Infrared and Visible Image Fusion Using Entropy and Neuro-Fuzzy Concepts

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Abstract. Image fusion is the process to derive the useful information from the scene captured by infrared (IR) and visible images. This derived information is used to improve the image content by enhancing the image visualization. Human identification or any living object identification in IR images is a challenging task. This paper proposes two fusion techniques namely Discrete Wavelet Transform with Neuro-Fuzzy (NF) and Entropy (EN) (DWT-NF-EN) and Integer Wavelet Transform with Neuro-Fuzzy and Entropy (IWT-NF-EN) and their results are compared and analyzed with existing fusion techniques using different quantitative measures. Subjective and objective evaluation of the results obtained is compared with other fusion techniques namely Redundancy Discrete Wavelet Transform (RDWT) and Integer Wavelet Transform and Neuro-Fuzzy (IWT-NF). The objective evaluation is done using the quantitative measures Entropy (EN), Peak Signal to Noise Ratio (PSNR) and Normalized Correlation Coefficient (NCC). From the experimental results it is observed that proposed methods provided better information (quality) using EN, PSNR and NCC measures for majority of the test images and the same is justified with the subjective results.

Keywords: Infrared and visible images, Integer Wavelet Transform, Discrete Wavelet Transform, Neuro-Fuzzy, RDWT, Fusion.

1 Introduction

Detection of objects emitting electromagnetic radiations is an important and challenging problem from the defense point of view. Surveillance of the most secured areas is required round the clock and is done automatically by setting up multiple sensors at high altitudes. The regular sensors used in the defense scenario are the infrared (IR) sensors and visible sensors. Accordingly, the images captured from these sensors are IR images and visible images respectively. The visibility of IR images in general is very dark with white color portioned boundary of object emitting the radiations. The image spans a specified region on the earth surface. The same area is also captured by the visible sensor and the visibility of the visible image is clear with the surface of the earth but the presence of the electromagnetic radiating objects is

S.C. Satapathy et al. (eds.), *ICT and Critical Infrastructure: Proceedings of the 48th Annual Convention of CSI - Volume I*, Advances in Intelligent Systems and Computing 248,
DOI: 10.1007/978-3-319-03107-1_11, © Springer International Publishing Switzerland 2014

difficult. In order to visualize the radiation emitting objects and the background surroundings clearly, both the IR image and the visible image need to be fused.

Many researchers have proposed different fusion techniques. The fusion techniques are categorized into three levels such as pixel, region and decision. Pixel level fusion is the simplest and the most popularly used technique in research field. The pixel level image fusion methods can be classified as spatial domain and transform domain. The spatial domain is the simplest method. Pixel Averaging, Pixel level Maximum and Minimum (MM) High pass filtering, Intensity-Hue-Saturation based method, Brovey method, Principle of Component Analysis (PCA) etc, fall into this category but the fused images have the problem of spatial distortion and spectral distortion. These problems are resolved in transform domain such as Contrast Pyramid [1], Laplacian Pyramid [2], Ratio Pyramid [3], Morphological Pyramid [4], Discrete Wavelet Transform (DWT) [5], Contourlet Transform (CT) [6], Curvelet Transform [7] and so on. All these methods have individual limitations in fusion process. In pyramid based methods, Contrast Pyramid method could not retain sufficient information from the source images; Laplacian Pyramid method is more sensitive to noise and hence provides wrong edges; Ratio Pyramid provides more false positive information; Morphological Pyramid creates many false edges. The majority of image fusion techniques are based on wavelet transform. In wavelet transform, regularly used DWT technique has the problem of shift invariance and it results in additive noise in the resultant fused image. The revised version of DWT is Redundancy Discrete Wavelet Transform (RDWT) [8], Integer Wavelet Transform (IWT) [9]. This method overcomes the problem of DWT, but they do have some limitations. As a whole, each method has its own limitation.

Based on the survey, it is observed that RDWT, IWT and Neuro-Fuzzy (IWT-NF) were recently used fusion techniques and are proven to be good for image fusion. To overcome these problems, two hybrid methods based on RDWT and IWT-NF are proposed.

RDWT [10] fusion technique can be performed for registered images of two different sensor images. This technique works in the three steps. In the first step, the IR and visible images are decomposed using Haar wavelet transform thus forming four subbands. In the second step, low subbands of IR and visible images are fused using average method forming a fused low sub band. The other three corresponding high subbands of IR and visible images are fused using entropy method thus forming three fused high subbands. Finally, inverse redundancy discrete wavelet transform is applied on the fused low and high subbands to form the fused image.

