Journal Of Harmonized Research (JOHR)

Journal Of Harmonized Research in Engineering
5(1), 2017, 34-41

ISSN 2347 – 7393

Review Article

A LITERATURE SURVEY ON IMAGE FUSION TECHNIQUES

Ashok Kumar Meena, Kalpana Rai

Dept. of Computer Science & Engineering, JNCT, Bhopal, India

Abstract: In the environment various type of noise is found which degrades the quality of images. To get the better quality of image or information a process is used which is called image fusion. This process fuses/ combines two or more image of same kind which produces the resultant image of better quality than the input image. Fusion process extremely utilizes more completely and superfluous information. Images counterfeit sometimes during accomplishment or transmission or due to error in memory locations in the hardware. Image fusion can be done at different levels such as pixel level, feature level and decision level. The image fusion techniques are classified into two category spatial domain and frequency domain techniques. In this paper, present literature study about the earlier work done in the field of image fusion to get better quality of image. We also describe the various image fusion techniques with their merits and demerits.

Keywords: Image Fusion, Spatial Domain, Frequency Domain, Noise

Introduction: Image processing is a wide area of research It offers alternatives quantities of fields and area in which examination work can be completed. Image fusion is one such field within the range of image processing amid which differed investigates are carried out to get improvement results. Image fusion is referred to as the process of obtaining a superior image from the input images by extracting certain features of the input images. The capacities of the imaging gadgets to catch the data are not the same as to each other, on the grounds that the optical focal points are broadly utilized in imaging gadgets, the optical focal point have a constrained profundity of field, so inside a specific scope of separations, just few objects will be captured from the imaging gadgets and recorded sharply, while others will be defocused and be obscured.[1] This is undesirable for precisely translating and breaking down pictures, so the multi-center picture combination method is exceptionally alluring to give a promising approach to make a solitary

For Correspondence:
ashok88meena@gmail.com.
Received on: January 2017
Accepted after revision: February 2017

picture in which every one of the articles inside the picture are in center by consolidating two or various pictures of a similar scene that are brought with assorted focuses.[2-4] According to Information extraction level, picture combination can for the most part be grouped into three sorts: pixel-level, highlight level and choice level. Pixel-level combination chooses and blends the data of the source pictures to develop the intertwined picture, as indicated by some combination criteria, for instance pixel by pixel, area by district. Include level combination first concentrates the elements of the source pictures, and after that wire some removed components into a solitary picture. Choice level combination frames the intertwined by considering the picture depictions, for example, social diagrams. At present, a large portion of the combination calculations are pixel-level. Pixel-level combination can be performed in either spatial space or changed area. In the spatial area, the sharp and neighborhood changes in source pictures are specifically figured from pixels or areas. So pixels or areas are straightforwardly chosen and consolidated in either a liner or non-direct approach to shape the combined picture [2]. The principle points of interest of these techniques are anything but difficult to be executed with a low computational intricacy, however yield pictures will be at the loss of the subtle elements of their information pictures. In the changed area, the sharp and neighborhood changes in power are shown by the high recurrence coefficients. So the specific recurrence or time-recurrence change is utilized to wire pictures, and the yield pictures can contain expansive extent of the subtle elements of info pictures. One of the established techniques is multi-scale strategies [1]. Be that as it may, these techniques as a rule have the high computational unpredictability and the requesting prerequisites for memory.

The different stages of image fusion system is shown in fig. 1.In this paper, we presents the literature study about the earlier work done and various image fusion techniques with their merits and demerits. The organization of the remaining section of the paper is done as follows: Section II Presents related work. In section III, various image fusion techniques is discussed with their merits and demerits. Section IV gives overall conclusion of the paper.

