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PERFORMANCE ENHANCEMENT OF MEDICAL IMAGE FUSION BASED ON DWT AND SHARPENING WIENER FILTER

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ABSTRACT

The fusion of multimodal medical images plays an important role in data integration and improving image quality. It has a fundamental role in the accuracy of medical analysis and diagnosis. Despite the recent technological development, medical images may be exposed to blur and noise from various sources. This will affect the accuracy of the medical analysis. Therefore, de-blurring or noise removal from medical images is essential in this field. Discrete Wavelet Transform, DWT, is generally utilized in image fusion spatially in the fusion of the multimodal images. It produces a good image representation. The drawback of DWT-based image fusion is the blur presented in the fused image due to the limited directionality of wavelets. To solve this problem, Sharpening Wiener Filter and DWT-based image fusion for multimodal medical images are proposed. The proposed fusion method is evaluated using some of focus operators that were used to measure the amount of focus in the test images. The results showed that the proposed fusion gives good values of focus operators compared with the values of focus operators of image fusion techniques that are based on wavelet domain.

KEYWORDS

Image fusion, Multimodal medical images, SWT, PCA, DT-CWT, DWT, Focus operators.

1. INTRODUCTION

Medical imaging techniques are processes for obtaining images of the human body or parts of it for diagnostic, therapeutic or research purposes. The most popular types of medical imaging are Computed Tomography (CT) and Magnetic Resonance Imaging (MRI). The CT is characterized by very high clarity of the image and shows the details of the bones in an extremely accurate manner, unlike the MRI, which visualizes soft tissues with high accuracy. They are used in the diagnosis of many diseases, especially diseases of the nervous system and the brain [1], [30]. The process of image fusion of multimodal medical images can be applied to obtain a fused image which contains complementary information about these images [2]. The image resulting from the fusion of multimodal medical images plays an important role in the diagnosis and treatment process. Image quality enhancement aims to produce a better image than the original image with some standard. The image from which noise is removed is better than the image that contains noise [23]-[24]. Therefore, the fused image should contain more details, information and quality [3]. Image fusion can be performed in spatial domain (such as Intensity Hue Saturation and Principal Component Analysis) or/and in frequency domain (such as Discrete Wavelet Transform, pyramid and contour) [31]. The fused image in spatial domain has no spectral information and contains spatial distortions which may lead to wrong diagnosis. Therefore, the fusion operation in the spatial domain is not suitable for multimodal medical images. The spatial information in the medical images should be focused and clear. Multimodal medical image fusion in frequency domain achieves these requirements. Generally, the operation of image fusion in frequency domain can be summarized in the following steps: 1) transforming the input images into the wavelet coefficients. 2) Performing a fusion rule on the coefficients. 3) Inversing the transform to obtain the fused image. The fused image should not contain any distortion and has more useful information than the original images [4]. The nature of the medical images is blurry and low contrast due to the imaging system, motion of the patient or means of transmission. This will affect the image quality and limit the visibility of fine details. Blurring weakens the strength of the edges in the image, which prevents small details from appearing and causes a loss of sharpness (focus) in the density of edges. In addition, the resultant image using image fusion in wavelet domain suffers from blur due to the limited directionality of the wavelet.

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To overcome the blur problem, the multimodal medical image fusion technique is proposed based on Discrete Wavelet Transform (DWT) and Sharpening Wiener Filter (SWF). The SWF contains two filters; one is the sharpening filter and the other is the Wiener filter. The multimodal medical images that contain some blur are enhanced using the SWF. The fusion process is achieved in wavelet domain using DWT. The DWT decomposes the filtered images producing low-frequency sub-bands and high-frequency sub-bands. The average rule is used to fuse the low-frequency sub-bands and the maximum rule is used to fuse the high-frequency sub-bands. The fused image is obtained by performing the inverse of the wavelet domain [21].

In the medical field, image clarity and quality play an important role in the diagnosis and treatment processes. Therefore, the importance of the proposed method is to clarify the quality of the image by improving the focus of the image, which facilitates other operations on medical images, such as segmentation and classification. The main goal of the proposed algorithm is to produce a fused image that involves high quality and more information with the advantage of focusing on the edges of the object.

The main contribution to this work is to propose a new filter called Sharpening Wiener Filter which consists of combining two filters; Wiener filter and sharpening filter. This filter works to highlight the edges and details of a blurry image. The combined image with clear details is obtained by using the sharpening Wiener filter and Discrete Wavelet Transform-based image fusion.

The rest of this paper is organized as follows: in Section 2, the related works to this work are discussed. Section 3 explains the methodology and proposed fusion method. In Section 4, the focus operators are explained. Sections 5 and 6 explain the results and conclusions, respectively.

