Multi-Sensor Image Fusion Based On Empirical Wavelet Transform

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***Abstract*— The advancement in technology had led to the requirement for a single image with high spatial and good spectral resolution in various applications such as remote sensing, surveillance and medical diagnosis. Most of the technology and equipment available has already reached the level of saturation in providing such convincing image or data. Image fusion techniques allow the integration of different information sources. From a pair of hyper- spectral image with low spatial and a pan image with high spatial resolutions, the aim is to synthesize a single image with highest spatial resolution and spectral content. However, apart from the standard image fusion techniques, in this paper we propose multi-sensor image fusion using empirical wavelet transform. In this image fusion scheme, the empirical wavelet transforms of the input images are appropriately combined, and the new image is obtained by taking the inverse empirical wavelet transform of the fused wavelet coefficients. With the necessity of multi-sensor data in many fields such as remote sensing, medical imaging, machine vision, military applications, sensor fusion has emerged as an upcoming and promising research area. The main objective of image fusion is to reconstruct new images that are more convincing for human visual perception, highly suitable for object detection and target recognition.**

Keywords Multi sensor image fusion, Empirical wavelet transform, Image reconstruction, Super reesolution.

I. INTRODUCTION

For many electronic imaging purposes, images with High Resolution (HR) are often desired. For example, a doctor can make a correct diagnosis with HR medical images. Similarly, in the case of satellite image processing the process of pattern recognition becomes more efficient with the help of HR images. From early 1970's, Charged Coupled Devices (CCD) have been generally used to acquire digital images. Though the CCDs are best match for many imaging applications, the present resolution level and customer pricing are not satisfied with these devices. For example, scientist requires a resolution level of about 35mm film with no visible artifacts when zoomed into it. Thus, the need for increasing the resolution level has risen.

The direct solution for this is by making use of sensor manufacturing techniques. Here to increase the spatial resolution, (i.e. reduce pixel size). This reduction in the pixel size limits the amount of light required for imaging. As a result, the image quality is degraded due to shot noise. So, the optimal limit is fixed at $40\mu m^2$ for a $0.35\mu m$ complementary metal-oxide-semiconductor process. The present image sensor technology has already attained this level.

Next way for increasing the spatial resolution is by increasing the size of the chip as mentioned in [1]. The increase in chip size has resulted in increase of capacitance. The drawback of this approach is decrease in charge transfer rate due to large capacitance. To overcome these drawbacks in sensor and optics manufacturing technology, a new and novel method for increasing the spatial resolution is needed.

One hopeful way is using image processing techniques to attain good resolution image from observed single or many Low Resolution (LR) images. Lately, this type of resolution enhancement has been an active research. This has been named as Super Resolution Image Reconstruction (SRIR) or resolution enhancement. Super resolution imaging is a sort of techniques used to enhance the resolution of the imaging module. The term Super Resolution (SR) is defined as process of joining two or more number of LR images of the same scene to obtain HR image [2]. In other word, it may be stated as effort to build up the original image with HR when provided with two or more LR images.

The recent advancement in resolution enhancement has come with development of various spatial domain algorithms such as iterative back projection approach [3], maximum likelihood approach [4], maximum a posteriori (MAP) approach [5, 6] and hybrid approach [7].

[8] addresses the complications of high resolution image reconstruction from multiple blurred, down sampled, noisy, shifted and rotated images by using Bayesian vibrational approximation. Bayesian method depends on image models that have the prior knowledge of the image and noise. [9] developed a Kernel regression method for SR. This method uses the Taylor series for the approximation of each pixel values in the image which helps in identifying the behavior of the neighborhood pixels. This method does not require any motion estimation as a pre-processing step which is considered as an added advantage. [10] proposed a method of SR image reconstruction. This method uses the idea of projecting a low-resolution image on to a high- resolution grid and then passing through the low pass filter having a cut off

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frequency equal to bandwidth of the image. The procedure is repeated in iterations with different cut off frequency to obtain HR image. [11] proposed a method projection on to convex sets. In this method, the high resolution image is reconstructed using a cost function which is on the idea of relevance between the HR and the LR images. But this method has its own drawbacks of high computation on non-unique solution.

