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Article

New Object Level Strategy for Image Fusion Quality Assessment of High Resolution Satellite Imagery

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Summary: Nowadays, topographic earth observation satellites provide panchromatic images at a higher spatial resolution and also multi-spectral images at a lower spatial resolution which is rich in spectral information. Image fusion techniques produce new images which inherent the merits of initial panchromatic and multi spectral images. Considering the importance of fusion accuracy on the quality of the next applications, it seems necessary to evaluate the quality of these processed pansharpened images. Lots of quality evaluation metrics have been proposed for quality assessment of fused images. These methods are mainly developed on the basis of applying quality metrics in pixel level and to evaluate the final quality by averaging computation. In this paper, an object level strategy for fusion quality assessment is proposed. Based on the proposed strategy, image fusion quality metrics are applied on image objects and quality assessments are conducted to inspect fusion quality in those image objects. Results obtained from applying several pan-sharpen QuickBird imagery, clearly show the in-consistency of fusion behaviour in different image objects and the weakness of traditional pixel level strategies in handling these heterogeneities.

Zusammenfassung: *Neue Strategie auf der Objektebene für die Qualitätsbewertung von hoch aufgelösten Satellitenbildern*. Heute erzeugen Erdbeobachtungssatelliten panchromatische Bilder mit hoher räumlicher Auflösung und multi-spektrale Bilder mit niedrigerer räumlicher Auflösung und vielfältigen spektralen Informationen. Bildfusionstechniken erstellen neue Bilder, die Eigenschaften der eingehenden panchromatischen und multispektralen Bilder aufweisen. Zieht man die Wichtigkeit der Fusionsgenauigkeit für neue Anwendungen in Betracht, erscheint es notwendig, die Qualität dieser bearbeiteten pan-geschärften Bilder zu bewerten. Viele Bewertungssysteme wurden bereits zur Bewertung der zusammengefügten Bilder angeboten. Diese Methoden sind hauptsächlich entwickelt worden, um die metrischen Bewertungssysteme auf Pixel-Niveau anzuwenden und die Endqualität anhand einer Durchschnittsberechnung auszuwerten. Die vorliegende Arbeit stellt eine Strategie auf der Objektebene vor. Grundlage dieser Strategie ist es, das Bildfusionqualitätsbewertungssystem auf der Objektebene einzusetzen und Qualitätsbewertungen durchzuführen, um die Fusionsqualität auf der Objektebene zu prüfen. Wird diese Strategie zur Verarbeitung von verschiedenen pan-geschärften Bilder von QuickBird verwendet, zeigen die Resultate eindeutig die Unvereinbarkeit im Verhalten der Fusion für verschiedene Objekte sowie die Schwäche der traditionellen Strategie auf Pixelebene mit diesen Verschiedenartigkeiten umzugehen.

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 but rich spectral information (Ranchin & Wald 2000, Reyes et al. 2004, Thomas & Wald 2004). Several technological limitations make it impossible to use a sensor of both high spatial and spectral characteristics (Thomas & Wald 2004).

To surmount these limitations, image fusion as a mean of enhancing the information

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content of the initial images to produce new images rich in information content, has drawn an increasing attention in recent years (Reyes et al. 2004, Thomas & Wald 2004). Remote sensing communities have also switched to merge multi-spectral and panchromatic images in order to exhibit complementary characteristics of spatial and spectral resolutions. This new product is called pan-sharpen image.

During last decades, a wide range of fusion methods have been developed to produce multi spectral images having the highest spatial resolution available within the dataset (Ranchin & Wald 2000, Reyes et al. 2004). Nevertheless, as these new images do not exactly show the behavior of the real objects, acquired by the remote sensing sensors, quality assessment of these data seems 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 developing methods for evaluating the quality of these processed images (Wald 2000, Piella et al. 2003, Zhang 2008).

Image quality assessment methods can be divided into two classes: Subjective assessments by humans and objective assessments by algorithms designed to mimic human subjectivity (Shi et al. 2005). Subjective analysis involves visual comparison of colors between original MS and fused images, and the spatial detail between original panchromatic and fused images (Zhang 2008). This method cannot be represented by rigorous mathematical models, and their techniques are mainly visual, costly and time consuming procedures (Shi et al. 2005).

Considering limitations of the subjective quality assessment, much effort has been devoted to develop objective image fusion quality assessment methods (Shi 2005, Zhang 2008, Alparone et al. 2004). These kinds of methods involve a set of predefined quality indicators for measuring the spectral and spatial similarities between the fused image and the original MS and/or Pan images (Zhang 2008). In parallel to the researches being conducted to inspect different fusion quality assessment metrics, a different strategy was also studied. In this strategy fusion quality is inspected in different levels of image information as pixels, features and objects. While most of researches on this issue are conducted in pixel level strategy, feature level quality assessment is also recommended. Xydeas & Petrovic (2000) correlated important visual information with edges and addressed an objective fusion performance measure associated with edge intensity and orientation. Besides, Chen & Blum (2005), inspected the quality of fusion by evaluating the amount of edge information transferred from the source images to the fused image. Besides, some other studies are conducted based on object level quality assessments. For example, Seetha et al. (2007) developed an object wise fusion quality assessment strategy. In the study an attempt was made to obtain the objective measurements using content based segmentation for evaluating the performance of the fused images.

To have a comprehensive evaluation over fusion quality, quality assessment techniques should have a detailed overview over spatial and spectral characteristics of fused images in object level. Doing so, it provides capabilities of monitoring and assessing fusion quality locally and based on effective parameters in application of images such as image object size, important and effective usage in next levels of processing.

