A hybrid approach for Medical Image Fusion Based on Wavelet Transform and Principal Component Analysis

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Abstract

This paper presents a hybrid approach for medical image fusion based on the Discrete Wavelet Transform (DWT) and Principal Component Analysis (PCA). The main idea of the approach is to select between two fusion methods; DWT and PCA based on the local variance estimated at each position in the fusion results. Simulation results on multi-modality images are presented in this paper. The two modalities adopted are Magnetic Resonance (MR) images and Computed Tomography (CT) images. Evaluation metrics such as entropy, edge intensity, contrast, and average gradient have been adopted for performance evaluation of the proposed method. The obtained results confirm that the proposed method is superior in performance to the DWT and PCA methods individually.

1. Introduction

The objective of the image fusion process is to integrate multiple images describing the same scene into a single fused image to extract all the useful information from the source images. Image fusion process is used in various application fields like medical imaging, remote sensing, automatic target recognition, machine vision, and military applications. So, image fusion aims at incorporating information from multiple source images to produce a more accurate, complete and reliable fused image for the same scenes or targets [1]. Compared with source images, the fused images are more convenient for observation, analysis, understanding, and

recognition. Medical image fusion recently became a term commonly used within medical diagnostics and management [2,3].
There are many medical imaging forms that include Magnetic Resonance (MR) images, Computed Tomography (CT) scan, and Positron Emission Tomography (PET) scan. In radiology and radio-oncology, these images serve different purposes. Both MR and CT images give complementary information. CT images are better for visualizing bone structures, while MR images are usually emp1oyed to visua1ize soft tissues. So, the fusion of MR and CT images is expected to yield an integrated image with more information [2-4].
Shahdoosti and Ghassemian presented a method for image fusion using (PCA). This method is a simple, non-parametric method, linearly transforming the correlated components into uncorrelated ones. The PCA transform is used as a dimensionality reduction technique.This helps in determining the weight for each input image by calculating the eigenvector corresponding to the largest eigenvalue of the covariance matrix of the image[5,6].
Rao et al. presented another method for image fusion based on wavelet transform. This transform decomposes the signal into a discrete set of the wavelet scales. In wavelet analysis, the source images are decomposed into approximation and detail coefficients. Then,the fusion rules are applied to the coefficients after decomposition. Reconstruction is performed on the fused wavelet coefficients in order to obtain the fused image[7].
Several hybrid methods have been proposed in the last decade,to integrate the advantages of two fusion methods [6,7]. In this paper, we present a hybrid method for multi-modality image fusion based on the wavelet transform and PCA. This method preserves spatial as well as spectral information. The paper is organized as follows. Section II reviews the algorithms of image fusion and their techniques. Section III presents a proposal of the adaptive hybrid image fusion method. Section IV processes simulation results of the source CT and MRI images. Section V gives an insight to image quality metrics that can be used for fusion results. Finally, Section VI gives the concluding results.

2. Image Fusion Algorithms

Image fusion methods can be classified into two categories; spatial domain fusion methods and transform domain fusion methods. Spatial domain fusion methods directly deal with pixels of input images such as the principal component ana1ysis (PCA). The fusion methods such as DWT fall under transform domain methods [8].

2.1 Discrete Wave1et Transform (DWT)

Wavelet transform is a multi-resolution image decomposition tool that means dividing the image features into high frequency components and low frequency components by different filtering processes at multi-scales. It is a common technique in analyzing signals. The discrete wave1et transform (DWT) is the transform that decomposes the signal into mutually orthogonal set of wavelet scales, which is the main difference from the continuous wave1et transform (CWT) as shown in fig. 1 [8-10].