The recent advancement for Super Resolution image is the use of wavelet transformation [12, 13]. In [14] SRIR is done using framelet transform. The framelet transform uses the tight frame filter banks has the additional property of symmetry and guarantees perfect reconstruction condition. A Singular Value Decomposition based SRIR is proposed in [15] which uses the singular values which are the characteristic information of an image for reconstruction of HR image. In [16] a SRIR procedure using normalized convolution is proposed which uses the Gaussian function for reconstructing HR image. A very computational cost effective method of super-resolution image reconstruction by use of filters is proposed in [17].

II. EMPIRICAL WAVELET TRANSFORM

A wavelet can be considered as a wave like oscillation whose amplitude starts in zero, progresses on and then gets reduced to zero. It can also be defined as the mathematical function used to divide a given function or continuous-time signal into different scale components. Wavelets can be combined, by using a process called convolution which uses reverse, shift, multiply and integration. If the unknown signal contains similar frequency information then the wavelet will correlate with the signal. Many practical applications of wavelet theory contain this concept of correlation.

First the image is divided into N Segments. Each segment will have the boundary limit denoted as ω_n [18]. Each partition in denoted as $\wedge_n = [\omega_{n-1}, \omega_n], \bigcup_{n=1}^{N} \wedge_n$. Around each ω_n , a small area $2\tau_n$ is defined which will be the transition phase. The empirical wavelets are defined on each of the $\wedge_n$. The sub bands are extracted through these filtering operations. Each partition has some central frequency and is each partition is considered as a mode. The boundaries are calculated by finding local maxima in the image spectrum and the sorting them in descending order scaling function and the empirical wavelet function are defined as [19]

$$\hat{\phi}_n(\omega) = \begin{cases} 1 \; if \; |\omega| \le \omega_n - \tau_n \\ \cos[\frac{\pi}{2}\beta(|\omega| - \omega_n + \tau_n)] if \; \omega_n - \tau_n \le \omega_n + \tau_n \\ 0 \; otherwise \end{cases}$$

$$\hat{\psi}_n(\omega) = \begin{cases} 1 \; if \; \omega_n - \tau_n \le |\omega| \le \omega_{n+1} - \tau_{n+1} \\ \cos[\frac{\pi}{2}\beta(\frac{1}{2\tau_{n+1}}(|\omega| - \omega_{n+1} + \tau_{n+1}))] if \; \omega_{n+1} - \tau_{n+1} \le |\omega| \le \omega_{n+1} + \tau_{n+1} \\ \sin[\frac{\pi}{2}\beta(\frac{1}{2\tau_n}|\omega| - \omega_n + \tau_n)] if \; \omega_n - \tau_n \le |\omega| \le \omega_{n+1} + \tau_{n+1} \\ 0 \; otherwise \end{cases}$$

The function $\beta(\mathrm{x})$ is an arbitrary function defined as,

$$\beta(\mathrm{x}) = \begin{cases} 0 \; if \; x \le 0 \\ 1 \; if \; x \ge 0 \end{cases}$$

and

$$\beta(\mathrm{x}) + \beta(1 - \mathrm{x}) = 1, \forall \, \mathrm{x} \in [0,1]$$

The τ_n is defined as $\omega_n : \tau_n = \gamma\omega_n, 0 < \gamma < 1, \forall n > 0$

Now the above equation gets simplified as,

$$\hat{\phi}_n(\omega) = \begin{cases} 1 \; if \; |\omega| \le \omega_n - \tau_n \\ \cos[\frac{\pi}{2}\beta(\frac{1}{2\tau_{n+1}}(|\omega| - (1-\gamma)\omega_n)] if (1-\gamma)\omega_n \le |\omega| \le (1+\gamma)\omega_n \\ 0 \; otherwise \end{cases}$$

$$\hat{\psi}_n(\omega) = \begin{cases} 1 \; if (1+\gamma)\omega_n \le |\omega| \le (1-\gamma)\omega_{n+1} \\ \cos[\frac{\pi}{2}\beta(\frac{1}{2\gamma\omega_{n+1}}(|\omega| - (1-\gamma)))] if (1-\gamma)\omega_{n+1} \le |\omega| \le (1+\gamma)\omega_{n+1} \\ \sin[\frac{\pi}{2}\beta(\frac{1}{2\gamma\omega_{n+1}}(|\omega| - (1-\gamma)))] if (1-\gamma)\omega_{n+1} \le |\omega| \le (1+\gamma)\omega_{n+1} \\ 0 \; otherwise \end{cases}$$

