Fusion of Hyper spectral and Multispectral Images using Non-Subsampled Contourlet Transform Domains

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***Abstract* — Multimodal Satellite image fusion is effectuated to limit the excess while enlarging the fundamental data from the given pictures gained utilizing diverse medicinal imaging sensors. The sole point is to yield a solitary fused picture, which could be more useful for a proficient clinical examination. This paper presents multimodal combination structure utilizing the non sub-sampled Contourlet transform (NSCT) areas for pictures gained utilizing two particulars Hyper Spectral and Multi Spectral Images. The significant favorable position of utilizing NSCT is to enhance upon the shift variance, directionality, and section facts in the eventually fused picture. The first part utilizes an NSCT space for combination and after that second stage to improve the difference of the demonstrative elements by using Guided picture. A quantitative examination of fused pictures is done utilizing devoted combination measurements.*

Keywords — *Multimodal Image, Hyper Spectral Image, Multi Spectral Image, Non sub-sampled Contour let transform (NSCT).*

I. INTRODUCTION

Image fusion is the process of fusing two images of the same scene in to a single fused image. The fused image shows all the data available in the given image. Image fusion technique is used for retrieving all the essential data in the image by eliminating noise. Noise is an unnecessary material which degrades the quality of an image affecting the clarity of an image. Noise can be of various types such as Gaussian noise, impulse noise, uniform noise etc. Images corrupt sometimes during acquisition or transmission or due to faulty memory locations in hardware.

Image fusion is possible at three levels such as pixel level fusion, feature level fusion, and decision level fusion. Two main types of image fusion techniques are spatial domain fusion techniques and temporal domain fusion techniques.

A. Image Fusion Techniques

Three levels of image fusion techniques are pixel level, feature level and decision making level. Pixel level image fusion combines the visual information from input images into single image based on the original pixel value and location. To form a fused image Feature level image fusion uses features like regions or edges in the image and combines these features. Decision level fusion merges image details directly in the form of relational graphs to produce a fused image. Pixel level fusion saves more significant information as compared to feature level and decision level fusion techniques. Two main types of image fusion methods are

- Spatial domain fusion.
- Temporal domain fusion

B. Spatial Domain Fusion

Spatial domain fusion offers mostly with the pixels of origin graphics. To fuse the entire graphics local spatial features as gradient, spatial volume, as well as local common deviation is used. Temporary domain fusion consists of the shift of entire graphics straight into the frequency domain. In this approach, source images tend to be projected on too localized bases which are designed to stand for sharpness as well as edges associated with an image. Most of these converted coefficients help to extract pertinent features from given input images to produce fused image.

C. Temporal Domain Fusion Techniques

Temporal domain fusion techniques can be performed by the following methods

- Discrete Wavelet Transform
- Stationary Wavelet Transform
- Discrete Cosine Transform

A. Discrete wavelet transform

It is based on wavelet idea in which the transformation is expected upon the set of wavelet functions. It provides good resolution both in the time domain and frequency domain. Low pass filters and high pass filters are used in this method. Scaling and translation operations are used by wavelets. In this method, wavelet transform, input images are decomposed into two sub-bands like low sub-bands and high sub-bands using this method. With the available fusion methods sub bands are fused. The inverse wavelet transform is applied to the fused coefficients of low sub-bands and high sub-bands at last to form the resultant image.

Principal component analysis technique in Discrete Wavelet Transform using averaging entropy includes three steps –

1. A fused image can be obtained with discrete wavelet transform using average and maximum fusion method.

Input images are first subdivided into low sub - bands and high sub-bands using discrete wavelet transform. These low sub-band coefficients and high sub-band coefficients are fused using maximum selection method. The inverse discrete wavelet transform is applied to fused coefficients to generate resultant image.

2. The Second fused image is generated using principal component analysis fusion method.

Fusion techniques of PCA are applied on the same input image to generate the second fused image.

3. The Resultant image is generated with entropy and maximum fusion method with discrete wavelet transform.

In this step, two fused images formed are considered as input images and are decomposed into low sub-bands and high sub-bands. Low sub-bands are fused using entropy method and high sub-bands are fused using maximum selection method. The Inverse discrete wavelet transform is applied to these bands to generate the resultant fused image.

