Comparison of Different Methods for Fusion of Multimodal Medical Images

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Abstract - *Image Fusion can be defined as a process of combining information from multiple input images in such way that final fused image having good quality information then individual image. Combining various modalities of medical images increases robustness and improve accuracy in medical research and diagnosis of diseases. A significant task for retrieving complementary information from different modalities of medical images such as MRI, CT, PET and SPECT can be achieved by multimodal medical image fusion. Different characteristics of low and high frequency sub bands are taken into account and fusion rules are applied. Medical imaging field demands images with high resolution and higher information contents for necessary disease diagnosis and visualization. This paper reviews different methods of image fusion i.e., PCA (principal Component Analysis), DCT (Discrete Cosine Transform), SWT (Stationary Wavelet Transform) and DWT (Discrete Wavelet Transform) and further comparative analysis is done.*

Key Words: Image Fusion, Multimodal Images, Discrete Cosine Transform, Principal Component Analysis, Wavelet Transform.

1. INTRODUCTION

Medical images from various modalities frequently contain complementary information which will be highly required in clinical diagnosis [5]. For example, MRI images shows evidently the extent of a tumor in relation to other soft tissues but do not describe whether the tumor has invaded any of the bony structures, while CT images shows clearly the bone involvement but gives poor images of the soft tissue extent of the tumor , Positron Emission Tomography (PET) image reveals actual information of flow of blood but lacks boundary information and so on. Image fusion can form a single composite image from the different modalities of images and then provide reliable source that will be useful for medical diagnosis [1]. The different transformation methods that can be used for image fusion are PCA, DCT, SWT and DWT. Principal Component Analysis (PCA) is a simple non-parametric method of extracting relevant information from confusing data sets. Discrete Cosine Transform (DCT) is used to express a sequence of finite data points in terms of a sum of cosine functions oscillating at different frequencies. Discrete Wavelet Transform (DWT) is a technique to transform image pixels into wavelets, which are then used for wavelet-based compression and coding. Stationary Wavelet Transform (SWT) is a translation-invariance modification of the Discrete Wavelet Transform that does not decimate coefficients at every transformation level.

2. PRINCIPAL COMPONENT ANALYSIS

Principal component analysis (PCA) is a vector space transform often used to reduce multidimensional data sets to lower dimensions for analysis. PCA is the simplest and most useful of the true eigen vector-based multivariate analyses because its operation is to reveal the internal structure of data in an unbiased way. Basically Principal component analysis is a technique in which number of correlated variables are transformed into number of uncorrelated variables called principal components. A compact and optimal description of datasets is computed by PCA. First principal component is taken to be along the direction with maximum variance. The second principal component is constrained to lie in the subspace perpendicular to the first within this subspace, this component points the direction of maximum variance. The third principal component is taken in the direction of maximum variance in the subspace perpendicular to the first two and soon. The PCA does not have a fixed set of basis vectors like FFT, DCT and wavelet etc. and its basis vectors depend on the data set [4].

2.1. FORMULATION

Let X be a d-dimensional random vector and assume it to have zero empirical mean. Orthonormal projection matrix V would be such that $Y = V^T X$ with the following constraints [6]. The covariance of Y, i.e., cov(Y) is a diagonal and inverse of V is equivalent to its transpose

($V^{-1} = V^T$). Using matrix algebra

$$\begin{aligned} \mathrm{cov}(Y) &= E\{YY^T\} \\ &= E\{(V^T X)(V^T X)^T\} \\ &= E\{(V^T X)(X^T V)\} \\ &= V^T E\{XX^T\} V \\ &= V^T \mathrm{cov}(X) V \end{aligned} \tag{1}$$

Multiplying both sides of Eqn (1) by V, one gets

$$V\ cov(Y) = VV^{T}cov(X)V = cov(X)V \quad (2)$$

One could write V as V=[V_1,V_2,……..,V_d] and Substituting Equation(1) into Equation (2) gives

$$[\lambda_1 V_1,{}_2V_2,\ldots\ldots,\lambda_d V_d]=[cov(X)V_1,cov(X)V_2,$$

$$\ldots..,(X)] \quad (3)$$

This could be rewritten as $\lambda i V i$= (X) where i = 1,2, ……,d and Vi is an eigenvector of cov(X) [4].

