Fusion of Coastal Images Using Curvelet Wavelet Transform Technique

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ABSTRACT: Image fusion for the coastal area is a challenging and rapidly growing field for the researchers to extract the information for environment monitoring. It is the process of combining relevant information from two or more images into a single image. The resulting image will be more informative than any of the input images. Various methods have been proposed earlier for satellite image fusion. The fusion performance of these methods often deteriorates for images derived from different sensor modalities. In this paper, a novel Curvelet Wavelet Transform (CWT) based fusion scheme is demonstrated. It splits the image decomposition process into two successive filtering operations using spectral factorization of the analysis filters. The actual fusion takes place after convolution with the first filter pair. The nonsubsampled nature of the CWT allows the design of nonorthogonal filter banks, which are more robust to artifacts introduced during fusion. The combination of these techniques leads to a fusion framework, which provides clear advantages over traditional multiscale fusion approaches. It is independent of the underlying fusion rule and reduces unwanted side effects such as ringing artifacts in the fused reconstruction. The results of the proposed method are evaluated and compared according to four measures of performance - Entropy (H), Root Mean Square Error (RMSE), Peak Signal to Noise Ratio (PSNR) and Correlation Coefficient (CC).

Keywords: Curvelet Wavelet Transform (CWT), Image fusion, Nonorthogonal filter banks, Spectral factorization.

1. Introduction

In last decade, remote sensing methods have attracted the researchers as an efficient tool for the monitoring the atmosphere and surface of the earth. The various scale used are local scale, global scale and regional scale and delivers the crucial information as coverage of the land area, mapping and land classification in the various classes such as soil, forest, water or mountains based on their features.

Due to the enhancements in the sensor technology, volume of the remote sensing images growing rapidly for spatial and temporal resolution. Similarly, the quantity of the satellite image data is also increasing for multi-resolution images, multi-temporal images, multi-frequency/ spectral bands images and multi-polarization image. In the field of remote sensing imaginary, coastal field is widely used for studying the ecological condition of the coastal regions. Coastal regions consists of beaches, residential areas and industrial areas. So for planning, development and environmental condition monitoring high quality of images are required which are captured by using satellite system. These images contain high spatial and temporal resolution which is used for the analysis and interpretation of the coastal area [1].

Remote sensing techniques are powerful source for the extraction of the information from the remotely sensed images at low cost of implementation. Due to various hindrances as cloud effect, elevation angle of solar and aerosol, surface energy and seasonal variation parameters are affected which causes the low information extraction for the researchers. The extraction of the efficient information from the remotely sensed data is a crucial task for the researchers [2]. To improve the information extraction process, image fusion techniques are adopted which is the technique to combine two or more images into a single image composition to make it more informative and convenient for visual perception.

According to the requirement of the information, the fusion technique can be applied at various levels of an image i.e. pixel level image fusion, feature based image fusion, object based fusion and decision levels fusion. Various researches have been done in recent years to achieve the high resolution –multispectral images. According to these researches High-Resolution Panchromatic (HRP) images comprises intensity information and color information of the satellite image data is stored in low-resolution multispectral images [3]. In remote sensing images higher resolution panchromatic images are fused with the low resolution images to achieve the better interpretation results. The main aim of fusion method to

ISSN 2229-5518

transfer all the important information acquired from the input images to the fused image without adding any noise and artifacts to maintain the quality of the image [4].

The process of image fusion can be applied at pixel level or at the decision level. Pixel level image fusion represents the information combination at the lower levels of the image because each pixel of the fused image is determined by the set of pixels of the source image. Image fusion based on the pixel level can be divided into two categories (i) Spatial domain image fusion and (ii) Transform domain method. The main issue with spatial and transform domain is the variations in the scale of the image and variations in the orientations of the image. To overcome these issues multiscale transform method is proposed. Multiscale transform can be applied based on the pyramid transform, discrete wavelet transform, dual-tree complex wavelet transform, curvelet transform, countourlet transform etc. Out of these various fusion methods for high resolution panchromatic data and low resolution data, many methods fail to control the quality of the image in terms of spectral consistency which is useful parameters for the satellite image data due to the informative property of the satellite image.

