S.Priyasaranya *et al*, International Journal of Computer Science and Mobile Applications,

Vol.2 Issue. 4, April- 2014, pg. 39-45 **ISSN: 2321-8363**

BONE CRACK DETECTION IN MEDICAL IMAGES USING MULTI MODEL IMAGE FUSION

S.Priyasaranya[1], R.J.Poovaraghan[2], J.Jagadeesan[3]

Department of Computer and Engineering

SRM University

ABSTRACT

In medical imaging, various modalities provide different features of the human body because they use different physical principles of imaging. CT and MRI images with high spatial resolution provide the anatomical details, while PET and SPECT show the biochemical and physiological information but their spatial resolutions are not good enough. So it is very useful and important to combine images from multi -modality scanning such that the resulting image can provide both functional and anatomical information with high spatial resolution. In this paper we present a wavelet-based image fusion algorithm. The images to be fused are firstly decomposed into high frequency and low frequency bands. We select four groups of images to simulate, and compare our simulation results with the pixel addition, weighted averaging method and wavelet method based on min-max and subtraction based fusion rule. Then, the low and high frequency components are combined by using different fusion rules. Finally, the fused image is instructed by inverse wavelet transform. The various objective and subjective evaluation metrics and Quality are calculated to compare the results. The wavelet based fusion methods using different fusion rules are compared both subjectively as well as objectively. The experimental results show that the pixel minimum method is giving the better results in respect of MSE, SNR and using edge based quality metrics addition method observed to be better in preserving the edge information. One Image fusion method can be perfect for one particular application but may not for another application. So it depends on which information to extract, enhance, and reconstruct or retrieve to use the particular fusion method

Keywords: Image, CT, MRI, DTCWT, Canny Edge Detection, Fusion

INTRODUCTION

Due to development in sensors and camera technology there is increase in different types of digital images from different cameras and sensors with different properties. These digital images are used for different purposes depending on the application where it is applied, for example, we have satellite images such as Panchromatic and multispectral, medical images like CT and MRI. It is not restricted with four types of images alone; there are many images from different sensors. Each image from different sensor has unique property of its own. There are also many methods to improve the property of the images like segmentation, image fusion, and edge detection. This paper discusses the image fusion and edge deduction. Image fusion becomes solution for many applications. In situation like some images requires spatial and spectral information in a single image in case of non availability of instruments for providing the above information obviously image fusion becomes the solution. In the field of medical the image fusion is used for medical diagnostics. Radiologists combine information from multiple image formats. Combined (fused) image are very much useful for diagnosing cancer. In many type of medical images this paper explains CT, MRI and PET image fusion. In the MRI image the inner contour is missing but it provides better information on soft tissues. The CT image provides the best information on denser tissue with less distortion, but it misses the soft tissue information. Hence both the technologies are fused to get an image with perfection. Edge detection is applied to the FUSED image for feature extraction and to detect the discontinuities in the surface, depth the outcome of the edge detection to an image is with a set of connected curves that clearly shows the boundaries of object. There is also a chance to reduce the amount of data by filtering out information that are irrelevant and at the same time it preserves the important structure of the image.

