Image Fusion Algorithms Using Human Visual System in Transform Domain

Radhika Vadhi1*, Veera Swamy Kilari2, Srinivas Kumar Samayamantula1
1Department of Electronics and Communication Engineering, Jawaharlal Nehru Technological University, Kakinada, Andhra Pradesh., India radhikav139@gmail.com
2Department of Electronics and Communication Engineering, QISCET, Ongole, Andhra Pradesh., India. kilarivs@yahoo.com
1 Department of Electronics and Communication Engineering, Jawaharlal Nehru Technological University, Kakinada, Andhra Pradesh., India.
samay_ssk2@yahoo.com

Abstract: The endeavor of digital image fusion is to combine the important visual parts from various sources to advance the visibility eminence of the image. The fused image has a more visual quality than any source images. In this paper, the Human Visual System (HVS) weights are used in the transform domain to select appropriate information from various source images and then to attain a fused image. In this process, mainly two steps are involved. First, apply the DWT to the registered source images. Later, identify qualitative sub-bands using HVS weights. Hence, qualitative sub-bands are selected from different sources to form high quality HVS based fused image. The quality of the HVS based fused image is evaluated with general fusion metrics. The results show the superiority among the state-of-the art resolution Transforms (MRT) such as Discrete Wavelet Transform (DWT), Stationary Wavelet Transform (SWT), Contourlet Transform (CT), and Non Sub Sampled Contourlet Transform (NSCT) using maximum selection fusion rule.

Keywords: Discrete Wavelet Transform, Human Visual System, Image Fusion, Maximum selection rule, Multiresolution Transforms.

1.INTRODUCTION

In digital image processing, the fusion of an image is a technique to enhance the visual quality of an image. The fused digital image is prepared by combining the information from various source images. The source images must be registered. The integrated visual information from different source images, is provided by individual sensors. The image fusion can be performed on multi sensor images, multifocused images, temporal images, infrared images, satellite images, and also on medical images.

Many researchers [1], [3], [4], and [17] developed the image fusion algorithms in the past few years. The single fused image contains more information than individual source images. The fusion algorithms are classified into two basic domains. One is spatial and other is transformed domain. The fusion algorithms from spatial domain are average method, max-abs method, min-abs method [3],[4], and weighted average methods that are focused to remove the
unwanted sharpen edge information. The transform domain algorithms are used to characterize the features of an image. The fusion of information is made without losing the significant features of the images.

MRT bases are developed for digital image fusion [17]; some of them are DWT [12], SWT [8], CT[9], [14], and NSCT [5], [6], [16]. Shutao et al. [13] proposed a traditional image fusion approaches using the maximum selection rule in MRT. The classical wavelets include terms like compression and efficient representation. The wavelet transforms decompose the image into a series of sub-band images with different resolutions, frequencies, and directional characteristics. Smooth singularities in images often occur at the boundaries of physical objects. Efficient representation in two dimensions is a hard problem. The CT and NSCT transform adopt the Directional filter Banks (DFB) to decompose the image in multiscale form instead of Laplacian pyramid transforms. But these fusion approaches suffers with edge aliasing or pseudo-Gibb’s phenomena. Huimin et al. [18] proposed an algorithm to reduce some localizing problems.

The precise visual information is not selected for fusion due to scaling and ringing artifacts. Also the mathematical complexity is more in SWT, CT and NSCT. To overcome these problems in the selection of precise visual information, HVS based fusion approach is proposed.

The proposed approach is very simple and easy in calculations. With less complexity, the HVS based fusion approach in DWT domain got tremendous results than traditional approaches. The performance measures such as Mutual Information (MI), Edge Strength Orientation and Preservation (ESOP), Feature Similarity (FSIM) and Normalized Cross Correlation (NCC) are used to assess the superiority of the proposed approach.

The organization of this manuscript is as follows. In section 2, the concise reviews are mentioned for DWT, SWT, CT, and the NSCT. Section 3, describes details of anticipated algorithms are offered. In section 4, results are discussed. Source images and fusion images using diverse fusion algorithms are also given in the same section. Conclusions are given in section 5.

