IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

ANALYSIS OF VARIOUS IMAGE FUSION ALGORITHMS IN REMOTE SENSING

[1]Babita Saxena , [2]Dr. Swati Pandey, [3]Dr. R.K. Arya, [4]Dr. Asmita M. Moghe

[1]Research Scholar, [2]Professor, [3]Sr. Scientist, [4] Prof. and Head

[1] EC, [2] EX, [3] Remote Sensing, [4] IT,

[1] SIRT , Bhopal , [2] SIRT Bhopal, [3]MPCST Bhopal, [4]UIT-RGPV Bhopal,

Abstract: - Multi-sensor image fusion techniques combine two or more geometrically registered images of the same scene into a single image that is more easily interpreted than any of the originals. Resolution of the PAN sensor is higher than that of the MS sensor. In addition, a high resolution MS image has a data volume significantly greater than that of a bundled high resolution PAN image and low resolution MS image. Considering these limitations, it is clear that development of an efficient image fusion technique is the best solution for providing high spatial resolution and high spectral resolution remote sensing images. An ideal fusion process should preserves the original spectral characteristics and add spatial characteristics to the image r . In this paper, we review the popular and state-of-the-art fusion methods in different levels especially in the pixel level.

Index Terms **– Image , Fusion , Remote sensing , resolution .**

I. INTRODUCTION

The fused image is a combination of two or more geometrically registered images of the same scene into a single image that is more easily interpreted than any of the originals. Image pixels are observed in different portions of electromagnetic spectrum, therefore the remotely sensed images are vary in spectral, spatial and temporal resolution. To collect more photons and maintain image Signal to Noise Ratio (SNR), the multispectral (MS) sensors (with high spectral resolution and narrow spectral bandwidth) have a larger Instantaneous Field Of View (IFOV) (i.e. larger pixel size and lower spatial resolution) compared to panchromatic (PAN) with a wide spectral bandwidth and smaller IFOV (higher spatial resolution) sensors. With appropriate algorithms it is possible to combine these data and produce imagery with the best characteristics of both, namely high spatial and high spectral resolution. This process is known as a kind of multisensor data fusion and also called pansharpening. The fused images may provide increased interpretation capabilities and more reliable results. Performing pansharpening with hyperspectral image is more complex than performing it with MS image. It is expected, because PAN and MS images are acquired almost in the same spectral range while the spectral The fused images can provide more interpretation capabilities and reliable results. The fusion techniques are performed at three different processing levels according to the stage at which the data fusion takes place: pixel level, feature level and decision level .
the full exploitation of multisource data, advanced analytical or numerical image fusion techniques have been developed [7]. The fused images may improve the interpretation capabilities and provide more reliable results. Multisensor image fusion techniques combine two or more geometrically registered images of the same scene into a single image that is more easily interpreted than any of the originals [7]. Considering these limitations, it is clear that development of an efficient image fusion technique is the best solution for providing high spatial resolution and high spectral resolution remote sensing images. An ideal fusion process should preserves the original spectral characteristics and add spatial characteristics to the image. An ideal fusion

process should preserves the original spectral characteristics and add spatial characteristics to the image. For example, LANDSAT satellites provide fine resolution images for land cover-mapping [10,11] while the nominal revisit rate of them is only 16 days, and so atmospheric restrictions seriously limit their potential use in monitoring of land cover changes at a seasonal or monthly scale [12]. In contrast, NOAA satellites with moderate resolution imaging spectroradiometer (MODIS) data is acquired twice a day, and therefore, the MODIS instrument is suitable for monitoring dynamic changes of land surfaces . Due to physical and financial limitations, no sensor has yet been designed to provide satellite images with both high spatial resolution and high temporal resolution. So, development of models for fusion of the data with a high temporal frequency but coarse spatial resolution with the data that has fine resolution but low temporal frequency is a feasible and less expensive way to obtain this kind of information. Remote sensing images fusion has been applied in land resources investigating, topographic mapping, flood monitoring, and information interpreting and so on.

