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Remote Sensing Image Fusion Method Based on Quantization Index Modulation and Discrete Wavelet Transform

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Abstract: High spectral and spatial information is obtained by Digital image Fusion technique in which single image is obtained by merging same scene of two or more images. For fusing same scene of two registered Multispectral (MS) and panchromatic (PAN) image with minimum errors we suggested a new remote sensing fusion process using Quantization Index Modulation (QIM) and Discrete Wavelet Transform (DWT). Quantization Index Modulation and Discrete Wavelet Transform used to performing Wavelet decomposition takes less computational cost when compared to earlier used various wavelet decomposition techniques. The DWT and QIM is the most effective approach which decompose the image into 4-levels. Wavelet decomposition technique which is used for obtaining the low and high frequency sub images corresponds to approximation and the specific data of original images respectively. The sub images of high and low frequency are fused separately. To fusing the image effectively, we have selected best coefficients using Euclidean Distance formula. Thus, the coefficient with minimal distance is attaining the high priority than the other coefficients. Final fused image is reconstructed by inverse DWT. The QIM+DWT fusion technique performs better when compared to other conventional fusion techniques such as IHS, DWT and PCA which is inferred from our investigational result

Key words— Discrete Wavelet Transform (DWT), image fusion, Multi spectral, Quantization Index Modulation (QIM).

I. INTRODUCTION

Now a day, more and more data have become existing for researches by the growth of different kinds of remote sensors, chemical sensors and bio-sensors on satellites. Due to the volumetric growth of data, there is a pressing need to fuse data together from various sources to mine the most valuable data. Combined analysis, data interpretation and data integrating are the different terms which have been used earlier. Later in 1990's, "Data fusion" was implemented and extensively used.

Image fusion is a powerful way for excellent utilization of large proportion of image from different sources which is an element of data fusion when type of data is firm to image format. For more visual and informative observation or computer processing [2] Image fusions is the procedure of merging data from two or more images of a scene into a single merged image. In 1998, Pohl and Genderen [3] gave in-depth appraisal paper on various sensors information fusion techniques and clarified the theories, approaches and applications of image fusion as an impact to multi-sensor integration adapted to data processing. Further systematic permits on fusion of image to be published with a prominence on enlightening quality of fusion and discovery many application zones.

Earlier launched earth observing satellites for the past twenty years such as Quickbird, Formosat, SPOT-5, Landsat-7, Landsat-8, Ikonos, Geoeye, Kompsat and more recently launched Worldview-2, collect a panchromatic image with a higher spatial resolution at the same time and many multispectral bands with higher spectral and lower spatial resolution. The high spatial resolution is essential in order to map and detect with accurateness small features and structures. At the same time, the high spectral resolution is considered necessary in order to classify and discriminate different land use and land-cover types.

Most remote sensing applications require at the same time high spatial and spectral resolution images that the satellites cannot provide due to technical constrains such as small data transfer rate, limited energy autonomy, and limited storage capacity. We can improve the visualization of the study area by fusing PAN and MS LISS IV images with corresponding characteristics which can produce better results.

The continuing paper is structured as follows. The related algorithms are analysis in section II. The suggested technique of image fusion in remote sensing via QIM (Quantization Index Modulation) and DWT (Discrete Wavelet Transform) is presented in Section III. The investigational result with statistical and pictorial analysis of dataset is providing in the Section IV and conclusion is provided in Section V.

II. RELATED WORK

Jin et al., [4] proposed fusion approaches based on non-sub sampled shearet transform and Pulse Coupled Neural Network (PCNN) to increase performance and effectiveness of fused image. In first step, transformed Multispectral and Panchromatic images into CIE color Lab space to develop various color components. Multispectral image comes in three color channel images.

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It is transformed straight into CIE color Lab space [6] .But panchromatic images come in one channel that is gray color. So translates PAN image of one channel into RGB images of three-channel, and then three color channel PANRGB is converted to Lab color space. In second step, NSST [7] used to decompose PAN and L component of Multispectral to acquire equivalent low and high coefficients frequency. Third step, Intersecting Cortical Model (ICM) used to fused coefficients of low frequency. Using OFG - PCNN [8], and ICM, the new frequency of low and high coefficients will be acquired. Then fused low coefficient frequency of L by ICM. At last stage, inverse NSST transform method used to acquire the fused L component image, and inverse CIE Lab transform used to acquire the fused RGB color image.

Cheng et al., [5] used sparse representation and wavelet transform for fusion method to attain fused images contain high resolution of spectral and spatial quantity. They applied intensity-hue-saturation transform on Multi Spectral images. After that wavelet transforms performed. Panchromatic (Pan) image are used in the Intensity component of Multi Spectral images used to construct multi-scale representation respectively.