2. Multiresolution Transforms

2.1 Discrete Wavelet Transforms (DWT)

The directional filter and sub sample operations in Wavelet decomposition of images are performed twice in state-of-the art [13] approaches. Given that the scaling and wavelet function are distinguishable, and decomposition of the image is computed with a separable extension of one dimensional decomposition on the sequence of the rows and columns of the signal. At every level of transforming, the image is divided into four sub-bands. DWT has good localization in frequency and time domain. Transform the whole image by introducing the inherent scaling property, has better identification and higher flexibility.

The source signal has foremost differences in division of energy involving DWT due to lack of shift invariance. The major applications of DWT are in data compression, bio-medical, non-destructive evaluation, denoising and also in source and channel encoding.
2.2. Stationary Wavelet Transforms (SWT)

SWT is also same as DWT but the only thing of down sampling is concealed and translation invariant. All the low frequency and high frequency sub-bands have an equal size of the source images. SWT [8] is an innately surplus system for every group of coefficients that has a similar amount of samples as in the input. So there is a redundancy of 2N for a disintegration of N levels. An important advantage of SWT is its translation invariance of the wavelet coefficients and the redundancy make possible the recognition of significant features in signal, particularly in recognizing the noise. Poor directionality and increase in computational complexity are its disadvantages.

2.3. Contourlet Transform (CT)

For a single dimensional piecewise smooth signals, the scan lines on an edges are normally positioned along smooth curves (i.e. Contours) owing to smooth the boundaries of substance. The CT [9], [14] is a multidirectional and multilevel transform, which is constructed by adopting Laplacian pyramid with the Directional Filter Bank (DFB). The CT has two dimensional illustrations for an image which desires the inherent geometrical formation of picturesque visual information. Also, it is identified as Pyramidal DFB and realized through a two dimensional filter bank that divide an image into a number of directional sub frequency divisions of multiple levels. This is accomplished by combining the Laplacian pyramid with DFB at every scale. Since the multi level and the directional decompositions are autonomous to one another. Any individual can decompose every level into an arbitrary power of two numbers of directions, and different levels can be decomposed into a number of directions. Advantages of CT are its small redundancy compared with other transforms; provided multiscale and multidirection decomposition.

2.4. Non Sub sampled Contourlet Transform (NSCT)

NSCT [5],[6] is a combination of Non Sub sampled Pyramids (NSP) and Non Sub sampled DFB (NSDFB). The NSP is completely different from the complement of CT. The structure wedge of NSP is a two channel Non Sub sampled filter bank and it has no down sampling or up sampling. Consequently, it is shift invariant. To achieve multiscale decomposition, NSPs are built by iterated Non Sub sampled filter banks. With the subsequent point, all filters are up sampled by two in two dimensions. NSDFB is a shift invariant copy of the significantly sampled DFB in the CT. It has good directionality. The building block of a NSDFB is also a two channel Non Sub Sampled filter bank. NSDFBs are iterated in regularly to attain filter directional decomposition.

An NSP divides the visual information into a Low Pass Filter (LPF) and a High Pass Filter (HPF) sub-band. Afterwards, the NSDFB decomposes the HPF sub-band into a number of sub-bands. The design is iterated on the LPF sub-band. The major advantages of using NSCT are efficient in image denoising, targeting applications where redundancy is not a major issue.
2.5. HVS weight calculation in the DWT domain

In the digital images, noise is present while capturing images with the digital camera, preprocessing, coding, and transmission. 2D-DWT is an efficient MRT method used for exploiting the 2D correlation of the image. The 2D-DWT for N x N image size is defined as

\[ \Psi_\phi(j_0, u, v) = \frac{1}{\sqrt{(N)(N)}} \sum_{i=-\frac{N}{2}}^{\frac{N}{2}} \sum_{j=-\frac{N}{2}}^{\frac{N}{2}} f(x, y) \phi_{j_0, u, v}(x, y) \]

(1)

\[ \Psi'_\psi(j, u, v) = \frac{1}{\sqrt{(N)(N)}} \sum_{i=-\frac{N}{2}}^{\frac{N}{2}} \sum_{j=-\frac{N}{2}}^{\frac{N}{2}} f(x, y) \psi'_{j, u, v}(x, y) \]

(2)

where \( \phi_{j_0, u, v}(x, y) = 2^{j_0/2} \phi(2^{j_0} x - u, 2^{j_0} y - v) \) is the 2D scaling function, \( \psi'_{j, u, v} = 2^{j/2} \psi(2^{j} x - u, 2^{j} y - v) \) is the translated basis function, \( i = \{H, V, D\} \) is the superscript that assumes the value rows, columns, and diagonals, \( j \) is the scaling function, and \( u = v = 0, 1, 2, 3 \ldots 2^{j_0}-1 \).

