A New Correlation Based Image Fusion Algorithm Using Discrete Wavelet Transform

Sourabh Sharma
Asst. Professor, Career Point University Kota
19.sourabh@gmail.com

Dr. Shishir Kumar
Jaypee University of Engineering & Technology Guna
shishir.kumar@juet.ac.in

Abstract- Image fusion is the method of combining two or more images into a single image to obtain more appropriate information. The resulting fused image will be more informative than any of the input images. In this paper Correlation based approach for fusion of images gathered by different wireless sensors on the basis of Pearson's correlation theory has been described. We present a comparative study of previously available and applied approaches for image fusion. Our method is based on calculating the intensities of the pixels of the image and its gray scale equivalent and then performs correlation for image fusion. This paper also describes the analytical techniques for evaluating the quality of image fusion by using various methods including Mean Square Error(MSE), Peak Signal-to Noise Ratio($PSNR$), to estimate the quality and degree of information improvement of a fused image quantitatively.

Keywords: Image Fusion, Pearson's Correlation theory, wireless sensors, Discrete wavelet transform

I. INTRODUCTION

The rapid growth and use of novel imaging sensors emphasize the necessity for narrative image processing techniques that can effectively fuse images from different sensors into a single composite image for elucidation. Image fusion characteristically begins with two or more registered images with different representations of the same scene. They may come from different viewing conditions, or even different sensors. Image fusion of multiple sensors in a vision system could significantly reduce human/machine error in detection and recognition of objects thanks to the inherent redundancy and extended coverage. This type of image fusion is also called pixel-level multisensory image fusion [1]. For example, fusion of forward looking infrared (FLIR) and Closed circuit television (CCTV) images obtained by a security sensor would aid to find out important clues about the crime happened.

This is why; Multisensor image fusion has become an area of intense research activity in the past few years [2, 3, 4]. Multisensor image fusion refers to the synergistic combination of different sources of sensory information into one representational format. The information to be fused may come from multiple sensors monitored over a common period of time or from a single sensor monitored over an extended time period. A correlation based image fusion method is to correlate the source images pixel by pixel. However, along with minimalism there come several undesired side effects including reduced contrast. In recent years, many researchers recognized that multiscale transforms are very useful for analyzing the information content of images for the purpose of fusion. Multiscale representation of a signal was first studied by A. Rosenfeld [5], A. Witkin [6] and others. Researchers such as D. Marr [7], P. J. Burt [8] and T. Lindeberg [9] established that multiscale information can be useful in a number of image processing applications. Recently, wavelet theory has emerged as a well developed yet rapidly expanding mathematical foundation for a class of multiscale representations. At the same time, some sophisticated image fusion approaches based on multiscale representations began to emerge and receive increased attention. Most of these approaches were based on combining the multiscale decompositions (MSDs) of the source images. Fig. 1 illustrates the descriptive block diagram of a wavelet based image fusion scheme based on multiscale analysis. The basic idea is to perform a multiscale transform (MST) on each source image, then construct a composite multiscale representation from these. The fused image is obtained by taking an inverse multiscale transform (IMST).

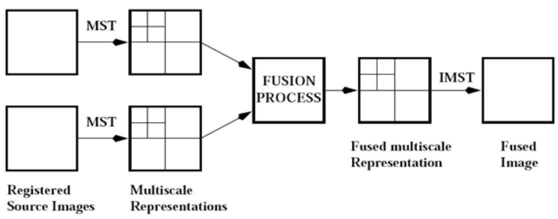


Fig.1. Block diagram of a wavelet based image fusion based on multiscale analysis.

A number of papers have proposed image fusion algorithms which are based on the orthogonal wavelet transform [10, 11, 12]. The wavelet transform success may be credited to certain advantages it offers over the laplacian pyramid based techniques. The wavelet bases may be chosen to be orthogonal, making the information gleaned at different resolution unique. The pyramid decomposition, on the other hand, contains redundancy between different scales. Furthermore, a wavelet image representation provides directional information in the high-low, low-high and high-high bands, while the pyramid representation fails to introduce any spatial orientation selectivity into the decomposition process. A major limitation in all recent wavelet-based fusion algorithms, however, is the absence of a good fusion criterion. Most existing selection rules are to a large extent similar to “choose max”. This in turn induces a significant amount of high frequency noise introduced by a systematic and sudden inclusion of the fused maximal wavelet coefficient of a given source. This is particularly problematic, knowing the highly undesirable perception of high frequency noise by human vision.