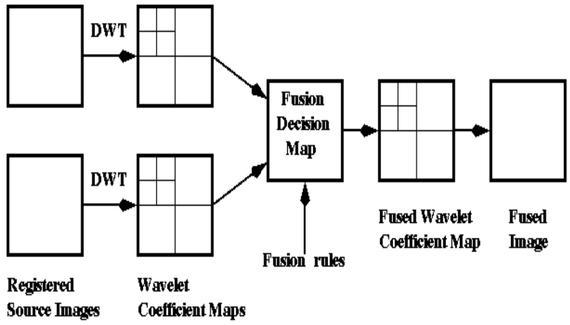

Fig.1: Processing stage of Image fusion system

The different stages of image fusion system is shown in fig. 1.In this paper, we presents the literature study about the earlier work done and various image fusion techniques with their merits and demerits. The organization of the remaining section of the paper is done as follows: Section II Presents related work. In section III, various image fusion techniques is discussed with their merits and demerits. Section IV gives overall conclusion of the paper.

Image Fusion Techniques:

Image fusion is the process that coalesce information in multiple images of the identical scene. These images may be captured from dissimilar sensors, acquired at dissimilar times, or having dissimilar spatial and frequency domain. The objective of the image fusion is to maintain the most enviable characteristics of each image. Image fusion techniques are classified into following two categories: Spatial domain and Frequency domain. The spatial domain combination offers mostly with the pixels of origin graphics. It fuses entire graphics utilizing local spatial features including gradient, spatial volume as well as local common deviation. Frequency domain combination consists of your shift of entire graphics straight into frequency domain. In this approach source images tend to be projected on to localized bases which are designed to stand for your sharpness as well as edges associated with an image. Most of these converted coefficients help in extracting pertinent features from input images to form fused image.

Spatial Domain Techniques: The spatial domain techniques are also of different types namely:

- Average Method
- Select Maximum
- PCA Based Method
- IHS Method
- Brovey Method
- High Pass Filtering

Average Method: Average Method: In this method, the resultant image is obtained by averaging every corresponding pixel in the input images. It is one of the simplest method and easy to understand and implement. It works well when images to be fused from same type of sensor and contain additive noise [5]. This method is very good for certain particular cases where in the input images have an overall high brightness and high contrast. However, it leads to undesirable side effect such as reduced contrast and some noise can easily introduced into the fused image, which will reduce the resultant image quality consequently. The average value is assigned to the corresponding pixel of the output image which is given in below equation.

$$P(i,j) = \frac{\{A(i,j) + B(i,j)\}}{2}$$

Where A (i,j) and B(i,j) are two input images. This is repeated for all pixel values.

Select Maximum: The greater the pixel values the more in-focus the image. Thus this algorithm chooses the infocus regions from each input image by choosing the greatest value for each pixel, resulting in highly focused output [5]. The value of the pixel P (i, j) of each image is taken and compared to each other. The greatest pixel value is assigned to the corresponding pixel.

$$P(i,j) = \sum_{i=1}^{M}\sum_{j=1}^{N} \text{Max } A(i,j)B(i,j)$$

Where A (i,j) and B (i,j) are the input images & P(i,j) is the resultant image.

Principal Component Analysis (PCA): PCA is a technique involving numerical procedure of transforming the correlated variables into uncorrelated variables called principal components [7]. Compact and optimal depiction of the data set is computed. PCA is the simple technique which reveals the internal structure of data in balanced way but it may produce spectral degradation. Application areas for using PCA are image classification and image compression.

