Novel Hybrid Multi Focus Image Fusion Based on Focused Area Detection

Dervin Moses[1], T.C.Subbulakshmi[2],

[1]PG Scholar,Dept. Of IT, Francis Xavier Engineering College,Tirunelveli
[2]Dept. Of IT, Francis Xavier Engineering College,Tirunelveli
dervin.moses@gmail.com

---***---

Abstract - *Image fusion is the process that combines information in multiple images of the same scene. These images may be captured from different sensors, acquired at different times, or having different spatial and spectral characteristics. The object of the image fusion is to retain the most desirable characteristics of each image. With the availability of multi-sensor data in many fields, image fusion has been receiving increasing attention in the wide spectrum of applications. A possible way to overcome this problem is to utilize multi-focus image fusion techniques, in which one can obtain one image with all of the objects in focus by way of it containing the best information from multiple original images. Image fusion methods are usually divided into spatial domain and transform domain fusion techniques.*

Key Words: Image fusion, NSCT, Sensor, Multi focus and Multiple Image

1.INTRODUCTION

In applications of digital cameras, optical microscopes or other equipment, because of the limited depth-of-focus of optical lens, it is often impossible to acquire an image that contains all relevant focused objects. Therefore, in the scene, some objects are in focus, but other objects at different distances from the imaging equipment will be out of focus and, thus, blurred. However, in reality, people tend to obtain a clear image of all targets. Fusion methods in the spatial domain are directly on pixel gray level or color space from the source images for fusion operation, so the spatial domain fusion methods are also known as single-scale fusion method [1]. For transform domain based methods, each source image is first decomposed into a sequence of images through a particular mathematical transformation. Then, the fused coefficients are obtained through some fusion rules for combination. Finally, the fusion image is obtained by means of a mathematical inverse transform. Thus, the transform domain fusion methods are also known as Multi-scale fusion methods[2]. The simplest spatial-based method is to take the average of the input images pixel by pixel. However, along with its simplicity, this method leads to several undesirable side effects, such as reduced contrast. To improve the quality of the fused image, some researchers have proposed to fuse input images by dividing them into uniform-sized blocks and having those blocks to take the place of single pixels. For the block-based methods, the blocks are combined according to a clarity index, which evaluates whether the blocks are clear or not. To overcome the limitations of Wavelet Transform, Curvelet transform is put forward which consists of special filtering process and multi-scale Ridgelet Transform. This includes realization, sub-band division, smoothing block, normalization and so on. The quality of the image at the edges is improved by removing the noise using Nonsubsampled Counterlet Transform. The construction proposed in this is based on pyramid and directional filters. The NSCT is fully shifting invariant, multiscale, and multidirectional.

To allow helicopter pilots navigate under poor visibility conditions (such as fog or heavy rain) helicopters are equipped with several imaging sensors, which can be viewed by the pilot in a helmet mounted display. A typical sensor suite includes both a low-light-television (LLTV) sensor and a thermal imaging forward-looking-infrared (FLIR) sensor. In the current configuration, the pilot can choose one of the two sensors to watch in his display. A possible improvement is combining both imaging sources into a single fused image which contains the relevant image information of both imaging devices[3].Due to the limited depth-of-focus of optical lenses (especially such with long focal lengths) it is often not possible to get an image which contains all relevant objects 'infocus'. One possibility to overcome this problem is to take several pictures with different focus points and combine them together into a single frame which finally contains the focused regions of all input images. Remote sensing is a typical application for image fusion. Modern spectral scanners gather up to several hundred of spectral bands which can be both visualized and processed individually, or which can be fused into a single image, depending on the image analysis task [4].

