IJCTA, 9(16), 2016, pp. 8051-8059

Variational Mode Decomposition based Multispectral and Panchromatic Image Fusion

Vishnu Pradeep V.*, V. Sowmya* and K. P. Soman*

ABSTRACT

The technique of fusing multispectral image with panchromatic image in order to get a resultant output image of relatively higher spectral resolution and higher spatial information is termed as pan sharpening. It is being used in many remote sensing tasks for different applications including classification, segmentation, change detection, etc. This paper proposes the usage of Variational Mode Decomposition (VMD) as a technique for fusing multispectral and panchromatic images. It also considers average fusion rule and weighing fusion rule during its procedural steps. The experiment is being done on datasets acquired by high resolution sensors on-board satellites such as QuickBird, WorldView-3, WorldView-2 and GeoEye-1. Quantitative assessment measures and visual perception evaluates the effectiveness of the method. The analysis from the obtained results suggest that the proposed method can be used as an image fusion technique and its performance is comparable to the pre-existing pan sharpening techniques like Multi-resolution Singular Value Decomposition (MSVD), Discrete Wavelet Transform (DWT) and Empirical Wavelet Transform (EWT).

Keywords: Variational mode decomposition, VMD, Pan sharpening, Image fusion, Average fusion rule, Weighing fusion rule, multispectral, panchromatic, quality metrics

1. INTRODUCTION

Remote sensing has emerged to be one of the highly competent and powerful technologies to perceive our planet with the aid of a massive volume of informational data. This ample knowledge has provided assistance in many applications and unveiled interests in many research domains such as resource exploring, environmental scrutiny, vegetation, land cover and many more. The atmospheric intrusion and sensor glitches leads to erroneous reporting in the obtained data from on-board receiver systems on satellite platforms. The science of enhancement of remote sensing images is being applied to remotely sensed data for better interpretation. Image fusion is one such derived field which intent to give a superior perception of data by merging multiple images of same arena [1]. The high resolution panchromatic image is short of high spectral quality while low resolution multispectral image is deficient of high spatial quality [2]. Pan sharpening is the approach of merging panchromatic image with multispectral image in yielding a multispectral image affluent of both spectral and spatial content. The pan sharpened output image would have better visual readability which in turn benefits in classification and detection tasks. Many algorithms and methods are being developed and used in this context. are provided.

One of the leading methods used in pan sharpening is the Intensity–Hue-Saturation(IHS) method [2-4]. In this procedure, the multispectral image in RGB space is transformed in to the IHS space. The intensity component is then interchanged with panchromatic image. The inverse transform is then applied to obtain the pan sharpened image. Brovey method [4,5] is another approach in which the bands of multispectral

* Centre for Computational Engineering and Networking (CEN), Amrita School of Engineering, Coimbatore, Amrita Vishwa Vidyapeetham, Amrita University, India, *Emails: vishnupradeep621897@gmail.com, v_sowmya@cb.amrita.edu, kp_soman@amrita.edu*

image are linearly combined to form the panchromatic image. This is done by normalizing the multispectral bands which is then multiplied with the pan image for fusion.

Wavelet transform also gained its own significance in this field, as it helps in getting sparse representations [6] of images and are very useful, as the amount of information being analysed is high. This method transforms the images into wavelet domain extracting the low frequency and high frequency coefficients [7]. After transformation, the decomposition to the desired level is being done on the low frequency components. The wavelet coefficients for pan sharpening are selected according to the fusion rule [8], that is, for example, the low frequency coefficients of pan image and high frequency coefficients of multispectral image are fused together [9]. Discrete wavelet transforms [10] and empirical wavelet transforms [11, 12] are some of its variants being used in this regard. Empirical wavelet transform is a pre-existing method in pan sharpening [13] as well as in multi focus image fusion [14]. It uses the concept of designing pertinent filter banks in order to extract different modes of the input image. The modes are formed around a central frequency, on which the fusion rule is applied. The inverse transform of modes is then used to get the final image. Low pass and high pass filters are used to filter separately the input image in multi-resolution wavelet transform. Decimation is done on the filtered outputs. Recursive repetition of this procedure is being done on the low pass filtered outputs till it achieved desired decomposition level. The Multi-resolution Singular Value Decomposition works identical to this such that Singular value Decomposition (SVD) replaces the filtering of the outputs [15]. The input image is decomposed to several levels by MSVD. The mean of the two MSVD eigen matrices at each decomposition level is taken as the fusion rule. The rule also takes average of detailed coefficients or approximation coefficients depending upon the level of decomposition at which the coefficients are taken [16].

This paper utilizes Variational Mode Decomposition algorithm for pan sharpening of a multispectral image with help of a panchromatic image. The work is based on the comparison between the results obtained with the proposed method and with other existing methods such as empirical wavelet transform, muti-resolution singular value decomposition and discrete wavelet transform based image fusion approaches.