Bone Crack Detection

1. Fusion of images

The main aim is to improve the spatial property and detect the edges of the medical images such as CT, MRI, PET images. For this purpose there are two approaches spatial domain and transform domain based methods such as Averaging method, Brovey method, Principle Compound Analysis, Intensity-hue –saturation [4]. These methods suffer from spatial distortion in the fused image which leads to problem in classification of problemical distortion. Now a days Modified Reconstructability Analysis (MRA) is widely used for image fusion method which contains methods like pyramid transform and multiscale Geometric Analysis (MGA) such as rigdlet, curvelet, bandlet etc.,. Pyramid based method is improper and the decomposes process is very poor for continuous function [3]. The Wavelet Transform (WT) gives good frequency division for continuous function processing and it has been widely used in medical image fusion. This method solves the problem of low contrast and blocking effects in space domain but it performs poor for curve shape, edge representation and there is also problem like directional selectivity and shift invariance. It is also expansive to represent the sharp edges [4]. This situation leads to emergence of new method which gives better information for easy diagnosis of medical images is contour let transform [1]. Contour let is the biggest area of MGA tool. It is best method for analyzing image containing lined, curves, and edges compared to wavelet and other MGA methods. Contour let has capability to produce different directional decomposition levels compared to the wavelet transform. While applying contour let to the image fusion it preserves the original property of the image and gives more information in the fused image. Discrete contour let transform (DCT), Complex Contour let Transform (CCT), Non_subsampled contour let transform (NSCT) are the methods of contour let transform [5]. Discrete contourlet transform (DCT), Complex Contour let Transform (CCT) has the problem of shift invariance and directional selectivity. Problems in the other two methods are overcome by Non_subsampled contour let transform (NSCT) [12]. Non_subsampled contour let transform (NSCT) is combination of Nonsubsample pyramid to produce multiscale decomposition and Nonsubsampled contour let directional filter bank to give directional decomposition. It avoids up sampling and down sampling and gives better artifacts [4].

2. *Edge detection of image* :

- Noise is filtered out – usually a Gaussian filter is used
- Width is chosen carefully
- Edge strength is found out by taking the gradient of the image
- A Roberts mask or a Sobel mask can be used

  $|G|=\sqrt{(Gx^2+Gy^2)}\approx|Gx|+|Gy|$

- Find the edge direction

  $\Theta=\tan^{-1}(Gy/Gx)$

- Resolve edge direction
- Non-maxima suppression – traces along the edge direction and suppress any pixel value not considered to be an edge. Gives a thin line for edge
- Use double / hysteresis thresholding to eliminate streaking
- Compare the results of Sobel and Canny

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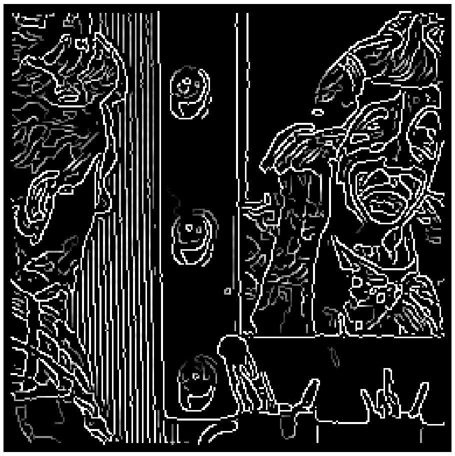
Fig1.

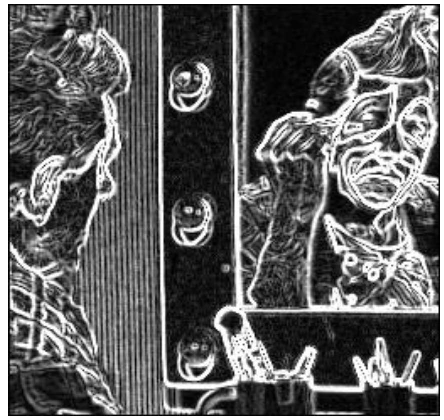
Fig2.

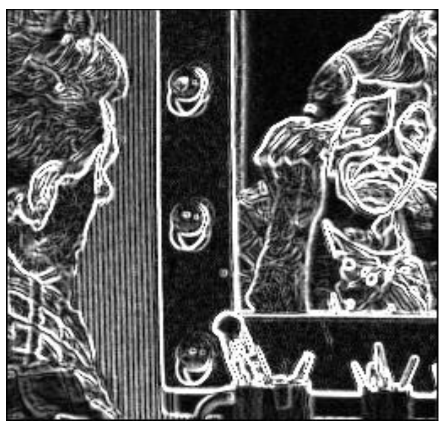
Fig3.

