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Principal Component Analysis based Multimodal Medical Image Fusion of MR and CT using Wavelet Transform

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Abstract. Image fusion of multi-model bio-medical images assists the general medical practitioner in diagnostics and therapeutic planning of the patient. The process of image fusion merges different images to make into one image so that the resultant image poses all the complementary information of the original images. The image fusion provides the complementary anatomic details of an organ, from the different modality images, during diagnostics and therapeutic planning of the patient. This research paper presents a novel and effective fusion method for medical images, by using the principal component analysis in the wavelet domain. This approach enhances both spectral and spatial quality of the fused image. The PCA technique, KL transform procedure is applied to reduce the noise and dimension of both MR and CT images, with improved geometrical resolution, which generates several principal component images. Initially, the first principal component image of source images is decomposed into different frequency bands using discrete wavelet transform. Then, the average fusion rule is applied to the coefficients of the low frequency band, and gradient weighted maximum fusion rule is applied to the coefficients of the high frequency band. Further by using inverse wavelet transform and inverse KL transform, the fused image is produced. In addition, the fused image was tested quantitatively with spatial and spectral quality measures. The spatial quality assessment is accessed by the parameters like SD, ACC, and RMSE. Similarly, the spatial quality assessment is accessed by the parameters like PSNR, AG and the entropy. The investigation shows that the presented algorithm, PCA-based wavelet technique for image fusion has the best measure concerning spectral and spatial qualities.

Keywords: Image Fusion, Karhunen-Loeve Transform, Multi resolution analysis, Discrete Wavelet Transform, Gradient operator, Quality Assessment.

1 Introduction

Since last decades, medical images acquired from recent technologies like CT, MR, MRA, PET, and SPECT have an extraordinary potential in modern medical practices on clinical diagnosis, surgery, and radiotherapy [1]. However, all these images vary by giving complementary information for the same organ. In particular, in anatomic radiology, CT image is suitably best on finding detail about thicker tissue structured organs whereas MR Image provides the best information on soft tissue organs without any information about bones [2]. In general, it is worthwhile to the medical practitioner if all the complementary information is available in a single image. The technique 'fusion' achieves the ability to maintain complimentary information in a single image. The image fusion is a promising and a very challenging task in the recent research scenario. In radiology, the impact of multispectral and multimodal image fusion image [3] fascinates ample responsiveness.

Image fusion is a method of merging different images of the similar object to get higher spectral information and sharper edges than source images by extracting the redundant and complementary information from the individual images. For fusion, it is necessary to have images either from different modalities or the same modality with different doses. At present fusion methods, pixel averaging, weighted pixel maximum, several techniques based on pyramid decomposition and wavelet decomposition fusion, are available [4].

The image fusion method based on pixel averaging technique [5] not desirable because it introduces a contrast reduction in fused image. However, the contrast reduction was eliminated in an alternate technique of weighted averaging fusion, in which the fused image contains the weighted average of intensity values. The difficulty in the alternate method is the selection of the threshold for the estimation. It is another milestone in the image fusion research is based on the pyramid and wavelet decomposition of images [6] which provide multi-resolution levels of sub-images. Researchers revealed that performing fusion in transform domain rather than the spatial domain, suits the HVS nature of human vision [7]. In pyramid transform based image fusion the coefficients of the pyramid structure of the source image, are modified according to the fusion rule. The pyramid based fused images having blocking effects and undesired edges. The next type of fusion techniques based on wavelet transform [8] does perform better on spatially and spectrally, than the pyramid based fusion, due to the nature of DWT's non-redundant image representation capability. Wavelet based image fusion methods are widely used because of its good SNR and zero blocking artifacts.

In all these methods the fusion rule is applied for all sub-images as uniform. It is not suitable and acceptable for using the same fusion rule for all sub-images because the physical meaning of the coefficients belongs to different frequency bands are different. In this research, the fusion rule is applied separately for LL and other LH, HL and HH sub-images. Pixel averaging fusion rule was applied to the coefficients belongs to low-frequency sub-images and gradient based maximum selection scheme was applied to higher frequency band sub-images. The experimental results show that both spectral and spatial quality of fused images of our scheme of fusion technique is impressive [9].

The remaining content of this research paper is given in six sections. Section2 explained KL transform techniques, and section 3 has the details of the existing wavelet-based image fusion technique. Section 4 discussed our novel fusion technique, Section 5 presents the evaluation techniques of both spatial and spectral contents of fused images, section 6 gives the experimental results with analysis, and finally, Section 7 concludes our fusion technique.

