International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878, Volume-8 Issue-3, September 2019

Performance of Spatial Frequency Discrete Wavelet Transform Based Remote Sensing Image Fusion Algorithm

Jinju Joy, Santhi N, Sanil Jayamohan, Ramar K

Abstract*: The high sensor cost for producing images with superior spectral and spatial qualities in remote sensing application have led to the development of image fusion algorithms. Image fusion technique combines a Panchromatic image and a Multispectral image with an aim to produce images with excellent spatial and spectral qualities. One of the major factors that affect the performance of any image fusion algorithm is the capability of the algorithm in extracting the spatial and spectral data from the respective images and how effective the so extracted information is blended together. One of the recently developed spectral domain algorithm to perform image fusion in remote sensing applications is Spatial Frequency Discrete Wavelet Transform abbreviated as SFDWT. The excellence of SFDWT image fusion algorithm is already proven better than the prevailing algorithms based on Discrete Wavelet Transform. This paper is coined with an eye to realize the performance of SFDWT based image fusion algorithm with respect to IHS-DWT, which being an enhanced form of a typical DWT based image fusion algorithm. The performance of SFDWT and IHS-DWT based image fusion algorithms will be evaluated by applying both techniques in the fusion of urban images received from Pléiades sensors with 1:4 resolution ratio using qualitative and quantitative image quality assessment methods. The consequence of varying the decomposition level on the quality of the images produced using SFDWT image fusion technique and three variants of IHS-DWT techniques based on substitution, averaging and maximum selection will be also evaluated. From the experimental analysis done using MATLAB simulation, it will be vivid that images obtained using image fusion algorithm based on SFDWT are much better than that obtained using IHS-DWT technique with excellent spatial and spectral qualities.

Keywords: Image Fusion Algorithm, Multispectral Image, Panchromatic Image, Remote Sensing, Spatial Frequency Discrete Wavelet Transform.

Manuscript published on 30 September 2019

* Correspondence Author

Jinju Joy*, Electronics and Communication, Noorul Islam Centre for Higher Education, Kumaracoil, Kanyakumari District, Thuckalay, Tamil Nadu, India. Email: jinjujoy1@gmail.com

Santhi N, Electronics and Communication, Noorul Islam Centre for Higher Education, Kumaracoil, Kanyakumari District, Thuckalay, Tamil Nadu, India. Email: santhiram@yahoo.com

Sanil Jayamohan, Electronics and Communication, Sarabhai Institute of Science and Technology, Vellanad, Trivandrum, India. Email: saniljayamohan@gmail.com

Ramar K, Computer Science, Muthayammal Engineering College (Autonomous), Rasipuram, Namakkal District, Tamil Nadu, India. Email: kramar.einstein@gmail.com

I. INTRODUCTION

In remote sensing, knowledge about an area or an object is achieved without having the need for any physical contact. This is very important as there are many applications where achieving physical contact is nearly impossible. In remote sensing the information gathering is usually done with the help of electronic sensors capable of capturing images. These electronics sensors are kept in satellites or high altitudes aircraft. It is from these obtained images the required information's are extracted. Remote sensing is part of many applications including, surveying, hydrology, meteorology, military, etc.

Resolution is the most important parameter that needs to be addressed while talking about remote sensing sensors. It can be defined as the capability of the sensor to distinguish between two adjacent objects. Thus, higher the resolution smaller the object that can be recognized. Spatial and Spectral resolution are the two types of resolutions that determines the image quality obtained using remote sensing sensors. Spatial resolution indicates the smallest object that can be distinguished while spectral resolution is an indication of the distinguishability in terms of wavelength [1].

Remote sensing sensor can be either an active sensor or a passive sensor. In remote sensing applications there are two sensors which are mainly used. The first sensor is known as the Panchromatic Sensor which is capable of producing high spatial and low spectral resolution images. The images obtained from such sensors are known as Panchromatic images (PAN). The second type of sensors which produces high spectral resolution and low spatial resolution images known as Multispectral Sensors and the images obtained from it as the Multispectral images (MS). PAN images are usually grey images with single band while MS images are color images which extends into different bands. In remote sensing they serve an important role as both contain useful information. There are many applications in remote sensing such as google maps, road extraction, etc. in which images having excellent spatial and spectral resolution are needed.

As aircrafts and satellites are the prime location of remote sensing sensors, certain aspects such as weight, power, bandwidth, cost, etc. come into the picture while designing such sensors.

Even though there are sensors that are capable of producing images with excellent spatial and spectral qualities, because of the limitations mentioned earlier such sensors are seldom used in real world scenarios. These limitations of remote sensing sensors and the eager to get high quality images have led to the concept of image fusion [1].

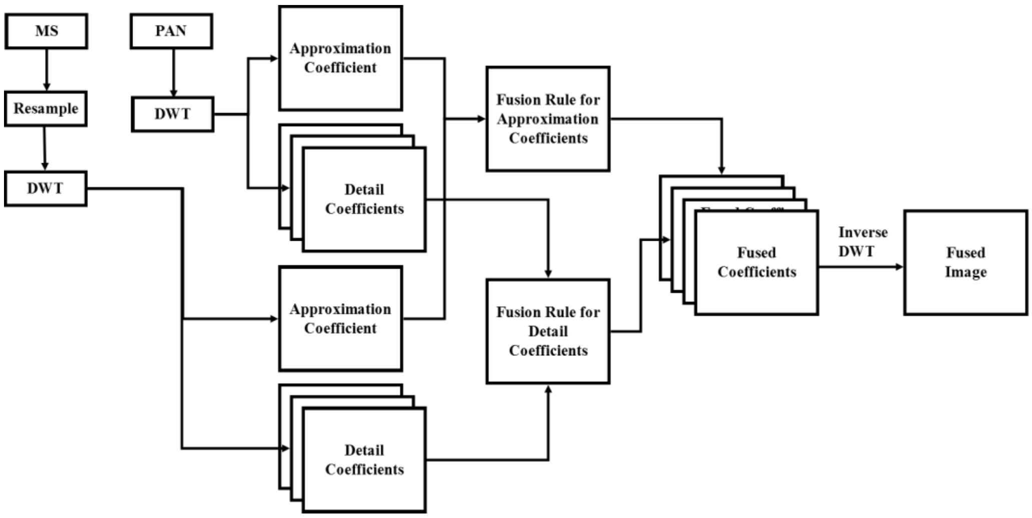

Fig.1. Schematic block diagram representation of Spatial Frequency DWT (SFDWT) Image fusion Algorithm

The technique known as image fusion involves in combining two or more images so as to obtain an image which will have all the qualities of the images that is been fused. Pan sharpening is an example of image fusion technique which involves in the merging of the low spectral resolution panchromatic image and low spatial resolution Multispectral image to obtain the pan sharpened image with superior spatial as well as spectral resolution. This concept of image fusion began to overcome the limitations imposed due to limited resources that are available in the aircraft or satellites.

Thus, image fusion involves in the extraction of useful data contained in the PAN image and inserting into the Multispectral image without introducing any distortion or artifacts. The two challenges faced by engineers while developing remote sensing image fusion algorithms are, information extraction and injection of extracted information onto the other image. Another hurdle is related to how the quality of the so obtained images will be evaluated.

There was an enormous development in connection with image fusion algorithms. Basically, image fusion algorithm is divided into spectral and spatial domain techniques. Pixel level modification is done in the case of spatial domain technique while frequency components are altered in spectral domain methods. Implementation of spatial domain techniques are fairly easy but they do get affected with spectral distortions while spectral domain technique involves much complicated frequency domain techniques.