B. Discrete Stationary Wavelet Transform (DSWT)

Discrete stationary wavelet transform (DSWT) is developed to overcome the translation invariance in DWT. The down-samplers and up-samplers in DWT are eliminated in DSWT and up-sample particular filtration by simply inserting zeroes in between to separate out coefficients. In this algorithm, filters are primarily placed on the particular rows than on the columns to create transform coefficients. Four images produced are of the same size as of original image but the resolution is half as compared to the original image. The transformed coefficients are then fused and inverse discrete stationary wavelet transform is applied to generate fused image.

C. Discrete Cosine Transform (DCT)

DWT techniques have number of disadvantages such as they need number of convolution calculations, require more memory resources and takes much time. DCT based fusion methods require less energy as compare to the DWT techniques. Hence it is appropriate to use DCT fusion methods for resource constrained devices. Data is compressed and fused before transmission in automated battlefields where the robots collect image data from sensor network as computational energy required is less than the transmission energy. In this technique both input images and fused images are coded in JPEG (Joint Photographic Experts Group) format. Contrast sensitivity method is used to generate the fused image.

The contrasts of the resultant AC (Alternating current) coefficients of various blurred images are analysed and the AC coefficient having the largest value is chosen as the AC coefficient for the image formed after fusion. By calculating the average of DCT representations of all the input images, DCT representation of fused image is found out. The DCT Coefficients have unwanted blurring effects which decreases the quality of the fused image.

In the existing system, sparse coding has been used for enhancing spatial resolution in the fusion of Hyperspectral images and Multi spectral images. Microstructures of the image are represented by structural primitives as lines, edges. These microstructures are same for all the images. Dictionary is constructed by the sparse matrix with the help of the structural primitives gained from the input images. Images will be reconstructed by utilizing the smallest dictionary atoms available in the dictionary.

Usually in dictionary, images are divided in to several patches. To construct an image with this dictionary, it is divided into several patches which are separately reconstructed by dictionary atoms. After constructing the proper dictionary high resolution hyperspectral images can be obtained from linear combination of atoms from the dictionary. Matrix with obtained coefficients is called sparse code, which is generated by orthogonal matching pursuit. The image is reconstructed with number of atoms with patches. Preprocessing is performed to reduce noise in the images, and then linear spectral unmixing model is applied.

In the existing method, end members are extracted using spectral properties of low resolution Hyperspectral images. Then initial abundance fractions are calculated with spatial properties from Multispectral images from the above initial set of High Resolution Hyper spectral images is obtained.

The fusion method iteratively updates the abundance fractions. At end spectrum of each HRHSI pixel is reconstructed based on LRHSI end members. A proper dictionary is constructed with several high spatial MSI. Based on dictionary initial HRHSI is obtained by LMM using sparse code and regularization term, abundance fractions are calculated. Final HRHSI is obtained from abundance fractions and members. Sparse coding has been used for enhancing spatial resolution in fusion of Hyperspectral and Multispectral images. In this method, initial dataset is spatially patched into sub images by constructing a dictionary. This dictionary does not consider the spectral distortion of the image.

II. PROPOSED SYSTEM

Multimodal Satellite image fusion is effectuated to limit the excess while enlarging the fundamental data from the info pictures gained utilizing diverse medicinal imaging sensors. The main aim is to yield a single fused image, which will be more informative for an efficient clinical analysis. In this paper, multimodal fusion framework using the non sub-sampled Contour let transform (NSCT) domains along with guided filter for images acquired using two distinct Hyper Spectral and Multi Spectral Images. To improve the shift in variance, directionality, and phase information in the fused image NSCT is used. The first stage employs a NSCT domain for fusion and the second stage to enhance the contrast of the diagnostic features by using Guided filter. For effective decision making Guided filter is used with Non-Subsampled Contourlet Transform.

