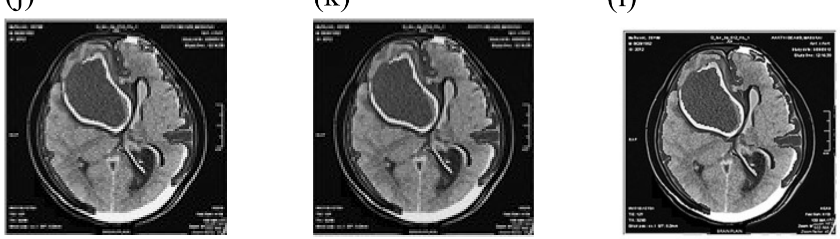
(a) (b) (c)

(d) (e) (f)

(g) (h) (i)



(j) (k) (l)



(m) (n) (o)

Figure 3 shows an (a) MRI image, (b) CT image, (c) WT fused image, (d) Curvelet Transform fused image, (e) Ridgelet Transform fused image, (f) Contourlet Transform fused image, (g) Ripplet Transform fused image, (h) Non Subsampled Contourlet Transform fused image (i) Hybrid of Curvelet Transform and Pulse Coupled Neural Network (CVT-PCNN) fused images, (j) Image Fusion Using a Wavelet-Curvelet (WT-CT) Hybrid, (k) Hybrid of Fuzzy Logic and Discrete Wavelet Transform (FL+DWT) fused images, (l) Hybrid of Guided Image Filter and Pulse Coupled Neural Network (GIF+PCNN) fused images (m) Hybrid fusion of NR+CNN, (n) Image fusion using VMD and LEM and (o) Proposed approach: Hybrid of Haar wavelet and weighted poison solver fused images.

4 PERFORMANCE EVALUATION METRICS

The metrics below are used to measure the efficiency of the proposed solution. When a reference image is available for evaluating the quality of pixel level image fusion, the metrics used are (i) Structural Similarity Index Metric (SSIM) (ii) Mutual Information (MI) (iii) Standard Deviation (SD) (iv) Entropy (E) (v) Root Mean Square Error (RMSE) (vi) Peak Signal to Noise Ratio (PSNR) (vii) Correlation (CORR) (viii) Quality Index (QI) (ix) Average Gradient (AG) and (x) Mean Absolute Error (MAE).

4.1 Structural Similarity Index Metric (SSIM)

The SSIM initially calculates the local region and then luminance, contrast, and structural scores for a global region in the image. Furthermore, the separate score is combined with equal weight to measure the SSIM score. The SSIM, a high metric score, reflects a high quality, and provides a score in the range between 0 and 1. A larger SSIM value denotes more luminance, contrast, and structural material preservation in Eq. (1).

$$\mathrm{SSIM}(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \tag{1}$$

where μ_x and μ_y represent the mean, σ_x and σ_y represent the variance, and σxy represents the covariance of x and y. C_1, C_2 are constants. The value of the SSIM index ranges from -1 to 1. The value 1 implies that the images are identical in all views.

4.2 Mutual Information (MI)

An index called MI uses the following equation to offer a dissociation of the joint distribution between two images (R, S) and assesses the degree of dependence between them (2).

$$I(r,s) = \sum_{r\in R}\sum_{s\in R} p(r,s)\log\left(\frac{p(r,s)}{p(r)p(s)}\right) \tag{2}$$

where $p(r)$ and $p(s)$ are the marginal functions of the two images for the distribution of probability are, and is the function of the joint distribution of probability in Eq. (3).

$$MI(r,s,f) = \frac{I(r,s)+I(r,f)}{H(r)+H(s)} \tag{3}$$

where, $H(r)$ and $H(s)$ are image entropies r and s.