2. VARIATIONAL MODE DECOMPOSITION

The primary intention of Variational Mode Decomposition (VMD) [17, 18] is to fetch a desired number of modes such that each of the obtained modes are band limited around a characteristic central frequency. These modes are often termed as intrinsic mode functions (IMF) and can be described as 2D signals modulated with both amplitude and frequency (AM-FM). The VMD algorithm tries to get a lock on the intrinsic mode functions and the central frequencies concurrently using an optimization procedure of ADMM (Alternating Direction Method of Multipliers). This results in VMD being a non-recursive algorithm by itself. Once the modes are obtained, a sparse form of the original image can be easily reconstructed by summing up the decomposed modes. In order for the frequency spectra of our 2D model to be single sided, heterodyne demodulation is done to shift the image frequencies to the baseband. The 2D analytic signal, in frequency domain will have one of its half planes fixed to zero. This is determined relative to vector $\vec{\omega}_k$. The desired 2D analytical signal in frequency domain is defined by,

$$\tilde{u}_{AS,k}\left(\vec{\omega}\right)=\begin{cases}2\tilde{u}_k(\omega), & if\ \vec{\omega}.\vec{\omega}_k>0\\ \tilde{u}_k(\omega), & if\ \vec{\omega}.\vec{\omega}_k=0\\ 0, & if\ \vec{\omega}.\vec{\omega}_k>0\end{cases} \tag{1}$$
$$=\left(1+\operatorname{sgn}\left(\vec{\omega}.\vec{\omega}_k\right)\right)\tilde{u}_k\left(\vec{\omega}\right)$$

The problem formulation is given by,

$$\min_{\tilde{u}_k,\vec{\omega}_k}\left\{\sum_k \left\|\nabla\left[\tilde{u}_{AS,k}\left(\vec{x}\right)e^{-j\left\langle\vec{\omega}_k,\vec{x}\right\rangle}\right]\right\|_2^2\right\}\ s.t.\ \ \sum_k \tilde{u}_k = f \tag{2}$$

The problem formulation can be stated as minimizing the summation of bandwidths of *k* modes with respect to the condition that, summation of *k* modes obtained by decomposition is equivalent to the original signal, *f*. So the *k* central frequencies and *k* functions associated with frequencies centered around these central frequencies need to be obtained. An unconstrained optimisation formulation is derived from a constrained one as in equation 2 using augmented Lagrangian method given by,

$$\begin{aligned} L\left(\tilde{u}_k,\omega_k,\lambda\right) = \alpha\sum_k \left\|\nabla\left[\tilde{u}_{AS,k}\left(\vec{x}\right)e^{-j\left\langle\vec{\omega}_k,\vec{x}\right\rangle}\right]\right\|_2^2 + \\ \left\|f-\sum u_k\right\|_2^2+\left\langle\lambda, f-\sum u_k\right\rangle \end{aligned} \tag{3}$$

The solution is then computed using ADMM method over a chain of iteration steps.

3. PROPOSED METHODOLOGY

The method for the purpose of image fusion of highly spatial panchromatic image and highly spectral multispectral image is proposed using VMD. Initially, system will be given a set of parameter values including the bandwidth constraint, desired number of modes, lagrangian multiplier time step, tolerance values and the DC component. VMD decomposes each of the bands in the multispectral image (namely band 1, band 2, .. , band M) into a desired number of modes. Decomposition is done based around a central frequency and the nearby frequency components. Once the modes for all the bands of the multispectral image and that of the single band panchromatic image are obtained, a fusion rule is applied for merging of the two images. Here, average fusion rule [19] and weighted fusion rule [20] are used. The fusion rules are executed on corresponding modes of multispectral image taking one band at a time and the panchromatic image. The average fusion rule averages the intensity values of corresponding pixels in both the input images to get the final fused image. The weighted fusion rule takes into account the weighted intensities of pixels corresponding to both the input images before merging. The weighted fusion rule is mathematically expressed as,

$$F(x)=\sum_{i=1}^{M}\left[\alpha_i(x)\,I_i(x) + \beta_i(x)\,J_i(x)\right] \tag{4}$$

where $F(x)$ denotes the fused image, (x) denotes the decomposed modes corresponding to each of the input image, $\alpha_i(x)$ and $\beta_i(x)$ denotes the weighted coefficients satisfying the condition $\alpha_i(x) + \beta_i(x) = 1$. Comparison of variance across modes is done to obtain the weighted coefficients. It is calculated by,