Latest remote sensing systems i.e. QuickBird, SPOT and LANDSAT etc. give high resolution panchromatic and various multispectral bands. Panchromatic images consists wide range of the wavelength. In order to achieve the incoming energy, PAN detector is used. In this way, on the same satellite or plane stage, the determination of the PAN sensor can be higher than that of the MS(Multi Spectral) sensor. The information volume of a high-determination MS image would be altogether bigger and relieve the issues of restricted on-board stockpiling limit and constrained information transmission rates between the stage and ground. Subsequent to various applications need both high spectral and high spatial determination, image fusion, or all the more accurately, sharpening the band, is utilized. Therefore, on the same satellite or airplane platform, the resolution of the PAN sensor can be higher than that of the MS sensor. On the other hand, the data volume of a high-resolution MS image would be significantly larger and could mitigate the problems of limited on-board storage capacity and limited data transmission rates between the platform and ground. Since a number of applications need both high spectral and high spatial resolution, image fusion, or more precisely, band sharpening or resolution merge, is used. Image fusion is a method, which increases the spatial resolution of multispectral images (ideally without the loss of spectral information), through the combination of low spatial but high spectral resolution multispectral data and higher spatial but low spectral resolution panchromatic data[5].

Vesteinsson et al. proposed a new technique for satellite image fusion to enhance the spectral consistency of the image and to maintain the quality of the image. This technique is called Spectral Consistent Pan sharpening (SCP). Observation for the spectral consistency was made based on the high-resolution single-channel data interpretation [8]. Principle Component Analysis (PCA), which is also known as Karhunen-Loéve transform, aims to transform random images[10-11]. It conducts multidimensional orthogonal linear transformation based on image statistical characteristics. According to dimension reduction technique, it transforms multiple components into a few comprehensive components, which contain as much original variable information as possible. PCA concentrates variance, compresses data size, and shows remote sensing information of the multiband data structure more precisely, which gets a best approximation to the original image statistically. PCA, which is with wide application, is mainly focused on fusion of multi-band images. Chavez is the first person to apply PCA to multisensor image fusion. He fused the Landsat-TM multispectral and Spot Panchromatic images, achieving a sensational result [12]. The research on image sparse modeling has attracted broad attention excellent tools (Curvelet [13], Bandelet [14], etc.) and methods (Basis Pursuit (BP) [15], Matching Pursuit (MP) [16], etc.) of image sparse representation were proposed. The development of compressed sensing (CS) theory [17] is based on sparse representation. CS samples and compresses at the same time. The basic idea is to collect information which is directly related to the useful object. The obtained value is the projection projected from high to low dimensional. The main research content of CS includes measurement method of projection, reconfigurable conditions, and image reconstruction methods [18].

The paper organization is as follows: Literature survey is given in section 2. The proposed model presented in Section 3. The results and the experimental study are presented in the section 4 and the concluding remark is discussed in the last section 5.

2. RELATED WORK

In this section, the existing methodologies used for the fusion of satellite image data in recent years are discussed. Numerous methods have been implemented to fuse multitemporal, multisensor, and multiresolution data. In general, the image fusion techniques can be divided into two classes: color related techniques and statistical or numerical methods. The first group comprises of the tristimulus color composition in the Red, Green, Blue (RGB) color space as well as more sophisticated transformations such as example IHS. Statistical approaches use channel statistics including correlation (PCA, regression) and filters (high pass).Numerical methods follow arithmetic operations such as image addition, division and subtraction. A sophisticated and very successful numerical approach uses wavelet transform in a multiresolution environment (Pohl and van Genderen, 1998). The newer geographical image processing software includes at least a basic set of image fusion methods. Among the hundreds of variations, the most popular and effective are IHS, PCA, arithmetic combinations, and wavelet base fusion (Zhang, 2004). Some of the fusion techniques are Intensity-Hue-Saturation method (IHS), Brovey transform (BT) and Multiplicative method (MULTI).These techniques were selected since they are well studied, simple and widely available.

More advanced methods, like high frequency addition and principal components analysis, have been also tested, but excluded in detailed analysis because of higher complexity, especially regarding the quality of the final result. Wavelet based methods are very promising because of the multiresolution approach. They have not been studied, since they are more computationally demanding and require special algorithms (wavelet transform), not yet available in off-the-shelf remote sensing software.

The IHS color transformation effectively separates spatial (intensity) and spectral (hue and saturation) information from an image (Chavez et al., 1991; Carper et al., 1990). The fusion method first converts a RGB image into intensity (I), hue (H) and saturation (S) components. In the next step, intensity is substituted with the high spatial resolution panchromatic image. The last step performs the inverse transformation, converting IHS components into RGB colors, the so-called synthetic multispectral bands. The Brovey transformation (Hallada and Cox, 1983) normalizes multispectral bands used for RGB display; each multispectral band is divided with the panchromatic image, obtained from the original multispectral data. Next, the result is multiplied by the original panchromatic image to add data intensity or the brightness component to the image. The Brovey transformation was developed to visually increase the contrast in the low and high ends of an image's histogram and thus change the original scene's radiometry. It was created to produce RGB images, and therefore only three bands at a time can be merged.