II. Sensor Based Image Fusion

Multi-sensor data often presents harmonizing information about the region surveyed, so image fusion provides an effective method to facilitate comparison and analysis of such data. The aim of image fusion, apart from reducing the amount of data, is to create new images that are more suitable for the purposes of human/machine perception, and for further image-processing tasks such as segmentation, object detection or target recognition in applications such as remote sensing and medical imaging. For example, visible-band and infrared images may be fused to aid pilots landing aircraft in poor visibility. Multi-sensor images often have different geometric representations, which have to be transformed to a common representation for fusion. This representation should retain the best resolution of either sensor. A prerequisite for successful in image fusion is the alignment of multi-sensor images. Multi-sensor registration is also affected by the differences in the sensor images.

A. SINGLE SENSOR IMAGE FUSION

In the single sensor image fusion system a sequence of same scene has been captured by a sensor, an illustration of a single sensor image fusion system is described in Fig.2. The sensor shown could be a visible-band sensor such as a digital camera. This sensor captures the real world as a sequence of images. The sequence is then fused in one single image and used either by a human operator or by a computer to do some task. For example in object detection, a human operator searches the scene to detect objects such intruders in a security area.

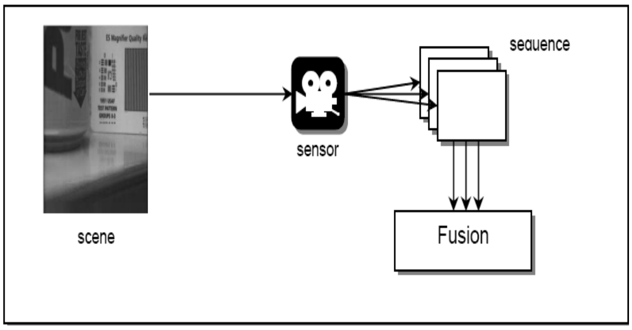


Fig.2. Single Sensor Image Fusion System

This kind of systems has some limitations due to the capability of the imaging sensor that is being used. The conditions under which the system can operate, the dynamic range, resolution, etc. are all limited by the capability of the sensor. For example, a visible-band sensor such as the digital camera is appropriate for a brightly illuminated environment such as daylight scenes but is not suitable for poorly illuminated situations found during night, or under adverse conditions such as in fog or rain.

B. MULTI-SENSOR IMAGE FUSION

A multi-sensor image fusion system overcomes the limitations of a single sensor vision system by combining the images from these sensors to form a composite image [13]. Fig. 3 shows an illustration of a multi-sensor image fusion system. In this case, an infrared camera is supplementing the digital camera and their individual images are fused to obtain a fused image. This approach overcomes the problems referred to before, while the digital camera is appropriate for daylight scenes, the infrared camera is suitable in poorly illuminated ones.

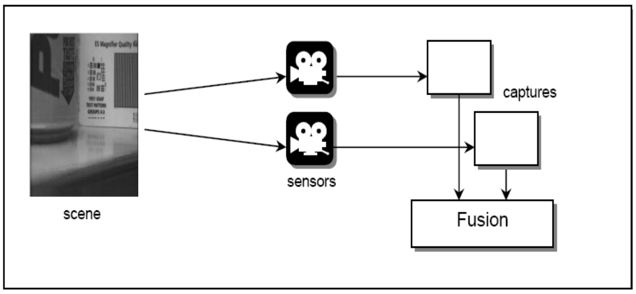


Fig.3. Multi-sensor Image Fusion System

III. Wavelet Based Image Fusion

Wavelets are the finite period oscillatory functions with zero average value. The irregularity and good localization properties make them better basis for analysis of signals with discontinuities. Wavelets can be described by using two functions viz. the scaling function $f(t)$, also known as ‘father wavelet’ and the wavelet function or ‘mother wavelet’. ‘Mother’ wavelet $\psi(t)$ undergoes translation and scaling operations to give self similar wavelet families as in Eq. 1.

