Image Fusion Quality Assessment of High Resolution Satellite Imagery based on an Object Level Strategy

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Abstract

Considering the importance of fusion accuracy on the quality of fused images, it seems necessary to evaluate the quality of fused images before using them in further applications. Current quality evaluation metrics are mainly developed on the basis of applying quality metrics in pixel level and to evaluate the final quality by average computation. In this paper, an object level strategy for quality assessment of fused images is proposed. Based on the proposed strategy, image fusion quality metrics are applied on image objects and quality assessment of fusion are conducted based on inspecting fusion quality in those image objects. Results clearly show the inconsistency of fusion behavior in different image objects and the weakness of traditional pixel level strategies in handling these heterogeneities.

Keywords: Image Fusion, Quality Assessment, Object Level, Pixel Level, High Resolution Satellite Imagery.

1. INTRODUCTION

Topographic earth observation satellites, such as IKONOS, Quick Bird and GeoEye, provide both panchromatic images at a higher spatial resolution and multi-spectral images at a lower spatial resolution enjoying rich spectral information [1],[2],[3],[4]. Several technological limitations make it impossible to have a sensor with both high spatial and spectral characteristics [2]. To surmount these limitations, image fusion as a mean for enhancing the information content of initial images to produce new images rich in information content, has drawn an increasing attention in recent years [1],[3]. Remote sensing communities have also switched to merge multi spectral and panchromatic images to exhibit complementary characteristics of spatial and spectral resolutions [2],[5]. This new product is entitled as pan-sharpen image. Nevertheless, as these new images do not exactly have the behavior of the real objects, acquired by remote sensing sensors, quality assessment of these data is crucial before using them in further process of object extraction or recognition. The widespread use of pan-sharpen images has led to a rising demand of presenting methods for evaluating the quality of these processed images [6],[7],[8],[9],[10].

2. IMAGE FUSION QUALITY METRICS (IFQMs)

Image quality metrics are classified based on the level of spectral information [9],[11]. Traditionally, these metrics are classified to mono-modal and multi-modal techniques [12]. A mono-modal metric applies to a single modality while a multi-modal metric applies to several modalities.

Thomas and Wald applied Difference In Variance (DIV), standard deviation and correlation coefficient as mono modal metrics. They applied the metrics for quality evaluation of well-known images of the mandrill and Lenna and images were acquired by satellite observing systems, SPOT-2 and SPOT-5 [11]. Similarly, Riyahi et al., made use of DIV and correlation coefficient as quality metrics to evaluate fusion performance of QuickBird satellite imagery [13]. Chen and Blum, performed some experimental tests according to evaluate quality of image fusion for night vision [14]. They used Standard deviation, SNR (Signal to Noise Ratio) and entropy index as standard quality metrics to extract features from fused image itself. They also used cross entropy based and information based measures to utilize feature of both fused image and source images. Shi et al. applied variety of objective quality metrics, such as correlation, mean value and standard variation, to evaluate wavelet based image fusion of panchromatic Spot image and multi spectral TM image [15].

Entropy, correlation coefficient and mean square error are some of mono modal metrics that were used by Vijarayaji for quantitative analysis of pan-sharpen images [16]. Sahu and Parsai also applied Entropy, SNR and Cross-Correlation to evaluate and have a critical review on recent fusion techniques [17]. Wang et al., introduced the main idea of Structural Similarity (SSIM) which is one of the mono modal metrics. A simplified version of the metric, entitled as Universal Image Quality (UQI) index was introduced by Wang and Bovik (2002) and applied for quality evaluation of IKONOS fused images by Zhang (2008) [8],[18]. Piella and Heijman, 2003, added weighted averaging to UQI to measure the performance of image fusion [7]. This new metric was entitled as saliency factor and was practiced by Hossny et al, for image fusion quality assessment [19]. Piella and Heijman, also introduced weighted saliency factor for fusion quality assessment [7].