2. RELATED WORKS

Generally, image fusion techniques are divided into three levels of fusion; decision-level fusion, feature-level fusion and pixel- or image- level fusion which is a low level of fusion. Although pixel-level fusion techniques have a high computational complexity compared to the other two-level techniques, it is characterized by high accuracy and no data loss occurs during it [5]. This makes pixel-level fusion methods more appropriate for application in multimodal medical image analysis. The DWT-based image fusion technique and other fusion techniques that work in the DWT domain are pixel-level fusion techniques.

The DWT is the most widely used in the image fusion process, because it produces spatial and spectral information in the fused image better than other fusion methods, such as the pyramid transform, Intensity Hue Saturation and Principal Component Analysis-based image fusion approaches. The most recent survey of medical image fusion can be found in [6]. Multimodal images are decomposed using DWT to four sub-band images (LL, LH, HL and HH, where L is Low sub-band and H is High sub-band) at each resolution level. Fusion rules are performed on these sub-bands. The most popular fusion rules are average and maximum. The final fused image is obtained by applying the inverse of DWT [7]-[8]. Figure 1 illustrates the general scheme of DWT-based image fusion.

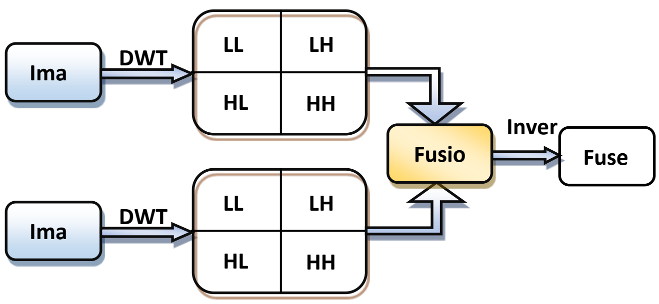

Figure 1. The general scheme of DWT-based image fusion.

The DWT-based image fusion has the main weaknesses which are the blur showing at the edges and surface areas as well as the absence of shift invariance [9]. To solve this problem, stationary wavelet transform (SWT) has been proposed which provides shift invariance. It cancels the down-sampling step which is presented in DWT and replaces up-sampling step by adding zeros between the wavelet coefficients [10]. The SWT- and DWT-based image fusion do not produce the directional information [11], [21], but Dual Tree Complex Wavelet Transform (DT-CWT) presents two characteristics; good directionality and shift invariance [12].

Principal Component Analysis (PCA) is used in many fields as a dimensionality reduction technique. Image fusion based on PCA produces an image with high spatial quality and low spectral quality. DWT-based image fusion produces an image with low spatial quality and high spectral quality. In order to take advantages of the two methods, PCA and DWT were combined to fuse the images. In PCA-DWT-based image fusion, the medical images are decomposed into sub-bands using DWT. The principal components (PC's) are evaluated and averaged. This average will constitute weights for the rule of fusion [13]. This fusion technique joins the upside of wavelet change into PCA combination as eigen estimations of multi-scale representations.

To capture an image with high visual quality and clear textures, the authors in [20] suggested using the convolution neural network for the purpose of creating a weight map. Meanwhile, the contrast pyramid is used for the purpose of analyzing the original image. The combined image is obtained based on the map of weights and on spatial frequency bands. In [22], the authors presented optimization fusion technique which contains three procedures. First, homomorphic filter is used to enhance the contrast quality of the original images. Second, DWT-based image fusion is applied to the result of the first step and third, to improve the efficiency of the fusion process, the optimization algorithm is applied using world cup and smell optimization algorithms. Finally, the inverse of the optimized DWT is applied to obtain the fused image.

The authors in [25] proposed a fusion method for multi-source medical images in the domain of the Non-subsampled Contourlet transform which converts the image into high- and low-pass images. To enhance the detailed features and preserve the original information of the medical images, the authors suggested using two fusion rules which are phase congruency and local Laplacian energy to fuse the images. The fused image is obtained by the inverse of the Non-subsampled Contourlet domain.

In [29], the authors proposed a fusion method to fuse three types of medical images which are MRI, CT and PET to obtain a single image which contains more information than the original images. The process of fusion is achieved using Simplified Pulse Coupled Neural Network in the Saturation-Hue-Value and Non-subsampled Shearlet Transformation domains using different fusion rules.

All these related works produced good results in the image fusion field for medical images; however, they didn't focus on sharpening (focusing) the blurry images.

