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Hybrid Medical Image Fusion based on Fast Filtering and Wavelet Analysis

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***Abstract*—Within medical imaging, there are various modalities of medical images like CT, X-rays, MRI and other modalities that provide information about a human body in different ways. Each modality has distinctive characteristics that provide various sources of information. Therefore, there are some problems like image comparison such as CT/PET, CT /MRI, and MRI/ PET were usually meet by the clinical treatment and diagnosis. Hence the need to combine the different images' information and this process is known as 'medical image fusion'. In this paper, two techniques for the 'medical image fusion' are introduced. The first proposed fusion technique is the combination of the fast filtering with the discrete wavelet transform 'DWT' methods for overcoming the low spatial resolution fused image provided by DWT and preserve the source images' salient features. Where we used the fast filtering method procedures for combining the corresponding 'low-frequency coefficients' to maintain the 'salient features' of the initial images, and the maximum rule with the high-frequency coefficients which lead getting better the resultant image contrast. The second proposed technique is the combination of fast filtering with stationary wavelet transform (SWT) methods, where 'SWT' has the shift-invariant property which enables to overcome the shift-variance DWT's drawback. The performance of the fused output is tested and compared with five of the common fusion methods like the Gradient pyramid, Contrast pyramid, DWT, Fast Filtering, and SWT techniques, using performance parameters: E, SNR, SD, and PSNR.**

Keywords—'image fusion', 'fast filtering', 'wavelet transform'

I. INTRODUCTION

Image fusion can be defined as combining more than one image with different characteristics with the aim to integrate matched information exist in these images into an informative one image [1]. In medical imaging, there are various modalities of medical images like: MRI 'Magnetic Resonance Imaging', X-ray, CT 'Computed Tomography', and other modalities that can provide information about a human body in different ways. Each one of these modalities has its own characteristics that provide various sources of information. Hence, there are some problems like image comparison such as MRI /PET, CT /MRI, MRI/PET, and CT/PET were usually faced by clinical treatment and diagnosis. Hence the necessity to gather the different images' information in one image in order to improve image quality. Registering and integrating some images from different modalities is named 'medical image fusion', the process that enhances the image quality for enhancing the treatment and diagnosis [2].

Fusion approach, when applied to medical images, includes a vast collection of mechanisms that focus on clinical purposes obtained through the human body, cells, and organs images [3]. Image fusion works on reducing the amount of data and time for transmissions, removing artifacts, and Improving reliability and capability through complementary information [4]. Image fusion has three basic processes: i. registration of the initial images; ii. fusion approach; iii. image fusion performance evaluation [5]. The registration process means correct the spatial misalignment between some images by determining the correspondence between all points in two images of the same object [6]. The initial images obtained from different sensors should be accurately registered first then the fusion process can be applied to the registered source images which yield to a perfect image fusion [5] [6]. Generally, there are two domains of the fusion methods the first domain is called the spatial domain and another one is the transform domain. The spatial domain methods deal directly the value of pixels to obtain the desired results [8]. While in the transform methods the images are first transformed into another domain like temporal domain, then fusion procedures are all applied and then applying the inverse transform to obtain the desired image [9].