On the other hand, Wald introduces ERGAS as a multi-modal index to characterize the quality of process and, present the normalized average error of each band of processed image [6]. Alparone et al., used ERGAS and SAM for image fusion assessment of IKONOS satellite imagery [9]. Riyahi et al., used ERGAS and its modified version RASE (Relative Average Spectral Error) for inspecting different image fusion methods [13]. Van der meer, studied SCM (Spectral Correlation Measure) and SAM for analysis of hyper spectral imagery [20].

Amongst all mono-modal Image Fusion Quality Metrics, UQI has been more frequently used and brought up to be more efficient, reliable and successful [7],[8],[19],[21]. The same story is factual for SAM in terms of multi modal image quality metrics [8],[9],[20]. Our previous results also proved this claim [22].

3. PROPOSED OBJECT LEVEL IMAGE FUSION QUALITY ASSESSMENT

To overcome limitations of the traditional strategies in evaluation of fusion quality with respect to different image objects, this paper presents an object level strategy based on both spectral and shape characteristics of objects (Fig. 1.). In proposed strategy, after generating pan-sharpen image in Phase 1, image objects are extracted from input and pan-sharpen imagery (Phase 2). These objects are computational units for evaluation of fusion quality metrics in phase 3. In phase 4, object level fusion quality assessment is conducted through the whole objects of data set. In the first step, initial panchromatic and multi spectral images are introduced to fusion engine and results in new pan-sharpen image. After generating fused image, the process of evaluating fusion quality based on new strategy is implemented through next three phases. The basic processing units of object-level image fusion quality assessment are image segments, known as image objects, not single pixels. In order to extract image objects, multi resolution image segmentation is carried out in a way that an overall homogeneous resolution is kept. In proposed strategy, based on bottom-up image segmentation, image objects are extracted. In numerous subsequent steps, smaller image objects are merged into bigger ones to minimize average heterogeneity of image objects. The heterogeneity criterion consists of two parts: a criterion for tone and a criterion for shape.

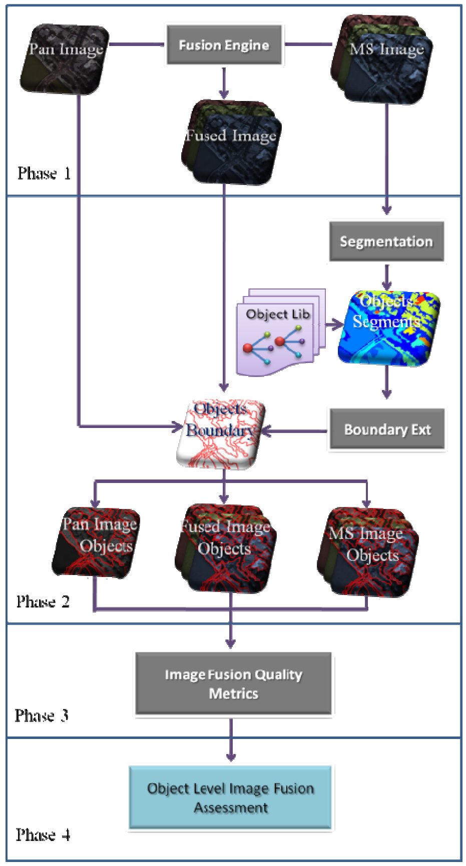


FIGURE 1: Flowchart of Proposed Object Level Fusion Quality Assessment.

When corresponding image objects of all images (panchromatic and multi spectral image and the produced fused image) are determined, image quality metrics are computed for each case. So, quality of corresponding image objects will be inspected. In this study, applied Image quality metrics are SAM and UQI. SAM index is given as:

$$cos(\alpha)=\frac{\sum_{i=1}^{N} x_i . y_i}{\sum_{i=1}^{N} x_i . x_i . \sum_{i=1}^{N} y_i . y_i} \tag{3.1}$$

Where N is the number of bands of images or the dimension of the spectral space, x=(x1, x2,…, xN) and y=(y1, y2,…, yN) are two spectral vectors from the multispectral and fused images respectively [6]. The computed α is the spectral angle for each specific pixel which ranges from 0 to 90 and the minor angle represents the major similarity [6],[9].