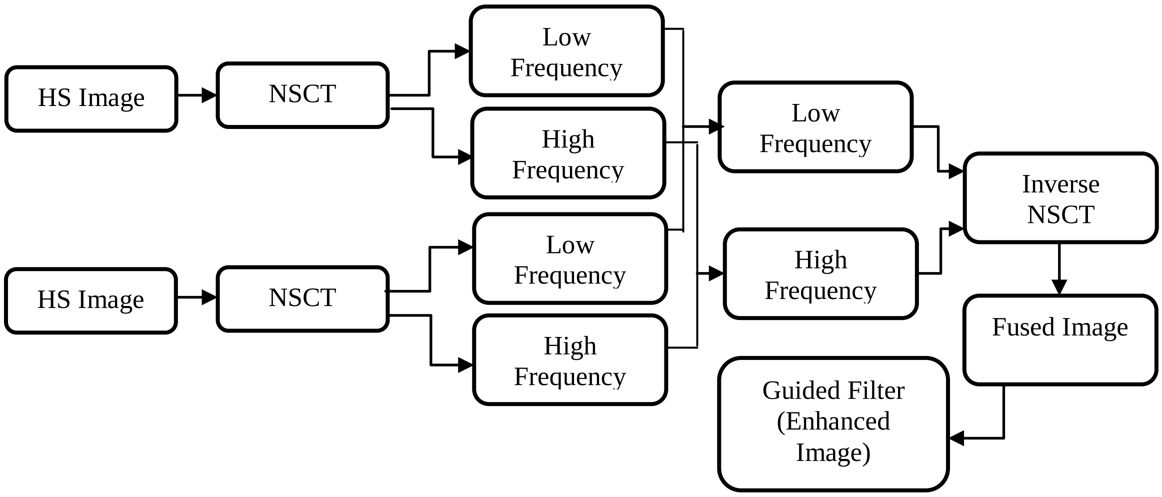

Figure 1 Block Diagram for fusing two images using NSCT and Guided Filter

Non - Subsampled Contourlet Transform is a new approach in pixel level image fusion which is used to produce highly informative fused images. Two distinct multispectral images and a hyperspectral image are given for fusion. Before fusing hyperspectral image is converted into gray scale image because of the various spectral color and the multispectral image is converted into separate color planes in the preprocessing stage.

The gray scale image of the hyperspectral image and red channel of the multispectral image both are decomposed using non-sub-sampled contourlet transform. After NSCT decomposition both images separated into low frequency and high frequency components. Low frequency components of hyperspectral & multispectral sub-bands are fused, same as high frequency components of hyperspectral & multispectral sub-bands are fused. For fusing the sub-bands maximum fusion method is implemented. In this method input image is compared pixel by pixel. Pixel having the maximum pixel value is selected for the construction of the new fused image.

Edge-saving on a fusion image is performed with guided filter, utilizing the substance of a second image, called a guidance image. This scheme has the best fusion performance. The recent trend to perform image fusion task is to use a multi-resolution image transform with novel fusion technique which combines the low-frequency and high-frequency sub bands. Combining a multi-resolution image analysis technique with intelligent decision making improves the fusion performance. The main advantage of this adaptive weighted averaging method is that it is easy to implement with less computational complexity than other NSCT based methods. The proposed methods yield excellent sharpness, clarity and edge preservation along with significant improvement in objective performance metrics than the existing multi-resolution transform based fusion schemes.

A. NSCT Based Multistage Decomposition

NSCT is multi-scale and multi-direction computation framework consisting of the discrete images. NSCT consists of two stages namely Non-Subsampled Pyramid (NSP) and Non-Subsampled Directional filter bank (NSDFB). At each level of NSCT decomposition, one low-frequency image and one high-frequency image are generated by utilizing two channel filter bank. The low frequency components in the image are decomposed using NSP decomposition stages. The property of NSP is gained by NSFB structure. NSFB structure is very much similar to that of Laplacian pyramid. Laplacian pyramid can be achieved using the Non – sub sampled filter banks. NSCT is shown in Figure 2 with the NSFB structure that implements the NSCT and frequency partitioning.

