CHAPTER 2

LITERATURE RELATED TO THE RESEARCH WORK

Owing to the importance of image fusion in different fields like medical imaging, military imaging applications, surveillance and remote sensing applications, fusion has become a prominent area of research. The main objective of fusion is to combine the low spatial resolution information (colour information) and the high spatial resolution data (detailed information) into a single image. This chapter gives the state-of-the-art image fusion techniques proposed by other researchers.

2.1 INTRODUCTION

The existing fusion methods can be broadly classified into two categories as spatial domain methods and transform domain methods. In the spatial domain, the fusion rules are applied directly on the pixel or region of the source image to form the fused image. In frequency domain method, the image is decomposed into sub-bands or multiresolution representation and the details are preserved based on the fusion rule or technique. Then, the image is reconstructed to get the composite image. The challenge here is to identify the efficient fusion rule to combine the co-efficient of the pixel from multiple source images into the final fused image. While considering the pixel-based fusion, most of the applications adopt various fusion algorithms based on ‘mean’ or choose max’ rule where the average or maximum value of the coefficients of the source image are fixed as threshold and fused. Later in
literature there are many rules and methods that have been proposed for extracting the features to make decisions and based on it fusion is performed.

2.2 EXISTING SPATIAL DOMAIN IMAGE FUSION METHODS

There are many fusion methods proposed by different researchers, the pioneers in the fusion were Mertens et al. (2009). They proposed an attractive fusion method based on basic parameters of an image like, contrast, saturation and well exposedness. Based on the pyramid decomposition, best parts of the pixels are blended using weight maps. Scalar weight maps of each pixel from multiple exposures are combined. The weighted average (Burt et al. 1984) along each pixel is computed, and Gaussian pyramid is applied for smoothening and edge preservation. Alpha mask is applied to decompose and reconstruct the image with Laplacian pyramid. Blending was adopted for each level separately, and the sharp edges and other details are preserved. This is one of the well known and best methods in fusion. The spatial domain methods perform the fusion from simple mean, maximum averaging methods to complex neural network-based methods.

2.2.1 Pixel-level Fusion based on Weighted Average Method

In the weighted averaging fusion, the fused image is generated by combining the weights of the same spatial locations from different input images. This method averages the weighted pixels and the scheme is simple and computationally efficient. (Li et al. 2005) proposed a method with subbanding architecture for decomposing and reconstruction of the images. Haar filters are used to separate the base and the detail layer. Analysis and synthesis filter bank decomposed the image at different scales, and noise level is suppressed by the gain control maps fused with multiresolution blending.
Goshtasby et al. (2005) proposed a technique to fuse the multiexposure images and multifocal images into a high quality image by multiresolution blending with the pixels which have higher weight. For every input image Laplacian pyramid is generated and multiplied with the Laplacian pyramid weight of each image at the same level of scales. From the fused pyramids, the final image is reconstructed.

Grundland et al. (2006) proposed a method for image blending with averaging techniques and linear interpretations. This method preserves the contrast by applying a linear color mapping, and the salience preserving method calibrates the weight to reflect the relative salience. This technique is applied to multiresolution images, which is used in the artistic editing and morphing applications.

2.2.2 Image Fusion based on Brovey’s Transform

Zhung & Wu (2008) proposed a method which is widely used in combining the panchromatic images with multi spectral images. The high resolution Luminance information from the Panchromatic (PAN) is fused with multispectral image using RGB color space. Data redundancy is reduced by re-correlation. The Brovey’s Transform can be obtained using Equation (2.1)

\[
\begin{bmatrix}
R_n \\
G_n \\
B_n
\end{bmatrix} = \frac{PAN}{I_{OG}} \begin{bmatrix}
R_{OG} \\
G_{OG} \\
B_{OG}
\end{bmatrix} \tag{2.1}
\]

Where \(I_{OG}, R_{OG}, G_{OG}, B_{OG}\) are the pixel intensities of the original spectral image with which the new intensity values can be obtained.
2.2.3 Artificial Neural Network-based Fusion

Artificial neural network-based fusion is implemented in most of the feature-level fusion where the features are extracted from multiple input images. Most of the ANN process uses a non-linear response function that iterates in the network structure to train and test the data. (Dong et al. 2009) presented fusion method for multispectral images which is a powerful and self-adaptive and pattern recognition method. In this ANN-based method, the registered input images are decomposed into several blocks and the features are extracted and trained with network and the blocks that contain the maximum details are blended into a single image. (Hsu et al. 2009) proposed the method for training the network with the pre-request features. In the training data the relational parameters are defined, and in the testing data, the fusion parameters are defined and the proper extraction of features is based on the statistical method through which the images are fused.