$$\begin{aligned} &\alpha_i(x)=0.4,\ if\ \operatorname{var}\{I_i(x)\}-\operatorname{var}\{J_i(x)\}<-\varepsilon \\ &\alpha_i(x)=0.5,\ if\ \left|\operatorname{var}\{I_i(x)\}-\operatorname{var}\{J_i(x)\}\right|<\varepsilon \\ &\alpha_i(x)=0.7,\ if\ \operatorname{var}\{I_i(x)\}-\operatorname{var}\{J_i(x)\}>\varepsilon \end{aligned} \tag{5}$$

where ε is a very small value greater than zero, $\operatorname{var}\{I_i(x)\}$and $\operatorname{var}\{J_i(x)\}$denotes the variance of decomposed modes of the input images. Similarly, the average fusion rule can also be written in terms of equation 4, by substituting $\alpha_i(x) + \beta_i(x) = 0.5$. Thus, average rule can be stated as a derived concept from weighing rule, which equally minimises the intensity of pixels under consideration.

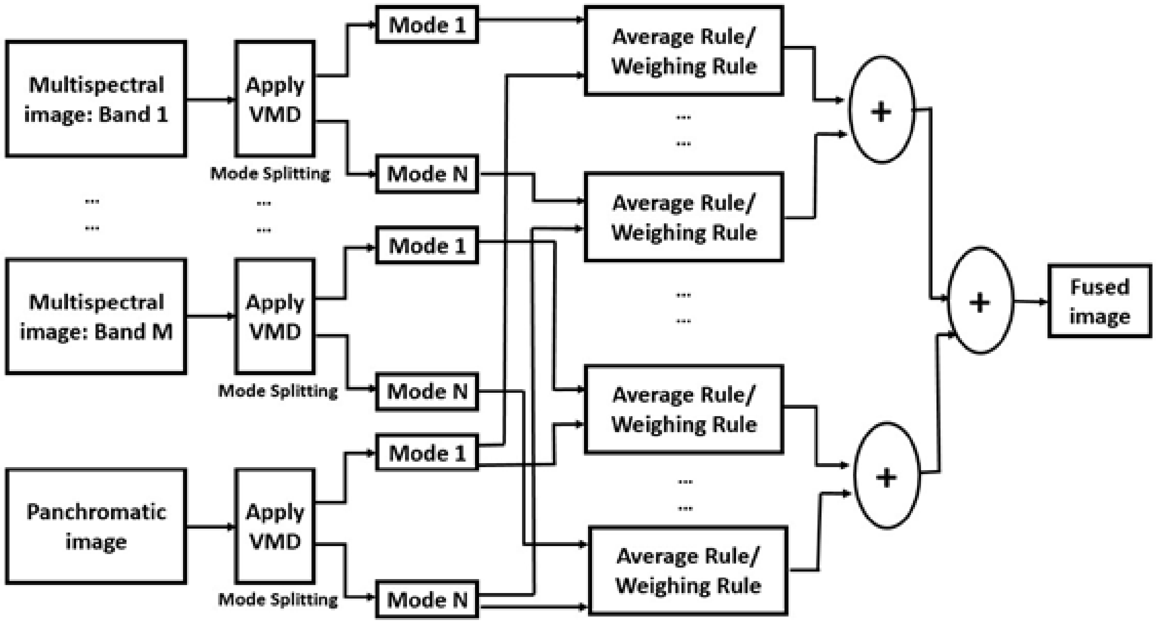

Figure 1: A schematic view of processes included in proposed work

The modes of the fused image are obtained, which are summed up together to reconstruct the original image. The summing up of the modes is done here, which is discussed as part of the problem formulation of VMD (as discussed in section 3). The entire process is repeated across all the bands in the multispectral image in yielding the final pan sharpened multispectral image. A pictorial description of the entire proposed algorithm is shown in Fig. 1.

4. EXPERIMENTAL RESULTS AND ANALYSIS

4.1. Dataset Description

The experiment is performed on four different datasets. Dataset 1 consists of a combo of panchromatic (60 cm resolution) and multispectral (2.4 m resolution) image of the location Rajasthan, India obtained by QuickBird satellite. Dataset 2 is a set of panchromatic (50 cm resolution) and multispectral (2 m resolution) image of the area Capetown, South Africa captured by the earth observation satellite, GeoEye-1. Dataset 3 provides images from WorldView-3 satellite, panchromatic with 30 cm resolution and multispectral with 1.2 m resolution of the scene Adelaide, Australia. Dataset 4 is a combination of panchromatic (50 cm resolution) and multispectral (2 m resolution) image of the region Sydney, Australia took by WorldView-2, high resolution earth observation satellite.

4.2. Metrics Performance Evaluation

A level of degradation will be formed during the fusion of two images. The image quality or the affected degradation is a relative aspect and there are many methods used to get an account of it. The quality of the fused image is measured by its comparison to a referenced image or by other non-referenced schemes. The image quality metrics which are considered in this paper includes Spatial quality (Filtered Correlation Coefficient) [13], Laplacian Mean Squared Error (LMSE) [21], Normalized Absolute Error (NAE) [21], Relative Average Spectral Error (RASE) [13] and Root Mean Squared Error (RMSE) [13].