1.1 Image Fusion Using NSCT

Various image fusion techniques have been proposed to meet the requirements of different applications, such as concealed weapon detection, remote sensing, and medical imaging. Combining two or more images of the same scene usually produces a better application-wise visible image [5]. The fusion of different images can reduce the uncertainty related to a single image. Furthermore, image fusion should include techniques that can implement the geometric alignment of several images acquired by different sensors. Such techniques are called a multi-sensor image fusion. The output fused images are usually efficiently used in many military and security applications, such as target detection, object tracking, weapon detection, night vision, etc [6]. The Brovey Transform (BT), Intensity Hue Saturation (IHS) transforms, and Principal Component Analysis (PCA) provides the basis for many commonly used image fusion techniques. Some of these techniques improve the spatial resolution while distorting the original chromaticity of the input images, which is a major drawback. Recently, great interest has arisen on the new transform techniques that utilize the multi-resolution analysis, such as Wavelet Transform (WT). The multi-resolution decomposition schemes decompose the input image into different scales or levels of frequencies. Wavelet based image fusion techniques are implemented by replacing the detail components (high frequency coefficients) from a colored input image with the details components from another gray-scale input image. However, the Wavelet based fusion techniques are not optimal in capturing two-dimensional singularities from the input images. The two-dimensional wavelets, which are obtained by a tensor-product of one-dimensional wavelets, are good in detecting the discontinuities at edge points. However, the 2-D Wavelets exhibit limited capabilities in detecting the smoothness along the contours. Moreover, the singularity in some objects is due to the discontinuity points located at the edges. These points are located along smooth curves rendering smooth boundaries of objects. Do and Vetterli introduced the new two- dimensional Contourlet transform. This transform is more suitable for constructing a multi-resolution and multi-directional expansions using non- separable Pyramid Directional Filter Banks (PDFB) with small redundancy factor [7].

Image fusion is the combination of two or more different images to form a new image by using a certain algorithm. The combination of sensory data from multiple sensors can provide more reliable and accurate information. It forms a rapidly developing area of research in remote sensing and computer vision. Most of fusion approaches were based on combining the multiscale decompositions (MSD's) of the source images. MSD-based fusion schemes provide much better performance than the simple methods studied previously. Due to joint information representation at the spatial-spectral domain, the wavelet transform becomes the most popular approximation in image fusion. However, wavelet will not "see" the smoothness along the contours and separable wavelets can capture only limited directional information. Contourlet transform was recently pioneered by Minh N. Do and Martin Vetterli .It is a "true" two-dimensional transform that can capture the intrinsic geometrical structure, which is key in visual information. Compared with wavelet, contourlet provides different and flexible number of directions at each scale. It has been successfully employed in image enhancement, denoising and fusion. Unfortunately, due to down samplers and up samplers presented in both the Laplacian pyramid and the directional filter banks (DFB), the foremost contourlet transform is not shift-invariant, which causes pseudo- Gibbs phenomena around singularities.

1.2 Principle of NSCT

In Fig.1, the wavelet transform is good at isolating the discontinuities at object edges, but cannot detect the smoothness along the edges. Moreover, it can capture limited directional information. The contourlet transform can effectively overcome the disadvantages of wavelet; contourlet transform is multi-scale and multi-direction framework of discrete image. In this transform, the multi-scale analysis and the multi-direction analysis are separated in a serial way. The Laplacian pyramid (LP) is first used to capture the point discontinuities, then followed by a directional filter bank (DFB) to link point discontinuities into linear structures. The overall result is an image expansion using basic elements like contour segments. First, multi scale decomposition by the Laplacian pyramid, and then a directional filter bank is applied to each band pass channel.

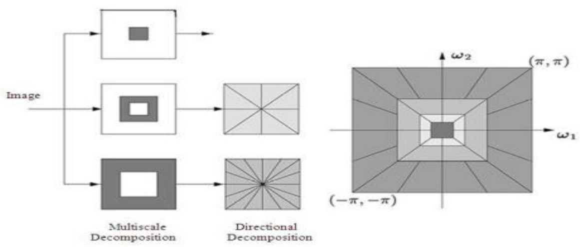

Figure 1: NonSubsampled Filter Bank Structure and Its Idealized

The multi scale property of the NSCT is a shift invariant filtering structure that achieves Subband decomposition similar to that of the Laplacian pyramid. By using two - channel non subsampled 2 - D filter banks. Such expansion is conceptually similar to the 1 D non subsampled wavelet ransform computed with the atrous algorithm. The filters for subsequent stages are obtained by upsampling the filters of the first stage.