4.3 Standard Deviation (SD)

By reflecting the contrast in the image, it illustrates the deviation from the average value. The image has more contrast the higher the standard deviation value. Therefore, a high standard deviation value indicates that an image is of high quality. In Eq, (4) it is defined.

$$SD = \sqrt{\frac{1}{M \times N} \sum_i^M \sum_j^N (I(i,j) - \mu)^2} \tag{4}$$

where I(i, j) represents the image's intensity at coordinates (i,j) and is the average image intensity. The image size is MN.

4.4 Entropy

A fused image's entropy is a gauge of how much information it contains. Given by Eq, (5) it is the typical amount of bits required to quantize the image's intensity.

$$E = -\sum_{g=0}^{L-1} p_g \log_2 p_g \tag{5}$$

where p_g is denoted by the gray-to-total-pixel ratio. Entropy would be high in an image with a high information content. More detail will be visible in the fused image if its entropy is higher than that of the original images.

4.5 Peak Signal to Noise Ratio (PSNR)

The PSNR represents the homogeneity of the region between the two images. It is employed to measure the quality of the two resulting merged images. The high value of the PSNR represents more quality in the fused image in Eq. (6).

$$PSNR = 10 \log_{10}\left(\frac{255^2}{MSE}\right) \tag{6}$$

where MSE stands for mean square error, an indicator of image fidelity that is used to quantitatively quantify the similarity of two images. For image $M \times N$, the MSE can be calculated as in Eq. (7).

$$MSE = \frac{1}{M \times N} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} \| F(i,j) - G(i,j) \|^2 \tag{7}$$

where the input image is F(i, j) and the output image, G(i, j), has m and n pixels.

4.6 Root Mean Square Error (RMSE)

Eq. (8) provides the root mean square error of the fusion that results

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}\|F(i,j) - G(i,j)\|^2}{M \times N}} \tag{8}$$

where G(i, j) is the outcome of the fusion and F(i, j) is either the MR or the CT image. The dimensions of the fusing images are M and N. The performance of the fusion algorithm improves as the RMSE value decreases.

4.7 Correlation (CORR)

The definition of the correlation function is given in Eq, (9) which specifies how pixels are related spatially.

$$\mathrm{CORR} = \frac{\sum_{x=0}^{m-1}\sum_{y=0}^{n-1}(x,y)f(x,y) - M_x M_y}{\sigma_x \sigma_y} \tag{9}$$

where the horizontal spatial domain's mean and standard deviation are M_x and σ_x, while the vertical spatial domain's mean and standard deviation are M_y and σ_y.

4.8 Quality Index (QI)

QI is used as a combination of three different variables for modelling any distortion: loss of correlation, distortion of luminance and distortion of contrast in Eq. (10). The QI range is –1 to 1. The value 1 shows the relationship and the images fused are identical.

$$\mathrm{QI} = \frac{4\sigma_{xy}\bar{x}\bar{y}}{(\sigma_x{}^2 + \sigma_y{}^2)((\bar{x})^2 + (\bar{y})^2)} \tag{10}$$

where $\bar{x}$ and $\bar{y}$ are the mean value of an image x, y. $\sigma_x{}^2$ and $\sigma_y{}^2$ are the variance of image x, y. where x and y are the mean values of an image x and y. The variance of the images x and y are $\sigma_x{}^2$ and $\sigma_y{}^2$ respectively. σ_{xy} is the covariance between x and y.

4.9 Average Gradient (AG)

It is defined as in Eq. (11) and it reflects the image's clarity.

$$\mathrm{AG} = \frac{1}{(M-1)(N-1)}\sum_{i=1}^{M-1}\sum_{j=1}^{N-1}\sqrt{\frac{1}{2}\left(\left(\frac{\partial I(i,j)}{\partial i}\right)^2 + \left(\frac{\partial I(i,j)}{\partial j}\right)^2\right)} \tag{11}$$

where I is the source image's M × N size. A higher value than the typical gradient indicates a higher-quality image.