The \( \Psi_\phi(j_0, u, v) \) coefficients describe the low frequency band (approximation) of \( f(x, y) \) at level \( j_0 \), and the \( \Psi'_\psi(j, u, v) \) coefficients insert high frequency band (horizontal, vertical, and diagonal details) for scales \( j \geq j_0 \).

Wavelet decomposition of an image is a two-dimensional filtering operation. An octave sub-sampling is performed to obtain the \( l \) number of levels of decomposition is used in [10] proposal. The Scaling and Wavelet functions are removable; the image order of decomposition can be computed with a separable extension of two one-dimensional decompositions along the sequence of rows and columns. At every stage of transforming, the image is divided into four sub images. The source image has major variations in the energy distribution between Wavelet coefficients due to lack of shift invariance.

HVS is a mathematical model developed for human eye vision that regards as a sensitivity of the eye to noise changes, local brightness, and local texture activities in the bands are in Barni et al. [2] proposal. The weights of the HVS are calculated as the combination of three terms, and are given in equation (3):

\[ S_j(u, v) = (\Theta(l, i) \Lambda(l, u, v) \cdot E(l, u, v))^{0.2} / 2 \]

(3)

Where \( l \) represents the level of decomposition, \( \Theta(l, i) \) represents the sensitivity of noise changes, \( \Lambda(l, u, v) \) illustrates the brightness, and \( E(l, u, v) \) represents the texture activity. Nasseer and Shaimaa [10] described the calculation of HVS weights in DWT domain.

The general block diagram for proposed Image fusion is shown in Figure 1. In the experiment, a common framework of a JPEG 2000 encoder is added with the proposed image fusion method. Any number of source images can be considered. The Fusion procedure is shown in Figure 2.

The proposed image fusion procedure is given in sequence. First, 2D-DWT is applied to each source image. Second, the HVS weights of all sub-bands of 2D-DWT are calculated. In the third step, the response of each band is calculated using HVS weights of the corresponding band. High-response bands are considered for image fusion.
The total weight of each sub-band is calculated by summing up all the weighted signals.

\[ w_i = \sum \sum \Psi(u,v) \]  

The absolute value of the activity level is given in equation (6)

\[ W_t = |w_i| \]  

The second step in fusion is selecting the higher sub-band by using activity level:

\[ A_s(u,v) = \begin{cases} A_1(u,v) & W_{i1} > W_{i2} \\ A_2(u,v) & \text{otherwise} \end{cases} \]  

Where \( A_1(u,v) \) the response of the first image is a sub-band and \( A_2(u,v) \) is the response of the second image sub-band. \( W_{i1} \) is the sum of weights of the sub bands in source 1 and \( W_{i2} \) Sum of weights of the sub bands in source image 2. The comparison is performed between the sum of sub-bands of each decomposition, and the high response subband is selected. Likewise, all the sub-band coefficients are selected to get a fused image.
3. Proposed algorithms based on multiscale image fusion

In the proposed work, consider the multifocus natural images with diverse modalities. In this procedure first the source concepts are divided into approximation (low frequency) sub-band and a sequence of detailed (high frequency) subband at different orientations and scales according to transform base. The fused image is constructed by pertaining inverse transform. The most salient features are selected through Shutao et al. [13] used the maximum-selection fusion rule in the fusion algorithm.

The proposed method that results better to existed methods. The generalized algorithm of HVS based fused approach in DWT domain is as follows:
1. Select the two or more source images to collect the information for fusion.
2. Apply the DWT on each source image as given in equation (2).
3. Calculate corresponding HVS weights using equation for each sub-band (3).
4. Multiply each sub-band coefficient with the corresponding HVS weights as per equation (4).
5. The response of each sub-band coefficient is calculated using equations (5) and (6).
6. The weights of sub-bands are compared, and the high-response sub-band is selected from the source images by using equation (7).
7. Inverse DWT is applied for high-responsive sub-bands to construct the fused image.

