A Comparison of Various Fusion Methods for CT and MR Liver Images

Saim Ervural
Department of Electrical and Electronics Engineering, KTO Karatay University, Konya, Turkey
Email: saim.ervural@karatay.edu.tr

Murat Ceylan
Department of Electrical-Electronic Engineering, Selcuk University, Konya, Turkey
Email: mceylan@selcuk.edu.tr

***Abstract*—In this study, liver Magnetic Resonance (MR) images and Computerized Tomography (CT) images were combined with wavelet-based image fusion methods to facilitate expert decision-making in identifying the type of liver focal lesions. For this purpose, 46 MR and 46 CT images were used belong to 36 different patients. These images include different type of focal liver lesions samples that cysts, Hepatocellular Carcinoma (HCC), Colagiocellular Carcinoma (CCC), Focal Nodular Hyperplasia (FNH), liver metastases and hemangioma. For the fusion, three different fusion rules including average rule, maximum selection rule and multiplication rule was applied to images and the results were compared. When the results were visually examined, it was observed that the multiplication rule was more successful. In addition to the visual results, the performances of fusion results are compared using, Peak to Noise Ratio (PSNR), Accuracy (ACC), Entropy (EN) and Fusion Factor (FF) metrics.**

***Index Terms*—image fusion, liver, MR imaging, CT imaging, discrete wavelet transform, image fusion rules**

I. Introduction

Detecting the focal lesions in the liver and determining their type are very important for the correct diagnosis and planning of the treatment. While some types of lesions require no treatment, for other types the need for surgery or medication requirement may emerge. The timely and accurate diagnosis of the focal lesions is of great importance. Imaging methods such as ultrasound, Magnetic Resonance Imaging (MRI), Computed Tomography (CT), spiral CT, Single Photon Emission Computed Tomography (SPECT), Positron Emission Tomography (PET) are used for the diagnosis of liver lesions. In order to increase the accuracy of the diagnosis, various image processing systems are needed. CT images provides electron density map required for accurate radiation dose estimation and superior cortical bone contrast; however, it is limited in soft tissue contrast. MRI provides excellent soft tissue contrast which permits better visualization of tumors or tissue abnormalities in different parts of the body. But MRI has lack of signal from cortical bone and has image intensity values that have no relation to electron density. For the precise diagnosis of disease and for more effective interventional treatment procedures, radiologists need the information from two or more imaging modalities [1]. This helps the radiologist for the precise diagnosis of disease and for more effective interventional treatment procedures.

This paper includes image fusion applications that are developed for the detection of liver focal lesions (hepatocellular carcinoma, colangiocellular carcinoma, focal nodular hyperplasia, metastases, cysts, hemangioma) using multi-resolution analysis methods. Database used in this study, T1-weighted dynamic contrast-enhanced MR and CT images of the liver from the radiology department of Selcuk University Faculty of Medicine.

In a wide variety of applications it is often desired to register two images to within a small fraction of a pixel for image processing tasks or assessment [2]. In this work we are primarily concerned with evaluation of reconstructed images by incompatibility and firstly performed subpixel image registration to align CT and MR images to each other. Multiresolution analysis [3]-[5] has been successfully used in image processing specially with image fusion, wavelet-based features has been used in various applications. In last several years, the Discrete Wavelet Transform (DWT) have been introduced as higher dimensional Multiresolution Analysis (MRA) tool. Secondly source images are decomposed by using DWT and obtained approximation and detail sub-images that convenient for image fusion methods. Three different image fusion rules are performed in this study. MR and CT sub-images' coefficients are combined using mean, maximum selection and multiplication rules. Finally combined coefficients reconstructed By Inverse Discrete Wavelet Transform (IDWT) and fused image was obtained.

This study is organized as follows: Section 2, summarizes multiresolution analysis algorithms, wavelet transform, registration algorithm and used image fusion rules. Section 3 explains the used data and quality metrics, PSNR, ACC, EN and FF values are calculated between fused images and original images. Section 4 presents the comparison of the results. Finally, we drew a conclusion in section 5.

Manuscript received July 14, 2017; revised December 1, 2017.

doi: 10.18178/joig.5.2.59-63

II. METHOD

A. Discrete Wavelet Transform

Discrete Wavelet Transform (DWT) is a mathematical tool for hierarchically decomposing an image. With strong spatial support, the DWT provides a compact representation of a signal's frequency component. DWT decomposes a image into frequency sub-band at different scale from which it can be perfectly reconstructed. The signal into high and low frequency parts is split by the DWT. The low frequency part contains coarse information of signal whereas high frequency part contains information about the edge components. The resolution of an image, which is a evaluate amount of detail information in the image, is changed by filtering operations of wavelet transform. And the scale is changed by sampling. The DWT analyses the image at different frequency bands with different resolutions by decomposing the image into approximation and detail coefficients [6].