Most popular spatial domain image fusion techniques belongs to Intensity, Hue and Saturation (IHS) [2] [3], Principal Component Analysis (PCA) [4], etc. As noted earlier one of the disadvantage using spatial domain based techniques is spectral distortion [4] and many remote sensing applications requires good spectral classification. In such applications, image fusion techniques based on spatial domain cannot be made use of and thus the concept of Multiresolution image fusion techniques came into the picture. In multiresolution image fusion techniques, the spatial information enclosed within the PAN image will be inserted into the Multispectral image thereby improving its spatial information.

Two things to be noted here is, how the high frequency information i.e. spatial information of PAN image will be pulled out and how the pulled information will be inserted into the MS image. The commonly used algorithm in multiresolution image fusion are based on wavelet transform. In image fusion techniques based on wavelet transform [5]–[9],[1], the wavelet coefficients of the PAN and MS images are evaluated and they are combined using some fusion rules such as substitution, averaging, maximum selection, etc. Different versions of wavelet transform such as Discrete Wavelet Transform [10], Stationary Wavelet Transform, Curvelet transform, etc. are used. Image fusion algorithm based on Laplacian pyramid [10] is also common when it comes to multiresolution image fusion techniques.

There are certain types of image fusion algorithm which are categorized into spatial and spectral domain image fusion techniques. In this techniques, spatial domain and spectral domain techniques are combined together to obtained images having better quality than that produced individually using spectral and spatial domain image fusion technique. IHS-DWT based image fusion techniques are one such example of this type.

A recent development belonging to spectral domain image fusion techniques is based on the spatial frequency discrete wavelet transform (SFDWT) [11]. In this algorithm, the extraction of data from the PAN and MS image is done by evaluating the DWT coefficients and then the extracted information is fused together based on the spatial frequency of the PAN and MS coefficients. It has been found that this image fusion algorithm produces pan sharpened images with superior quality when compared with that obtained using typical DWT based image fusion technique.

The main objective of this paper is to evaluate the quality of the images obtained using SFDWT image fusion technique with respect to that obtained using IHS-DWT based image fusion technique. When it comes to image fusion techniques using wavelet transform, the level of decomposition at which the algorithm operates is another deciding factor of the image quality. In order to clearly understand the effect of the level of decomposition, SFDWT and IHS-DWT are applied at different levels and quality of the corresponding pan sharpened images are compared to find out the best image fusion algorithm.

The paper is divided into following sections with section 2 explaining the methodology of SFDWT image fusion algorithm, a brief explanation of the different image quality assessment parameter used is given in section 3, Materials used for simulation is given in section 4, results obtained using the image fusion algorithms is presented and discussed in section 5 and section 6 comprehend the conclusion of the paper.

II. METHODOLOGY

Spatial Frequency Discrete Wavelet Transform image fusion algorithm is based on the concepts of Spatial Frequency and Discrete wavelet transform. In this image fusion technique, information extraction from PAN and MS images is done with the help of DWT and the concept of Spatial Frequency [2] is utilized for fusing the extracted information. The schematic block diagram representation of the SFDWT image fusion algorithm extracted from [11] is given in Fig. 1. A general outline of SFDWT image fusion algorithm is given below

1) MS image is resampled to match with the resolution that of PAN Image.
2) DWT coefficient of Multispectral image and Panchromatic image are evaluated.

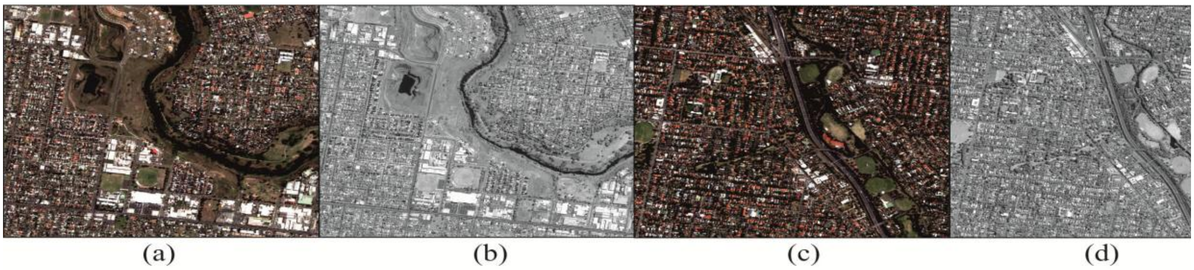

Fig.2. MS & PAN Images: (a) Set 1 - MS Image, (b) Set 1 - PAN Image, (c) Set 2 - MS Image, (d) Set 2 - PAN Image.

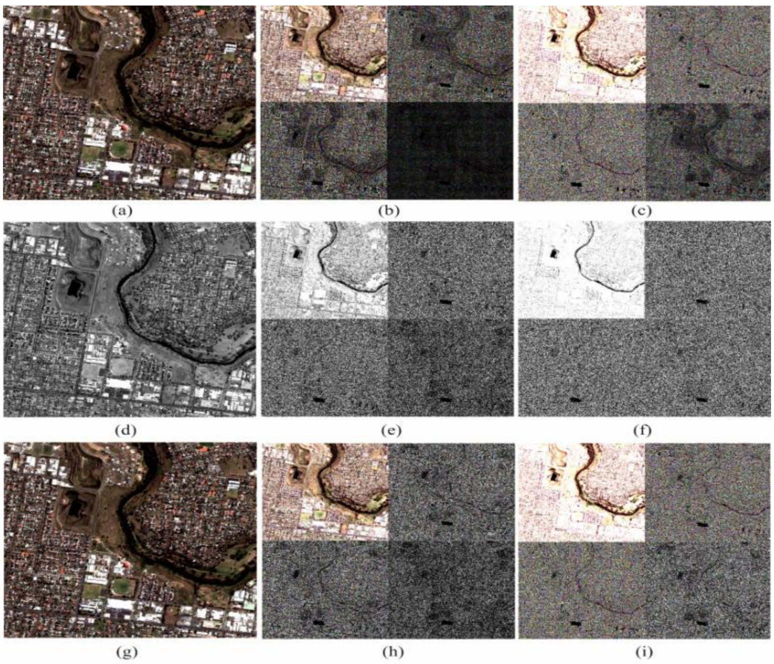

Fig.3. Different stage outputs using SFDWT image fusion algorithm: (a) MS Image, (b) Level 1 – MS DWT Coefficients , (c) Level 2 -MS DWT Coefficients, (d) PAN Image, (e) Level 1 -PAN DWT Coefficients, (f) Level 2 -PAN DWT Coefficients, (g) Fused Image, (h) Level 1 -Merged DWT Coefficients and (i) Level 2 - Merged DWT Coefficients.

Retrieval Number: C6402098319/2019©BEIESP
DOI:10.35940/ijrte.C6402.098319
Journal Website: www.ijrte.org