The Multiplicative method (MULTI) can be performed with any number of input bands. The algorithm is derived from the four-component technique, as described by Crippen (1989). Of the four possible arithmetic methods that can be used to incorporate an intensity image into a chromatic image (addition, subtraction, division, and multiplication), only multiplication is unlikely to distort the color. The relatively simple multiplicative algorithm can be used to merge PAN and MS images; however special attention has to be paid to color preservation. Many recent papers have demonstrated that the spectral content of an image changes as the spatial resolution changes; for example, an extensive discussion is given in Wald et al. (1997). Moreover, a number of authors have mentioned, that the input images need preprocessing, but usually no attention is given to the algorithms of changing the input data and its effects on the quality of the fused image. Image fusion methods can be broadly classified into spatial domain and transform domain fusion Brovey method, Principal Component analysis (PCA) IHS (intensity hue saturation) and High pass filtering methods fall in the spatial domain fusion techniques Spatial image fusion work by combining the pixel values of the two or more images. The simplest is averaging the pixel values of the input images [20] wavelet transform and laplacian transform come in the transform domain. In the transform domain method the multiscale decomposition of the images is done and the composite image is constructed by using the fusion rule. Then inverse multiscale transform is applied to achieve the fused image.

The Brovey Transform was developed to visually increase contrast in the low and high ends of an images histogram (i.e., to provide contrast in shadows, water, and high reflectance areas such as urban features). Consequently, the Brovey Transform should not be used if preserving the original scene radiometry is important. However, it is good for producing RGB images with a higher degree of contrast in the low and high ends of the image histogram and for producing "visually appealing" images. Since the Brovey Transform is intended to produce RGB images, only three bands at a time should be merged from the input multispectral scene [2] The Brovey transform is based on the mathematical combination of the multispectral images and high resolution Pan Image. Each multispectral image is normalized based on the other spectral bands and multiplied by the Pan image to add the spatial information to the output image [3].

The IHS technique is one of the most commonly used fusion techniques for sharpening of the images. It has become a standard procedure in image analysis for color enhancement, feature enhancement, improvement of spatial resolution and the fusion of disparate data sets [4]. In the IHS space, spectral information is mostly reflected on the hue and the saturation. From the visual system, one can conclude that the intensity change has little effect on the spectral information and is easy to deal with. For the fusion of the high-resolution and multispectral remote sensing images, the goal is ensuring the spectral information and adding the detail information of high spatial resolution, therefore, the fusion is even more adequate for treatment in IHS space [5]. The commonly used RGB (XS3, XS2, and XS1) color space is not suitable for a merging process, as the correlation of the image channels is not clearly emphasized. The IHS system offers the advantage that the separate channels outline certain color properties, namely intensity (I), hue (H), and saturation (S). This specific color space is often chosen because the visual cognitive system of human beings tends to treat the three components as roughly orthogonal perceptual axes.

Principal component analysis (PCA) has been called one of the most valuable results from applied linear algebra. PCA is used abundantly in all forms of analysis - from neuroscience to computer graphics - because it is a simple, non-parametric method of extracting relevant information from confusing data sets. With minimal additional effort PCA provides a roadmap for how to reduce a complex data set to a lower dimension to reveal the sometimes hidden, simplified dynamics that often underlie it. [6] The principal component transform is a statistical technique which is used to transform the multivariate dataset of correlated variables into a dataset of uncorrelated linear combinations of the original variables. For images, it creates an uncorrelated feature space which can be used for further analysis instead of the original multispectral feature space. The PC is applied to the multispectral bands.

The PC analysis transform converts inter correlated MS bands into a new set of uncorrelated components. The first component also resembles a PAN image. It is, therefore, replaced by a high-resolution PAN for the fusion. The PAN image is fused into the low-resolution MS bands by performing a reverse PCA transform [7].The panchromatic image is histogram matched to the first principal component (sometimes to the second). It then replaces the selected component and an inverse PC transform takes the fused dataset back into the original multispectral feature space The advantage of the PC fusion is that the number of bands is not restricted (such as for the original IHS or Brovey fusions). It is, however, a statistical procedure which means that it is sensitive to the area to be sharpened. The fusion results may vary depending on the selected image subsets. [8]. The High Pass Filtering For the high pass filtering (HPF) fusion, first the ratio of the spatial resolution of the panchromatic and the multispectral image is calculated. A high pass convolution filter kernel is created and used to filter the high resolution input data with the size of the kernel based on the ratio. The HPF image is added to each multispectral band. Before the summation, the HPF image is weighted relative to the global standard deviation of the multispectral bands with the weight factors are again calculated from the ratio. As a final step, linear stretch is applied to the new multispectral image to match the mean and standard deviation values of the original input multi spectral image [9]. It shows acceptable results also for multisensoral and multi temporal data. Sometimes the edges are emphasized too much [10].