The detailed coefficients or the high frequency components are obtained by performing inverse convolution between f and ψ_n. In case of frequency domain multiplication of two functions gives the convoluted output.

$$W_f^{\varepsilon}(\mathrm{n}, \mathrm{t}) = \left(\left(f\,\hat{(\omega)}\right)\overline{\hat{\psi}_n(\omega)}\right)^{-1} = \langle f, \psi_n \rangle$$

Similarly the approximate coefficients or the LR components are obtained by taking inverse convolution operation between f and ϕ_n

$$W_f^{\varepsilon}(0, \mathrm{t}) = \left(\left(f\,\hat{(\omega)}\right)\overline{\hat{\phi}_1(\omega)}\right)^{-1} = \langle f, \phi_1 \rangle$$

The signal $f(\mathrm{t})$ can be reconstructed as

$$f(\mathrm{t}) = \left((0, \omega)^*(\omega) + \sum_{n=1}^{N} (\mathrm{n}, \omega)^*(\omega) \right)^{-1}$$

The empirical mode function f_k is given as

$$f_0(\mathrm{t}) = W_f^{\varepsilon}(0,\mathrm{t}) * \phi_1(\mathrm{t})$$
$$f_k(\mathrm{t}) = W_f^{\varepsilon}(\mathrm{k},\mathrm{t}) * \phi_k(\mathrm{t})$$

The idea followed in wavelet transform is to get the different modes of a signal by constructing an appropriate wavelet filter bank. While extracting the different modes of signals there leads to a wavelet transform called Empirical Wavelet Transform (EWT). This concept is based on wavelet decomposition. The decomposed image is transformed into a tight frame by the EWT and it can be obtained by properly choosing the parameter ϒ, then the proportion is as follows

if ϒ<min((ω(n+1)- ωn) /((ω(n+1))+ ωn)),

then $\phi(t), \{n(t)\} n = 1$ to $\mathrm{N}\}$ is a tight frame, if

$$\sum_{k=-\infty}^{\infty}((\left|\phi^{(\omega+2k\pi)}\right|)^2 + \sum_{n=1}^{N}(\left|\psi^{n(\omega+2k\pi)}\right|)^2) = 1$$

The modes decomposed in EWT are in the increasing order of frequency from mode 1 to mode N.

Extending 1D to 2D can be done by processing separately the rows and columns using 1-D EWT. Inverse EWT is the process of combining the different modes into single one.

III. PROPOSED METHOD

In this section a new methodology for reconstruction of HR images from multi-sensor images are discussed. Figure 1 gives the pictorial representation of the image of the proposed method for multi sensor image fusion is given below

The first step is registration of panchromatic and hyper-spectral images to avoid the discrepancies in alignment of images i.e. translation and rotation. The Empirical Wavelet Transform is applied on panchromatic and hyper-spectral images. The Empirical Wavelet Transform decomposes the panchromatic and hyper-spectral images into several numbers of modes. Each modes have different frequencies, starting with the first mode having only low frequency components and the successive modes have little more frequency range compared to its predecessor and finally the N^{th} mode has only high frequency component. Then these modes are processed under multi sensor image fusion to get N modes as a whole. This is done by the implementing the simplest fusion technique that is the fused image is obtained by averaging the pixels of each corresponding mode. The value of the pixel P(r , s) of source modes are used to get the mean value which is assigned to the corresponding pixel of output image using equation (1). The same process is repeated for all pixel values.

f(r , s)={X(r , s)+Y(r , s)/2 (1)

The inverse empirical wavelet transform is applied which yields a single image from the N modes and this fused image has both high spatial and high spectral resolutions as required.

