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Feature Level Fusion of Multimodal Images Using Haar Lifting Wavelet Transform

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Abstract**—**This paper presents feature level image fusion using Haar lifting wavelet transform. Feature fused is edge and boundary information, which is obtained using wavelet transform modulus maxima criteria. Simulation results show the superiority of the result as entropy, gradient, standard deviation are increased for fused image as compared to input images. The proposed methods have the advantages of simplicity of implementation, fast algorithm, perfect reconstruction, and reduced computational complexity. (Computational cost of Haar wavelet is very small as compared to other lifting wavelets.)

Keywords**—**Lifting wavelet transform, wavelet transform modulus maxima.

I. Introduction

THE aim of image fusion is to maximize the information content of an image by collecting the strongest features provided by different modalities.

As different modalities of imaging systems are based on different physical phenomena, they capture different features. To collect the complementary information of different imaging system in a single image, fusion is required. It is also used for multi-focused images, where partially defocused images are fused to obtain sharply focused image objects in one image. The image fusion can be classified into four different levels:- Signal level, Pixel level, Feature level and Decision level. The signal level is the low level image fusion, in which, raw images are fused. In pixel level image fusion, information content associated with each pixel is enhanced through fusion. Feature level fusion is an intermediate level fusion, in which relevant features are abstracted from input images and then fused. Decision level fusion is high level fusion, in which decisions coming from different experts are fused. Different techniques are used for image fusion. Chetty [1] presented block based image fusion method using lifting wavelet transform integrated with neural network. Laliberte [2] proposed pixel level fusion techniques. Xia [3] presented neural fusion regularization (CNFR) algorithm for image restoration when images are degraded with non-Gaussian noise. To enhance the quality of restored images, they proposed a cooperative neural fusion (CNF) algorithm for image fusion. Gupta [4] proposed a mathematical description for image fusion differential entropy analysis and showed its usefulness in image fusion scene content matching. Geng [5] presented a method based on 9/7 lifting wavelet transform with weighted average image fusion rule and maximum pixel value fusion rule. A multispectral image fusion based on wavelet transform combined with filtering in the Fourier domain is proposed by Wu [6]. A fusion based on integer wavelet transform and neuro fuzzy is presented by Kavitha [7]. Liu [8] presented a comparative study on 12 selected image fusion metrics over six multiresolution image fusion algorithm for two different fusion schemes and input image with distortion. Ren [9] presented a multifocus image fusion method based on multi band vector wavelet decomposition and reconstruction. Prabhu [10] presented a wavelet transform based image fusion using gradient and relative smoothness criterion. Wavelets have many applications in signal and image processing because of its sparse representation of signal. We presented the same method as in our previous paper [11], but instead of using D4, we used Haar wavelet as the computational cost of Haar wavelet is 3 as compared to 9 in case of D4 wavelet, but still it gives good fusion results. This paper is organized as follows. Section II presents a brief introduction to lifting wavelet transform. Section III describes the wavelet transform modulus maxima criteria. Section IV gives the proposed method. Section V presents the discussion and simulation results.

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II. Lifting Wavelet Transform

The lifting scheme is a simple and powerful tool to construct second generation wavelet [12]. Lifting is a technique to factor existing wavelet filter into basic building blocks. In lifting scheme, the discrete wavelet transform (DWT) is viewed as a prediction error decomposition. The scaling coefficients at a given scale (j) are predictors for or data at the next higher resolution or scale (j-1). The wavelet coefficients are simply the prediction errors between the scaling coefficients and the higher resolution data that they are attempting to predict. Lifting wavelet transform is implemented using following three steps:-

(i). Lazy wavelet transform: If the samples of original data correspond to smooth, slowly varying function, then even and odd polyphase components of the data are highly correlated. This correlation property allow us to predict each odd polyphase components form the nearby even polyphase coefficients. This step divides the original data into its even and odd polyphase components.

$$x_e(n) = x(2n) \quad (1)$$

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$$x_o(n) = x(2n+1) \tag{2}$$

where, $x = (x_k)_{k\in z}$ with $x_k \in R$.

