Comparative Analysis of Multimodal Medical Image Fusion using PCA and Wavelet Transforms

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***Abstract*— nowadays, there are a lot of medical images and their numbers are increasing day by day. These medical images are stored in large database. To minimize the redundancy and optimize the storage capacity of images, medical image fusion is used. The main aim of medical image fusion is to combine complementary information from multiple imaging modalities (Eg: CT, MRI, PET etc.) of the same scene. After performing image fusion, the resultant image is more informative and suitable for patient diagnosis. There are some fusion techniques which are described in this paper to obtain fused image. This paper presents two approaches to image fusion, namely Spatial Fusion and Transform Fusion. This paper describes Techniques such as Principal Component Analysis which is spatial domain technique and Discrete Wavelet Transform, Stationary Wavelet Transform which are Transform domain techniques. Performance metrics are implemented to evaluate the performance of image fusion algorithm. An experimental result shows that image fusion method based on Stationary Wavelet Transform is better than Principal Component Analysis and Discrete Wavelet Transform.**

***Index Terms:* Image Fusion, Discrete Wavelet Transform, Principal Component Analysis, Stationary Wavelet Transform**

I. INTRODUCTION

Image fusion is the process of combining complementary information from two or more images, resultant image more informative than any of source images. These fused images are help in medical diagnosis, remote sensing, surveillance system and target tracking. Medical images (such as X-ray image, CT-scan image, MRI image etc) are increasing day by day. To optimize the storage capacity and minimize the redundancy medical image fusion is used. In medical imaging, X-Ray, Computed Tomography (CT), Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET), Single Photon Emission Computed Tomography (SPECT) and other modes of medical images show human information from various angles. CT scan is generally used for visualizing dense structure and is not suitable for soft tissues and physiological analysis. It also provides details cross sectional view. On the other hand MRI provides better visualization of soft tissues and is generally used for detection of tumors and other tissue abnormalities. PET gives information about blood flow, oxygen and glucose metabolism in the tissues of the brain [1].

II. CLASSIFICATION OF MULTIMODAL IMAGE FUSION METHODS

Image fusion methods can be classified in three categories: Pixel level, feature level and decision level. Pixel level image fusion deals with the information content corresponding to individual pixels of the input images. This type of image fusion generates an image in which each pixel is appraised from pixels in input images. It is also known as signal level fusion. Advantages of pixel level image fusion are simple and straight forward and disadvantage is altering the spectral information of the original image [2].

In feature level image fusion, the source image is divided into various regions depending upon the features like texture; edges, boundaries etc, and then fused the images. It is also known as object level fusion.

In decision level image fusion, image fusion is done by decision. It is also known as symbol level image fusion. Decision level represents probabilistic decision information based on the voting or fuzzy logic, employed on the output of feature level processing on the images.

As Compared to feature and decision level, pixel level methods are more suitable for medical imaging as they can preserve spatial details in fused images.

III. MEDICAL IMAGE FUSION METHODS

There are various medical image fusion methods but pixel level methods are mostly used for medical image fusion. Some pixel level methods are Wavelet transforms, Principal Component Analysis (PCA) as discussed in this paper. Principal Component Analysis falls under spatial domain where as discrete wavelet transform (DWT) and Stationary Wavelet Transform (SWT) fall under transform domain technique.

PRINCIPAL COMPONENT ANALYSIS (PCA):

PCA is a mathematical tool which transforms a number of correlated variables into a number of uncorrelated variables. The PCA is used widely in image compression and image classification. The PCA involves a mathematical procedure that transforms a number of correlated variables into a number of uncorrelated variables called principal components. It computes a compact and optimal description of the data set.

The first principal component accounts for as much of the variance in the data as possible and each succeeding component accounts for as much of the remaining variance as possible. First principal component is taken to be along the direction with the maximum variance. The second principal component is constrained to lie in the subspace perpendicular of the first. Within this Subspace, this component points the direction of maximum variance. The third principal component is taken in the maximum variance direction in the subspace perpendicular to the first two and so on. The PCA is also known as Karhunen-Loève transform or the Hotelling transform. 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 [3].