The Laplacian Pyramid implements a "pattern selective" approach to image fusion, so that the composite image is constructed not a pixel at a time, but a feature at a time. The basic idea is to perform pyramid decomposition on each source image, and then integrate all these decompositions to form a composite representation, and finally reconstruct the fused image by performing an inverse pyramid transform. The first step is to construct a pyramid for each source image. The fusion is then implemented for each level of the pyramid using feature selection decision.

There are two modes of the combination averaging and the selection. In the selection process the most salient component pattern from the source image are copied while less salient patterns are discarded. In the averaging case source patterns are averaged reducing the noise. Selection is used where the source images are distinctly different and the averaging is used where the source images are similar. The laplacian pyramid has the steps such as images size checking, construction of pyramid level n, pyramid level fusion, final level analysis, reconstruction of fused image [11].

3. PROPOSED METHODOLOGY

The image fusion framework proposed in the current work is shown in Fig 1. Initially source images are considered. This process includes factorization, detailed coefficient computation for fusion, spectral factors computation, image approximation, inverse transform and finally fused image. Images are transformed to the CWT domain using the filter pair by using filter bank analysis. After the fusion of the high-pass coefficients, the second filter pair, consisting of all remaining spectral factors, is applied to the approximation and fused, detail images. This yields the first decomposition level of the proposed fusion approach. Next, the process is recursively applied to the approximation images until the desired decomposition depth is reached. After merging the approximation images at the coarsest scale the inverse transform is applied to the composite CWT representation, resulting in the final fused image. The development of filter bank is done using Curvelet Wavelet Transform.

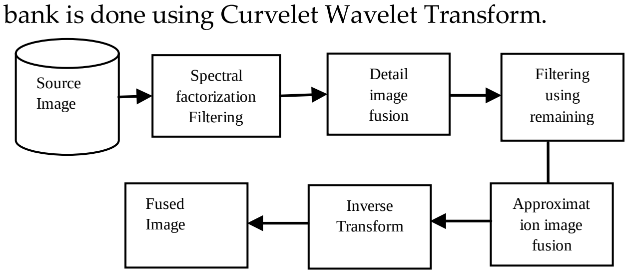

Fig 1: Framework of image fusion

CWT is implemented using a filter bank by decomposing one-dimensional (1-D) signal c_0 into a set$=\{w_1, \dots w_J, c_J\}$, which

ISSN 2229-5518

shows the high-pass coefficients by w_j and low-pass coefficients are given asC_J. Resolution of image is obtained by using "a trous" methodology.

In this paper, a novel CWT-based fusion approach that splits the filtering process into two successive filtering operations is proposed. It performs the actual fusion after convolving the input signal with the first filter pair, exhibiting a significantly smaller support size than the original filter. The proposed method is based on the fact that the low-pass analysis filter *H(z)* and the corresponding high-pass analysis filter *G(z)* can be expressed in the form by spectral factorization in the *z*-transform domain

$$\mathrm{H(z)} = (1+z^{-1})P(z) \qquad \text{(i)}$$
$$\mathrm{G(z)} = (1-z^{-1})Q(z) \qquad \text{(ii)}$$

Thus, in framework the input images are first decomposed by applying a Haar filter pair, represented by the first spectral factors $(1+z^{-1})$ and $(1-z^{-1})$ respectively. The resulting horizontal, vertical and diagonal detail images can afterwards be fused according to an arbitrary fusion rule. Next, the filter pair represented by the second spectral factor (*P(z)* and *Q(z)*), is applied to the approximation and fused detail images, yielding the first decomposition level of the proposed fusion scheme. For each subsequent level, the analysis filters are upsampled according to the "à trous" algorithm, leading to the following, generalized analysis filter bank.

$$H(z^{2j-1}) = \left(1+z^{-2^{j-1}}\right)P(z^{2j-1}) \qquad \text{(iii)}$$
$$G(z^{2j-1}) = \left(1-z^{-2^{j-1}}\right)P(z^{2j-1}) \qquad \text{(iv)}$$

The procedure is recursively applied to the approximation images, until the desired number of decomposition levels is reached. After merging the low-pass approximation images, the final fused image is obtained by applying the inverse transform, using the corresponding synthesis filter bank without spectral factorization.