IWT [11] is implemented in three stages. In the first stage integer wavelet transform is performed based on the lifting scheme. In next stage output of the lifting scheme is fused using neuro-fuzzy. Finally the fused image is retrieved using inverse integer wavelet transform procedure.

The rest of the paper is organized as follows: Proposed method is described in section-2 and experimental results and performance evaluation are presented in section-3. Finally section-4 concludes the work.

2 Proposed Methodology

Two hybrid methods based on the two fusion techniques discussed in introduction are proposed in this section.

2.1 Proposed Method-I (DWT-NF-EN)

The architecture of the proposed method-1 is given in Fig. 1. This proposed system works in three steps. In first step, both the IR and visible images are decomposed by 2D Haar Wavelet Transform. In the second step, the low bands of the IR and visible image are combined using Neuro-Fuzzy method. The three high subbands of IR and visible image are fused using entropy concept. The Neuro-Fuzzified low band and the entropy applied high subbands are combined and inverse wavelet transform is applied. The resultant image is the fused image.

Low Subband Fusion. The IR and visible image low subbands (A, B) are fused using Neuro-Fuzzy method. The low band coefficients are converted into fuzzy domain using triangular membership function. The fuzzified coefficients are used as input to feed forward neural network for training the pattern. Using the training pattern, the fuzzy inference system is created.

High Subband Fusion. The high subband blocks are fused based on the entropy calculation of each block [10]. The entropy is defined as:

$$e_{jk}^{i} = \ln \sqrt{\left(\mu_{jk}^{i} - \sum_{x,y=1}^{3,3} AB_{jk}^{i}(x,y) / \sigma_{jk}^{i} \right)^{2} / m^{2}} \tag{1}$$

where j=(v, d, h) denotes the subbands, k represents the block number, m=3 is size of each block and i = (1,2) is used to differentiate the two input images A and B. μ^{i}_{jk} and σ^{i}_{jk} are the mean and standard deviation of the each DWT coefficients. Using the entropy values fused image AB_v^F, AB_d^F and AB_h^F are calculated. The fused image block is AB_{jk}^F derived from A is selected if the entropy value of the particular block of A image is greater than the particular block of B image, otherwise derived from B show in Eq. 2.

$$AB_{jk}^{F} = \begin{Bmatrix} AB_{1}^{F}, if e_{jk}^{1} > e_{jk}^{2} \\ AB_{F}^{2}, otherwise \end{Bmatrix} \tag{2}$$

Reconstruction of Fusion Image. Inverse DWT is applied on all the fused subbands to generate fused image ABF.

$$AB^{F} = IDWT\,(AB_{a}^{F}, AB_{v}^{F}, AB_{d}^{F}, AB_{h}^{F}) \tag{3}$$

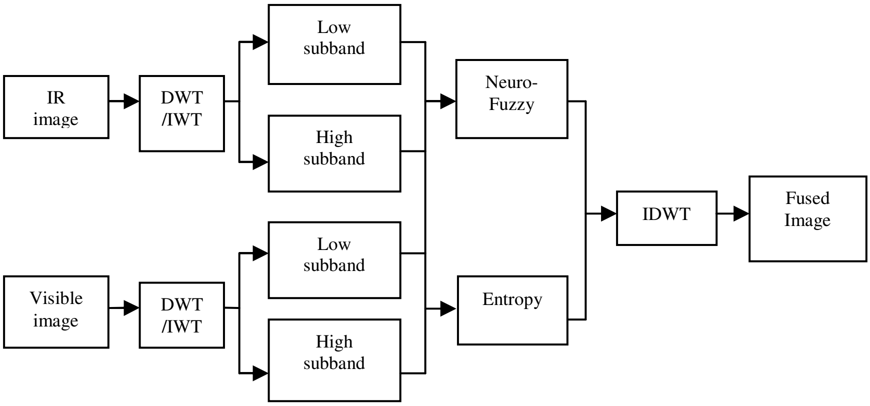

Fig. 1. Block Diagram of proposed method-1 and proposed method-2

2.2 Proposed Method-2 (IWT-NF-EN)

The second proposed method is given in this sub section. This method is similar to proposed method-1 except that instead of DWT, IWT is used. The block diagram for the proposed method shown in Fig. 1.