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right), \quad (1)$$

Where $(a,b) \in R \; and \; a > 0$

Here, a is the scale parameter and b is the translation parameter.

A Practical execution of wavelet transforms requires discretisation of its translation and scale parameters by taking the values of a and b as,

$$a = a_0^j, b = m a_0^j b_0, \quad \text{Where } j,m \in Z \quad (2)$$

Thus, the wavelet family can be defined by Eq. 3 as:

$$\psi_{j,m}(t) = a_0^{-j/2}\psi\left(a_o^{-j}t - mb_0\right), \text{Where } j,m \in Z \quad (3)$$

If the discretisation is on a dyadic grid with $a_0 = 2$ and $b_0 = 1$ then it is known as standard DWT [14]. Wavelet transformation involves constant Q filtering and subsequent Nyquist’s sampling as given by Fig. 4 [15], the source image is decomposed in rows and columns by low-pass (h) and high-pass (g) filtering and subsequent down sampling at each level to get approximation $\left(LL^{i+1}\right)$ and detail $\left(LH^{i+1}, HL^{i+1}\ and\ HH^{i+1}\right)$ coefficients. Scaling function is associated with smooth filters or low pass filters and wavelet function with high-pass filtering. Orthogonal, regular filter bank when iterated infinitely gives orthogonal wavelet bases [16]. The scaling function is treated as a low pass filter and the mother wavelet as high pass filter in DWT implementation.

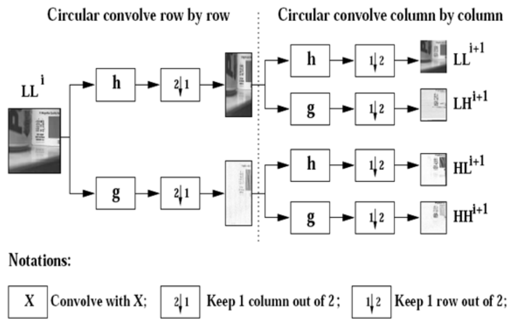


Fig.4. Two-dimensional Discrete Wavelet Transform

The advent of multiresolution wavelet transforms gave rise to wide developments in image fusion research. Several methods were proposed for various applications utilizing the directionality, orthogonality and compactness of wavelets [10], [11], [17]. Fusion process should conserve all important analysis information in the image and should not introduce any artifacts or inconsistencies while suppressing the undesirable characteristics like noise and other irrelevant details [11], [18].

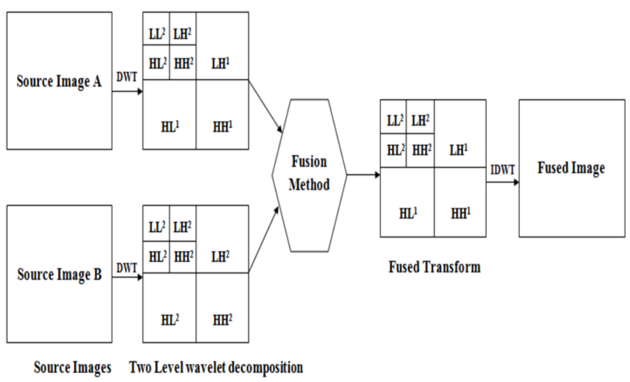


Fig.5. Wavelet based image fusion method

Fusion can be performed on pixel, feature or decision level [19]. The complexity of pixel based algorithms is lesser than other methods. They are used in applications where both pixel spacing's and spectral properties of source images are same or similar [20]. The advent of region based image fusion can be attributed to the inefficiencies faced by pixel algorithms in cases where the salient features in images are larger than one pixel. Region based rules are more complicated than simple pixel algorithms and used when pixel spacing's of images are different. Decomposition coefficients are segmented into small regions and activity measure along each region is computed. Coefficients with maximum activity level are preserved, retaining the salient features. Popular methods include computation of variances of small regions [10] in the image or energy based salience measurement [21] and [22].