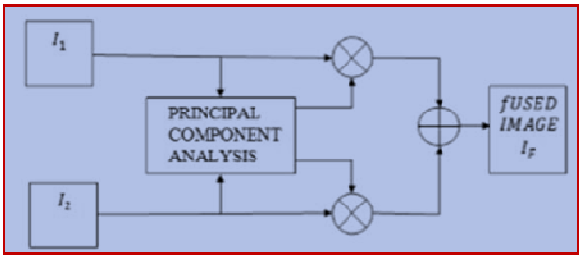

Fig.2: Information flow diagram in image fusion scheme employing PCA

HIS Method: The IHS technique is one of the most commonly used fusion techniques for sharpening. It has become a standard procedure in image analysis for color enhancement, feature enhancement, improvement of spatial resolution and the fusion of disparate data sets [6]. In the IHS space, spectral information is mostly reflected on the hue and the saturation. From the visual system, one can conclude that the intensity change has little effect on the spectral information and is easy to deal with. For the fusion of the high-resolution and multispectral remote sensing images, the goal is ensuring the spectral information and adding the detail information of high spatial resolution, therefore, the fusion is even more adequate for treatment in IHS space [7].

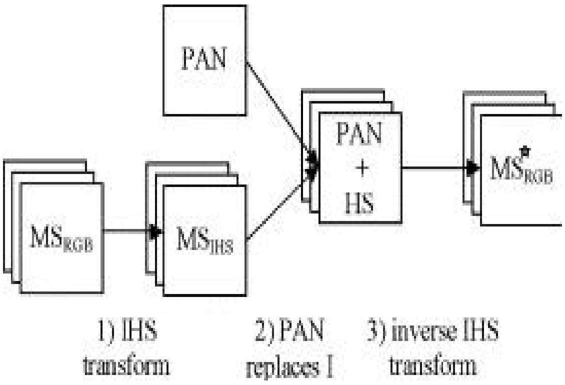

Fig. 3 IHS Image fusion

Brovey Method

Brovey Transform is also known as the color normalization transform as it entails a red-green-blue (RGB) color transform method. It is statistical/numerical methods. Brovey Transform employs the addition, division and multiplication for the fusion of three multispectral bands. The Brovey Transform was developed to visually develop contrast in the small and high ends of an images histogram (i.e., to supply contrast in shadows, water, and high reflectance areas such as urban features). The Brovey transformation was developed to circumvent the disadvantages of the multiplicative method. The subsequent equation shows the mathematical algorithm for the Brovey method [10].

$$\boldsymbol{f_i} = \boldsymbol{M_i} / \textstyle\sum_{i=1}^{M} \boldsymbol{M_i} + \boldsymbol{P}$$

Where $\boldsymbol{f_i}$ is the fused Band, $\boldsymbol{M_i}$ is the multispectral Band, P is the Panchromatic Band.

High Pass Filtering: The low spatial resolution image is incorporated by means of statistical functions such as subtraction, addition, multiplication or ratios, with the spatial information received using high pass type filtering on the high spatial resolution image. The high frequency information from the high resolution panchromatic image is added to the low resolution multispectral image to obtain the resultant image. It is performed either by filtering the High Resolution Panchromatic Image (HRPI) with a high pass filter or by taking the original HRPI and subtracting LRPI (Low Resolution Panchromatic Image) from it. The spectral information contained in the low frequency information of the HRMI (High resolution Multispectral Image) is conserved by this method. When the low pass filter is used, it shows a smooth transition band along with a high ripple outside the pass band [8].

Frequency Domain Technique: The frequency domain techniques are also of different types namely:

- Discrete wavelet transform
- FSD pyramid
- Laplacian Pyramid
- Gradient Pyramid
- DT-CWT

Discrete Wavelet Transform [11]

First Approach: Wavelet transform is a mathematical tool developed in the field of signal processing. The wavelet transform decomposes the signal based on elementary functions: the wavelets. By using this, a digital image is decomposed into a set of multi resolution images with wavelet coefficients. For each level, the coefficients contain spatial differences between two successive resolution levels. As shown in block diagram PAN image is decomposed using DWT. The image will get divided into four components namely approximation, diagonal, vertical and horizontal. Out of this four component approximation component carries maximum information. Now this approximation component is replaced by MS image.