The IWT decomposition performed with lifting schemes. Lifting consists of three steps: split, predict and update. The details of the steps are as follows:

Split: Divide the source image dataset into odd subset S_i^0 and even subset d_i^0

Predict: Use odd subset S_i^{n-1} to predict the even subset based d_i^n on the correlation present in the source image. Find a prediction operator P, independent of the data, so that the construction of a prediction operator P is typically based on some model of the data which reflects its correlation structure.

$$d_i^n = d_i^{n-1} + \sum_k P_n(k) S_i^{n-1} \tag{4}$$

Update: Some global properties of the original data set in the subsets need to be maintained. For this to find better S_i^n. Construct an operator U and update S_i^n as

$$S_i^n = S_i^{n-1} + U_n(k) d_i^n \tag{5}$$

Low Subband Fusion. The decomposed IR and visible images LL band fused using neuro-fuzzy. Neuro-fuzzy means combinations of neural network and fuzzy logic. To perform that first defines membership function and fuzzy rules using these adaptive neuro-fuzzy interference system created.

High Subband Fusion. High subbands are fused using entropy method.

Reconstruction of Fused Image. Finally, inverse integer transform form is performed to get the fused image by using reverse order of lifting scheme.

2.3 Quantitative Analysis

Quantitative measure is helpful to measure the fused image subjective and objective information. Here, the following quantitative measures are used to analyze the fused image.

Entropy (EN). Entropy can reflect the amount of information in certain image. The higher value of entropy indicates the better fusion result is obtained.

Peak Signal to Noise Ratio (PSNR). PSNR is used to measure the quality of the fused image with respect to the source image [12]. It is defined as:

$$PSNR = 10 \log_{10}\left(MAX^{2}/MSE\right) \tag{6}$$

$$MSE = \frac{1}{pq}\sum_{i=0}^{p-1}\sum_{j=0}^{q-1}\left[F(i,j) - I(i,j)\right]^2 \tag{7}$$

where MAX is the maximum value in an image. p, q are the height and weight of an image. I(i, j) is the value of input image and F(i, j) is the value of fused image.

Normalized Correlation Coefficient (NCC). A measure that determines the degree to which the similarity of two matrices / images possesses. Normalized Correlation Coefficient calculated as:

$$NCC = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n} F(i,j) * I(i,j)}{\sqrt{\sum_{i=1}^{m}\sum_{j=1}^{n} F(i,j)^2}\ \sqrt{\sum_{i=1}^{m}\sum_{j=1}^{n} I(i,j)^2}} \tag{8}$$

Where F(i,j) is the fused image value and I(i,j) is the input image value. The correlation coefficient ranges vary from -1 to +1. A -1 indicates the negative correlation and +1 indicates the positive correlation.

3 Experimental Results

The experimental results of fusion techniques are tested with two categories [13] (dune, trees). Each category contains five IR and visible images used in Defense. Each IR image combined with visible image consider as one set for fusion. Totally derives twenty combinations of input images. All images have the same size of 256 X 256 pixels, with 256-level gray scale. Some of the input sample images and proposed methods fused images are shown in Fig. 2.

The fused image obtained from each technique is analyzed with quantitative measures EN, PSNR and NCC. The results of all the fusion techniques, analyzed for the fused image with quantitative measures from each category are shown in Fig. 3-5.