IV. PROPOSED ALGORITHM

This paper proposes a correlation based image fusion method which fuses the images to obtain a more appropriate image which signifies all the details of the image captured by different sensors. Pixel based rules operate on individual pixels in the image, but does not take into account some important details like edges, boundaries and salient features larger than a single pixel. Region based fusion may reduce the contrast in some images and does not always succeed in effectively removing ringing artifacts and noise in source images. The inadequacies of these two types of fusion rules point to the importance of developing a correlation based architecture combining the advantages of both. Correlation based architecture in Fig. 6 describes different stages for fusing the source images and obtain the fused image.

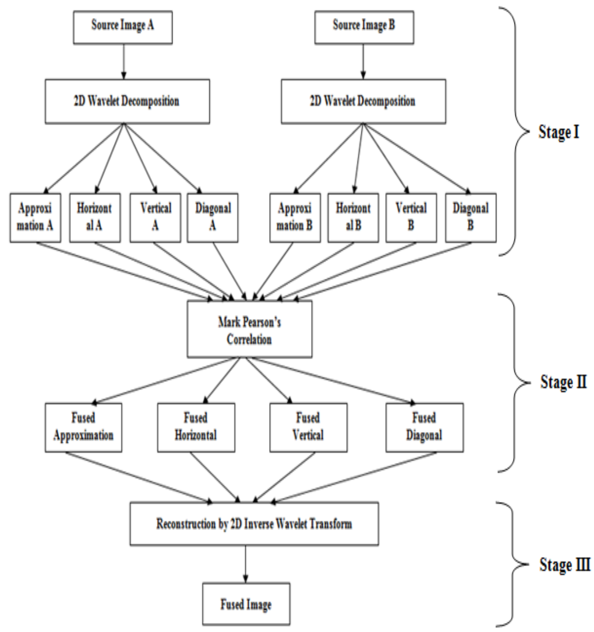


Fig.6. Proposed correlation based image fusion

Algorithm:

The algorithm for correlation based image fusion can be described into three different stages with reference to Fig. 6.

Stage I

1) Read the two source images A and B to be fused.
2) Perform discrete wavelet transform decomposition of the two source images A and B, Until level L to get approximation $\left(LL^{L}\right)$and detail $\left(LH^{L}, HL^{L}, HH^{L}\right)$ coefficients for L=1,2,3....,l.

Stage II

1) As we obtained the transform coefficients of the source image A $\left(LL_A^L, LH_A^L, HL_A^L, and\ HH_A^L\right)$ and B

$\left(LL_B^L, LH_B^L, HL_B^L, and\ HH_B^L\right)$ perform the correlation over these transform, obtain the correlation coefficients and generate a correlation matrix.

$$r = \frac{\sum_i (A_i - A_m)(B_i - B_m)}{\sqrt{\sum_i (A_i - A_m)^2}\sqrt{\sum_i (B_i - B_m)^2}} \qquad (4)$$

Here, A_i is the intensity of the i[th] pixel in source image A, B_i is the intensity of the i[th] pixel in source image B, A_m is the mean intensity of source image A and B_m is the mean intensity of source image B.

2) Now transform coefficients which have the max value of correlation coefficient r as obtained in Eq.4 are fused together to obtain the fused transforms $(LL_f^L, LH_f^L, HL_f^L, HH_f^L)$.

Stage III

1) We obtain the final fused transforms approximation LL_f^L, and detail $LH_f^L, HL_f^L\ HH_f^L$ coefficients by correlation based fusion method.
2) The coefficient matrix is obtained by concatenating fused approximation and detail coefficients.
3) Perform the inverse wavelet transform over the concatenating fused transforms and obtain the fused image.

V. Implementation Analysis

The proposed correlation based image fusion method has been implemented on different types of source image [23] as depicted in the Table I.

