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Block based Image fusion technique using Lifting wavelet transform and Neural networks on Medical Images

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Abstract— **Now-a-days, medical image fusion is one of the upcoming fields which helps in easy diagnostics and helps to bring down the time gap between the diagnosis of the disease and the treatment. There are more benefits in combining anatomical imaging modalities with functional ones. In Magnetic Resonance Image (MRI), anatomy and soft tissues are visible and it has high spatial resolution. In Computed Tomography (CT) images, bony structures appears brighter. Positron Emission Tomography (PET) images have low spatial resolution and high spectral resolution. In PET images, functional tissues are visible but anatomy is not well depicted. Hence, by fusing PET and CT images, lung cancer can be detected and by fusing MRI and PET images, brain tumors can be detected and fusion of Single Photon Emission Computed Tomography (SPECT) and CT images help in abdominal studies. The present paper proposes an improved block based feature level image fusion technique using lifting wavelet transform and neural network (BFLN) to combine these pair of images. The present fusion study is experimented on the pair of CT with MRI images and a pair of MRI and PET images. The proposed method helps to diagnose the disease with more accurate information. So, the fused image using the proposed BFLN method can preserve the edges and smoothens the image without introducing any artifacts or inconsistencies as possible. Experimental results prove that the proposed method has obtained a high-resolution image with a good visual quality.**

Keywords- image fusion, lifting wavelet transform, neural network, block based features, performance measures

I. INTRODUCTION

Image fusion is a common term used within medical diagnostics and treatments. Fusion is used when multiple patient images are registered and merged to provide additional information. Fused images are created from multiple images from the same imaging modality [1] or by combining information from multiple modalities [2] such as Magnetic Resonance Image (MRI), Computed Tomography (CT), Positron Emission Tomography (PET), Single Photon Emission Computed Tomography (SPECT). In radiology and radiation oncology, these images serve different purposes. For eg., CT images are used more often to ascertain differences in tissue density while MRI images are typically used to diagnose brain tumors. The PET images indicate the functioning of brain; MRI images show the brain tissue anatomy and contains no functional information. Hence, a perfect fused image should contain both more functional information and more spatial characteristics with no spatial and color distortions.

Radiologists integrate the information of multiple image formats for perfect diagnosis. Fused images which are anatomical helps in diagnosing and treating cancer diseases. Medical image fusion software has been created by some companies such as IKOE, Nicesoft, Velocity medical solutions, etc., for both improved diagnosis and radiation treatment planning systems. These new technologies help radiation oncologist to use intensity modulated radiation therapy (IMRT) to overlay diagnostic images onto radiation planning images which results in more accurate results.

Few requirements imposed on the fusion results are - (a) the fused image should contain all relevant information contained in both the images (b) the fusion process should not introduce any artefacts or inconsistencies (c) irrelevant features and noise should be totally suppressed. The simplest fusion methods are to take the average of the two images pixel by pixel. However, this method usually leads to undesirable side effects such as reduced contrast [3]. The present paper compares the fusion results using the averaging method and the proposed (BFLN) method which integrates lifting wavelet transform with neural networks.

The section 2 deals with image fusion based on lifting wavelet transform; section 3 describes the proposed BFLN algorithm; section 4 deals with quality assessment techniques; section 5 deals with results and discussions; conclusions in section 6.

II. IMAGE FUSION BASED ON LIFTING WAVELET TRANSFORM

Wim Sweldens proposed a new wavelet transform called lifting wavelet transform using the lifting scheme in time domain. One of the features of LWT is that it provides a spatial domain interpretation of the transform. The LWT requires less memory and computation compared with other wavelet transforms and can produce integer-to-integer wavelet transform. The decomposition stage of LWT consists of three steps: split, prediction and update. The following Figure 1 shows a simple lifting wavelet scheme transform.

