CHAPTER 2

LITERATURE REVIEW

2.1 INTRODUCTION

Image Fusion (IF) process consists of three major steps namely, decomposition, fusion and reconstruction. Decomposition is the process of partitioning the given level to get the several sub images at each level. The sub images are categorized into two groups such as low and high frequency sub bands. The low frequency sub band contains approximation details of the image and the high frequency sub band contains detailed information of an image. Fusion of the image is to combine both low and high frequency sub bands at each level using certain fusion rule. Reconstruction is the process to inverse the composite fused coefficients to get the desired output (fused) image. The image contains noise during image acquisition and environmental condition, the quality of image must be improved before the fusion process. The noise not only degrades the image quality it also hides the image information, due to this image segmentation, feature extraction, quantitative analysis (Shujin Fu et al. 2006). Practically it is not possible to eliminate all the noise components present in the image, but it is possible to reduce the noise at physician acceptable level. So, once the image enhancement (de-noising) is done to improve the image quality that aids to further process on image processing like segmentation, analyzing, fusion etc.

2.2 IMAGE ENHANCEMENT

Normally, the medical image processing application is affected by the noise due to some environmental situations. In most of the image processing cases, the radiologists are facing problems in diagnose the
disease due to the presence of noise components in the image. Before analyzing an image, enhance the quality of the image using pre-processing technique like enhancement (de-noising). De-noising is a fundamental process and it is mainly used to improve the appearance of an image and makes it easier for visual interpretation, understanding, and analysis of image. In this work, assuming the Gaussian noise is uniformly scattered over the input image which means each pixel in the noisy image is added in the random Gaussian distributed noise values within the original pixel value. (Pierre Gravel et.al 2004). Medical image is categorized into two types namely, anatomic or structural images like CT, MRI and the functional images are PET, SPECT. The above types of images contain the visual noise. The presence of noise gives an image as mottled, grainy, textured and snowy appearance. As image noise comes from different sources, image enhancement reduces the noise in an image and improves the image quality. As there is no noise free imaging method, but the noise is more common in convinced types of imaging procedure that in others.

In past years, many approaches have been developed for noise reduction to improve the image quality. The image de-noising methods are classified into two core class vise, spatial and the transform domain. Spatial domain filtering method will directly operate on the image pixel but it leads to the unclear image edges and other information. In this domain, a number of filtering techniques have been developed such as averaging filter, median filter, wiener filter, etc. to acquire a good de-noised image. In the above mentioned algorithms, the median filter is most commonly used for suppressing the salt and pepper noise. However, as in the Gaussian noise present in an image, the medium filter is not suitable due to the image appearance and poor feature localization of smoothed image. (Bhandari et.al. 2016). Even though, the linear filters reduce the Gaussian noises but not effectively with edge accuracy and including the textures details which lay in
an image. To address the problem of edge-preserving, a variety of modified Gaussian noise removal techniques has been presented (Portilla et.al. 2003, Luisier et.al. 2007, Liu and Liu 2012).

According to the selection of pixels, spatial domain oriented filters can be divided into local and non-local filters. A number of local filtering algorithms in spatial are designed and implemented for noise reduction such as, wiener filter (Wiener 1949), Gaussian filter (Shapiro and Stockman 2001), least mean squares filter (Widrow and Haykin 2003). In terms of time complexity, the local filtering methods are effective but it cannot achieve well when the noise level exceed 50% due to an adjacent pixel has been corrupted by the rigorous noise. In non-local filtering approach like Non-local means (NLM) was proposed by Buades et.al (Buades et.al. 2005) to obtained de-noised pieces by using the weighted average. Recently, many enhancement methods in non-local filtering are being developed (Zimmer et.al. 2008, Yan et.al. 2012). However, still the problems of over smoothing are existence. (Brailean et.al 1995). The transform domain filtering methods is being divided into two major heads: spatial-frequency filtering and low pass filtering using FFT (Coifman and Donoho 1995). These approaches produce high time consuming and suddenly disconnect the frequency function. A number of thresholding based wavelet approaches have been developed and implemented. But, Selection on optimal value of thresholding is not an easy task. Whenever the threshold value is small, it will permit the entire noisy coefficients, the resultant image may contain noisy. If it is high, it will allow changing a number of coefficients to zero which leads to over smoothing, so it may cause blur and artifacts may loss some signal values. So, the selection or finding the optimal threshold is an important point of an image. The traditional threshold methods like soft and hard threshold function does not give the fine results when the noise level is high which may present in the large coefficients.
Generally, selection of threshold is based on two type’s namely non-adaptive and adaptive threshold. Whenever the threshold is high, the non-adaptive thresholding filtering like VISU shrink (Motwani et al. 2004) to give the good results. Adaptive thresholding filter like SUREShrink, Bayes Shrink is violated when noise level is higher than signal magnitudes (Simoncelli and Adelson 1996).