2.2.4 Principal Component Analysis-based Image Fusion Techniques

Principal component analysis is a mathematical approach based on linear transform of an N dimensional space exhibiting the properties of sample against the coordinate positions. Eigen vector and Eigen value are computed based on the computation of covariance matrix. Kumar et al. (2006) proposed a simple PCA-based fusion to fuse the IR and visible images. In PCA, original inter-correlated data is mathematically transformed to new uncorrelated image, which is called as component or axes. The PCA method of fusion can be approached by two phases. In the first method, different sensor images replace the multiple channels. In the second, these multi sensor images are fed to the PCA procedure.
2.3 EXISTING TRANSFORM DOMAIN IMAGE FUSION METHODS

Transform or a frequency domain, is a technique to manipulate the orthogonal structure of an image rather manipulating the image itself. The frequency content of the image is enhanced in transform domain. Discrete Cosine transform (DCT), Discrete Wavelet Transform (DWT) or the Fourier Transform are performed on the image and the frequency component is enhanced. Magnitude and phase are the two components of the image and they are influenced by transformation operator. After the transform, the inverse transform is applied to restore the image.

2.3.1 Multiresolution Transform based Fusion

In the transform domain, the image is decomposed and enhanced with different fusion rules. Multiresolution transform is a small set of resolution ranging from 2 to 6, higher frequency components are represented by smaller sized blocks and lower frequency components are represented using bigger sized blocks. In multiresolution, decomposition is applied to multiple levels until the desired output transform is obtained. Multi Resolution Transform (MRT) is very commonly used for image fusion for multiexposure, multifocal and multispectral images (Song et al. 2010). In MRT, Discrete wavelet transform, Independent Component Analysis (ICA), Contourlet Transform, Framelet Transform and Pyramid Transform are the very commonly used transforms in multiresolution transform.

2.3.2 Discrete Wavelet Transform-based Fusion

Discrete wavelet transform is a mathematical tool for decomposition of image in hierarchical method. Unlike conventional Fourier transform, wavelet provides both spatial and frequency descriptions of image.
Image is decomposed into 4 non-overlapping bands with 2D filter. Image I is decomposed to LL, LH, HL, HH bands at first level, further depending upon the requirement further decomposition can be achieved. Figure 2.1 shows a simple discrete wavelet transform with two input images. Mallat et al. (1989) proposed a single decomposition mathematical model associated with multiresolution representation which defines a method for extracting the information with wavelet representation. The major advantage of this wavelet is that they offer a simultaneous localization in both time and frequency domains. Though wavelet theory is introduced in 1980, it has been extensively used from 1989 for image fusion. In image wavelet based fusion there are three major steps. The first step is that the registered image is decomposed, the second is to combine the transform coefficient and the third step is to reconstruct the combined coefficients.

![Figure 2.1 Block diagram of simple wavelet decomposition](image)

**Figure 2.1 Block diagram of simple wavelet decomposition**

Pajares & Cruz (2004) proposed a spatial decomposition which is represented in multiresolution form. The main drawback of DWT is shift invariance due to down sampling; hence there is a possibility of introducing shadowing and artefacts. This can be overcome by introducing the Dual Tree
Discrete Wavelet Transform (DTDWT) or Discrete Wavelet Frame Transform (DWFT).

2.3.3 Discrete Cosine transform-based Fusion

Discrete Cosine Transform (DCT) is a frequency domain-based image fusion. The problems caused by the pyramid-based fusion and averaging method can be solved using the frequency domain. Britanak et al. (2007) proposed a simple averaging method or improved DCT method where the DCT representation of the input images is averaged to fuse the image. Naidu et al. (2014) proposed a DCT based wavelet structure in fusion with five different architectures. They found that WSDCT architecture is better compared with other architectures. The fusion techniques were block-based algorithms.

2.3.4 Pyramid-based Fusion

Pyramid structure is obtained by performing a recursive reduction in a multi-scale representation, which can be Laplacian pyramid or Gaussian pyramid or Morphological pyramid. By using Laplacian pyramid both feature-based or pixel-based technique can be performed with “Pattern selective” method proposed by Zheng et al. (2009).