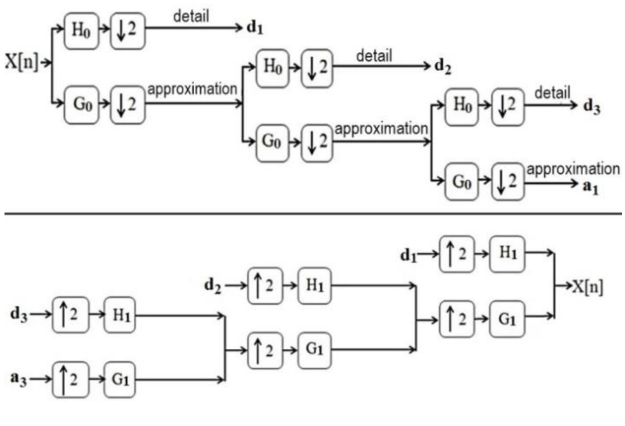

Figure 1. Third level discrete wavelet transform decomposition and reconstruction structure.

Analyzed in the diagrams shown in Fig. 1 is the image matrix expressed by x [n]. When the low pass filter is shown as G0, the high pass filter is shown as H0. At each level (n) the low-pass filter forms the rough approach components shown by a [n]. The high-pass filter expresses the detail components as stated d [n].

The DWT approximation and detail coefficient is defined by the following equations:

$$W_{\varphi}[j_0, k] = \frac{1}{\sqrt{M}} \sum f[n] \phi_{j_0,k}[n] \quad (1)$$

$$W_{\varphi}[j, k] = \frac{1}{\sqrt{M}} \sum f[n] \varphi_{j,k}[n] \quad j \geq j_0 \quad (2)$$

here $f[n], \phi_{j_0,k}[n]$ *and* $\varphi_{j,k}[n]$ are discrete functions defined in [0, M - 1], totally M points. Because the sets $\{\phi_{j_0,k}[n]\} k \epsilon Z$ *and* $\{\varphi_{j,k}[n]\} k \epsilon Z^2$, $j \geq j_0$ are orthogonal to each other.

B. Image Registration

Image registration is a process of two and more image alignment. In practice, cross-correlated efficient sub-pixel registration is used as the registration algorithm. With this process, images obtained at different times and at different positions can be used together with different methods. Registers two images within a fraction of a pixel specified by the difference of imaging techniques MR and CT.

With this procedure all the image points are used to compute the upsampled cross-correlation in a very small neighborhood around its peak. This algorithm can achieve registration with a high accuracy in a small fraction of the computation time and with greatly reduced memory requirements [7].

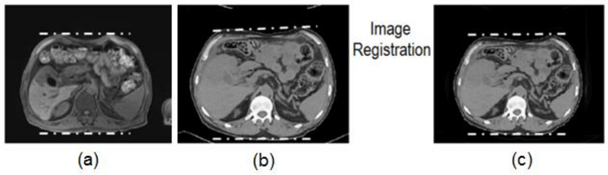

Figure 2. a) reference image (MR), b) incompatible image (CT), c) registered CT image.

As shown in Fig. 2, the planar distortion occurring in the image (b) is corrected by accepting one of the images to be used in the fusion as a random reference, and the registration is performed

C. Image Fusion

In the DWT-based image fusion algorithm, image registration is applied first so that the components such as critical points, curvilinear lines and edge lines in two images overlap at the same pixels. Then all images are divided into low frequency (AF) and high frequency (YF) components by 3rd level DWT decomposition and discrete wavelet coefficients are obtained. Acquired approximation coefficient and detail coefficients combined among themselves by using various fusion rules. The new wavelet coefficients obtained as a result of the fusion process are converted to gray scale image format by applying inverse discrete wavelet transform and a new result image is obtained that contains both information of the image.