Algorithm:

The basic steps involve in principal component analysis algorithm is discussed below.

Let the source images (images to be fused) be arranged in two-column vectors. The steps followed to project this data into two dimensional subspaces are:

1. Organize the data into column vectors. The resultant matrix Z is of dimension $2 \times n$.
2. Compute the empirical mean along each column. The empirical mean vector M_e has a dimension of 1×2.
3. Subtract the empirical mean vector M_e from each column of the data matrix Z. The resultant matrix X is of dimension $2 \times n$.
4. Find the covariance matrix C of X i.e. $C=XX^T$ mean of expectation = cov(X).
5. Compute the eigenvectors V and eigen value D of C and sort them by decreasing eigen value. Both V and D are of dimension 2×2.
6. Consider the first column of V which corresponds to larger eigen value for computation of P_1 and P_2 as:

$$P_1 = \frac{V(1)}{\sum V} \quad \text{and} \quad P_2 = \frac{V(2)}{\sum V} \qquad \text{....(1.1)}$$

where V (1) and V (2) are the first and second element of that column which corresponds to larger eigen value and $\sum V$ is summation of eigen vector matrix.

Image Fusion using PCA

The information flow diagram of PCA-based image fusion algorithm is shown in Fig. 1.1. The input images to be fused $I_1(x, y)$ and $I_2(x, y)$ are arranged in two column vectors and their empirical means are subtracted. The resultant vector has a dimension of n x 2, where n is length of each image vector. Compute the eigenvector and eigen values for this resultant vector and then find the eigenvectors corresponding to the larger eigen value. The normalized components P_1 and P_2 (i.e., $P_1 + P_2 = 1$) using Eq. are computed from the obtained eigenvector. The fused image (I_f) is given by:

$$I_f = P_1 I_1(x, y) + P_2 I_2(x, y) \qquad \text{......(1.2)}$$

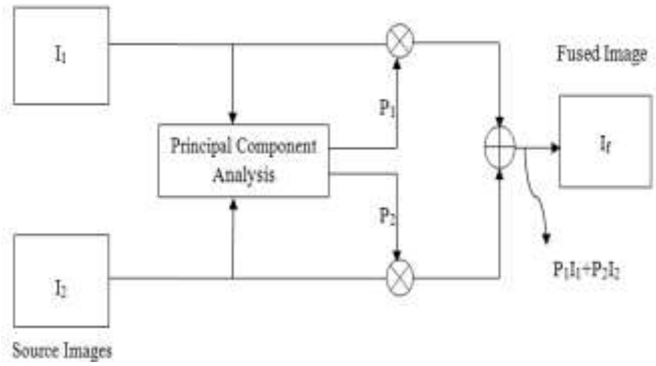


Fig.1.1: Information flow diagram employing PCA

Wavelet Transform

The most common transform type medical image fusion algorithms are the wavelet transform. It is very simple and ability to preserve time and frequency related content of the images to be fused. In this method, first input images are decomposed into lower sub-bands and higher sub-bands. Then, lower sub-bands (LL, LH) are combining by particular fusion rule and higher sub-bands (HL, HH) are also combining by particular fusion rule. Finally, the fused image is reconstructed by inverse wavelet transform. The two dimensional DWT is very useful for image processing because the image data are discrete and spatial and spectral resolution is dependent on the frequency. The DWT (Discrete Wavelet Transform) has property that the spatial resolution is smaller in lower-frequency bands but larger in higher frequency bands.