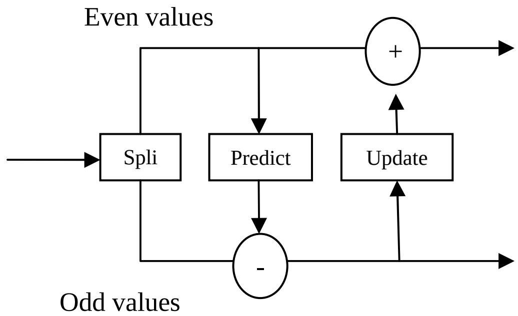

Figure 1: Lifting wavelet scheme transform

The predict step lifts the high pass subband with the low pass subband which can be seen as prediction of the odd samples from the even samples. The update step lifts the low pass subband with the high pass subband to keep some statistical properties of the input stream of the low pass subband. The split step in predict wavelet transform divides the data set into odd and even elements. The predict step uses a function that approximates the data set. The difference between the approximation and the actual data replaces the odd elements of the data set. The even elements are kept as they are and become the input for the next step in the transform. The inverse predict transform adds the prediction value to the odd element. In the inverse transform, the predict step is followed by a merge step which interleaves the odd and even elements back into a single data stream. The update step replaces the even elements with an average value. This result in a smooth input for the next step of the wavelet transforms. The odd elements also represent an approximation of the original data set which allows filters to be constructed. The update phase follows the predict phase. The original value of the odd elements has been overwritten by the difference between the odd element and its even "predictor". So in calculating an average, the update phase must operate on the differences that are stored in the odd elements. Figure 2 depicts the structure of two step lifting wavelet forward transform.

In the split step, the original signal a_l is split into even samples and odd samples using Equation (1)

$$a_{l+1} = a_l(2i), \quad d_{l+1} = a_l(2i+1) \qquad (1)$$

In the prediction step, a prediction operator P is applied on a_{l+1} to predict d_{l+1} using Equation (2). The resultant prediction error d_{l+1} is regarded as the detail signal of a_l.

$$d_{l+1}(i) = d_{l+1}(i) - \sum_{r=-\frac{M}{2}+1}^{M/2} p_r a_{l+1}(i+r) \qquad (2)$$

where p_r is one of the coefficients of P and M is the length of the prediction coefficients.

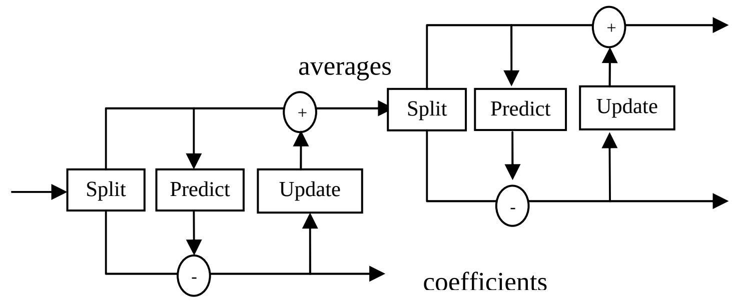

Figure 2: Two steps in lifting wavelet forward transform

In the update step, an update of even samples a_{l+1} is calculated by using an update operator U to detail signal d_{l+1} and adding the result to a_{l+1}, the resultant a_{l+1} can be regarded as the approximation signal of a_l which is calculated using Equation (3)

$$a_{l+1}(i) = a_{l+1}(i) + \sum_{j=-\frac{N}{2}+1}^{N/2} u_j d_{l+1}(i+j-1) \qquad (3)$$

where u_j is the coefficient of U and N is the length of update coefficients.

Let a_l be the input signal for the lifting scheme, the detail and approximation signals at the lower resolution level can be obtained by iterating the above three steps on the output a. The inverse LWT can be performed by reversing the prediction and update operators and changing each '+' into '-' and vice versa. The complete expression of the reconstruction of LWT is shown in Equations (4) to (6). The computational costs of the forward and inverse transform are exactly the same. The prediction operator P and update operator U can be designed by the interpolation subdivision method introduced in [4]. Choosing different P and U is equivalent to choosing different biorthogonal wavelet filters [5].

$$a_{l+1}(i) = a_{l+1}(i) - \sum_{j=-\frac{N}{2}+1}^{N/2} u_j d_{l+1}(i+j-1) \qquad (4)$$

$$d_{l+1}(i) = d_{l+1}(i) + \sum_{r=-\frac{M}{2}+1}^{M/2} p_r a_{l+1}(i+r) \qquad (5)$$

$$a_l(2i) = a_{l+1}, \quad a_l(2i+1) = d_{l+1} \qquad (6)$$

Properties of LWT [6] are –

- The inverse LWT can be performed easily by just changing the signs of all the scaling factors, replacing "split" by "merge" and proceed from right to left.
- Lifting can be done in-place i.e., at every summation point the old stream can be replaced by the recent new stream since the output of the previous lifting step is not needed. Hence, the in-place lifted filters will end up with interlaced coefficients.

