

Image Fusion using Lifting Wavelet Transform with Neural Networks for Tumor Detection

T. Prabhakara Rao¹, Dr. B. Rama Rao²

¹Research Scholar, Shri Venkateswara University Gajraula, Uttar Pradesh, INDIA.

²Professor, Shri Venkateswara University Gajraula, Uttar Pradesh, INDIA.

Abstract- The medical image fusion is useful for extracting the information from the multimodality images. The main aim of the proposed work is to improve the image quality by fusing CT (Computer Tomography) and MRI (Magnetic Resonance Image). This paper proposes an efficient Lifting wavelet based algorithm for detection of tumor, which utilizes redundant information from the CT and MRI images. The fused image provides precise information to clinical treatment planning systems. The wavelet is used to perform a multiscale decomposition of each image. The proposed system uses lifting wavelet transform due to its de-correlating property. The Neural Networks is used for fusing the wavelet coefficients. The experimental result shows that the proposed fusion technique can be efficiently used to provide discriminatory information which suitable for human vision.

Key words – Image Fusion Neural Network, Lifting Wavelet Transform, CT, MRI and Multimodality

1. INTRODUCTION

Now-a-days medical image fusion is one of the upcoming fields which helps in easy medical diagnostics and helps to bring down the time gap between the diagnosis of the disease and the treatment. Wavelet theory employs the spatial resolution and spectral characteristics. LWT maintains the edge information about the image and it occupies less memory. [1][2] This paper proposes a new image fusion using LWT and fuzzy. Registered CT & MRI images of the same person and same spatial part are used for fusion. First the images are decomposed by LWT. The lifting wavelet coefficients are then fused by applying neuro fuzzy fusion rule. Membership functions are used for fusing the coefficient. Then the inverse lifting wavelet transform is applied to the fused coefficient to get the fused image.

The rapid and significant advancements in medical imaging technologies and sensors, lead to new uses of medical images in various healthcare and bio-medical applications including diagnosis, research, treatment and education etc. Different modalities of medical images reflect different information of human organs and tissues, and have their respective application ranges. For instance, structural images like magnetic resonance imaging (MRI), computed tomography (CT), ultrasonography (USG) and magnetic resonance

angiography (MRA) etc., provide high-resolution images with excellent anatomical detail and precise localization capability. Whereas, functional images such as position emission tomography (PET), single-photon emission computed tomography (SPECT) and functional MRI (fMRI) etc., provide low-spatial resolution images with functional information, useful for detecting cancer and related metabolic abnormalities. A single modality of medical image cannot provide comprehensive and accurate information. Therefore, it is necessary to correlate one modality of medical image to another to obtain the relevant information. Moreover, the manual process of integrating several modalities of medical images is rigorous, time consuming, costly, subject to human error, and requires years of experience. Therefore, automatically combining multimodal medical images through image fusion (IF) has become the main research focus in medical image processing [3], [4].

The feature level improvements on the images by combining wavelets with other techniques have proved to be useful for wavelet based image fusion. The most prominent approach of wavelet image fusion is with neural network [10, 11, 12], where the neural network often takes the roles of feature processing and wavelets take the role of a fusion operator. Similar to neural network, the kernel based operators such as support vector machines (SVM) can be used along with wavelets to achieve image fusion at feature levels [13].

This Paper proposes a block based feature level image fusion technique using lifting wavelet transform and neural network (BFLN) to combine CT, MRI and PET images with feedforward backpropagation learning algorithm. The proposed BFLN method can diagnose the disease with more accurate information since the fused image using the proposed BFLN method can preserve edges and smoothens the image without introducing any artifacts or inconsistencies as possible. The simplest fusion method is to take the average of the two images pixel by pixel. But by using averaging method, the undesirable side effects such as reduced contrast are introduced in the fused image. The present chapter compares fusion results of Averaging method and the proposed BFLN method which integrates lifting wavelet transform with neural networks. Experimental results proved that the fused image using BFLN method contains high-resolution and a good visual quality.

2. IMAGE FUSION BASED ON LIFTING WAVELET TRANSFORM

In medical field Image fusion is used to provide additional information when multiple patient images are registered and merged. Fused images are created from multiple images from the same imaging modality [5] or by combining information from multiple modalities [6] such as CT, MRI, PET, SPECT. In radiology and radiation oncology, these images serve different purposes. Therefore, a perfect fused image should contain maximum functional information and maximum spatial characteristics with no spatial and color distortions.