II. OBJECTIVE ANALYSIS OF THE PERFORMANCE OF THE DIFFERENT FUSION ALGORITHMS

Mean value (Mean), standard deviation (STD), information entropy (IE), correlation coefficient (CC), spectral distortion degree (SPD) and deviation index (DC) are employed as objective criteria. The mean value, standard deviation and information entropy reflect the spatial information of image. When the greater the mean value, standard deviation and the information entropy of fused image, the more the spatial information contained in the fusion image, the better the visual effect is. In addition, the correlation coefficient, spectral distortions and deviation index reflect the image spectral information. When the correlation coefficient is bigger, the spectral distortion and deviation index are smaller, that means that the similarity between the fused image and the original MS image is higher. In other words, the degree of spectral distortion is smaller, the matching degree is higher and the fusion effect is better.

III. **CLASSIFICATION OF FUSION ALGORITHM** -

Image fusion is performed at three different processing levels: 1) pixel level 2) feature level 3) decision level.The urban remote sensing image data fusion is discussed in [20]. The Data Fusion Committee of the IEEE geoscience and remote sensing society launched a public contest for pan sharpening algorithms to identify the ones that perform best in January 2006, testing eight algorithms following different philosophies such as component substitution, multi resolution analysis, detail injection, etc.

IV. PIXEL LEVEL FUSION METHODS—

Multisensor image fusion combines two or more geometrically registered images of the same scene into a single image that is more easily interpreted than any of the originals. The fusion algorithms at pixel level are generally divided into four classes: component substitution (CS), multiresolution analysis (MRA), hybrid methods (a combination of CS and MRA), and model based algorithms. Table 2 represents an overview of these classes

Different Types of Fusion	**Method**
Component substitution (CS)	IHS and different versions of it
	Fast HIS
	Generalized HIS
	Brovey transform (BT)
	PCA
	Gram-Schmidt
Multiresolution analysis (MRA)	Decimated wavelet transform
	Discrete “wavelet packet”
	Undecimated Wavelet Transform
	À trous
	Ripplet
	Laplacian Pyramid
	Contourlet and Curvelet
	Multicontourlet
	Curvelet and contourlet [67]
	Multiresolution fusion based on superresolution

	sed on superresolution [73] High-Pass Filter Additive (HPFA) [71]
	Filter-based [72] Least-squares support vector machine (LS-SVM) [76]
Hybrid	àtrous wavelet and PCA transform [79]
	Non-separable wavelet frame transform (NWFT)
	Wavelet transform and sparse representation [82]
	Ripplet transform and the compressed sensing [66]
	ICA and Curvelet [63]
	ICA and wavelet decomposition [77]
	Curvelet and IHS [78]
	Model based Online coupled dictionary learning (OCDL) [86]
	Spatial correlation modeling [93]
	MRF model [89],[90],[91] Statistical model

n fact, strong correlations exist among each image patch and its spatially-adjacent neighbors[10]. The fusion performance may be greatly improved if a local consistency prior is taken into account during the fusion process Designing more sophisticated activity levels and fusion rules for SR (Sparse reprentation)-based image fusion methods presents an interesting research topic for my research the future. There are some other issues related to the SR-based fusion methods [7] that should be considered in our research work. First, most of the SR-based image fusion algorithms have high computational complexity because of the increased time consumed during the sparse coding. This prevents SR-based methods from being used in the applications that demand real-time operation. Secondly, most of the current SR-based fusion methods are performed in a patch-based way. In order to improve the

robustness to mis-registration while reducing the spatial artifacts, a sliding window technology is often employed. This results in the loss of detail information in the fused image and in the huge increase of computational complexity. Alternatively, the newly merged convolutional SR-based (CSR) fusion method [8] may be an interesting attempt to address such lems. Fusion process must satisfy three conditions [32]: preservation of all relevant information, elimination of irrelevant information and noise, and minimization of artefacts and inconsistencies in the fused image. The noise produced by image sensors can significantly reduce the image fusion quality. Before fusing the images, an image registration algorithm is usually needed to be applied in order to align the source images [34]. In other words, all images to be processed must be coregistered and georeferenced. Low spatial resolution MS images should be resampled into new images with the same resolution as PAN images. The registration errors ignored in the fusion process can significantly affect the fusion quality.

V. CS METHODS -

The CS based methods are based on the projection of MS image into another space using a transformation that separates the spatial structure from the spectral information in different components. Then, the component containing the spatial structure is replaced with the PAN image. The greater correlation between the replaced component and the PAN image, produces less distortion. Thus, we must perform histogram matching between the PAN image and the selected component before its substation. The histogram-matched PAN will have the same mean and variance of the replaced component. Finally, by bringing the data back to the original space through the inverse transformation, the pansharpening process is completed. Intensity-Hue-Saturation (IHS) [39], principal component analysis (PCA) [9], Brovey transform (BT) [40], and Gram-Schmidt (GS) [41] belong to this class of pansharpening.