Lal et al., [9] improved the performance of the fusion process by proposing enhanced dictionary-based sparse representation (EDSR) for multitemporal image fusion. In this method a locally adaptive dictionary is produced. The dictionary contains patches mined from both source images. The maximum absolute coefficients performed through the learned dictionary are used for the reconstruction of the image.

Rai et al., [10] proposed the approaches Fast Approximate Nearest Neighbor (FANN) [12] for spontaneous registration. In the registration steps, key points are extract from both images using Scale Invariant Feature Transform [13] and then FANN used to selects the most appropriate indexing. Approximate Nearest Neighbor method used to match selected Indexed features. Further filtering done by Random Sample Consensus (RanSAC) to obtain only the co-register and inliers in the images. Finally fusion performed by Intensity Hue Saturation (IHS) transforms method to acquire a high spatial resolution in the Multi Spectral image. This approach is computationally efficient.

Mao et al., [11] suggested unified Bayesian frame work for exploring unique segments iteratively from Panchromatic images then used Multispectral images to allocating labels for cluster segments. Then generalized metaphor of the Chinese restaurant franchise (gCRF) used to describe the probabilistic propagative process on the Panchromatic and Multi Spectral images, which involves two random iterative processes such as dish selection and table selection for determining unique segments in Panchromatic images. After that cluster labels are assigning in the segments using Multispectral images. Major assistances are of two folds: 1) CRF is comprehensive into the framework of image fusion by classily decomposing into two random processes, 2) applying spatial constraints in the neighboring pixels CRF is transformed into stochastic image segmentation on the random process for table selection.

Yang et al., [1] suggested a new image fusion procedure based on non-subsampled contourlet transform to decompose two unique images into a low frequency and high frequency subband. Laplacian filter was used to signify the performance of both texture and edge. The superior reconstruction of an image can be created by average filter which can provide smoothing image. The pulse-coupled neural networks (PCNN) were used for fusing coupling coefficients from different images. A reconstructed fused image obtained by inverse NSCT which is found to be a superior method to various conventional image fusion methods.

III. PROPOSED METHOD

Novel remote sensing image fusion frameworks with minimum errors were proposed in this paper as shown in Fig. 1. For image fusion process, we considered two sources of images such as PAN and MS images. The proposed fusion framework, wavelet decomposition is performed using QIM Quantization Index Modulation) and DWT (Discrete Wavelet Transform). DWT and QIM is the most effective approach which decompose the image into 4-levels. The low and high frequency sub images are acquired using wavelet decomposition method, in which the approximation of original images in the low frequency sub images and the detail information of source images in the high frequency sub images are the respectively. The low and high frequency sub images are fused separately. To fuse the image effectively, we have selected best coefficients using Euclidean Distance formula. Thus, the coefficient with minimal distance is attaining the high priority than the other coefficients.

Proposed QIM-DWT based Algorithms

Input: PAN and MS (LISS IV) image at time T1

Output: Fused image F

Initialize window size=128X128

Step 1: remove salt& pepper noise and Gaussian noise using Bayesian Filter to both PAN and MS images

Step 2: PAN and MS image use to determine two dimension grids of the images

Step 3: Use Quantization Index Modulation method to decompose each image into four levels to provide deep level of information

Step 4: Apply Discrete Wavelet Transform to obtain high frequency (M_{HL}, M_{HH}) and low frequency (M_{LL}, M_{LH}) sub-images of MS images.

Step 5: Apply Discrete Wavelet Transform to obtain high frequency (P_{HL}, P_{HH}) and low frequency (P_{LL}, P_{LH}) sub-images of PAN images.

Step 6: From low and high frequency sub images we gather detail information of source image .

Step 7: Select best coefficients of Low and high frequency component of both PAN and MS image using Euclidean Distance formula.

Step 8: Perform inverse Discrete Wavelet Transform in high and low frequency sub-images to construct fused image effectively.