IV. RESULT AND DISCUSSION

The proposed method is tested on a large data of simulated and real-time images in-order to validate the performance of the algorithm. We present results with one image evaluating the performance of the proposed method. The reconstruction image i.e. the high resolution image is evaluated based on two performance measures

1) Peak Signal to Noise Ratio (PSNR)

2) Sharpness Index Measure

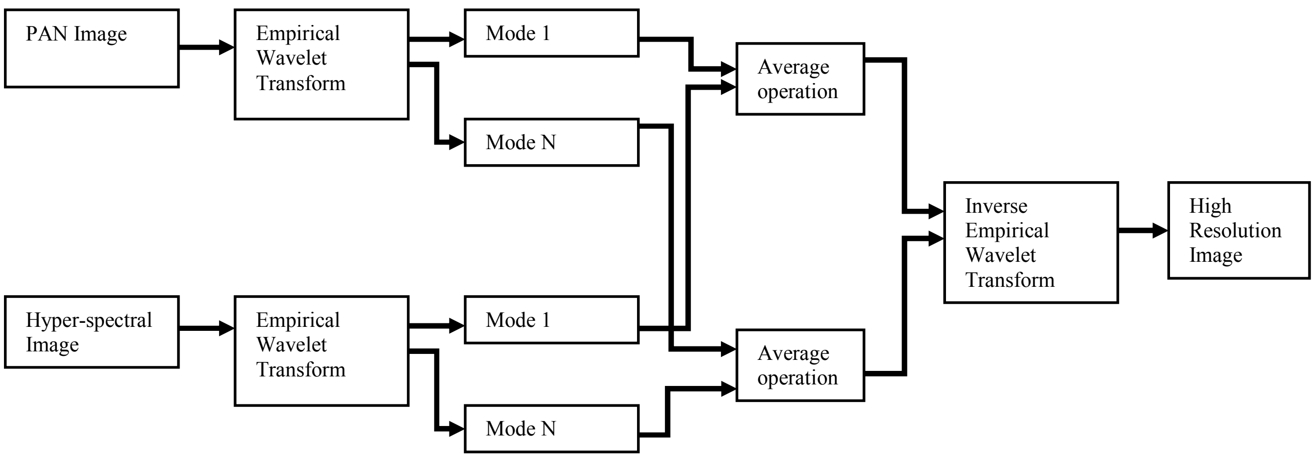

Fig.1.Pictorial representation of the proposed method

Figure 2-3 shows the reconstruction results of these two data sets. In these Figures (a) is panchromatic image; (b) hyper-spectral image; (c) is the reconstruction result of proposed method