2.3.4.1 Laplacian Pyramid

Laplacian pyramid is derived from Gaussian Pyramid (GP), which is represented in multi-scale fashion. The Laplacian pyramid transform decomposes the source image and after transformation it integrates into the composite image. An inverse transform reconstructs the image. There are different levels and decomposition and various modes of combinations like averaging and selection.
2.3.4.2 Gaussian Pyramid

In Gaussian pyramid is similar to Laplacian but differs in the gradient filter operations. GP operates horizontally, vertically and diagonally in both directions. The edge information and details are well preserved in the Gaussian pyramids. Burt & Kolczynski et al. (1989) implemented the Gaussian pyramid approach to decompose the input image into different scales and directions. This method preserves only the well defined orientation images at all the scales. Geetha et al. (2012) proposed a method to sharpen the images with multiresolution transform and phase coherence measure. In this method, the image is sub-banded by multiresolution, and the image is reconstructed with sharp details preserved in the fused image by applying a fast bilateral filter.

2.3.4.3 Morphological Pyramid

Morphological pyramid is the multi scale representation of an image similar to Laplacian and Gaussian pyramid. Xiaoli et al. (2013) used the morphological pyramid to decompose the input image into L scale with 3*3 structuring element followed by (L-1) level followed by down sampling. Multiresolution rendering algorithms used here are similar to wavelet split. Morphological pyramid filters are involved in enhancing the connectivity between the operators. Fusion operation with different images from different sensors can be used with the pyramid decomposition along with dilation and corrosion operators.

2.3.5 Independent Component Analysis

Independent Component Analysis (ICA) is one of the most widely used transforms which uses the multi-dimensional random vectors which are independent from each other based on image component (Hvarinen & Oja
ICA-based image fusion is efficient compared with wavelet and dual tree in terms of the degree of orientation which depicts the image fusion accurately. Mitianoudis & Sakthi (2007) implemented a transform using Independent Component Analysis and topographic Independent Component Analysis method for image fusion. The images are fused based on training them with image content to the observed scene either with rule-based or pixel-based fusion techniques. Figure 2.2 shows the block diagram for general ICA-based fusion techniques. \( T \{ . \} \) is the estimated ICA transform. The drawback of ICA bases is that it cannot capture all the salient features of the input images, however, it offers the shift variances in limited directions. In image representation, instead of using the bases of Fourier transform or wavelet, a set of trained ICA bases is used which gives promising results in the fusion of multispectral and multimodal images.

![Block diagram of Independent Component Analysis used in image fusion](image)

**Figure 2.2** Block diagram of Independent Component Analysis used in image fusion

In the above sections there are so many techniques discussed based on the decomposition type, transformation on both spatial and frequency domains. In the forthcoming sections, these methods are referred to based on the input images. The input images are multiexposure, multimodal, multi-
spectral and multifocal images. So, depending on the type of images, the fusion technique changes. In forthcoming sections, the review concentrates on fusion techniques based on the images.

2.4 FUSION TECHNIQUES FOR MULTIEXPOSURE IMAGES

In image processing applications depending on the need, the images are processed in such a way that there is no loss in the details. In order to get better pictures, photographers restore the images of the same scene at different exposures, different shutter speed, and then they combined those images into a single image which is a high dynamic range image. Since it preserves the well exposed pixels from multiple images it conserves to have high dynamic range. Hence the process of blending progressed to have good quality of images. Higher the scene density, the higher will be the final composite image. This process was initially carried out, and there were many solutions tried out to blend these multiple exposure images. There comes another challenge of displaying that high dynamic range of images into low dynamic display devices. From this, the processing of image fusion came into existence which is an alternative solution to this problem. The fusion of multi exposure images has been carried out with different methods. The input images can be two are multiple input images.

Debevec & Malik (1997) presented an algorithm for constructing the high dynamic range images into a single image with an operator named as tone mapping operator. The input images were different exposure images and panoramic videos from which the radiance map was constructed based on the intermediate HDR image. Final output was a single composite image, with high resolution.

Tomasi et al. (1998) designed a bilateral filter with non-linear method with neighboring pixels of the image. This method is non-iterative
and simple to implement. Image fusion is based on the similarity of photometric and geometric closeness of the image. In this filter, CIE-color space is taken for smoothening and the edge is preserved. The main advantage of this filter is it reduces the phantom colors along the edges. The limitation is that there is no iteration in the method to optimize the clarity of the image.