4.3. Results and Discussion

This section gives a description of the comparison results for the method discussed with other existing pan sharpening methods. The interpretation is done with the aid of various quality metrics and also by visual perception. Lower the value for metrics like Laplacian Mean Squared Error, Normalized Absolute Error, Relative Average Spectral Error and Root Mean Square Error, the higher will be the fused image quality. Larger values for spatial metric corresponds to better fused image. The final obtained results of the VMD based image fusion method and other methods are presented in Fig. 2 to 5. The result of computing various quality metrics using the described VMD based image fusion method (includes both average rule method and weighing rule method) are presented in Table 1 to Table 4. The metric values of other comparing algorithms used are referred from Moushmi S et al. [13].

Table 1
Tabulation of dataset 1-quality metrics

Fusion Technique	*FCC*	*LMSE*	*NAE*	*RASE*	*RMSE*
VMD - Average Rule (Method Proposed)	0.89	2.54	0.13	4.95	6.56
VMD- Weighing Rule(Method Proposed)	0.93	3.45	0.12	5.49	7.30
EWT	0.98	0.78	0.29	36.69	48.89
DWT	0.98	1.21	0.31	40.13	53.47
MSVD	0.62	1.19	0.32	40.59	54.08

Table 2
Tabulation of dataset 2 - quality metrics

Fusion Technique	*FCC*	*LMSE*	*NAE*	*RASE*	*RMSE*
VMD - Average Rule (Method Proposed)	0.68	0.69	0.16	10.86	7.28
VMD- Weighing Rule(Method Proposed)	0.60	0.41	0.17	11.21	7.51
EWT	0.98	0.67	0.22	28.17	18.64
DWT	0.97	0.88	0.20	28.79	19.06
MSVD	0.96	0.97	0.24	31.25	20.68

Table 3
Tabulation of dataset 3 - quality metrics

Fusion Technique	*FCC*	*LMSE*	*NAE*	*RASE*	*RMSE*
VMD - Average Rule (Method Proposed)	0.72	0.79	0.13	5.65	5.05
VMD- Weighing Rule(Method Proposed)	0.69	0.75	0.13	5.56	4.97
EWT	0.98	0.66	0.23	30.07	26.57
DWT	0.96	0.83	0.23	30.85	27.26
MSVD	0.63	0.84	0.22	29.84	26.37

Table 4
Tabulation of dataset 4 - quality metrics

Fusion Technique	*FCC*	*LMSE*	*NAE*	*RASE*	*RMSE*
VMD - Average Rule (Method Proposed)	0.79	0.72	0.22	16.64	9.44
VMD- Weighing Rule(Method Proposed)	0.68	0.75	0.24	18.43	10.46
EWT	0.97	0.58	0.25	35.44	19.63
DWT	0.95	1.09	0.25	38.98	21.59
MSVD	0.62	0.99	0.29	37.83	20.95