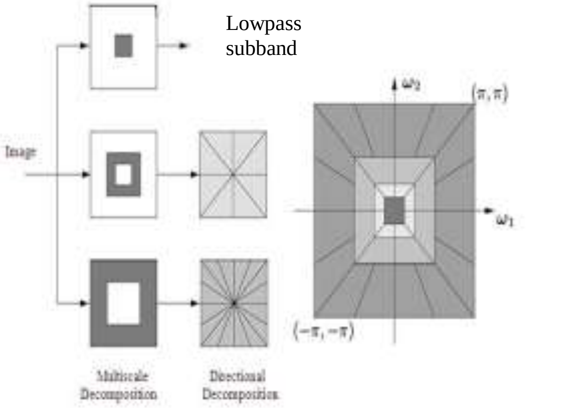

Figure 2 Non-sub-sampled Counterlet Transform. (a) NSFB structure that implement NSCT.

(b) Idealize frequency partitioning.

Non-Subsampled Pyramid NSP constructs k+1 sub image, containing one low-frequency image and k high-frequency images of the same size as the source image. Decomposition levels are denoted by K. The NSDFB is two-channel non-sub-sampled filter bank. By combining the directional filter bank, NSDFB is constructed. Directional decomposition is made with l stages in high frequency from NSP at each scale which generates 2l directional sub-images as the source image. Image denoising and image enhancement can be effectively done using NSCT. The NSCT structure is implemented by pyramid decomposition and frequency plane for multiresolution expansion as shown in figure 3.

By combining critically-sampled two-channel filter banks and resampling operations, NSDFB is constructed. With NSDFB a shift-invariant directional expansion is obtained. Down samplers and up samplers are eliminated in the DFB to construct NSDFB. Elimination is conducted by switching off the down sampler or the up sampler in the DFB.

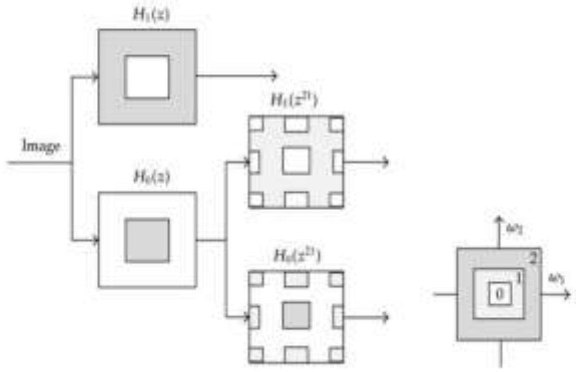

Figure 3 Nonsubsampled Pyramid (a) Three-stage pyramid decomposition. (b) Sub-band frequency plane.

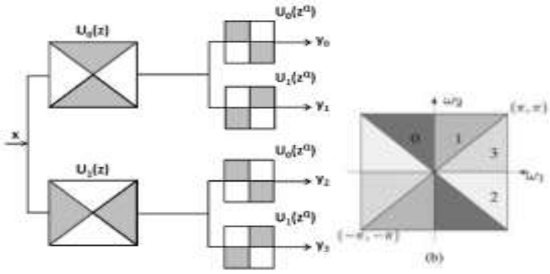

Figure 4 Nonsubsampled directional filter bank constructed with two-channel fan filter banks. (a) Filtering structure. (b) Corresponding frequency decomposition

Figure 4 shows the need for upsampling in the NSCT. Without upsampling, the high-pass at higher scales will be filtered by directional filter has “bad” response which is shown in fig (a). Fig (b) shows upsampling ensures that filtering is done in the “good” region. In image fusion technique of NSCT a pair of images is used to generate a composite image. The basic criteria in this are that all the source images must be registered in order to align the corresponding pixels.

A low-frequency and a series of high-frequency sub-images is obtained at each level and direction θ, By performing l-level NSCT on the source images

$$A:\{C_l^A\ ,C_l^A,\theta\}\ and\ B:\{C_l^A,C_l^A\ ,\theta\}$$

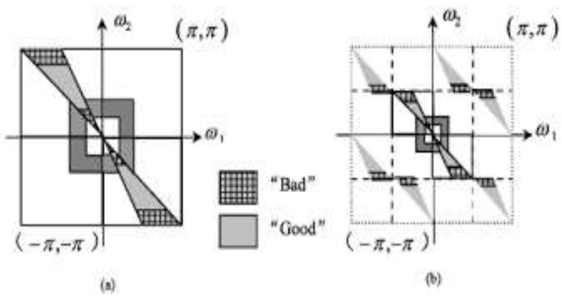

Figure 5 Sampling in the NSCT. (a) With no upsampling. (b) With upsampling.