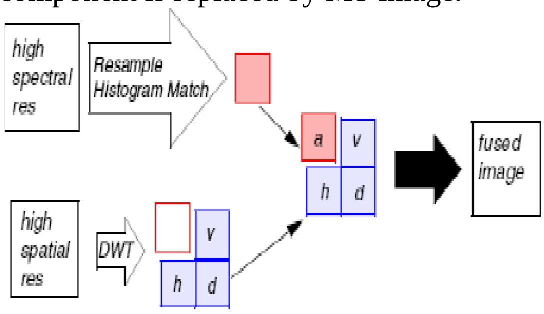

Fig.4: DWT First Approach

Processing steps of wavelet based image fusion

1- Decompose a high resolution P image into a set of low resolution P images with wavelet coefficients for each level.

2- Replace a low resolution P images with a MS band at the same spatial resolution level.

3- Perform a reverse wavelet transform to convert the decomposed and replaced P set back to the original P resolution level.

For the processing the replacement and reverse transform does three times, each for one spectral band

Second Approach: This is the second approach for wavelet based image fusion. In this method second level DWT of PAN & of MS image is taken. Then LL component in second level decomposition of MS image is replaced by the PAN image. By doing this minute details are obtained and hence there are more chances of obtaining better quality image .

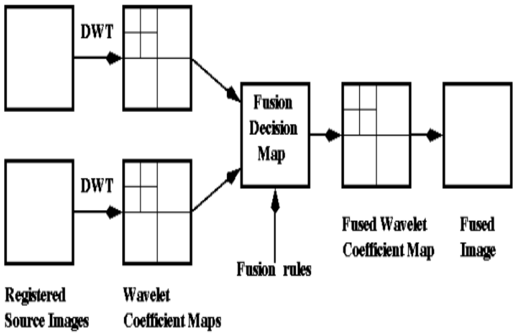

Fig.5: DWT Second Approach

Processing steps of wavelet based image fusion :

1- Decompose a high resolution P image into a set of low resolution P images with wavelet coefficients for each level.

2- Decompose a low resolution MS image into a set of low resolution MS images with wavelet coefficients for each level

3- Replace a low resolution MS images with LL component of a PAN image a MS band.

4- Perform a reverse wavelet transform to convert the decomposed and replaced P set back to the original P resolution level.

Filter Subtract Decimate (FSD) Pyramid: FSD Laplacian pyramid [14] is defined as the difference between Gk and the filtered copy of Gk prior to sub sampling to formG_{n+1}. FSD pyramid is generated by using the following recursive rules:

$\tilde{G}_{n+1} = w * G_n$ Low-Pass Filter

$L_n = G_n - G_{n+1}$ Subtract

$G_{n+1} = Decimate\, G_n - 1$ Decimate

Laplacian Pyramid: The Laplacian pyramid $\tilde{L}_k$ [12, 13] is defined as the difference between successive levels of the Gaussian pyramid and is given by:

$\tilde{L}_k = G_k - 4w * G_{k+1} \uparrow 2$

Here … ↑2 indicates up sampling by *2. n-1* rows and columns of zero vale are inserted between the original rows and columns. Convolution by *w* has the effect of interpolating the missing samples.

Gradient Pyramid: Gradient pyramid Fusion- the Gaussian pyramid is a sequence of images in which each member of the sequence is a low pass filtered version of its predecessor. Gradient pyramid Fusion method uses Gradient pyramids instead of Laplacian with Gradient pyramids.