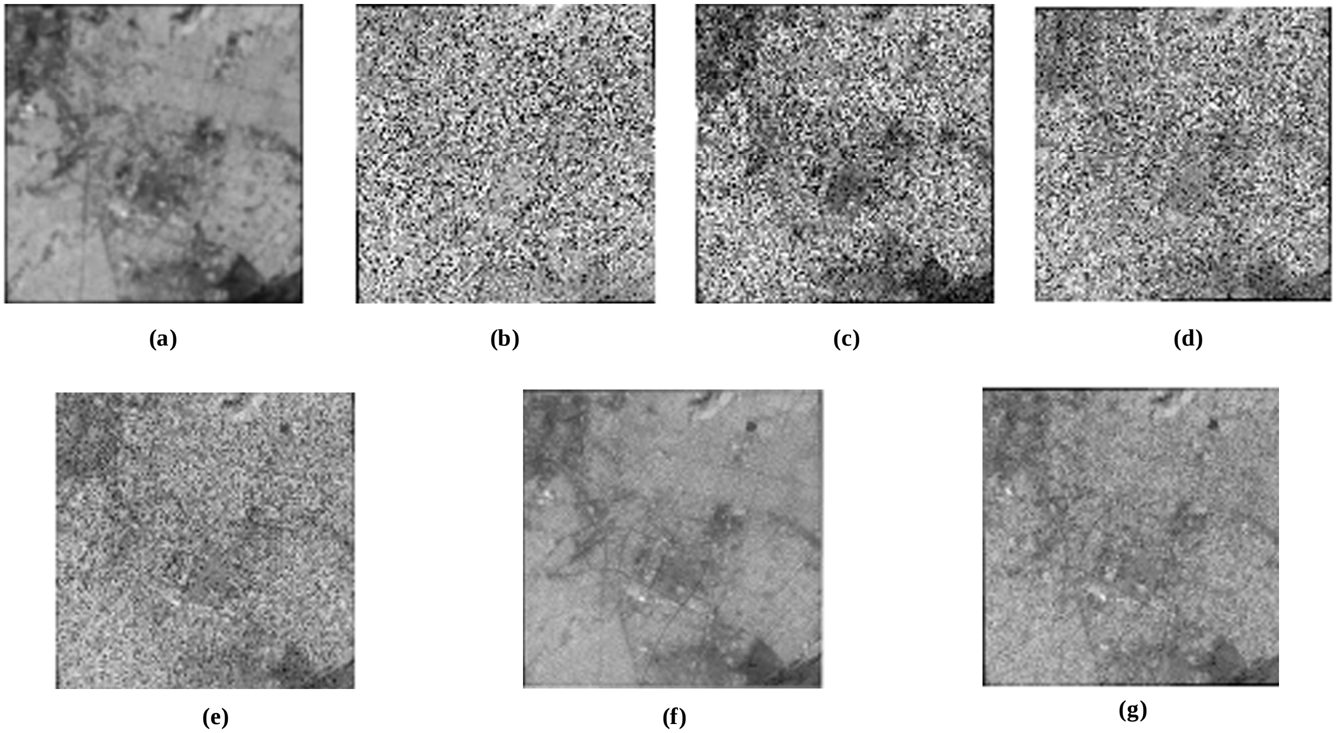

Figure 2: Fused output for dataset 1: (a) Multispectral image, (b) Panchromatic image, (c) MSVD based fusion, (d) DWT based fusion, (e) EWT based fusion, (f) Output of proposed method (VMD - Weighing rule method), (g) Output of proposed method (VMD - Average rule method)

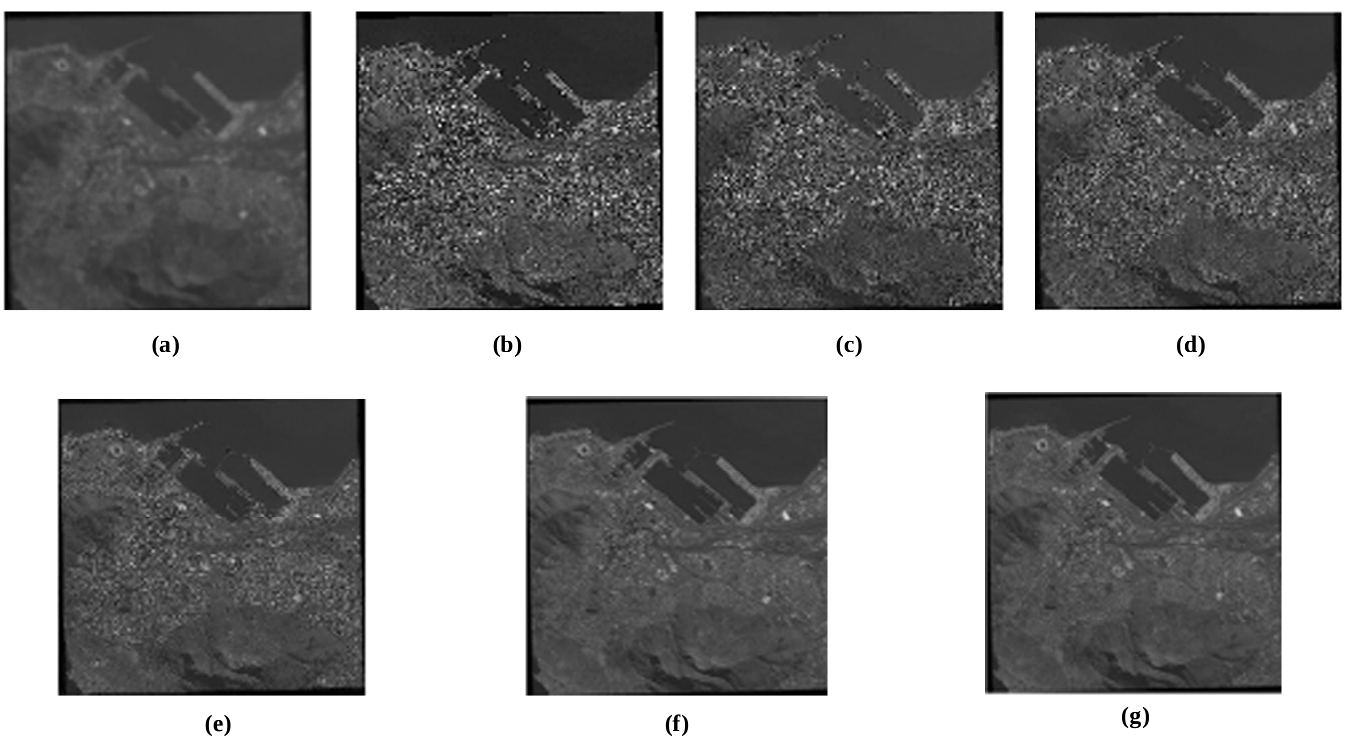

Figure 3: Fused output for dataset 2: (a) Multispectral image, (b) Panchromatic image, (c) MSVD based fusion, (d) DWT based fusion, (e) EWT based fusion, (f) Output of proposed method (VMD - Weighing rule method), (g) Output of proposed method (VMD - Average rule method)