4. Performance measures and Experimental results

The experiments are performed on four benchmark images, that are shown in Figure 3. The MI [15] is an effective measure to determine the fusion image quality. ESOP values can be calculated without the benchmark images. This kind of analysis is useful in medical and remote sensing images. FSIM [7] Index can be based on the gradient measure. NCC [11] is used to measure the correlation between two images. The mentioned metrics are used to calculate the amount of visual information, transferred between source images to fused image. From, the information point of view, MI statistically depends on two random variables. The metric ESOP evaluates the edge information. With the feature similarity metric phase congruent and edges between source images and fused image are obtained.

4.1. Qualitative Analysis

The different number of decomposition orders and filters for every MRT for digital image fusion structure is given in proceeding sub sections. The coefficient of course resolution responds largely in pixel values when compared with the remaining decomposed levels. An error in course resolution causes more effect on final fused image. A few numbers of decompositions are performed to reduce the blocking effect in MRTs. The evaluated results of all the MRTs and the proposed method are tabulated in Table 1.

To evaluate the presentation of DWT with numbers of decomposition levels and wavelet bases, Haar family is considered. The best results are bolded in Table1. In SWT, the Symlet2 filters from wavelet family is (Sym N, N = 3, 6, 10, 13) are considered. When comparing with the DWT some of the metrics SWT are so close to the DWT. Evaluation of CT depends on pyramidal filters and directional filters. Each metric of performance evaluation for all approaches are given in Table1. The Non Sub Sample Contourlet (NSCT) transforms are based on pyramidal filtering (max flat) and directional filters (dmaxflat7). These filters are upsampled at every scale. In general, there are four types of filters, namely
‘9-7’, ‘Pyr’ ‘max flat’, and ‘Pyr ex’. When compared with the other mentioned multiresolution transforms, NSCT results best.

Fig. 3. Source images

Fig. 4. (a) Benchmark image (b), (c), (d), (e), and (f) are the result of DWT, SWT, C T, NSCT and HVS+DWT respectively

Fig. 5. Battle field images: (a) field 1 image, (b) field 2 image, and (c) fused image (DWT+HVS)
Table I

| Category      | Fusion rule | Transform | Filter | MI  | $\Omega^{AB/F}$ (ESOP) | FSIM  | NCC  |
|---------------|-------------|-----------|--------|-----|------------------------|-------|------|
| Multifocus    | Clock       | SWT       | Sym 2  | 3.1239 | 0.7544              | 0.9527 | 0.9853 |
|               | Clock       | DWT       | Haar   | 2.6823 | 0.7259              | 0.9479 | 0.9792 |
|               | Clock       | Con.T     | Pyr    | 2.6524 | 0.7460              | 0.9543 | 0.9816 |
|               | Clock       | NSCT      | Pyr    | 3.0012 | 0.7589              | 0.9526 | 0.9854 |
|               | Clock       | DWT + HVS | Haar   | 4.4910 | 0.9166              | 0.9997 | 0.9992 |
| Pepsi         | Clock       | SWT       | Sym 2  | 3.2823 | 0.8134              | 0.9776 | 0.9958 |
|               | Clock       | DWT       | Haar   | 3.1709 | 0.8054              | 0.9754 | 0.9942 |
|               | Clock       | Con.T     | Pyr    | 2.7860 | 0.7360              | 0.9685 | 0.9859 |
|               | Clock       | NSCT      | Pyr    | 3.0029 | 0.7393              | 0.9704 | 0.9910 |
|               | Pepsi       | DWT + HVS | Haar   | 4.0096 | 0.8871              | 0.9996 | 0.9974 |
| Toy           | Clock       | SWT       | Sym 2  | 3.1207 | 0.8770              | 0.9859 | 0.9962 |
|               | Clock       | DWT       | Haar   | 9313   | 0.8689              | 0.9846 | 0.9950 |
|               | Clock       | Con.T     | Pyr    | 2.5143 | 0.8150              | 0.9719 | 0.9878 |
|               | Clock       | NSCT      | Pyr    | 2.8105 | 0.8244              | 0.9703 | 0.9907 |
|               | Toy         | DWT + HVS | Haar   | 3.4135 | 0.8691              | 0.9996 | 0.9960 |
| Disk          | Clock       | SWT       | Sym 2  | 2.8712 | 0.8049              | 0.9609 | 0.9888 |
|               | Clock       | DWT       | Haar   | 2.6878 | 0.7904              | 0.9562 | 0.9846 |
|               | Clock       | Con.T     | Pyr    | 2.2792 | 0.7265              | 0.9466 | 0.9704 |
|               | Clock       | NSCT      | Pyr    | 2.6394 | 0.7392              | 0.9474 | 0.9797 |
| Disk          | Dish        | DWT + HVS | Haar   | 3.9216 | 0.8958              | 0.9995 | 0.9978 |