Sweldens proposed a new wavelet transform named 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 Fig. 6.1 shows a simple lifting wavelet scheme transform.

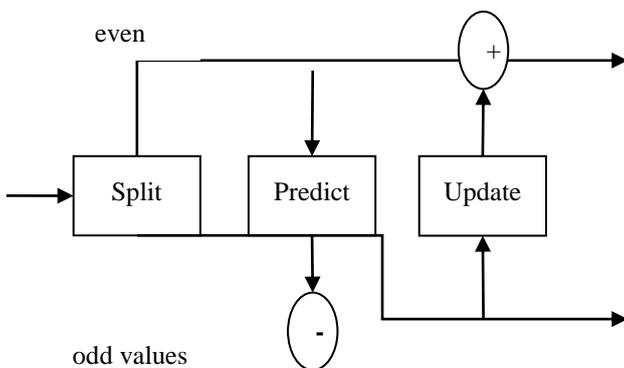


Fig. 1: Lifting wavelet scheme transform.

2.1 Lifting Wavelet Theory

Lifting wavelet theory is a new approach for constructing wavelet, which is also called as second generation wavelet introduced by Sweden [14]. The objective of LWT is to transform coarser signal s_{-1n} into a detailed signal $dn-1$. The major feature of lifting scheme is that all constructions are represented in spatial the domain. Moreover lifting scheme is a simple and an efficient algorithm that any wavelet with FIR filters can be factorized into a sequence of lifting steps and Sweden establish that all the conventional WT based on Mallet algorithm have their equivalent lifting scheme. Construction of wavelet using lifting schemed composed of three steps. 1) Split 2) Predict 3) Update.

Split: The input data $x(n)$ divided into odd and even numbered samples, $x_e(n)$ and $x_o(n)$ and it is point out as lazy WT System.

$$X(n) = x(2n), x(n) = x(2n + 1) \quad (1)$$

Predict: Even samples are maintained as unpredictable and use $x_e(n)$ predicts $x_o(n)$. The difference between the prediction value of $P[X_e(n)]$ is defined as detail signal $D(n)$.

$$D(n) = x(n) - P[X_e(n)] \quad (2)$$

Update: The genuine data set have some universal properties and by introducing update operator (U) and N detailed signal the subsets are carried out in this performance

$$(d_n) S_{n-1} = \text{even} + u(d_{n-1}) \quad (3)$$

The predict step lifts high pass sub-band with low pass sub-band which can be seen as prediction of odd samples from even samples. The update step lifts the low pass sub-band with the high pass sub-band to stay some statistical properties of the input stream of the low pass sub-band. The wavelet transform divides the data set into odd and even elements by split step. The predict step uses a function that approximates the data set. The difference between the actual and the approximation a data replaces the odd elements of the data set. The even elements are kept as they are and become input for the next step in the transform and add 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 consequence 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 odd elements has been overwritten by 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. Fig. 2 shows the structure of two step lifting wavelet forward transform.

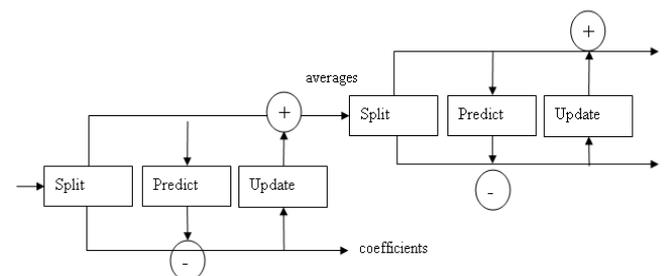


Fig. 2: Steps in lifting wavelet forward transform.

The original signal a_l is split into even samples and odd samples using Equation (4) as per the split step, $a_{l+1} = a_l(2i), d_{l+1} = a_l(2i + 1) \quad (4)$

In the prediction step, a prediction operator P is applied on a_{l+1} to predict d_{l+1} using Equation (5). The resultant prediction error (d_{l+1}) is regarded as the element signal of a_l .