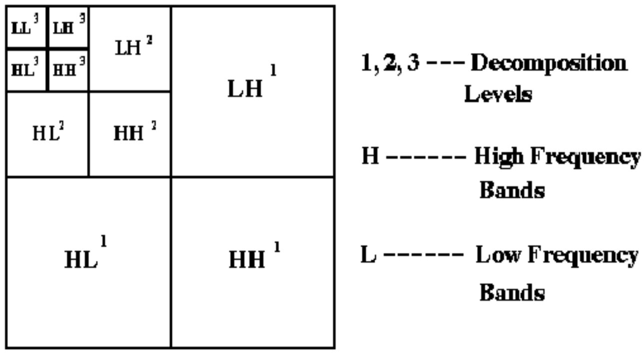

Fig. 1 Wavelet decomposition

The source images, $I_1(x.y)$ and $I_2(x.y)$are decomposed into approximation and detailed coefficients at the required level (lower level) using 2-Dimensional Discrete Wavelet Transformation (2DWT), which converts the image from the spatial domain to the frequency domain. Coefficients of both images are subsequently combined using a fusion rule as shown in fig. 2. The fused image $I_f(x.y)$ is then obtained by the inverse DWT as follows in equation (1):

$$I_f(x.y) = IDWT\left[\emptyset\left\{DWT\left(I_1(x.y)\right).DWT\left(I_2(x.y)\right)\right\}\right] \qquad (1)$$

The image is divided by vertica1 and horizonta1 lines and represents the first-order of DWT, and the image can be separated with four parts; those are LL1, LH1, HL1, HH1 [11].

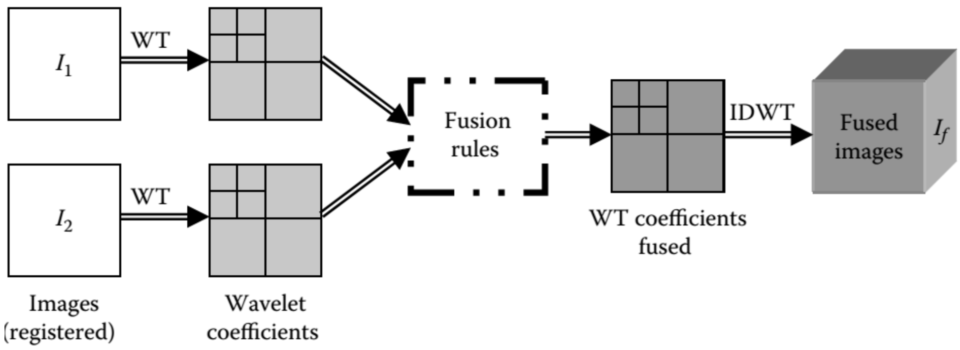

Fig. 2 Image fusion process with Wavelet

General process of image fusion using DWT can be listed as: Step 1. Implement DWT on both the source images to build wave1et 1ower decomposition.

Step2. Fuse each decomposition level by the average of the approximation and the detailed coefficients in each sub band with the 1argest magnitude.

Step 3. Carry inverse DWT on fused decomposed level using (2IDWT), which means to reconstruct the image "F".

2.2 Principal Component Analysis (PCA) Method:

Shahdoosti and Ghassemian presented method on image fusion using Principa1 component ana1ysis (PCA) that can be applied using three different methods. These three methods are calculating eigenvalues and eigenvectors, singu1ar va1ue decomposition (SVD) and co-variance matrix. The first method is calculating eigenva1ues and eigenvectors in which quality factors for the fused image are high but this method causes blurring of the output image. The second method is applied by using SVD and this method produces better fused images, however, it has delay which becomes more longer with large image sizes (in pixels). The third method is implemented by using co-variance matrix and this method produces convenient fused, more clear and informative images. The weights for each input image are determined by using the eigenvector corresponding to the largest eigenva1ue of the co-variance matrix of each source image [12,13].

Principal component method has the following steps: [14]

1. Produce the column vectors from i/p image.
2. Calculate the co-variance matrix of the two co1umn vectors in step 1 by this equation:

$$covariance\ (X.Y) = \frac{\sum_{i=1}^{n}(\overline{X_i}-X)(\overline{Y_i}-Y)}{(n-1)} \quad (2)$$

where, X is the CT reference image and Y is the MRI reference image.(X)¯is the mean value of the image X, and Y¯is the same as.