In this paper two 'medical image fusion' techniques will be suggested to improve the image quality which provides more beneficial details for 'clinical diagnosis'. The first proposed technique builds on combining the 'discrete wavelet transform' with the fast filtering technique. Where in the traditional 'DWT' based fusion method, the 'average' fusion rule commonly utilized to merge the corresponding 'low-frequency coefficients' or the 'approximation' coefficients which contain most of the image 'information' and that leads to providing a less spatial resolution fused images and failed to preserve the source images' salient features [10]. In order to overcome these drawbacks, we used the fast filtering method procedures for combining the corresponding 'low-frequency coefficients' to maintain the 'salient features' of the initial images, and the maximum rule with the high-frequency coefficients which lead getting better the resultant image contrast. The second proposed technique is the combination of fast filtering with stationary wavelet transform 'SWT' methods, where 'SWT' has the shift-invariant property which enables us to overcome the shift-variance DWT's drawback [3]. Part V in this paper presents the evaluation process that checks the performance of the fused output using the proposed algorithms that has been examined and compared with five of the other image fusion methods like the Contrast Pyramid, Gradient Pyramid, DWT, SWT, and the Fast Filtering techniques, using performance metrics: 'PSNR', 'SD', 'SNR', and 'E'. It will be illustrated from this part in the paper, the extent to which the suggested techniques outweigh the other techniques and improved significantly to the contrast of the resulting image while maintaining the details and salient features of the source images. The suggested techniques have been implemented on 2 medical image datasets. The first dataset consists of eight pairs of 'medical images' of (PET and SPECT) modalities. The second dataset consists of eight pairs of 'medical images' of (CT and MRI). This implementation will be illustrated in part VI.

II. RELATED WORK

Within the image fusion prospect, massive researches have been performed in both the spatial and the temporal domain. Pyramid and wavelet transform techniques are vastly used transforms for image fusion [11]. The wavelet transform fusion method has been proposed in [12] and [13] for medical applications. Within the wavelet scheme, firstly the DWT is performed on the initial images for getting the wavelet decomposition at the desired level, and then fuse each decomposition level using the combination rules, and then obtain the resulting image through performing IDWT on the fused decomposed level [14]. In the DWT fusion method, fusion can be performed at different levels which leads to providing a good quality fused image [15]. However, DWT fusion-based methods provide a less spatial resolution fused images and failed to preserve the source images' salient features [10]. DWT method has been combined with many other fusion techniques like the PCA in [16]. The proposed hybrid method includes decomposition using DWT. Then, PCA is used to merge the DWT coefficients which enhance the resolution. Another type of wavelet transform is the stationary wavelet transform that proposed in [17]. The combination of the SWT and 'Non-Sub sampled Contourlet Transform' proposed in [18]. The main advantage of this introduced method is to gather advantage of the advantages of both methods in the final image. Stationary wavelet method based fusion can preserve more information on source image but on the other hand, SWT is not efficient for clinical analysis, it has a problem of the spatial resolution [19]. One of the most extremely used types of the 'pyramid transform' is the contrast pyramid in [20] and the gradient pyramid in [21]. Pyramid based image fusion methods maintain the good visual information of an image for multi-focus images, however, all pyramid decomposition- based fusion techniques provide more or less similar output, in addition to the decomposition levels number affects fused image [20]. For the spatial domain image fusion methods, the PCA method is one of the most widely used methods, which has been proposed in [22]. Various filters of 'edge-preserving' type have too been efficiently accomplished in the image fusion field like the cross bilateral filter [23], the combination of the bilateral filter and the directional filters in [24]. Another 'edge- preserving' filter has been proposed in [25]. Spatial domain image fusion methods are very simple for implementation and produce highly focus resulted images with more spatial features, while the main spatial fusion methods drawbacks of are blurring effect that may occur in the resulted image and the spectral degradation. Otherwise, fusion methods under the transform domain can improve the spectral information in the fused image by enhancing image characteristics of the contrast. But these methods are complex and provide lower spatial resolution [26]. The major objectives of the techniques suggested in this paper are to integrate the transformation and spatial domain advantages and overcome the drawbacks of both, which will be illustrated in parts IV, V, and I.

III. IMAGE FUSION TECHNIQUES

In this part, three image fusion techniques will be discussed: Wavelet transform, and Stationary Wavelet Transform methods from the transform domain methods. In addition, the Fast Filtering (FF) method from the spatial domain fusion methods.