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

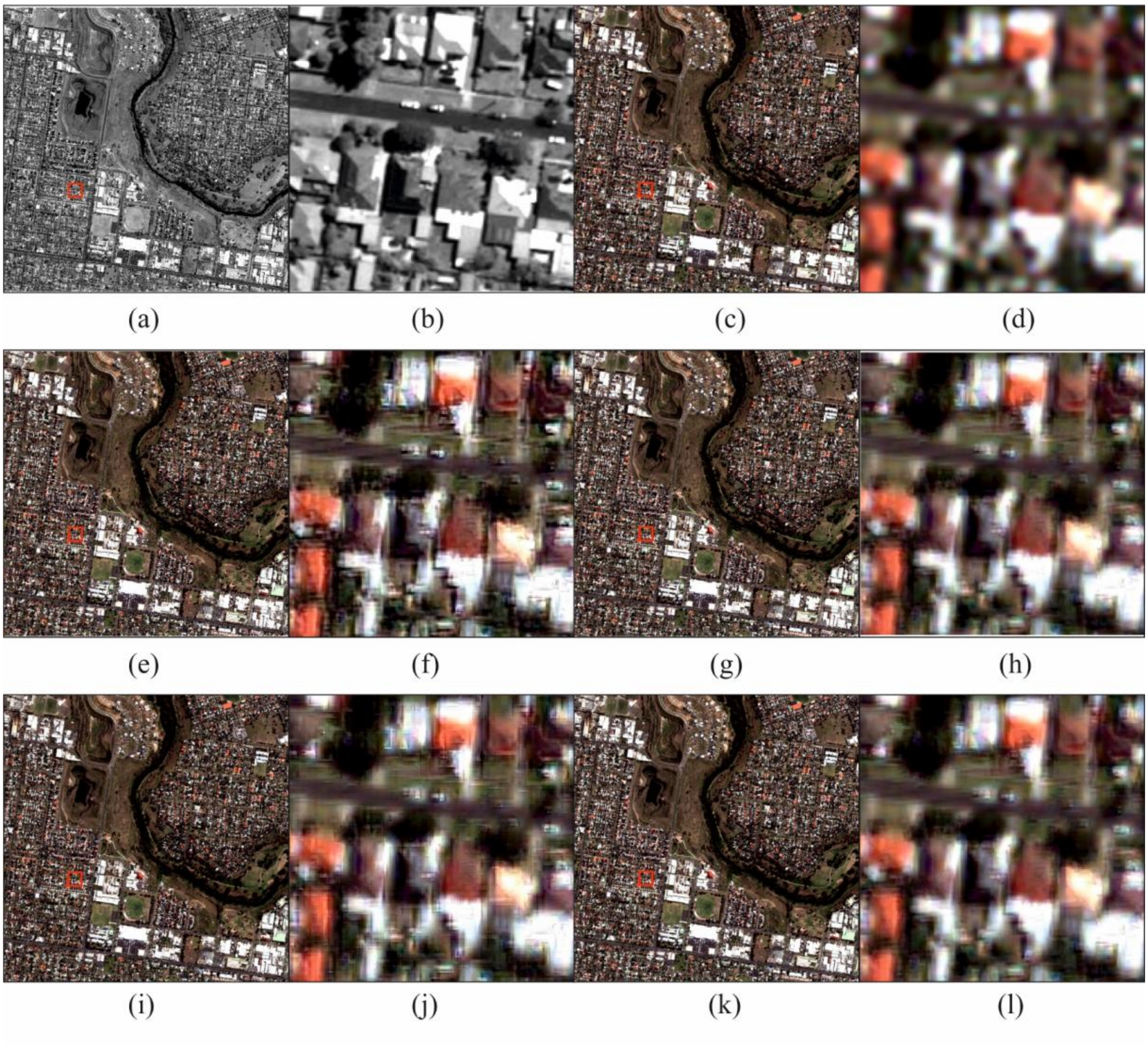

Fig.4. Set 1 Pléiades Original and fused output of (Red box indicates Zoomed portion): (a) PAN, (b) PAN Zoomed Section, (c) MS, (d) MS Zoomed Section, (e) IHS-DWT-S, (f) IHS-DWT-S Zoomed Section, (g) IHS-DWT-A, (h) IHS-DWT-A Zoomed Section, (i) IHS-DWT-MS, (j) IHS-DWT-MS Zoomed Section, (k) SFDWT and (l) SFDWT Zoomed Section.

3) The merged approximation coefficient is obtained by replacing the PAN coefficients with that of MS.
4) Details coefficients of PAN and MS images are merged with the help of the spatial frequency fusion rule.
5) Inverse DWT is taken to get the merged pan sharpened image.

The detailed explanation of the algorithm is well versed in [11], hence not included in this paper.

III. IMAGE QUALITY ASSESSMENT

Evaluating the quality [12] of the fused image is very important as it is a clear indication of the quality of the image fusion algorithm. There are two types of image quality assessment techniques namely qualitative and quantitative. The qualitative assessment method is also known as a subjective method, here the quality of the images is evaluated by visual interpretation and ranking of the images by comparing fused and reference pan sharpened images. On the other hand, quantitative image quality assessment [13] involves in the evaluation of spectral and spatial qualities in terms of some quality metrics. Availability of the reference pan sharpened image determines the type of quality metrics used.

In this paper, the quality of the fused image is evaluated qualitatively and quantitively. SFDWT and IHS-DWT image fusion algorithms will be applied where a pan sharpened image is available from the sensor. In this paper a total of nine image quality assessment metrics is made use of for evaluating the quality of the fused image. The details of the reference and non-reference [14] image quality assessment metrics are given below.

1)Edge Stability mean square error (ESMSE) [15]

High frequency information of an image is usually represented as Edges. Many remote sensing applications need good edge consistency between the reference pan sharpened and fused images. ESMSE is a clear indication of how good the edges are preserved in the fused image. ESMSE is defined as