2 Karhunen-Loeve Transform

The KLT is a method of principal component analysis in image data. It is a unitary rotation transformation technique which aligns a data set into a sequence of the uncorrelated coefficient with the different eigen values. It preserves the essential information content of a multi-spectral (satellite images) or multi-model (bio-medical images) with a reduced number of dimensions [10]. Data Reduction is possible with the rotation transformation ability of KL transform. The orthonormal eigen vectors of autocorrelation matrix Rx of an image X (i, j) gives the basis vectors for the KL transform. The KL transform decomposes an image into principal component images called basis image. Each eigen vector produces one basis image from its corresponding eigen value. In turn, an image covariance matrix determines the choice of the principal component image [11].

The following tasks are performed to compute the KL transform for a given image of size N x N:
Calculate the mean vector, which is the ratio of the sum of all intensity values of the image and to the number of pixels:

$$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i \tag{1}$$

Derive covariance matrix using the following expression.

$$C = \frac{1}{N}\sum_{i=1}^{N} (x_i - \mu)\,(x_i - \mu)^T \tag{2}$$

Find the eigen values of the covariance matrix, and its corresponding eigenvectors. The order of the eigen values is $\lambda_1 > \lambda_2 > \lambda_3 \ldots\ldots\ldots\ldots > \lambda_n$.

Use the eigenvectors to form a transformation matrix 'A', whose first row is the eigenvector corresponds to the highest eigen value 'λ_1' and the last row is the eigenvector corresponds to the lowest eigen value 'λ_n'.

Finally, construct the transformed image using the given transform matrix.

$$y_i = A\,(x_i - \mu) \tag{3}$$

The covariance matrix of transformed image Y is similar to the diagonal matrix whose diagonal values are eigen values. The transformed image is less correlated than the original image:

$$C_y = \begin{bmatrix} \lambda_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \lambda_n \end{bmatrix} \tag{4}$$

The following equation reconstructs the original image from the transformed image.

$$\hat{x} = A^T y + \mu \tag{5}$$

3. Wavelet Transform Based Image Fusion

3.1. Continuous Wavelet Transform

A small wave, which is used to transform a signal into sequences of orthonormal basis signal, is called mother wavelet Ψ (t). It offers a technique for investigating signals, in time-frequency scale. It has the capability to approximate the real world signal with sharp discontinuities [12]. Any signal can be approximated by combining these basis function, which are the translated and scaled version of mother wavelet Ψ (t). Translated and scaled version of mother wavelet is called as child wavelet. The mathematical equation for the child wavelet is given in the equation in which 'a' represents the scaling factor and 'b' represents the translation factor [13].

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\,\psi\left(\frac{t-b}{a}\right) \tag{6}$$

An inner product between child wavelet and function *f(t)* will give the transformed coefficient '$w_{a,b}$' which is related to a function f(t), can be achieved by the following equation.

$$w_{a,b} = \langle \psi_{a,b}, f(t) \rangle = \int_{-\infty}^{\infty} \psi_{a,b}\, f(t)\, dt \tag{7}$$

f(t) can be reconstruct from $w_{a,b}$ by double integration of the product of wavelet coefficient and mother wavelets.

$$f(t) = \frac{1}{C_\psi} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} w_{a,b}\, \psi_{a,b}(t) \frac{dadb}{a^2} \tag{8}$$

Wavelet transform represents a signal in time-frequency scale. This ability leads to the multi-resolution analysis of a real-time signal by avoiding the limitation in bands according to Heisenberg uncertainty principle. At higher frequencies, wavelet technique offers a good time resolution and a poor frequency resolution. However, it gives the inverse response at lower frequencies [14].

3.2 Discrete Wavelet Transform

The analysis and synthesis implementation of discrete wavelet transform afford necessary data calculating repetitive operations. It decreases the time for computation satisfactorily and very simple to execute. It can examine and investigate an image in multi-resolution at a different frequency band. It decomposes the image into a set of detail and approximation coefficient [15].

The forward equation for the computation of wavelet coefficient is given by

$$w_{m,n} = \langle\, f(t), \psi_{a,b} \rangle = a_0^{m/2} \int (f(t)\, \psi(a_0^m\,(t) - nb_0) dt \tag{9}$$

The synthesis equation to rebuild the signal *x(n)*is given by

$$x(n) = \sum_m \sum_n w_{m,n}\ \psi_{a,b}(n) \tag{10}$$

Wavelet split a signal into a series orthogonal functions of scaled and the translated version of a basis function, mother wavelet. In the analog implementation, the scaling and translation operations are analogous to the high pass and a low pass filter. In digital counterpart, they are a moving average and moving difference respectively [16].

Fig. 1 displays the 2D DWT analysis of an MR brain image, taken from our image sets. Fig. 1 (a), (b), (c) and (d) shows the original image, sub-bands after applying DWT, 2 level wavelet decomposition, and 3 level decomposition respectively.

