

A Secure method for Medical Image Fusion

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Abstract--Medical image fusion has been used to derive useful information from multimodality medical image data. The idea is to improve the image content by fusing complimentary images like computer tomography (CT) and magnetic resonance imaging (MRI) images, so as to provide more information to the doctor and clinical treatment planning system. However in existing image fusion software, there is no element of image authentication and security, vital for fields like forensics. We have proposed a unique method in which we perform watermarking on input images of MRI and CT, fuse them using an efficient fusion algorithm and hide the fused image using a suitable steganographic technique, thus authenticating and securing the fused image. Our work covers the selection of best frequency domain based fusion algorithms for medical image fusion, implementation of fusion rules and the fusion image quality evaluation, with special emphasis on the 2-D wavelet transform for images. The fusion performance is evaluated on the basis of the root mean square error (RMSE) and peak signal to noise ratio (PSNR).

Keywords: Medical image fusion, Multimodality images, Wavelet transform, Fusion rules.

I. INTRODUCTION

Image fusion refers to the techniques that integrate complementary information from multiple image sensor data such that the new images are more suitable for the purpose of human visual perception and the compute-processing tasks. Image fusion has become commonplace in satellite imaging, forensics, medicine and so on. The advantages of image fusion are improving reliability and capability [1]-[3].

As the clinical use of various medical imaging systems extends, the multi-modality imaging plays an increasingly important role in medical imaging field. Medical images have difference types such as CT, MRI, PET, ECT, and SPECT. These different images have their respective application ranges. For instance, functional information can be obtained by PET and SPECT. They contain relatively low spatial resolution, but suffer from spectral distortion. CT and MRI provide complimentary information about a body part. For instance, doctors combine the CT and MRI medical images of a patient with a tumor to make a more accurate diagnosis, but it is inconvenient and tedious to finish this especially when a large database of images is involved. And more importantly, using the same images, doctors with different experiences make inconsistent decisions. Thus, it is necessary to develop the efficiently automatic image fusion system to decrease doctor's workload and improve the consistence of diagnosis.

The simplest way of image fusion is to take the average of the two images pixel by pixel. However, this

method usually leads to undesirable side effects such as reduced contrast. Other methods based on intensity-hue saturation (IHS), principal component analysis (PCA), synthetic variable ratio (SVR) etc. In recent years, many image fusion techniques and algorithms have been exploited and they have been successfully used in the fusion process. Images fused by frequency domain methods of image fusion show less spatial and spectral distortion compared to pixel domain methods. More recently, with the development of wavelet theory, many people applied wavelet multi-scale decomposition to take the place of pyramid decomposition for image fusion [8]-[10]. The evolution flowchart of image fusion is as shown in Fig. 1.

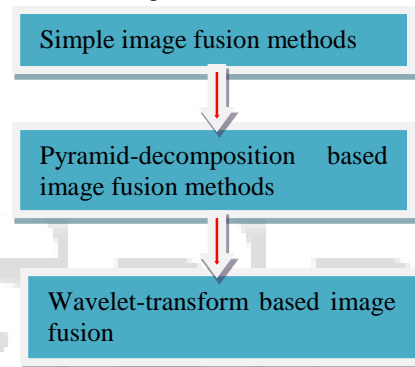


Fig. 1: The flowchart of evolution of image fusion

In this paper, the image fusion is performed at the pixel level, other types of image fusion schemes. We select three frequency domain methods to experiment and to compare with. They are Discrete Cosine transform (DCT), Principal Component Analysis (PCA) and Wavelet-transform-based image fusion. In this research, we are mainly focusing on image fusion methods keeping in mind the superiority of frequency domain based approaches over spatial domain ones.

II. IMAGE FUSION BASED ON WAVELET TRANSFORM

The original concept and theory of wavelet-based multiresolution analysis came from Mallat. The wavelet transform is a mathematical tool that can detect local features in a signal process. It also can be used to decompose two-dimensional (2D) signals such as 2D gray-scale image signals into different resolution levels for multiresolution analysis. Wavelet transform has been greatly used in many areas, such as texture analysis, data compression, feature detection, and image fusion. In this section, we briefly review and analyze the wavelet-based image fusion technique.