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

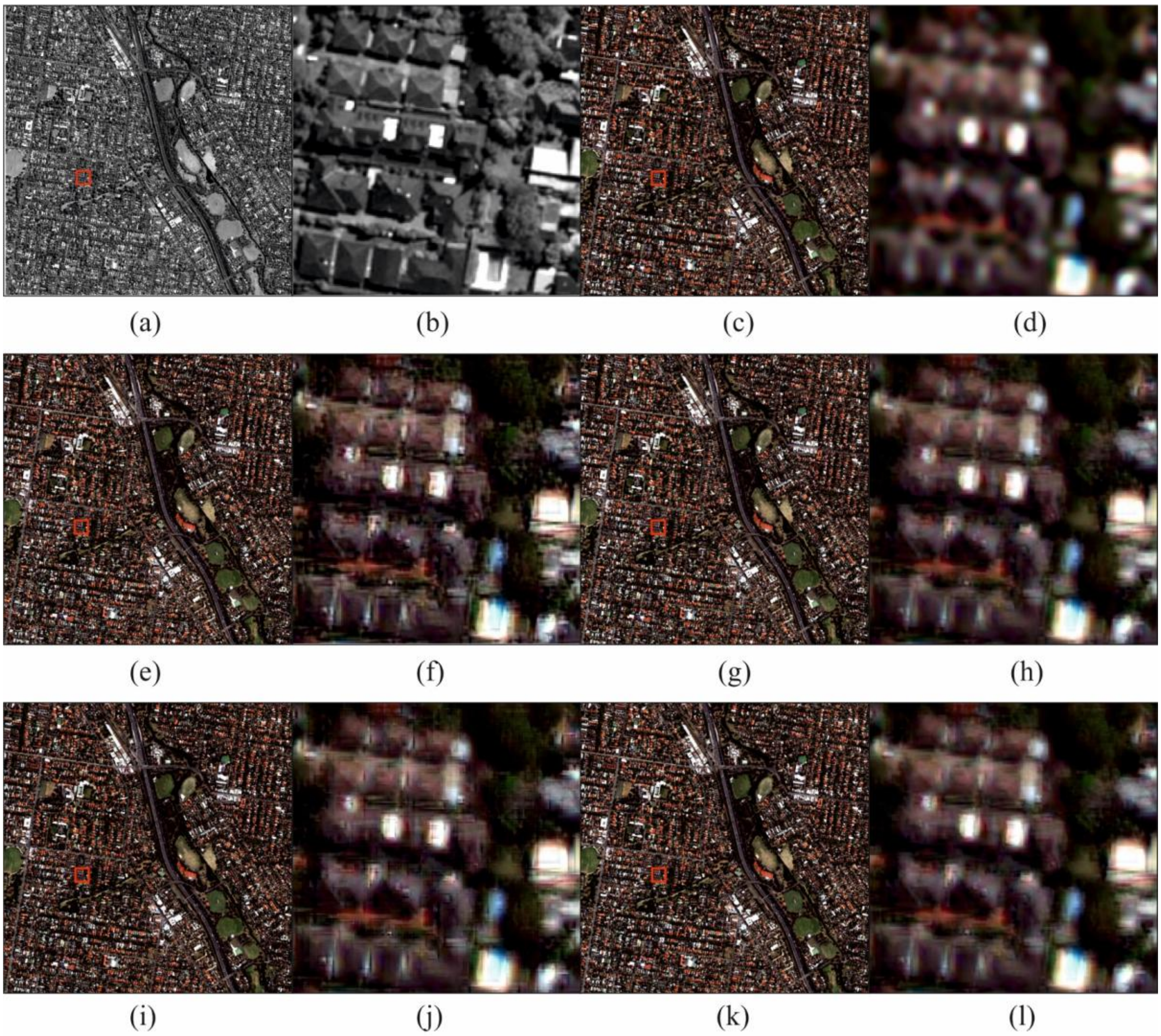

Fig.5. Set 2 Pléiades Original and fused output of (Red box indicates Zoomed portion): (a) PAN, (b) PAN Zoomed Section, (c) MS, (d) MS Zoomed Section, (e) IHS-DWT-S, (f) IHS-DWT-S Zoomed Section, (g) IHS-DWT-A, (h) IHS-DWT-A Zoomed Section, (i) IHS-DWT-MS, (j) IHS-DWT-MS Zoomed Section, (k) SFDWT and (l) SFDWT Zoomed Section.

$$ESMSE = \frac{1}{N_{SB}} \sum (Ed_{ref} - Ed_{fus})^2 \qquad (1)$$

The edge maps of fused (I_{fus}) and reference (I_{ref}) images are denoted as Ed_{fus}, Ed_{ref} respectively and the number of spectral bands associated with the image is denoted as N_{SB}.

2) Root Mean square error (RMSE) [16]
It is the most commonly used metric to indicate the error between the fused and reference images. Root mean square error between the images is defined as

$$RMSE = \sqrt{\frac{1}{XY} \sum_{i=1}^{X} \sum_{j=1}^{Y} (\mathrm{I}_{ref}(i,j) - \mathrm{I}_{fus}(i,j))^2} \qquad (2)$$

Horizontal and Vertical dimension of the image is given by X, Y. The corresponding row and column indexes are denoted by i & j respectively. $\mathrm{I}_{ref}(i,j), \mathrm{I}_{fus}(i,j)$ indicates the $(i,j)^{th}$ pixel of the reference and fused images. As RMSE indicates the error between the fused and reference images, a lower value will be well appreciated.

3) Peak Signal to Noise Ratio (PNSR) [13]
Another commonly used metric is peak signal to noise ratio, which is a dimensionless metric being a ratio. A higher value indicates less noise content in the fused image. PSNR is mathematically represented as

$$PSNR(dB) = 20 \log \frac{255}{\sqrt{\frac{1}{XY} \sum_{i=1}^{X} \sum_{j=1}^{Y} \mathrm{I}_{ref}(i,j) - \mathrm{I}_{fus}(i,j)^2}} \qquad (3)$$

where $\mathrm{I}_{ref}(i,j), \mathrm{I}_{fus}(i,j)$

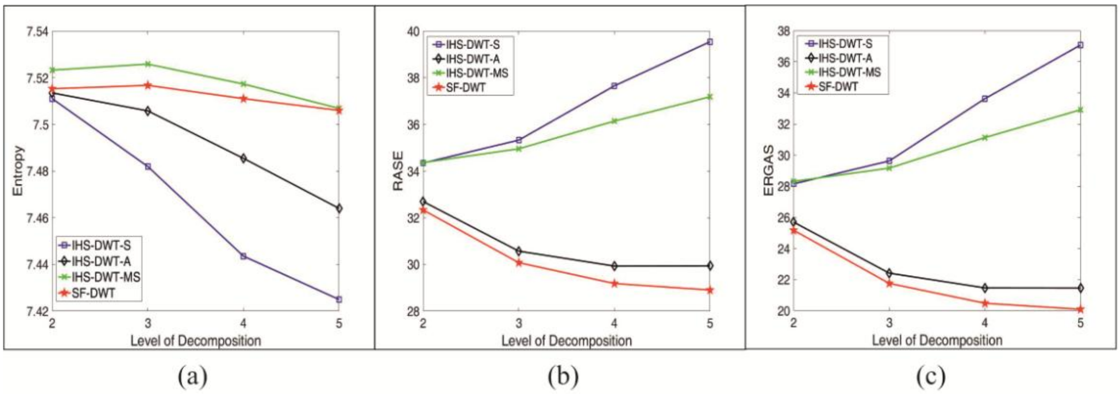

Fig.6. Image Quality Assessment parameters vs decomposition levels of SFDWT and different versions of IHS-DWT image fusion algorithm applied to Set 1 Image: (a) Entropy, (b) RASE and (c) ERGAS.

represents the $(i, j)^{th}$ pixel value of reference and fused images having X, Y dimension.

4) Structural similarity measure (SSIM) [13]
This image quality assessment metric shows the structural similarity between the fused and reference images. SSIM is a better metric than PSNR as it directly indicates the structural quality. SSIM is given by

$$SSIM = \frac{2(\mu_{ref}\mu_{fus})(2\sigma_{ref-fus})}{(\mu^2_{ref}+\mu^2_{fus})(\sigma^2_{ref}+\sigma^2_{fus})} \quad (4)$$

where the mean and variance of the reference and the fused image is denoted as $\mu_{ref}, \mu_{fus}, \sigma^2_{ref}, \sigma^2_{fus}$ respectively. The covariance between the reference and fused images is given by $\sigma_{ref-fus}$.
A value closer to unity indicates both reference image and fused image are identical.

5) Errur Relative Globale Adimensionnelle de Synthese (ERGAS) [17], [18]
ERGAS represents the relative global dimensional synthesis error between the fused and reference images. Being an error, a lower value indicates a better similarity between the images. ERGAS is mathematically defined as

$$ERGAS = \frac{100}{M_{res}}\sqrt{\frac{1}{N_{SB}}\sum_{i=1}^{N_{SB}}\left(\frac{RMSE(\mathrm{I}_{ref}(i), \mathrm{I}_{fus}(i))}{\mu(\mathrm{I}_{ref})}\right)^2} \quad (5)$$

M_{res} denotes the ratio of the resolution of PAN image and MS image, RMSE gives the root mean square error, N_{SB} is the number of spectral bands of the images, $\mu(\mathrm{I}_{ref})$ gives the mean value of the reference image.

6) Correlation Coefficient (CC) [17]
Correlation Coefficient gives the correlation between the fused image and the reference image. CC value of unity indicates both images are same and a lower value indicates poor image fusion. CC is represented mathematically as

$$CC = \frac{\sum_{i,j}(\mathrm{I}_{fus}(i,j)-\bar{\mathrm{I}}_{fus})(\mathrm{I}_{ref}(i,j)-\bar{\mathrm{I}}_{ref})}{\sqrt{\sum_{i,j}(\mathrm{I}_{fus}(i,j)-\bar{\mathrm{I}}_{fus})^2(\mathrm{I}_{ref}(i,j)-\bar{\mathrm{I}}_{ref})^2}} \quad (6)$$

where $(i, j)^{th}$ pixel values of the reference and fused images is represented as $\mathrm{I}_{ref}(i, j), \mathrm{I}_{fus}(i, j)$ and $\bar{\mathrm{I}}_{ref}, \bar{\mathrm{I}}_{fus}$ denotes the mean value of the reference image and fused image.

Image quality assessment metrics given in (1) to (6) gives the reference image quality assessment metrics used in this paper for evaluating the quality of the fused image. The non-reference image quality metrics are mentioned below, which doesn't need a reference pan sharpened image for its evaluation.