On the other hand, Universal Quality Index is computed as:

$$Q=\frac{4.\sigma_{xy}.\bar{x}.\bar{y}}{(\sigma_x{}^2+\sigma_y{}^2).(\bar{x}^2+\bar{y}^2)} \tag{3.2}$$

where $\bar{x}$ and $\bar{y}$ are the local sample means of x and y, σ_x and σ_y are the local sample standard deviations of x and y, and σ_{xy} is the sample cross correlation of x and y after removing their means [18]. Therefore, object level quality assessment will be performed comparing values of these two metrics. This means, the computational domain of quality evaluation switches from pixel level to object level.

There are two scenarios for object level quality assessment; the type of objects and the effective size of objects in data set. In some applications, the users' purposes about fusion are to make progress and improve the identification potentiality of some specific objects, such as buildings. The quality of these objects should not be less than a specified level of accuracy. In this case, despite the acceptable configuration of general quality of image, fusion process should satisfy a level of quality about specific objects. On the other hand, wide spread objects have more visual effects on pan-sharpen image users. Thus, another object level quality indicator is the evaluation of frequency of image objects pixels against the value of their image quality metric.

4. EXPERIMENTS AND RESULTS

Proposed strategy is implemented and evaluated for quality assessment of high-resolution QuickBird image data over an urban area. The original panchromatic QuickBird has 0.61m pixel while the original multi spectral image has 2.4m pixel spatial resolution (for more information visit digital globe website) [23]. Utilizing PCI software a fused QuickBird image generated with 0.61 meter spatial resolution and three (R,G,B) bands (Fig. 2).

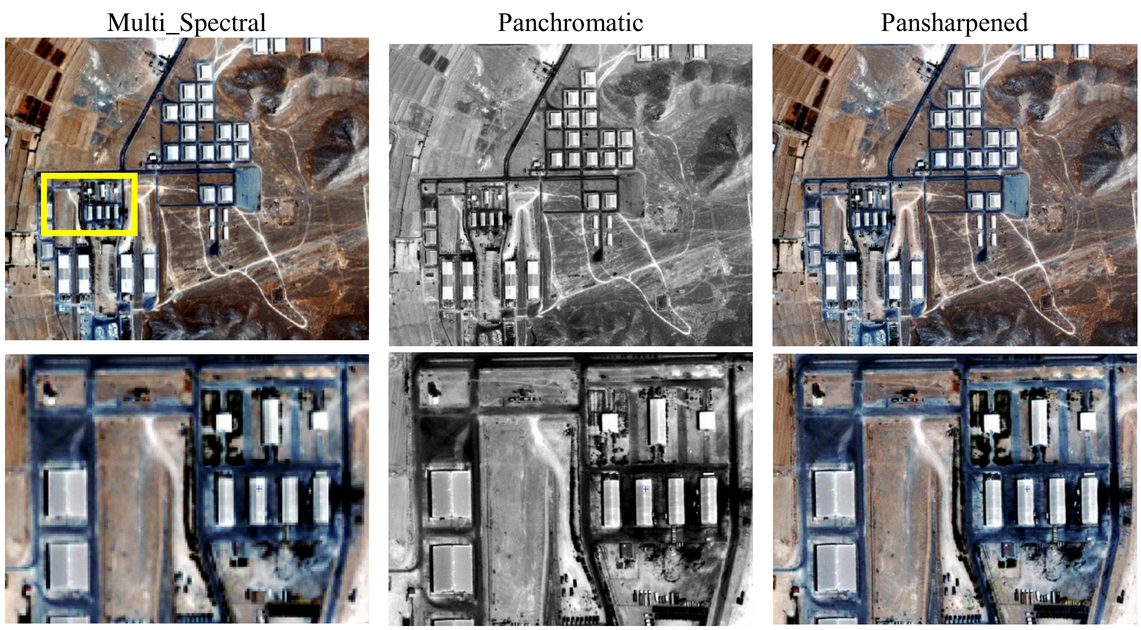
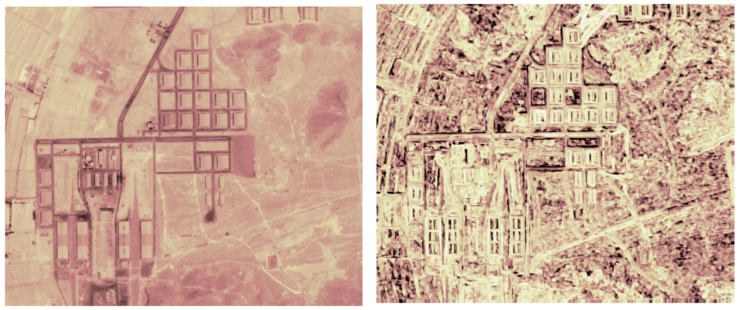