3. Methodology and Proposed Fusion Method

3.1 Image Degradation

Figure 2 shows the model of the degradation and restoration system. Image restoration aims to reconstruct or estimate the original image which has been exposed to noise and blur. In order to obtain the enhanced image I_{ij}, two conditions must be met: 1) the original image Io_{ij} is uncorrelated with the noise η_{ij}. 2) The degradation function is known. The following equations represent the degradation and restoration system [14].

$$g_{ij} = Io_{ij} \otimes h_{ij} + \eta_{ij} \tag{1}$$

$$I_{ij} = f_{ij} \cdot g_{ij} \tag{2}$$

where h_{ij} and f_{ij} are the degradation function and restoration filter, respectively. g_{ij} is the degraded (blurred or noisy) image. The symbol '⊗' is the convolution operation and '.' is the de-convolution operation.

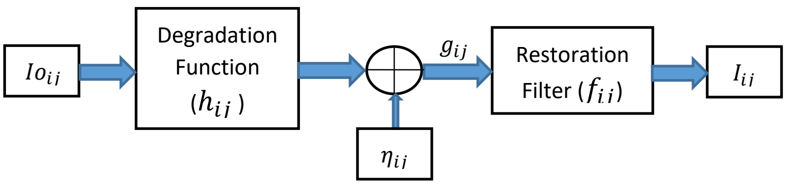

Figure 2. Degradation and restoration system.

Generally speaking, the convolution process is a multiplication operation between the pixels of the original image and the pixels of degradation kernel or filter and the noise signals are added to the results of the convolution process producing a degraded image. To estimate the original image, the de-convolution process is applied, which is a multiplication operation between the degraded image and the restoration filter such as Wiener filter [28].

3.2 Sharpening Wiener Filter

The Sharpening Wiener Filter (SWF) is proposed in this paper to obtain a robust sharpening (de-blurring/focusing) filter, assuming that the degradation function is known in this work. The traditional Wiener filter (WF) is a restoration filter for blurred and noisy images. By applying Fourier transformation (FT), Equation (1) can be represented in the frequency domain by:

$$G_{uv}=IO_{uv} \,.\, H_{uv}+\ N_{uv} \tag{3}$$

where G_{uv},IO_{uv}, H_{uv} and N_{uv} are the 2D of FT for g_{ij}, Io_{ij}, h_{ij} and η_{ij} respectively and '.' is the multiplication operation. To estimate the original image in frequency domain, the following equation of the enhanced (de-blurred) image can be defined by:

$$IF_{uv} = \frac{H^*_{uv}}{H^*_{uv}\,.\,H_{uv}+(\frac{1}{SNR})} . G_{uv} \tag{4}$$

where H^*_{uv} is the conjugate complex of H_{uv}, SNR is the Signal to Noise Ratio. $1/SNR$ is a constant value and can be chosen between [0.0001- 0.01]. The WF is widely used and simple in implementation. The disadvantages of the traditional WF are blurring and loss of sharpness in the image edges and Spatial invariance [15]. Finally, the enhanced image is obtained in spatial domain by applying 2D inverse of Fourier Transformation (IFT) of IF_{uv}. To solve the problem of the WF, the sharpening filter is embedded with WF to obtain an image with good quality in terms of de-blurring and focusing. Generally, the sharpening filter is a high-pass filter which is used to preserve the edges and line details in the image. The matrix center of the sharpening filter is positive, while the surrounding values are negative [26].

Figure 3 illustrates the steps of the proposed Sharpening Wiener Filter. First, read the blurred image (original image), Io_{ij} and the 3×3 sharpening filter matrix, k. Second, convert the image and the filter into the frequency domain by applying Fourier Transform (FT). The results of FT are Fourier transform coefficients of the image (G_{uv}) and Fourier transform coefficients of the filter (K_{nn}), where $u \times v$ pixels are the size of the image coefficients and $n \times n$ pixels is the size of sharpening filter coefficients. Third, apply the Wiener Filter equation on G_{uv} and K_{nn}. The results are IFW_{uv} and $\mathcal{R}_{nn}$. Fourth, the de-convolution operation (multiplication operator) is applied between IFW_{uv} and $\mathcal{R}_{nn}$ and the result is IF_{uv}. Finally, the inverse of the Fourier transform is achieved on IF_{uv} to obtain the focused image in time domain.

The proposed Sharpening Wiener Filter is performed in order to handle the blur degradation of the image before the fusion process of multimodal medical images. This will increase the quality of the fused image through increasing the focus of the image. Figure 4 shows the block diagram of the multimodal image fusion based on DWT and SWF.

The proposed fusion algorithm was performed by a computer with the following properties: processor Intel(R), Core ™, @ 2.00 GHz. The RAM is 8.00 GB. The system type is a 64-bit OS, Windows 10. The program language is MATLAB R2017b.