The proposed algorithm for satellite image fusion uses 'a trous algorithm to perform the fusion, which has following steps:

Step 1: Initiate the original and reference input image
Step 2: Apply Haar pairing for filtering
Step 3: Decompose the image in spectral factor i.e. $(1+z^{-1})$and $(1-z^{-1})$
Step 4: Compute frequency of each decomposed subband given as $\mathcal{F}\ \alpha\ (\mathcal{P}_0\mathcal{F}, \delta_1\mathcal{F}, \delta_2\mathcal{F}, \mathcal{K})$ where $\mathcal{F}$ is the image matrix, $\mathcal{P}_0$ low-pass filter,δ_1,δ_2 are the band pass filter
Step 5: Perform smoothing partition using dyadic square grid
Step 6: Design the non-orthogonal, 1-D filter bank
Step 7: Derive the coefficient by using B3-spline coefficient.
Step 8: Generate the curvelet coefficient using 2-D filter bank
Step 9: Renormalization of the square grid
Step 10: Fuse the coefficients and reconstruct the image

4. EXPERIMENTAL RESULTS

In this section the performance of the proposed fusion framework is investigated using various different sets of image-pairs. In order to achieve the goal, the experiment is carried out to study the performance of the proposed method.
During experimental study, three scenarios are considered which are: (1) experiment with book image (2) experiment with coastal image (3) experiment with remotely sensed image.
In order to compare the performance the parameters entropy, RMSE, PSNR and correlation coefficient are considered.

EXPERIMENT 1:

To test the performance of the proposed method conventional image data is used. In image processing it is important to have the test image to compare the result. The first input images are shown in Fig 2(a) and Fig 2(b). Considered image is multifocal image. In the Fig 2(a), the information in the left half is distorted and in Fig 2(b) the information in the right half is distorted. Hence combining both the images gives clear and complete information in a single image. Fig 2(a) and Fig 2(b) are fused using proposed method and the result is shown in Fig 2(c).The statistical result of different fusion methods is compared for the fused image. From the Table I, it is observed that entropy, PSNR and CC is high and RMSE is low for the proposed method. Table I depicts statistic performance for book image considering different fusion scheme. This performance includes Entropy, RMSE, PSNR and correlation coefficient. The proposed approach provides 61.27%. 64.88%, 53.18%, 18.98% and 31.24% improvements when compared to existing schemes in terms of entropy. Hence it is analyzed that the proposed method performs well for image fusion.

Fig 2: (a) Input Image (b) Input Image (c) Fused image.

Table 1: Statistic results of different fusion methods

Fusion method	Entropy	RMSE	PSNR	CC
Select maximum	3.8151	6.87	34.67	0.89
Select Minimum	3.4589	21.05	24.88	0.68
Simple Average	4.6117	15.74	29.56	0.87
PCA	7.9812	8.37	37.55	0.67
Laplacian Method	6.7734	11.17	40.44	0.94
Proposed method	9.8514	1.95	61.34	0.99

EXPERIMENT 2:

In this experiment coastal image is considered for analysis. These images extract information about water cover and land use scenarios. It also provides data for assessment and analysis of shore line changes, coastal erosion, hydrology, salinity, change detection and potential threats to coastal area. In this experiment, multispectral image is considered which has a panchromatic resolution of 0.5 and multispectral resolution is 4. For our experimental results input images are shown in Fig 3(a) and Fig 3(b). In Fig 3(a), some of the information is lost, but is present in Fig 3(b). In Fig 3(b) some information is not available but is present in Fig 3(a). Hence by fusing Fig 3(a) and Fig 3(b), a complete image is obtained by applying the proposed method. The resulting image is shown in Fig 3(c). The various statistical parameters are compared for different fusion methods. From Table II, it is observed that RMSE is low, Entropy, PSNR and CC is high for the fused image. Table II depicts statistic performance for image shown in Fig 3(a), Fig 3(b) and Fig 3(c). The proposed approach provides 40.5%. 50.1%, 71.9%, 44.81% and 26% improvements when compared to existing schemes in terms of entropy. Therefore the proposed algorithm gives better results for the given image.

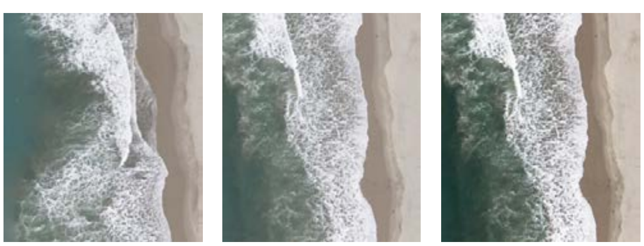

Fig 3: (a) Input Image (b) Input Image (c) Fused image.