Experiments are also performed with naturally acquired images that are determined and tabulated in Table II. The performance of MI, FSIM, and NCC measures were calculated in reference to the ground truth image. Edge strength orientation and preservation (ESOP) [15], is a metric that does not require the ground truth image. The results in Fig 5, shows that the proposed method is effective for all natural images.
Table II

| Fusion rule                  | Remote sensing images | Filter | ESOP  | Elapsed time in seconds |
|------------------------------|-----------------------|--------|-------|-------------------------|
| DWT+HVS (proposed)           | Field 1, Field 2      | Haar   | 0.5477| 0.161753                |
| DWT (max. selection) [3]     | Field 1, Field 2      | Haar   | 0.0167| 2.310168                |
| DWT (Average) [4]            | Field 1, Field 2      | Haar   | 0.3580| 0.178262                |
| DWT+HVS (proposed)           | gun 1, gun 2          | Haar   | 0.5927| 0.166719                |
| DWT (max. selection) [3]     | gun 1, gun 2          | Haar   | 0.0312| 1.921300                |
| DWT (Average) [4]            | gun 1, gun 2          | Haar   | 0.3885| 0.171202                |
| DWT (max. selection) [3]     | flir, lltv            | Haar   | 0.4429| 0.160571                |
| DWT (Average) [4]            | flir, lltv            | Haar   | 0.0583| 2.373511                |
| DWT+HVS (proposed)           | CT, MRI               | Haar   | 0.7266| 0.163805                |
| DWT (max. selection) [3]     | CT, MRI               | Haar   | 0.2253| 1.643815                |
| DWT (Average) [4]            | CT, MRI               | Haar   | 0.6276| 0.385489                |
| DWT+HVS (proposed)           | Remote 1,remote 2     | Haar   | 0.5787| 0.163989                |
| DWT (max. selection) [3]     | Remote 1,remote 2     | Haar   | 0.0312| 1.724461                |
| DWT(Average) [4]             | Remote 1,remote 2     | Haar   | 0.4118| 0.171512                |

Fig. 6. Remote sensing images: (a) gun 1 image, (b) gun 2 image, and (c) the fused image (DWT+HVS)

Fig. 7. Remote sensing images: (a) remote1 image, (b) remote2 image, and (c) the fused image (DWT+HVS)
Fig. 8. Medical images: (a) CT image, (b) MRI image, and (c) the fused image (DWT+HVS).

The experimental results for the remote sensing images in Fig. 6 and Fig. 7, using different filters are given in Table III, which show that the calculated ESOP of the proposed method using ‘Haar’ filter is found to be superior to all other measurements. The experiments on medical images are shown in Fig 8. However, the run time is low for DWT average using ‘Haar’ filter [4].