The following steps explain the DWT- SWF-based image fusion:

1. Preprocessing step: first, the registration process of the two images in each pair was performed. The purpose of this step is matching the two images by transforming them into one coordinate system. In this work, it is assumed that the images in each pair in the dataset are previously registered. Second, the image resize function is applied to all images to convert their sizes into 256×256 pixels. Third, each image in the dataset is converted into a 2D image (grayscale image).
2. Applying SWF on the images.
3. The resultant images of SWF are transformed into the DWT domain. The DWT works to decompose the images into their sub-bands (Low-frequency (LF) coefficients and High-frequency (HF) coefficients).

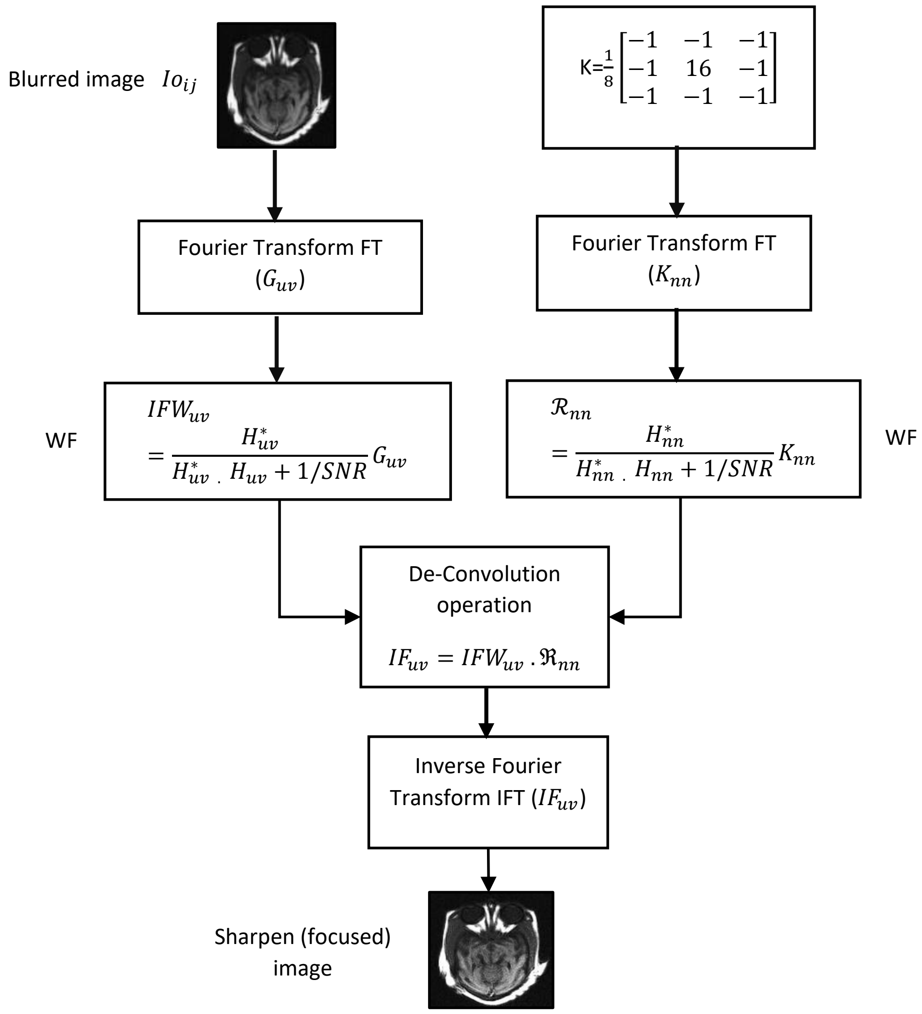

Figure 3. The proposed sharpening Wiener filter.