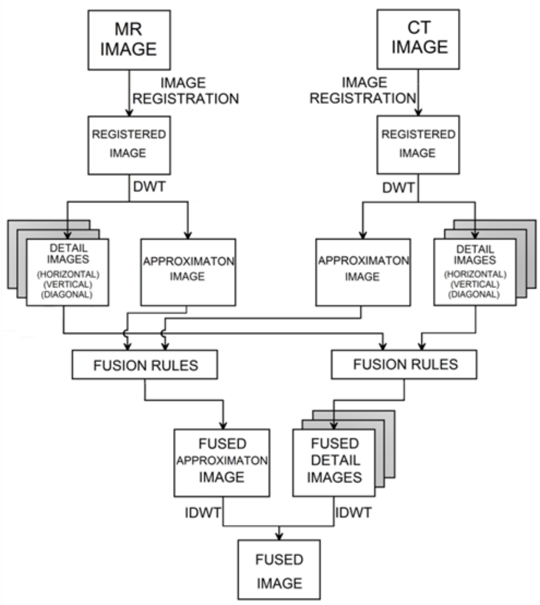

Figure 3. Proposed method of MR - CT image fusion.

The block diagram of the applied fusion method is shown in Fig. 3.

By applying wavelet transforms to images, we obtain wavelet coefficients called approximate coefficients, horizontal detail coefficients, vertical detail and diagonal detail coefficients. These corresponding coefficients of each image will be fused together in a specific way [8].

1) Average Rule.

The task of image fusion is to combine complementary information carried with multimodal images. For this reason, the approach and detail coefficients are compared one by one and average values are taken.

$$C_F^k(i,j) = average\ \left((C_A^k(i,j), C_B^k(i,j)\right) \quad (3)$$

In this equation, $C_F^k(i,j)$, $C_A^k(i,j)$ and $C_B^k(i,j)$ are discrete wavelet coefficients of fused image, MR image and CT image, respectively.

2) Maximum Selection Rule

Maximum selection rule compares the coefficients of the two images and coefficient with greater value is transmitted to the result image.

$$C_F^k(i,j) = max\ \{C_A^k(i,j), C_B^k(i,j)\}\ | \quad (4)$$

3) Multiplication Rule

The general principle of preparing fusion rules is to ensure that as many features as possible are retained in new images such as regions and edges. Accordingly sub-images' coefficients multiplying one by one to access fused image by following equation.

$$C_F^k(i,j) = \left(C_A^k(i,j) * C_B^k(i,j)\right) \quad (5)$$

III. Used Data and Performance Evaluation

In a typical image fusion algorithm, the evaluation metrics has been employed into two stages, which are visual stage and numeric stage. In this section, we provided information about the quality metrics that used in numerical evaluation and the data sets that we use in study.

A. Used Data

In this study, we use 46 liver MR images and 46 liver CT images from 36 different patients that taken from radiology department of Selcuk University Faculty of Medicine. Image collection is labeled by different type of focal liver lesions samples that benign lesions that focal nodular hyperplasia (FNH), cysts, hemangioma and malignant lesions that Hepatocellular Carcinoma (HCC), Colangiocellular Carcinoma (CCC), liver metastases by radiologists using biopsy reports.

Fig. 4 represents 6 different patients' CT and MR image pair that used in practice.

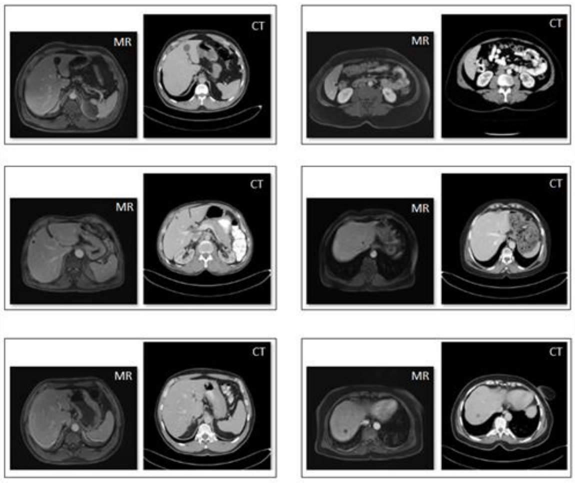

Figure 4. Random selected MR and CT image pairs used in the study.

B. Quality Metrics

The objective quantitative analyses of the resultant images are performed with image quality metrics. The accuracy (ACC), peak signal to noise ratio (PSNR), entropy (EN) and fusion factor (FF) metrics were used for evaluate.

By ACC we define the number of correct classified pixel ratio with finding correct classified pixels by thresholding technique. The difference between 416*512 sized reference image (IR) and fused image (IF) produce pixel difference. If the difference, more than the threshold value (β) between IR and IF, number of incorrect classified pixel increased. The ratio calculates with dividing total pixels number (416x512=212992) to correct classified pixels number [9].