To achieve the better de-noised image, it is required for changing the coefficients using the convinced rule. Many researchers have been attempted to develop the number of superior thresholding function for improving the de-noising process (D.L. Donoho 1995). In order to improve the efficiency of the thresholding function, a number of thresholding functions with shape tune parameter have been developed. For instance, Zhang thresholding function is used to select the trivial coefficients (Zhang and Desai 1998, 2001). Nasri (Nasri et.al. 2009) has introduced a novel adaptive thresholding function based on the wavelet transform thresholding neural network (WT-TNN) methodology to improve the efficiency of de-noising system but it is more time consuming (Bhutada et al. 2011). To improve the wavelet transform based thresholding neural network for the computational cost and also the presented edge preserving on image enhancement technique which is de-noised by wavelet and curvelet transform. In addition, the same author has presented the subband adaptive thresholding function based on PSO optimization (Bhutada et.al. 2012). In traditional PSO, is very difficult to find out the best global value for the particles. A modified particle swarm optimizer mechanism is the best method but the selection of possible value of inertia weight is normally too difficult (Yuhui Shi and Russell Eberhart 1998). In new PSO, each particles moves to a new position without comparing the present solution and moves unconditionally. In the worst case, the chance to moves the poor position (Chunming Yang and Dan Simon 2005). Based on Particle Swarm optimization (PSO) techniques are not functioning systematically and it is very difficult to find out the best global
value for the particles. The main drawbacks of GA algorithm are given as, it
does not define the fitness function properly, and it is not easy to operate the
dynamic data set and the existence of same quantity of time complexity in a
particular optimization problem (Somnath Mukhopadhyay and Mandal 2013).
A new non-linear thresholding function with three shape tuning parameters
using JADE optimization technique for de-noising an image. The JADE with
adaptive thresholding scheme does not obtain the value of thresholding and
the thresholding function; simultaneously it is not good for improving the
dge-preserving for the Gaussian noise (A.K. Bhandari et.al. 2016). In recent
years, many wavelet transforms (WT) have been used to operate the de-
noising with adaptive thresholding function. However, DWT based wavelet
noise reduction sometimes produces a visual artifacts due to the lack of shift
in-variance and the above optimization approaches do not expand the suitable
solution for optimization problems. Only few algorithms are giving fine
results for some exacting problems compared with others.

A new noise reduction algorithm is implemented to improve the
visual quality of the medical image with in the physician acceptable level. It
would be very much helpful for a physician for further processing in medical
image analysis like image fusion. In this proposed work, it overcomes the
primary drawback of wavelet approaches, DTCWT (Dual-Tree Complex
Wavelet Transform) (I. W. Selesnick et.al. 2005) method is used and the
mLOT with Enhanced optimized adaptive thresholding function based
structures replaced the existing optimization technique on JADE for medical
image de-noising. The proposed de-noising approach gives the optimum
resulted image, that image performance is measured with respect to PSNR,
MSE, and SSIM.
2.3 IMAGE FUSION