(ii). Predict:- The odd polyphase coefficients are predicted from the neighboring even polyphase coefficients using a predictor P and the wavelet coefficients are generated as the error in predicting the odd samples from the even using prediction operator

$$d(n) = x_o(n) - P[x_e(n)] \tag{3}$$

where P is a predictor and $d(n)$ is detail coefficients of the original signal $x(n)$.

(iii).Update:- This step updates the even set using the wavelet coefficients to compute the scaling coefficients. It applies an update operator U to detail coefficients obtained in step (ii).

$$s(n) = x_e(n) + U[d(n)] \tag{4}$$

Practically, lifting scheme is implemented by decomposing the wavelet filter polyphase matrix into lifting steps using Euclidean algorithm. Daubechies showed that any discrete wavelet transform or two band subband filtering with finite filters can be decomposed into a finite sequence of simple filtering steps, called filtering steps or ladder structures. This decomposition corresponds to a factorization of the polyphase matrix of the wavelet or subband filters into elementary matrices. Perfect reconstruction condition can be made using matrices with polynomial or Laurent polynomial entries. A lifting step then becomes an elementary matrix, that is, a triangular matrix (lower or upper) having one in all diagonal entries. Subband transforms built using elementary matrices are known as ladder structures. Implementing Euclidean algorithm to (unnormalized) Haar wavelets, the polyphase matrix can be written as

$$P(z) = \begin{bmatrix} 1 & \frac{-1}{2} \\ 1 & \frac{1}{2} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} 1 & \frac{-1}{2} \\ 0 & 1 \end{bmatrix} \tag{5}$$

On the analysis part we have,

$$P(z)^{-1} = P(1/z) \begin{bmatrix} 1 & \frac{1}{2} \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ -1 & 1 \end{bmatrix} \tag{6}$$

This corresponds to the following implementation of the forward transform:-

$$s_l^{(0)} = x_{2l} \tag{7}$$

$$d_l^{(0)} = x_{2l+1} \tag{8}$$

$$d_l = d_l^{(0)} - s_l^0 \tag{9}$$

$$s_l = s_l^{(0)} + \frac{1}{2} d_l \tag{10}$$

The inverse transform is given by

$$s_l^{(0)} = s_l - \frac{1}{2} d_l \tag{11}$$

$$d_l^{(0)} = d_l + s_l^{(0)} \tag{12}$$

$$x_{2l+1} = d_l^{(0)} \tag{13}$$

$$x_{2l} = s_l^{(0)} \tag{14}$$

Lifting implementation of wavelet transform has several advantages. Lifting allows the calculation of wavelet transform without allocating auxiliary memory as it allows inplace implementation of the wavelet transform. All operations except the order of lifting operations can be done in parallel. Further, it is possible to implement integer to integer wavelet transform using lifting. Also, the computational cost of Haar wavelet is very much smaller than other wavelets.

III. Wavelet Transform Modulus Maxima Criteria

Mallat and Zhong [13] showed that a Canny edge detector is equivalent to finding the local maxima of a wavelet transform modulus in following way. Consider a 2-D smoothing function $\theta(x, y)$, whose integral over x and y is equal to 1 and converges to 0 at infinity. The image $f(x, y)$ is smoothed at different scales s with $\theta_s(x, y)$, where $\theta_s(x, y)$ is dilated version of $\theta(x, y)$ by a factor of s. The directional derivative of $f(x, y)$ has the largest value along the direction of the gradient vector $\vec{\nabla}(f * \theta_s)(x, y)$ at a point (x_0, y_0) in the image plane (x, y). The edge detection is related to $2-D$ wavelet transform in following way.