III. THE PROPOSED BFLN METHOD

The present BFLN method incorporates the concepts of neural network into lifting wavelet transform for fusion of medical images. The performance of neural networks depends on the sample images. The feedforward backpropagation neural network (NN) is actually composed of two neural network algorithms i.e., feedforward and backpropagation. A neural network recognizes a pattern using 'feedforward' method and training using 'backpropagation' method, which is a 'supervised training' used to train a feedforward neural network. In a feedforward neural network, neurons are connected to the neurons only in the next layer. NN proved to be a more powerful and self-adaptive method of pattern recognition as compared to traditional linear and simple nonlinear analysis [7], [8]. Krista Amolins, Yun Zhang, Peter dare suggested that "schemes that combine standard methods with wavelet transforms produce superior results than either standard methods or simple wavelet-based methods alone". Li et al. describes the application of neural networks to pixel-level fusion of multi-focus images taken from same scene [9].

Sahoolizadeh et al. proposed a new hybrid approach for face recognition using Gabor wavelets and neural networks [4]. C.M.Sheela Rani et al. proposed an efficient block based feature level image fusion technique using wavelet transform with neural network (BFWN) method [10], which integrated wavelet transform with neural network, and proposed an improved block based feature level image fusion technique using contourlet transform with neural network (BFCN) method [11], which integrated contourlet transform with neural network and also proposed an improved block based feature level image fusion technique using multiwavelet transform with neural network (BFMN) method [12], which integrated multiwavelet transform with neural network. Rong *et al.* presented a feature-level image fusion method based on segmentation region and neural networks. The results indicate that this combined fusion scheme is more efficient than the traditional methods [13]. The ANN-based fusion method exploits the pattern recognition capabilities of artificial neural networks, and meanwhile, the learning capability of neural networks makes it feasible to customize the image fusion process. Many applications indicate that the ANN-based fusion methods had more advantages than the traditional statistical methods, especially when input source data were incomplete or with much noise.

It is strictly assumed that the source images are registered. The step wise working of the proposed BFLN method is discussed below.

(1) Read both the images and apply lifting wavelet transform at second level decomposition on the source images into one low frequency sub image and a series of high frequency sub images.

(2) Consider the low frequency sub images of both the images and partition the low frequency sub images of both the source images into k blocks of M*N size and extract the features - contrast visibility, spatial frequency, energy of gradient, variance and edge information from every block.

(3) Subtract the feature values of the i^{th} block related to the first image from the corresponding feature values of the i^{th} block related to second image. If the difference is zero then denote it as 1 else -1.

(4) Construct an Index vector for classification which will be given as an input for the neural network. Create a neural network with adequate number of layers and neurons. Train the newly constructed neural network with random index value.

(5) Simulate the neural network with feature vector index value and if the simulated output > 1 then the i^{th} subblock related to the first image is considered else i^{th} subblock related to the second image is considered.

(6) Reconstruct the entire block and apply inverse lifting wavelet transform to obtain the fused image.

The block diagram of the proposed BFLN method is shown below in Figure 3.

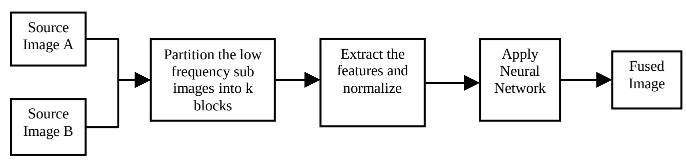

Figure 3. Block diagram of the proposed method

A. Features Selection

In feature-level image fusion, the selection of different features is an important task. The five different features used to characterize the information level contained in a specific portion of the image are Contrast Visibility, Spatial Frequency, Variance, Energy of Gradient (EOG), and Edge information. R.Maruthi and Dr.K.Sankarasubramanian proposed a fusion procedure by using a selection mode according to the magnitude of the spatial frequency and Visibility [14].