2.2. PROCESS FLOW DIAGRAM OF PCA

The information flow diagram of PCA-based image fusion algorithm is shown in Fig.1 .

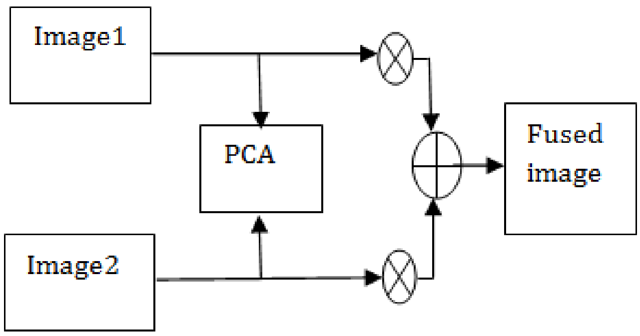

Fig -1: Information flow diagram in image fusion scheme employing PCA.

2.3. PCA ALGORITHM

Image fusion process using PCA is described below .$I1$ (x, y) and $I2$ (x, y) are the two input images which are to be fused [4].

1. From the input image matrices produce the column vertices.
2. Compute the covariance matrix of two column vectors formed before.
3. Compute the Eigen values and Eigen vectors of the covariance matrix.
4. The column vector corresponding to the larger Eigen value is normalized by dividing each element with mean of Eigenvector.
5. Normalized Eigen vector value act as the weight values which are respectively multiplied with each pixel of the input images.
6. The fused image matrix will be sum of the two scaled matrices.

2.4. ADVANTAGES OF PCA

1. Selects optimal weighting coefficients based on information content.
2. Removes redundancy present in input image.
3. Compress large amounts of inputs without much loss of information.

2.5. DISADVANTAGES OF PCA

1. Usually selects first Eigen value which does not contain all of the patterns between inputs.
2. Fused image will be of lesser quality than any of the input images.
3. Strong correlation between the input images and fused image is needed.

3. DISCRETE COSINE TRANSFORM

The digital images are displaying on a display right after they are captured. There are two represent types for digital image that is spatial domain or frequency domain. Spatial domain image may be realized through human eyes, but frequency domain use to analysis of spatial domain .A Discrete Cosine Transform (DCT) is a significant transform in image processing [6]. It is obviously used to express a sequence of finite data points when it comes to a amount of cosine functions oscillating at dissimilar frequencies [3]. Large DCT coefficients are concentrated in the reduced frequency region; hence, it is acknowledged to have brilliant energy compactness properties. Discrete Cosine Transformation (DCT) are essential to frequent applications in art, engineering and in images compact, like MPGE, JVT, etc [7].

3.1. FORMULATION

The 2D DCT is nothing but a direct extension of 1D DCT. The 2D discrete cosine transform of an image or 2D signal x (nl,n2) of size NI xN2 is defined as,

$$x(k1,k2)=\alpha(k1)\alpha(k2) \quad (9)$$

$$\sum_{n1=0}^{N1-1}\sum_{n2=0}^{N2-1} x(n1,n2)\cos\left(\frac{\pi(2n1+1)k1}{2N1}\right) \quad (10)$$

$$cos\left(\frac{\pi(2n2+1)k2}{2N2}\right) \qquad \text{for } 0\le k1\le N1\text{-}1 \ \text{ and } \ 0\le K2\le N2\text{-}1$$

Where,

$$\alpha(k1) = \begin{cases} \frac{1}{\sqrt{N1}}\ , & K1 = 0 \\ \sqrt{\frac{2}{N1}}\ , & 1 \le k1 \le N1-1 \end{cases} \quad (11)$$

$$\alpha(k2) = \begin{cases} \frac{1}{\sqrt{N2}}, & K2 = 0 \\ \sqrt{\frac{2}{N2}}, & 1 \le k2 \le N2-1 \end{cases} \quad (12)$$

Where Kl & K2 are discrete frequency variables. Similarly, the 2D inverse discrete cosine transform is defined as,

$$X(n_1,n_2) = \alpha(k1)\alpha(k2) \quad (13)$$

$$\sum_{n1=0}^{N1-1}\sum_{n2=0}^{N2-1} \alpha(k1)\,\alpha(k2) X(k1,k2) \cos\left(\frac{\pi(2n1+1)k1}{2N1}\right) \quad (14)$$

$$\cos\left(\frac{\pi(2n2+1)k2}{2N2}\right) \quad \text{For } 0 < kl < Nl\text{-}l \text{ and } 0 < K2 < N2\text{-}l$$

Where α(k1) & α(k2) are same as equation (11) & (12) [6].