DT-CWT (Dual Tree Complex Wavelet Transform): The dual-tree complex wavelet transform (DT-CWT) is an over-complete wavelet transform that provides both good shift invariance and directional selectivity over the DWT. But, there is an increased memory and computational cost. Two fully decimated trees are computed, one for the odd samples and one for the even samples generated at the first level. The DT-CWT has reduced over completeness compared with the SIDWT and is able to distinguish between positive and negative orientations giving six distinct sub-bands at each level, the orientations of which are ±150, ±450, ±750. Different fusion strategies have been used to fuse DTCWT sub-bands. Chabi et al proposed min, max, and energy schemes for fusing DT-CWT sub-bands in [15]. In [16], Cai and Hu proposed DT-CWT for image fusion of palm print and palm vein. In [17], Guomundsson and Sveinsson proposed DTCWT for the fusion of TOF and CCD camera images. In [18], Ioannidou et al applied DT-CWT and SIDWT on quickbird images and proved its effectiveness over DWT and IHS. In [19], Chen and Gao implemented variation of DT-CWT called Double Density DT-CWT for image fusion. Canagarajah et al proposed a region level DT-CWT based image fusion and proved its advantages over pixel level image fusion schemes in [20].

Related Work: This section describes the earlier work done in the field of image fusion by various author.

Author /Researcher	**Year**	**Description**
Bhavana. V, Krishnappa. H.K [21]	2015	In this work, MRI and PET images are preprocessed along with enhancing the quality of the input images which are degraded and non-readable due to various factors by using spatial filtering techniques like Gaussian filters. The enhanced image is then fused based on Discrete Wavelet Transform (DWT) for brain regions with different activity levels. The system showed around 80-90%

		more accurate results with reduced color distortion and without losing any anatomical information in comparison with the existing techniques in terms of performance indices including Average Gradient and Spectral Discrepancy, when tested on three datasets - normal axial, normal coronal and Alzheimer's brain disease images
Singh et al.[22]	2009	In this, a fusion algorithm is proposed to combine pairs of multispectral magnetic resonance imaging such as T1, T2 and Proton Density brain images. The proposed algorithm utilizes different features of Redundant Discrete Wavelet Transform; mutual information based non-linear registration and entropy information to improve performance. Experiments on the Brain Web database show that the proposed fusion algorithm preserves both edge and component information, and provides improved performance compared to existing Discrete Wavelet Transform based fusion algorithms
Daneshvar et al.[23]	2015	In this paper a new method based on lifting scheme is suggested to fuse modals of MR. in this algorithm, lifting wavelet transform is used to decompose source images into different sub-bands. Different fusion rules are applied to fuse sub-bands and achieve fused image. Numerical and visual analyses prove efficiency of propped method in gathering complementally information of source images in one image
Aishwarya et al.[24]	2016	In this paper, a novel fusion algorithm based on Discrete Wavelet Transform (DWT) and Sparse Representation (SR) is proposed. Initially, DWT is applied to extract the low frequency components and high frequency components of source images. High frequency components are merged using SR based fusion approach and low frequency components are combined using variance as activity level measurement. Finally, inverse DWT is performed on the fused coefficients to get the fused image. Experimental results demonstrate the effectiveness of proposed method in terms of visual perception and quantitative analysis
Cavalcanti et al.[25]	2012	This paper describes two image fusion algorithms in the frequency domain that are based on focus: Contrast in DCT domain and Spatial Frequency. The algorithms divide the images in fixed size blocks to decide which image should be selected to constitute the final result. Improvements are made to both techniques to decide when to choose an entire block or pixels individually. The proposed approach combines the different techniques (or different settings of a single technique), by comparing evaluation metrics (PSNR) values obtained for each block independently and selecting the technique that performs better for the analyzed block.
Nirmala Paramanandham, Kishore Rajendiran	2016	In this paper, a simple and competent image fusion algorithm based on standard deviation in wavelet domain is proposed and compared with both transform domain as well as spatial domain techniques. The techniques are evaluated with various databases quantitatively and qualitatively.
Zhang [27]	2015	In this paper, proposed an efficient image fusion algorithm which combined with the advantage of space domain and transform domain. they employ the Principal Component Analysis (PCA) in the low frequency domain, and combine the biggest value selection method with weighted mean method in the high frequency domain. Finally, the output image is obtained by inverse wavelet transform. The experimental results show that this algorithm can produce high-contrast fusion images that are clearly more appealing and have more useful information than the PCA and the wavelet transform.
Mini et al. [28]	2015	Utilized Stationary Wavelet Transform (SWT), modulus maxima and high boost filtering. The image is decomposed using SWT and its modulus maximum is determined. A fraction of the high pass filtered image obtained as the result of SWT decomposition and modulus maxima is added to original