7) Relative Average Spectral Error (RASE) [17]
It is another metric that can be used to find out the global spectral quality of the fused image. A lower value indicates better performance. RASE of a fused image I_{fus} is calculated as follows

$$RASE = \frac{100}{M_{Rad}}\sqrt{\frac{1}{N_{SB}}\sum_{i=1}^{N_{SB}}RMSE^2(\mathbf{B}i)} \quad (7)$$

where $M_{Rad}, N_{SB}, \mathbf{B}i$ denotes the mean radiance, number of spectral bands and the i^{th} spectral band of Multispectral image.

8) Standard Deviation (SD) [19]
The contrast of an image can be found out by evaluating the standard deviation of the image. A low value of the standard deviation indicates good spectral quality.

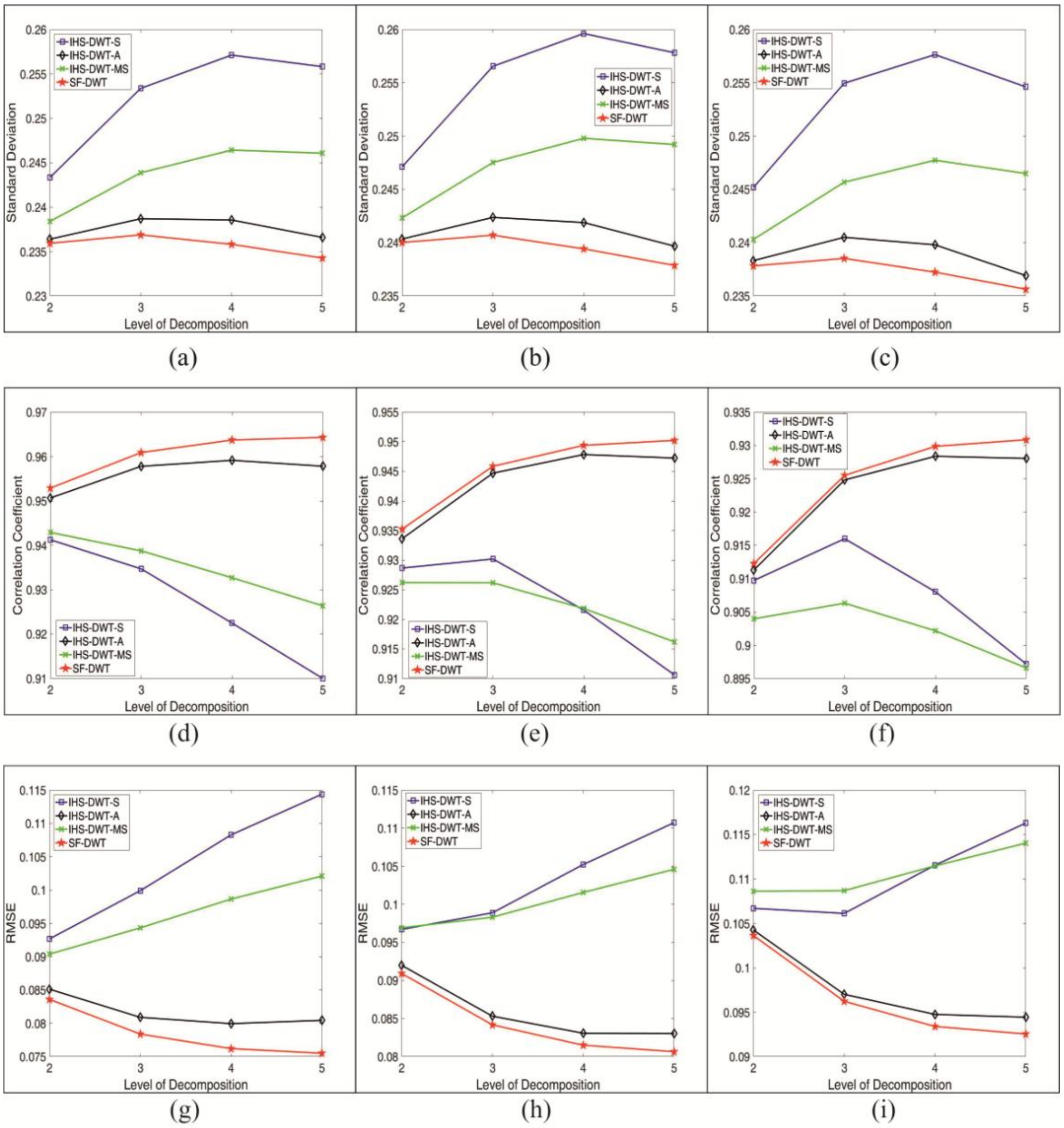

Fig.7. Image Quality Assessment parameters vs decomposition levels of SF-DWT and different versions of IHS-DWT image fusion algorithm applied to Set 1 Image (a) Standard Deviation-Red band, (b) Standard Deviation-Green band, (c) Standard Deviation-Blue band, (d)Correlation Coefficient-Red band, (e) Correlation Coefficient- Green band, (f) Correlation Coefficient-Blue band, (g)Root Mean Square Error-Red band, (h) Root Mean Square Error -Green band and (i) Root Mean Square Error -Blue band.

$$SD = \sqrt{\frac{1}{XY}\sum_{j=0}^{Y-1}\sum_{i=1}^{X-1}\left[\mathrm{I}_{fus}(i,\mathrm{j}) - \overline{\mathrm{U}}\right]} \qquad (8)$$

where

$\overline{\mathrm{U}} = \frac{1}{XY}\sum_{j=0}^{Y-1}\sum_{i=0}^{X-1}\left|\mathrm{I}_{fus}(i,j)\right|$ denotes the mean value of the fused image.

9) Entropy (E) [19]

The information content of an image is indicated using the metric Entropy. Higher the entropy value higher will be the information content.

The entropy of an image is given as

$$E = \sum_{i=0}^{G_L} pr_i \log_2 pr_i \qquad (9)$$

IV. MATERIALS

The quality of SFDWT image fusion algorithm is evaluated using the experimental analysis which is done by making use of the images obtained from the sensors kept in the French-Italian ORFEO program satellite. The Pléiades sensors are capable of producing PAN, MS and Pan sharpened images. The Multispectral Pléiades sensor is able to achieve a resolution of 2m with 4 spectral bands including Red, Green, Blue and Near infrared. In this paper, the RGB