3.2. PROCESS FLOW DIAGRAM OF DCT

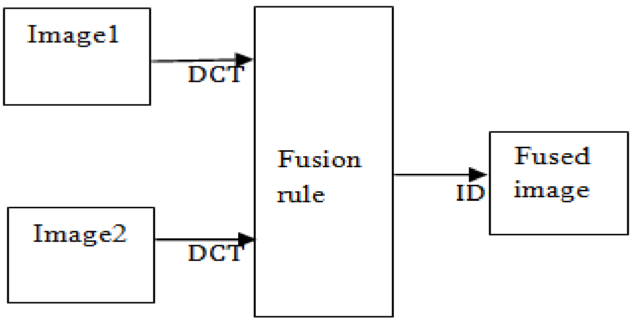

Fig -2: Process flow graph of DCT

In DCT the Images to be fused are divided into non-overlapping blocks of size NxN as shown in above Fig-2. For each block DCT coefficients are computed and fusion rules are applied to get fused DCT coefficients. Then apply the IDCT on the fused coefficients to produce the fused image/block [5]. The following only two fusion rule is used for image fusion process. They are the simple averaging method and by using equation method as in eq (15). Let the X1 be the DCT coefficients of image block from image 1 and similarly let X2 be the DCT coefficients of image block from image 2. Assume the image block is of size N x N and X be the fused DCT coefficients. Here, all DCT coefficients from both image blocks are averaged to get fused DCT coefficients. It is very simple and basic image fusion technique in DCT domain

$$X_f(k_1,k_2) = 0.5X_1(k_1,k_2) + X_2(k_1,k_2) \quad (15)$$

Where k_1,k_2=0,1,2..........,N-1 [6].

3.3. ADVANTAGES OF DCT

1. DCT provides efficient output. It reduces the complexity and decomposes the images into series of waveform.

3.4. DISADVANTAGES OF DCT

1. This method leads to undesirable side-effect including blurring.

4. STATIONARY WAVELET TRANSFORM

Wavelet Transform is basically used in feature detection of MRI, signal de-noising, pattern recognition and brain image classification. In SWT, first the filters are applied to the rows and then the columns, as a result four images are produced (one approximation and three horizontal, vertical and diagonal). Translation invariance is achieved by removing the down samples and up samples in the DWT and up sampling the coefficients by the factor of 2^{j-1} in the jth level of the algorithm. Therefore, The SWT is redundant technique as the output of each level of SWT contains the same number of samples as input. In SWT, even if the signal is shifted, the transformed coefficient will not change and also performs better in de-noising and edge detecting. SWT can be applied to any arbitrary size of images rather than size of power of two and has shown better fusion performance in medical and other images. SWT is similar to DWT is more commonly known as "algorithm a trous" in French meaning "with holes" which refers to inserts zeros in the filter for up sampling the filter and suppressing the down sampling step of the DWT [8].

4.1. FORMULATION

SWT decompose the important features of source images into different levels by its multiresolution analysis power. The SWT decomposition is represented as follows:

Get wavelet coefficients of X and Y by taking SWT:

$D_X(m,n, k,l)$, $D_Y(m,n, k,l)$, where m,n indicate the spatial position in a given frequency band, l the decomposition level and k the frequency band of the MSD representation, k = a, h, v, d , a indicates the approximation band, h the horizontal band, v the vertical band and d the diagonal band. Calculate the activity level of each pixel for X andY, $A_X(m,n)$ and $A_Y(m,n)$.

$$A_1(m,n) = \sum_{k\in K l\in L} w(k,l)\,|D_1(m,n,k,l)|$$

$$K=\{h,v,d\} \quad L=\{1,2,\ldots,N\}$$

Where N indicates the maximum decomposition level and w(k,l) the weight coefficient of the corresponding pixel in k band at level l such that