The 2D-DWT technique decomposes the image into LL, LH, HL, and HH sub-frequency bands, as shown in Fig.1.b. Two level DWT gives an approximated image, the horizontal edged image, the vertical edged image and the diagonal edged image. As shown in Fig. 1. (c), Two level DWT divides the original image into four sub-images, which are shown in four quadrants. The sub-image LL, in the upper left quadrant, is an approximated version of the original image, which comprises the low-resolution coefficients of the original image. The upper right quadrant image contains the coefficients belongs to horizontal edges. The lower left quadrant contains the coefficients of vertical edges. Finally, the lower right quadrant contains the coefficients of the diagonal edges.

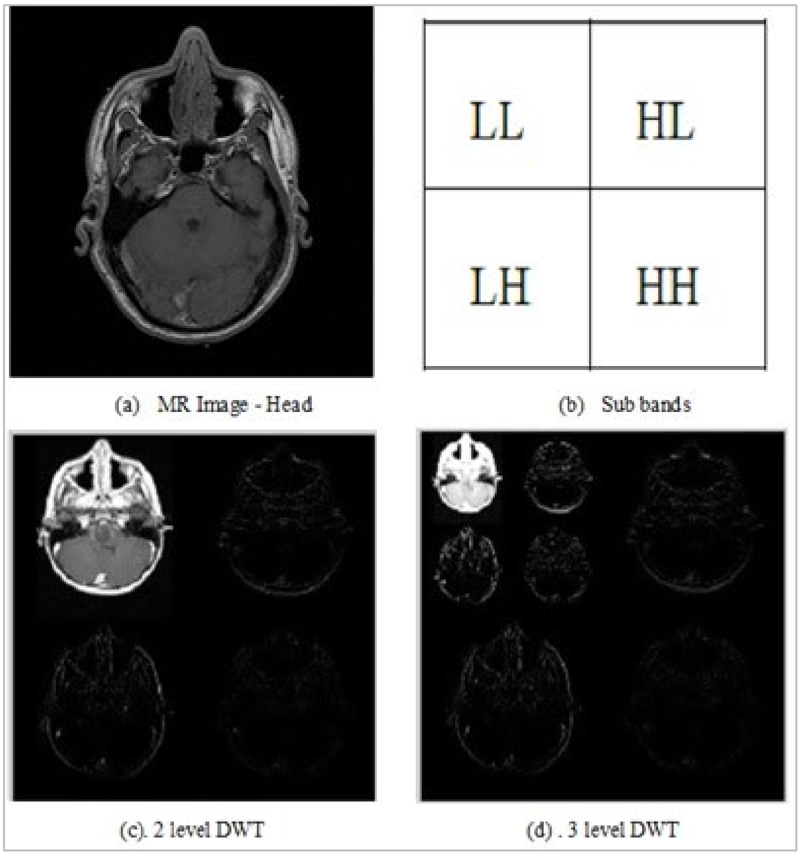

Fig. 1. Daubechies DWT Analysis of MR image.

3.3 WT Fusion Method

The multi-resolution based image fusion and the wavelet based fusion [17] are a significant method in the transform domain. The fusion rule is applied to the transformed coefficients, and the modified coefficients are used to construct the fused image in the spatial domain, using inverse transform, in all transformed domain technique.

In wavelet transform fusion, pre-registered images, m (x, y) and c (x, y), are fused to get a transform domain, the fused image F (u, v) with the help of wavelet transform ψ and a fusion rule α. The equation gives the mathematical representation of this process [18]. Similarly, the fused image in spatial domain f(x, y), is going to be reconstructed from F (u, v) with the help of inverse wavelet transform ψ^{-1}.

$$F(u,v) = \alpha\left(\psi\big(m(x,y)\big), \psi\big(c(x,y)\big)\right)$$
$$f(x,y) = \psi^{-1}(\mathrm{F(u,v)}) \quad (11)$$

Fig. 2 shows the block diagram representation of the process of wavelet fusion method between MR and CT images.