4.10 Mean Absolute Error (MAE)

When comparing the fused image to the source image, MAE. The MAE can be defined as in Eq. (12).

$$\mathrm{MAE} = \frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} |F(i,j) - G(i,j)| \tag{12}$$

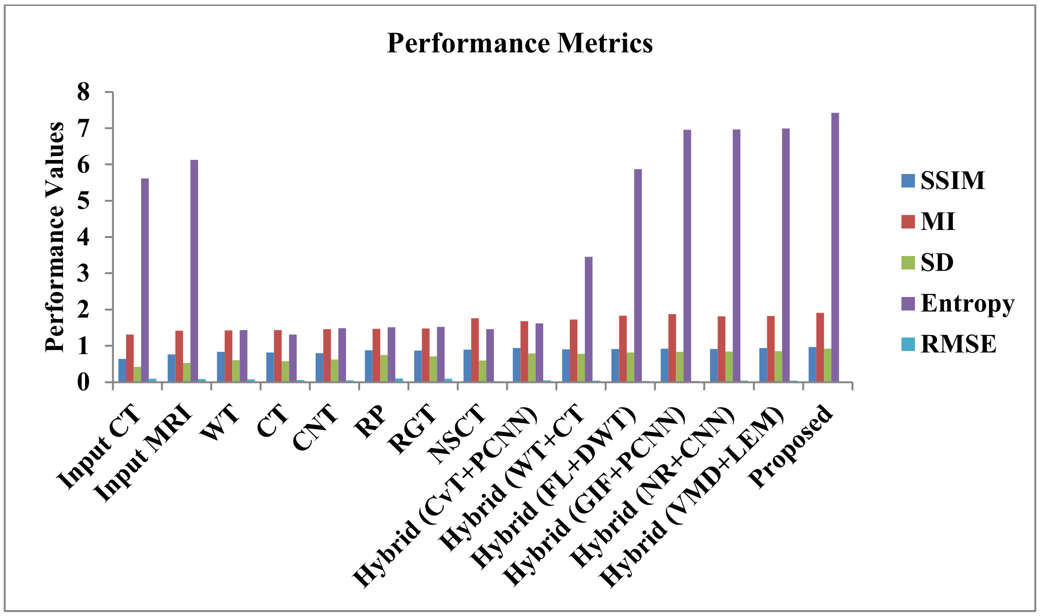
Between the original image F(i,j) and the fused image G(i,j) a lower value denotes a greater similarity.

Table 1 lists the performance metrics attained for various medical image fusion techniques. Comparing the suggested strategy to other ones that are currently in use, it can be demonstrated that it yields better results for the majority of parameters. Figure 4(a) and 4(b) depict graphical illustrations of performance metrics.

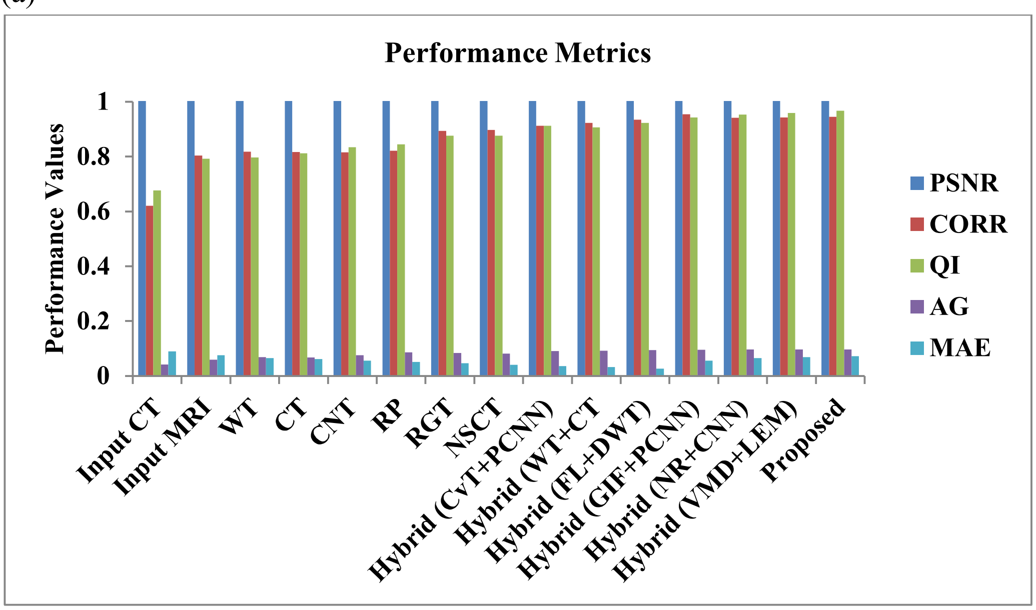
Table 1 Quality metrics obtained for various algorithms for Medical Image Fusion