This gives the multiscale property without the need for additional filter design. The proposed structure is thus different from the separable nonsubsampled wavelet transform (NSWT). In particular, one bandpass image is produced at each stage resulting in J + 1 redundancy. By contrast, the separable NSWT produces three directional images at each stage resulting in 3J + 1 redundancy. The perfect reconstruction system can be seen as a particular case of our more general structure. The advantage of our construction is that it is less restrictive and as a result, better filters can be obtained. The directional filter bank of Bamberger and Smith is constructed by combining critically sampled two channel fan filter banks and resampling operations. The result is a tree structured filter bank that splits the frequency plane in the directional wedges. The number of channels is L = 2l, where l is the number of stages in the tree structure. Using multirate identities, the tree - structured DFB can be put into the equivalent form. It is clear from the above that the DFB is not shift invariant. A shift invariant directional expansion is obtained with a non subsampled DFB (NSDFB). The NSDFB is constructed by eliminating the downsamplers and upsamplers. This is equivalent to switching off the down samplers in each two channel filter bank in the DFB tree structure and upsampling the filters accordingly. This results in a tree composed of two - channel non subsampled filter banks. The NSCT is constructed by combining the NSP and the NSDFB. In constructing the non subsampled contourlet transform, care must be taken when applying the directional filters to the coarser scales of the pyramid. Due to the tree structure nature of the NSDFB, the directional response at the lower and upper frequencies suffers from aliasing which can be a problem in the upper stages of the pyramid. Thus we see that for coarser scales, the high pass channel in effect is filtered with the bad portion of the directional filter pass band. This results in severe aliasing and in some observed cases a considerable loss of directional resolution.

(a) With no upsampling, the high pass at higher scales will be filtered by the portion of the directional filter that has “bad” response.

(b) Upsampling ensures that filtering is done in the “good” region. NSCT decomposition is to compute the multi scale and different direction components of the discrete images.

In Fig. 2, involves the two stages such as non sub sampled pyramid(NSP) and non sub sampled directional filter bank(NSDFB) to extract the texture, contours and detailed coefficients. NSP decomposes the image into low and high frequency sub bands at each decomposition level and it produces n+1 sub images if decomposition level is n.

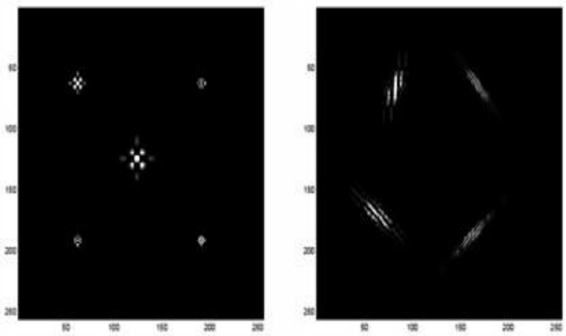

Figure 2 : Comparison Between Actual 2-D Wavelets And Contourlets

There are three relationships in contourlet coefficients, which are shown in Fig 3. The reference coefficient has eight neighbors (NX) in the same subband, parent (PX) at the same spatial location in the immediately coarser scale and cousins (CX) at the same scale and spatial location but in directional subbands. The mutual information is utilized as a measure of dependencies to study the joint statistics of contourlet coefficients. Suppose I (X;Y) stands for the mutual information between two random variables X and Y. Estimation results in show that at fine scales I (X;NX) is higher than I (X;CX) , which is higher than I (X;PX) .It indicates that the eight neighbor coefficients contain the most information about the coefficients, less information is contained in cousins and the least information is contained in the parent coefficients. Inspired by the estimation results, salience measure, based on region energy of neighborhood coefficients and correlation of cousin coefficients, is defined to combine the coefficients of source images in the fusion process in NSCT-based Fusion Algorithm.