Table 2: Statistic results of different fusion methods

Fusion method	Entropy	RMSE	PSNR	CC
Select maximum	6.71	16.15	34.67	0.91
Select Minimum	5.63	17.46	24.88	0.87
Simple Average	3.17	21.12	29.56	0.92
PCA	6.22	23.50	37.55	0.73
Laplacian Method	8.34	24.83	40.44	0.92
Proposed method	11.27	6.47	61.34	0.98

EXPERIMENT 3:

In this experiment remotely sensed image is considered for analysis. This experiment is conducted with same process as that of previous experiment 1 and 2. The image shown in Fig 4(a) is the optical image captured by LISS-111 sensor of ResourceSat-2 satellite which represents coastal image. Hence to get complete information, fusion is performed for Fig 4(a) and Fig 4(b) using proposed method and resulted image is shown in Fig 4(c. From Table III, it is observed that entropy, PSNR and CC is high and RMSE is low for proposed method. Table III depicts statistic performance for image shown in Fig 4(a), Fig 4(b) and Fig 4(c). The proposed approach provides 37.03%, 57%, 67.7%, 43.11% and 49.6% improvements when compared to existing schemes in terms of entropy. Hence the given algorithm works well for the coastal image .

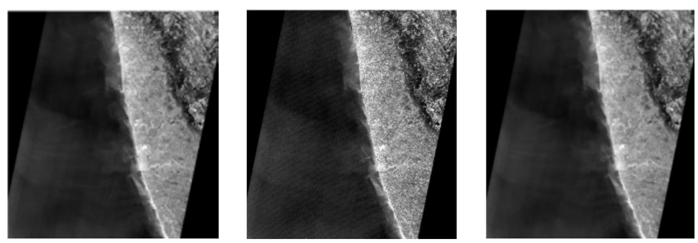

Fig 4: (a) Input Image (b) Input Image (c) Fused image.

Table III: Statistic results of different fusion methods

Fusion method	Entropy	RMSE	PSNR	CC
Select maximum	9.22	14.22	31.12	0.92
Select Minimum	6.30	15.34	29.32	0.89
Simple Average	4.73	21.12	22.56	0.86
PCA	8.33	31.23	33.21	0.85
Laplacian Method	7.36	26.54	37.38	0.89
Proposed method	14.64	11.39	42.12	0.96

The performance comparison of proposed model with other state-of-art techniques in terms of PSNR, RMSE, entropy and CC is shown in Fig 5(a), Fig 5(b), Fig 5(c) and Fig 5(d). It is analyzed that, the proposed model has higher Entropy, PSNR, CC value and lower root mean square error values for the three different set of images. Curve let transform holds the highest value and closer to the unity for correlation coefficient.

In Fig 5(a), the performance comparison is given in terms of entropy, for different test cases of image which is denoted as image index. Proposed approach is compared with state-of-art approaches of image fusion. Results shows that proposed image fusion scheme outperforms when compared to other techniques. Similarly, Fig 5(b), Fig 5(c) and Fig 5(d) show performance in terms of RMSE, PSNR and correlation coefficient. Hence for the given images, the proposed algorithm gives better results in the process of fusion.

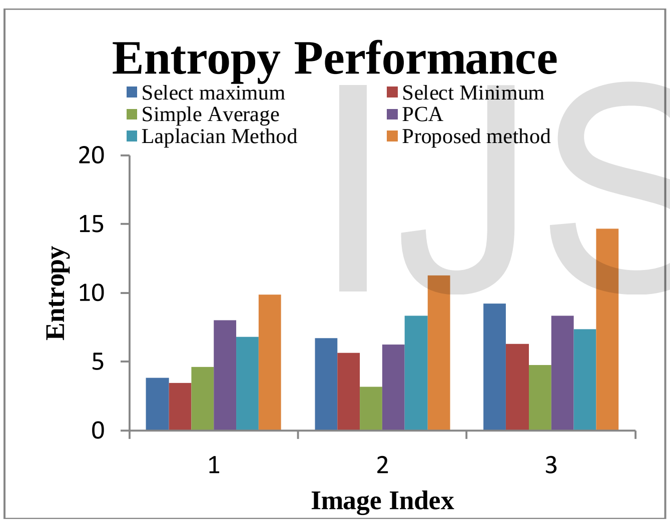

Fig 5: a) Performance comparison of proposed model with other state-of - art techniques in terms of Entropy.

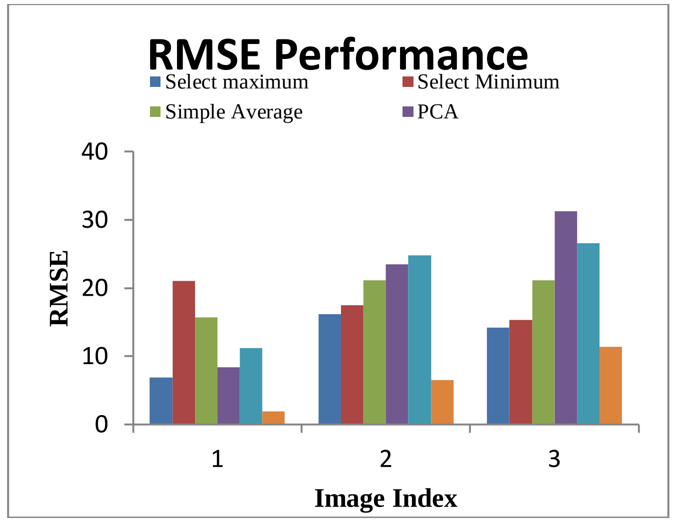

Fig 5: b) Performance comparison of proposed model with other state-of - art techniques in terms of RMSE