The Root Mean Squared Error value obtained for dataset 1 is 6.5872 for average rule method and 7.3040 for weighing rule using proposed VMD based method, while the values obtained for other described methods are higher, showing the improvement of output using VMD. Normalized Absolute Error and Relative Average

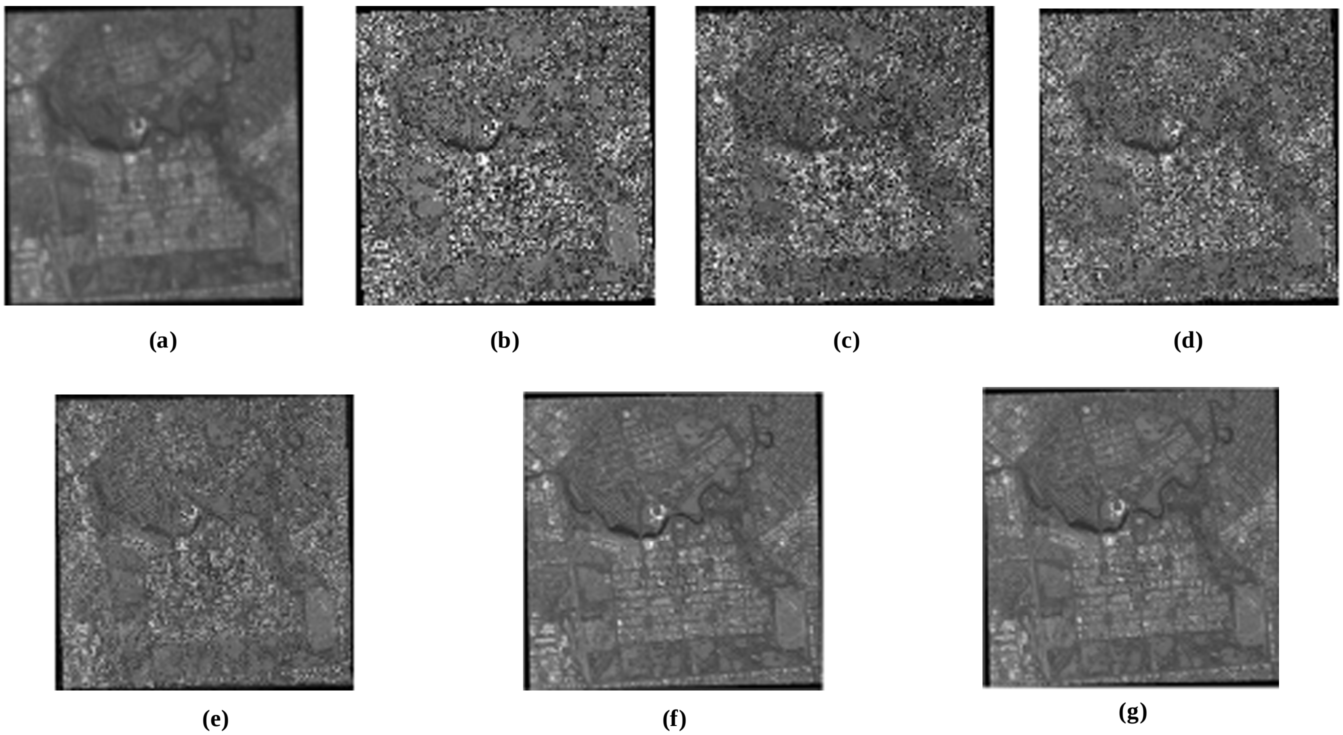

Figure 4: Fused output for dataset 3: (a) Multispectral image, (b) Panchromatic image, (c) MSVD based fusion, (d) DWT based fusion, (e) EWT based fusion, (f) Output of proposed method (VMD - Weighing rule method), (g) Output of proposed method (VMD - Average rule method)