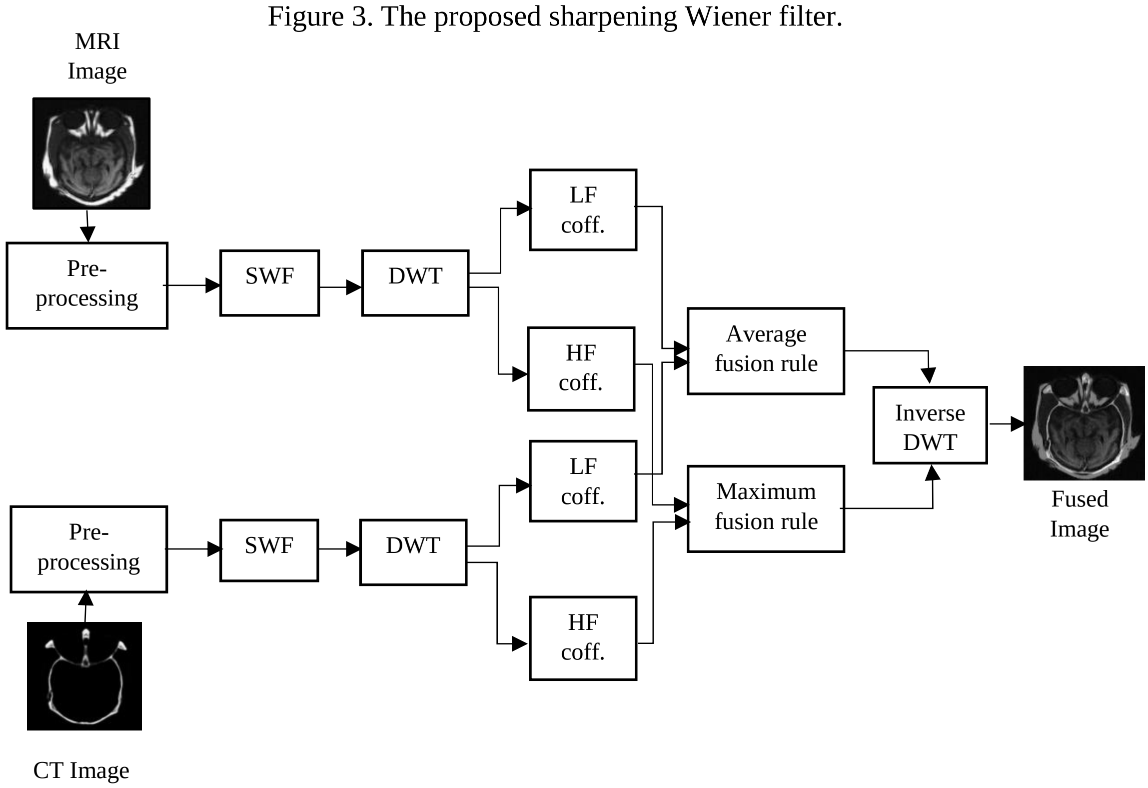

Figure 4. Block diagram of the multimodal image fusion based on DWT and SWF.

4. Average fusion rule is applied on the low bands of the coefficients of the two images. In the average fusion rule, the averages of the corresponding pixels of the LF coefficients are the pixels of the fusion result. Maximum rule is applied on the high bands of the coefficients of the two images. In the maximum fusion rule, the pixels of the fusion result are represented as the maximum values of the pixel intensity of the corresponding pixels of HF coefficients of the multimodal images.
5. Fused image is obtained by performing the inverse of the wavelet transform.

Depending on our computer system and the amount of data (two input images and one output image at each time), the proposed algorithm has an order of small-time complexity. Therefore, the algorithm is considered efficient in terms of runtime and storage space in memory.

4. PERFORMANCE EVALUATION METRICS

In this section, image quality metrics with no reference image, which are named as focus operators, are presented. The performance of the proposed fusion method is evaluated using the focus operators. The spatial quality and spectral quality have been measured. Table 1 shows the equations of these metrics with their descriptions. The higher the value of each one of these operators, the higher the focus in the enhanced image.

Table 1. The focus metrics with their equations and descriptions.

Metric	**Formula**	**Description**
Energy of Laplacian (EoL)	$EoL_{x,y} = \sum_{(i,j)\in\Omega(x,y)} \Delta If(i,j)^2$	EoL measures the amount of edges in the enhanced image by using Laplacian of image [16].
Modified Laplacian (ML)	$ML(x,y) = \sum_{(i,j)\in\Omega(x,y)} \Delta_m If(i,j)$ $\Delta_m If = abs(If * L_x) - abs(If * L_y)$ $L_x = [-1\ 2 - 1] and\ L_y = L_x^T$	ML measures the amount of edges in the enhanced image by using modified Laplacian of image [16].
Variance of Laplacian (VL)	$VL_{i,j=} \sum_{(i,j)\in\Omega(x,y)} (\Delta f(i,j) - \overline{\Delta f}^2)$ where $\overline{\Delta f}$ is the mean value of the image Laplacian within its neighborhood $\Omega(x,y)$.	VL measures the amount of edges in the enhanced image by using Variance of Laplacian of image [19], [16].
Sum of Wavelet Coefficients (SWAV)	$\text{SWAV} = \sum_{(i,j)\in\Omega_D} abs\big(W_{LH1}(i,j)\big) + abs\big(W_{HL1}(i,j)\big) + abs(W_{HH1}(i,j))$ where Ω_D is the corresponding of the neighbourhood $(\Omega(i.j))$ of the enhanced image pixel $If(i,j)$.	SWAV computes the focus score of the enhanced image using Sum of Wavelet Coefficients [17], [16].
Variance of Wavelet Coefficients (VWAV)	$\text{VWAV} = \sum_{(i,j)\in\Omega_D} (W_{LH1}(i,j) - \mu_{LH1})^2 + \sum_{(i,j)\in\Omega_D} (W_{HL1}(i,j) - \mu_{HL1})^2 + \sum_{(i,j)\in\Omega_D} (W_{HH1}(i,j) - \mu_{LL1})^2$ where Ω_D is the corresponding window of Ω in the DWT sub-bands and μ_{LH1}, μ_{HL1}, μ_{HH1} denote the mean value of the respective DWT sub-bands within Ω_D.	VWAV computes the focus score of the enhanced image using Variance of wavelet coefficients [17], [16].
Ratio of Wavelet Coefficients (RWAV)	$\text{RWAV} = \frac{C_H^2}{C_L^2}$ where C_H and C_L are defined as follows: $C_H^2 = \sum_k \sum_{(i,j)\in\Omega_D} W_{HLk}(i,j)^2 + W_{HLk}(i,j)^2 + W_{HHk}(i,j)^2$	RWAV computes the ratio between the high-frequency coefficients and the low-frequency coefficients [16].