DAUBECHIES COMPLEX WAVELET TRANSFORM

(DCXWT)

The scaling equation of multi resolution theory is given by

$$\Phi(x)=2\sum_{k} \alpha k\Phi(2x-k)$$

where $\sum ak=1$ are the coefficients and Daubechies's wavelet bases $\{\Psi j,k(t)\}$ in one dimension are defined through the above scaling function and multi resolution analysis of L2(R). To provide general solution, Daubechies considered ak to be real valued only.

The Daubechies complex wavelet transform has the following advantages:

a) It has perfect reconstruction.
b) It is non redundant wavelet transform, unlike Dual tree complex wavelet transform (DTCWT) which has redundancy of 2m : 1 for m-dimensional signal.

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c) It has the same number of computation steps as in DWT (although it involves complex computations), while DTCWT have 2m times computations as that of DWT for an m- dimensional signals.
d) It is symmetric. This property makes it easy to handle edge points during the signal reconstruction. However, shift invariance and availability of phase information are the two important properties of the DCxWT that directly influence the performance of image fusion.

THE PROPOSED METHOD

The proposed method uses DCxWT for multimodal medical image fusion. Initially source images are decomposed into low pass and high pass wavelet coefficients using DCxWT. Shift invariance and availability of phase information in DCxWT provide better fusion process through merging of wavelet coefficients. The weighted fusion scheme is simple, yet effective. It was proposed originally in [16], but the use of this fusion rule in recent fusion work [17] influenced us to incorporate it with DCxWT. The steps of the proposed fusion method can be summarized as follows (i) Decompose source images X and Y using DCxWT . (ii) Compute saliency measure x S and y S . (iii) Compute matching measure 2 xy C M Sx Sy = + where xy C stands for covariance between X and Y . (iv) Calculate fused wavelet coefficients using x y Z = w X + w Y (a) if M > T (T = 0.75) then min 1 .5(1) 1 M w o T - = - - and max min w = 1- w (weighted average mode including mean mode for M =1), else min w = 0 and max w =1.

RESULTS AND DISCUSSIONS

The proposed method is experimented with several sets of multimodal medical images and the results have been shown for two sets of medical images. The first set of medical image is MRI and CT image. Second set of medical images are T1- MR and MRA image showing some abnormality as calcified white structure in the image.

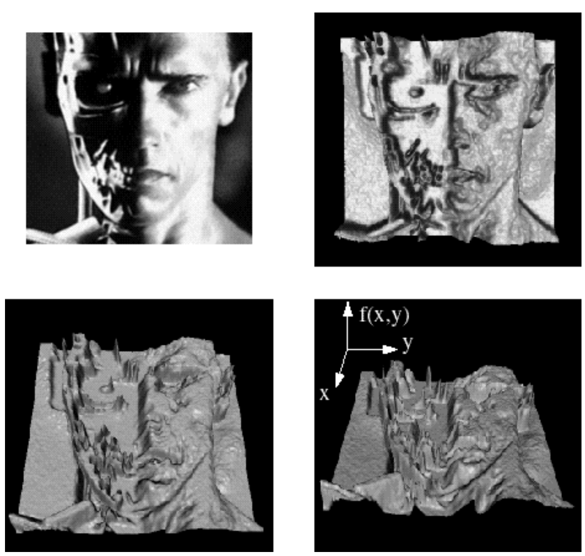

Fig4.

Performance comparison for medical images

Method	QFAB	MI
The proposed method	0.7739	2.3079
DCTWT fusion	0.6278	1.3936
DWT fusion	0.5764	1.1189
CT fusion	0.5287	1.0281

We have compared our results with existing DCxWT, DTCWT, DWT, NSCT and CT based fusion methods with maximum fusion scheme [3, 10, 18], which is widely used and accepted fusion rule. Fusion results for these methods are shown n Fig. are used in two sets of medical images. For multimodal medical image fusion, the objective evaluation of fusion results [18] with non-reference metrics is required, as no reference image is available for quantitative evaluation of the fusion method.