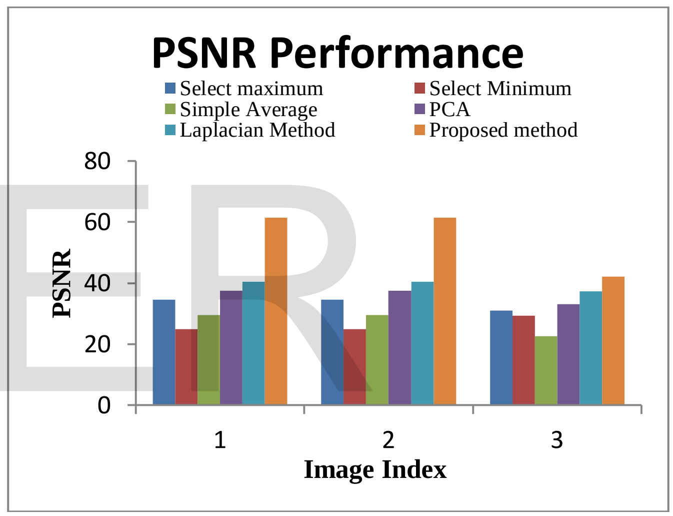

Fig 5: c) Performance comparison of proposed model with other state-of -art techniques in terms of PSNR

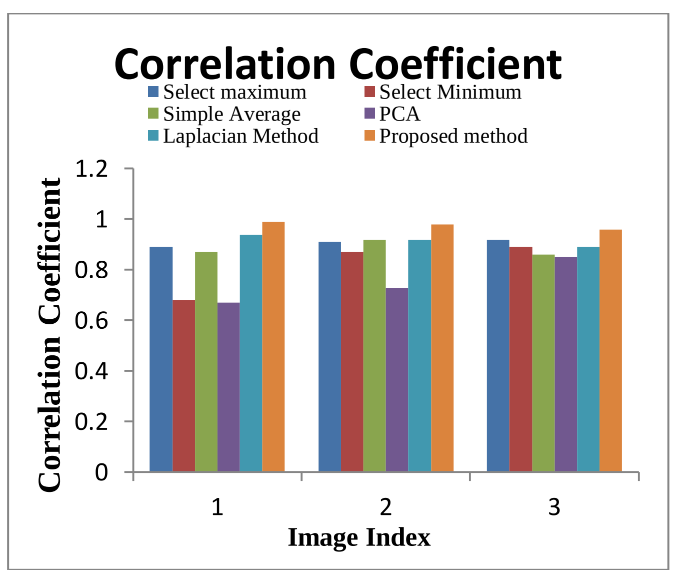

Fig 5: d) Performance comparison of proposed model with other state-of-art techniques in terms of correlation coefficient.

5. CONCLUSION

A novel CWT-based pixel-level satellite image fusion methodology is exhibited in this paper. It effectively enhances fusion results for pictures showing highlights at closest or incidental pixel areas. This system frightfully partitions the investigation channel pair into two elements which are then independently connected to the info image pair. It parts the image deterioration method into two progressive channel operations. The real combination step happens after convolution with the first channel pair. Along these lines, the impact of the coefficient spreading issue, which tends to significantly muddle the element choice procedure, is effectively decreased. This prompts a superior preservation of elements which are found near one another in the info images. Likewise, this methodology leaves space for further changes by exploiting the nonsubsampled way of the CWT, which allows the configuration of non-orthogonal channel banks where both blend channels show just positive coefficients. The experimental result shows that the proposed method is good for fusion as compared on the basis of Entropy, PSNR, RMSE and CC. Hence, the proposed method is effective than with other methods and increases quality of the image

ACKNOWLEDGEMENT

The authors would like to immensely thank to Research and Development Centre of Department of Information Science and Engineering, Bangalore Institute of Technology for providing me an opportunity for carrying my research work. The authors also thank the Management of BIT, Bangalore and Visvesvaraya Technological University (VTU), Belgaum for kind cooperation to carry out my research work.