	$C_L^2 = \sum_{k} \sum_{(i,j)\in\Omega_D} W_{LLk}(i,j)^2$	
Entropy (En)	$En = -\sum_{i=0}^{255} P_i log_2 P_i$ where P_i is the probability of the gray level i in the enhanced image.	En computes the information content in the enhanced image [18].
Spatial Frequency (SF)	$SF(x,y) = \sqrt{\sum_{(i,j)\in\Omega(x,y)} (If_x(i,j))^2 + \sum_{(i,j)\in\Omega(x,y)} (If_x(i,j))^2}$ where $SF(x,y)$ is the first derivative of the two directions ($If_x(i,j)$ and $If_y(i,j)$) of the image If.	SF computes the focus of the image in the spatial frequency [32].

5. RESULTS AND DISCUSSION

In the experiments, three pairs of original medical images of size 256×256 pixels were used in order to verify the effectiveness of the proposed fusion algorithm. These images were collected from the site specialized in medical images of the brain (http://www.med.harvard.edu/AANLIB/home.html) [27]. Medical images generally are defocus images (Figure 5). This means that they contain some blur. Increasing blur score means more blur in the image. At first, we want to know the amount of blurring in the medical images using a blur score. The score of blurs to an image is determined by blurring the image with a low-pass filter and comparing the intensity variations between the adjacent pixels before and after adding the filter. The range of the blur score is from 0 (the best quality) to 1 (the worst quality). More details about the blur score can be found in [19]. Table 2 illustrates the amount of blur in each image from each pair. Then, the amount of blurring is measured in the fused images that resulted from the proposed fusion method and other fusion techniques (DWT, SWT, DWT-PCA and DT-DWT) as in Table 3.

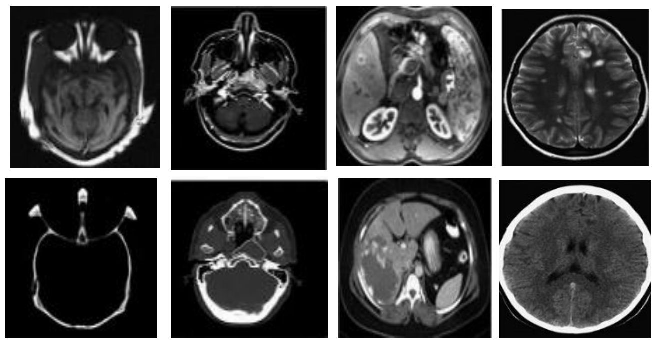

Figure 5. The four pairs of original medical images.

Table 2. The numerical values of the blur score in the original images.

Multimodal image	Original image	Blur score
Pair-1	Mri-1	0.5236
	CT-1	0.3875
Pair-2	Mri-2	0.2800
	CT-2	0.3282
Pair-3	Mri-3	0.4446
	CT-3	0.4778
Pair-4	Mri-4	0.3908
	CT-4	0.3244

Table 3. The numerical values of the blurring in the fused images of the proposed fusion technique compared with those of existing fusion techniques.