Table I.
Source Images used for Experiments

Source Image Type	Source Images	File Format	Size (In pixels)
Scans	CT Scan MRI Scan	TIFF	256x256
Clocks	Large Clock Focused Small Clock Focused	TIFF	256x256
Cameraman	Background Blur Foreground Blur	TIFF	256x256
Girl	Face Blur Background Blur	TIFF	256x256
Lenna	Left Blur Right Blur	TIFF	256x256

The proposed algorithm is implemented on the source images with help of MATLAB and the results are depicted in the Fig.7 and Fig.8.

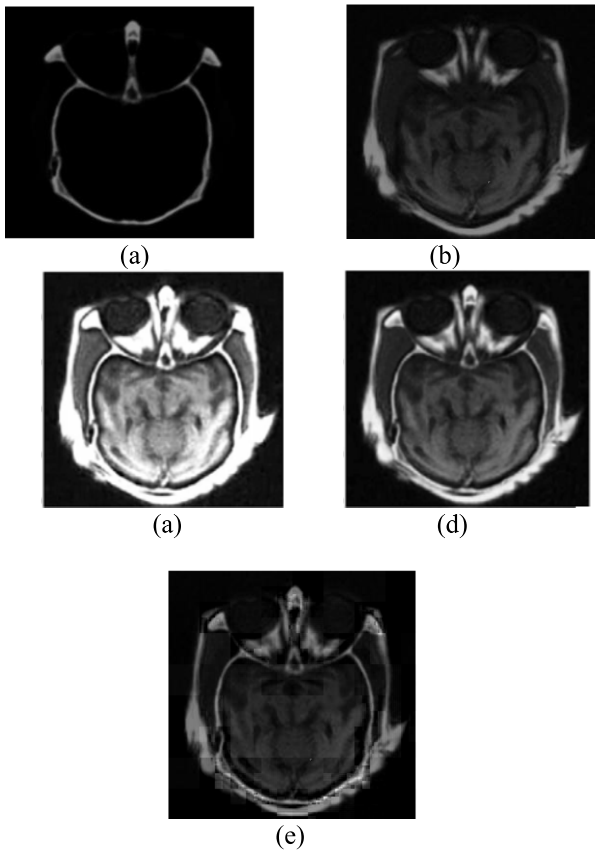
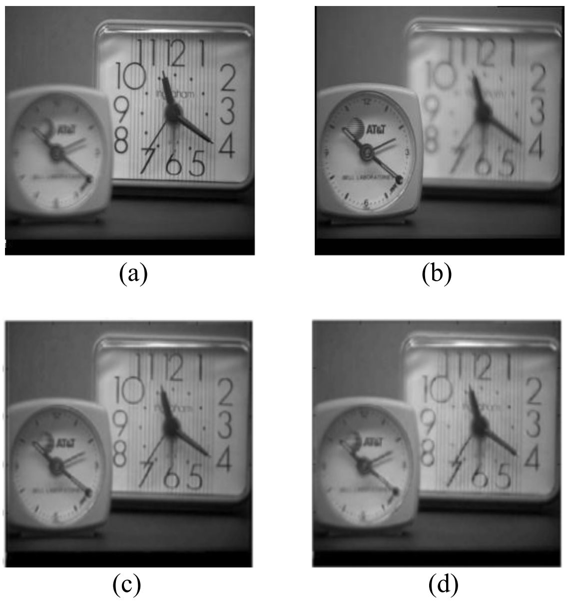


Fig.7. (a) Source image A: CT Scan, (b) Source image B: MRI Scan. (a) and (b) are fused using pixel based fusion method to give the fused image in (c), energy based fusion method to give the fused image in (d); while (e) gives the fused image for correlation based image fusion method.



(e)

Fig.8. (a) Source image A: Focus on large clock (b) Source image B: Focus on small clock. (a) and (b) are fused using pixel based fusion method to give the fused image in (c), energy based fusion method to give the fused image in (d); while (e) gives the fused image for correlation based image fusion method.

