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Medical Image Fusion Using Discrete Wavelet Transform

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ABSTRACT
Medical image fusion is the process of registering and combining multiple images from single or multiple imaging modalities to improve the imaging quality and reduce randomness and redundancy in order to increase the clinical applicability of medical images for diagnosis and assessment of medical problems. Multimodal medical image fusion algorithms and devices have shown notable achievements in improving clinical accuracy of decisions based on medical images. The domain where image fusion is readily used nowadays is in medical diagnostics to fuse medical images such as CT (Computed Tomography), MRI (Magnetic Resonance Imaging) and MRA. This paper aims to present a new algorithm to improve the quality of multimodality medical image fusion using Discrete Wavelet Transform (DWT) approach. Discrete Wavelet transform has been implemented using different fusion techniques including pixel averaging, maximum minimum and minimum maximum methods for medical image fusion. Performance of fusion is calculated on the basis of PSNR, MSE and the total processing time and the results demonstrate the effectiveness of fusion scheme based on wavelet transform.
KEYWORDS: *Image Fusion, Multimodal medical image fusion, fusion rules, PSNR, MSE.*

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 computer processing tasks. The fused image should have more complete information which is more useful for human or machine perception. The advantages of image fusion are improving reliability and capability [1-3]. The successful fusion of images acquired from different modalities or instruments is of great importance in many applications such as medical imaging, microscopic imaging, remote sensing computer vision and robotics. Image fusion techniques can improve the quality and increase the application of these data. As the use of various medical imaging systems is rapidly increasing so multi-modality imaging is playing an important role in medical imaging field. The combination of the medical images can often lead to additional clinical information not apparent in the separate images [4-7]. The functional and the anatomical information are combined in a single image. Most of the available equipment is not capable of providing such data convincingly. Image fusion techniques allow the integration of different information sources. The fused image can have complementary spatial and spectral resolution characteristics [8].

Many fusion techniques have been proposed in the literature. Use of the simplest image fusion technique like pixel averaging will not recover well fused image due to reduced contrast effect. Other methods based on intensity hue saturation (IHS),

principal component analysis (PCA) etc. has also been developed [9].

In this paper a novel approach for fusion of different medical images of MRI and CT has been proposed using wavelet transform. The CT and MRI of the same people and same spatial parts have been used for analysis and different fusion rules have been implemented on them.

A. Levels of Fusion

Analogous to other forms of information fusion, image fusion is usually performed at one of the three different processing levels: signal, feature and decision [10].

1) Signal level image fusion, also known as pixel-level image fusion, represents fusion at the lowest level, where a number of raw input image signals are combined to produce a single fused image signal.
2) Object level image fusion, also called feature level image fusion, fuses feature and object labels and property descriptor information that have already been fusion of probabilistic decision information obtained by local decision makers operating on the results of feature level processing on image data produced from individual sensors extracted from individual input images
3) The highest level, decision or symbol level image fusion represents fusion of probabilistic decision information obtained by the local decision makers operating on the results of feature level processing on image data produced from the individual sensors.

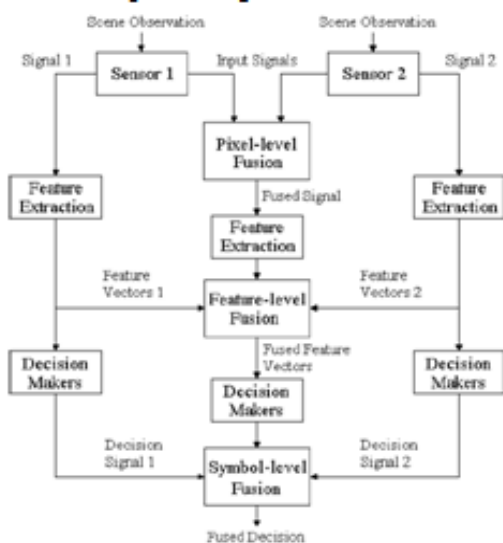Figure 1 instances a system using image fusion at all three levels of processing.