Metric	**Input CT**	**Input MRI**	**WT**	**CT**	**CNT**	**RP**	**RGT**	**NSCT**	**Hybrid (CVT+ PCNN)**	**Hybrid (WT+ CT)**	**Hybrid (FL + DWT)**	**Hybrid (GIF+ PCNN)**	**Hybrid (NR + CNN)**	**Hybrid (VMD + LEM)**	**Proposed**
SSIM	0.642	0.766	0.836	0.812	0.799	0.874	0.867	0.892	0.939	0.902	0.913	0.922	0.912	0.938	0.967
MI	1.312	1.414	1.426	1.437	1.4586	1.467	1.479	1.756	1.678	1.723	1.8256	1.8765	1.8120	1.8188	1.912
SD	0.422	0.523	0.608	0.576	0.6178	0.746	0.712	0.595	0.789	0.776	0.812	0.836	0.842	0.851	0.922
Entropy	5.612	6.127	1.429	1.312	1.487	1.512	1.523	1.457	1.614	3.452	5.872	6.951	6.962	6.991	7.421
RMSE	0.092	0.081	0.078	0.0589	0.0512	0.1012	0.0892	0.021	0.045	0.0412	0.0322	0.0311	0.0357	0.0398	0.0124
PSNR	12.67	15.39	20.67	18.22	19.88	17.65	21.22	22.74	22.12	23.44	23.12	24.16	24.73	25.22	26.45
CORR	0.621	0.804	0.818	0.8167	0.8156	0.821	0.894	0.897	0.912	0.923	0.934	0.954	0.941	0.943	0.945

QI	0.676	0.792	0.797	0.812	0.834	0.845	0.876	0.876	0.912	0.906	0.923	0.942	0.953	0.959	0.967
AG	0.042	0.059	0.069	0.067	0.075	0.086	0.084	0.081	0.0912	0.0923	0.0945	0.0953	0.0968	0.0968	0.097
MAE	0.089	0.076	0.065	0.061	0.056	0.051	0.046	0.041	0.036	0.032	0.026	0.056	0.065	0.068	0.072



(a)



(b)

Figure 4 Depict graphical illustrations of performance metrics. (a) SSIM, MI, SD, Entropy and PMSE. (b) PSNR, CORR, QI, AG and MAE

5 CONCLUSION

The various medical picture fusion techniques are described in detail and compared in this comparative study. In contrast to other methods now in use both subjective and objective evaluation criteria are improved by the suggested technique's experimental findings, which also show superior processing performance. For MRI and CT brain medical imaging, a number of medical image fusion algorithms have been examined and their performance assessed. It is evident from the data that, generally speaking, the proposed fusion process produces better outcomes than previous techniques. It is the best method for fusing medical CT and MRI images.

REFERENCES

[1] Sahu DK, Parsai MP. Different Image Fusion Techniques – A Critical review. *International Journal of Modern Engineering Research (IJMER)*. 2012;2(5):4298-4301.