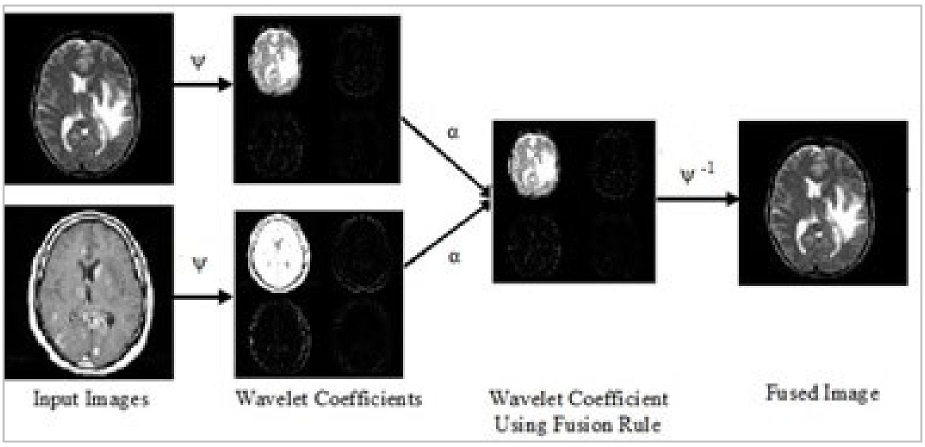

Fig. 2. Wavelet Transform Fusion

3 Proposed Image Fusion Method

Our proposed fusion method differs from the conventional wavelet method of fusion by applying KL transform prior to the wavelet decomposition. The proposed technique performs wavelet decomposition on the first principal component image instead of the whole image, which resulting good spectral resolution in the fused image. Also, the proposed scheme differs in fusion rule with conventional, by applying different fusion rule for different frequency band coefficients which resulting in good spatial resolution in the fused image. The proposed scheme of image fusion between MR and CT images is depicted in Fig. 3.

First, KL transform is performed on pre-registered input images to get the first principal component image with the reduction in dimensionality and noise. All the other principal component images belong to lower eigen values of the corresponding image are unaltered. The first principal component images from both CT and MR images which contains the most amount of information from the original images are divided into different bands of coefficients for the required levels using DWT. The fusion rule is applied separately for LL and other LH, HL and HH sub-images. Pixel averaging fusion rule was applied to the coefficients belongs to low-frequency sub-images and gradient based maximum selection scheme was applied to higher frequency band sub-images. Then the inverse wavelet transform gives the fused first PC image. Finally, inverse KL transform is performed on the fused first PC images and unaltered other PC images to obtain a higher resolution and a sharper edge image.

The complete fusion phases of our proposed method are given below.

1. KL Transform is applied to both MR and CT input images to produce the first principal component image and all the other principal component images are unaltered.
2. WT is then applied to the first PC images to get LL, HL, HH, and LH sub-band images.
3. The sub-band image coefficients are combined with a different fusion rule.
4. The synthesis wavelet function is performed to the fused sub-band coefficients from step 3 to form the fused first PC image.
5. Finally, the inverse KL transform is applied at the fused first PC images from step 5 and unaltered other PC images from step 1 to obtain a higher resolution and a sharper edge image.

The complete algorithm stated above is depicted as the flowchart in Fig. 3, and the rule is shown in Fig. 4. In Fig. 3, M (x, y) and C (x, v) represent the first principal component images of MRI and CT images respectively. hM (x, y) and h C(x, y) represent the HH band of sub-image of M (x, y) and C (x, y) respectively. lM (u, v) and lC (x, y) represent the other bands of sub-images of M (x, y) and C (x, y) respectively.

In the fusion rule, the coefficients of the LL band are fused by the average fusion rule while the coefficients of the other LH, Hl and HH bands are fused with a gradient-based maximum selection scheme.

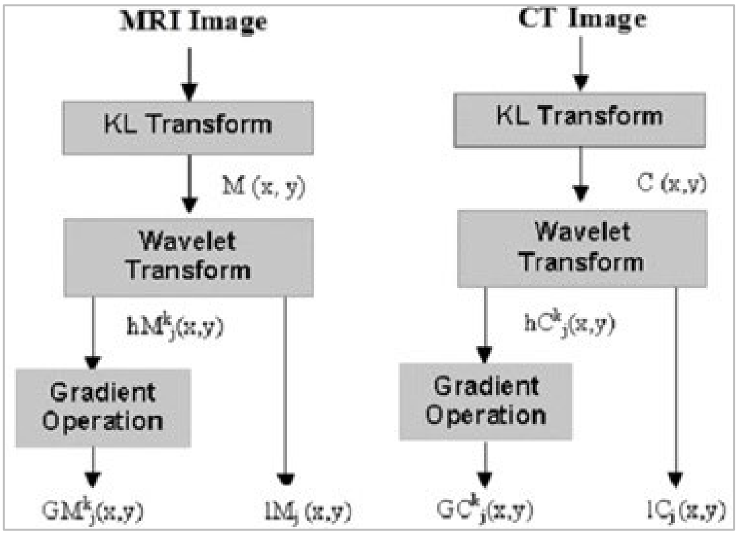

Fig. 3. Image Decomposition Using Wavelet Transform.