Figure 1: An information fusion system at all three processing

II. MEDICAL IMAGE FUSION

Multimodal medical image fusion algorithms and devices have shown notable achievements in improving clinical accuracy of decisions based on medical images. The selection of the imaging modality for a targeted clinical study requires medical insights specific to organs under study. It is practically impossible to capture all the details from one imaging modality that would ensure clinical accuracy and robustness of the analysis and resulting diagnosis. Figure 2 shows the three major focused areas of studies in medical image fusion: (a) Identification, improvement and development of imaging modalities useful for medical image fusion (b) Development of different techniques for medical image fusion (c) Application of medical image fusion for studying human organs of interest in assessments of medical conditions.
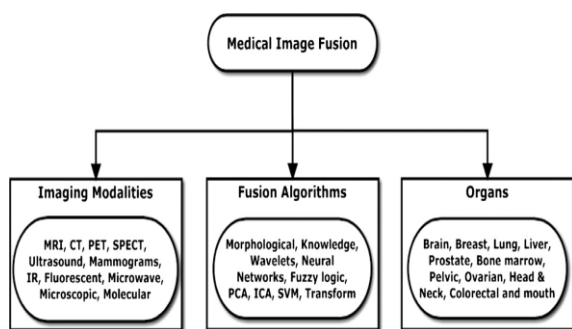

Figure 2: Nature of modalities, methods and organs used in medical image fusion

III. METHODS FOR IMAGE FUSION

Various methods are available for image fusion applications but image fusion techniques are basically classified into two broad categories i.e. spatial domain fusion method and transform domain fusion method. These are explained below:

i. Spatial Domain Fusion Techniques

In spatial domain techniques, we directly deal with the image pixels. The pixel values are manipulated to achieve desired result. These techniques are based on gray level mappings, where the type of mapping used depends on the criterion chosen for enhancement. The disadvantage of spatial domain approaches is that they produce spatial distortion in the fused image.

ii. Transform domain based fusion technique

Transformation or frequency domain techniques are based on the manipulation of the orthogonal transform of the image rather than the image itself. Transformation domain techniques are suited for processing the image according to the frequency content.

III. 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 analysis represents the next logical step: a windowing technique with variable-sized regions. Wavelet analysis allows the use of long time intervals where we want more precise low-frequency information, and shorter regions where we want high-frequency information.
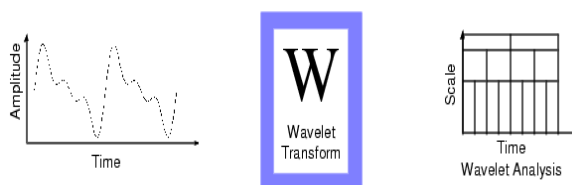

Figure 3: Wavelet Transform on a signal

In one dimension (1D) the basic idea of the DWT is to represent the signal as a superposition of wave lets.

Suppose that a discrete signal is represented by f (t); the wavelet decomposition is then defined as

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

where $\psi_{m,n}(t) = 2^{-m/2} \psi[\, 2^{-m} t - n \,]$ and m and n are integers.

B. Wavelet Transform for Image Fusion

The schematic diagram for wavelet based fusion techniques is shown in figure 3:
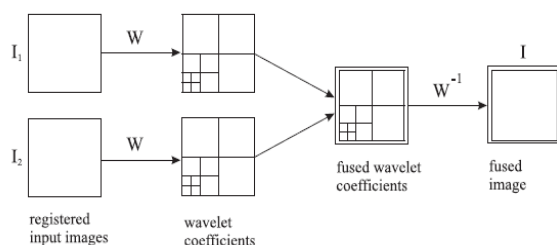

Figure 4: Image Fusion using discrete wavelet transform [11]

In all wavelet based image fusion techniques the wavelet transforms W of the two registered input images $I_1(x, y)$ and $I_2(x, y)$ are computed and these transforms are combined using some kind of fusion rule Ø. This is given by equation (2) below:

$$I(x, y) = W^{-1}\left(\emptyset\left(W\left(I_1(x, y)\right), W\left(I_2(x, y)\right)\right)\right) \ (2)$$

where W^{-1} is the inverse discrete wavelet transform (IDWT).

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. After that, the fused image is obtained by performing the inverse DWT (IDWT) for the corresponding combined wavelet coefficients.