A. Wavelet Transform

Wavelet transforms provide a framework in which a signal is decomposed, with each level corresponding to a coarser resolution or lower frequency

band and higher-frequency bands. There are two main groups of transforms, continuous and discrete. The discrete wavelet transform (DWT), which applies a two-channel filter bank (with down sampling) iteratively to the low-pass band (initially the original signal). The wavelet representation then consists of the low-pass band at the lowest resolution and the high-pass bands obtained at each step. This transform is invertible and non-redundant. The DWT is a spatial-frequency decomposition that provides a flexible multi-resolution analysis of an image. In one dimension (1D) the basic idea of the DWT is to represent the signal as a superposition of wavelets. Suppose that a discrete signal is represented by $f(t)$; the wavelet decomposition is then defined as

$$f(t) = \sum_{m,n} c_{m,n} \psi_{m,n}(t) \quad (1)$$

where $\psi_{m,n}(t) = 2^{-m/2} \psi(2^{-m}t - n)$ and m and n are integers. There exist very special choices of ψ such that $\psi_{m,n}(t)$ constitutes an orthonormal basis, so that the wavelet transform coefficients can be obtained by an inner calculation:

$$c_{m,n} = \langle f, \psi_{m,n} \rangle = \int \psi_{m,n}(t) f(t) dt \quad (2.1)$$

In order to develop a multiresolution analysis, a scaling function is needed, together with the dilated and translated version of it,

$$\psi_{m,n}(t) = 2^{-m/2} \psi(2^{-m}t - n) \quad (2.2)$$

According to the characteristics of the scale spaces spanned by and the signal $f(t)$ can be decomposed in its coarse part and details of various sizes by projecting it onto the corresponding spaces. Therefore, to find such a decomposition explicitly, additional coefficients $a_{m,n}$ are required at each scale. At each scale $a_{m,n}$ and $a_{m-1,n}$ describe the approximations of the function $f(t)$ at resolution 2^m and at the coarser resolution 2^{m-1} respectively, while the coefficients $c_{m,n}$ describe the information loss when going from one approximation to another. In order to obtain the coefficients $c_{m,n}$ and $a_{m,n}$ at each scale and position, a scaling function is needed that is similarly defined to (2). The approximation coefficients and the wavelet coefficients can be obtained:

$$a_{m,n} = h_n 2^{n/2} a_{m-1,k} \quad (3)$$

$$c_{m,n} = g_n 2^{n/2} a_{m-1,k} \quad (4)$$

Here h_n is a low-pass FIR filter and g_n is related high-pass FIR filter. To reconstruct the original signal, the analysis filters can be selected from a bi-orthogonal set which have a related set of synthesis filters. These synthesis filters h' and g' can be used to perfectly reconstruct the signal using the reconstruction formula:

$$a_{m-1,l}(f) = [h' 2^{n/2} a_{m,n}(f) + g' 2^{n/2} c_{m,n}(f)] \quad (5)$$

Equations (3) and (4) are implemented by filtering and down sampling. Conversely eqn. (5) is implemented by an initial up sampling and a subsequent filtering.

B. Wavelet Transform for Fusing Image

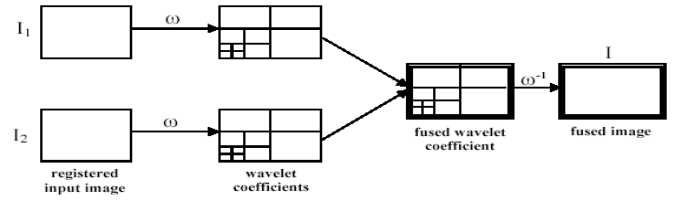


Fig.2: The scheme for image fusion using the wavelet transform

In general, the basic idea of image fusion based on wavelet transform is to perform a multiresolution decomposition on each source image; the coefficients of both the low-frequency band and high-frequency bands are then performed with a certain fusion rule as displayed in the middle block of Figure 2. The widely used fusion rule is maximum selection scheme. This simple scheme just selects the largest absolute wavelet coefficient at each location from the input images as the coefficient at the location in the fused image. After that, the fused image is obtained by performing the inverse DWT (IDWT) for the corresponding combined wavelet coefficients. Therefore, as shown in Figure 2, the detailed fusion steps based on wavelet transform can be summarized below:

Step1. The images to be fused must be registered to assure that the corresponding pixels are aligned.