FIGURE 2: QuickBird Dataset.

4.1 Pixel Level Image Fusion Quality Assessment

Pixel level quality assessment of obtained pan-sharpen image is done by computing SAM and UQI statistics for image fusion quality assessment. SAM index is computed for each image pixel of fused image with respect to corresponding multi spectral image pixel, based on equation 3.1. To represent disparity of achieved SAM values, they are represented as pixels intensity values. Achieved image is depicted in Fig. 3.a. By averaging the whole computed SAM indices global measurement of spectral distortion yield and it is presented in Table 1. This final averaged value is what is usually reported as fusion quality in most literatures. Moreover, to have a better perception of fusion behavior, not only the global SAM value, but also the Min, Max and STD values of computed SAM index of all image pixels are presented in Table 1. Moreover, UQI is used to inspect quality of achieved pan-sharpen image as a mono modal metric. This index is computed within a sliding patch with the size of 9 pixels. Final value of UQI is achieved by averaging computed values of all patches. In order to illustrate UQI behavior, achieved UQI values for each image patch in three layers, R-R, G-G and B-B are averaged and obtained image is depicted in Fig. 3.b.



a. SAM b. UQI

FIGURE 3: Pixel Level Behavior of IFQM Through Data Set.

Moreover, the final value of UQI index, achieved via averaging, and the Min, Max and STD values of achieved UQI in all image patches, are presented in Table 1. Based on the concept of mono modal metrics, they are evaluated for each band of image separately. Consequently, UQI results are presented as the average amount of achieved UQI values for all bands. But, since multi modal metrics treat the image as a 3D data vector and compare the fused image only with the reference multi spectral image, SAM index results are restricted to only one layer. Inspecting results of applying pixel level fusion quality assessment, it is clear that fusion function does not behave uniformly towards the whole image.

TABLE 1: Pixel Level Results of SAM.

Metric	Min/Max	Mean	STD
SAM	0/26	12.56	2.69

It is obvious that the average value for quality metric differs saliently from the min or max values and cannot comprehensively reflect quality of entire image. So, it is an emphasis on non-efficiency of traditional methods of evaluating fusion quality via a single value. Besides, it can be observed that image patches, defined using sliding window for evaluating UQI index, does not match the real image objects and cannot be reliable enough for quality assessment of pan-sharpen image objects. On the other hand, it is obvious that quality values, achieved via each quality metric are completely different. For example in case of SAM it ranges 0-26 while it ranges 0-1 for UQI quality metric. It is realized that there is no individual reference for comparing the outcomes of applying different quality metrics in traditional pixel level fusion quality assessment. All disadvantages of traditional pixel level quality assessment hint to superiority of applying an object level fusion quality assessment for lessening mentioned limitations of traditional pixel level assessment approach.

TABLE 2: Pixel level results of UQI.