C. ALGORITHM
Following algorithm has been developed and implemented in MATLAB software.
STEPS:
  i. Read the image I1 and find its size.
  ii. Read the second image I2 and find its size.
  iii. Compute and match the size if not same, make it same.
  iv. Convert both images from grayscale to indexed image to perform various wavelet functions. If the color map is smooth, the wavelet transform can be directly applied to the indexed image; otherwise the indexed image should be converted to grayscale format.
  v. Perform multilevel wavelet decomposition using any wavelet (haar, db2, bior1.5).
  vi. Generate the coefficient matrices of the level-three approximation and horizontal, vertical and diagonal details.
  vii. Construct and display approximations and details from the coefficients.
  viii. Regenerate an image by multilevel inverse wavelet transform.
  ix. Repeat the same with second image.
  x. Now fuse the wavelet coefficients using either of averaging, maximum or minimum technique.
  xi. Generate a final matrix of fused wavelet coefficients.
  xii. Compute the inverse wavelet transform to get the fused image.
  xiii. Finally compute the PSNR and MSE and display the results.
  xiv. Also, compute and compare the processing time by each technique.

D. Block Diagram for Image Fusion
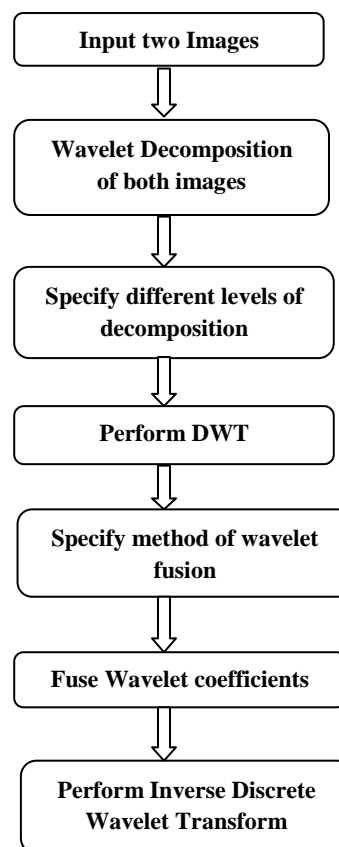The block diagram for image fusion is shown in figure 5.

Figure 5: Block diagram for image fusion

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The two input images are first read and converted to indexed images. After that the wavelet decomposition is done to find the approximate, horizontal, vertical and diagonal details. The decomposition level and the type of wavelet used are specified. DWT is then performed on the input images. The coefficients found are then fused used a specific fusion rule and then the images are restored back using inverse discrete wavelet transform.

E. Fusion Techniques
The different fusion techniques used are mentioned below:

i) Averaging Technique
This algorithm is a simple way of obtaining an output image with all regions in focus. The value of the pixel P (i, j) of each image is taken and added. This sum is then divided by 2 to obtain the average. The average value is assigned to the corresponding pixel of the output image which is given in equation (2). This is repeated for all pixel values. The fused image K(i, j) is given as

$$K\,(i,j)\;=\;\{X\,(i,j)\;+\;Y\,(i,j)\}/2 \qquad (3)$$

where X (i , j) and Y (i , j) are two input images and K (i , j) is the fused image.

ii) Maximum Selection Scheme
This scheme just picks coefficient in each subband with largest magnitude. A selection process is performed here wherein, for every corresponding pixel in the input images, the pixel with maximum intensity is selected, and is put in as the resultant pixel of the fused image K (i , j).

$$K(i,j)\;=\;Max[w(I_1(x,y)),w(I_2(x,y))] \qquad (4)$$

where $I_1(x,y)$ and $I_2(x,y)$ are the input images.

iii) Minimum Selection Scheme
This scheme just picks coefficient in each subband with smallest magnitude. A selection process is performed here wherein, for every corresponding pixel in the input images, the pixel with minimum intensity is selected and is put in as the resultant pixel of the fused image K(i , j).

$$K(i,j)\;=\;Min[w(I_1(x,y)),w(I_2(x,y))] \qquad (5)$$

where $I_1(x,y)$ and $I_2(x,y)$ are the input images.

IV. RESULTS
We have considered three different types of wavelets namely Haar, Daubechies (db2) and Bior (Bior1.5) for fusing the CT and MRI images. Also different fusion rules including pixel averaging, maximum minimum and minimum maximum rules were implemented. Since Haar wavelet along with maximum rule produced better results in terms of PSNR and MSE so they were used for further analysis.