A. Fast Filtering Method (FF)

The Fast filtering fusion method [27] is a spatial domain method that uses the discrete gradient magnitude to detect contrast and image sharpness, and it is refined with a fast morphological filtering operation. Moreover, a structure-preserving filter is utilized to obtain a desired weight map in the spatial domain. The Fast filtering fusion method is described in five procedures:

First, compute the given images' gradient magnitude, to measure the saliency information where the gradient image contains rich texture and boundary information of image structure. Assuming $I^{(1)}$ and $I^{(2)}$ are two given images where the superscript denotes the image index. where the superscript denotes the image index. The gradient magnitude equation can be expressed as follows:

$$M^r = \left|\frac{\partial I^{(r)}}{\partial x}\right| + \left|\frac{\partial I^{(r)}}{\partial y}\right| \qquad , r \in \{1,2\} \tag{1}$$

Second, perform the fast morphological closing operation on image gradient magnitude to refine the gradient map where there are some gaps and holes that may be caused by the salient structure detection in a homogeneous region. The morphological closing operation can be presented as:

$$g^r = \left(M^r \oplus S \right) \ominus S \tag{2}$$

Where the morphological 'dilation' operation is represented by $\oplus$ and $\ominus$ represents the morphological 'erosion' operation, and S represents a structuring element object.

Third, obtain the weight map from the source images' gradient magnitude where the gradient magnitude is high if the pixel has a vital role in representing the scene, while it is low if the pixel represents unimportant information. By comparing the saliency map, the weight map w is obtained by:

$$W = \text{step}\left[g^1, g^2 \right] \tag{3}$$

Where, step $[g^{(1)}, g^{(2)}]$ returns one for the current element of w if the corresponding value of $g^{(1)}$ is higher than $g^{(2)}$, otherwise it returns zero.

Then, perform the structure-preserving filter:

$$\widehat{w}_p = \mu_k + \frac{\sigma_k^2}{\sigma_k^2+\lambda}\left(w_p - \mu_k \right), p \in \Omega_k \tag{4}$$

Where, W_p denotes the input of the linear filter, μ_k denotes the mean of sliding 'm×n' window Ω_k centered at the pixel k by calculating the mean of all pixel values within the sliding window of the image Ω_k. This equation (4) checks that pixels with variance larger than λ are preserved, whereas regions with variance smaller than λ are smoothed. If the intensity belongs to a structure with a very large variance σ_k^2 changes sharply within Ω_k, then the structure can be preserved, i.e., if $\sigma_k^2 \gg \lambda$, then we have $\frac{\sigma_k^2}{\sigma_k^2+\lambda} \approx 1$, and $\widehat{w}_p \approx w_p$. If the intensity is not changed a lot in a noise region with a much smaller variance σ_k^2 than structures, then the linear mean filter is used to smooth these regions, i.e., if $\sigma_k^2 \ll \lambda$, then we have $\widehat{w}_p \approx \mu_k$ and $\frac{\sigma_k^2}{\sigma_k^2+\lambda} \approx 0$. In this filter, the pixel intensity is preserved while the pixel belongs to the main structure. The λ is utilized as a regularization parameter penalizing large variance.

Finally, obtain the fused image by using a weighted-sum fusion rule.

$$F = \widehat{w} I^{(1)} + (1 - \widehat{w}) I^{(2)} \tag{5}$$

B. *Discrete Wavelet Transform 'DWT'*

'DWT' is a process of decomposition of an image and provides a non-redundant image representation [28]. Wavelet transform gives wanted resolution in the 'time' and 'frequency' domains together, whilst 'Fourier' transform provides good information only in the frequency domain [29]. Wavelets are given via using two functions [14]; 'scaling' and 'wavelet' or "mother wavelet" functions. The transformation is represented by:

$$f(x) = \sum_k C_{JK} \phi_{JK} \sum_{j=1}^{J} \sum_K d_{jk} \psi_{jk} \tag{6}$$