Metric	Bands	Min/Max	Mean	STD
UQI	R-R	0/0.89	0.49	0.24
	G-G	0/0.82	0.54	0.18
	B-B	0/0.80	0.49	0.19
	R-P	0/0.82	0.52	0.20
	G-P	0/0.80	0.51	0.20
	B-P	0/0.83	0.45	0.20

4.2 Object Level Image Fusion Quality Assessment

In order to extract image objects, a multi resolution image segmentation method is performed based on the original multi spectral image [24]. For implementation of segmentation, eCognition software system that provides multi resolution object-oriented image analysis is applied (eCognition 4 Professional User guide) [25]. Through the segmentation procedure, the whole image is segmented and image objects are extracted based on adjustable criteria of heterogeneity in color and shape. Achieved segmented image via eCognition software is presented in Fig. 4.a. By implementing image segmentation, different image objects are extracted each of which presents an individual image district. By extracting boundaries of determined image objects and applying them on source panchromatic and pan-sharpen images, corresponding image objects in those imagery are extracted. When image objects extracted, fusion quality is determined for each image object based on SAM and UQI metrics. SAM index evaluated for all pixels of each image object and final value achieved through averaging of all. To show the fusion behavior over image objects, final SAM index for each image object are assigned as pixels intensities and illustrated in Fig. 4.b. On the other hand, in case of UQI, each image segment is considered as image patch, so UQI index achieved for each image object directly applying Equation. 3.2. Average amount of achieved UQI value for all three pan-sharpen image bands with respect to bands of multi spectral image are assigned as pixel intensity values and illustrated in figure. 4.c.

a. Image objects of MS Image
b. Object level SAM
c. Object level UQI

FIGURE 4: Extracted Image Objects and Object Level Behavior of IFQM Through Data Set.

The same as pixel level assessments, the achieved amount of metrics in each individual segment with the Min, Max, Mean and STD values of all segments are determined. Achieved results of both SAM index and UQI are presented in Table 3 and 4.

Table. 2 shows dissimilar statistical behavior of quality index in different image objects for both situation of UQI (mono modal metric) and SAM (multi modal metric).

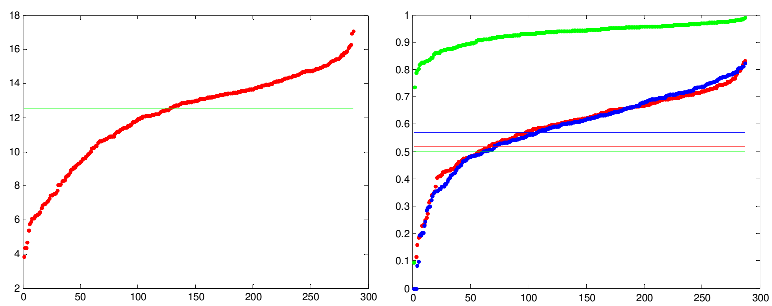
TABLE 3: Object Level Results of SAM.

Metric	Min/Max	Mean	STD
SAM	3.83/17.07	12.14	2.69

TABLE 4: Object Level Results of UQI.

Metric		Min/Max	Mean	STD
UQI	R-R	0/0.83	0.59	0.13
	G-G	0.09/0.98	0.92	0.06
	B-B	0/0.82	0.58	0.14
	R-P	0/0.79	0.58	0.12
	G-P	0.50/0.98	0.91	0.07
	B-P	0.50/0.99	0.96	0.04

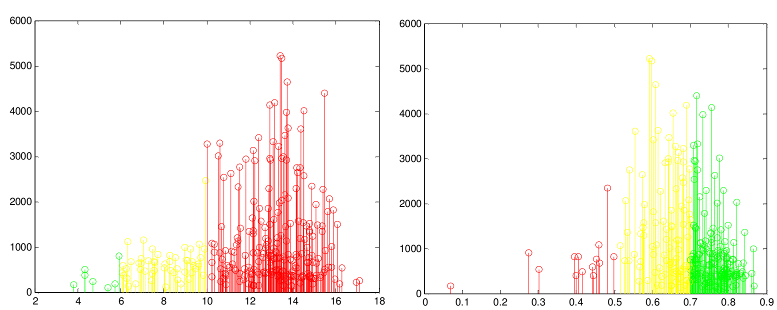
To assess object level fusion quality, the final results for each metric in all image segments are sorted and visually illustrated to provide better view of fusion behavior (Fig 5). Moreover, to provide a comparative view, all metrics evaluated based on the traditional pixel level strategy and illustrated. Results of applying SAM are presented in Fig 5a. In case of UQI which is a mono modal metric, results are graphically presented in comparison with multi spectral (R-R, G-G, B-B) image (Fig 5.b). The quality metric values achieved traditionally are also plotted.