3. Ca1culate the eigenvector corresponding to the 1argest eigenva1ue of the co-variance.

For C (p*p) covariance matrix, the scalar values λ_p are the eigenvalues of C like that,

$$CU_p = \lambda_p U_p \quad (3)$$

Where, U_p is called the eigenvector corresponding to the eigenva1ue λ_p. Compute the eigenvalues λ_p of C where $\lambda_1 > \lambda_2 > \cdots > \lambda_p$ from the relation below:

$$|C - \lambda_p I| = 0 \quad (4)$$

4. Normalize the column vectors and form a feature vector.
5. Normalized eigenvalues which are mu1tiplied with each pixel.
6. Fuse the two sca1ed matrices producing the fused image matrix as:

$$X = UDV^T \quad (5)$$

Where

• Columns of U & V are the eigenvectors of XX^T and X^TX respectively.

• The squares of the diagona1 e1ements of D are the eigenva1ues of XX^T and X^TX.

3. Proposed Algorithm

The proposed fusion technique is a hybrid algorithm based on wave1et transform and principa1 component ana1ysis based local variance. The physical mean of local variance evaluation is detecting the edges of an image. One method for removing many of false edges is to require that the local variance is large at an edge point. The local variance can be estimated as σ^2 (I,j).

The output image contains both high spatia1 reso1ution and high qua1ity spectra1 content. The proposed principal of applying the wavelet transform in implementing medical images is done by the use of asingle-level two-dimensional wavelet decomposition in the implementation of the local variance matrix. The energy of a typical image is mainly concentrated in its 1ow frequency components [15].

The stepwise procedure for hybrid approach is given below:

1. The source images are picked out of MR and CT images.
2. Perform the DWT fusion a1gorithm that as follows:

$$\mathrm{I(x.y)} = \mathrm{IDWT}\left[\emptyset\left\{\mathrm{DWT}\left(\mathrm{I_1(x.y)}\right).\mathrm{DWT}\left(\mathrm{I_2(x.y)}\right)\right\}\right] \quad (6)$$

As IDWT is inverse DWT, and $I_1(x, y)$ and $I_2(x, y)$are MR and CT images, then $I_f(x, y)$is the fused image of I.

3. Perform PCA fusion a1gorithm that gives image fusion II.
4. Subject the fused image 'I' of DWT to a low pass filter to get the average of the image to build a matrix that forms the "Local Mean" $\mathrm{m_I(k_1, k_2)}$ which is considered as the brightness of the image according to the equation:
5. Calculate the "Local Variance" by the equation:

$$\mathrm{v1(k_1, k_2)} = \frac{1}{(2M+1)^2}\sum_{k_1=n_1-M}^{n_1+M}\sum_{k_2=n_2-M}^{n_2+M}[\mathrm{I(k_1, k_2)} - \mathrm{m_I(k_1, k_2)}]^2 \quad (7)$$

6. Repeat steps 5 and 6 on the fused image II of PCA.
7. The final enhanced informative fused image is obtained by the process as follows:

$$\mathrm{Fusedimage} = \begin{cases} \mathrm{I1(k_1, k_2)ifv1(k_1, k_2)} \geq \mathrm{v2(k_1, k_2)} \\ \mathrm{I2(k_1, k_2)ifv2(k_1, k_2)} > \mathrm{v1(k_1, k_2)} \end{cases} \quad (8)$$

Figure (3) shows the proposed hybrid fusion technique.

4. Simulation Results

The general requirement of an image fusing process is to preserve all valid and useful information from the source images, while simultaneously it should not introduce any distortion in resultant fused image. The presented work is tested using MATLAB 7 environment. The images used are grey scale JPEG with size of 128 x128. Source images are of CT, MRI and PET types. Figure (4) a& b show the original images for BrainTumor and Carcinoma. Fusion using PCA algorithm is shown in figure (4) c. Wavelet fusion technique is shown in figure (4) d. Fusion using the two step proposed approach is shown in figure (4) e. Hybrid fusion result is shown in the figure.