A. Qualitative Analysis
In qualitative analysis image quality indices try to figure out some or the combination of the various factors that determine the quality of the image which include sharpness, contrast, distortion etc.

The figures below show the original CT images (6(a), 7(a), 8(a)), MRI images (6(b), 7(b), 8(b)) and the fused images (6(c), 7(c), 8(c)) using maximum minimum fusion rule, (6(d), 7(d), 8(d)) using pixel averaging rule and (6(e), 7(e), 8(e)) using minimum maximum rule respectively.
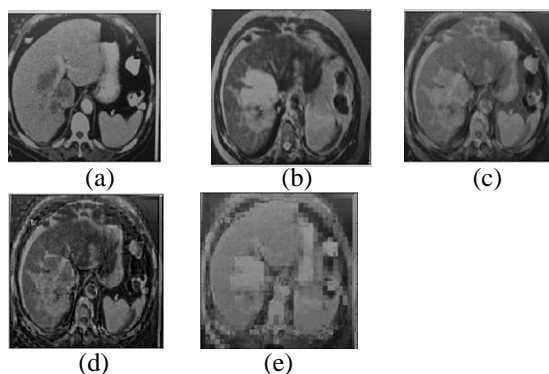
(a)   (b)   (c)

(d)   (e)

Figure 6: (a) CT image (b) MRI image (c, d and e) fused images using max-min, min- max and pixel averaging rules respectively
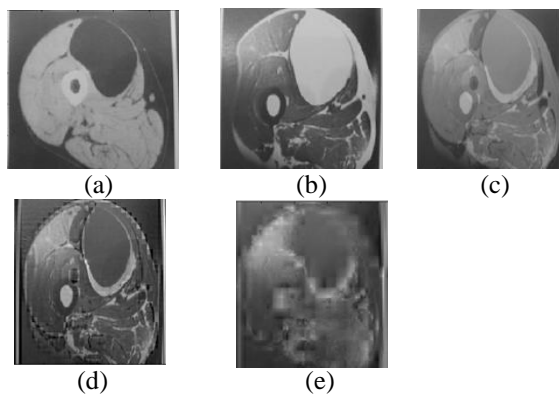
(a)   (b)   (c)

(d)   (e)

Figure 7:(a) CT image (b) MRI image (c, d, and e) fused images using max- min, min max and pixel averaging rules respectively
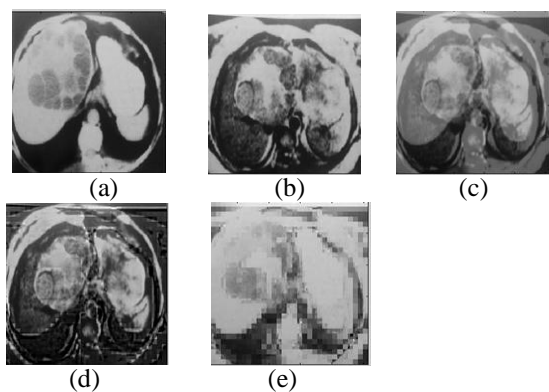
Figure 8: (a) CT image (b) MRI image (c d, e) fused images using max- min, min-max and pixel averaging rules respectively

The above images can be interpreted in the way that the images that are fused using the maximum rule have better contrast because the image is not blurred which effects the contrast of image. Also this method gives the clearer images as there is no variation in the focus of the images having different gray scale intensities.

B. Quantitative Analysis

For evaluating the results various performance metrics were used like PSNR and MSE. The quality of a test image is evaluated by comparing it with a reference image that is assumed to have perfect quality.

i) Peak Signal to Noise Ratio(PSNR)

PSNR is the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. The PSNR measure is given by:

$$PSNR = 10\, log_{10}\, (R^2/\, MSE) \qquad (6)$$

R is the maximum fluctuation in input image data type.

ii) Mean Squared Error (MSE)

The mathematical equation of MSE is given by the equation below

$$MSE = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n}\ [\,I_{1(i,j)} - I_{2(i,j)}\,]^2}{m*n} \qquad (7)$$

where, I_1 is the perfect image, I_2 is the fused image to be assessed, i is pixel row index, j is pixel column index; m and n give the dimensions of the image.