In the equation, C_{JK} and d_{jk} denote the 'scaling' and the 'wavelet' coefficients respectively at a given scale J. The initial part in eq. (6) provides the 'approximation' coefficient of the image, while the other part produces the 'detailed' information. DWT performing approach can be described as a group of filters, 'low pass' filter, and 'high pass' filter. The 'scaling' and 'wavelet' filters are one-dimensional, so with a two- dimensional image one level of decomposition provides four different 'frequency bands' which are: LH (involves the horizontal details), HL (involves the vertical details), HH (involves the diagonal details) bands at various scales and the LL (involves the approximation image) band at the coarsest scale. Higher absolute values of the high bands wavelet coefficients mean salient features like edges or lines in the image [30]. The DWT fusion method can be derived in the following steps [31]:

a) The given initial images are decomposed using DWT.

b) The DWT coefficients, 'approximation' and 'detailed' coefficients, of given initial images are fused through some of the rules (commonly, the 'average' and the 'maximum' rules are utilized).

c) Get the resulting image via computing the 'inverse discrete wavelet transforms' (IDWT).

Figure 1 depicts the DWT fusion method.

C. *Stationary Wavelet Transform 'SWT'*

'SWT' is one of the 'wavelet' family but the SWT differs from DWT in it doesn't include the down-sampling step of the 'DWT' method. Then, the four images generated from decomposition are at the same initial image size and at the half resolution of the initial image. 'SWT' has the shift invariant property which enables to overcome the shift-variance DWT's drawback [3].

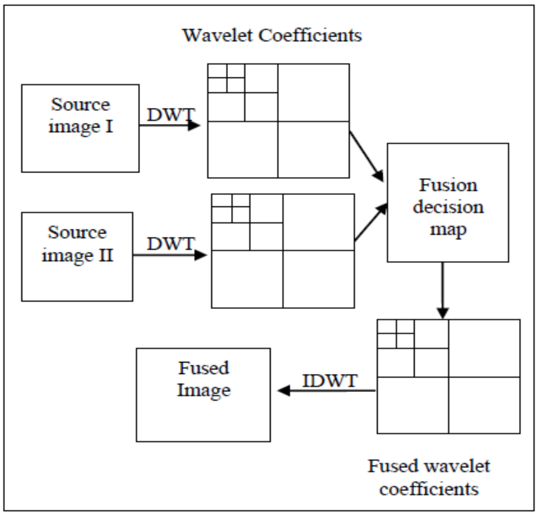


Fig. 1. DWT image fusion.

The SWT algorithm is applied firstly on rows and then to columns, to generate four images. One of them is approximation coefficients (LL), and the other three of them are the detailed coefficients (LH, HL, and HH). These four sub-images are at the same initial image size but their resolution is half of the source image [32].

The 'SWT' fusion method can be derived in the following steps [30]:

a) Implement the 'SWT' on each of the initial images.

b) Determine a 'fusion decision map' through a set of rules. Then, the SWT coefficients of the given initial images are fused through the 'fusion decision map'

c) Get the resulting image via computing the 'inverse stationary wavelet transform' (ISWT) to the fused coefficients.

IV. PROPOSED 'IMAGE FUSION' TECHNIQUES

Within this paper, the first proposed technique is a hybrid technique through the combination of the 'discrete wavelet transform' with the 'fast filtering' methods. The wavelet fusion based method provides a less spatial resolution fused images and failed to preserve the source images' salient features. In order to overcome these drawbacks, the fast filtering method procedures are utilized to merge the corresponding 'low-frequency coefficients' to maintain the 'salient features' of the initial images, and the maximum rule with the high-frequency coefficients which lead to getting better the resultant image contrast. The first proposed 'image fusion' method can be described by the next steps:

Step 1: Get the registered source images.
Step 2: Implement the 'DWT' on the registered source images.
Step 3: Get the approximation and detail coefficients for both images.
Step 4: For the approximation coefficients:

- ✓ Get the gradient magnitude.
- ✓ Perform the morphological closing operation.
- ✓ Obtain the weight map from approximation images' gradient magnitude and then filtered by the structure-preserving filter.
- ✓ Fuse the corresponding approximation coefficients by using a weighed-sum rule.