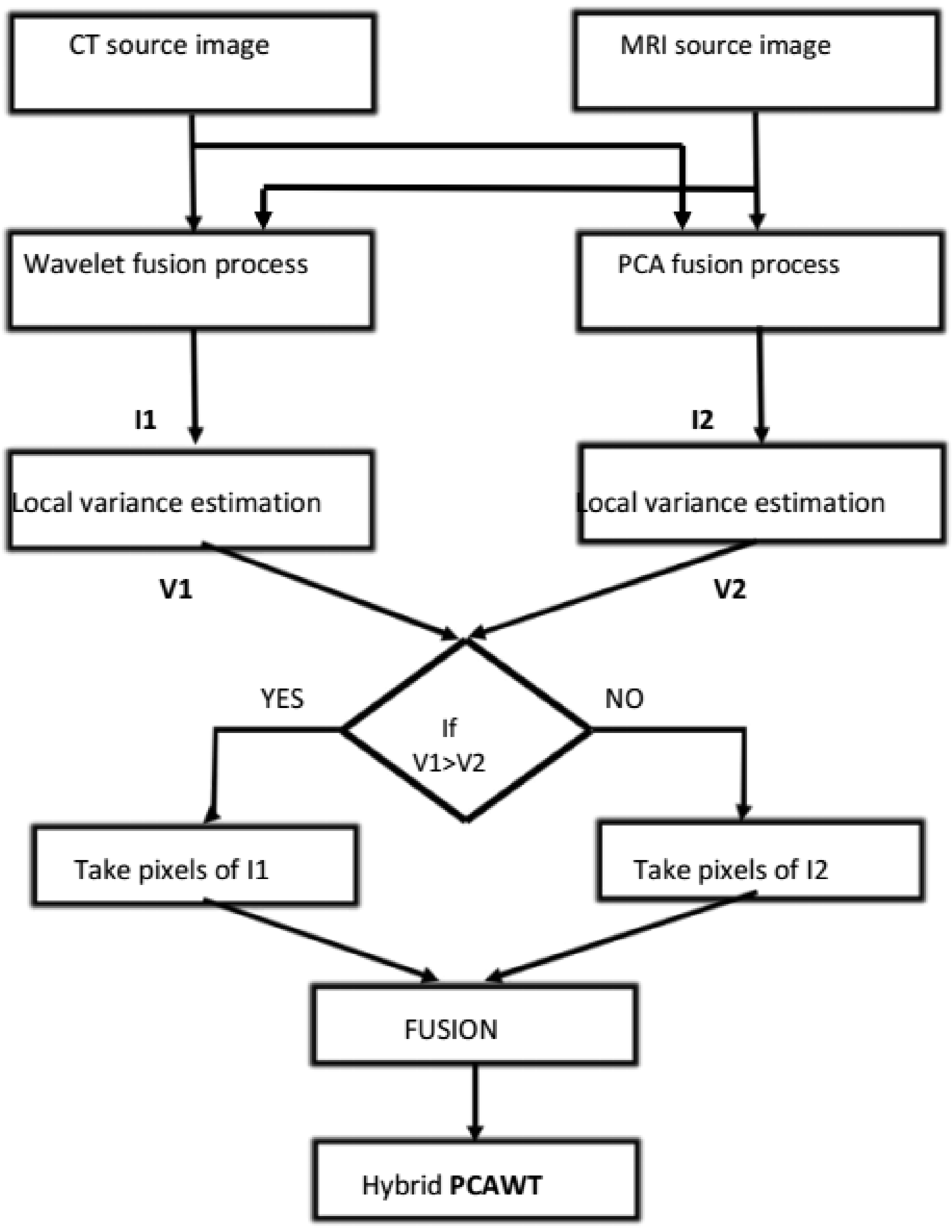

Fig. 3 The hybrid approach block diagram

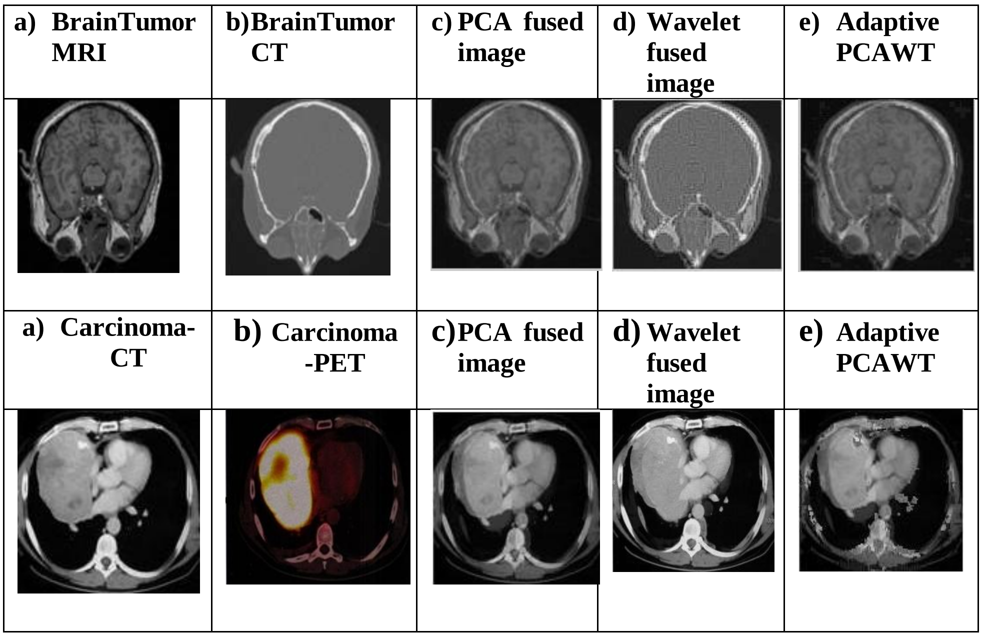

Fig. 4 Source images and fusion results of CT, MRI and PET axial images of the medcine for the input datasets (Carcinoma, and Brain tumor cases).

5. Evaluation Metrics

Evaluation metrics are used to assess the quality of the proposed method as shown in Table (1) and (2). These metrics are entropy, contrast, average gradient and edge intensity. The two step fusion proposed algorithm has the highest metric values.

1. Entropy (E): to measure the amount of image information. The entropy of the image is defined as:

$$E = -\sum_{i=0}^{n} p(x_i) \log p(x_i) \quad (9)$$

Where, n is the total of grey levels, P={p_0,p_1,.....p_n} is the probability distribution of each level [16].

2. Average Gradient (AVG) is computed as:

$$g = \frac{1}{(M-1)(N-1)} \sum_{i=1}^{(M-1)(N-1)} \sqrt{\frac{\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2}{2}} \quad (10)$$

3. Local Contrast (local C) is computed as the contrast of the differences between the corresponding pixels of reference and fused images totheir summation:

$$C_{local} = \frac{|\mu_{target} - \mu_{background}|}{\mu_{target} + \mu_{background}} \tag{11}$$

Where, μ_{target} is the mean grey level value of the target in the local region of interest, and $\mu_{background}$ is the mean of the background in the same region. The image view purity and its quality is said to be larger when it has a large value of C_{local} .

4. Edge Intensity (S): The calculation formula is:

$$h_x = \begin{pmatrix} 1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{pmatrix} . h_y = \begin{pmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{pmatrix} \tag{12}$$

$$S_x = P \text{ x } h_x,\ S_y\ P= \text{ x } h_y \tag{13}$$

where P acts as an image and the two filters "h_x" and "h_y" represent the horizontal andvertical differentiation of the image representing vertical and horizontal edges, respectively.

$$\mathbf{S = \sqrt{(S_x^2 + S_y^2)}} \tag{14}$$

The Sobel edge detection (S) can be larger when the S value is larger [17].

Table (1) presents comparison of image quality metrics of size 128x128 pixels between CT and MRI images at different fusion techniques on dataset brain tumor.