Where C_l^* represents low-frequency sub-images and C_l^*, represents the high-frequency sub-images at level l ϵ [1, *l*] in the orientation θ.

The Fusion of low frequency sub-images is represented by the approximation components of the source images. To produce the composite bands conventional averaging method is used. Features extracted from low frequency sub images are denoted by P. Then the low-frequency sub-images are fused as

$$C_l^F(X,Y) = \begin{cases} C_l^A\ (X,Y), \text{if}\ \ P_{cl}^A(X,Y) > P_{cl}^B(X,Y) \\ C_l^A\ (X,Y), \text{if}\ \ P_{cl}^A(X,Y) > P_{cl}^B(X,Y) \\ \dfrac{\sum K_{A,B} C_l^K(x,y)}{2}\ \ , \text{if}\ \ P_{cl}^A(X,Y) > P_{cl}^B(X,Y) \end{cases}$$

For fusing high-frequency sub-images, here the coefficients in the high-frequency sub-images includes detail component of the source image. The noise is always related to high-frequencies which lead to miscalculation of sharpness value by affecting the fusion performance. To eliminate this, directive contrast is done which is first applied on high frequency sub-image of NSCT at each scale by

$$C_{l,\theta}^F(X,Y) \begin{cases} \\ C_{l,\theta}^B\ (X,Y), \text{if}\ \ D_{cl,\theta}^A(X,Y) > D_{cl,\theta}^B(X,Y) \end{cases}$$

frequency C^F

$$C_{l,\theta}^A\ (X,Y), \text{if}\ \ D_{cl,\theta}^A(X,Y) > D_{cl,\theta}^B(X,Y)$$

generate the fused image (F).

B. Guided Filter

It is an explicit image filter. The Output of the guided filter is generated by considering the given input image and a second image called a guidance image. To have better behavior at the edges, guided filter itself, behaves as an edge-preserving and smoothing operator. Because of its fast and on-approximate linear-time algorithm guided filter is independent of its kernel size. The guided filter is very effective in noise reduction, smoothing/enhancement of an image, image matting/feathering, haze removal, and joint upsampling. The guided filter is implemented by using Gabor filter.

Gabor filters are band pass filters. In image processing technique these filters are used for feature extraction, texture analysis, and stereo disparity estimation. By multiplying a Gaussian envelope function with a complex oscillation, gabor filters impulse response is created. Space uncertainty product is minimized by gabor filters with the help of some elementary functions. The response of Gabor filters is approximately linear under certain conditions. This property is exploited by stereo approaches. These approaches use the phase-difference of the left and right filter responses to estimate the disparity in the stereo images.

Let $\boldsymbol{x}=[x_1\ \ x_2]^T$ be the image coordinates. The Gabor filter $g(\boldsymbol{x})$ impulse response is then given by:

Bandwidth and the orientation selectivity of the filter are determined by the matrix A.

$$\boldsymbol{A}_{mn} = \begin{bmatrix} \cos\phi_m & -\sin\phi_m \\ \sin\phi_m & \cos\phi_m \end{bmatrix} \begin{bmatrix} a_n^{-2} & 0 \\ 0 & b_n^{-2} \end{bmatrix} \begin{bmatrix} \cos\phi_m & \sin\phi_m \\ -\sin\phi_m & \cos\phi_m \end{bmatrix}$$

If the modulation frequency vector $\boldsymbol{k}_0$ is in the same direction as one of the envelopes axes, with

$$g_{mn}(\boldsymbol{x}) = \frac{1}{2\pi a_n b_n} e^{-\frac{1}{2}\boldsymbol{x}^T \boldsymbol{A}_{mn} \boldsymbol{x}}\, e^{j\boldsymbol{k}_{0mn}^T \boldsymbol{x}}$$

$$\boldsymbol{k}_{0mn} = k_{0n} \begin{bmatrix} \cos\phi_m \\ \sin\phi_m \end{bmatrix}$$

