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The Dynamic Image Fusion Using Wavelet Transform And Neural Networks

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ABSTRACT

In this paper, wavelet transform is integrated with neural network, which is one of the feature extraction or detection machine learning applications. This paper derived an efficient block based feature level wavelet transform with neural network (BFWN) model for image fusion. The proposed BFWN model integrates discrete wavelet transform (DWT) with neural network (NN) for fusing IRS-1D images using LISS III scanner about few locations in India. The proposed BFWN model is compared with DWT alone to assess the quality of the fused image. Experimental results clearly prove that the proposed BFWN model is an efficient and feasible algorithm for image fusion.

Keywords : Image fusion, Discrete Wavelet Transform, Neural Network, block based features, performance measures

INTRODUCTION

The concept of image fusion has been used in many applications like remote sensing, medicine, automatic change detection, biometrics etc. To acquire an image with all the relevant and necessary information is not possible by using image-capturing devices. Hence, there is a need to fuse multiple images. Image fusion mainly focuses on combining spatial information of a high resolution Panchromatic (PAN) image and spectral information of a low resolution Multispectral image (MS) to produce an image with highest spatial content while preserving spectral resolution. The technique of image fusion helps to obtain an image with all the relevant information. Depending upon the purpose of fusion, the fusion techniques can be classified into five groups. Fusion of multi-view images, multimodal images, multitemporal images, multifocus images and fusion for image restoration. Multiview image fusion integrates the images from the same modality and taken at the same time but from different viewpoints. Multimodal image fusion integrates the images taken by different sensors to arrive at conclusions that are not feasible from a single sensor. Multitemporal fusion combines the images taken at different times in order to detect changes between them or to synthesize realistic images of objects which were not photographed in a desired time. Multifocus fusion of images deals with 3D scene taken repeatedly with various focal lengths. The multisensor image fusion helps in understanding the existing surroundings in a better way, which leads in better planning, decision-making, and control of autonomous and intelligent machines.

IMAGE FUSION BASED ON WAVELET TRANSFORM

The wavelet-based approach is appropriate for performing fusion task for the following reasons:

- It is a multiscale approach which well suits to manage the different image resolutions. The multiscale information can be useful in a number of image processing applications including image fusion.
- It allows image decomposition in different kinds of coefficients preserving the image information. These coefficients can be appropriately combined to obtain new coefficients so that the information in the source images is collected appropriately.
- The final fused image is achieved by simply performing inverse wavelet transform.

The wavelet transform decomposes an image into four frequency bands: low-low (LL), low–high (LH), high–low (HL) and high–high (HH). It provides a framework in which an image is decomposed, with each level corresponding to a coarser resolution band. For example, for fusing a MS image with a high-resolution PAN image using wavelet fusion technique, the PAN image is first decomposed into a set of low-resolution PAN images with corresponding wavelet coefficients for each level. An individual band of the MS image then replaces the low-resolution PAN at the resolution level of the original MS image. The high resolution spatial information is injected into each MS band by performing an inverse wavelet transform on each MS band together with the corresponding wavelet coefficients. In the wavelet-based fusion schemes, detailed information is extracted from the PAN image using wavelet transforms and injected into the MS image. This entire process is represented in Figure 1.

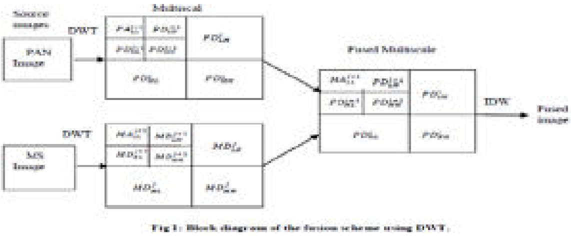

Fig 1: Block diagram of the fusion scheme using DWT.

ARTIFICIAL NEURAL NETWORKS

The Artificial Neural Network (ANN) based method employs a nonlinear response function that iterates many times in a special network structure in order to learn the complex functional relationship between the input and output training data. A neural network consists of three layers – input layer, hidden layer and output layer. The input layer contains many neurons, which represent the feature factors extracted and normalized from the source images. The hidden layer consists of several neurons for processing and the output layer can have one or more neurons. In general, the i^{th} neuron of the input layer connects with the jth neuron of the hidden layer by some specified weight and the j^{th} neuron of the hidden layer connects with the k^{th} neuron of output layer by some specified weight. The weighting function is used to simulate and recognize the response relationship between the features of fused image and corresponding features from the source images.

The first step of neural network based data fusion is to decompose the two registered images into several blocks with some pre-defined size. The features are extracted from the two images of the corresponding blocks, and the normalized feature vector incident to the neural network is constructed. Generally, the features used for extraction are spatial frequency, visibility, edge, etc. Next, the NN is trained by selecting a sample vector. After training, the NN model can remember a functional relationship and can be used for further calculations.