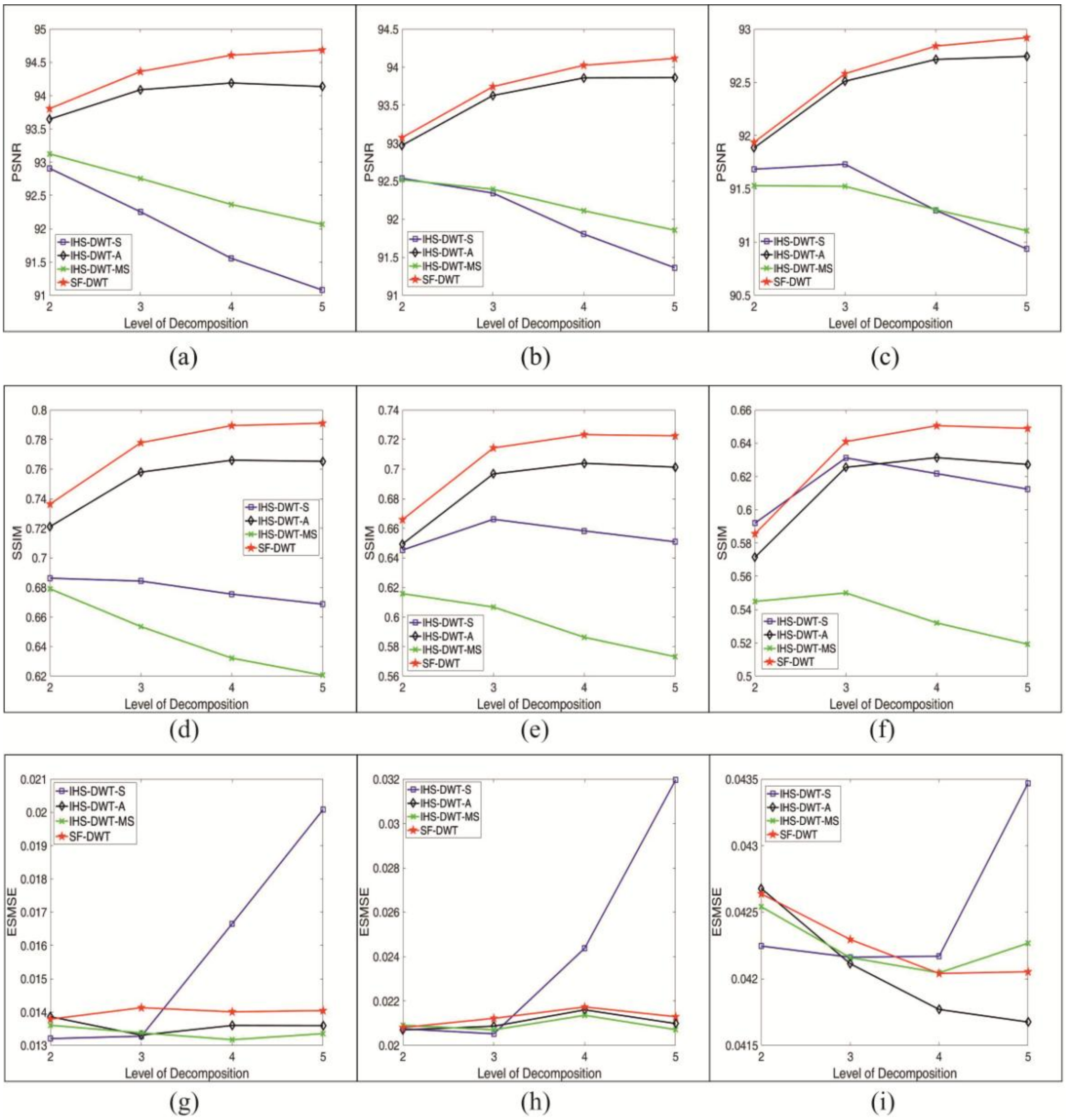

Fig.8. Image Quality Assessment parameters vs decomposition levels of SF-DWT and different versions of IHS-DWT image fusion algorithm applied to Set 1 Image: (a) Peak Signal to Noise Ratio -Red band, (b) Peak Signal to Noise Ratio -Green band, (c) Peak Signal to Noise Ratio -Blue band, (d)Structural Similarity Measure -Red band, (e) Structural Similarity Measure -Green band, (f) Structural Similarity Measure -Blue band, (g)Edge Stability MSE-Red band, (h) Edge Stability MSE –Green band and (i) Edge Stability MSE –Blue band.

spectral bands of the MS image are being utilized for the experimental analysis. The Panchromatic Pléiades sensor has the capability of producing high spatial resolution images with resolution of as high as 50cm. An attracting feature of sensors kept in Pléiades satellite is that it is also capable of producing pan sharpened images with resolution of 50cm.

As the resolution of both PAN and MS images are very large and due to the hardware limitations, SFDWT and IHS-DWT image fusion algorithm will be applied only to a portion of the actual imagery obtained from the satellite. The resolution ratio between PAN image and MS image is kept at 1:4. In this paper a PAN image with resolution of 4096 X 4096 and MS image with resolution of 1024 X 1024 will be considered for the analysis.

As SFDWT uses spatial frequency (measure of high frequency contents) evaluation of the PAN and MS image components for fusion, to test the performance of the image fusion algorithm Urban images with buildings, roads, green patches of land are utilized.

As the resolution of MS image and PAN image is different, the first step before applying the image fusion algorithms includes resampling of MS image using lanczos3 interpolation technique [20] to a factor of 4. The interpolated Multispectral image and the Panchromatic image will be given to SFDWT image fusion method, IHS-DWT image fusion technique based on different fusion rules like substitution (IHS-DWT-S), averaging (IHS-DWT-A) and maximum selection (IHS-DWT-MS).

Table- II: Comparison of SFDWT, IHS-DWT-S, IHS-DWT-A, IHS-DWT-MS Image Fusion Algorithm with respect to Standard Deviation, Correlation Coefficient & Root Mean Square Error.

Algorithm	Standard Deviation			Correlation Coefficient			Root Mean Square Error		
	Red Band	*Green Band*	*Blue Band*	*Red Band*	*Green Band*	*Blue Band*	*Red Band*	*Green Band*	*Blue Band*
Set 1 Image									
SFDWT	0.2368	0.2407	0.2385	**0.9608**	**0.9458**	**0.9255**	**0.0783**	**0.0841**	**0.0962**
IHS-DWT-S	**0.2533**	**0.2565**	**0.2549**	0.9346	0.9301	0.9159	0.8842	0.0988	0.1061
IHS-DWT-A	0.2387	0.2423	0.2405	0.9577	0.9446	0.9248	0.0808	0.0853	0.0970
IHS-DWT-MS	0.2438	0.2475	0.2456	0.9387	0.9261	0.9063	0.0943	0.0983	0.1086
Set 2 Image									
SFDWT	0.2276	0.2130	0.2089	**0.9591**	**0.9364**	**0.9098**	**0.0735**	**0.0778**	**0.0904**
IHS-DWT-S	**0.2428**	**0.2290**	**0.2247**	0.9343	0.9196	0.8996	0.0938	0.0919	0.0996
IHS-DWT-A	0.2283	0.2137	0.2094	0.9556	0.9339	0.9064	0.0761	0.0794	0.0921
IHS-DWT-MS	0.2338	0.2197	0.2154	0.9356	0.9118	0.8842	0.0898	0.0927	0.1037

V. zRESULTS AND DISCUSSIONS

This section includes the experimental analysis of SFDWT and IHS-DWT image fusion algorithms. The experimental analysis is done using two separate sets of images obtained from Pléiades sensor cropped to a resolution of 4096 X 4096 PAN image and 1024 X 1024 MS image. Second level SFDWT and IHS-DWT image fusion is done and the fused image will be evaluated for quality using both quantitative and qualitative image quality assessment techniques. The two sets of images that are used for the experimental analysis is given in Fig, 2 (a), (b), (c) & (d). The output obtained at different levels of decomposition in the case of first set of images is given in Fig. 3.

A. Qualitative Image Quality Assessment

The quality of the fused image obtained using SFDWT and IHS-DWT image fusion algorithm can be visually interpreted using Fig. 4 & 5. Fig. 4 & 5 shows the results obtained using the image fusion algorithms for the two sets of images given in Fig. 2. The entire image and zoomed version of a portion of the image are given in Fig. 4 & 5 for visual evaluation. From the figures it can be clearly seen that the fused image obtained using SFDWT image fusion technique is much better than that obtained using different versions of IHS-DWT image fusion technique.

Table- I: Comparison of SFDWT, IHS-DWT-S, IHS-DWT-A, IHS-DWT-MS Image Fusion Algorithm with respect to Entropy, RASE & ERGAS.