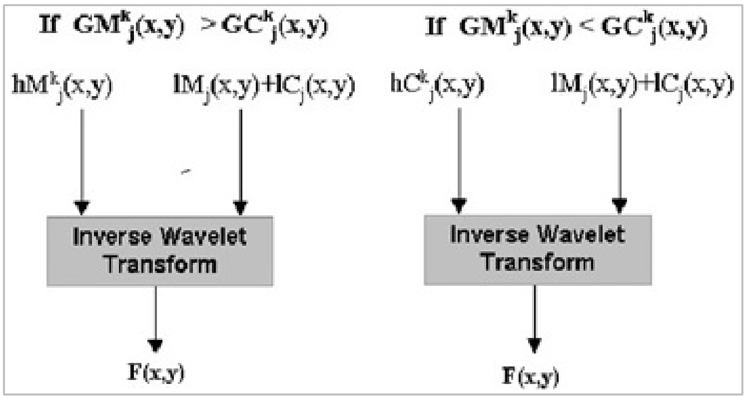

Fig. 4. Fusion Rule.

4 Evaluation Techniques

Both spatial and spectral quality measure are used for the quantitative assessment of the proposed fusion technique. The analysis indicates that our proposed algorithm, PCA-based wavelet technique for image fusion scheme has the best measure of spectral and spatial qualities.
In our assessment, the parameters like ACC, SD, and RMSE are used for the evaluation of the spectral quality of fused images.

ACC implies the correlation between each band of the fused image and reference MRI, CT images. If the value of correlation is high, it indicates lower spectral distortion [19].

The RMSE gives the difference intensity values between two images. The lower the value of RMSE indicates a better performance of fusion. RMSE is calculated for M X N images using the following formula.

$$RMSE = \frac{1}{MN}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}(R(i,j) - X(i,j)^2 \tag{12}$$

SD is a second-order measure of the relative deviation of image contrast with respect to the first-order statistic ‘mean’ μ. Better the value of standard deviation, the spatial content is superior. The mathematical expression for the mean and standard deviation are given below.

$$\sigma^2 = \frac{1}{MN}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}(X(i,j) - \mu)^2 \tag{13}$$

$$\mu = \frac{1}{MN}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}X(i,j) \tag{14}$$

For the purpose of assessment, the parameters PSNR, entropy, and AG are used for the evaluation of the spatial quality of fused images [20].

The amount of information in an image can be measured by entropy, and the higher value indicates more information content. If the probability distribution of each gray level is given as p= {p0, p1, p2…… pL-1} with 'L' total gray levels, then the value of entropy is calculated by

$$H = -\sum_{i=0}^{L-1}(P_i x \log_2 P_i) \tag{15}$$

The average gradient is a measure to access the amount of spatial resolution in an image which reflects the clarity of that image. Better the value of the average gradient, the spatial content is superior.

The AG of an image is calculated by the following equation.

$$AG = \frac{1}{(M-1)(N-1)}\sum_{m=1}^{M-1}\sum_{m=1}^{N-1}\sqrt{\left[\left(\frac{\partial f(m,n)}{\partial m}\right)^2 + \left(\frac{\partial f(m,n)}{\partial n}\right)^2\right]\Big/ 2} \tag{16}$$

PSNR is also another spatial content measure of an image based on RMSE and its maximum gray value 'f_{max}'. The higher value indicates the better fusion performance. It is calculated using the formula:

$$PSNR = 10\ \log(\frac{255^2}{RMSE^2}) \tag{17}$$

5 Experimental results and Discussions

The experiment was performed on four sets CT and MRI images of male Head, Brain, Thorax, and Pelvis for accessing the performance of our fusion technique. The algorithms are coded in MATLAB Version: 7.14.0.739 (R2012a). Daubechies wavelet is applied with three levels on CT and MRI image sets which are obtained from the U.S. National Library of Medicine. Fig. 5 shows the CT and MR image sets. Their statistical values such as entropy, average gradients, and standard deviation are given in Table 1. The performance of the proposed method is compared with three other methods, Averaging, Pyramid and DWT.

Table 1. The quantitative measure of the original CT and MRI image pair

Metric	Image Set 1-Head		Image Set 2-Brain		Image Set 3-Thorax		Image Set 4-Pelvis	
	CT	MRI	CT	MRI	CT	MRI	CT	MRI
Entropy	4.512	3.698	6.633	2.225	6.115	4.848	6.470	3.970
AG	4.003	1.843	5.357	2.853	4.297	2.001	4.897	1.230
SD	37.21	31.12	57.12	36.56	30.06	29.22	36.01	30.09