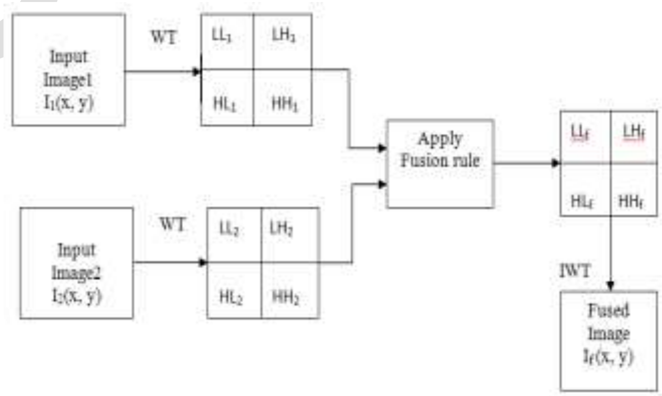


Fig. 1.2: General representation of fusion process in wavelet transforms

DWT suffers from certain disadvantages like loss of edge information due to down-sampling, blurring effect and high storage cost etc. In order to eliminate these disadvantages, stationary wavelet transform (SWT) technique is used.

Stationary Wavelet Transform:

Stationary Wavelet Transform (SWT) is similar to Discrete Wavelet Transform (DWT), the only difference is that in

SWT process of down-sampling is suppressed which means it is translation-invariant [4].

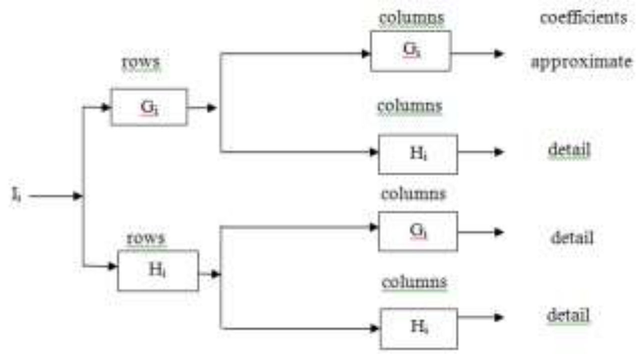


Fig. 1.3: SWT decomposition scheme

where I_i , G_i , H_i represent source images, low-pass filter and high-pass filter, respectively.

The 2D Stationary Wavelet Transform (SWT) is based on the idea of no decimation. It applies the Discrete Wavelet Transform (DWT) and omits both down-sampling in the forward and up-sampling in the inverse transform. More precisely, it applies the transform at each point of the image and saves the detail coefficients and uses the low frequency information at each level. The Stationary Wavelet Transform decomposition scheme is illustrated in fig. 1.3.

SWT Algorithm

The basic algorithm of stationary wavelet transform is explained below [5].

1. Decompose the two source images using SWT at one level resulting in three detail sub bands and one approximation sub band (HL, LH, HH and LL bands).

2. Compute the average of approximate parts of images.

3. Find the absolute values of horizontal parts of the image by subtracting second part of image from first.

$$D = |H_1L_2| - |H_2L_2| >= 0 \qquad \text{….. (1.3)}$$

where D denotes the difference and H_1L_2, H_2L_2 are the horizontal part of image.

4. Make element wise multiplication of D and horizontal part of first image and then subtract another horizontal part of second image multiplied by logical not of D from first for the fusion of horizontal part.

5. Find D for vertical and diagonal parts and obtain the fused vertical and details of image.

6. Obtain the fused image by taking inverse stationary wavelet transform.

Performance Parameters

Performance evaluation is necessary for qualitative and quantitative analysis of the image fusion techniques. The performance parameters or the quality metrics namely entropy, standard deviation, root means square error and peak signal to noise ratio are explained in the following section [6-9].

Entropy:

Entropy is one of the most important quantitative measures in image fusion. Higher entropy indicates more informative image. For an image consisting of L gray levels, the entropy of an image is defined as.

$$H = \sum_{\mathrm{i=i}}^{\mathrm{L}} \mathrm{p(i)} \log_2 \mathrm{p(i)} \qquad \text{.….(1.4)}$$

where p (i) is the probability of each gray scale level.