Step2. These images are decomposed into wavelet transformed images, respectively, based on wavelet transformation. The transformed images with K -level decomposition will include one low-frequency portion (low-low band) and $3K$ high-frequency portions (low-high bands, high-low bands, and high-high bands).

Step 3. The transform coefficients of different portions or bands are performed with a certain fusion rule.

Step 4. The fused image is constructed by performing an inverse wavelet transform based on the combined transform coefficients from Step 3.

III. DISCRETE COSINE TRANSFORM

Discrete cosine transform (DCT) manipulates the image edges to make the image transformed into the form of even functions. It's one of the most common linear transformations in digital signal processing. Two-dimensional discrete cosine transform (2D-DCT) is defined as

$$F(jk) = a(j)a(k) \sum_{m=0}^{N-1} \sum_{n=0}^{N-1} f(mn) \cos \frac{(2m+1)j\pi}{2N} \cos \frac{(2n+1)k\pi}{2N} \quad (6)$$

The corresponding inverse transformation (2D-IDCT) is defined as

$$f(mn) = \sum_{m=0}^{N-1} \sum_{n=0}^{N-1} a(j)a(k) F(jk) \cos \frac{(2m+1)j\pi}{2N} \cos \frac{(2n+1)k\pi}{2N} \quad (7)$$

The 2D-DCT can not only represent the main information of original image into the smallest low-frequency coefficient, but also it can cause the image blocking effect being the smallest, which can realize the good compromise between the information centralizing and the computing complication. So it has wide-spreading applications in domains such as compression coding.

IV. PRINCIPAL COMPONENT ANALYSIS

Principle component analysis or PCA is a mathematical procedure that transforms a number of potentially correlated variables into a smaller number of uncorrelated variables called principal components. The objective of PCA is to reduce the dimensionality (the number of variables) of the dataset while retaining most of the original variability in the data. The first principal component accounts for as much of the variability in the data as possible, and each succeeding component accounts for as much of the remaining variability as possible.. Thus, PCA is concerned with the variance and covariance structure of a high-dimensional random vector through a few linear combinations of the original component variables.

A common way to find the principal components of a data set is by calculating the Eigenvectors of the data covariance matrix. These eigenvectors give the directions in which the data distribution is stretched most. The projections of the data on the Eigen vectors are the principal components. The corresponding Eigen values give an indication of the amount of information that the respective principal components represent. Principal components corresponding

to large Eigen values represent a large amount of information in the data set and thus tell us much about the relations between the data points.

V. STEGANOGRAPHY

A. Lsb Modification Technique

Least significant bit (LSB) coding is the simplest way to embed information in a digital audio file. By substituting the least significant bit of each sampling point with a binary message, LSB coding allows for a large amount of data to be encoded. LSB data hiding technique is one of the simplest methods for inserting data into digital signals in noise free environments, which merely embeds secret message-bits in a subset of the LSB planes of the audio stream.