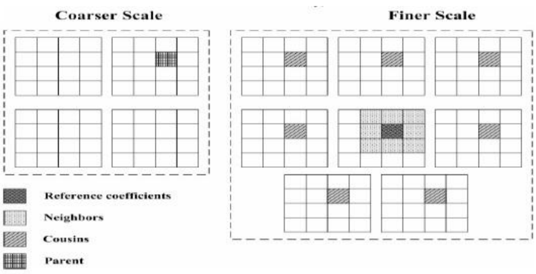

Figure 3: Contourlet Coefficient Relationships

1.3 Cubic Interpolation

Cubic Convolution Interpolation determines the grey level value from the weighted average of the 16 closest pixels to the specified input coordinates, and assigns that value to the output coordinates. The image is slightly sharper than that produced by Bilinear Interpolation, and it does not have the disjointed appearance produced by Nearest Neighbors Interpolation. First, four one-dimension cubic convolutions are performed in one direction and then one more one-dimension cubic convolution is performed in the perpendicular direction (vertically in this paper). This means that to implement a two-dimension cubic convolution, a one-dimension cubic convolution is all that is needed. For one-dimension Cubic Convolution Interpolation, the number of grid points needed to evaluate the interpolation function is four, two grid points on either side of the point under consideration. For Bicubic Interpolation (cubic convolution interpolation in two dimensions), the number of grid points needed to evaluate the interpolation function, two grid points on either side of the point under consideration for both horizontal and vertical directions.

2. PROPOSED METHOD

Proposed image fusion technique is based on Non Sub-sampled Contourlet Transform method (NSCT), which is a shift-invariant version of the contourlet transform. The NSCT is built upon iterated non-subsampled filter banks to obtain a shift-invariant directional multiresolution image representation. The contourlet transform employs Laplacian pyramids for multiscale decomposition, and directional filter banks (DFB) for directional decomposition. To achieve the shift-invariance, the non-subsampled contourlet transform is built upon non-subsampled pyramids and non-subsampled DFB.

NSCT decomposition is to compute the multi scale and different direction components of the discrete images. It involves the two stages such as non sub sampled pyramid(NSP) and non sub sampled directional filter bank(NSDFB) to extract the texture, contours and detailed coefficients. NSP decomposes the image into low and high frequency subbands at each decomposition level and it produces n+1 sub images if decomposition level is n. NSDFB extracts the detailed coefficients from direction decomposition of high frequency subbands obtained from NSP. It generates m power of 2 direction sub images if number of stages be m.

2.1 PIXEL Level Fusion

Pixel level fusion can be used to increase the information content associated with each pixel in an image formed through a combination of multiple images, e.g., the fusion of a range image with a two dimensional intensity image adds depth information to each pixel in the intensity image that can be useful in the subsequent processing of the image. Different images to be fused can come from a single imaging sensor or a group of sensors. The fused image can be created either through the pixel by pixel fusion or through the fusion of associated local neighbourhoods of pixels in each of the images. The improvement in quality associated with pixel level fusion can most easily be accessed through the improvements noted in the performance of image processing tasks such as (segmentation, feature extraction, and restoration) when the fused image is used to compare the use of the individual images. The fusion of multisensory data at the pixel level can serve to increase the useful information content of an image so that more reliable segmentation can take place and more discriminating features can be extracted for further processing Pixel level fusion can take place at various levels of representation: the fusion of the raw signals from multiple sensors prior to their association with a specific pixel, the fusion of corresponding pixels in multiple registered images to from a composite or fused image, and the use of corresponding pixels or local groups of pixels in multiple registered images for segmentation and pixel level feature extraction.

Fusion at the pixel level is useful in terms of total system processing requirements because fusion is made of the multisensory data prior to processing intensive functions like feature matching, and can serve to increase overall performance in tasks like object recognition because the presence of certain substructures like edges in an image from one sensor usually indicates their presence in an image from another sufficiently similar sensor. In order for pixel level fusion to be feasible, the data provided by each sensor must be able to be registered at the pixel level and in most cases, must be sufficiently similar in terms of its resolution and information content.