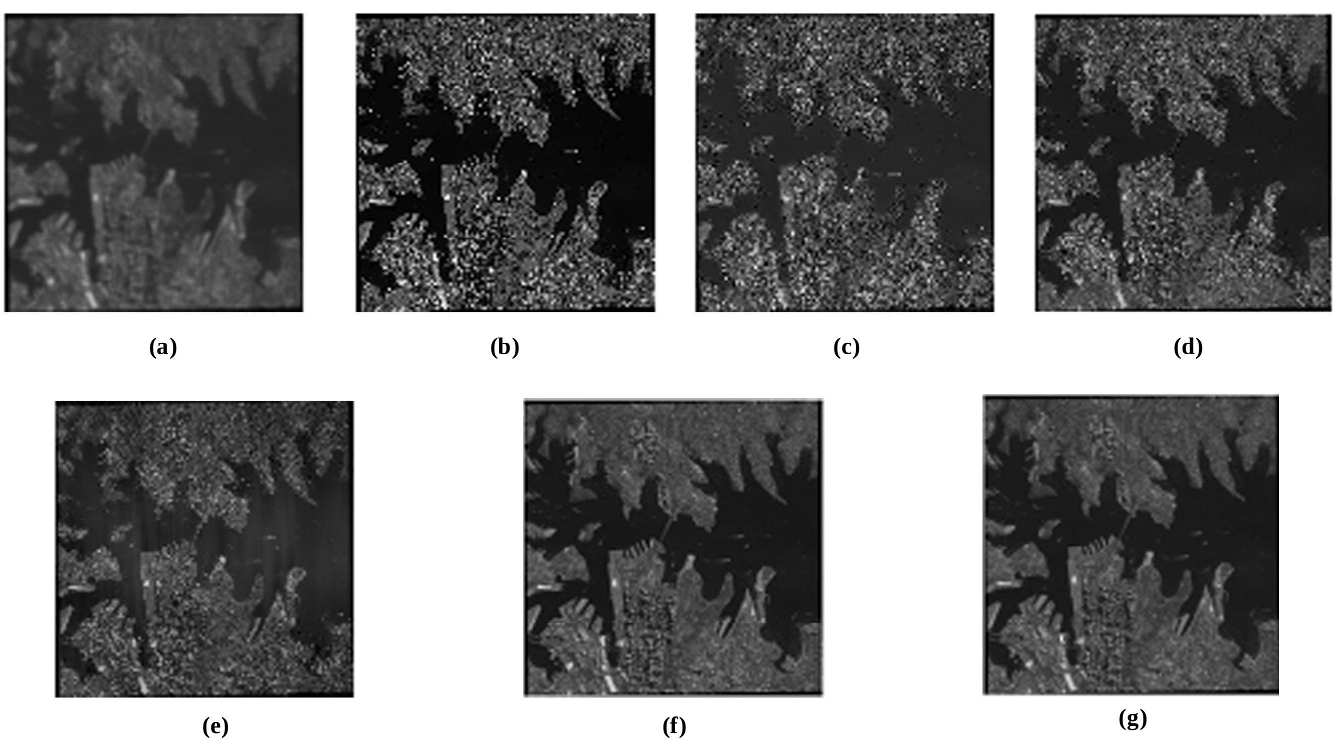

Figure 5: Fused output for dataset 4: (a) Multispectral image, (b) Panchromatic image, (c) MSVD based fusion, (d) DWT based fusion, (e) EWT based fusion, (f) Output of proposed method (VMD - Weighing rule method), (g) Output of proposed method (VMD - Average rule method)

Spectral Error metric shows similar behaviour for dataset 1 where its value in the case of VMD is better compared to other methods. For dataset 1, the Laplacian Mean Squared Error while using VMD for the two fusion rules gives a value higher than the existing methods while that of the spatial metric gives a medium value between the other algorithms. This shows the detrimental side of the method. The metric values of RMSE, RASE and NAE shows the same better trend to other fusion methods for all the other datasets. In the case of other datsets, variations in results can be seen for LMSE and spatial metrics. The LMSE for VMD provides comparable results to other methods while spatial value is lower for other methods for remaining datasets. This shows that a bargain is occurring between spatial information and spectral information in the fused image using VMD. The resultant fused image is having better spectral information than spatial information compared to that of the other fusion methods. It can also be noted that the average rule method provide better results compared to the weighing rule method for the VMD based fusion method for the datasets.

Visual perception and the quality metric calculations for the datasets utilised in this analysis, shows a better and comparable performance of VMD based fusion methods to that of the other examined methods. Even though, the experimental results shows that a trade-off is formed on the basis of spectral and spatial content, VMD can be used as a technique for pan sharpening of multispectral images. Hence, a conclusion can be drawn that the proposed VMD based fusion of panchromatic and multispectral images has been able to sustain the detailed features of the original images.

5. CONCLUSION

The presented work proposes a new method for the fusion of panchromatic and multispectral images based on Variational Mode Decomposition. It takes in to consideration two fusion rules, namely Average rule and Weighing rule in its fusion procedure. Quality metrics such as spatial, RMSE, LMSE, RASE and NAE and also visual interpretation are employed in the assessment of the resultant fused image. The detailed analysis gives enough information to adopt VMD as a significant fusion technique, as it gives comparable results to other pre-existing image fusion approaches.