Goshtasby et al. (2005) proposed a method for exposure fusion for images taken from static camera with multiple exposures. The input image is decomposed into blocks and the best well exposed block or the blocks which contain more well exposed pixels are grouped into a single image. The information is measured in terms of entropy. Higher the entropy of the block, higher is the clarity in the fused image.

Lee & Lin (2009) proposed a method where they derive a global operator which is computationally simpler than a local operator. Most of the tone mapping operators suffer from halo and artifact; In order to overcome this drawback, the intensity domain-based transformation is implemented. The gradient fields are modified by manipulating the neighboring pixel at different scales along with Poisson equation. Here, the images are multiple exposure images with different exposure and shutter speed where they are combined to get a single image.

Mertens et al. (2009) proposed a well known and efficient exposure fusion method. With Laplacian pyramid, they proposed a method with basic components like variation, saturation and well exposedness for fusing the color images. This method was implemented only with multiple exposure images.

Raman & Chaudhuri (2009) derived a method for composing the multiple exposure image scenes into single low dynamic range image, which was computationally efficient. Bilateral edge preserving filter was used to
Piella & Gemma (2009) proposed a model for fusion while preserving the salient information and enhancing the local contrast. This model combines the multiple exposure images with geometric merging by assuming that the local intensity of the images changes in the edge and contours are preserved by gradient operation.

Alsam & Farup (2010) proposed a solution for achieving a high dynamic range maps by using a gradient operator. The gradient operates extract the details from multiexposure image and fuse them into single image. Non-linear thresholding of gradient-based algorithm with maximum gradient in both horizontal and vertical directions is used for fusion of multiple exposure images. This method has an advantage that it does not generate any intermediate HDR map, but it blends the varying exposure image. This method has been taken for study since the multiple input images are fused to get a single composite image.

He et al. (2010) proposed a sub-band architecture based fusion for multiple exposure images with Quadrature Mirror Filter (QMF). QMF decomposes the image into different sub-bands based on frequency. The weight maps are calculated based on the saturation, contrast and exposure. The non-linear distortion is removed by introducing the gain control map. The coefficient of the sub-band is finally blended to get a fused image with the well exposed details preserved in it.

Kotwal & Chaudhari (2011) proposed a model to compute a fused image from a sequence of LDR images. The key idea behind this work is to calculate the average weight of the input images and optimizing it using Euler-Lagrange technique. This model smoothens the input images to arrive...
at the final output. However, this method has some limitations in image sharpening.

Shutao & Kang (2012) introduced a weighted sum-based exposure fusion of multiexposure images. From image features like color dissimilarity, brightness and local contrast, the weight map is refined by using the recursive filters. The fused image is obtained from the weighted sum of multiple exposure images. The main advantage of this method is that, refined weight maps give accurate weight values. This method is extended to dynamic scene which contains the motion objects. Subjective and the objective test results prove the superiority of the method.

Zhang & Cham (2012) presented a method for multiexposure image with the gradient information obtained from input sources. With discrete cosine transformation the gradient information was obtained and a training and a learning process were performed and the images were fused to get pleasant high dynamic range which can be adopted for both static and the dynamic images.

Shen & Zhao (2014) proposed a method for exposure fusion focusing on local weight and global weight considering the exposure quality measure and the saliency weight. A hybrid weight guides the relative exposure images with boosted Laplacian pyramid filter which extracts the base and the detail layers for the fusion. This method is based on the color property and the texture property of the image. Based on the distortion between the local weight and the global weight of the image the Just Noticeable Distortion (JND)-based saliency is calculated to enhance the image.

Wang & Tu (2014) emphasized a useful method for directly fusing the multiple exposure images into high dynamic range image. Weight
modification factor is proposed in this method. Saturation, contrast and well exposedness of the pixel in the image are considered, and the weight is modified with information from the ultra dark or ultra-bright areas. Multiresolution Laplacian blending is applied for blending the multi resolution image. This method has promising results when compared with the other distortion maps of Mertens.

Fu et al. (2015) assessed various fusion methods by proposing a comprehensive evaluation metric based on fuzzy theory. The single factor indices such as mutual information, entropy, cross entropy and other six parameters are considered for fuzzy input. Single factor evaluation is performed with fuzzy evaluation algorithm to find the weight of each method and a pair-wise mapping is adopted to judge the performance. This evaluation method is used for static scene image fusion methods.