The high frequency subbands of two source images obtained from NSCT are utilized for morphing process to get the enhanced information. Here, the pixel level fusion method is approached for this process. It will be implemented based on maximum rule and energy measurement for coefficient selection. At fusion stage, the low frequency subband of multi spectral image remains unchanged and high frequency subbands will be fused by energy and maximum rule to select desired coefficients. Finally, fused frequency subbands are inverse transformed to reconstruct the fused image and parameters will be evaluated between input and fused image.

Here, the pixel level fusion method is approached for this process. It will be implemented based on Gabor filter bank and Gradient detection for coefficient selection. The low frequency subbands of two source images will be fused by Gabor coefficients selection and high frequency subbands will be fused by Gradient measurement to select desired coefficients. Finally, fused two different frequency subbands are inverse transformed to reconstruct the fused image and parameters will be evaluated between input and fused image

2.2 GABOR FILTER Approach

In Fig.5 the low frequency subbands of two source images are fused based on selection of appropriate coefficients using Gabor filtering. It is useful to discriminate and characterize the texture of an image through frequency and orientation representation. It uses the Gaussian kernel function modulated by sinusoidal wave to evaluate the filter coefficients for convolving with an image.

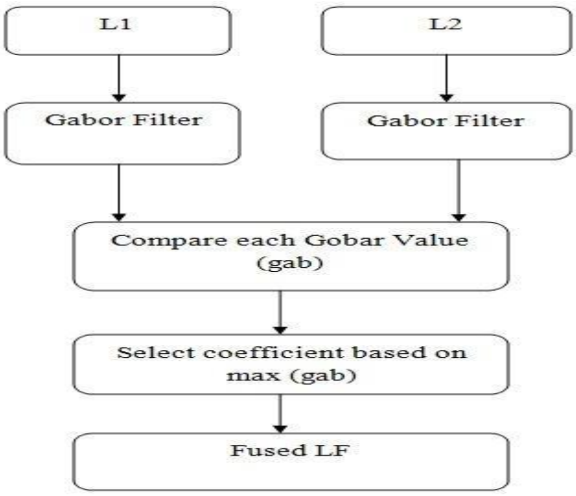

Figure 5: Gabor Filter for LF

2.3 FUZZY C MEANS Clustering Model

The Fuzzy C Means Clustering method is used to find the missing pixel in the image fusion. After finding the missing pixels the image is fused with the original image to get the clear image without missing data. The algorithm flow is given below.

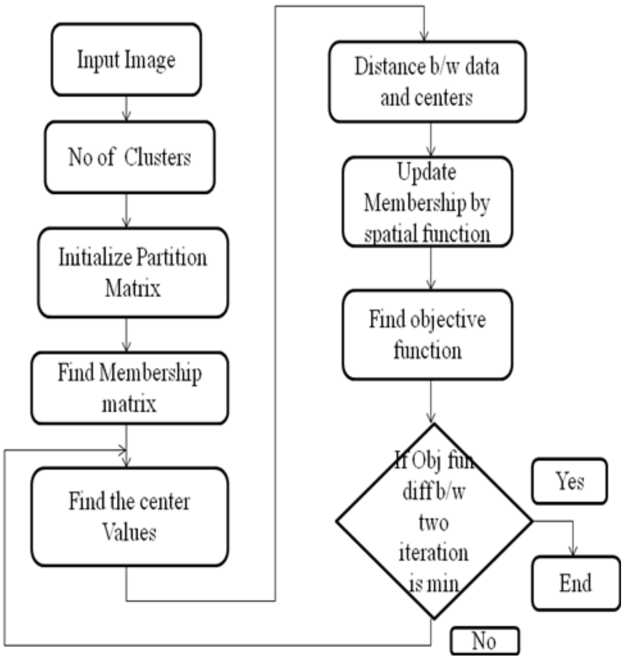

Figure 6: Algorithm Flow

Initialize the Fuzzy Weights.

In order to comparing the FCM with FCFM, our implementation allows the user to choose initializing the weights using feature vectors or randomly. The process of initializing the weights using feature vectors assigns the first Kinit (user-given) feature vectors to prototypes then computes the weights.