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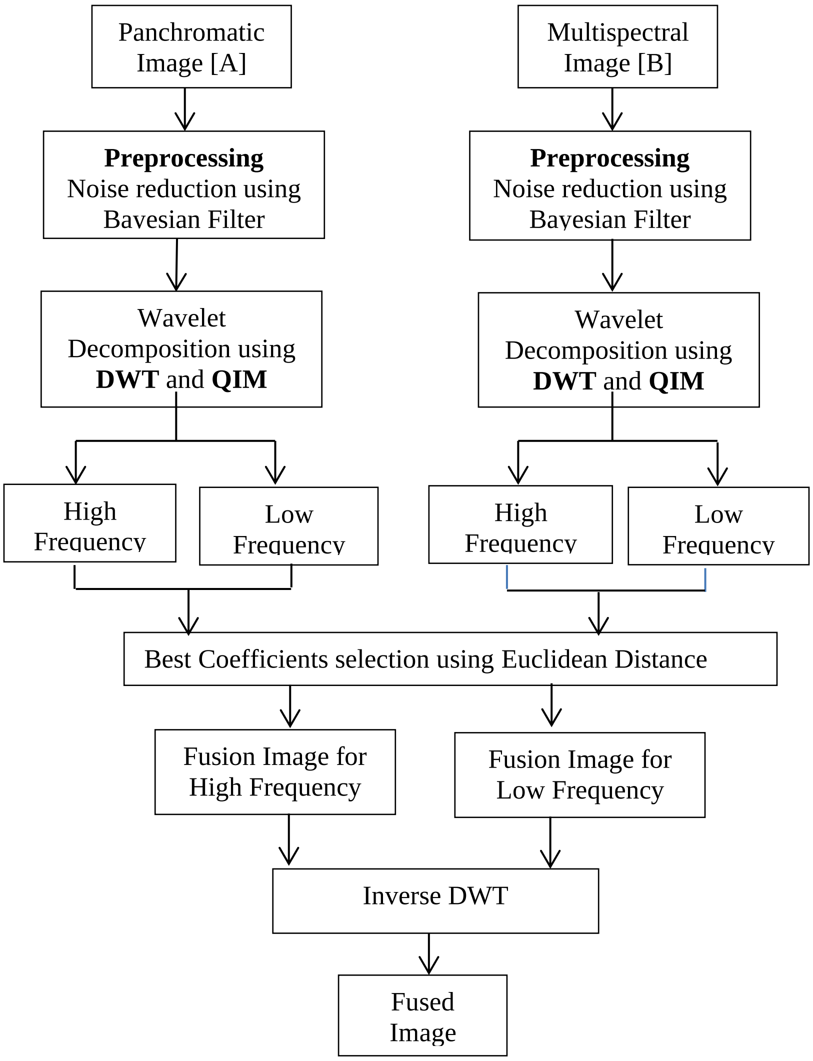

Fig. 1. Proposed framework of QIM+DWT

IV. EXPERIMENTAL RESULTS AND ANALYSIS

Experiment Setting and Implementation Details

The suggested technique compared with existing image fusion techniques like IHS, PCA, and DWT. Carry out an investigational analysis for evaluating the efficiency of the recommended approach. In that we considered PAN and Multispectral datasets to the geographical regions of Madurai city in Tamil Nadu, India. A complete explanation of each dataset is specified below.

Study Area and Data set

In Tamil Nadu one of the major cities is Madurai. It is the third biggest city and Located on the banks of River Vaigai in Tamil Nadu . It is placed between longitude 78 04′ 47″ E to 78 11′23″ E and latitude 9 50′ 59″ N to 9 57′ 36″ N. The geography of Madurai is almost 101 m above the mean sea level. MS image was captured by the IRS P6/LISS IV Satellite/Sensor which has 5.8 m resolution. PAN image was captured by the Cartosat-2 Satellite/Sensor which has a resolution of 1 m. A sector of 512 X 512 pixels has been selected as the test site.

Image Fusion Metrics for Evaluation

Peak Signal to Noise Ratio is the proportion between the maximum probable power of a signal and to the power of noise that disturbs the reliability. The PSNR value is specified by

$$\mathrm{PSNR} = 10^{*}\ \log_{10}\frac{\mathrm{peak}^2}{\sqrt{\sum_{i=1}^{M}\sum_{j=1}^{N}(\mathrm{F(i,j)}\text{-}\mathrm{MS(i,j)})^2}} \quad (1)$$

Where, MS is the reference image, F is the fused image to be measured, i is the pixel row index, j is the pixel column index, M is number of rows, number of columns is denoted by N and peak^2 is maximum likely pixel value of images. Larger PSNR indicates less amount of image distortion. It reflects the quality of reconstruction.

Structural Similarity Index Matrix (SSIM) is defined as follows,

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$$SSIM(F, MS) = \frac{(2\mu_F\mu_{MS} + c_1)(2\sigma_{FMS} + c_2)}{(\mu_F^2 + \mu_{MS}^2 + c_1)(\sigma_F^2 + \sigma_{MS}^2 + c_2)} \quad (2)$$

Where μ_F, μ_{MF} represents mean value of image F and MS, σ_F denotes the standard deviation of image F and c_1, c_2 are constant.