b. SAM a. UQI

FIGURE 5: Behavior of Object Based IFQMs.

In our experiments, the quality of objects are categorized in three levels, high quality, mean quality objects and low quality objects (Fig 6). Fig 6 shows the frequency of image objects pixels to the value of their image quality metrics of SAM and UQI in the test area.



a. UQI b. SAM

FIGURE 6: Categorization of Fusion Quality in Test Area.

Conducted experiments and obtained results showed that fusion process does not behave uniformly towards the whole image. So, it is not reliable to evaluate fusion quality by a unique quality value. Since for most applications, quality of image objects are of fundamental importance, an object level fusion quality assessment can be helpful in evaluating quality of fusion in different image objects. Object level quality assessment of fusion lessens the limitations of traditional pixel level strategies. It is also less sensitive to selection of fusion quality metrics.

5. CONCLUSION

There is a wide range of image fusion quality metrics in literature which have been used in different applications and for variety of remote sensing images. In most experiments, these metrics are applied for pixel level fusion quality assessment. This means they evaluate fusion quality in whole image paying no attention to spatial and textural behaviors. This paper proposed an object level fusion quality assessment to model non-uniform behavior of image fusion process. Based on the proposed strategy, image fusion quality assessment is performed for each individual image objects autonomously. Using the high capabilities of this object level image fusion quality assessment strategy, one can solve most of the main problems of traditional pixel level strategies. However, this method still needs some more modifications in the field of definition of image objects which is used in recognition process. Moreover, incorporating of other image quality metrics could efficiently modify the potential of the proposed methodology.

6. REFERENCES

1. D. Fasbender, D. Tuia, P. Bogaert, M. Kanevski, 2008. *Support-Based Implementation of Bayesian Data Fusion for Spatial Enhancement: Applications to ASTER Thermal Images*, IEEE Geoscience and Remote Sensing Letters, Volume: 5 , Issue: 4 Digital Object Identifier: 10.1109/LGRS.2008.2000739 Publication Year: 2008 , Page(s): 598 – 602

2. H. Chu, and W. Zhu, 2008. *Fusion of IKONOS Satellite Imagery Using IHS Transform and Local Variation*. IEEE Geoscience and Remote Sensing Letters, Vol. 5, No. 4

3. F. Bovolo, L. Bruzzone, L. Capobianco, A. Garzelli, S. Marchesi, F. Nencini, 2010, *Analysis of the Effects of Pansharpening in Change Detection on VHR Images*, IEEE Geoscience and Remote Sensing Letters, Volume: 7 , Issue: 1 Digital Object Identifier: 10.1109/LGRS.2009.2029248, Page(s): 53 – 57

4. S. Rahmani, M. Strait, D. Merkurjev, M. Moeller. and T. Wittman, 2010. *An Adaptive IHS Pan-Sharpening*, *IEEE Geoscience and Remote Sensing Letters*, vol. 7, no. 4, October 2010

5. T. Tu, W. Cheng, C. Chang, P.S. Huang and J. Chang, *Best Tradeoff for High-Resolution Image Fusion to Preserve Spatial Details and Minimize Color Distortion*. IEEE Geoscience and Remote Sensing Letters, Vol. 4, No. 2, April 2007

6.Wald, L., 2000, *Quality of High Resolution Synthesized Images: Is There a Simple Criterion*? Proc. Int. Conf. Fusion Earth Data.