Contrast Visibility: It calculates the deviation of a block of pixels from the block's mean value. Therefore, it relates to the clearness level of the block. The visibility of the image block is obtained using Equation (7).

$$VI = \frac{1}{m * n} \sum_{(i,j)\in B_k} \frac{|I(i,j) - \mu_k|}{\mu_k} \tag{7}$$

Here, μ_k and $m \times n$ are the mean and size of the block B_k respectively.

Spatial Frequency: Spatial frequency measures the activity level in an image. It is used to calculate the frequency changes along rows and columns of the image. Spatial frequency is measured using Equations (8) - (10).

$$SF = \sqrt{(RF)^2 + (CF)^2} \tag{8}$$

$$RF = \sqrt{\frac{1}{m*n}\sum_{i=1}^{m}\sum_{j=2}^{n}[I(i,j) - I(i,j-1)]^2} \tag{9}$$

$$CF = \sqrt{\frac{1}{m*n}\sum_{j=1}^{n}\sum_{i=2}^{m}[I(i,j) - I(i-1,j)]^2} \tag{10}$$

Here, I is the image and *m*× *n* is the image size. A large value of spatial frequency describes the large information level in the image and therefore, it measures the clearness of the image.

Variance: Variance is used to measure the extent of focus in an image block. It is calculated using Equation (11).

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$$Variance = \frac{1}{m*n}\sum_{i=1}^{m}\sum_{j=1}^{n}[I(i,j) - \mu]^2 \tag{11}$$

Here, µ is the mean value of the block image and m*n is the image size. A high value of variance shows the greater extent of focus in the image block.

Energy of Gradient (EOG): It is used to measure the amount of focus in an image. It is calculated using Equation (12).

$$EOG = \sum_{i=1}^{m-1}\sum_{j=1}^{n-1}(f_i^2 + f_j^2) \tag{12}$$

Where $f_i = f(i+1,j) - f(i,j)$
$f_j = f(i,j+1) - f(i,j)$

Here, m and n represent the dimensions of the image block. A high value of energy of gradient shows greater amount of focus in the image block.

Edge Information: The Canny edge detector is used to identify the edge pixels in the image block. It returns 1 if the current pixel belongs to some edge in the image otherwise it returns 0. The edge feature is just the number of edge pixels contained within the image block.

IV. QUALITY ASSESSMENT TECHNIQUES

To assess the quality of fused image, some quality measures are required. Goal of image quality assessment is to supply quality metrics that can predict perceived image quality automatically. While visual inspection has limitation due to human judgment, quantitative approach based on the evaluation of "distortion" in the resulting fused image is more desirable for mathematical modeling.

A. Quality metric parameters

The goals of the quantitative measures are normally used for the result of visual inspection due to the limitations of human eyes. In Mathematical modeling, quantitative measure is desirable. One can develop quantitative measure to predict perceived image quality. The quality assessment using noise-based measures are used to evaluate the noise of the fused image. The following optimal noise-based measures are implemented to judge the performance of the fusion methods [15] as follows:

Peak signal to noise ratio (PSNR): PSNR is used to reveal the radiometric distortion of the final image compared to the original image. It is calculated by using Equation (13).

$$PSNR = 10\log_{10}\left(\frac{255 * 255}{MSE}\right) \tag{13}$$

where MSE is used to measure the spectral distortion in the fused image. It is defined by using the Equation (14)

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$$\mathrm{MSE} = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}(I_R(i,j) - I_F(i,j)^2)}{M*N} \tag{14}$$

where $I_R(i,j)$ denotes pixel (i,j) of the image reference and $I_F(i,j)$ denotes pixel (i,j) of the fused image, M*N is the image size.