Standardize the Weights over Q.

During the FCM iteration, the computed cluster centers get closer and closer. To avoid the rapid convergence and always grouping into one cluster, we use

$$w[q,k] = (w[q,k] - wmin)/(wmax - wmin) \quad (1)$$

before standardizing the weights over Q. Where wmax, wmin are maximum or minimum weights over the weights of all feature vectors for the particular class prototype.

2.4 Eliminating Empty Clusters

After the fuzzy clustering loop we add a step to eliminate the empty clusters. This step is put outside the fuzzy clustering loop and before calculation of modified XB validity. Without the elimination, the minimum distance of prototype pair may be the distance of empty cluster pair. We call the method of eliminating small clusters by passing 0 to the process so it will only eliminate the empty clusters. After the fuzzy c-means iteration, for the purpose of comparison and to pick the optimal result, we add Step 9 to calculate the cluster centers and the modified Xie-Beni clustering validity κ :

The Xie-Beni validity is a product of compactness and separation measures. The compactness-to-separation ratio ν is defined by

$$\nu = \{(1/K)\sum(k=1,K)\sigma k2\}/Dmin2 \quad (2)$$

$$\sigma k2 = \sum(q=1,Q)\ wqk\ ||\ x(q) - c(k)\ ||2 \quad (3)$$

Dmin is the minimum distance between the cluster centers.

The Modified Xie-Beni validity κ is defined as

$$\kappa = Dmin2/\ \{\sum(k=1,K)\sigma k2\ \} \quad (4)$$

The variance of each cluster is calculated by summing over only the members of each cluster rather than over all Q for each cluster, which contrasts with the original Xie-Beni validity measure.

$$\sigma k2 = \sum\{q: q \text{ is in cluster } k\}\ wqk\ ||\ x(q) - c(k)\ ||2 \quad (5)$$

3. RESULTS

INPUT IMAGE

In Fig.7, blurred image is taken from the satellite and the clear grey image is taken by passing the ultra violet rays are given as the input for the image fusion process.

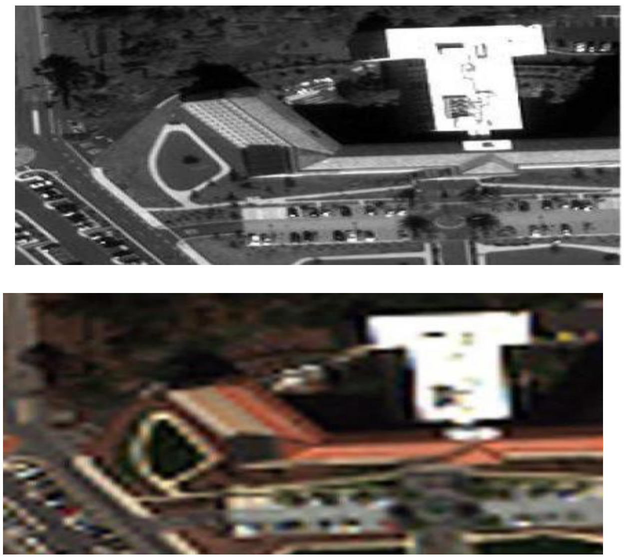

Figure 7. Input images

NSCT DECOMPOSITION

In Fig.8, input images are decomposed using NSCT decomposition method. At the second level of NSCT decomposition the image obtained is given below .

Figure 8 : Level 2 NSCT Coefficients

In Fig.9, the low frequency and high frequency NSCT coeffients are extracted at the level 3 decomposition process.

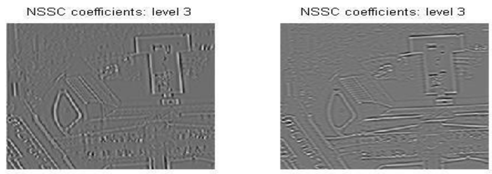

Figure 9: LEVEL 3 NSCT coefficients

In Fig.10, Fourth level decomposition is applied and again the image is divided into high and low frequency NSCT coefficient.