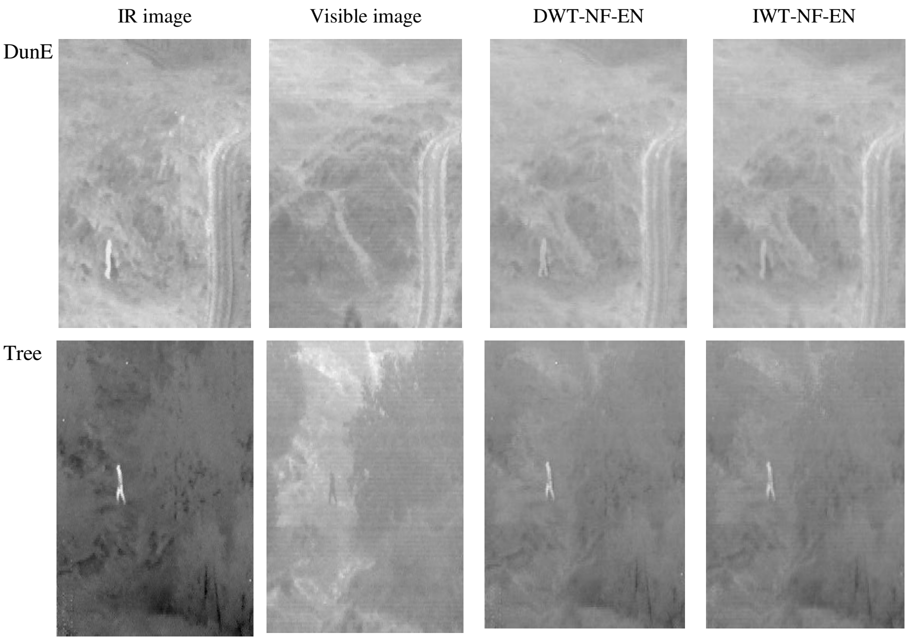

Fig. 2. Sample input and output image of each category

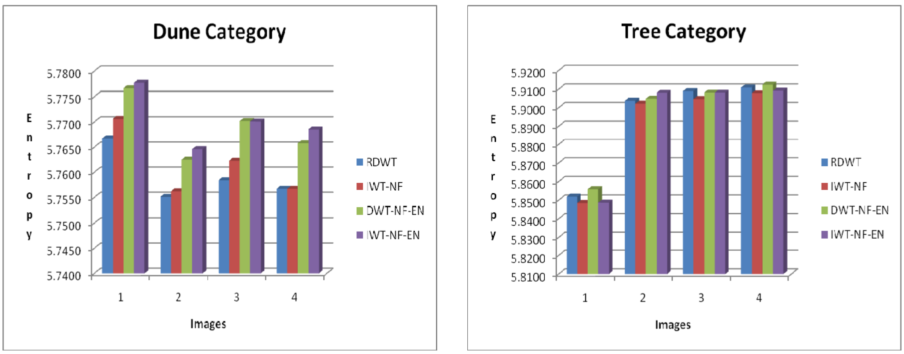

Fig. 3. Entropy comparison of same images in two categories

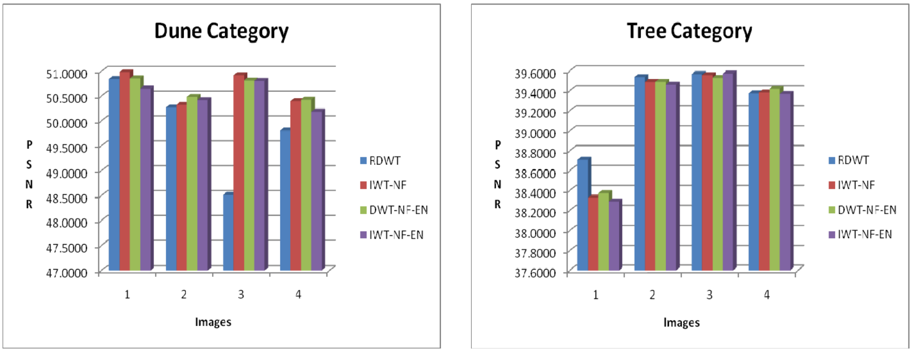

Fig. 4. Peak Signal to Noise Ratio comparison of same images in two categories

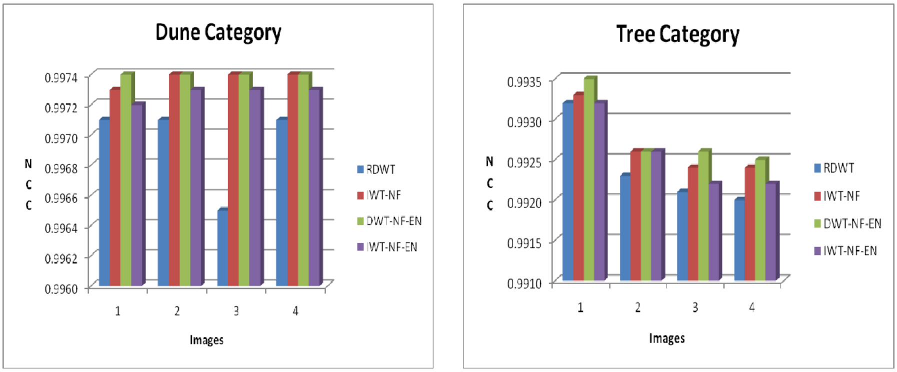

Fig. 5. Normalized Correlation Coefficient comparison of same images in two categories

4 Conclusion

In this paper two hybrid methods are proposed for fusion of IR and visible images. The results obtained are compared and analyzed with various quantitative measures. The results show that the proposed fusion techniques provide better results than the existing methods in both subjective and objective evaluation. This fusion technique can be widely used in different applications such as object recognition, target detection, security surveillance. In addition, it can be used as a pre-processing step for noisy images.

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