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

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

In the update step, an update of even samples a_{l+1} is accomplished 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 approximation signal of a_l which is calculated using Equation (6)

$$a_{l+1}(i) = a_{l+1}(i) + \sum_{j=-\frac{N}{2}+1}^{\frac{N}{2}} u_j d_{l+1}(i+j-1) \quad (6)$$

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 .

By reversing the prediction and update operators and changing each '+' into '-' and vice versa the inverse LWT can be performed. The complete expression of the reconstruction of LWT is shown in Equations (7)-(9). The computational costs of inverse transform and forward transform are exactly the same. The prediction operator P and update operator U can be designed by interpolation subdivision method introduced in [15]. By choosing different P and U is equivalent to choosing different biorthogonal wavelet filters [16].

$$a_{l+1}(i) = a_{l+1}(i) - \sum_{j=-\frac{N}{2}+1}^{\frac{N}{2}} u_j d_{l+1}(i+j-1) \quad (7)$$

$$d_{l+1}(i) = d_{l+1}(i) + \sum_{r=-\frac{M}{2}+1}^{\frac{M}{2}} p_r a_{l+1}(i+r) \quad (8)$$

$$a_l(2i) = a_{l+1}, \quad a_l(2i+1) = d_{l+1} \quad (9)$$

Properties of LWT [17] 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.

Since the output of the previous lifting step is not needed, Lifting can be done in-place that is, at every summation point the old stream can be replaced by the recent new stream. Hence, the in-place lifted filters will end up with interlaced coefficients.

3. THE PROPOSED BFLN METHOD FOR IMAGE FUSION

The proposed BFLN method for fusion of medical images, it is incorporates the concepts of neural network into lifting wavelet transform. The performance of neural networks depends on sample images. The feed forward back-propagation neural network (NN) is actually composed of two neural network algorithms i.e., feed forward and back-propagation. Neural network recognizes a pattern using 'feedforward' method and

training using 'back-propagation' method, which is a 'supervised training' used to train a feedforward neural network. The proposed method exploits the pattern recognition capabilities of artificial neural networks and the learning capabilities of neural networks makes it feasible to customize the image fusion process.

It is stringently assumed that the source images have been registered. The step wise working of the proposed BFLN method is given below.

Step1: Read both Source images and apply lifting wavelet transform at second level decomposition on both images into one low frequency sub image and a series of high frequency sub images.

Step2: Consider low frequency sub images of source images and partition low frequency sub images of both the source images into k blocks of $M \times N$ size and extract the features - spatial frequency, contrast visibility, energy of gradient, variance and edge information from every block.

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

Step 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.

Step 5: Simulate the neural network with feature vector index value and if the simulated output > 1 then the i_{th} sub block related to first image is considered else i_{th} sub block related to the second image is considered.

Step 6: Re-construct the complete block and apply inverse lifting wavelet transform to obtain the fused image.

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

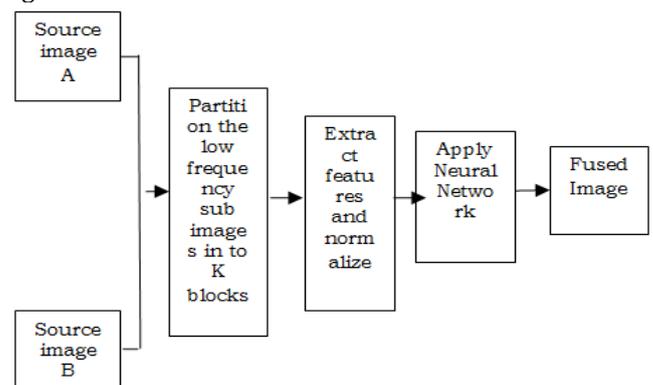


Fig. 3: Block diagram of the proposed BFLN method.

4. RESULTS AND DISCUSSIONS

Proposed BFLN method is experimented on source images of CT, MRI and PET images for fusion process. First experiment is conducted on source images of CT and MRI images which are fused using proposed BFLN method. The results of CT, MRI and fused images are shown in Fig. 4 (a), (b) and (c) respectively. Fig. 4(c) depicts the fused image which clearly identifies the cranial vault, bonystructure along with soft tissues. This fused image is helpful in diagnosing lung cancer. In the second experiment, source images considered are MRI and PET images which are fused using proposed BFLN method. Results of MRI, PET and fused images are shown in Fig. 5 (a), (b) and (c) respectively. The Fig. 5(c) depicts the fused image which clearly identifies soft and functional tissues. This fused image is helpful in diagnosing brain tumors.