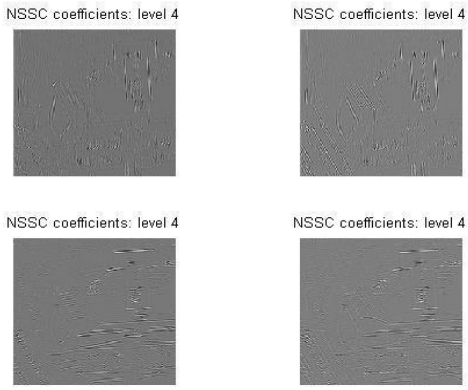

Figure 10 : LEVEL 4 NSCC Coefficients

In Fig.11, finally the low frequencies of the two images are combined by using the Gabor filter and the high frequencies are combined by using the gradient filter. Then the fused output is obtained by applying the Inverse NSCT to the low and high frequency coefficients.

Figure 11: Fused Image

In the focused area detection Fig 12, the missing pixels in the fused color image are identified by using Fuzzy c means clustering. Firstly the color images are converted in to gray scale image and the missing pixels are identified by using fuzzy c means clustering.

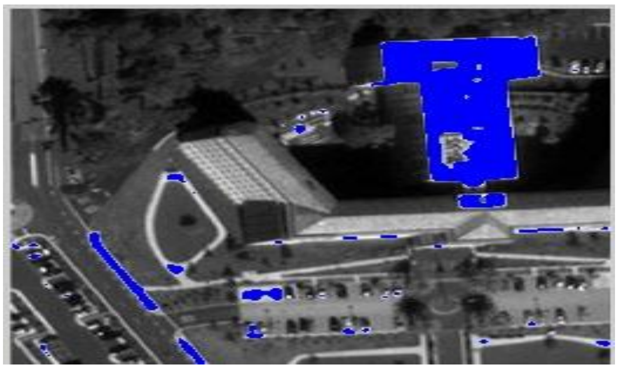

Figure 12: Missing Pixel

OUTPUT IMAGE

The fused color image is then converted to gray scale image and fused with the missing pixel, that are obtained by fuzzy c means clustering. The proposed and existing method comparison is given in Table 1.

Table 1 : Performance Table

	EXISTING			PROPOSED		
	IMAGE1	IMAGE2	IMAGE3	IMAGE1	IMAGE2	IMAGE3
CC	0.8602	0.9771	0.9851	0.854	0.9798	0.9855
RMS	13.724	10.7487	2.9803	12.9162	9.6022	2.8804
PSNR	36.756	37.8172	43.3883	37.0195	38.3071	43.5363

Figure13: Fused Gray Scale Image

In Fig.13, the performance of the Gray scale image and the RGB images are compared by analyzing the average values of Root Mean Square, Peak Signal to Noise Ratio and Correlation Coefficient. In this, the proposed system gives the better performance than the existing system.

PERFORMANCE GRAPH

In Figures 14, 15 and 16, The performance of the Gray scale image and the RGB images are compared by analyzing the average values of Root Mean Square, Peak Signal to Noise Ratio and Correlation Coefficient. In this, the proposed system gives the better performance than the existing system.