7. G. Piella, H. Heijmans, 2003. *A new quality metric for image fusion*. In: IEEE International Conference on Image Processing, pp. 137–176.

8. Y. Zhang, 2008, *Methods for Image Fusion Quality Assessment-a Review, Comparison and Analysis*, the international archives of photogrammety, remote sensing and spatial information sciences, Vol XXXVII,(B7). Beijing , China.

9. L. Alparone, S. Baronti, A. Garzelli, and F. Nencini, 2004. *A Global Quality Measurement of Pan-Sharpened Multispectral Imagery*. IEEE Geoscience And Remote Sensing Letters, Vol. 1, No. 4, October 2004

10. S. Li, Z. Lib, J. Gonga, 2010, *Multivariate Statistical Analysis of Measures for Assessing the Quality of Image Fusion*, International Journal of Image and Data Fusion Vol. 1, No. 1, March 2010, 47–66

11. C. Thomas and L. Wald, 2006a. *Analysis of Changes in Quality Assessment with Scales*. In Proceedings of FUSION06, 10-13 July 2006, Florence, Italy.

12. C. Thomas and L. Wald, 2006b. *Comparing Distances for Quality Assessment of Fused Products*, In Proceedings of the 26th EARSeL Symposium "New Strategies for European Remote Sensing", 29-31 May 2006, Varsovie, Pologne.

13. R. Riyahi, C. Kleinn and H. Fuchs, 2009. *Comparison of Different Image Fusion Techniques for Individual Tree Crown Identification Using Quickbird Images*, in proceeding of ISPRS Hannover Workshop 2009,

14. Y. Chen, R.S. Blum, 2005. *Experimental Tests of Image Fusion For Night Vision*, in: Proceeding of the 8th International Conference on Information Fusion, 2005

15. W. Shi, Ch. Zhu, Y. Tian, and J. Nichol, 2005, *Wavelet-Based Image Fusion and Quality* Assessment. International Journal of Applied Earth Observation and Geoinformation. v6. 241-251.

16. V. Vijayaraj, 2004. *Quantitative Analysis of Pansharpened Images*, Mississippi State University.

17. D. Kumar Sahu and M.P.Parsai, 2012, *Different Image Fusion Techniques –A Critical Review*, International Journal of Modern Engineering Research (IJMER), Vol. 2, Issue. 5, Sep.-Oct. 2012 pp-4298-4301

18. Z. Wang and A. C. Bovik, 2002. *A Universal Image Quality Index*, IEEE Signal Process. Letter, 3 81–4

19. Hossny, M., Nahavandi, Saeid and Creighton, Douglas 2007. A quadtree driven image fusion quality assessment, in *5th IEEE International Conference on Industrial Informatics*, 2007, IEEE Xplore, Piscataway, N.J, pp. 419-424.

20. F. Van Der Meer, 2005. *The Effectiveness of Spectral Similarity Measures for The Analysis of Hyperspectral Imagery*, International Journal Of Applied Earth Observation And Geoinformation, vol. 93, 1-15.

21. Z. Wang, A.C. Bovik, 2009, *Mean Squared Error: Love It or Leave It*? IEEE Signal Processing Magazine, 2009, {26} (1): 98-117

22. F. Samadzadegan and F. DadrasJavan, 2011. *Evaluating the Sensitivity of Image Fusion Quality Metrics*, Journal of Indian Society of Remote Sensing, Published by Springer.

23. QuickBird spacecraft information and specifications, http://www.digitalglobe.com/index.php/85/ QuickBird

24. U. Benz, P. Hofmann, G. Willhauck, I. Lingenfelder, M. Heynen, 2004. *Multi-Resolution, Object-Oriented Fuzzy Analysis of Remote Sensing Data for GIS-Ready Information*. ISPRS Journal of Photogrammetry & Remote Sensing, 58: 239–258.

25. eCognition 4 Professional User guide http://www.gis.unbc.ca/help/software/ecognition4/userguide.pdf.