IF

$$I_R - I_F = K \quad (6)$$

$$K<\beta, \quad (7)$$

THEN

Number of Correct Classified Pixel (CCP) increase by 1

ELSE

Number of incorrect classified pixel (iCCP) increase by 1

Finally, we measured the accuracy of proposed methods using the equation,

$$Accuracy = \frac{CCP}{CCP+iCCP} \quad (8)$$

Threshold value, determined with experimental results. Iterations made by β=0.5, β=1, β=1.5, β=5 and optimum compare results had given at β=1, because of its observability. If threshold value increases up to critical value, the algorithm can't detect the errors between images. In order to have a meaningful result, threshold value has to be lower than the pixel differences between the images and also as close as possible to it.

PSNR refers to the ratio between the power of disruptive noise affecting the accuracy of the representation of the signal with the highest power possible [10].

The PSNR measure is given by;

$$PSNR = 10 \ log_{10} \frac{I_{max}{}^{2}}{\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(Y_{i,j}-S_{i,j})^{2}} \tag{9}$$

I_{max} describes as the maximum grayscale value of fused image. Where, $S_{i,j}$ the perfect image, $Y_{i,j}$ the fused image to be assessed, i, pixel row index, j, pixel column index, M, N: number of of row and column.

Entropy is an index that evaluates the amount of information in an image. If the entropy value increases after fusing, it indicates that the information increases and the fusion performances increase. Entropy is defined as;

$$EN = -\sum_{i=0}^{L-1} p_{i\log_2 p_i} \tag{10}$$

where L is the total of grey levels, $p = \{p0, p1, ..pL-1\}$ is the probability distribution of each level [11].

The fusion factor, which is the other quality metric used in the fusion algorithm, For two input images A, B and fused image F, fusion factor is defined as;

$$FF = I_{af} + I_{bf} \tag{11}$$

I_{af} and I_{bf} are mutual information values between the original image and the images obtained as a result of fusion. The high fusion factor value shows that fused image has more information [12].

IV. Results and Discussion

In this study, the analysis performed on three different fusion rules and obtained results compared by visual outputs and numeric values. The MR and CT images are fused by proposed method DWT and the implementation of this project is done using platform of Matlab.

As shown in Fig. 5, multiplication rule results have higher contrast and more liver information than the others. Circles numbered 1, 2 and 3 in the MR image show focal lesions. Numbered rectangles 4, 5 and 6 in the CT image shows blood flow and vascularity. Thus we can easily realize the liver edges, focal lesions' volumes, amount of blood in the veins in Fig. 5(e). On the contrary Fig. 5(c) and Fig. 5(d) do not contain all necessary information.

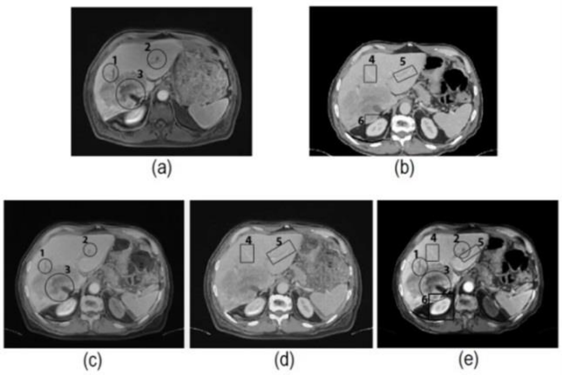

Figure 5. a)MR input image, b)CT input image, c)mean rule applied fused image, d) maximum selection rule applied fused image, e)multiplication rule applied fused image.

Table I show the quality metrics results as ACC, PSNR, EN and FF between result average, maximum selection and multiplication rules. As the shown in Table I, there are some differences between values. The reason of this difference is that accuracy focuses every pixel one by one, PSNR focuses the whole image. That's why accuracy is more sensitive to detect errors. Obtained numeric results given by Table I and Table II.

TABLE I. Quantitative Comparison of Different Fusion Rules with Proposed Image Fusion Method

Quality Metrics	FUSION RULES		
	Maximum Selection Rule	Average Rule	Multiplication Rule
ACC	0,94	0,99	0,99
PSNR	17,89	19,55	17,49
EN	5,06	4,84	4,28
FF	9,40	9,18	8,35

TABLE II. Quantitative Comparison of Fusion Rules According to Lesion Types with Proposed Image Fusion Algorithm

Quality Metrics	LIVER FOCAL LESION TYPES					
	CCC	FNH	HCC	HEM.	CYST	MET.
ACC	0,98	0,96	0,98	0,98	0,98	0,97
PSNR	18,55	17,89	18,60	18,58	19,89	17,82
EN	5,05	4,32	4,83	4,56	4,53	5,11
FF	9,64	7,89	9,38	8,45	8,58	9,98

V. Conclusions

In this study, proposed method is compared with three different fusion rules including average rule, maximum selection rule and multiplication rule with the DWT based image fusion algorithm. The proposed method was tested on CT and MR liver images of different patients. MR and CT images are fused to facilitate expert assessment of liver focal lesions and to combine images from different modalities into a single image. When the fusion process is applied, average, maximum selection and multiplication rules are used and visual and numerical results are presented. When the visual results obtained are examined, there are images that will help the experts to make a diagnosis, including both structural and functional information.