Algorithm	Metrics		
	Entropy	*RASE*	*ERGAS*
Set 1 Image			
SFDWT	**7.5267**	**30.0783**	**21.7548**
IHS-DWT-S	7.4819	35.3276	29.6258
IHS-DWT-A	7.5058	30.5720	22.4132
IHS-DWT-MS	7.5258	34.9570	29.1632
Set 2 Image			
SFDWT	**7.3794**	**38.0697**	**29.6556**
IHS-DWT-S	7.3305	44.7925	40.4994
IHS-DWT-A	7.3779	38.9760	31.0350
IHS-DWT-MS	7.3740	44.9830	41.0770

B. Quantitative Image Quality Assessment

In order to overcome the disadvantages of qualitative image quality assessment technique, a total of nine objective image quality assessment metrics given in section 3 is evaluated for the two set of images and the performance of SFDWT is compared with that of IHS-DWT image fusion algorithms. Tables 1-3 indicates the metric values obtained and the best value is bolded for easy interpretation.

Table I shows the performance of SFDWT and other variants of IHS-DWT image fusion algorithm in terms of image quality assessment metrics entropy, RASE, & ERGAS. From the table, it is clear that entropy of the fused image using SFDWT is 7.5267 & 7.3794 for set 1 & 2 images respectively which is better than that obtained using IHS-DWT image fusion techniques. The least entropy is obtained in the case of image fused using IHS-DWT-S image fusion technique with a value of 7.4819 & 7.3305. RASE and ERGAS as mentioned in section 3 are errors and hence a low value indicates better performance. RASE and ERGAS obtained using SFDWT are 30.0783 & 21.7548 in the case of first set of images and for second of image the corresponding values are 38.0697 & 29.6556. When comparing with other algorithm IHS-DWT-S has produced images with highest RASE and ERGAS in the first set while for the second set IHS-DWT-MS has the maximum error. Among the three variants of IHS-DWT image fusion algorithms the best variant in terms of lower RASE and ERGAS is IHS-DWT based on averaging.

Following conclusion can be drawn from Table 1, SFDWT was able to produce fused images with better entropy, i.e. the information content and with less RASE and ERGAS. The same performance was observed in the two sets of urban images simulated which shows the consistency of the algorithm.

Table II gives the performance of the image fusion algorithms with respect to the image quality assessment parameters standard deviation

Table- III: Comparison of SFDWT, IHS-DWT-S, IHS-DWT-A, IHS-DWT-MS Image Fusion Algorithm with respect to Peak Signal to Noise Ratio, Structural Similarity Measure & Edge Stability Mean Square Error.

Algorithm	Peak Signal to Noise Ratio			Structural Similarity Measure			Edge Stability Mean Square Error		
	Red Band	*Green Band*	*Blue Band*	*Red Band*	*Green Band*	*Blue Band*	*Red Band*	*Green Band*	*Blue Band*
Set 1 Image									
SFDWT	**94.3622**	**93.7436**	**92.5809**	**0.7778**	**0.7142**	**0.6409**	0.0141	0.0212	0.0422
IHS-DWT-S	92.2548	92.3437	91.7307	0.6842	0.7579	0.6534	**0.0132**	**0.0205**	**0.0421**
IHS-DWT-A	94.0883	93.6270	92.5104	0.6660	0.6967	0.6067	0.0133	0.0208	**0.0421**
IHS-DWT-MS	92.7544	92.3943	91.5235	0.6311	0.6255	0.5500	0.6534	0.6067	0.5500
Set 2 Image									
SFDWT	**94.9108**	**94.4260**	**93.1218**	**0.7666**	**0.6837**	**0.5981**	**0.0090**	0.0205	0.0362
IHS-DWT-S	92.7965	92.9725	92.2801	0.6766	0.6365	0.5853	0.0096	0.0202	0.0362
IHS-DWT-A	94.6194	94.2494	92.9553	0.7465	0.6626	0.5775	**0.0090**	0.0202	0.0362
IHS-DWT-MS	93.1761	92.9050	91.9286	0.6400	0.5715	0.5034	0.0096	**0.0201**	**0.0361**

(SD), correlation coefficient (CC), and root mean square error (RMSE). These parameters are calculated for each spectral band separately namely Red, Green and Blue spectral band. As defined in section 3, standard deviation indicates the overall contrast of the image and SFDWT being a spectral domain image fusion algorithm, SD value is the least among the algorithms as expected. That is, it shows that the spectral quality of the fused image is better than that of the other algorithms. It can be noted from table II that the SD of images obtained using SFDWT technique in Red, Green and Blue bands are 0.2368, 0.2407 & 0.2385 for set 1 image and 0.2276, 0.2130 & 0.2089 for set 2 images. These SD values obtained is the least among the algorithms. The best algorithm when it comes to standard deviation is IHS-DWT-S, which was able to achieve a SD values of 0.2533, 0.2565 & 0.2549 for set 1 and 0.2428, 0.2290 & 0.2247 for set 2 images in Red, Green & Blue spectral bands respectively. While correlation coefficient which clearly indicates the similarity between the reference and fused image is found to be better in the case of images obtained using SFDWT image fusion algorithm. CC of 0.9608,0.9458 & 0.9255 is obtained in the case of first set of images in Red, Green and Blue spectral bands. For the second image the correlation coefficient values are 0.9591, 0.9364 & 0.9098. Mixed behavior is seen in the case of all the three variants of IHS-DWT image fusion algorithm. Similarly, the root mean square error in the case of SFDWT is 0.0783,0.0841 & 0.0962 for Set 1 image is also the least.

Thus, it can be concluded that the performance of SFDWT is better than other algorithms in terms of SD, CC, and RMSE. The same behavior is seen for both sets of images used for the experimental analysis.

Table III belongs to metrics PSNR, SSIM & ESMSE. PSNR and SSIM of the fused image using SFDWT are better than others. SSIM which directly shows the structural quality of the images is closer to unity in the SFDWT which indicates that the reference pan sharpened and fused images are very close to each other. However, when it comes to ESMSE images obtained using IHS-DWT-S and IHS-SWTA slightly outperforms than that obtained using SFDWT. Similar performance is obtained for both set of images.

Thus, from Table I, II & III, it can be concluded that SFDWT image fusion algorithm is able to produce fused images with better spatial and spectral quality than that obtained using IHS-DWT based image fusion algorithms.

Another important parameter that affects the performance of any spectral domain-based image fusion algorithm is the level of decomposition at which extraction and fusion take place. In order to study the effect of level of decomposition, the level of decomposition is varied from level 2 to level 5 and corresponding all nine image quality assessment parameters are evaluated and plotted. Fig. 6, 7 & 8 shows the performance of different parameters with respect to the different level of decompositions.

Fig. 6 shows the variation of performance metrics entropy, RASE, and ERGAS. From Fig. it is clear that as the level of decomposition increases, the entropy, RASE and ERGAS of the fused image is also improved. In all the three metrics the least performance is seen in the case of IHS-DWT-S image fusion algorithm. Fig. 7 indicates the performance of image fusion algorithms in terms of SD, CC & RMSE. Here also a similar performance as expected can be seen. SFDWT becomes better and better as the level of decomposition is increased. IHS-DWT-S is found to be the worst image fusion algorithm with least value for all the performance metrics. Fig. 8 gives the metrics PSNR, SSIM & ESMSE. In the case of SSIM metric IHS-DWT-MS is observed to give least value while SFDWT is the best. But in the case of ESMSE as the level of decomposition increases SFDWT, IHS-DWT-MS, IHS-DWT-A offer close performance while the metric obtained using IHS-DWT-S becomes worst among all other image fusion algorithms.

Fig. 6, 7 & 8 can be utilized to conclude that the quality of the fused image obtained using SFDWT image fusion algorithm is much better than that obtained using IHS-DWT based image fusion algorithm and at the same time as the level of decomposition increases the performance of SFDWT is even better.