FEATURE 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.

Contrast Visibility: Contrast visibility relates to the clearness level of the block. It calculates the deviation of a block of pixels from its block's mean value. The visibility of the image block is obtained using below equation.

$$VI = \frac{1}{p*q}\sum_{m,n\in B_k}\frac{|I(m,n)-\mu_k|}{\mu_k}$$

where µk and p*q are the mean and size of the block Bk 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. It is measured using below equations.

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

$$\text{Where} \quad RF = \sqrt{\frac{1}{p*q}\sum_{m=1}^{p}\sum_{n=2}^{q}[I(m,n) - I(m,n-1)]^2}$$

$$CF = \sqrt{\frac{1}{p*q}\sum_{n=1}^{q}\sum_{m=2}^{p}[I(m,n) - I(m-1,n)]^2}$$

where I is the image and p*q is the image size. A large value of spatial frequency describes good 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 below.

$$\text{Variance} = \frac{1}{p*q}\sum_{m=1}^{p}\sum_{n=1}^{q}(I(m,n) - \mu)^2$$

where µ is the mean value of the block image and p*q is the image size. A high value of variance shows the

greater extent of focus in the image block.

Energy of Gradient (EOG): EOG is used to measure the amount of focus in an image.

$$EOF = \sum_{m=1}^{p-1}\sum_{n=1}^{q-1}(a_m^2 + a_n^2)$$

$$\text{where} \quad a_m = a(m+1,n) - a(m,n)$$

$$\text{and} \quad a_n = a(m,n+1) - a(m,n)$$

where p and q 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.

Proposed BFWN Algorithm

The proposed block based feature level algorithm which integrates wavelet transform with neural networks is discussed clearly below.

Step1: Read PAN and MS image.

Step2: Apply second level discrete wavelet transform to both the images as shown in Figure 2.

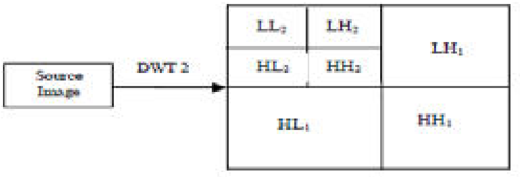

Fig. 2 Second level decomposition

Step3: Consider the LL2 component of both the images.

Step4: Partition the LL2 component of both the images with into k blocks of M > N size and extract the features for every block. The features under study are contrast visibility, spatial frequency, energy of gradient, variance and edge information.

Step5: Subtract the feature values of the jth block of LL2 subband of PAN from the corresponding feature values of the jth block of LL2 subband of MS. If the difference is 0 then denote it as 1 else -1.

Step6: Construct an Index vector for classification which will be given as an input for the neural network.

Step7: Create a neural network with adequate number of layers and neurons. Train the newly constructed neural network with random index value.

Step8: Simulate the neural network with feature vector index value.

Step9: If the simulated output > 1 then the jth subblock of LL2 subband of PAN image is considered else the jth subblock of LL2 subband of MS image is considered.

Step10: Reconstruct the entire block and apply inverse wavelet transform to get back the fused image.

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

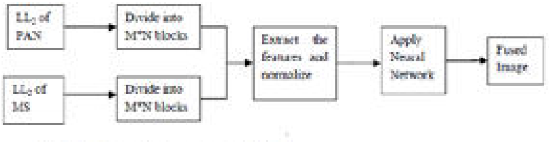

Fig. 3 Block diagram of the proposed method BFWN

QUANTITATIVE MEASURES

There are different quantitative measures which were used to evaluate the performance of the fusion techniques. We used measures say Entropy, Correlation coefficient, Standard Deviation (SD), Peak Signal to Noise ratio (PSNR), Mutual Information Measure (MIM), Fusion Factor (FF) and Mean Ab-

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solute Error (MAE) when the reference image was available. For blind image fusion (reference image was not available) we have used Entropy, Standard Deviation, Correlation coefficient and Mean Absolute Error (MAE).

CONCLUSIONS

In this, the potentials of image fusion using the proposed method BFWN are explored. The results are better performance and image quality is good. In this technique, the computation time and cost is less. In the proposed technique, only one neural network is created whereas in PNN-based image fusion, neural network for every pair of multi-focus images is created which is really time consuming. The various fusion results are analyzed by using quality performance metrics. For all the image data sets, the higher value for PSNR, MIM and FF is achieved for the proposed BFWN method. The metric parameters PSNR, MIM and FF are maximum for the proposed BFWN model, and SD and MAE are minimum for the proposed BFWN model. Hence, it is ascertained that BFWN model has superior performance than wavelet transform alone. The results are verified for LISS III images and the study can be extended to other types of images.

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