Step 5: For the detail coefficients:

- ✓ Fuse the corresponding detail coefficients by the Maximum rule.

Step 6: Apply the 'Inverse Discrete Wavelet Transform' on the merged coefficients and get the resulting image.

The second proposed 'image fusion' technique depends on the combination of the 'stationary wavelet transform' and the 'fast filtering' methods. 'SWT' has the shift invariant property which enables to overcome the shift-variance DWT's drawback. The second proposed fusion technique is illustrated via the next steps:

Step 1: Get the registered source images.
Step 2: Apply the SWT to the registered source images.
Step 3: Get the approximation and detail coefficients for both images.
Step 4: For the approximation coefficients:

- Get the gradient magnitude.
- Perform the morphological closing operation.
- Obtain the weight map from approximation images' gradient magnitude and then filtered by the structure-preserving filter.
- Combine the corresponding approximation coefficients by applying a weighed-sum rule.

Step 5: For the detail coefficients:

- Fuse the corresponding detail coefficients by the Maximum rule.

Step 6: Apply the 'Inverse Stationary Wavelet Transform' on the merged coefficients and get the resulting image.

Fig. 2 depicts the proposed algorithms scheme.

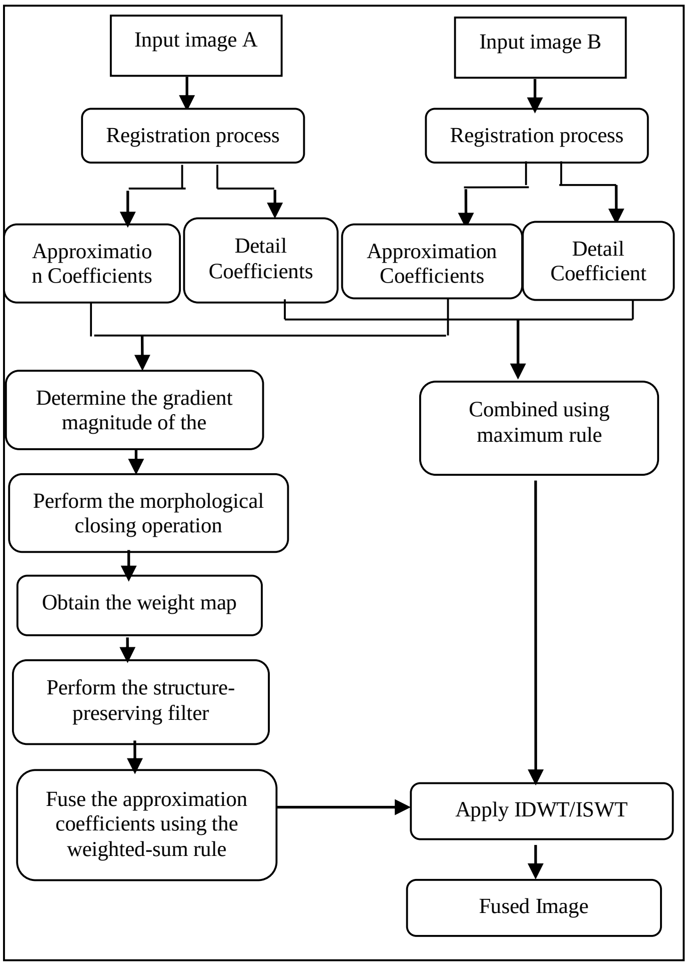


Fig. 2. The Proposed Techniques Block Diagram.

V. PERFORMANCE EVALUATION

The evaluation step checks the most important image fusion process requirements, some general requirements that it should preserve all the source images valid and original information, in addition, it should be reliable, robust and, it should not output any artifacts or inconsistencies [33].