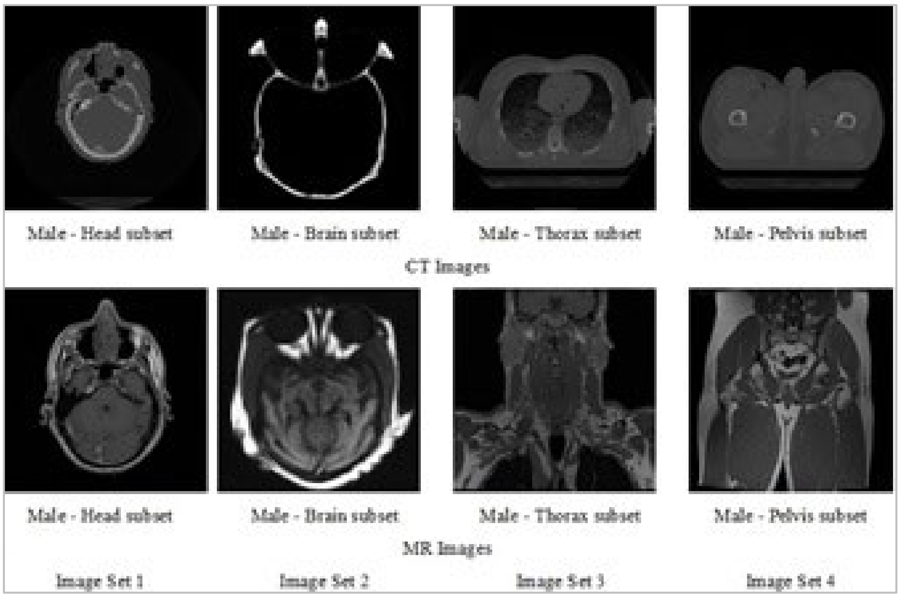

Fig. 5. Test Image Sets

The experimental result of fusion for the CT-MR image sets is given in Fig. 6. Each row of Fig. 6, provides the fused images of four sets of CT- MR Image pair. It is ordered as pixel averaging, the pyramid, wavelet and our proposed scheme of fusion methods. It is evident from the Fig. 6 the fused image of our scheme looks best among all methods in clarity with sharp edges.