Fused Image Name	DWT	SWT	DWT-PCA	DT-DWT	Proposed SWF-DWT
Pair-1	0.4314	0.4060	0.4235	0.4457	**0.3490**
Pair-2	0.2814	0.2657	0.2241	0.2709	**0.2108**
Pair-3	0.4264	0.4202	0.4483	0.4214	**0.3234**
Pair-4	0.3507	0.3102	0.3669	0.3299	**0.2562**

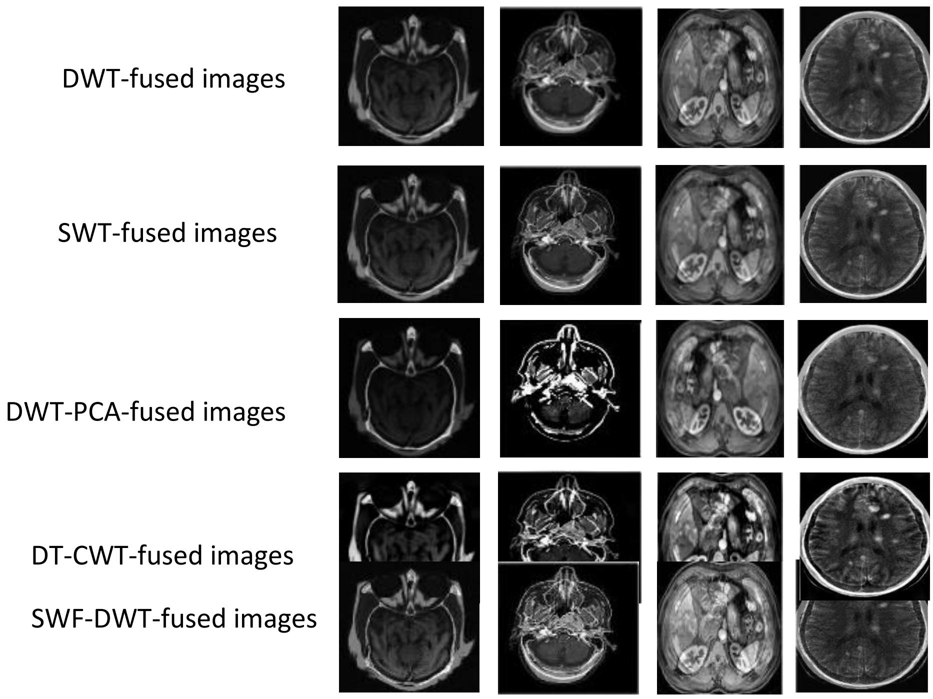

Figure 6. The resultant fused images using the proposed fusion and other fusion techniques.

Table 4. Focus metric values for the comparison of the proposed fusion technique and the existing fusion techniques for pair-1 of medical images.

Fusion techniques / Metrics	DWT	SWT	DWT-PCA	DT-DWT	Proposed fusion SWF-DWT
EoL	27.1301	26.2892	16.6045	31.0789	**43.3688**
ML	4.0694	3.7980	2.5409	4.6629	**8.0715**
VL	68.4137	55.0769	41.1258	106.0811	**293.5792**
Entropy	6.0399	6.0855	5.3133	5.6464	**6.4007**
SWAV	2.2862	2.1525	1.3204	2.3567	**4.7265**
VWAV	5.6402	4.3132	3.1391	6.2300	**19.6959**
RWAV	0.1018	0.0761	0.0625	0.0988	**0.3637**
SF	2.8216	2.9073	1.9821	3.3825	**3.1702**

It is observed from Table 2 that the original medical images naturally have some blur. From Table 3, the image fusion process using the proposed fusion method based on SWF-DWT and the other fusion techniques leads to reducing the blur level in the merged images. However, the proposed fusion method gives lower values of blur score compared with the other fusion techniques. The proposed fusion method gives visually more focus in the resultant images compared with other fused images. Tables 4, 5, 6 and 7 show comparisons of the performance of the proposed fusion method and the existing fusion techniques using the focus metrics on the medical images.

Table 5. Focus metric values for the comparison of the proposed fusion and the existing fusion techniques for pair-2 of medical images.

Fusion techniques / Metrics	DWT	SWT	DWT-PCA	DT-DWT	Proposed fusion SWF-DWT
EoL	45.0893	44.4590	43.8890	46.9290	**61.9868**
ML	8.4693	7.3517	13.0498	8.9971	**18.6924**
VL	273.2873	222.2005	1.1182e+03	359.1289	**1.2083e+03**
Entropy	5.1524	5.1759	3.8058	4.8093	**5.7311**
SWAV	4.7489	4.1874	8.4955	4.9091	**11.4291**
VWAV	23.1164	18.2136	74.4336	24.3379	**80.1349**
RWAV	0.3869	0.3088	1.4604	0.3830	**1.3634**
SF	3.7094	3.6936	3.3926	3.9191	**4.3940**

Table 6. Focus metric values for the comparison of the proposed fusion and the existing fusion techniques for pair-3 of medical images.