To evaluate the quality of the resulting images, standards performance parameters have been used such as PSNR 'Peak Signal to Noise Ratio', SD 'Standard Deviation', E 'Entropy', and SNR 'Signal to Noise Ratio' [34] [35].

TABLE I. THE PERFORMANCE PARAMETERS: 'PSNR', 'SD', 'SNR', AND 'E'.

Performance metrics	**properties**	
	Description	***Equation***
'Entropy'	The entropy measure information included in the resulting image. A high 'E' value for fused image indicates more information content in it.	$E = -\sum_{n=0}^{L-1} P_n Log P_n$
'Standard Deviation'	'SD' measure the contrast of an image. A high 'SD' value marks a high contrast in the resulting image.	$SD = \sqrt{\frac{1}{mn}\sum_{m=0}^{L-1}\sum_{n=0}^{L-1} f(m,n) - \mu}$
'Signal to Noise Ratio'	'SNR' Measures the resemblance between the 'fused' and the initial images. A high 'SNR' value, marks that the resulting image and 'source' images are similar.	$SNR = 10\,Log_{10}\frac{\sum_{i=1}^{m}\sum_{j=1}^{n}(I_r(i,j))^2}{\sum_{i=1}^{m}\sum_{j=1}^{n}(I_r(i,j) - I_f(i,j))^2}$
'Peak Signal to Noise Ratio'	Used to represents the 'fused' and 'source' images relationship. A high 'PSNR' rate means the resulting image and 'source' images are similar.	$PSNR = 20\,Log_{10}\frac{(255)^2}{\frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}(I_r(i,j) - I_f(i,j))^2}$

Table I lists performance parameters: PSNR 'Peak Signal to Noise Ratio', SD 'Standard Deviation', E 'Entropy', and SNR 'Signal to Noise Ratio', that have been used to evaluate the quality of the resulting images.

VI. RESULTS AND DISCUSSIONS

The proposed 'image fusion' techniques have been implemented on 2 medical image datasets of size 256 × 256. These datasets are from this website [36].

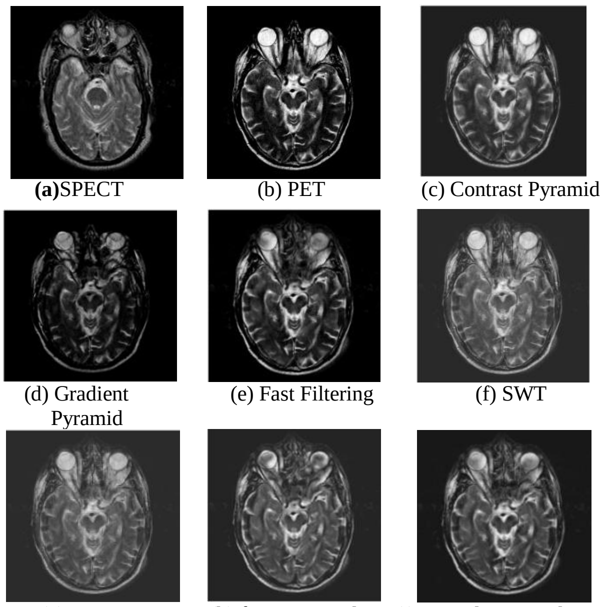
The first dataset consists of eight pairs of 'medical images' of (PET and SPECT) modalities. The Positron Emission Tomography (PET) modality provides functional imaging capability and high sensitivity, but it provides a limited resolution, in addition to motion artifacts. While the SPECT

'Single Photon Emission Computed Tomography' modality has a higher penetration depth and high sensitivity, and it used to confirm (Alzheimer, Parkinson) diseases, but it has blurring effects [26].

The second dataset consists of eight pairs of 'medical images' of (CT and MRI). The Computed Tomography (CT) modality reflects the bone tissues anatomical structure clearly, but it has a limited tissue characterization and a limited sensitivity. While the Magnetic Resonance Imaging (MRI) modality provides high accuracy images with high contrast detail of soft tissue in the brain and anatomic structures, but it relatively sensitive to the movement of patients and organs that involve movement [26].