Two wavelet functions $\psi^1(x, y)$ and $\psi^2(x, y)$ are defined as

$$\psi^1(x, y) = \frac{\partial\theta(x, y)}{\partial x} \, and \, \psi^2(x, y) = \frac{\partial\theta(x, y)}{\partial y} \tag{15}$$

Let

$\psi_s^1(x, y) = \frac{1}{s^2}\psi^1(\frac{x}{s}, \frac{y}{s})$ and $\psi_s^2(x, y) = \frac{1}{s^2}\psi^1(\frac{x}{s}, \frac{y}{s})$.

Then the wavelet transform of $f(x,y) \in L^2(R^2)$ at the scale s has two components given as

$$W_s^1 f(x,y) = f * \psi_s^1(x,y) \tag{16}$$

$$W_s^2 f(x,y) = f * \psi_s^2(x,y) \tag{17}$$

Thus the wavelet transform of $f(x,y)$ can be written as a multi scale differential operator:

$$\begin{pmatrix} W_s^1 f(x,y) \\ W_s^2 f(x,y) \end{pmatrix} = s \begin{pmatrix} \dfrac{\partial(f*\theta_s(x,y))}{\partial x} \\ \dfrac{\partial(f*\theta_s(x,y))}{\partial y} \end{pmatrix} = s\vec{\nabla}(f*\theta_s)(x,y) \tag{18}$$

The two components of the wavelet transform are proportional to the coordinates of the gradient vector of $f(x,y)$ smoothed by $\theta_s(x,y)$. Canny defined the edge points of $f(x,y)$ at the scale s, as the points where the modulus of the gradient vector of $f*\theta_s(x,y)$ is maximum in the direction, where the modulus of the gradient vector points too. The orientation of the gradient vector indicates the direction where partial derivative of $f(x,y)$ has an absolute value which is maximum. This is the direction of the sharpest variation of $f(x,y)$. Inflection points of the surface $f*\theta_s(x,y)$ are the edge points.

The modulus of this gradient vector is proportional to the wavelet transform modulus

$$Mf(x,y,s) = \sqrt{|W_s^1 f(x,y,s)|^2 + |W_s^2 f(x,y,s)|^2} \tag{19}$$

The function $Mf(x,y,s)$ is called the modulus of the wavelet transform at the scale s. For the wavelet defined by (15), (18) proves that $Mf(x,y,s)$ is proportional to the modulus of the gradient vector $\vec{\nabla}(f*\theta_s)(x,y)$ and its angle is given as

$$Af(x,y,s) = \begin{cases} \alpha, W^1(x,y,s) \geq 0 \\ \pi - \alpha, W^1(x,y,s) < 0 \end{cases} \tag{20}$$

where

$$\alpha = \begin{cases} \tan^{-1}[\dfrac{W^2 f(x,y,s)}{W^1 f(x,y,s)}] when W^2 f(x,y,s) \neq 0 \\ +\dfrac{\pi}{2}, otherwise \end{cases} \tag{21}$$

IV. Proposed Method

The fusion algorithm consists of following steps:-

(1) Decomposition of input images using lifting wavelet transform
(2) Calculation of the modulus of the wavelet transform at the scale s.
(3) Image fusion using threshold value of modulus of wavelet transform.
(4) Inverse wavelet transform of the fused image.

Then image fusion performance is evaluated using standard deviation, entropy and gradient parameters. The entropy gives the average information of image, the gradient gives detail information of the image and standard deviation gives image contrast. Two preregistered images $A(x,y)$ and $B(x,y)$ are decomposed into the subband images using the lifting wavelet transform. We represent the low frequency subimages of A and B by $LA_J(x,y)$ and $LB_J(x,y)$ respectively, where J represents the scale. The modulus of the wavelet transform generated from $HA_J^k(x,y)$ and $HB_J^k(x,y)$ are represented by $GA_J^k(x,y)$ and $GB_J^k(x,y)$ respectively, where for every J, $k = 1,2,3$ corresponds to horizontal, vertical and diagonal directions. We exchange the high frequency components according to the following fusion rule:

If

$$GA_J^k(x,y) - Gb_J^k(x,y) > \delta_k$$

then

$$HF_J^k(x,y) = HA_J^k(x,y)$$

otherwise

$$HF_J^k(x,y) = HB_J^k(X,y)$$

where δ_k is the threshold value and $HF_J^k(x,y)$ is the high frequency component of the fused image.