Fusion techniques / Metrics	DWT	SWT	DWT-PCA	DT-DWT	Proposed fusion SWF-DWT
EoL	50.2176	45.4960	39.3105	60.1983	**86.6782**
ML	6.7471	5.5930	4.7656	7.9568	**16.5056**
VL	101.4639	66.5640	48.1794	146.8988	**565.8526**
Entropy	7.2673	7.2797	7.3042	7.1876	**7.6446**
SWAV	3.5331	2.7849	2.0746	3.7073	**9.2858**
VWAV	5.8358	3.7028	2.4055	5.8451	**21.9226**
RWAV	0.0620	0.0363	0.0173	0.0626	**0.3196**
SF	5.0327	5.1485	5.0032	6.1892	**6.0506**

Table 7. Focus metric values for the comparison of the proposed fusion and the existing fusion techniques for pair-4 of medical images.

Fusion techniques / Metrics	DWT	SWT	DWT-PCA	DT-DWT	Proposed fusion SWF-DWT
EoL	54.8010	65.2433	45.9720	68.3392	**80.3525**
ML	9.9298	11.2523	7.0232	12.0920	**16.9428**
VL	410.4178	428.8384	188.9500	517.8509	**764.2706**
Entropy	6.7890	6.8568	6.7521	6.7358	**6.9162**
SWAV	5.9777	7.1859	4.2600	7.6850	**10.0184**
VWAV	26.1873	31.7202	16.0987	36.4523	**44.3586**
RWAV	0.3991	0.4445	0.1479	0.4772	**0.7993**
SF	4.5343	5.0945	4.0933	5.5460	**6.1219**

From Tables 4, 5, 6 and 7, the proposed fusion method based on Sharpening Wiener Filter and DWT gives good values of the focus operators (EoL, MF, VL, Entropy, SWAV, VWAV, RWAV and SF) on three pairs of medical images compared with the existing fusion techniques (DWT, SWT, DWT-PCA and DT-DWT) that are based on wavelet domain.

6. CONCLUSIONS

The quality of medical images has a great influence on the processes of analysis, diagnosis and medical treatment. Fusion of multimodal medical images takes the benefits of the characteristics of the images and gives a more complete image that helps in reaching a more accurate medical diagnosis. The image fusion based on DWT is widely used for medical images. It produces a good image representation in time and frequency domains. Due to the limited directionality of wavelets, the fused image using DWT suffers from blur. Therefore, a multimodal medical image fusion method is proposed to solve this problem using sharpening Wiener filter and DWT. The performance of the proposed fusion method was evaluated by using different focus operators. The experimental results showed that the proposed fusion method gives good values of focus operators compared with the existing DWT, SWT, DWT-PCA and DT-DWT image fusion techniques. Sharpening Wiener filter handles the problem of blurring in medical images. This is useful for clinical diagnosis. Also, the proposed fusion method can be used to increase the focus of any type of images. In future work, sharpening Wiener filter can be used with the other fusion techniques to reach more robust fusion operations.

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ملخص البحث:

يلعب دمج الصّور الطّبيّة متعددة الأنماط دوراً مهماً في تكامل البيانات وتحسين جودة الصّور، وله دور أساسي في دقّة التحليل والتشخيص الطّبّيّيْن. وعلم الرغم من التطورات التكنولوجية الحديثة، قد تتعرض الصّور الطّبيّة الى قِلّة الوضوح بفعل الزَّيْغ والتشويش من مصادر متنوعة. وهذا من شأنه أن يؤثر سلباً في دقّة التحليل الطّبّي. لذا، فإنّ توضيح الصّور الطّبيّة وإزالة التشويش منها أمرٌ أساسي في هذا المجال.

يُستخدم النّقل المجرّد للمويجات (DWT) بشكلٍ عامّ في دمج الصّور مكانيّاً بالنسبة للصّور متعددة الأنماط، ويُنتج تمثيلاً جيداً للصّور. إلّا أنّ من مساوئ هذه التقنية قلّة الوضوح بسبب الزّيْغ الحاصل في الصّور المدمجَة نتيجة الاتّجاهية المحدودة للمويجات. ولحل هذه المشكلة، نقترح في هذه الورقة طريقةً لدمج الصّور الطّبيّة متعددة الأنماط ترتكز على استخدام مرشّح فينر (Wiener) لزيادة الحِدّة جنباً الى جنبٍ مع النّقل المجرّد للمويجات.

كذلك تم تقييم الطريقة المقترحة عبر عددٍ من عوامل التّركيز المستخدمة لقياس مقدار التّركيز في الصّور المفحوصة. وقد كشفت النتائج أنّ الطريقة المقترحة تُعطي قيماً جيدة لعوامل التّركيز مقارنةً بقيم تلك العوامل التي يتم الحصول عليها من طرقٍ أخرى لدمج الصّور قائمة على حقْل المويْجات.