We have started with the initial 'source' images registration to ensure that there is no misalignment between them and to obtain perfect image fusion.

MATLAB 2015R is used as a platform to execute the experiment. The performance of the fused output using the proposed algorithms has been examined and compared with five of the other image fusion techniques like the Contrast Pyramid, Gradient Pyramid, DWT, SWT, and the Fast Filtering techniques, using performance metrics: 'PSNR', 'SD', 'SNR', and 'E'.



(a)SPECT (b) PET (c) Contrast Pyramid
(d) Gradient Pyramid (e) Fast Filtering (f) SWT
(g) DWT (h) first proposed Method (DWT+FF) (i) second proposed Method (SWT+FF)

Fig. 3. Comparison of fused output with the input PET and SPECT images for the normal axial brain (one sample of the first medical dataset (PET and SPECT)).

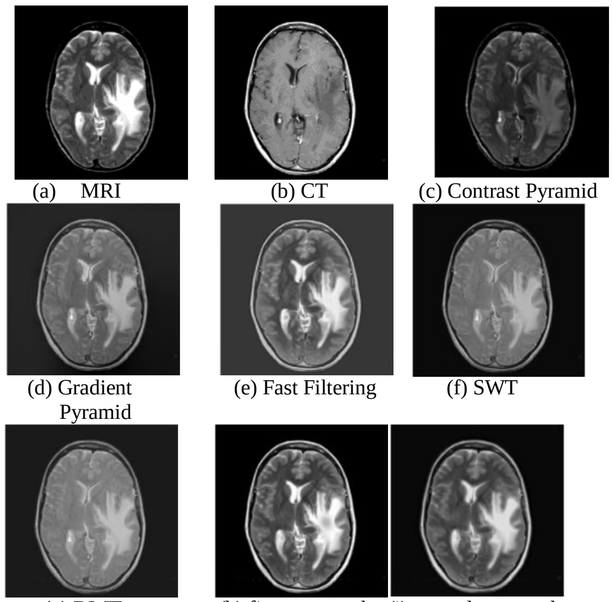
As shown in Fig. 3, it can be noticed that the two images (h), (i) resultant by the two proposed techniques are clearer at the visual level, in addition, they have much 'details' and 'texture' information; compared to the other images.

Table II lists a comparison of performance metrics which are 'E', 'SNR', 'SD', and 'PSNR', using Contrast pyramid, Gradient pyramid, DWT, SWT, FF, and the two proposed 'image fusion' techniques. The results in the table are the average of quality metrics results values for 8 'fused' images by implementing the first dataset.

Confirmation of the previous analysis of Fig. 3, from Fig. 4, it is illustrated that the two images (h), (i) resultant by the two proposed techniques have much 'details' and 'texture' information; compared to the other images. Also, they are clearer at the visual level.

TABLE II. THE AVERAGE OF QUALITY METRICS RESULTS VALUES FOR 8 'FUSED' IMAGES BY USING THE FIRST MEDICAL DATASET.

Metric / *Method*	*Entropy*	*SD*	*SNR*	*PSNR*
Contrast Pyramid	1.00	22.75	1.07	-27.13
Gradient Pyramid	0.95	21.65	1.15	-27.21
Fast Filtering	1.21	22.76	6.35	-23.97
DWT	1.16	21.03	7.90	-22.42
SWT	1.70	21.34	7.99	-22.55
First proposed algorithm DWT and FF	**1.885**	**24.79**	**8.03**	**-22.29**
Second proposed algorithm SWT and FF	**1.880**	**24.81**	7.48	-22.84



(a) MRI (b) CT (c) Contrast Pyramid
(d) Gradient Pyramid (e) Fast Filtering (f) SWT
(g) DWT (h) first proposed Method (DWT+FF) (i) second proposed Method (SWT+FF)

Fig. 4. Comparison of fused output with the input CT and MRI images for the normal axial brain (one sample of the second medical dataset (CT and MRI)).