Σw(k,l)=1 k€Kl€L

4.2. PROCESS FLOW DIAGRAM OF SWT

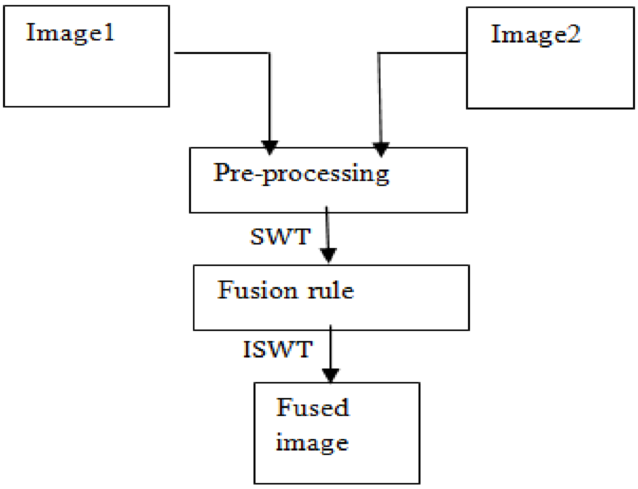

Fig -3: Process flow diagram of SWT

4.3. SWT ALGORITHM

The SWT process is described below [9]:

1. Decompose the two source images using SWT at one level resulting in three details sub-bands and one approximation sub-band (HL, LH, HH and LL bands).
2. Then take the average of approximate parts of images.
3. Take the absolute values of horizontal details of the image and subtract the second part of image from first. D = (abs (H1L2)-abs (H2L2))>=0.
4. For fused horizontal part make element wise multiplication of D and horizontal detail of first image and then subtract another horizontal detail of second image multiplied by logical not of D from first.
5. Find D for vertical and diagonal parts and obtain the fused vertical and details of image.
6. Same process is repeated for fusion at first level.
7. Fused image is obtained by taking inverse SWT.

4.4. ADVANTAGES OF SWT

1. SWT has main advantage of undecimation.
2. It can preserve more information of source image by its redundant properties at each scale.

4.5. DISADVANTAGES OF SWT

1. SWT is not efficient for the clinical analysis.
2. It has problem of the spatial resolution.

5. DISCRETE WAVELET TRANSFORM

DWT decomposes an image into coarse and detailed layers, corresponding to which lower frequency and higher frequency sub bands. Presently, DWT is well familiar fusion method using multi-resolution analysis. Wavelet transforms are multi-resolution image decomposition tool that provide a variability of channels representing the image feature by different frequency sub-bands at multi-scale. It is a famous technique in analyzing signals. When decomposition is performed, the approximation and detail component can be separated 2-D Discrete Wavelet Transformation (DWT) converts the image from the spatial domain to frequency domain. The image is divided by vertical and horizontal lines and represents the first-order of DWT, and the image can be separated with four parts those are LL1, LH1, HL1 and HH1 [6].

5.1. FORMULATION

The DWT transformation equations:

$$F(u,v)=\frac{2c(u)c(v)}{N}\sum_{m=0}^{N-1}\sum_{n=0}^{N-1} f(m,n)\cos\left(\frac{2m+1}{2N}u\pi\right)\cos\left(\frac{2n+1}{2N}v\pi\right)$$

$u=0,1,2,\ldots\ldots..N-1$ $v=0,1,2\ldots\ldots\ldots..N\text{-}1$

where $c(k)=\frac{1}{\sqrt{2}}$ for $k=0$

$=1$, otherwise

5.2. PROCESS FLOW DIAGRAM OF DWT

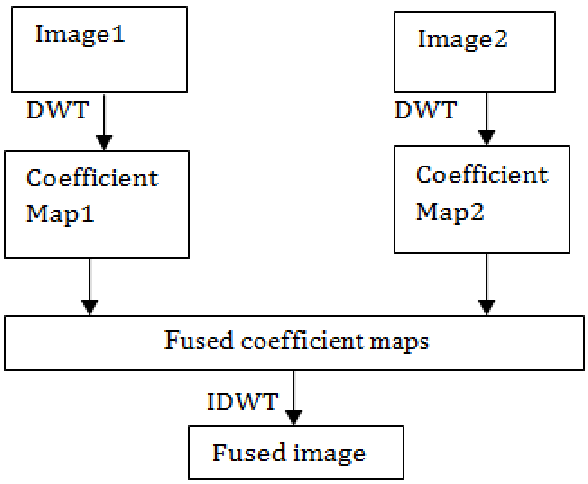

Fig -4: Process flow diagram of DWT

5.3. DWT ALGORITHM

The process steps are given below [4]:

1. Accept the two images.
2. Perform DWT on both images A and B.
3. Perform level 2 DWT on both images A and B.
4. Let the DWT coefficient of image A will be [HHaHLaLHaLLa].
5. Let the DWT coefficient of image B will be [HHbHLbLHbLLb]
6. Take the average of pixels of the two band from HHa and HHb and store to HHn.
7. Take the average of pixels of the two band from HLa and HLb and store to HLn.
8. Take the average of pixels of the two band from LHa and LHb and store to LHn.
9. Take the average of pixels of the two band from LLa and LLb and store to LLn.
10. Now we have new HHn, HLn, LHn, LLn DWT coefficients.
11. Take Inverse DWT on the HHn, HLn, LHn, LLn coefficients.
12. Obtain the fused image and display.

5.4. ADVANTAGES OF DWT

1. It provides good resolution both in time domain and frequency domain.
2. Simple and easy to understand and implement.

5.5. DISADVANTAGES OF DWT

1. Some noise may be introduced in fused image.
2. Low accuracy for curved edges.

6. IMAGE FUSION PARAMETERS

6.1. Mean Square Error

$$MSE = \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}(A_{ij} - B_{ij})^2$$

6.2. Peak Signal to Noise Ratio

$$PSNR = 10 \times \log_{10}\left[\frac{peak^2}{MSE}\right]$$

6.3. Average Difference

$$AD = \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}(|A_{ij} - B_{ij}|)$$

6.4. Structural Content

$$SC = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n}[A_{ij}]^2}{\sum_{i=1}^{m}\sum_{j=1}^{n}[B_{ij}]^2}$$

6.5. Normalized Cross Correlation

$$NCC = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n}(A_{ij} * B_{ij})}{\sum_{i=1}^{m}\sum_{j=1}^{n}(A_{ij})^2}$$

6.6. Maximum Difference

$$MD = max(|A_{ij} - B_{ij}|), i = 1, 2, ...m; j = 1, 2, ...n$$

6.7. Normalized Absolute Error

$$NAE = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n}(|A_{ij} - B_{ij}|)}{\sum_{i=1}^{m}\sum_{j=1}^{n}(A_{ij})}$$

7. COMPARATIVE ANALYSIS

Table -1: Comparative analysis of PCA, DCT, SWT, DWT

FACTORS	METHODS			
	PCA	DCT	SWT	DWT
Peak signal to noise ratio	35.83	39.70	40.59	41.643
Mean square error	10.87	4.454	5.544	4.4544
Normalized absolute error	0.009	0.004	0.003	0.0038
Maximum difference	29	27.5	27.5	27.50
Average difference	0.957	0.421	0.421	0.4212
Normalized cross correlation	0.998	0.999	0.999	0.999
Structural content	1.004	1.002	1.002	1.0016

8. CONCLUSION

In this paper different image fusion techniques have been reviewed. Each technique has its own advantages and disadvantages depending on the application. These techniques improve the clarity of the image to some extent but it has been observed that most of the techniques suffer from the problem of color artefacts and roughness of edges of the image. The medical imaging field demands more information content and visualization in an image.

DCT is more appropriate and suitable in real-time systems using discrete cosine transform based standards of stationary image or video.PCA & DCT based image fusion technique can be used for applications which does not require high quality & precision. From the analysis, it has been found that, in general, wavelet-based schemes perform better than standard schemes, particularly in terms of minimizing color distortion. DWT based fusion techniques provide us good quality fused images than PCA & DCT based techniques. But, the DWT is lack of translation variant property which can be nullified by using SWT .Also, SWT can be applied to noisy image source. Therefore, SWT is better image fusion technique compared to DCT, PCA and DWT.

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