The quantitative evaluation results show that the average of the two images provides more information with a higher peak signal rate.

The visual analysis of the experimental results reveals that the contrast of the CT image with the contrast enhances the details of the border, lesion, vessel, bony tissue and soft tissue in the MR image.

After development of new multiresolution analysis methods and new fusion rules in future works will lead to more useful results in expert evaluation.

ACKNOWLEDGMENT

This study was supported by the Scientific and Technological Research Council of Turkey (TUBITAK, project number: 113E184).

REFERENCES

[1] R. J. Amdur, D. Gladstone, K. A. Leopold, and R. D. Harris, "Prostate seed implant quality assessment using MR and CT image fusion," *Int. J. Radiat. Oncol. Biol. Phys.*, vol. 43, pp. 67-72, 1999.

[2] J. R. Fienup, "Reconstruction of an object from the modulus of its Fourier transform," *Opt. Lett.*, vol. 3, pp. 118-123, July 1978.

[3] J. L. Starck, M. Elad, and D. Donoho, "Redundant multiscale transforms and their application for morphological component separation," *Advances in Imaging and Electron Physics*, vol. 132, pp. 287-348, 2004.

[4] A. Mojsilovic, M. Popovic, S. Markovic, and M. Krstic, "Characterization of visually similar diffuse diseases from B-scan liver images using nonseparable wavelet transform," *IEEE Transactions on Medical Imaging*, vol. 17, no. 4, pp. 541–549, 1998.

[5] S. Alzu'bi and A. Amira, "3D medical volume segmentation using hybrid multiresolution statistical approaches," *Advances in Artificial Intelligence*, pp. 1-15, 2010.

[6] S. G. Mallat, "A theory for multiresolution signal decomposition: the wavelet representation," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 11, pp. 674-693, 1989.

[7] M. Guizar-Sicairos, S. T. Thurman, and J. R. Fienup, "Efficient subpixel image registration algorithms," *Opt. Lett.*, vol. 33, pp. 156-158, 2008.

[8] S. Ervural, "Görüntü füzyonu yöntemleri ile karaciğer lezyon görüntülerinin değerlendirilmesi," MSc thesis, Dept. Elect. Elt. Eng., Number: 10116881, Selcuk University, Konya, 2016.

[9] M. Ceylan and Y. Ozbay, "A novel method for lung segmentation on chest CT images: Complex-valued artifical neural network with comlex wavelet transform," *Turk. J. Elec. Eng. & Comp. Sci.*, vol. 18, no. 4, 2010.

[10] S. Vekkot and P. Shukla, "A novel architecture for wavelet based image fusion," *World Academy of Science, Engineering and Technology*, vol. 57, 2009.

[11] M. Chandana, S. Amutha, and N. Kumar, "A hybrid multi-focus medical image fusion based on wavelet transform," *International Journal of Research and Reviews in Computer Science*, vol. 2, no. 4, p. 948, Aug. 2011.

[12] R. Singh and A. Khare, "Fusion of multimodal medical images using Daubechies complex wavelet transform – A multiresolution approach," *Information Fusion*, vol. 19, pp. 49-60, 2014.

Saim Ervural was born in Turkey on March 23, 1990. He received a bachelor's degree and a master's degree in Electrical-Electronics Engineering from Selcuk University in Konya, Turkey. Currently he is doing his PhD at Selçuk University. He is interested in biomedical, pattern recognition and image processing.

He worked as a scholar at the liver focal lesion identification project and at the same time worked as an electrical and electronic engineer in a private company in 2014. Since 2015 he has been working as a research assistant in the electrical and electronics engineering department of KTO Karatay University.

Murat Ceylan was born in 1978. He received the M.S. (2004) and Ph.D. (2009) degrees in Electrical and Electronics Engineering from Selcuk University, Konya, Turkey. He is currently an Assistant Professor at Selcuk University. He is the author of more than 50 articles.

His research interest includes the development of signal, image and video processing. He completed a project about determination and classification of the liver focal lesions by using multi-resolution analysis methods.