VI. MRA METHODS

In recent years, multi-scale decomposition (MD) based approaches have been successfully applied to image fusion for different applications such as hyperspectral image fusion [54]. Varied MD methods such as pyramid transform and discrete wavelet transform have been applied to image fusion. Three steps can be considered in the MD-based image fusion approaches. At first, the source images are decomposed into several scale levels using a pyramid transform or a wavelet transform. Second, fusion is applied at each level of the source images, and third, the transform is inverted to synthesize the fused image. While the use of the transform increases the computational complexity, the MD-based image fusion approach provides both spatial and frequency domain localization and achieves much better performance.

VII. HYBRID METHODS

Hybrid methods use the advantages of both the CS and MRA methods with combination of them. An improved ICA fusion method, which uses a wavelet decomposition to extract the detail information of PAN, is proposed in [77]. An image fusion method based on curvelet and ICA is proposed in [63]. A remote sensing image fusion using combining IHS and curvelet transform is proposed and compared with IHS, decimated wavelet transform, wavelet à trous algorithm, ridgelet and curvelet transform in [78]. Different wavelet-based pansharpening methods are available in [79]. In these wavelet-based fusion methods, the high frequency detail coefficients are obtained from the high spatial resolution PAN image and are combined with the spectral information obtained from the MS image through a combination model. PCA transformation can acquire higher spatial resolution but provides more serious distortion of spectral characteristics. On the other hand, the àtrous wavelet transformation is able to preserve the spatial information while the result has a lack of high spatial resolution. A technique, based on additive wavelet decomposition and PCA transformation is developed for fusing in [80]. A color transfer based fusion algorithm by using the non-separable wavelet frame transform .

VIII. MODEL BASED METHODS

A fast multi-band image fusion is proposed in [84], which forms the likelihoods of the observations. In this fast algorithm, maximizing the likelihoods leads to solving a Sylvester equation. A closed form solution for the Sylvester equation is obtained by exploiting the properties of the circulant and downsampling matrices associated with the fusion problem. This method can be generalized to incorporate prior information for the fusion problem, allowing a Bayesian estimator An online coupled dictionary learning (OCDL) approach for image fusion has been introduced in [86]. The OCDL makes the full use of the available lower spatial resolution MS image and the high spatial resolution PAN image to decrease the spectral distortion and preserves the spatial information of the MS image. A superposition strategy is adopted in the OCDL method to produce two intermediate images for the coupled dictionary construction for each band.

IX. FEATURE LEVEL FUSION METHODS.

Feature level fusion methods deal with data at higher processing levels than pixel level methods. Normally, at first, feature extraction procedures are applied. Then, the fusion process using advanced ACCEPTED MANUSCRIPT ACCEPTED MANUSCRIPT techniques takes place. For example, the extraction of objects using segmentation procedures is required in fusion at feature level. Features correspond to characteristics, which are depending on their environment such as shape, extent and neighborhood, are extracted from the original images. The similar objects from multiple sources are assigned to each other and then fused for further assessment.

X. DECISION LEVEL FUSION METHODS

Decision fusion (or interpretation level) is the highest processing level. It is the process of merging information from several individual data sources after each data source has undergone a preliminary classification. In the decision level fusion, the received results from different local classifiers will be combined to determine the final decision. In other words, the input images are processed individually for information extraction. Then, the decision rules are used to combine extracted information to reinforce common interpretation and resolve differences and furnish a better understanding of the observed objects.

XI. COMPARISON

The reviewed methods are located in four different classes: CS, MRA, hybrid, and model based approaches. CS methods are generally fast and easy to implement. But, they may produce significant spectral distortions. In contrast to CS methods, MRA methods cause a higher spatial distortion but a superior spectral consistency. To take the advantage of both methods, hybrid methods were introduced. To have an intuitive interpretation of the fusion process, the fusion of MS and PAN images can be conveniently formulated within a model such as the Bayesian inference framework. The assessment of fused product can be done with or without need to a reference image with different approaches which each one has its advantages and disadvantages. The former approach needs to a rescaling of images and the later approach is done at native scale ages