Table III lists a comparison of performance metrics which are 'E', 'SNR', 'SD', and 'PSNR', using Contrast pyramid, Gradient pyramid, DWT, SWT, FF, and the two proposed 'image fusion' techniques. The results in the table are the average of quality metrics results values for 8 'fused' images by implementing the second dataset.

As from Tables II and III, the two proposed 'image fusion' techniques resulted in a high spatial and spectral fused image, without any color and texture distortions. Tables II and III, indicate that the 'entropy' and the 'standard deviation' of the images (h), (i) in Fig. 3 & Fig. 4 resultant by the two proposed techniques are the highest, which demonstrates that the 'fused' images by implementing the two proposed techniques have more details than the other fused images and having higher sharpness and contrast, that is corresponding to the visual evaluation results. As well as the 'SNR' and 'PSNR' values of the image (h) in Fig. 3 and Fig. 4, resultant by the first proposed algorithm (DWT and FF) is the highest, which proves that the first proposed algorithm keeps the resemblance between the resulting and the 'source' images.

TABLE III. THE AVERAGE OF QUALITY METRICS RESULTS VALUES FOR 8 'FUSED' IMAGES BY USING THE SECOND MEDICAL DATASET

Metric / *Method*	*Entropy*	*SD*	*SNR*	*PSNR*
Contrast Pyramid	0.87	59.76	3.01	-35.03
Gradient Pyramid	0.72	53.01	5.13	-32.54
Fast Filtering	0.77	66.11	6.91	-31.12
DWT	0.82	53.25	7.39	-30.64
SWT	1.25	53.77	7.53	-30.51
First proposed algorithm DWT and FF	**1.54**	**67.10**	**8.46**	**-29.58**
Second proposed algorithm SWT and FF	**1.48**	**67.00**	6.47	-31.57

VII. CONCLUSION

Within this paper, two 'medical image fusion' techniques have been suggested to improve the image quality which provides more beneficial details for 'clinical diagnosis'. The first proposed technique builds on combining the 'discrete wavelet transform' with the fast filtering technique. The wavelet fusion-based method provides a less spatial resolution fused images and failed to preserve the source images' salient features. In order to overcome these drawbacks, we used the fast filtering method procedures for combining the corresponding 'low-frequency coefficients' to maintain the 'salient features' of the initial images, and the maximum rule with the high-frequency coefficients which lead getting better the resultant image contrast. The second proposed technique is the combination of fast filtering with stationary wavelet transform (SWT) methods, where 'SWT' has the shift-invariant property which enables to overcome the shift-variance DWT's drawback. The performance about the fused output using the proposed algorithms has been examined and compared with five of the other image fusion techniques like the Contrast Pyramid, Gradient Pyramid, DWT, SWT, and the Fast Filtering techniques, using performance metrics: 'PSNR', 'SD', 'SNR', and 'E'. Through the experimental results, the first proposed hybrid image fusion technique builds on the combination between the 'DWT' and the fast filtering method is superior to other methods and it greatly improved spatial resolution and get better the contrast of the resulting image while maintaining the details and salient features of the source images. Where, the 'standard deviation' and the 'entropy' of the resulting images by this proposed algorithm are the highest as well as the SNR and PSNR values as compared to the images resultant by the traditional 'DWT', 'SWT', Contrast pyramid, Gradient pyramid, and the fast filtering methods. The second suggested hybrid technique builds on the combination between the 'SWT' and the fast filtering method extremely improved the contrast and the entropy of the resultant fused image while didn't enhance the PSNR and SNR values. So, that first suggested technique (builds on the combination between the DWT and the fast filtering) can be considered superior to the second suggested technique (that builds on the combination between the SWT and the fast filtering) method in that it keeps the resemblance between the fused image and the input images.

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