VI. PERFORMANCE EVALUATION

To Evaluate the performance quality of the image obtained by performing the correlation based image fusion can be evaluated by taking Mean Square Error (MSE) and Peak Signal-to-Noise Ratio (PSNR) as given by (5) and (6) respectively.

$$MSE = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}[S(i,j) - F(i,j)]}{M \times N} \quad (5)$$

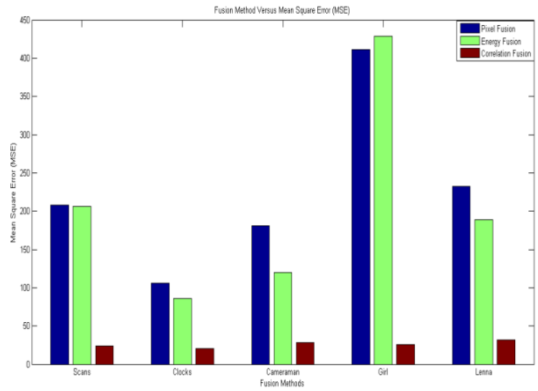
$$PSNR = 10\log_{10}\left(\frac{255^2}{MSE}\right) \quad (6)$$

Where S is the source image and F is the fused image. Table II describes all the results obtained. Fig. 9 describes that the Correlation based image fusion gives the least values for Mean Square error (MSE) and the highest value of Peak Signal to Noise ratio (PSNR) for all test images. The 5X5 averaging filter mask gives a better performance with less noise when compared to a square mask, in all test cases as evident from Table II.

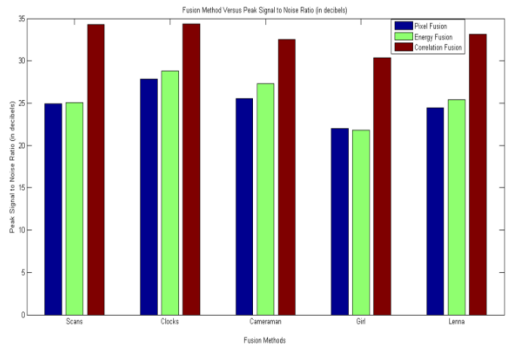
Table II
Comparison between Pixel, Energy and Correlation based Fusion method on MSE and PSNR

Source Images	**Fusion Method**	**MSE**	**PSNR** (in decibels)
CT / MRI Scan	Pixel based	207.56	24.96
	Energy based	206.22	25.03
	Correlation based	24.06	34.31
Clocks	Pixel based	106.27	27.87
	Energy based	85.92	28.79
	Correlation based	20.68	34.38
Cameraman	Pixel based	180.57	25.56
	Energy based	120.28	27.33
	Correlation based	28.33	32.55
Girl	Pixel based	411.15	21.99
	Energy based	428.84	21.81
	Correlation based	25.78	30.34
Lenna	Pixel based	233.62	24.45
	Energy based	188.52	25.38
	Correlation based	31.47	33.15

Pixel based [17], Energy based [21] and Correlation based fusion methods are experimented.



(a)



(b)

Fig.9. Comparison between fusion methods based on objective strategies: (a) Using MSE (b) Using PSNR. In all test cases the highest value for PSNR and least MSE are obtained for Correlation based image fusion method.

Results obtained by using Correlation based image fusion method shows that the filter mask removes noise and other artifacts in the image and preserves boundary information and structural details without introducing any other inconsistencies to the image. Fig 8 Shows (a) Source image A: CT Scan (b) Source image 2: MRI Scan. (a) and (b) are fused using pixel based maximum selection rule to give the fused image in (c), energy based rule to give the fused image in (d) while (e) gives the fused image for correlation based image fusion method using 5X5 square filter masks. The high contrast fused image using pixel based rules may not always give a clear detection of boundaries while the energy based rule compromises on image contrast.

VII. CONCLUSION

In this paper, we proposed a new correlation based image fusion algorithm aimed at integrating complementary information from multi-sensor data, so that the fused images are enhanced and more human perception friendly. We formulate the image fusion as an optimization problem whose solution is achieved by the proposed method.

We have successfully tested the proposed method on different types of source images with the help of MATLAB. The presented algorithm clearly outperforms contemporary wavelet based fusion methods in preserving significant features from a variety of sources without the common shortcomings such as artifacts.