Hafner et al. (2015) proposed a model by evaluating the energy function. The energy function is formulated by employing histogram modification and contrast enhancement of input images. This model is efficiently tested for fixed sized multi-exposure images.

Yang et al. (2015) proposed a method to enhance the detail and adjust the exposure, which improves the brightness of the image. The input images are sub-banded with low pass and high pass bands using the contourlet transform, and the weights of the images are calculated. With gain control map, the synthesis filter adjusted bands are fused to get the composite image. This method is validated with visual inspection and objective evaluation. There are many researches going on towards fusing the multiple exposure images. The discussed methods and algorithms are some of them which are related to the research.
2.5 FUSION TECHNIQUES FOR MULTI FOCUS IMAGES

Maruthi & Subramanian (2007) proposed a region-based fusion method for multifocal images at information level or activity level. Image is split into different regions and the spatial frequency and the visibility of the region are calculated. The method is based on the visibility and the information received from the sensor. Hence the visibility will be higher for the image for which the information level is more. Such regions are blocked to get the fused image.

Shutao Li & Yang (2008) proposed an algorithm to fuse the multifocal images in spatial domain, which effectively proves the results with various parameters. The input source images are fused with simple averaging method, and the image was segmented using normalized cut. With the segmented results, the partitioned images are fused, spatial frequency is calculated and the quality metrics is proving that the method is better compared with DWT.

Rodrigo et al. (2009) proposed a variational method for color correction of digital images. An energy function is derived for color correction with explicit functional method. This method is employed for multifocal and multispectral images.

Zaveri & Zaveri (2010) segmented the multifocal images into blocks based on graph partitioned method with normalized cut graph theory. The segmented image blocks contain the global features using the local features. Even a small change in the feature affects the segmented results. After segmentation, with the global features the spatial frequency and the energy is calculated and the fuzzy based fusion rules are formed. Based on the fusion rules the blocks from various image is fused to get a single image.
Chai & Li (2012) proposed a method for fusing the multi focus images with local features and non-sub sampled Contourlet transform (NSCT). In this method, the noise and the edge structures are distinguished clearly with NSCT. The sub-band coefficients of the decomposed image are fused with multi scale resolution blending. The visual quality of the image is preserved with noise-free fused multi-focus image.

Wan et al. (2013) executed a PCA-based method for fusing the multifocal image. Using robust principal component analysis (RPCA), the local sparse features of the input image are extracted, and they contribute to the final fused image. Generally, the spatial resolution blending will introduce a small amount of color distortions which lead to spectral fidelity, but this can be avoided by using this multi resolution fusion.

Singh et al. (2014) proposed a method with guided image filter where the multifocal or the multiexposure images are considered as the input and the fusion is performed. By applying the filter, the input image is divided into base and the detail layer. The base layers from different source image are fused with pyramid, and the detail layer is enhanced with multi resolution blending. The local spatial information from low pass and high pass is blended with both Gaussian and Laplacian pyramids. Free parameters and the fusion metrics are calculated to compare the results with the existing method.

Singh H et al. (2014) preserved the edges with sharp details and fused the multiexposure images with weighted least square (WLS) filter. The base and the detail layers are decomposed using the Anisotropic diffusion and the saliency, and the weight maps are calculated with color saturation. The weak and the strong texture features are considered for generating the weighted mask to control the pixel information. By using WLS filter, the weights are refined and enhanced with sigmoid function. This method was used for both multiexposure and multifocus images.
Liu & Wang (2015) derived a new method for fusing the multifocal images by developing activity level measurement to measure the clarity of the image. The Shift Invariant Feature Transform (SIFT) is employed to find the local feature descriptor which can be used for activity level measurement. This descriptor develops initial decision map through which the feature matching and the local focus measurement are compared. The misregistered pixels between the original images and the blended image is identified with a sliding window.

### 2.6 FUSION TECHNIQUES FOR MULTISPECTRAL IMAGES

Pajares & Manuel (2004) presented a simple wavelet-based fusion method for different modality images. The image is decomposed based on the wavelet transformation. The coefficients are the separated with multi scale decomposition. The coefficients are grouped based on Choose max method, blended with activity level measurements. This fusion method holds good for multispectral, multifocal and multiexposure images. The fusion metrics were tried to check the quality of the image.