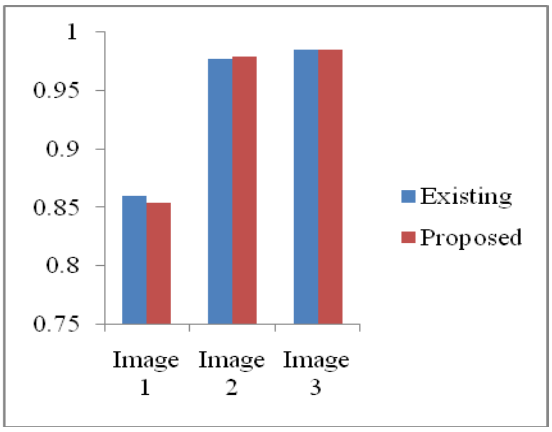

Figure 14: Comparison of Correlation Coefficient Values

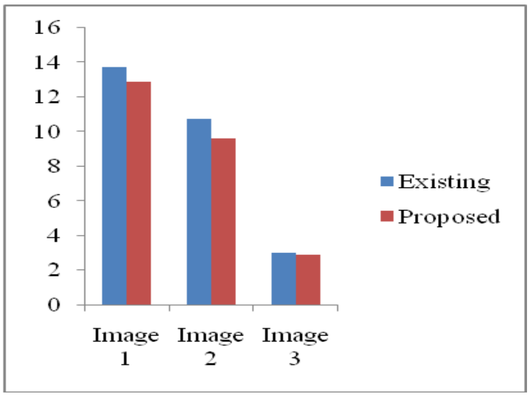

Figure 15: Comparison of Root Mean Square Values

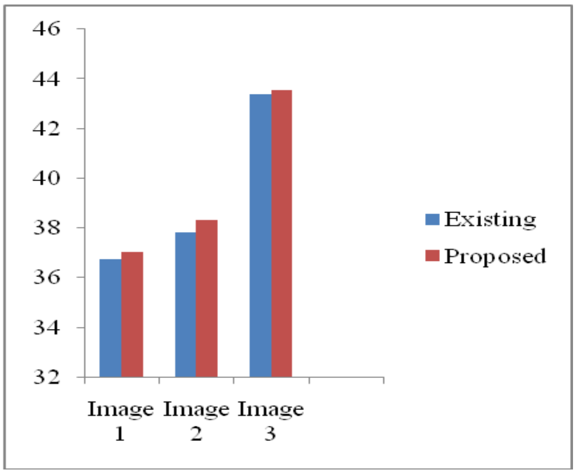

Figure 16: Comparison of Peak Signal to Noise Ratio Values

4. CONCLUSIONS

NSCT was helped to represent an image with better contour edges in different directions. The pixel level fusion was performed to fuse relevant details from low and high frequency using Gabor and gradient filters. The fused image contains high spatial resolution and spectral resolution rather than input original image. It is used in the remote sensing imaging system for analysis of satellite images. The fused image is again fused with the missing pixel for obtaining better results. The fusion performance are measured with parametric such as Root Mean Square, Peak Signal to Noise Ratio and Correlation Coefficient which gives the better result than the existing system.

REFERENCES

[1] V. Aslantas and R. Kurban, "Fusion of multi-focus images using differ-ential evolution algorithm," *Expert Syst. Appl.*, vol. 37, no. 12, pp. 8861-8870, Dec. 2010.

[2] S. Chen, R. Zhang, H. Su, J. Tian, and J. Xia, "SAR and Multispectral Image Fusion Using Generalized IHS Transform Based on à Trous Wavelet and EMD Decompositions," *IEEE Sensors J.*, vol. 10, no. 3, pp. 737-745, Mar. 2010.

[3] A. L. Cunha, J. Zhou and M. N. Do, "The non-subsampled contourlet transform: Theory, design and applications," *IEEE Trans. Image Process.*, vol. 15, no. 10, pp. 3089-3101, Oct. 2006.

[4] I. De and B. Chanda. "Multi-focus image fusion using a morpholo-gy- based focus measure in a quad-tree structure," *Inf. Fusion*, vol. 14, no.2,136-146, Apr. 2013.

[5] M. N. Do and M. Vetterli, "The contourlet transform: an efficient directional multiresolution image representation," *IEEE Trans. Image Pro-cess.*, vol. 14, no. 12, pp. 2091-2106, Dec. 2005.

[6] W. Huang and Z. Jing, "Evaluation of focus measures in multi-focus image fusion," *Pattern Recognit. Lett.*, vol. 28, no. 4, pp. 493-500, Mar. 2007.

[7] N. Indhumadhi and G. Padmavathi, "Enhanced image fusion algorithm using laplacian pyramid and spatial frequency based wavelet algorithm," Int. *J. Comput. Sci. Eng.*, vol. 1, no. 5, pp. 298-303. Nov. 2011.