CONCLUSIONS

In the present work, we have proposed a new weighted fusion scheme using Daubechies complex wavelet transform (DCxWT). Shift invariance and availability of phase information properties improved the performance of image fusion in complex wavelet domain. Therefore, we used DCxWT for fusion of multimodal medical images and showed simulation results for two different modalities of medical images. The proposed fusion method has been visually and quantitatively compared with existing DCxWT, DTCWT, DWT, NSCT and CT based fusion method. The quantitative evaluation of the proposed method has been performed with edge strength (F AB Q) and mutual information (MI) metrics. The proposed fusion method has the highest values of edge strength (F AB Q) and mutual information (MI) metrics (shown in Tables 1-2 for two sets of multimodal medical images). Thus, qualitatively and quantitatively, the proposed weighted fusion method with DCxWT showed and proved the effectiveness and goodness over existing DCxWT, DTCWT, DWT, NSCT and CT based fusion methods.

REFERENCES

[1] A. Toet, Image fusion by a ratio of low-pass pyramid, Pattern Recognition Letters 9(4): 245–253, 1989.

[2] A. Toet, J. J. Van Ruyven, J. M. Valeton, Merging thermal and visual images by a contrast pyramid, Optical Engineering 28(7):789–792, 1989.

[3] H. Li, B. S. Manjunath, S. K. Mitra, Multisensor image fusion using the wavelet transform, Graphical Models and Image Processing. 57(3):235–245, 1995.

[4] S. Li, B. Yang, J. Hu, Performance comparison of different multi-resolution transforms for image fusion, Information Fusion 12(2):74-84, 2011.

[6] Z. Qiang, W. Long, L. Huijuan, M. Zhaokun, Similarity-based multimodality image fusion with shiftable complex directional pyramid, Pattern Recognition Letters, 32(13):1544-1553, 2011.

[7] A. Khare, M. Khare, Y. Y. Jeong, H. Kim, M. Jeon, Despeckling of medical ultrasound images using Daubechies complex wavelet transform, Signal Processing, 90(2):428-439, 2010.

[8] A. Khare, U. S. Tiwary, M. Jeon, Daubechies complex wavelet transform based multilevel shrinkage for deblurring of medical images in presence of noise, International Journal on Wavelets, Multi resolution and Information Processing, 7(5):587-604, 2009.

[9] D. Clonda, J. M. Lina, B. Goulard. Complex Daubechies Wavelets: Properties and statistical image modeling. Signal Processing, 84(1):1–23, 2004.

[10] J. M. Lena, Image processing with complex Daubechies wavelets, Journal of mathematical imaging and vision, 7 (3): 211-223, 1997.

[11] P. J. Burt, R. J. Kolczynski, Enhanced image capture through fusion, in: Proceedings of the 4th IEEE International Conference on Computer Vision (ICCV '93), 1993, pp. 173–182.

[12] A. Loza, D. Bull, N. Cangarajah, A. Achim, Non-Gaussian model-based fusion of noisy images in the wavelet domain, Computer Vision and Image Understanding, 114(1):54-65, 2010.

[13] R. Singh, A. Khare, Objective evaluation of noisy multimodal medical image fusion using Daubechies complex wavelet transform, in: Proceedings of the 8th Indian conference on vision, graphics and image processing (ICVGIP-12), IIT Mumbai, India, 2012. http://dx.doi.org/10.1145/2425333.2425405.

[14] S. Xydeas, V. Petrovic, Objective Image Fusion Performance Measure, Electronics Letters, 36(4): 308-309, 2000.

[15] Q. Guihong, Z. Dali, Y. Pingfan, Information Measure for Performance of Image Fusion, Electronics Letters, 38(7): 313-315, 2002.