Nencini & Filippo (2007) proposed a method for remote sensing images with a curvelet-based fusion which is an efficient method for pan-sharpening of multispectral (MS) bands, based on non-separable multi resolution analysis (MRA). High pass directional details are extracted from the high-resolution Pan image by means of curvelet transform. This method is based on multiresolution analysis whose fusion is to analyze the directional edge and to improve the resolution.

Wenbo et al. (2008) proposed a framework for fusion technique for the satellite images with thematic mapping of panchromatic images. The five image fusion techniques like high pass filter, PCA, Smoothing, Filter-based Intensity Modulation (SFIM), Modified Brovey, are tested with various
parameters like mean, entropy, standard deviation, correlation coefficient of MS image and PAN images. The HPF and SFIM are the two methods proven to be good when compared with the existing results. The spectral information of the original image is preserved in these methods compared with those of the other methods.

Yu et al. (2008) presented a technique to align the input image. The matching points between the source images are automatically detected using the affine transform and the Scale Invariant Feature Transform (SIFT). The feature points are detected using Harris Corner detector, and the piecewise linear transform technique help in feature extraction, and the registration of the image is carried out between the images which give a better image. The experiments are carried out for analyzing various data sets like SPOT5, SPOT4 and TM remote sensing data.

Dong & Zhaung (2009) discussed the various fusion methods and algorithms based on the multi sensor images along with the recent developments in this area. This study presents the latest methods, image fusion techniques, the advantages and the disadvantages of each method. Some of the recommendations and suggestions are provided to improve the fusion algorithm. This study includes the object classification, identification and target tracking along with quality assessment metrics.

Rani & Vijaykumar (2012) proposed a method for fusing the multi spectral and Panchromatic (PAN) images which have high spatial content. With contourlet transform with neural network, model image containing the contours and textures are utilized to derive the block-based feature level transform for fusion. Feed forward propagation in neural network trains the various sets of images for classification, and the contourlet fuses the images.
Dammavalam et al. (2013) proposed an iterative fuzzy logic approach to fuse images from different sensors. Results show that the iterative fuzzy fusion preserves the spectral information while improving the spatial resolution.

Swarupa et al. (2013) proposed a feature level fusion algorithm for merging multispectral and panchromatic images in NSCT domain. Region Correlation Coefficient (RCC) is computed based on spatial weight factor between the source image and the base image, which has better spatial resolution and spectral quality. NSCT decomposition is performed on individual regions of panchromatic image and intensity component of multispectral image at different scales and directions. The regions are combined using the spatial weightage factor. Performance study shows improved performance over IHS fusion and NSCT method.

2.7 FUSION TECHNIQUES FOR MULTIMODAL IMAGES

Diagnosis procedure has been made easier with the advancement in the medical imaging technology. Doctors are provided with much more information from the images due to the enhancement in the acquisition speed and the resolution of the image quality. There are many imaging modalities like Positron Emission Tomography (PET), Magnetic Resonance Imaging (MRI), Computed Tomography, Single-Photon Emission Computed Tomography (SPECT), X-rays used in the medical field. Some of the fusions techniques are discussed in this section.

Xiao-Bo & Qu (2008) proposed a method with Pulse Coupled Neural Networks (PCNN) by global coupling and synchronization of neurons. Non Sub-sampling Contourlet transform overcomes the Pseudo-Gibbs Phenomena under anisotropy and directional expansion of the image. PCNN is a feedback network and each PCNN neuron consists of three parts: the
receptive field, the modulation field, and the pulse generator. The input image is decomposed by Multi Scale Decomposition (MSD). The band coefficients are trained with PCNN, and the saliency measure is computed followed by the rule base fusion. This method is proved to be efficient for multispectral and multimodal images.

Teng et al. (2010) proposed a method for fusing the multimodal medical images using fuzzy theory. Instead of getting the pixel information, or the color information, this method takes the texture information, and the fusion rules are formed based on the texture feature combining the complementary information.

Yang (2011) proposed a method based on wavelet which decomposes the image into high frequency and low frequency components. High frequency components based on the variance band and low frequency component based on the edge are selected and coefficients are blended. The image is again reconstructed with inverse wavelet transform. This is the simple and efficient method performed with multimodal and multifocal images.

Bindu & Sathya Prasad (2012) modified the same contourlet method, with Non-Negative matrix Factorization. The images decomposed based on contourlet transform and the low frequency low pass coefficients are blended to optimize the W and H optimization method. Based on Neighborhood Homogeneous Measurement (NHM) rule high frequency coefficients are fused to get the bad pass coefficients. The inverse transformation is performed to get the fused images.