VI. CONCLUSION

Image fusion is an important step in any remote sensing applications. In this how effective the information can be extracted and fused together determines the performance of the image fusion algorithm. Spatial Frequency Discrete Wavelet Transform image fusion algorithm is an improved version of DWT image fusion algorithm utilizing the concept of spatial frequency. The performance of SFDWT based image fusion algorithm is compared with that of IHS-DWT based image fusion algorithms. The quality of the fused image is evaluated qualitatively and using nine quantitative image quality assessment parameters. From the experimental analysis, it is clear that images obtained using SFDWT image fusion algorithm outperforms other algorithms.

ACKNOWLEDGMENT

The authors would like to express their gratitude towards the Editor in Chief and reviewers of this journal for their constructive feedback on the paper. The authors would also like to thank Noorul Islam Centre for higher education for providing the facilities.

REFERENCES

1. L. Fonseca, L. Namikawa, E. Castejon, L. Carvalho, C. Pinho, and A. Pagamisse, "Image Fusion for Remote Sensing Applications," Image Fusion Its Appl., pp. 153–178, 2011.
2. B. Deng, H. Guo, C. Wang, and Y. Nie, "A comparison study on SPOT5 image fusion and quality assessment," in Proceedings of SPIE, 2009, vol. 7146, pp. 714618-1-714618–8.
3. M. Chikr El-Mezouar, N. Taleb, K. Kpalma, and J. Ronsin, "An IHS-Based Fusion for Color Distortion Reduction and Vegetation Enhancement in IKONOS Imagery," IEEE Trans. Geosci. Remote Sens., vol. 49, no. 5, pp. 1590–1602, May 2011.
4. M. Gonzalez-Audicana, J. L. Saleta, R. G. Catalan, and R. Garcia, "Fusion of multispectral and panchromatic images using improved IHS and PCA mergers based on wavelet decomposition," IEEE Trans. Geosci. Remote Sens., vol. 42, no. 6, pp. 1291–1299, Jun. 2004.
5. F. Palsson, J. R. Sveinsson, M. O. Ulfarsson, and J. A. Benediktsson, "Model-Based Fusion of Multi- and Hyperspectral Images Using PCA and Wavelets," IEEE Trans. Geosci. Remote Sens., vol. 53, no. 5, pp. 2652–2663, 2015.
6. S. Singh and M. V Patil, "Multi Focus Image Fusion Based on Spatial Frequency and Contrast Based Analysis under Stationary Wavelet Transform Domain," Int. J. Sci. Eng. Res., vol. 7, no. 5, pp. 225–230, 2016.
7. Y. Kim, C. Lee, D. Han, Y. Kim, and Y. Kim, "Improved Additive-Wavelet Image Fusion," IEEE Geosci. Remote Sens. Lett., vol. 8, no. 2, pp. 263–267, 2011.
8. M. Ghahremani and H. Ghassemian, "Remote Sensing Image Fusion Using Ripplet Transform and Compressed Sensing," IEEE Geosci. Remote Sens. Lett., vol. 12, no. 3, pp. 502–506, 2015.
9. X. Luping, G. Guorong, and F. Dongzhu, "Multi-focus image fusion based on non-subsampled shearlet transform," IET Image Process., vol. 7, no. 6, pp. 633–639, 2013.
10. H. O. S. Mishra and S. Bhatnagar, "Survey on Different Image Fusion Techniques," Int. J. Sci. Eng. Res., vol. 5, no. 2, pp. 167–172, 2014.
11. J. Jinju, N. Santhi, K. Ramar, and B. Sathya Bama, "Spatial frequency discrete wavelet transform image fusion technique for remote sensing applications," Eng. Sci. Technol. an Int. J., vol. 22, no. 3, pp. 715–726, Jun. 2019.
12. J. Marcello, A. Medina, and F. Eugenio, "Evaluation of Spatial and Spectral Effectiveness of Pixel-Level Fusion Techniques," IEEE Geosci. Remote Sens. Lett., vol. 10, no. 3, pp. 432–436, May 2013.
13. V. P. S. Naidu and J. R. Raol, "Pixel-level Image Fusion using Wavelets and Principal Component Analysis," Def. Sci. J., vol. 58, no. 3, pp. 338–352, 2008.
14. G. Vivone et al., "A Critical Comparison Among Pansharpening Algorithms," IEEE Trans. Geosci. Remote Sens., vol. 53, no. 5, pp. 2565–2586, 2015.
15. I. Avcıbas, B. Sankur, and K. Sayood, "Statistical evaluation of image quality measures," J. Electron. Imaging, vol. 11, no. 2, pp. 206–223, 2002.
16. Y. Yang, W. Wan, S. Huang, F. Yuan, S. Yang, and Y. Que, "Remote Sensing Image Fusion Based on Adaptive IHS and Multiscale Guided Filter," IEEE Access, vol. 4, pp. 4573–4582, 2016.
17. D. Sylla, A. Minghelli-roman, P. Blanc, A. Mangin, and O. H. F. D'Andon, "Fusion of Multispectral Images by Extension of the Pan-Sharpening ARSIS Method," IEEE J. Sel. Top. Appl. EARTH Obs. Remote Sens., vol. 7, no. 5, pp. 1781–1791, 2014.
18. Q. Wei, J. Bioucas-dias, N. Dobigeon, and J.-Y. Tourneret, "Hyperspectral and Multispectral Image Fusion Based on a Sparse Representation," IEEE Trans. Geosci. Remote Sens., vol. 53, no. 7, pp. 3658–3668, 2015.
19. V. R. Pandit and R. J. Bhiwani, "Image Fusion in Remote Sensing Applications: A Review," Int. J. Comput. Appl., vol. 120, no. 10, pp. 975–8887, 2015.
20. S. Fadnavis, "Image Interpolation Techniques in Digital Image Processing : An Overview," Int. J. Eng. Res. Appl., vol. 4, no. 10, pp. 70–73, 2014.

AUTHORS PROFILE

JINJU JOY Procured Her M Tech Degree In VLSI And Embedded Systems From Cochin University Of Science And Technology, Cochin, In 2013 And Doing Phd-Part Time.

She is currently working as Assistant Professor in the Department of Electronics and Communication Engineering, Lourdes Matha College of Science and Technology, Trivandrum, Kerala, India. Her innovate scientific analysis was published by IEEE in 2013. Statistical signal processing, estimation and image fusion are her research interests

Dr. Santhi N received a Ph.D. degree from Dr. M.G.R. Educational and Research Institute University, Chennai, India. She has published many papers in journals and conferences. Her research interests are in Image Processing, Pattern Recognition, Image Retrieval, and Soft Computing.

She is working as Associate Professor in the Department of Electronics and Communication Engineering, Noorul Islam Center for Higher Education, Kumaracoil, Tamil Nadu, India. She has been in the teaching and research field for more than 20 years.

Sanil Jayamohan procured his M Tech degree in VLSI and Embedded Systems from Cochin University of Science and Technology, Cochin, in 2013 and doing PhD-Part Time.

He joined the Department of Electronics and Communication Engineering, Sarabhai Institute of Science and Technology, Vellanad, Trivandrum, India in 2010, where he is presently an Assistant Professor. He has published many innovate scientific papers in reputed International Journals and Conferences. Image Processing, Remote sensing, Statistical signal processing, detection, estimation, stochastic filtering, target tracking, and Monte Carlo methods are his research interests. A university 6th rank for M Tech is his crowning achievement.

Dr. K Ramar received a Ph.D. degree in Computer Science and Engineering from Mononmaniam Sundarnar University, Thirunelveli, Tamil Nadu, India. He has published many Journals, conferences and guided many Ph.D. scholars. His area of interest is distributed computing in Real time systems and Image Processing.

He is currently the Professor and Dean in the Department of Computer Science of Muthayammal Engineering College, Rasipuram, Namakkal, Tamil Nadu, India. He has been in the teaching and research field for more than 30 years