XII. CONCLUSION.

Mathematical methods were used to judge the quality of merged imagery in respect to their improvement of spatial resolution while preserving the spectral content of the data. Statistical indices, such as cross entropy, mean square error, signal-to-noise ratio, have been used for evaluation purpose[2].The results will be visually and quantitatively verified to demonstrate the effectiveness of the proposed method. The fusion results were evaluated by using the widely-popular Wald's synthesis protocol [2]. According to this protocol, the original LRM and the HRP images are preliminarily decimated by the scale ratio p. Then, pan-sharpening is performed on the degraded data and the sharpened results are compared with the original LRM image which plays the role of a ground-truth reference. The pan-sharpened results were assessed by root mean square error (RMSE) as a distortion measurement, cross-correlation coefficient (CC) and a quaternion-based coefficient (Q4) [2] as quality indices [12] . The quality of the fusion results was also calculated by QNR index which is composed of a spectral distortion (DA) index and a spatial distortion (Dr) index, without requiring the high resolution reference LRM image.

[1] G.Simone, A.Farina, F.C.Morabito, S.B.Serpico and L.Bruzzone "*Image Fusion Techniques For Remote Sensing Applications" ,* Information Fusion, Vol. 3, No. 2, March **2002**.

[2] Luciano Alparone, Stefano Baronti, Member, Andrea Garzelli, Member, and Filippo Nencini IEEE *"A Global Quality Measurement of Pan-Sharpened Multispectral Imagery"* Geoscience And Remote Sensing Letters, Vol. 1, No. 4, October **2004.**

[3] Jan Flusser, Filip Sroubek, and Barbara Zitov , *"Image Fusion: Principles, Methods, and Applications"* Tutorial EUSIPCO 2007 .

[4] Sheida Rahmani, Melissa Strait, Daria Merkurjev, Michael Moeller, and Todd Wittman *"An Adaptive IHS Pan-Sharpening Method"* , IEEE Geoscience And Remote Sensing Letters, Vol. 7, No. 4, October **2010**

[5] Dong Jiang, Dafang Zhuang, Yaohuan Huang and Jinying Fu , *"Survey of Multispectral Image Fusion Techniques in Remote Sensing Applications"*, **2011**

[6] R.Johnson Suthakar, J.Monica Esther M.E, D.Annapoorani, F.Richard Singh Samuel *"Study of Image Fusion- Techniques, Method and Applications" ,* International Journal of Computer Science and Mobile Computing , ISSN 2320–088X IJCSMC, Vol. 3, Issue. 11, November **2014.**

[7] Ming Cheng, Cheng Wang, and Jonathan Li, *"Sparse Representation Based Pan-sharpening Using Trained Dictionary",* IEEE Geoscience And Remote Sensing Letters, Vol. 11, No. 1, January **2014**

[8] Hassan Ghassemian , *"A Review of Remote Sensing Image Fusion Methods, Information Fusion"* (2016), doi: 10.1016/j.inffus.**2016**.

[9] Saleha Masood, Muhammad Sharif, Mussarat Yasmin, Muhammad Alyas Shahid and Amjad Rehman/ *"Image Fusion Methods: A Survey"*, Journal of Engineering Science and Technology **2017.**

[10] Qiang Zhang, Yi Liu, Rick S. Blum, Jungong Han, Dacheng Tao , 2017, *" Sparse Representation based Multi-sensor Image Fusion for Multi-focus and Multi-modality Images: A Review" ,* Information Fusion, doi: 10.1016/j.inffus. 2017

[11] Zhiliang Wu1 , Yongdong Huang1 , Kang Zhang, *"Remote Sensing Image Fusion Method Based on PCA and Curvelet Transform"* , Indian Society of Remote Sensing **2018**.

[12] Mariana Belgiu * and Alfred Stein , "Spatiotemporal Image Fusion in Remote Sensing" , MPDI **2019.**

[13] Morteza Ghahremani, Yonghuai Liu, Peter Yuen and Ardhendu Behera.“*Remote sensing image fusion via compressive sensing*”, ISPRS Journal of Photogrammetry and Remote Sensing, Pages 34-*48* DOI:10.1016/j.isprsjprs , Volume 152, **2019.**

[14] Anna de Juan, Cyril Ruckebusch, “Data Fusion Methodology and Applications” Data Handling in Science and Technology, 2019.