		image. The scheme is evaluated visually and objectively using measures like contrast, PSNR etc. The performance measures are evaluated for different category of images and found to be suitable to all categories of mammographic images
S. Anbumozhi, P.S. Manoharan [29]	2014	Focused to classify the brain image into normal and abnormal image using minimum distance classifier algorithm. The proposed methodology consists of spatial domain filter, fusion, clipping circuit and minimum distance classifier algorithm. The difference features are extracted from fused image and compared with trained extracted feature set. The low power architecture for the proposed brain image classification method is presented in this paper. The proposed hardware architecture consumes power of 151mW in CMOS 90nm technology.

Conclusion: Image fusion is the extensively used approach to get improved quality of image. The importance of fusion in multimodality imaging is introduced in this paper. The literature study about the earlier work done by various researchers and image fusion technique is also discussed. After studying these techniques, we analyzed that the existing system is not much suitable for fusing the image. So in future work, need to design such technique by selecting the best features of the existing technique and combine them to get improved quality of image.

Reference

[1] Lixia Zhang, Guangping Zeng "Novel Multi-focus Image Fusion Method Research", International Conference on Intelligent Networks and Intelligent Systems, 2015.

[2] Z.Zhou, S. Li and B. Wang, "Multi-scale weighted gradient-based fusion for multi-focus image", Information Fusion, vol.20, 2014, pp. 60-72, doi:10.1016/j.inffus.2013.11.005

[3] Zhiping xu, "Medical image fusion using multi-level local Extrema" Information Fusion, vol.19, 2014, pp. 38-48,doi:10.1016/j.inffus.2013.01.001

[4] Yong Jiang, Minghui Wang , "Image fusion with morphological component analysis, " vol.18, 2014, pp.107-118, doi: 10.1016/j.inffus.2013. 06. 001

[5] Anita, Moses, "Survey on Pixel level image fusion techniques", IEEE Conference, Year 2013.

[6] Hui Y. X. and Cheng J. L., 2008. "Fusion Algorithm for Remote Sensing Images Based on Non sub-sampled Contourlet Transform". ACTA AUTOMATICA SINICA, Vol. 34, No. 3.pp. 274-281.

[7] Pohl C. and Van Genderen J. L. (1998), Multi-sensor Image Fusion in Remote Sensing: Concepts, Methods and Applications (Review Article), International Journal of Remote Sensing, Vol. 19, No.5, pp. 823-854

[8] K Sharmila, S Rajkumar, V Vijayarajan. "Hybrid method for Multimodality Medical image fusion using Discrete Wavelet Transform and Entropy concepts with Quantitative Analysis" International conference on Communication and Signal Processing (ICCSP), IEEE, April 3-5, 2013.

[9] C. Pohl and J. L. Van Genderen, "Multisensory image fusion in remote sensing: concepts, methods and applications," International Journal of Remote Sensing, Vol. 19, no. 5, pp. 823–854,1998.

[10] Vinay Sahu, Gagan Sharma "A Hybrid Approach of Image Fusion Using Modified DTCWT with High Boost Filter Technique", IJCSNS International Journal of Computer Science and Network Security, VOL.16 No.3, March 2016.

[11] Rohan Ashok Mandhare, Pragati Upadhyay, Sudha Gupta "Pixel-Level Image Fusion Using Brovey Transforme And Wavelet Transform", International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering, ISSN ONLINE(2278-8875) PRINT (2320-3765).

[12] Burt P.J. and Adelson E. H., (1983), The Laplacian Pyramid as a Compact Image Code, IEEE Transactions on

Communications, Volume (31(4)), 532 – 540.