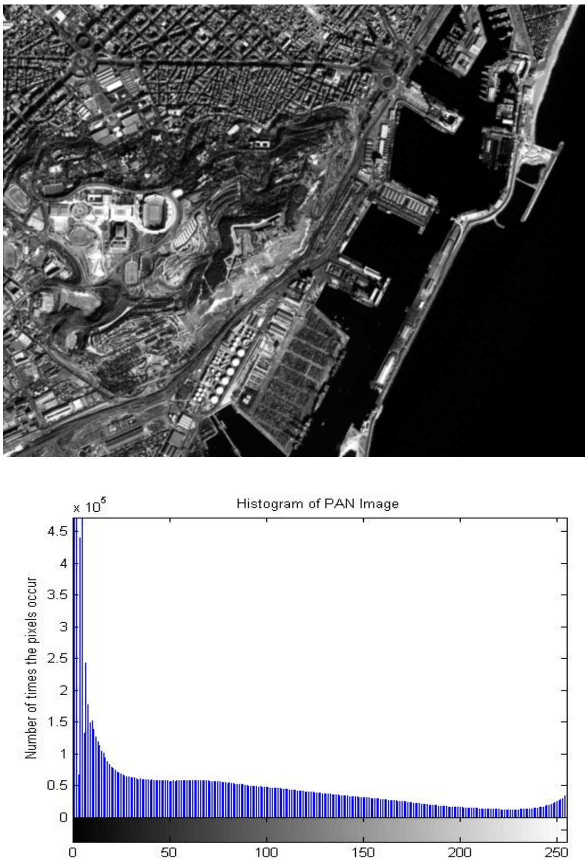

Fig.2 (a), Panchromatic Image and its Histogram

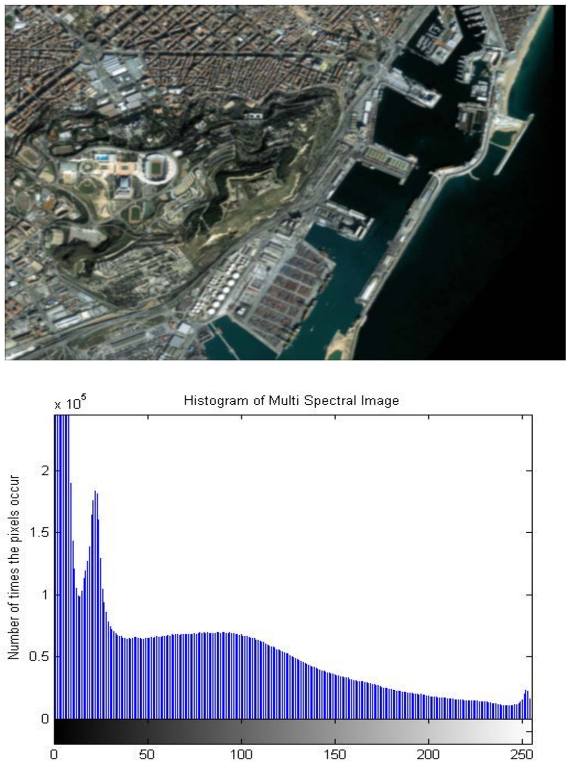

Fig.2 (b). Hyper-spectral Image

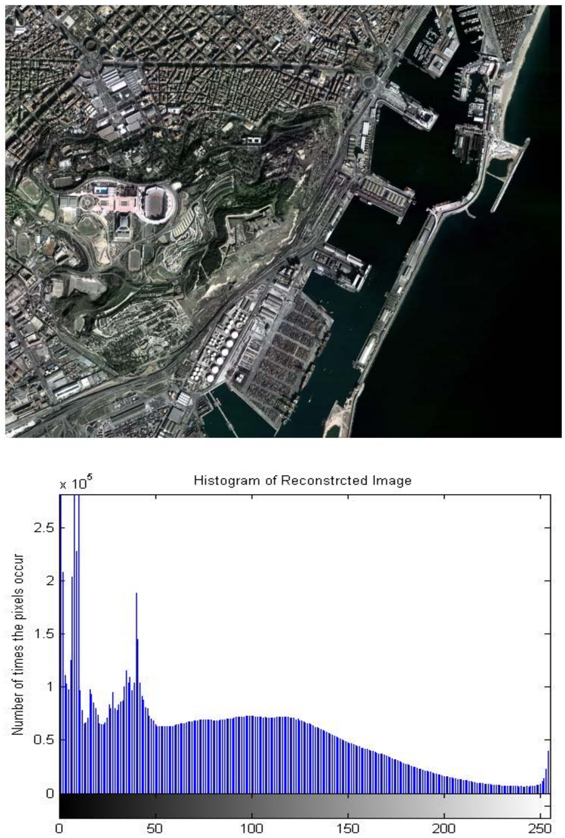

Fig.2(c). High Resolution Image using EWT

The increase in the value of PSNR and the sharpness index for the proposed fused image using proposed method proves the increase in resolution using SRIR technique. It is seen that the edge information are enhanced and the spectral information get a better quality. This is because the panchromatic image has high spatial information and the hyper-spectral image has very good spectral information. Thus fusion of these two images has resulted in a HR image with high spatial and spectral information content. The comparison is done based on histogram. The image is said to be an ideal image when the histogram plot is distributed evenly and no ups only in the sides. The panchromatic image and the Hyper-spectral images have greater number of pixels clustered at darker region when compared with the reconstructed image. Similarly there is a greater spread of pixels in the case of reconstructed high resolution image when compared with the panchromatic image and hyper-spectral image. Thus the histogram plot also proves that the proposed method of super resolution image reconstruction is has improved the quality of the image.

Table I

Image Name	PSNR (db)	Sharpness Index
Panchromatic Image	14.75	106.59
Hyper-spectral Image	15.92	127.58
HR Image Based on proposed method	25.28	140.67

V. CONCLUSION

The interpolation methods are used for super resolution which actually does not increase the resolution bus just adds the pixels, resulting in increase of size of image but not the resolving power. In the proposed work, a new method for image reconstruction by fusion of multi-sensor images i.e. panchromatic and hyper-spectral images is proposed based on Empirical Wavelet Transform. Evaluation of results is done based on quality metrics like PSNR and Sharpness Index. Experimental results proves that proposed method of SRIR using Empirical Wavelet Transform gives a qualitatively and quantitatively better results.

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