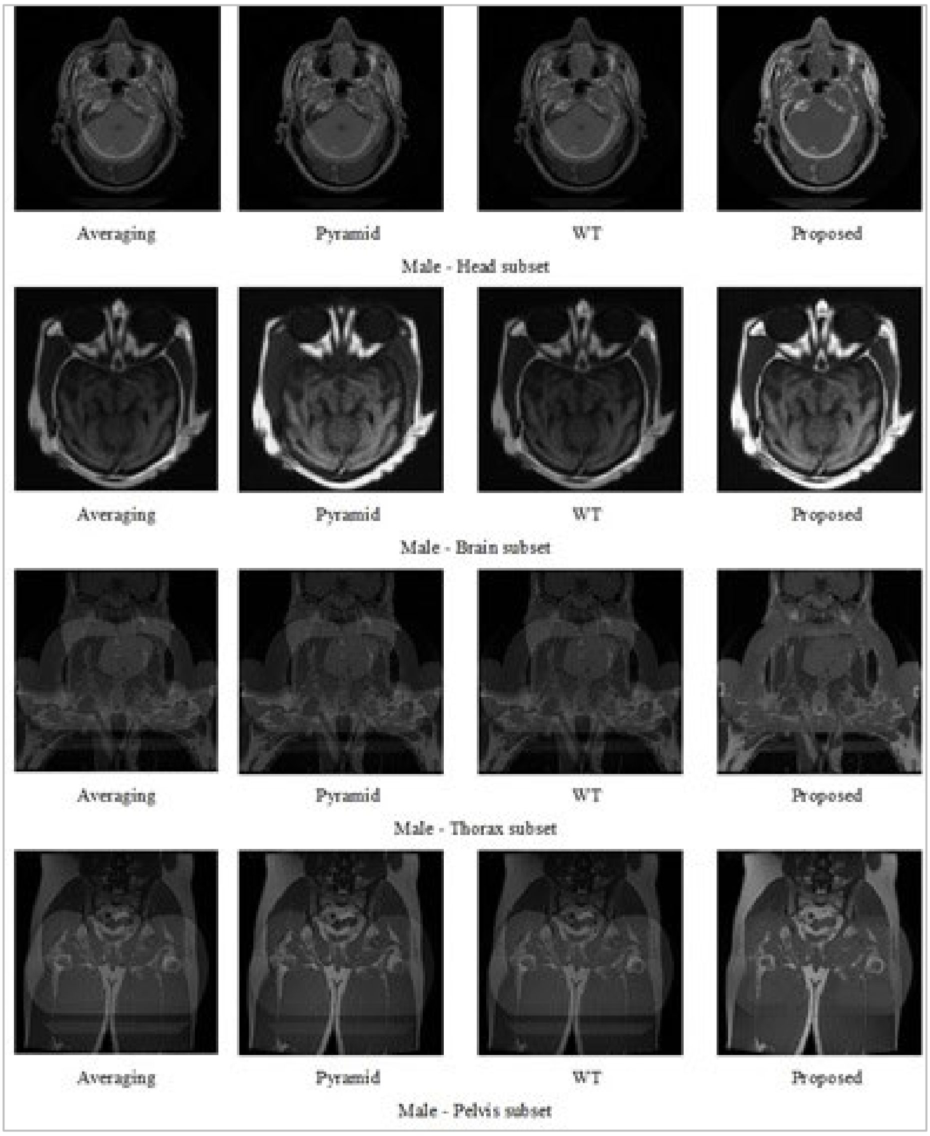

Fig. 6. Fused Images

Fig. 7 shows the comparison of the entropy, AG and SD of CT, MR and our fused images of four dataset. It is clearly showed that the values of these three parameters are higher in our proposed fused images than CT and MR images. So our proposed method of fusion technique comprises complementary information of both CT and MR images.

The spectral and spatial quality measures for pixel averaging, the pyramid, wavelet, and our proposed fusion technique, are indexed in the Table 2. It is evident from Table 2, Fig. 8 and Fig. 9, that the average correlation coefficients, standard deviation, the average gradient, entropy, PSNR of our fused images are higher than the other three methods of fusion. The RMSE value of our method is lower than the other methods of fusion. This lower RMSE value of our scheme is the better measure of the effectiveness of our fusion scheme.

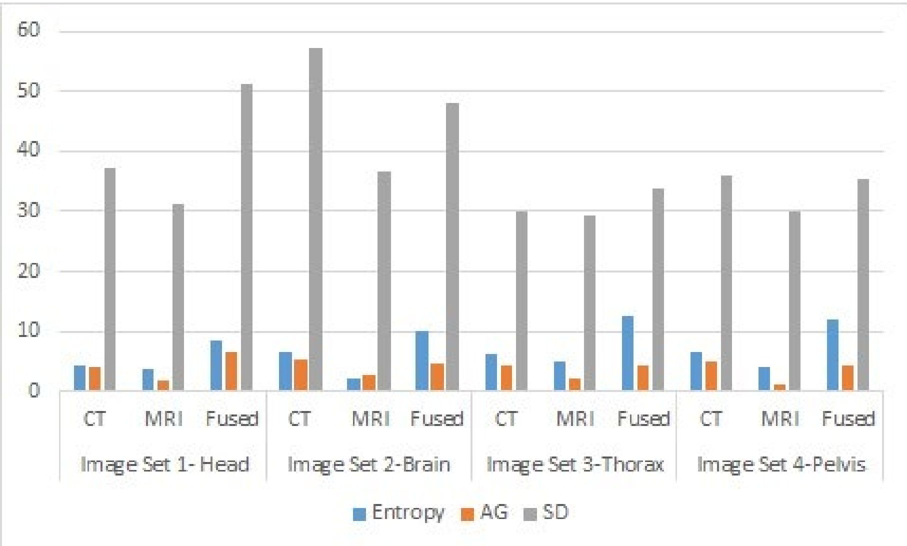

Fig. 7. Comparison of the entropy, AG and SD of CT, MR and our fused images

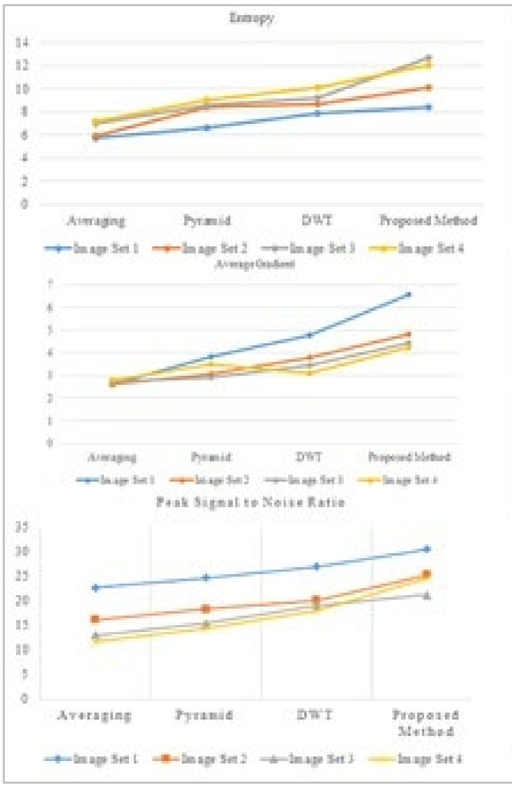

Fig. 8 Spectral Quantity Assessment

Fig. 9 Spatial Quantity Assessment

Table 2. The quantitative evaluation results

Type	Parameter	Method	Image Set 1	Image Set 2	Image Set 3	Image Set 4
Spectral Quality Assessment	ACC	Averaging	0.8216	0.8007	0.7474	0.8152
		Pyramid	0.8839	0.8545	0.8203	0.8914
		DWT	0.9042	0.9112	0.8494	0.9328
		Proposed Method	0.9481	0.9393	0.9064	0.9716
	RMSE	Averaging	24.9266	40.0056	30.4261	29.1402
		Pyramid	23.7128	34.6452	28.6027	23.7557
		DWT	18.9266	24.0056	21.7936	17.1402