The PSNR and MSE of the three set of images are tabulated in Table 1.

Table I: Results of PSNR and MSE for the fused image (figure 6 (c), 7(c) and 8(c)) using maximum fusion rule.

Image Set	Technique Applied	PSNR	MSE	Elapsed Time
Image Set 1	**Pixel averaging**	35.9714	16.442	4.3057
	Max-min	46.9357	1.3165	5.7508
	Min- max	35.3818	18.832	5.5071
Image Set 2	**Pixel averaging**	37.5378	11.463	2.836
	Max-min	44.3493	2.3886	3.6577
	Min- max	38.4631	9.2635	3.6293
Image Set 3	**Pixel averaging**	36.8417	13.456	4.3341
	Max- min	46.2188	1.5531	5.6608
	Min-max	35.6617	17.657	5.6899

Quantitatively the images can be interpreted in the way that the maximum minimum rule for fusion gives the higher values of PSNR and lower values of MSE which implies the improvement in the quality of the fused image, less error and it contains more information. Thus, it is clear that the maximum rule performs better than the other two methods of pixel averaging and maximum minimum rule.
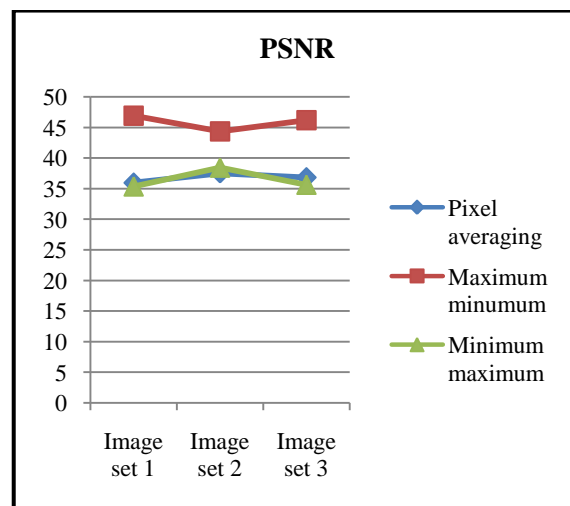

Figure 9: Comparison of different fusion rules for fused images in image set 1, 2 and 3 based on PSNR

The above figure shows the comparison of pixel averaging, maximum minimum and minimum maximum rules in terms of PSNR. It is very clear from the plot that there is increase in PSNR value of image with the use of proposed method over other methods. This increase represents improvement in the objective quality of the image.

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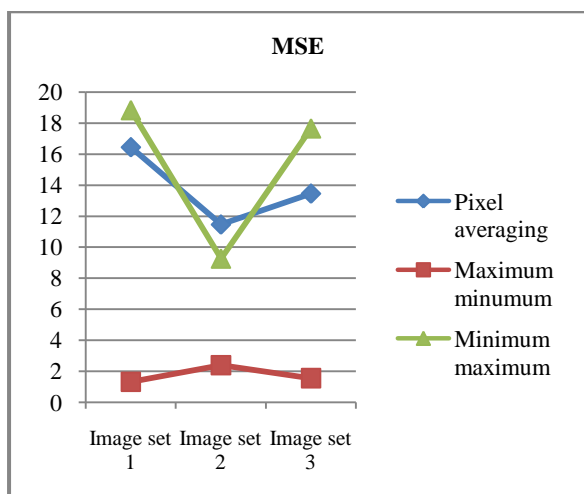*ISSN : 2248-9622, Vol. 4, Issue 9(Version 5), September 2014, pp.165-170*

Figure 10: Comparison of different fusion rules for fused images in image set 1, 2 and 3 based on MSE

The above figure shows the comparison of pixel averaging, maximum minimum and minimum maximum rules in terms of MSE. It is very clear from the plot that there is decrease in MSE value of image with the use of the proposed method giving better image quality.

IV. CONCLUSION

The experimental results show that the wavelet transform is a powerful method for image fusion. This method gives encouraging results in terms of PSNR and MSE. Also from the results it was observed that the maximum minimum fusion rule along with Haar wavelet gives better results and the values of PSNR increase and MSE decrease as the decomposition level increases.

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