Table III

| Fusion rule               | Filter | ESOP  | Elapsed time |
|---------------------------|--------|-------|--------------|
| DWT+HVS (proposed)        | Haar   | 0.6678| 0.413864     |
| DWT (max.selection) [3]   | Haar   | 0.0348| 1.921300     |
| DWT (Average) [4]         | Haar   | 0.3885| 0.177191     |
| DWT+HVS (proposed)        | Db2    | 0.5927| 0.189545     |
| DWT (max.selection) [3]   | Db2    | 0.0396| 2.256725     |
| DWT (Average) [4]         | Db2    | 0.2513| 0.193051     |
| DWT+HVS (proposed)        | Db5    | 0.5927| 0.232771     |
| DWT (max.selection) [3]   | Db5    | 0.0364| 2.372006     |
| DWT (Average) [4]         | Db5    | 0.3832| 0.206951     |
| DWT+HVS (proposed)        | Sym2   | 0.5927| 0.184902     |
| DWT (max.selection) [3]   | Sym2   | 0.0396| 2.233882     |
| DWT (Average) [4]         | Sym2   | 0.2513| 0.187266     |
| DWT+HVS (proposed)        | Sym6   | 0.5927| 0.241161     |
| DWT (max.selection) [3]   | Sym6   | 0.0390| 2.392888     |
| DWT (Average) [4]         | Sym6   | 0.2555| 0.217881     |
| DWT+HVS (proposed)        | coif1  | 0.5927| 0.196165     |
| DWT (max.selection) [3]   | coif1  | 0.0365| 1.990912     |
| DWT (Average) [4]         | coif1  | 0.3743| 0.192766     |
| DWT+HVS (proposed)        | Bior1.3| 0.5927| 0.219888     |
| DWT (max.selection) [3]   | Bior1.3| 0.0394| 2.155807     |
| DWT (Average) [4]         | Bior1.3| 0.3632| 0.207811     |
| DWT+HVS (proposed)        | Bior3.5| 0.5927| 0.259649     |
| DWT (max.selection) [3]   | Bior3.5| 0.0364| 2.137232     |
| DWT (Average) [4]         | Bior3.5| 0.2610| 0.243520     |
| DWT+HVS (proposed)        | rbio1.1| 0.5927| 0.192448     |
| DWT (max.selection) [3]   | rbio1.1| 0.0348| 2.100788     |
| DWT (Average) [4]         | rbio1.1| 0.3885| 0.191210     |
| Method                          | Filter | PSNR  | SSIM  |
|--------------------------------|--------|-------|-------|
| DWT+HVS (proposed)             | rbio2.2| 0.5927| 0.209056 |
| DWT (max.selection) [3]        | rbio2.2| 0.0375| 2.012377 |
| DWT (Average) [4]              | rbio2.2| 0.3377| 0.216133 |

In Fig 9, the superiority of our proposed method DWT + HVS in MI is clearly visible in the graphical comparison among all mentioned multi resolutions transforms.

5. Conclusions

In this manuscript, the HVS based fused image in DWT domain approach is used in the application of Image Fusion. The most perceptual quality sub-bands are identified with the help of HVS weights. The JPEG 2000 format is used to achieve an efficient result in both storage and transmission. The performance comparisons are made among MRTs. Higher visual quality and less blocking artifacts are desired in the anticipated HVS based fused image approach. The proposed method surpasses in qualitative information from the other MRTs. The qualitative measure MI is comparatively high due to less scaling and ringing artifacts are observed in HVS based fused image. The proposed approach is suitable for remote sensing, panchromatic and multi focus images. Hence, this approach is more suitable for real time applications. The proposed approach is not optimal for medical imaging because some of the visual information is lost in the selection process. In future scope the curvelets with HVS may give better results for medical imaging.

REFERENCES

[1] A Garzelli, “Possibilities and limitations of the use of wavelets in image fusion,” In: IEEE Geoscience and Remote Sensing Symposium, Vol.1, pp. 66-68, 2002.
[2] Barni, Bartolini, Piva, “Improved Wavelet based Watermarking through Pixel wise masking,” IEEE Transactions on Image Processing, vol. 10 no. 5, pp.783-791, 2001.
[3] Dattatraya, Deepali, “Wavelet based Image Fusion using Pixel based maximum selection rule,” International Journal of Engineering Science and Technology (IJEST), vol. 3, no. 7, pp.5572-5577, 2011.

[4] Davy Sannen, Hendrik Brussel, “A multilevel Information Fusion Approach for visual quality inspection,” Information Fusion, Vol. 13, no.1, pp. 48-59, 2012.

[5] Guo B.L., Q. Zhang, “Multi Focus Image fusion using the Non Sub sampled Contourlet Transform,” Signal processing, vol. 89, no.7, pp.1334-1346, 2009.