		Proposed Method	15.0412	20.4142	17.3387	13.0157
	SD	Averaging	34.7332	28.7332	21.9033	23.9373
		Pyramid	38.1163	30.1163	22.1955	28.1846
		DWT	42.7284	34.7284	27.9068	30.9307
		Proposed Method	51.0598	48.0598	33.6747	35.3494
Spatial Quality Assessment	Entropy	Averaging	5.6995	5.8981	6.9736	7.1262
		Pyramid	6.5832	8.4271	8.6057	8.9997
		DWT	7.8643	8.6800	9.1796	10.0734
		Proposed Method	8.371	10.1291	12.6743	12.0508
	AG	Averaging	2.6045	2.5944	2.7172	2.7861
		Pyramid	3.839	3.0616	2.9056	3.4795
		DWT	4.7893	3.7944	3.4623	3.1199
		Proposed Method	6.568	4.8013	4.4472	4.241
	PSNR	Averaging	22.6234	16.1224	12.9611	11.6494
		Pyramid	24.6192	18.2678	15.3845	14.4079
		DWT	26.9764	20.1124	18.9789	18.0238
		Proposed Method	30.4518	25.2817	21.2309	24.5804

The fusion of MR and CT medical image gives combinational data in a single image which is fundamental to the clinical conclusion and radiotherapy. In this research, a novel PCA based wavelet method for fusing MR and CT images is proposed, which involves five phases. In the initial step, KL transform is applied to both CT and MR images to create different principal component images, according to the eign values. In the second step, first principal component images of both CT and MR images are decomposed into sub-images for the required levels by applying discrete wavelet transform. In the third step, the average fusion rule is applied to the coefficients of the low frequency band and gradient weighted maximum fusion rule is performed to the coefficients of the high frequency band. In the fourth step, the fused first PCA image is computed by inverse wavelet transform with the composite coefficients. In the last step, the reverse KL transform is performed on the fused first PC image and unaltered other PC images to acquire a higher resolution and a sharp-edged image. The spatial and spectral resolution of our fused

6 Conclusion

Images are quantitatively assessed by two sets of metric measure. The spectral quality is assessed by the average correlation coefficient, root mean square error, and the standard deviation. The spatial quality evaluation is gotten to by the peak signal to noise ratio, entropy, and an average gradient, and Peak Signal to Noise Ratio. The investigation demonstrates that our proposed methodology, the PCA-based wavelet method of image fusion scheme has the satisfactory measure concerning spectral and spatial features. The fused image also preserved greater valuable details with significant spatial resolution.

An integrated algorithm for medical image fusion of CT and MR images is devised based on the principal component analysis in the wavelet domain. This approach enhances both spectral and spatial quality of the fused image, which would be useful for image-guided brain surgery. There is a scope to evaluate and adopt empirical mode decomposition of signal decomposition and analysis, instead of PCA, to fuse the images obtained from different sensor modalities. There is also a possibility to use empirical mode decomposition in image fusion for image set other than CT and MR modalities.

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Appendix

Nomenclature

PCA	Principal Component Analysis.
KL	Karhunen-Love.
CT	Computed Tomography.
MR	Magnetic Resonance.
ACC	Average Correlation Coefficient.
PSNR	Peak Signal to Noise Ratio.
RMSE	Root Mean Square Error.
AG	Average Gradient.
SD	Standard Deviation.
MRA	Magnetic Resonance Angiogram.
PET	Positron Emission Tomography.
SPECT	Single Positron Emission Computed Tomography.
HVS	Human Visual System.
DWT	Discrete Wavelet Transform.
LL	Low – Low.
LH	Low – High.
HL	High – Low.
HH	High – High.

Biography

Dr. Yosef Hasan Jbara is an Assistant Professor in the College of Engineering and Information Technology at Buraydha Colleges. He received his Ph.D. in Artificial Intelligence from the Faculty of Computer Information Systems, University of Banking and Financial Sciences. He has published in the areas of artificial intelligence; simulation modelling; image processing and data mining. He has published several research papers in International Journals and conferences. His email addresses are yosef.hasan@bpc.edu.sa and yosefjbara@ieee.org.