[13] Adelson E. H., Anderson C. H., Bergen J. R., Burt P. J., and Ogden J. M., (1984), Pyramid methods in image processing, RCA Engineer, Volume(29(6)).

[14] Burt P.J., (1984), The Pyramid as a Structure for Efficient Computation, Multiresolution Image Processing and Analysis, Springer.

[15] Chabi, Negar, Mehran Yazdi, and Mohammad Entezarmahdi. "An efficient image fusion method based on dual tree complex wavelet transform", IEEE Iranian Conference on Machine Vision and Image Processing (MVIP), 2013.

[16] Cai, Runbin, and Dewen Hu. "Image fusion of palmprint and palm vein: Multispectral palm image fusion.", 3rd International Congress on Image and Signal Processing (CISP), Vol.6, 2010.

[17] Guomundsson, S. A., and Johannes R. Sveinsson. "TOF-CCD image fusion using complex wavelets", IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2011.

[18] Ioannidou, Styliani, and Vassilia Karathanassi. "Investigation of the dual-tree complex and shift-invariant discrete wavelet transforms on Quickbird image fusion", Geoscience and Remote Sensing Letters, vol. 4, no.1, 2007, pp. 166-170.

[19] Chen, Guangqiu, and Yinhan Gao. "Multisource image fusion based on double density dual-tree complex wavelet transform", IEEE International Conference on Fuzzy Systems and Knowledge Discovery (FSKD), 2012.

[20] Lewis, J. J., et al. "Region-based image fusion using complex wavelets", Seventh International Conference on Information Fusion (FUSION). Vol-1. 2004.

[21] Bhavana. V, Krishnappa. H.K "Multi-Modality Medical Image Fusion using Discrete Wavelet Transform", International Conference on Eco-friendly Computing and Communication Systems, ICECCS,2015. Procedia Computer Science 70, 625 – 631. Elsevier.

[22] Richa Singh, Mayank Vatsa, Afzel Noore "Multimodal Medical Image Fusion using Redundant Discrete Wavelet Transform", International Conference on Advances in Pattern Recognition,2009 978-0-7695-3520-3/09. In proceeding of IEEE.

[23] Tannaz Akbarpour Mousa Shamsi, Sabalan Daneshvar "Medical image fusion using discrete wavelet transform and lifting scheme", 22nd Iranian Conference on Biomedical Engineering(ICBME 2015), Iranian Research Organization for Science and Technology (IROST), Tehran, Iran, 25-27 November 2015978-1-4673-9351-5/15. IEEE

[24] Aishwarya N, Abirami S, Amutha R "Multifocus Image Fusion Using Discrete Wavelet Transform And Sparse Representation", In IEEE WiSPNET 2016 conference .

[25] Hugo R. Albuquerque, Tsang Ing Ren and George D. C. Cavalcanti "Image Fusion Combining Frequency Domain Techniques Based on Focus", 24th International Conference on Tools with Artificial Intelligence, IEEE-2012.

[26] Nirmala Paramanandham, Kishore Rajendiran "A Simple and Efficient Image Fusion algorithm based on Standard Deviation in Wavelet Domain", IEEE WiSPNET 2016 conference.

[27] Lixia Zhang, Guangping Zeng "Novel Multi-focus Image Fusion Method Research", International Conference on Intelligent Networks and Intelligent Systems, International Conference on Intelligent Networks and Intelligent Systems, 2015.

[28] Arya Devi P. S. and M. G. Mini, "Mammographic Image Enhancement Based on SWT and High Boost Filtering", International Journal of Computer Theory and Engineering, Vol. 7, No. 5, October 2015.

[29] S. Anbumozhi, P.S. Manoharan "Performance Analysis of Fusion Based Brain Image Classification Using Minimum Distance classifier" Journal of Theoretical and Applied Information Technology20th April 2014. Vol. 62 No.2.