REFERENCES

[1] YounggiByun; Jaewan Choi; Youkyung Han, "An Area-Based Image Fusion Scheme for the Integration of SAR and Optical Satellite Imagery," in Selected Topics in Applied Earth Observations and Remote Sensing, IEEE Journal of , vol.6, no.5, pp.2212-2220, Oct. 2013

[2] Ferris, M.H.; Blasen, E.; McLaughlin, M., "Extension of no-reference deblurring methods through image fusion," in Applied Imagery Pattern Recognition Workshop (AIPR), 2014 IEEE , vol., no., pp.1-6, 14-16 Oct. 2014

[3] Hossny, M.; Nahavandi, S.; Creighton, D.; Bhatti, A.; Hassan, M., "Image Fusion Metrics: Evolution in a Nutshell," in Computer Modelling and Simulation (UKSim), 2013 UKSim 15th International Conference on , vol., no., pp.443-450, 10-12 April 2013

[4] Prakash, O.; Srivastava, R.; Khare, A., "Biorthogonal wavelet transform based image fusion using absolute maximum fusion rule," in Information & Communication Technologies (ICT), 2013 IEEE Conference on , vol., no., pp.577-582, 11-12 April 2013

[5] Hongli Chen; Zhaohua Huang, "Medical Image Feature Extraction and Fusion Algorithm Based on K-SVD," in P2P, Parallel, Grid, Cloud and Internet Computing (3PGCIC), 2014 Ninth International Conference on , vol., no., pp.333-337, 8-10 Nov. 2014

[6] Junyong Ma; Shengwei Zhang; CaibingYue, "Multi-resolution Image Fusion Algorithm Based on Gradient and Texture Features," in Information Science and Cloud Computing Companion (ISCC-C), 2013 International Conference on , vol., no., pp.623-628, 7-8 Dec. 2013

[8] A. Vesteinsson, H. Aanæs, J.R. Sveinsson, and J.A. Benediktsson. Spectral consistent satellite image fusion: using a high resolution panchromatic and low resolution multi-spectral images. Geoscience and Remote Sensing Symposium, 2005. IGARSS '05. Proceedings. 2005 IEEE International, 4:2834–2837, 2005

[9] Zhang, Y., 2004. Understanding image fusion, Photogrammetric Engineering & Remote Sensing, 70(6), 657–661.

[10] J. Shlens, A Tutorial on Principal Component Analysis, Systems Neurobiology Laboratory, University of California at San Diego, 2005.

[11] C. Proppe, "Multiresolution analysis for stochastic finite element problems with wavelet-based karhunen-loève expansion," Mathematical Problems in Engineering, vol. 2012, Article ID 215109, 15 pages, 2012

[12] P. S. Chavez Jr., S. C. Sides, and J. A. Anderson, "Comparison of three different methods to merge multiresolution and multispectral data:Landsat TM and SPOT panchromatic," Photogrammetric Engineering & Remote Sensing, vol. 57, no. 3, pp. 295–303, 1991.

[13] E. J. Candès and D. L. Donoho, "New tight frames of curvelets and optimal representations of objects with piecewise C2 singularities," Communications on Pure and Applied Mathematics, vol. 57, no. 2, pp. 219–266, 2004. View at Publisher · View at Google Scholar · View at Zentralblatt MATH · View at MathSciNet

[14] E. le Pennec and S. Mallat, "Sparse geometric image representations with bandelets," IEEE Transactions on Image Processing, vol. 14, no. 4, pp. 423–438, 2005. View at Publisher · View at Google Scholar · View at MathSciNet

[15] S. S. Chen, D. L. Donoho, and M. A. Saunders, "Atomic decomposition by basis pursuit," SIAM Review, vol. 43, no. 1, pp. 129–159, 2001

[16] S. G. Mallat and Z. Zhang, "Matching pursuits with time-frequency dictionaries," IEEE Transactions on Signal Processing, vol. 41, no. 12, pp. 3397–3415, 1993.

[17] D. L. Donoho, "Compressed sensing," IEEE Transactions on Information Theory, vol. 52, no. 4, pp. 1289–1306, 2006

[18] E. J. Candès, J. Romberg, and T. Tao, "Robust uncertainty principles: exact signal reconstruction from highly incomplete frequency

ISSN 2229-5518
information," IEEE Transactions on Information Theory, vol. 52, no. 2, pp. 489–509, 2006

[19] Miao, Z.; Shi, W.; Samat, A.; Lisini, G.; Gamba, P., "Information Fusion for Urban Road Extraction From VHR Optical Satellite Images," in Selected Topics in Applied Earth Observations and Remote Sensing, IEEE Journal of , vol.PP, no.99, pp.1-14

[20]Anjali Malviya1, S. G. Bhirud a short paper on 'Image Fusion of Digital Images' in International Journal of Recent Trends in Engineering, Vol 2, No. 3, November 2009 pp. 146-148.

[21] J.-L. Starck, J. Fadili, and F. Murtagh, "The curvelet wavelet decomposition and its reconstruction," IEEE Trans. Image Process., vol. 16, no.2, pp. 297–309, Feb. 2007.

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