Mutual Information Measure (MIM): MIM is used to furnishes the amount of information of one image in another. Given two images M (i, j) and N (i, j), it is defined using Equation (15).

$$I_{MN} = \sum_{x,y} P_{MN}(x,y)\log\frac{P_{MN}(x,y)}{P_M(x)P_N(y)} \tag{15}$$

where $P_M(x)$ and $P_N(y)$ are the probability density functions in the individual images and $P_{MN}(x,y)$ is joint probability density function.

Fusion Factor(FF): FF is defined using Equation (16).

$$FF = I_{AF} + I_{BF} \tag{16}$$

where A and B are given two images and F is the fused image. A higher value of FF indicates that fused image contains moderately good amount of information present in both the images.

Standard Deviation (SD): SD is used to measure the contrast in the fused image as given in Equation (17). A well contrast image has high standard deviation.

$$SD = \sqrt{\sum_{i=0}^{L} (i - \bar{i})^2 h_F(i)} \qquad (17)$$

where h_F is the normalized histogram of fused image and L is the number of gray levels.

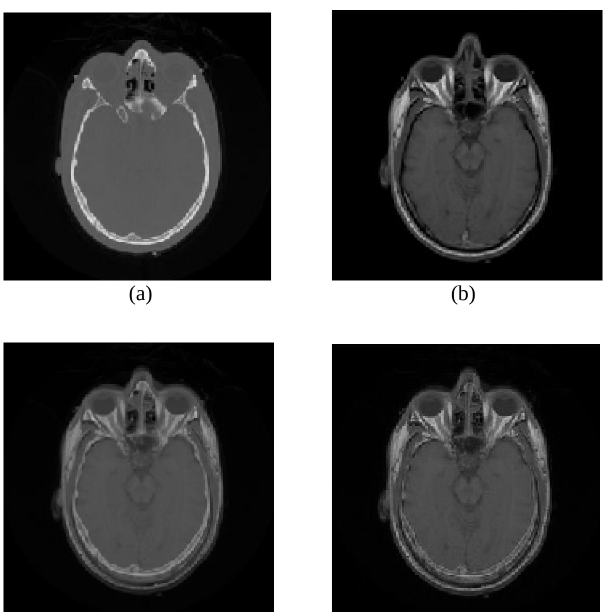
Mean Absolute Error (MAE): MAE is used to measure the average magnitude of the errors in a set of forecasts, without considering their direction. It measures accuracy of continuous variables using Equation (18).

$$MAE = \frac{1}{M * N} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} (I_R(x,y) - I_F(x,y)) \qquad (18)$$

where $I_R(x,y)$ denotes pixel (x,y) of the image reference and $I_F(x,y)$ denotes pixel of the fused image, M*N is image size.

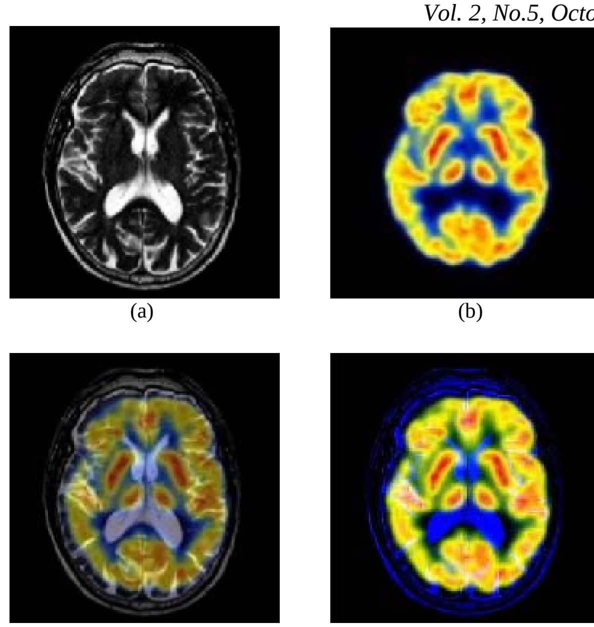
V. Results and Discussions

The following Figure 4 represents the fused images for the Test case 1 i.e., CT and MRI images and Figure 5 represents the fused images for the Test case 2 i.e., MRI and PET images using Averaging method and the proposed BFLN method.