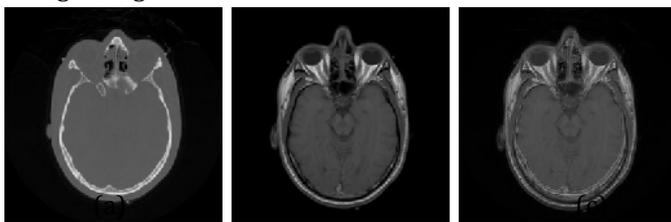


Fig. 4: (a) CT image (b) MRI image (c) BFLN

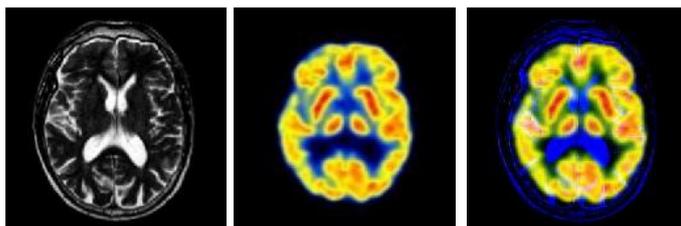


Fig. 5: (a) MRI image (b) PET image (c) BFLN

The Table 1 shows the results of quality metrics using proposed BFLN method for both the experiments. By observing the results of Table 1 of the proposed BFLN method, the following observations are made.

Average value of Peak Signal to Noise Ratio (PSNR) is greater than 70, which implies that the spectral information of MS image is preserved and high signal is effectively transferred.

Average value of Mutual Information Measure (MIM) is around 1, which indicates that good amount of information of source images is furnished in the fused image.

Average value of Fusion Factor (FF) is above 1, which indicates that the similarity of image intensity distribution of the corresponding image pair is induced in the fused image.

Average value of Standard Deviation (SD) is less than 50, which implies that not much deviation is induced in the fused image.

Average value of MAE is less than 0.1, indicates that less average magnitude of the errors in a set of forecasts is induced in the fused image.

Table 1: Quality metrics using the proposed BFLN method

Metrics	Experiment 1	Experiment 2	Average
PSNR	90.0894	70.5096	80.2995
MIM	0.9624	0.8819	0.92215
FF	1.7924	1.7638	1.7781
SD	20.2411	30.2826	25.26185
MAE	0.0017	0.0028	0.00225
PSNR	90.0894	70.5096	80.2995

Comparison Of The Proposed BFLN Method With The Other Fusion Methods

The following Fig. 6 and 7 shows the fused images of CT and MRI and MRI and PET using the Averaging and the proposed BFLN method.

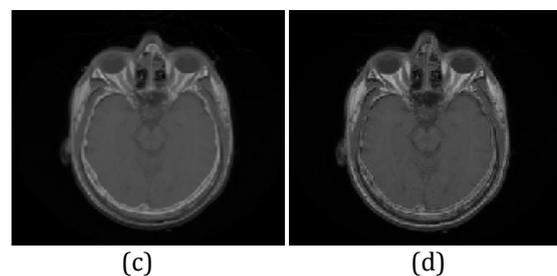
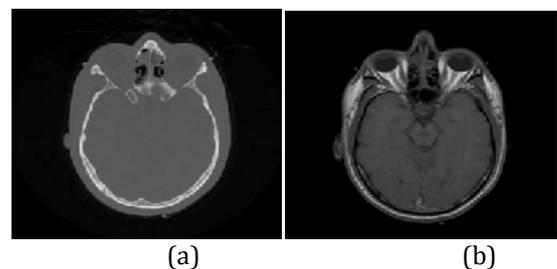
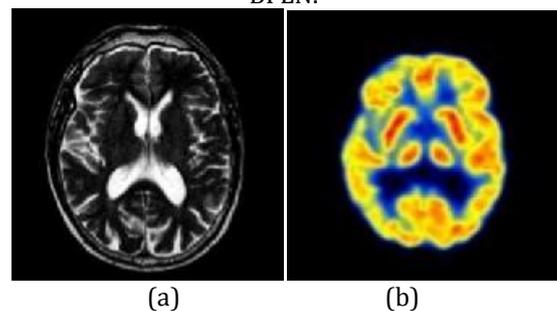


Fig. 6: (a) CT image (b) MRI image (c) Averaging (d) BFLN.