[15] Y. Xu, P. Ma, E. Ng, H. Lin, Fusion of WorldView-2 Stereo and Multitemporal TerraSAR-X Images for Building Height Extraction in Urban Areas, IEEE Geoscience and Remote Sensing Letters,12 (8) (2015) 1795-1799

[16] C. Berger, M.Voltersen, R. Eckardt, J. Eberle, T. Heyer, N. Salepci, S. Hese, C. Schmullius, J. Tao, S. Auer, R. Bamler, K. Ewald, M. Gartley, J. Jacobson, A. Buswell, Q. Du, F. Pacifici, Multi Modal and Multi-Temporal Data Fusion: Outcome of the 2012 GRSS Data Fusion Contest, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 6 (3) (2013) 1324-1340.

[17] G. Simone, A. Farina, F.C. Morabito, S.B. Serpico, L. Bruzzone, Image fusion techniques for remote sensing applications, Information Fusion, 3 (2002) 3–15.

[18] C. Thomas, T. Ranchin, L. Wald, J. Chanussot, Synthesis of Multispectral Images to High Spatial Resolution: A Critical Review of Fusion Methods Based on Remote Sensing Physics, IEEE Transactions on Geoscience and Remote Sensing, 46 (5) (2008) 1301-1312.

[19] P. Gamba, F. Dell_Acqua, B. V. Dasarathy, Urban remote sensing using multiple data sets: Past, present, and future, Information Fusion, 6 (2005) 319–326.

[20] A. Garzelli, F. Nencini, Fusion of panchromatic and multispectral images by genetic algorithms, in: proceedings of the IEEE International Geoscience and Remote Sensing Symposium, 2006, pp.

[21] C. Pohl, J. L. Van Genderen, Remote sensing image fusion: an update in the context of Digital Earth, International Journal of Digital Earth, 7 (2) (2014) 158–172.

[22] C. Pohl, J. L. Van Genderen, Review Article, Structuring contemporary remote sensing image fusion, International Journal of Image and Data Fusion, 6 (1) (2015) 3–2

[23] L. Snidaro, J. Garcia, J. Llinas, Context-based Information Fusion: A survey and discussion, Information Fusion, 25 (2015) 16–31.

[24] W. Wenbo,Y. Jing,K. Tingjun, Study of Remote Sensing Image Fusion and Its Application In Image Classification, The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 2008, pp. 1141-1146.

[25] L. Wald, Some terms of reference in data fusion, IEEE Transactions on Geoscience and Remote Sensing, 37 (3) (1999) 1190–1193. [29] G. Piella, A general framework for multiresolution image fusion: from pixels to regions, Information Fusion, 4 (4) (2003) 259-280

[26] Y. Zhang, Understanding image fusion, Photogrammetric engineering and remote sensing, 70 (6) (2004) 657-661.

[27] J. J. Lewis, R. J. O’Callaghan, S. G. Nikolov, D. R. Bull, C. N. Canagarajah, Region-based image fusion using complex wavelets, The 7th International Conference on Information Fusion, 2004, pp. 555–567.

[28] O. Rockinger, Pixel level fusion of image sequences using wavelet frames, in: proceedings of the 16th Leeds Annual Statistical Research Workshop, 1996, pp. 149–154. [

[29] W. Zhao, Z. Xu, J. Zhao, Gradient entropy metric and p-Laplace diffusion constraint-based algo algorithm for noisy multispectral image fusion, Information Fusion, 27 (2016) 138–149.

[30] P. K. Varshney, B. Kumar, M. Xu, A. Drozd, I. Kasperovich, Image registration: A tutorial, in: proceedings of the IEEE NATO advance Science institutes series, 2005.

[31] P. Cheng, T. Toutin, C. Pohl, A comparison of geometric models for multisource data fusion. Remote Sensing, GIS and GPS in Sustainable Development and Environmental Monitoring, GeoInformatics ’95, in: proceedings of the International Symposium, 1995, pp. 11- 17.

[32] B. Aiazzi, S. Baronti, M. Selva, L. Alparone, Bi-cubic interpolation for shift-free pansharpening, ISPRS Journal of Photogrammetry and Remote Sensing, 86 (2013).

[33] Q. Zhang, Z. Cao, Z. Hu, Y. Jia, X. Wu, Joint Image Registration and Fusion for Panchromatic and Multispectral Images, IEEE Geoscience and Remote Sensing Letters, 12 (3) (2015) 467- 471.