[2] Umer Javed, Muhammad M.Riaz, Abdul Ghafoor, Syed Sohaib Ali, Tanveer Ahmed Cheema. MRI and PET image fusion using fuzzy logic and image local features. *Scientific world journal*. 2014;1-8. https://doi.org/10.1155/2014/708075.

[3] Barra V, Boire JY. A general framework for the fusion of anatomical and functional medical images. *NeuroImage.* 2001;13(3):410-424. https://doi.org/10.1006/nimg.2000.0707.

[4] Yang Y, Park DS, Huang S et al. Medical Image Fusion via an effective Wavelet-Based Approach. *Eurasip Journal on Advances in Signal Processing*. 2010;13:1-13. https://doi.org/10.1155/2010/579341.

[5] Ali FE, Saad AA, El-Dokany IM et al. Curvelet fusion of MR and CT images. *Progress In Electro Magnetics Research.* 2008;3:215-224. https://doi.org/10.2528/PIERC08041305.

[6] Jothi C, Elvina N, Vetrivelan P. Medical image fusion using ridgelet transform. *IJCA Proceedings on International Conference on Innovations in Intelligent Instrumentation, Optimization and Electrical Sciences*. 2013.

[7] YangL, Guoa BL, Ni W. Multimodality medical image fusion based on multiscale geometric analysis of contourlet transform. *Neurocomputing*. 2008;72(3):203-211. https://doi.org/10.1016/j.neucom.2008.02.025.

[8] Jun Xu, Lei Yang, Dapeng Wu. Ripplet: A new transform for image processing. *Journal of Visual Communication and Image Representation*. 2010;21(7):627-639. https://doi.org/10.1016/j.jvcir.2010.04.002.

[9] Jyoti Agarwal, Sarabjeet Singh Bedi. Implementation of hybrid image fusion technique for feature enhancement in medical diagnosis. *Human-centric Computing and Information Sciences*.

2015;5(3):1-17. https://doi.org/10.1186/s13673-014-0020-z.

[10] N. Myna AN, Prakash J. Fusion of CT and MRI Images Based on Fuzzy Logic and Discrete Wavelet Transform. Int. J. of Comp. Science and Information Technologies. 2015;6(5):4512-4519.

[11] Rajalingam B, Priya R. Hybrid Multimodality Medical Image Fusion based on Guided Image Filter with Pulse Coupled Neural Network. *International Journal of Scientific Research in Science, Engineering and Technology (IJSRSET)*. 2018;5(3):86-100.

[12] Gomathi PS, Kalaavathi B. Multimodal Medical Image Fusion in Non-Subsampled Contourlet Transform Domain. *Scientific Research Publishing, Circuits and Systems*. 2016;7:1598-1610.

[13] Cheng S, He J, Lv Z. Medical image of PET/CT Weighted Fusion Based on Wavelet Transform. *2nd International Conference on Bioinformatics and Biomedical Engineering*. 2008;8(3):2523–2525. https://doi.org/10.1109/ICBBE.2008.964.

[14] Bhutto JA, Tian L, Du Q, Sun Z, Yu L, Tahir MF. CT and MRI Medical Image Fusion Using Noise-Removal and Contrast Enhancement Scheme with Convolutional Neural Network. *Entropy*. 2022;24(3):393. https://doi.org/10.3390/e24030393.

[15] Polinati S, Bavirisetti DP, Rajesh KNVPS, Naik GR, Dhuli R. The Fusion of MRI and CT Medical Images Using Variational Mode Decomposition. *Applied Sciences*. 2021; 11(22):10975. https://doi.org/10.3390/app112210975.

[16] Narayanan K, Thangaraj P, Rajalakshmi N. Fusion of Computed Tomography and Magnetic Resonance Brain Tumor Images Based on Weighted Poison Solver. *NeuroQuantology*. 2022;20(6);7835-7850. https://doi.org/10.14704/nq.2022.20.6.NQ22781.