(a) (b) (c) (d)

Figure 4: (a) CT image (b) MRI image (c) Averaging (d) BFLN



(a) (b) (c) (d)

Figure 5: (a) MRI image (b) PET image (c) Averaging (d) BFLN

The calculated values of SD, PSNR, MAE, MIM and FF for the methods Averaging and the proposed BFLN methods are mentioned in the Table I.

TABLE I. Comparision of different metrics on two test cases using Averaging and the proposed BFLN method

	Test case 1		Test case 2	
	Average	BFLN	Average	BFLN
PSNR	76.5938	**90.0894**	67.6817	**70.5096**
MIM	0.8942	**0.9624**	0.8217	**0.8819**
FF	1.7884	**1.7924**	1.6434	**1.7638**
SD	23.5322	**20.2411**	35.7898	**30.2826**
MAE	0.0119	**0.0017**	0.0370	**0.0028**

By comparing the Averaging and BFLN methods, the results show that higher value of PSNR is achieved for the proposed BFLN method for both the Test cases. The graph is depicted in Figure 6. Similarly, by comparing the values of SD for fusing the two test cases, the results show that smaller value of SD is achieved for the proposed BFLN method. The graph is depicted in Figure 7.

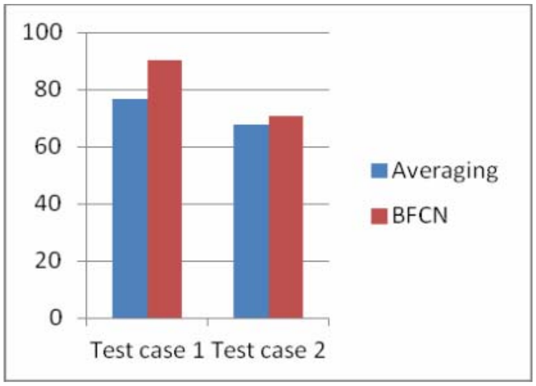


FIGURE 6. COMPARING PSNR VALUES

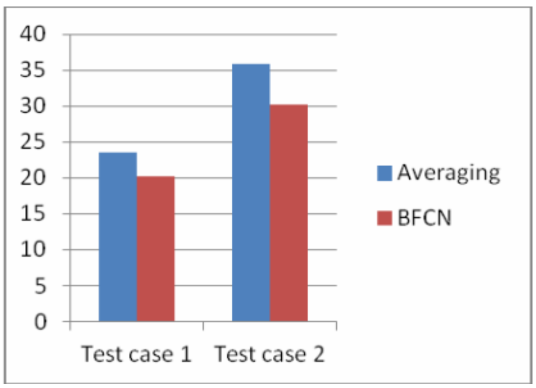


FIGURE 7. COMPARING SD VALUES

VI. CONCLUSIONS

The potentials of image fusion using the proposed block based feature level lifting wavelet transform is integrated with neural network are explored. Axial tissue, weighted MRI segment, all soft tissue structures like eye ball, extracular muscles (lateral and medial rectus) with optic nerve, brain parenchyma can be depicted but the cranial wault is hypo-intensive. Hence, fusion can be performed on CT with MRI or vice versa since cranial wault, bone and soft tissues are clearly visible. The quality of the fusion results are analyzed by using performance metrics. The higher value for PSNR, MIM and FF is achieved for the proposed BFLN method for both all the two test cases. The higher value of PSNR implies that, the spectral information in MS image is preserved effectively and high signal is also preserved. The higher value of MIM and FF indicate that symmetry is achieved by retaining the spectral information. The higher value of FF indicates that fused image contains moderately good amount of information present in both the images. The smaller value of SD and MAE is obtained for the proposed BFLN method for both the test cases. The smaller value of SD indicates that not much deviation is induced in the fused image. The smaller value of MAE indicates that error rate is reduced in the fused image. The metric values of PSNR, MIM and FF are maximum for the proposed BFLN method, and the values of SD and MAE are minimum for the proposed BFLN method. The experimental results indicate that BFLN outperforms the traditional averaging method. Hence, it is ascertained that lifting wavelet transform with neural network has superior performance as it contains high resolution and necessary information from the original source images. The results are verified for a pair of CT and MRI images and a pair of MRI and PET images and the study can be extended for other types of medical images.

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