Standard Deviation:

Standard deviation reflects discrete case of the image grey intensity relative to the average. It represents the contrast of an image. If the standard deviation is large, then the image grey scale distribution is scattered and the image's contrast is high then it means more information in the image. It can be defined as given in eq 1.3.

$$\sigma = \sqrt{\frac{\sum_{\mathrm{i=1}}^{\mathrm{M}} \sum_{\mathrm{j=1}}^{\mathrm{N}} \left(\mathrm{F(i,j)} - \bar{\mathrm{f}}^2\right)}{\mathrm{M} * \mathrm{N}}} \qquad \text{… … (1.5)}$$

where F (i, j) is the grey value of fused image at point (i, j). $\bar{f}$ is the mean value of grey-scale image fusion and M×N is the size of image.

Root Mean Square Error (RMSE):

Root Mean Square Error presents the error between the reconstructed image and the original image as a percentage of the mean intensity of the original image. The RMSE is calculated by.

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{M} * \mathrm{N}} \sum_{\mathrm{x}} \sum_{\mathrm{y}} [\mathrm{I_{true}}(\mathrm{x,y}) - \mathrm{I_{fused}}(\mathrm{x,y})]^2} \qquad \text{…..(1.6)}$$

where $I_{true}(x, y)$ represents the reference image, $I_{fused}(x, y)$ represents the fusion image and M, N are the dimensions of the images.

Peak Signal to Noise Ratio (PSNR):

Peak signal to noise ratio is commonly used to measure of quality of reconstruction of loss compression codec's (e.g., for image compression). In this case, the signal is the original data of the image, and the noise is the error introduced by compression. When comparing compression codes it is used as an approximation to human perception of reconstruction quality, therefore in some cases, one reconstruction may appear to be closer to the original than another, even though it has a lower PSNR. A higher PSNR will generally indicate that the reconstruction is of higher quality.

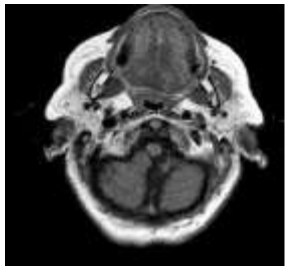
The PSNR is calculated by using the following formula.

$$PSNR = 10 * \log_{10} \left(\frac{M*N}{RMSE} \right) \qquad \text{.....(1.7)}$$

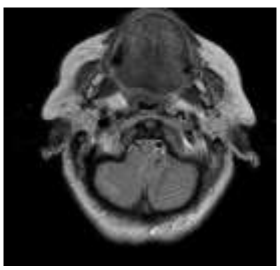
where M, N are the dimensions of the image. PSNR is generally expressed in decibel i.e. db.

Results and Discussion:

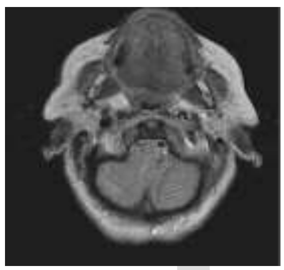
Input image 1 (CT-scan)



Input image 2 (MRI-scan)



(a) DWT-Avg.



(b) DWT-Avg.-Max

(c) SWT

(d) PCA

Fig 1.5 Fused images for dataset

Table 1.1 Results for tested dataset for Different Techniques

Performance Parameters / Techniques	Entropy	Standard deviation	Peak Signal to Noise Ratio (PSNR) db	Root Mean Square Error (RMSE)
PCA	4.5752	44.4132	28.3416	96.02
DWT(avg.)	4.8530	47.1878	30.3299	60.74
DWT(avg.-max)	5.0567	47.4620	30.3147	60.96
SWT	4.9882	48.0827	37.6482	11.2632

IV. CONCLUSION

In this paper medical image fusion using pixel level methods are implemented. In spatial domain, Principal component analysis is implemented and in transform domain discrete wavelet transform and stationary wavelet transform are implemented. Principal component analysis has blurring problem. The discrete wavelet transform method provides a high quality spectral content. But DWT in transform domain is time invariant, this problem is overcome by using SWT. It can be concluded from Entropy, Standard deviation, RMSE and PSNR values that SWT is better image fusion technique compared to PCA and DWT.

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