Medical Image Fusion (MIF) is the process of combining two or more images to get the distortion less and the information lossless fused image. The image must contain redundant and complementary information from the source images so it as to get easy visualization, perception and processing of image analysis. (Zhang and Blum, 1999). As the medical image fusion gives the additional information and storage for single image instead of multiple images, the storage cost is reduced efficiently. Therefore, different modality of medical images by automatic combining through the image fusion technique will acquire the complementary information employed in biomedical research and treatment planning of clinical diagnosis for doctors (Sudab Das, Malay KmarDundu 2013). There are wide varieties of medical images with individual application boundaries are grouped together like CT and MRI are anatomic and PET and SPECT are functional image. The far more edge and other component information is saved by its fusion of CT and MRI with high quality fused image to produce useful and accurate diagnosis. In recent years, the multimodal medical image fusion technique grabs the attention of specialists and scholars (Zhaodong Lu et.al. 2014).

The image fusion methods can be grouped into three major categories, namely, pixel level or sensor level, feature level, and decision level (Redondoet al. 2009). The pixel level fusion has advantage over the other techniques that this original measured quantities in the images and algorithms used are computationally efficient and easy for implementation, the pixel level based methods are generally used in most of the image fusion applications. One of the easiest methods in the image fusion technique is to compute the average value of the pixel by pixel in the couple of images. It has a main drawback in contrast reduction (Li and Yang, 2008). In the weighted
average algorithm the fused pixel is estimated as the weighted average for the corresponding output pixels and the weight is estimated by the specified thresholding based on user requirements. On the other hand the spatial domain oriented approach like Intensity-Hue-Saturation (IHS), (Tu et.al. 2001) which leads to color distortion in terms of the original image and suffers artifacts and noise, Principal Component Analysis (PCA) (Naidu and Raol, 2008) is very criticized because it is spectral distortion characteristic between the source images with low resolution. Brovey method produces the higher results but suffers from the spectral degradation. (Pradhan et.al. 2006).

The above mentioned problems can be overcome by Multi-Resolution Analysis (MRA) Techniques. MRA is broadly classified into two types such as, Pyramid and the Wavelet Transform. The Multi-Resolution Analysis was initiated by Burt and Adelson, called as Gauss Lapacian Pyramid and the Gradient Pyramid. For instance, Lapacianpyramid (Burt and Adelson 1983), contrast pyramid (Toet et.al. 1989), and the gradient pyramid (Burt and Kolczynski, 1993). During the decomposing process, the pyramid based fusion techniques does not satisfy the spatial selectivity and may cause blocking effects in the fused results. (Li et.al. 1995). Morphological pyramid (Matsopoulos and Marshall, 1995) creates a many undesired edges.

Another family in the MRA fusion is called as wavelet based method (Yong Yang 2010). In 1984, Grossman and Morlet (Grossman and Morlet 1984) have formulation of the Continuous Wavelet Transform (CWT). The basic and real concepts and theory of wavelet transform comes from Mallet theory (Mallat 1989). Most of the fusion works are considerable by the wavelet transform domain on remote sensing images, infrared images and the multi-focus images (Chipman et.al. 1995, Pu and Ni. 2000, Ma et.al. 2005, Acerbi Junior et.al. 2006). Today, some few fusion works are done by medical images using wavelet transform. Yu et.al used the MS rule fusion the medical images using wavelet transform (Yu et al. 2001). These methods
suffer noise, artifacts and higher contrast. Qu et.al used the Modulus maxima selection criteria for fusion the medical images (Qu et.al. 2001). Cheng et.al proposed weighted based wavelet transform in the field of medical image fusion (Cheng et.al 2003). In this method the weights are defined by the user requirements, different weights lead to the different fused results. This method brings existence of problem of selecting the weights. Most recently, shuneza syeed and smita jangale proposed a new fusion approach such as GEM (Global Energy Method) and REM (Regional Energy Method) in multimodal medical image fusion using wavelet transform (shuneza syeed and smitajangale, 2010). This approach takes more time consuming and edge preserve is blurred (Yong Yang et.al. 2010).