[6] Huafei, Chai, Zhaofei, “A Multi Focus Image fusion based on non sub sampled Contourlet Transform and Focused Regions Detected,” Optik, vol. 24, no.1, pp. 40-51, 2012.

[7] Lin, Xuanqin, “FSIM: A Feature Similarity index for Image quality assessment,” IEEE Transactions on image processing, vol. 20, no.8, pp. 2378-2386, 2011.

[8] Mirajkar P., Sachin D. Ruikar, “Image fusion based on Stationary Wavelet Transform,” International Journal of Advanced Engineering Research and Studies, vol. 2, no. 4, pp. 99-101, 2013.

[9] M. Qigong, W. Baoshu, “A novel Image Fusion method using Contourlet Transform,” International Conference on communications, Circuits and Systems, vol. 1, pp. 548-552, 2006.

[10] M. Qigong, W. Baoshu, “A novel Image Fusion method using Contourlet Transform,” International Conference on communications, Circuits and Systems, vol.1, pp. 548-552, 2006.

[11] Radhika V, Veeraswamy K, Srinivas Kumar S, “Image Fusion using HVS in Discrete Wavelet Transform domain,” Graphics, Vision and Image Processing GVIP, Vol. 16, no.2, pp.1-13, 2016.

[12] Rockinger O, “Image sequence fusions using a shift-invariant wavelet transform,” Proceedings of IEEE international conference on image processing, vol. 3, pp. 288-91, 1997.

[13] Shutao, Bin, Hu, “Performance comparison of different Multi Resolution transforms for Image Fusion,” Information fusion, vol. 12, no. 2, pp. 74-84, 2011.

[14] Vetterli, Minh N, “The Contourlet Transform: An Efficient directional Multi Resolution image representation,” IEEE Transaction on Image Processing, vol. 14, no.12, pp. 1-16, 2005.

[15] Xydeas C.S, PetrovicV, “Objective image fusion Performance measure,” Electronic Letters, vol. 36, no. 4, pp.308-309, 2000.

[16] Yi, H. Li, Zhang, “Multi focus Image Fusion based on features contrast of multi scale products in Non Sub Sampled Contoulet Transform Domain,” Optik, vol.123, no. 7, pp. 569-581, 2012.

[17] Yotam Ben-Shoshan, Yitzhak, “Improvements of Image Fusion methods,” J. Electron Imaging. Vol. 23, no. 2, pp.1-12, 2014.

[18] Huimin Lu, Lifeng Zhang, Seiichi Serkawa, “Maximum local energy:An effective approach for multi sensory image fusion in beyond Wavelet Transform domain,” Computers and Mathematics with Applications. Vol. 64, pp. 996-1003, 2012.
V. Radhika is a research Scholar at JNTUKCE, Kakinada. She received her M.Tech. from the same institute. She has eleven years experience of teaching undergraduate and post graduate students. Her research interests are in the areas of image fusion and image watermarking. She has published 3 papers in the reputed International Conferences, 3 International Journals having good impact factor, Thomson & Routers indexing and Science Expanded index.

K. Veera Swamy is currently working as Professor in ECE Department and Principal, QIS College of Engineering and Technology, Ongole, India. He received his Ph.D and M.Tech. from JNTU, Kakinada, India. He has fifteen years experience of teaching undergraduate and post graduate students. He has published 13 research papers in National and International Journals. He has published 28 research papers in National and International Conferences. Presently he is guiding one Ph.D. student in the area of Image Fusion. His research interests are in the areas of image compression, image watermarking, image fusion, and networking protocols.

S. Srinivas Kumar is currently working as Professor and Director, Sponsored Research, Jawaharlal Nehru Technological University, Kakinada, India. He received his Ph.D. from E&ECE Department IIT, Kharagpur. He received his M.Tech. from Jawaharlal Nehru Technological University, Hyderabad, India. He has twenty one years experience of teaching undergraduate and post-graduate students and guided number of post-graduate thesis. He has guided 4 Ph.D scholars. He has published 50 research papers in National and International journals. Presently he is guiding ten Ph.D. students in the area of Image processing. His research interests are in the areas of digital image processing, computer vision, and application of artificial neural networks and fuzzy logic to engineering problems.