REFERENCES

[1] R. C. Luo and M. G. Kay, *Multisensor Integration and Fusion for Intelligent Machines and Systems*. Ablex Publishing Corp, 1995.

[2] P. K. Varshney, “Scanning the special issue on data fusion,” *Proc. IEEE*, vol. 85, pp. 3–5, January 1997.

[3] J. Llinas and E. Walts, *Multisensor data fusion*. Boston: Artech House, 1990.

[4] M. A. Abidi and R. C. Gonzalez, *Data Fusion in Robotics and Machine Intelligence*. Academice Press, Inc., 1992

[5] A. Rosenfeld and M. Thurston, “Edge and curve detection for visual scene analysis,” *IEEE Trans. Computers*, vol. C-20, pp. 562–569, 1971.

[6] A. Witkin and J. M. Tenenbaum, “On the role of structure in vision,” in *Human and Machine Vision*, pp. 481–544, New York: Academic Press, 1983.

[7] D. Marr, *Vision*. San Francisco, California: W.H. Freeman, 1982.

[8] P. J. Burt and E. Adelson, “The laplacian pyramid as a compact image code,” *IEEE Trans. Communications*, vol. Com-31, no. 4, pp. 532–540, 1983.

[9] T. Lindeberg, *Scale-Space Theory in Computer Vision*. Kluwer Academic Publisher, 1994.

[10] H. Li, B.S. Manjunath and S.K. Mitra, Multisensor image fusion using the wavelet transform, *Graphical Models and Image Processing* (57) (1995), 235–245.

[11] O. Rockinger, *Pixel level fusion of image sequences using wavelet frames,* Proc. 16th Leeds Annual Statistical Research Workshop, 1996, pp. 149–154.

[12] D.A. Yocky, Artifacts in wavelet image merging, *Optical Eng* (35) (1996), 2094–2101.

[13] Ravi K. Sharma, Probabilistic Model-based Multisensor Image Fusion. *PhD thesis, Oregon Graduate Institute of Science and Technology*, Portland, Oregon, 1999.

[14] I. Daubechies, “The wavelet transform, time-frequency localization and signal analysis,” IEEE Trans. Info. Theory, 36:961-1005, 1990.

[15] S.G.Mallat, “A theory formultiresolution signal decomposition: the wavelet representation,” *IEEE Trans. Pattern Anal. Machine Intell.*, vol. PAMI-11, pp. 674–693, July 1989.

[16] M.Vetterli and C.Herley, “Wavelets and filter banks: theory and design,” IEEE Transactions on Signal Processing, 40(9):2207-2232, September 1992.

[17] A. Wang, H. Sun and Y. Guan, “The application of wavelet transform to multimodality medical image fusion,” Proc. IEEE International Conference on Networking, Sensing and Control (ICNSC), Ft. Lauderdale, Florida, 2006, pp.270-274.

[18] M. Sasikala and N. Kumaravel, “A comparative analysis of featurebased image fusion methods,” Information Technology Journal, 6(8):1224- 1230, 2007.

[19] R. C. Luo and M. G. Kay, “Data fusion and sensor integration: state of the art 1990s,” Data Fusion in Robotics and Machine Intelligence, M. A. Abidi and R. C. Gonzalez eds., Academic Press, San Diego, 1992, pp.7-135.

[20] Y. Du, P. W. Vachon, and J. J. V. Sanden, “Satellite image fusion with multiscale wavelet analysis for marine applications: preserving spatial information and minimizing artifacts (PSIMA),” Can. J. Remote Sensing, 29(6):14-23, November 2003.

[21] Z. Yingjie and G. Liling, “Region-based image fusion approach using iterative algorithm,” Proc. Seventh IEEE/ACIS International Conference on Computer and Information Science(ICIS), Oregon, USA, May 2008.

[22] H. Zhang, L. Liu and N. Lin, “A novel wavelet medical image fusion method,” International Conference on Multimedia and Ubiquitous Engineering (MUE’07), Seoul, Korea, April 2007.

[23] O. Rockinger, “Various Registered Images,” Available Online, URL:http:www.imagefusion.org, 2005