V. Results and Discussion

We used T1 and T2 weighted MRI images as input and extracted the edges using modulus of wavelet transform function. Edges are fused using threshold value of modulus of wavelet transform function. Table I gives the values of entropy, gradient and standard deviation for input and output images. Then one of the input images is blurred and fusion is performed. The values show that these parameters are increased in case of fused image. Also, visually good image is obtained when one of the input images is blurred.

TABLE I
Parameters Evaluation for Fusion of T1 and T2 Weighted Images

Parameters	Input Image	Output Image
Gradient	0.2304	0.2909
Entropy	4.6860	4.9516
Standard Deviation	0.4195	0.4235

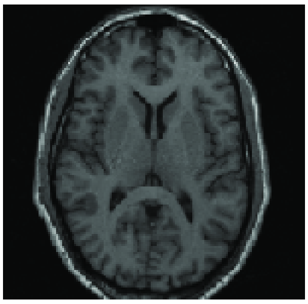

Fig. 1 T1 weighted image

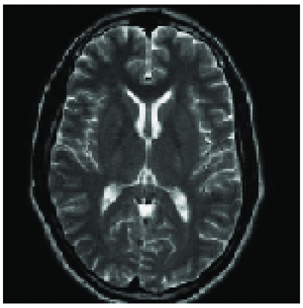

Fig. 2 T2 weighted image

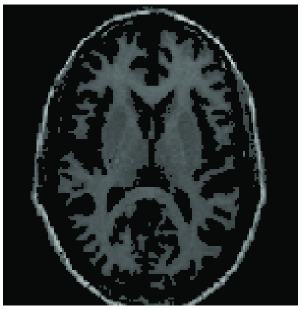

Fig. 3 Blurred T1 weighted image

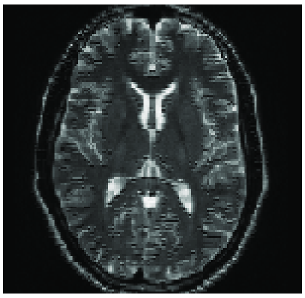

Fig. 4 Fusion result of T2 and blurred T1 weighted image

TABLE II
PARAMETERS EVALUATION FOR FUSION OF T2 AND BLURRED T1 IMAGES

Parameters	Input Image	Output Image
Gradient	0.2598	0.3182
Entropy	3.7253	4.9635
Standard Deviation	0.4365	0.4243

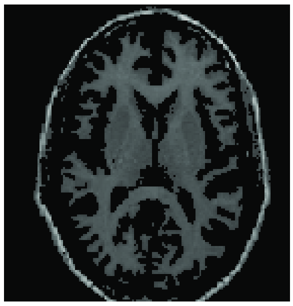

Fig. 5 Blurred T2 weighted image

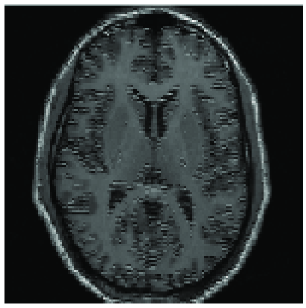

Fig. 6 Fusion result of T1 and blurred T2 weighted image

TABLE III
PARAMETERS EVALUATION FOR FUSION OF T1 AND BLURRED T2 IMAGES

Parameters	Input Image	Output Image
Gradient	0.2579	0.3012
Entropy	3.4151	4.6419
Standard Deviation	0.4400	0.4164

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