[34] Y. Li, Z. He, H. Zhu, W. Zhang, Y. Wu, Jointly registering and fusing images from multiple sensors, Information Fusion, 27 (2016) 85–94.

[35] W. Carper, T. Lillesand, R. Kiefer, The use of intensity-huesaturation transformations for merging SPOT panchromatic and multispectral image data, Photogrammetric Engineering and Remote Sensing, 56(4) (1990) 459-467.

[36] Earth Resource Mapping Pty Ltd, The Brovey tra ansform explained, EMU Forum, 2 (11) (1990), available in http: // www. ermapper.com/ forum_new/emuf2-11.htm # aiticle_5. [

[37] C. A. Laben, B. V. Brower, Process for enhancing the spatial resolution of multispectral imagery using pan-sharpening, U.S. Patent 6011875 A (2000).

[38] H. Chu, W. Zhu, Fusion of IKONOS Satellite Imagery Using IHS Transform and Local Variation, IEEE. Geoscience and Remote Sensing Letters, 5 (4) (2008) 653-657.

[39] Q. Guo, A. Li, H. Q. Zhang, Z. K. Feng, Remote Sensing Image Fusion Based on Discrete Fractional Random Transform for Modified HIS, International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 2013, pp. 19-22.

[40] T.-M. Tu, P. S. Huang, C.-L. Hung, C.-P. Chang, A fast intensity-hue-saturation fusion technique with spectral adjustment for IKONOS imagery, IEEE Geoscience and Remote Sensing Letters, 1 (4) (2004) 309–312.

[41] M. González-Audícana, J. L. Saleta, R. G. Catalán, R. García, Fusion of multispectral and panchromatic images using improved IHS and PCA mergers based on wavelet decomposition, IEEE Transactions on Geoscience and Remote Sensing, 42 (6) (2004) 1291–1299.

[42] M. Choi, A New Intensity-Hue-Saturation Fusion Approach to Image Fusion With a Tradeoff Parameter, IEEE Transactions on Geoscience and Remote Sensing, 44 (6) (2006) 1672-1682

[43] X. Zhou, J. Liu, S. Liu, L. Cao, Q. Zhou, H. Huang, A GIHS-based spectral preservation fusion method for remote sensing images using edge restored spectral modulation, ISPRS Journal of Photogrammetry and Remote Sensing, 88 (2014) 16–27.

[44] T.-M. Tu, S.-C. Su, H.-C. Shyu, P. S. Huang, A new look at IHS-like image fusion methods, Information Fusion, 2 (3) (2001) 177–186.

[45] M. González-Audícana, J. L. Saleta, R. G. Catalán, R. García, Fusion of multispectral and panchromatic images using improved IHS and PCA mergers based on wavelet decomposition, IEEE Transactions on Geoscience and Remote Sensing, 42 (6) (2004) 1291–1299.

[46] H. R. Shahdoosti, H. Ghassemian, Combining the spectral PCA and spatial PCA fusion methods by an optimal filter, Information Fusion, 27 (2016) 150–160.

[47] A. A. Green, M. Berman, P. Switzer, M. D. Craig, A transformation for ordering multispectral data in terms of image quality with implications for noise removal, IEEE Transactions on Geoscience and Remote Sensing, 26 (1988) 65–74.

[48] J. Choi, K. Yu, Y. Kim, A new adaptive component-substitution based satellite image fusion by using partial replacement, IEEE Transactions on Geoscience and Remote Sensing, 49 (1) (2011) 295–309.

[49] G. Vivone, L. Alparone, J. Chanussot, M. Dalla Mura, A. Garzelli, G. A. Licciardi, R. Restaino, L. Wald, A Critical Comparison Among Pansharpening Algorithms, IEEE Transactions on Geoscience and Remote Sensing, 53 (5) (2015) 2565 – 2586.

[50] Y. Zhang, S. De Backer, P. Scheunders, Noise-resistant waveletbased Bayesian fusion of multispectral and hyperspectral images, IEEE Transactions on Geoscience and Remote Sensing, 47 (11) (2009) 3834–3843.

[51] J. Zhou, D. Civo, J. Silander, A wavelet transform method to merge Landsat TM and SPOT panchromatic data, Int. J. Remote Sensing, 19 (4) (1998) 743-757.