Root Mean Square Error (RMSE) is the root mean square difference between the reference MS image and the fused F image. Lesser RMSE specifies better fusion result. It is the simple and most widely used method to measure image quality.

$$RMSE(I_R I_F) = \sqrt{\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left(F(i,j) - MS(i,j)\right)^2} \quad (3)$$

Fusion mutual information (FMI) provides the measure of information from source image to the fused result. The value of indicator is larger, and then information in fused image is always richer. Generally, FMI between two random variables is given by

$$FMI_{XY}(x, y) = \sum_{x,y} P_{XY}(x, y) \log \frac{P_{XY}(x, y)}{P_X(x)P_Y(y)} \quad (4)$$

Where, X and Y are the any two random variables with corresponding probability distributions $P_X(x)$ and $P_Y(y)$ respectively.

Visual Analysis

MS image is used for obtaining the spectral information and the PAN image is used for obtaining the spatial information which were extracted from the above methods reflects the spectral as well as detailed features of the fusion images. High spatial resolution information is provided by IHS fusion technique in the component I. Hence, the fused image of IHS method shown in (Fig. 4). Fused images as shown in (Fig. 5) achieved by PCA fusion method can sustain spatial information high but provides definite spectral distortion. The image contrast was reduced in DWT fused results as shown in (Fig. 6) which causes the image contour and edge blur in a definite range. Fused outcome of our method was represented as shown in (Fig. 7) which had effectively improved the spectral distortion.

Objective Analysis

Peak Signal to Noise Ratio (PSNR), Structural Similarity Index Matrix (SSIM), Root Mean Squared Error (RMSE), and Fusion Mutual Information (FMI) are employed as objective criteria to obtain the concert of the various fusion techniques. The performance calculation of different fusion methods can be shown in the Table 1 for MS images and PAN images, respectively. The greatest performance metrics of various fusion methods are mentioned in bold typeface. Then proposed QIM+DWT algorithm can increase the spatial information and retaining the spectral characteristic which is inferred from the Table 1. Results from Table 1 show that the proposed QIM+DWT method has the lowest RMSE value and the highest PSNR and FMI, as well as the best value for SSIM compared with IHS, PCA, and DWT. These findings indicate that the QIM+DWT outperform IHS, PCA, and DWT for fusion of multitemporal remote sensing images.

Fig. 2. PAN image

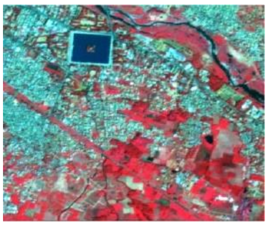

Fig. 3. MS image

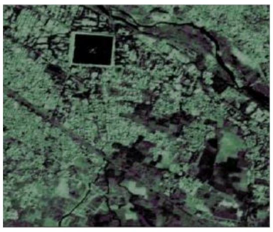

Fig.4. Fused image HIS

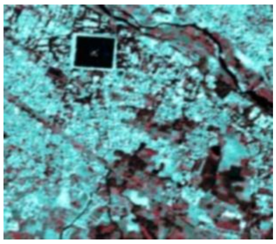

Fig.5. Fused image PCA

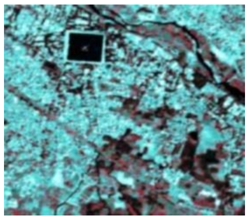

Fig.6. Fused image DWT

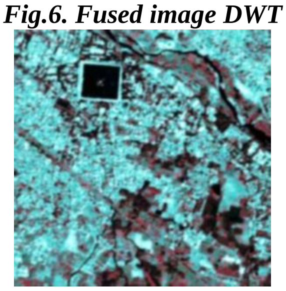

Fig.7.Fused image (QIM+DWT)

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Table 1
Performance of Different Fusion Methods

Method	PSNR	SSIM	RMSE	FMI
IHS	39.6	0.74	9.74	0.63
PCA	45.3	0.82	9.12	0.72
DWT	46.9	**1.30**	7.84	0.84
QIM+DWT	**49.7**	1.25	**7.05**	**0.9**

V. CONCLUSION

In this paper, we combined Quantization Index Modulation (QIM) and Discrete Wavelet Transform (DWT) which can improve the image decomposition level with Discrete Contourlet transform and can retain the complete information of source images like region boundaries, lines, edges. QIM and DWT were used for proposing a new fusion algorithm. Simulation results showed that the proposed new ***QIM+DWT*** technique provide better performance in the objective evaluation indexes and visual effects. Still, it is inferred that the new fusion procedure became further complex than tradition methods, by using the proposed scheme. This new technique is not beneficial to real time image fusion because the sensor images are large size in real time. The proposed QIM+DWT had taken advantage of the adaptive regularization parameter and also choose the maximum absolute fused vectors for fusion. Thus, the QIM+DWT perform better than the traditional methods and basic sparse representation fusion.

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