Gabor filter using Fourier transform of the impulse response transfer function G(k) is given by

$$G_{mn}(\boldsymbol{k}) = e^{-\frac{1}{2}(\boldsymbol{k}-\boldsymbol{k}_{0mn})^T (\boldsymbol{A}_{mn}^{-1})^T (\boldsymbol{k}-\boldsymbol{k}_{0mn})}$$

Where $\boldsymbol{k} = [k_1\ \ k_2]^T$ is the spatial frequency. To establish a multi-resolution strategy for image, a set of N Gabor filters along with different modulation frequencies and bandwidths.

C. Image Fusion Algorithm

In this paper maximum fusion is implemented for fusing two images. In this method two or more input image is compared pixel by pixel. For constructing a new fused image, pixel with the maximum value is selected. This method can be represented as:

$$Y(i,j) = \mathbf{0} \le \boldsymbol{i} \le \boldsymbol{m}\ \boldsymbol{max}(\boldsymbol{P}\ \boldsymbol{i},\boldsymbol{j}\ \mathbf{0} < j)$$

Where P(i,j) and Q(i,j) are the input image and Y(i,j) is the output fused image.

III. EXPERIMANTAL ANALYSIS

Preserving all essential and useful information from the source images should be the main aim of any image fusion technique. The resultant image generated by the fusion technique should not introduce any distortion. Performance measures are used to detect the benefits obtained with fusion technique. In this paper, fusion performance is accessed with PSNR, Mean Square Error (MSE), and Entropy methods.

A. Peak Signal to Noise Ratio (PSNR)

The peak signal to noise ratio (PSNR) is defined as the ratio the maximum possible signal power and the tainting noise power that influences the constancy of its representation. Since numerous signals have a wide dynamic range, PSNR is typically communicated in terms of the logarithmic decibel scale (db). Quality of reconstructed image after fusion and restoration is mostly verified using PSNR. It can be characterized by means of the Mean Square Error (MSE). For 2 dimensional images, the PSNR computation is given by equation

$$PSNR = 10\ log_{10}\left[\frac{I_{max}^2}{MSE}\right]$$

Higher the PSNR better is the quality.

B. Mean Square Error

Mean Square Error (MSE) is used to calculate the average error of the pixels. MSE does not show that the denoised image endures more errors rather it alludes to a more prominent distinction between the original and the denoised image. This implies that there is a noteworthy noise decrease.

$$MSE = \frac{1}{NxM}\sum_{i=0}^{N-1}\sum_{j=0}^{M-1}[X(i,j) - Y(i,j)]^2$$

X represents the original image, bar Y denotes the fused image.

C. Entropy (EN)

Entropy calculates the amount of information. If entropy value is higher, it indicates increase in information and the fusion performance. Entropy is implemented using

$$Entropy = -\sum P_i\ Log_2 P_j$$

	MSE	PSNR	ENTROPY
IMAGE 1	0.0297	63.3988	7.5907
IMAGE 2	0.0202	65.0676	7.6146
IMAGE 3	0.0371	62.4403	7.6110
IMAGE 4	0.0318	63.1087	7.8912
IMAGE 5	0.0339	62.8292	7.7281
IMAGE 6	0.0363	62.5336	7.5228

Table I Evaluation measures of the various fused images using PSNR, Mean Square Error (MSE), and Entropy.

(a) (b)

Figure 6(a) Hyperspectral image (b) Multispectral image

Figure 7 Fused Image using NSCT and guided filter.

IV. CONCLUSION

In the proposed method for intelligent decision making a soft computing algorithm is used that replaces the fusion rules in conventional fusion systems. The proposed method aims at generating a highly informative fused image with all salient information from the input images

Combination of NSCT with guided filter is very effective in image fusion and suitable for combining multi-sensor image information from disparate imaging sensors. The proposed methods yield excellent sharpness, clarity and edge preservation along with significant improvement in objective performance metrics than the existing multi-resolution transform based fusion schemes available in literature.

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