BrainTumor 128 * 128	**CT**	**MRI**	**DWT fusion**	**PCA fusion**	**Pcawt fusion**
Entropy	5.4600	6.5088	6.5810	6.4832	6.6790
Local C	0.4887	0.8480	0.6105	0.5682	0.6233
AVG	0.0212	0.0346	0.0338	0.0236	0.0348
Edge I	0.2129	0.3497	0.3240	0.2389	0.3332

Table (2) presents comparison of image quality metrics of size 128x128pixels between CT and PET images at different fusion techniques on dataset Carcinoma.

Carcinoma 128 * 128	CT	PET	DWT fusion	PCA fusion	Pcawt fusion
Entropy	6.6837	5.8293	7.0947	6.7700	6.8151
Local C	0.8665	0.8323	0.8702	0.8182	0.8161
AVG	0.0430	0.0212	0.0484	0.0323	0.0328
Edge I	0.4400	0.2127	0.4769	0.3290	0.3237

6. Conclusion

The process of image fusion combines the input images from any cases and extracts useful information giving the resultant image. Spatial domain image fusion techniques give high spatia1 resolution. However, spatial domain has image blurring problem. The wavelet transform gives high quality spectra1 content. Different image fusion performance metrics have been evaluated. The combination of DWT and PCA provides better performance and improves the image fusion quality based on the proposed local variance approach.

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المنهج المختلط لدمج الصور الطبية بناءاً على تحويل المويجات وتحويل المكونات الرئيسية

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هذا البحث يقدم نهجا هجيناً لدمج الصور الطبية اعتماداً على كلا من تحويل المويجات المنفصلة وتحليل المكونات الرئيسية .وتعتمد الفكرة الرئيسية لهذا النهج علي الاختيار بين طريقتين للدمج؛ طريقة تحويل المويجات المنفصلة و طريقة تحليل المكونات الرئيسية على أساس التباين المحلي المقدرة في كل موقف في نتائج الدمج .يتم عرض نتائج المحاكاة التى طبقت على الصور متعددة الأنواع في هذا البحث. أنواع الصور التي اعتمدت فى هذا البحث هي صور الرنين المغناطيسي وصور الأشعة المقطعية . وقد أعتمدت مقاييس للتقييم مثل الانتروبيا، وكثافة الحافة، والتباين، ومتوسط الانحدار لتقييم أداء النهج المقترح .والنتائج التي تم الحصول عليها تؤكد أن النهج المقترح متفوق في الأداء عن طريقة تحويل المويجات المنفصلة و طريقة تحليل المكونات الرئيسية عند استخدامهما كلاً على حدة.

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Synthetic Aperture Radar Sidelobe Reduction Using Different Optimization Techniques

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Abstract

The synthetic aperture radar (SAR) can be used on either an aircraft or a LEO satellite for high resolution imaging on the earth's surface. The transmitted pulse is to be shaped and modulated before transmission. A matched filter is used to construct a compressed time domain echo pulsed signal in the receiver. The main lobe level represents the desired target in the received echo compressed pulse to be detected. The sidelobe levels represent a false alarm (undesirable detection). This paper presents different optimization algorithms to reduce the sidelobe levels. These optimization algorithms are particle swarm optimization (PSO) algorithm, pattern search (PS) algorithm and Multi-Objective Genetic Algorithm (MOGA). The algorithms will be applied on different higher orders of polynomial instantaneous frequency modulation signals. A comparison study for these different optimization algorithms for reduction the sidelode levels is presented.

Keywords: Synthetic aperture radar (SAR), polynomial frequency modulation, Sidelobe level (SLL) reduction, Pulse compression ratio (PCR), Range Resolution, Particle swarm optimization (PSO), Pattern search (PS) algorithm, Multi-Objective Genetic Algorithm (MOGA).

1. Introduction

The idea of the Synthetic aperture radar (SAR) is based on the generation of an effective long antenna by signal processing means rather than by the actual use of a long physical antenna [1]. The signal processing involves the motion of the radar antenna over a targeted region by transmitting pulses to it. The echo of each pulse is received and recorded [2]. The