ACKNOWLEDGMENT

The authors would like to show their gratitude towards CEN faculty, research scholars of CEN – Neethu Mohan, Divya Pankaj, Nidhin Prabhakar, CEN students - Hari Kumar, Athira S, Reshma R and CEN alumni for the help they provided through sharing their pearls of wisdom during the progress and execution of this work.

REFERENCES

[1] S. Chaudhuri and K. Kotwal, Hyperspectral Image Fusion. Springer, 2013.

[2] S. Rahmani, M. Strait, D. Merkurjev, M. Moeller, and T. Wittman, "An adaptive ihs pan-sharpening method," *Geoscience and Remote Sensing Letters, IEEE*, vol. 7, no. 4, pp. 746-750, 2010.

[3] F. A. Al-Wassai, N. Kalyankar, and A. A. Al-Zuky, "The ihs transformations based image fusion," *arXiv preprint arXiv:1107.4396,* 2011.

[4] Q. Du, N. H. Younan, R. King, and V. P. Shah, "On the performance evaluation of pan-sharpening techniques," *Geoscience and Remote Sensing Letters*, IEEE, vol. 4,no. 4, pp. 518-522, 2007.

[5] G. Sarp, "Spectral and spatial quality analysis of pan-sharpening algorithms: A case study in istanbul," *European Journal of Remote Sensing*, vol. 47, pp. 19-28, 2014.

[6] Y. Liu and Z. Wang, "A practical pan-sharpening method with wavelet transform and sparse representation," in *Imaging Systems and Techniques (IST), 2013 IEEE International Conference on*. IEEE, 2013, pp. 288-293.

[7] K. Soman *et al., Insight into wavelets: from theory to practice*. PHI Learning Pvt. Ltd., 2010.

[8] N. Mitianoudis, G.. Tzimiropoulos, and T. Stathaki, "Fast wavelet-based pansharpening of multi-spectral images," in *Imaging Systems and Techniques (IST), 2010 IEEE International Conference on*. IEEE, 2010, pp. 11-16.

[9] K. Amolins, Y. Zhang, and P. Dare, "Wavelet based image fusion techniques an introduction, review and comparison," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 62, no. 4, pp. 249-263, 2007.

[10] M. Moeller, T. Wittman, and A. L. Bertozzi, "Variational wavelet pan-sharpening,"*CAM Report*, pp. 08-81, 2008.

[11] J. Gilles, “Empirical wavelet transform,” *Signal Processing, IEEE Transactions on*, vol. 61, no. 16, pp. 3999-4010, 2013.

[12] J. Gilles, G. Tran, and S. Osher, “2d empirical transforms. wavelets, ridgelets, and curvelets revisited,” *SIAM Journal on Imaging Sciences*, vol. 7, no. 1, pp. 157-186,2014.

[13] S. Moushmi, V. Sowmya, and K. Soman, “Multispectral and panchromatic image fusion using empirical wavelet transform,” *Indian Journal of Science and Technology*, vol. 8, no. 24, 2015.

[14] S. Moushmi, V. Sowmya, and K. Soman, “Empirical wavelet transform for multifocus image fusion,” in *Proceedings of the International Conference on Soft Computing Systems*. Springer, 2016, pp.257-263.

[15] B. Akhbari and S. Ghaemmaghami, “Watermarking of still images using multiresolution singular value decomposition,” in *Intelligent Signal Processing and Communication Systems, 2005. ISPACS 2005. Proceedings of 2005 International Symposium on*. IEEE, 2005, pp. 325-328.

[16] V. Naidu, “Image fusion technique using multi-resolution singular value decomposition,” *Defence Science Journal*, vol. 61, no. 5, p. 479, 2011

[17] K. Dragomiretskiy and D. Zosso, “Variational mode decomposition,” *Signal Processing, IEEE Transactions on*, vol. 62, no. 3, pp. 531-544, 2014.

[18] K. Dragomiretskiy and D. Zosso, “Two-dimensional variational mode decomposition,” in *Energy Minimization Methods in Computer Vision and Pattern Recognition*. Springer, 2015, pp. 197-208.

[19] D. K. Sahu and M. Parsai, “Different image fusion techniques-a critical review,” *International Journal of Modern Engineering Research (IJMER)*, vol. 2, no. 5, pp. 4298-4301, 2012.

[20] D. Looney and D. P. Mandic, “Multiscale image fusion using complex extensions of emd,” *Signal Processing, IEEE Transactions on*, vol. 57, no. 4, pp. 1626-1630,2009.

[21] S. Krishnamoorthy and K. Soman, “Implementation and comparative study of image fusion algorithms,” *International Journal of Computer Applications (0975-8887) Volume*, 2010.