Chai & Li (2012) enhanced the Non sub-sampled Contourlet transform by decomposing the image, and the high frequency and the low frequency components are blended using multi scale resolution. The edge
structure and noise are removed by the proposed method. The subjective and the objective metrics are calculated and the results are compared with the existing methods.

Pavithra & Bhargavi (2013) proposed medical image fusion for MRI and CT images with wavelet transform. The source images of different modalities are decomposed into high pass and low pass bands with gradient smoothening criterion. This method does not go with any complex methodologies, instead the image is decomposed and fused with wavelet, where the results are proved significantly good compared with curvelet.

Ganasala & Kumar (2014) presented a method to fuse the bony anatomy image of CT image with soft tissue anatomy of MRI. The input image is decomposed with NSCT. Based on the entropy, local window method is used for identifying the coefficient of low frequency. High frequency coefficients are selected using maximum weighted sum modified laplacian WSML. Both selective high frequency and low frequency bands are fused to get the fused image. This method is used exclusively for medical image and the results are proved.

Wang & Tian (2014) developed a model-based fusion method with Explicit Generalized Gaussian Density Dependency (EGGDD). This model is developed based on Shift Invariant Shearlet Transform (SIST), and high pass sub-banding is carried out with Generalized Gaussian Density. Dependency between the sub-bands is created using Hidden Markov Tree (HMT) model and Kullback-Leibler distance (KLD). After embedding the dependency, the fusion scheme is developed by fusing the high pass sub-band coefficient with visual cortex model. This method is purely model-based with greater computational time but the results are efficient.
Yang & Li (2015) proposed a statistical medical image fusion with Generalized Gaussian Density (GCD) with Non sub sampled contourlet transform. Input images are sub-banded and the coefficients are separated with statistical dependencies. Similarity measures between the sub-bands are computed using GCD. New fusion rule is framed to fuse the images, such that using the activity measures, the low frequency sub-band coefficients are combined and based on Shannon entropy, the high frequency sub band coefficients are fused. Based on the weights of the coefficients, the image is reconstructed.

Srivastava & Khare (2015) integrated the information from different medical source images into single image based on local energy. Sub-banding of image is performed with contour transform. The energy-based fusion rule is framed based on the current as well as the neighboring coefficients. Instead of single coefficient-based fusion rule, this method is proved to give better results with quantitative analysis. Mutual information and edge strength of the proposed method performs with significantly good result.

Bhatnagar & Wu (2015) proposed a fusion rule for medical image fusion. This frame work also uses the decomposition method based on contourlet transform. The motivation of this work is to fuse the different coefficient from sub bands by combining with energy, where energy is based on spatial feature and the functional information. This method proves to be good for all multiexposure images and multifocal images and multimodal images.

2.8 SUMMARY

Spatial and transform domain image fusion techniques are discussed in this chapter. The detailed state-of-art on pixel level and feature
level image fusion algorithms are also described. The merits and demerits of different methods available in the literature were considered for the study. Multi resolution transforms under pixel level enhancement gives promising results. Hence the pixel-level fusion algorithms based on the dynamic adaptive weight map and the energy-based fusion techniques are proposed in the forthcoming chapters.

There are different approaches addressed by different researchers. The statistical-based method with PCA-based algorithms draws the attention by its promising results, but it is computationally demanding in terms of hardware complexity. In the multi scale analysis the Laplacian and Gaussian pyramid-based fusions have restrictions only at the decomposition levels. This motivated the present researcher to select the Dual Tree Discrete wavelet transform for multi resolution decomposition.

This research work involves the design and evaluation of pixel level fusion algorithms specifically for multiexposure, multifocal applications. The motivation for this arises from the need to present more efficient techniques for the specific application in bioinformatics field and defence. The algorithms developed for remote sensing applications can seldom be adopted for surveillance-related fusion due to the varied imaging environment. The Pixel-based and energy-based technique was chosen as the tool for fusion because of its efficient fusion performance and properties that are better than other transformations, in spite of a higher complexity.

The new techniques proposed in this thesis are aimed to be computationally effective and simpler to implement than the existing methods while giving an equivalent performance in terms of fused image quality. Apart from the design of fusion schemes, the research has been directed towards identifying efficient performance evaluation metrics for evaluating the algorithms.