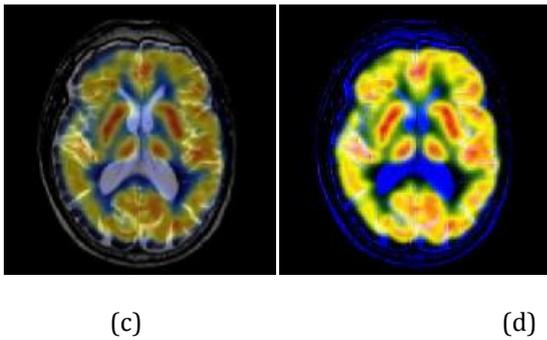


Fig. 7: (a) MRI image (b) PET image (c) Averaging (d) BFLN.

From the visual perception of Fig. 6 and .7, it is clear that the fused images using BFLN method retain edge information and are having more clarity because they contain high resolution from the source images. The edge features and component information of the objects from different modalities are preserved in the fused image effectively. Quality parameters of the proposed BFLN method are compared with Averaging method and with other existing methods proposed by Qu et al. [7], Nikolov et al. [8], Krishnamoorthy et al. [9] on the medical images. The Table 2 lists the average values of each quality parameter on the above images.

Table 2: Quality metrics of the proposed BFLN method with other image fusion methods applied on medical images.

Quality Metrics	Existing Methods				Proposed Method
	Averaging	Qu et al.,	Nikolov et al.,	Krishnamoorthy et al.	BFLN
PSNR	72.13775	74.7587	78.8764	73.7368	80.2995
MIM	0.85795	0.8986	0.9025	0.8459	0.9221
FF	1.7159	1.7567	1.7593	1.5638	1.7781
SD	29.661	26.9675	27.2156	30.6578	25.2618
MAE	0.02445	0.0154	0.0258	0.0567	0.0022

Average values of PSNR, MIM and FF are higher for the proposed BFLN method. Similarly, average value of SD and MAE is smaller for the proposed BFLN method. Hence, the proposed BFLN method is better performance than the existing methods which are compared in Table 2.

Fig. 8 represents the graph which gives comparative analysis of the proposed BFLN method when compared with the Averaging method and other existing methods about the quality parameters.

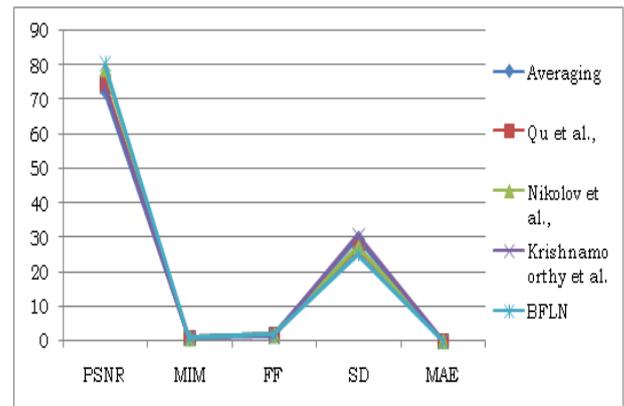


Fig. 8: Comparative analysis of the proposed BFLN method with already existing methods.

5. CONCLUSION

A new fusion rule is proposed using lifting Wavelet Transform and neural Network. The potentials of image fusion using block based feature level lifting wavelet transform included with neural network are explored. Axial tissue, weighted MRI segment, all soft tissue structures like eye ball, with optic nerve, brain parenchyma can be depicted but the cranial vault is hypo-intensive. The edge features and component information of the objects from different modalities are conserved in the fused image effectively. So, the fused image using the BFLN method retains edge information because they contain high resolution from the source images and more clarity. The quality of fusion results are analyzed by using performance metrics. 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 result shows that BFLN method better than the traditional averaging method and other existing methods. It is ascertained that lifting wavelet transform with NN is outperform method. The results are confirmed from CT, MRI and PET images and the study can be extended for other medical images.

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