In wavelet based approaches with different fusion rules has weak position of shift invariance and directional selectivity. The Stationary Wavelet Transform (SWT) solves the shift in-variance as the down-sampling operations are being eliminated (Pusit Borwon watanadelok et.al. 2009). Though this approach gives very redundancy, the geometric image features on edges and ridges becomes complicated due to lack of directional selectivity. The directional selectivity has been served out by the Complex Wavelet Transform called as ‘Dual-Tree Complex Wavelet Transform’ proposed by kingsbury (kingsbury 1998). The DT-CWT with Maximum and Average rule is used in medical image fusion which gives good appropriate fused results (Hill et.al. 2005). The Fast Discrete curvelet transform was proposed by Candies and Donoho (Li et al. 2006). Based on this transform, various image fusion works is done with different fusion rule (Alie.t.al. 2008). Based on curvelet transform fusion approach, it efficiently done by the edge and curve representation but it could not achieve the directional selectivity and the shift in-variance. So, a new proposed approach of hybrid system (DTCWT and Curvelet) is applied for the medical image fusion with maximum selection rule and the Binary Particle Swarm Optimization. This method gives a blurred
image with higher contrast and it hides most of the information due to the higher contrast.

Da Cunha et.al designed the Non Sub-sampled Contourlet Transform theory and applications (Da Cunha et.al. 2006). Using the NSCT, Yang et.al has to apply the medical image fusion with Log-Gabor Energy (Yanget.al. 2014). This method cannot give the asymptotic optimal representation of contours, but also possesses shift-invariance, and effectively suppresses pseudo-Gibbs phenomena. Qu et al. (Qu et.al. 2008) proposed an image fusion method based on Spatial Frequency-motivated Pulse Coupled Neural Networks (SF_PCNN) in the NSCT domain, and proved that this method could extract more useful information and provide much better performance than the typical fusion methods. Das and Kundu used this approach for image fusion with SF_PCNN (Das and Kundu 2012). However, the NSCT based algorithm is time consuming and does not achieved for showing the internal edges (weak edges) (Yang Yang et.al. 2014). Dual-Tree Complex Wavelet with PSO (DTCWT-PSO) (Junli Tao et.al. 2010) used for multi modal medical image fusion. This approach is used in the MS rule for the fusion of high frequency coefficients. MS just picks the coefficient in each sub-band with the largest Magnitude. Commonly, higher values of coefficients have most significant information for the images like edges and corners. Therefore, this fusion rule replaces the lower magnitude coefficients to higher magnitude coefficients. The maximum intensity value is chosen for each and every pixel in the input image. But, this rule creates a noise and an artifact i.e. this cannot gives guarantee homogeneity in the fused image. The weighted average rule is used for the low frequency coefficients. This scheme is used over a small local area in the normalized correlation between the two image sub-bands. The resultant coefficient for reconstruction is calculated from this measure via a weighted average of the coefficient for two images. Generally, traditional weighted average rule means, inserting some weights to
all images and to perform the averaging technique to calculate by adding some weights to obtain the fused results that become a reducing the contrast and cannot adaptively give optimal fused results. So, the rule is modified and utilized for the image fusion. The weights are determined by the user, but not automatically. In PSO, it automatically finds the optimum weights setting to obtain an optimal fused result. In PSO, each particle moves to a new position whether the new solution may be good or not compare than the present solution and moves unconditionally. In the worst case, there is a chance to moves to the poor position (Chunming Yang and Dan Simon 2005). PSO based optimization techniques are not done systematically; still a lot of work is available in this area.

The proposed approach will conserve the region features and emphasize the different parts adaptively, exploitation the region based on weighted average fusion rule used to fuse the low frequency coefficients. The weights are optimized with mLOT. In this Technique it is anticipated that the optimum fused results are adaptively on intensity. The Intensity Co-variance Verification expeditiously verifies the frequency components from the high frequency coefficients. Grouping of these two will preserve the additional details for source images and improves the standard for fused images. The potency of the proposed framework is dispensed by the in-depth fusion experiments which are totally different from multimodal CT/MRI and PET/SPECT/MRI dataset. Further, a visual and quantitative analysis shows the proposed framework which provides a more robust fusion of outcome than the traditional image fusion technique applies.