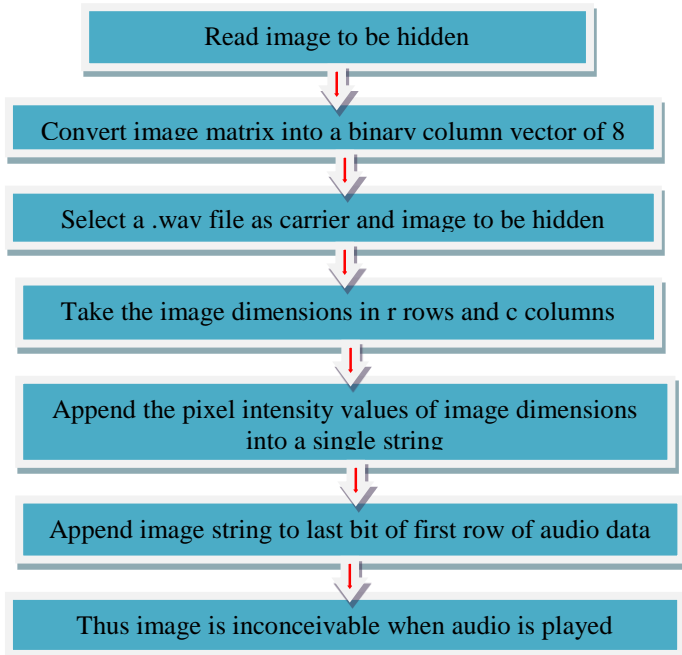


Fig 3: Flowchart for LSB technique of audio steganography

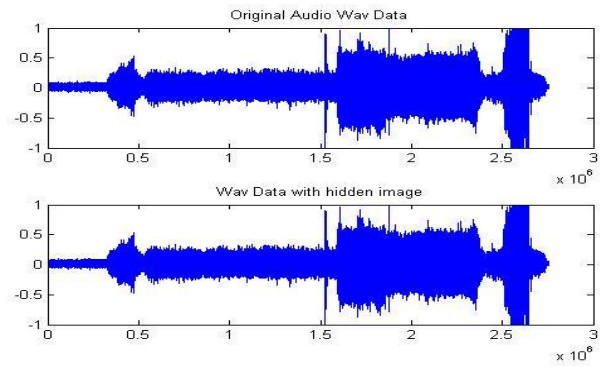


Fig.4: Waveform representation of audio file hiding image

VI. QUALITY EVALUATION

We selected Root Mean Square Error (RMSE) and Peak Signal- to- Noise Ratio (PSNR) to evaluate the effect of the fused images. Suppose R is the source image (standard reference image) and F is the fused image; the root mean square error is defined as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^M \sum_{j=1}^N [R(i, j) - F(i, j)]^2}{M \times N}}$$

The RMSE is used to measure the difference between the source image and the fused image; the smaller the value of RMSE and the smaller the difference, the better the fusion performance. Similarly PSNR (in db) is given as:

$$PSNR = 10 \log_{10} (255 * 255) / (MSE)$$

Higher the value of PSNR, greater is the quality of fused image, depending on the fusion technique used.

VII. EXPERIMENTAL RESULTS

Three frequency domain methods, namely DCT, DWT and PCA were tested in our project for image fusion, Respect to the performance parameters RMSE and PSNR. These are tabulated as follows.

Method	RMSE (dB)	PSNR(dB)
DWT	240	23.801
PCA	352	25.461
DCT	255	26.065

Table.1: Evaluation of different fusion methods

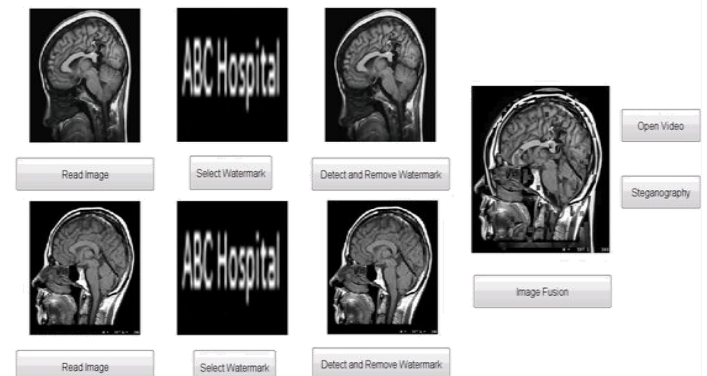


Fig.5: MATLAB GUI of project illustrating proposed secure image fusion technique

VIII. CONCLUSION

We have used the wavelet transform and various fusion rules to fuse CT and MRI images. The experiment results show that the wavelet transform is a powerful method for fusion of images. DWT method gives encouraging results in terms of smaller RMSE and higher PSNR values. We observed that fusion algorithms based on wavelet transform are an effective approach in the domain of image fusion. Thus, for a large database of images, security and authentication in image fusion software is bound to aid fields like medicine and forensics in the future.

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