2 Image Fusion Quality Metrics

Image fusion quality metrics (IFQMs) are classified based on the level of spectral information that considers in quality assessment process. Traditionally, these metrics are classified to mono-modal and multi-modal techniques (Alparone et al. 2004, Thomas & Wald 2006a). A mono-modal metric applies to a single modality (such as Entropy, UQI) while a multi-modal metric applies to several modalities (Like ERGAS and SAM) which in case of fusion quality assessment means they consider all spectral bands of images for evaluation.

Mono Modal IFQMs: Thomas & Wald (2006a) 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 Lena and images were acquired by satellite observing systems, SPOT-2 and SPOT-5. Similarly, Riyahi et al. (2009) made use of DIV and correlation coefficient as quality metrics to evaluate fusion performance of QuickBird satellite imagery. Chen & Blum (2005), performed some experimental tests according to evaluate quality of image fusion for night vision. 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. (2005) 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.

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 (Vijayaraj 2004). Wang et al. (2004) introduced the main idea of Structural Similarity (SSIM) which is one of the mono modal. A simplified version of the metric, entitled as Universal Image Quality (UQI) index was introduced by Wang & Bovik (2002) and applied for quality evaluation of IKONOS fused images by Zhang (2008). Piella & Heijman (2003) added weighted averaging to UQI to measure the performance of image fusion. This new metric was entitled as saliency factor and was practiced by Hossny et al. (2007) for image fusion quality assessment. Piella & Heijman (2003) also introduced weighted saliency factor for fusion quality assessment.

Multi Modal IFQMs: On the other hand, Wald (2000) introduces ERGAS as a multimodal index to characterize the quality of process and, present the normalized average error of each band of processed image. Alparone et al. (2004) used ERGAS and SAM for image fusion assessment of IKONOS satellite imagery. Riyahi et al. (2009) used ERGAS and its modified version RASE (Relative Average Spectral Error) for inspecting different image fusion methods. Van der Meer (2005), studied SCM (Spectral Correlation Measure) and SAM for analysis of hyper spectral imagery.

Amongst all mono-modal Image Fusion Quality Metrics, UQI has been more frequently used and brought up to be more efficient, reliable and successful (Wang & Bovik 2009, Zhang 2008). The same story is factual for SAM in terms of multi modal image quality metrics (Zhang 2008, Carvalho et al. 2000, Van der Meer 2005).

2.1 *Universal Quality Index*

Structural Similarity Image Metric (SSIM) is a common mono modal metrics introduced by Thomas & Wald (2006a), and more formally distilled in Wang et al. (2004). The basic form of SSIM is very easy to understand. Suppose that x and y are local image patches taken from the same location of two images that are being compared. The local SSIM index measures the similarities of three elements of the image patches: the similarity $l(x, y)$ of the local patch luminance (brightness values), the similarity $c(x, y)$ of the local patch contrasts, and the similarity $s(x, y)$ of the local patch structures. These local similarities are expressed in the following equation (Wang & Bovik 2009).

$$S(x,y) = l(x,y)\cdot C(x,y)\cdot S(x,y) = \frac{2\cdot\bar{x}\cdot\bar{y}+c_1}{\bar{x}^2+\bar{y}^2+c_1}\cdot\frac{2\cdot\sigma_x\cdot\sigma_y+c_2}{(\sigma_x^2+\sigma_y^2+c_2)}\cdot\frac{\sigma_{xy}+c_3}{\sigma_x\cdot\sigma_y+c_3} \tag{1}$$

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. The items c_1, c_2, and c_3 are small positive constants that stabilize each term. The Universal Quality Index (UQI) corresponds to the case that $c_1 = c_2 = c_3 = 0$ (Wang et al. 2004).

$$Q = \frac{4\cdot\sigma_{xy}\cdot\bar{x}\cdot\bar{y}}{\left(\sigma_x^2+\sigma_y^2\right)\left[\bar{x}^2+\bar{y}^2\right]} \tag{2}$$

Q index is bounded in [-1,1] and its maximum value of $Q = 1$ achieved when patch x has the same statistical properties as patch y. In this study Q index is computed locally using a sliding window moving through images. Q index of the whole image is computed by averaging the achieved local quality indices over local regions.

$$Q = \frac{1}{N} \sum_{w=1}^{N} Q_w \tag{3}$$

Where Q_w indicates the calculated quality index within the sliding window w, and N is the total number of patches used to calculate Q index.

2.2 *Spectral Angle Mapper*

One of the most common multi modal metrics is Spectral Angle Mapper (SAM) which is a tool that permits rapid mapping of spectral similarity of image spectra to reference spectra (Wald 2000). The algorithm attempts to obtain the angle formed between the reference spectrum and the processed spectrum treating them as vectors in space by dimensionality equal to the number of bands (Leung et al. 2001), consequently SAM is a multi modal image quality metric. For a specific image pixel i ($i = 1,2,3,\ldots,m$; m = number of image pixels) SAM index is given as:

$$\cos(\alpha) = \frac{\sum_{i=1}^{N} x_i \cdot y_i}{\sum_{i=1}^{N} x_i \cdot x_i \sum_{i=1}^{N} y_i \cdot y_i} \tag{4}$$

where N is the number of bands of images or the dimension of the spectral space, $x = (x_1, x_2,\ldots, x_N)$ and $y = (y_1, y_2,\ldots, y_N)$ are two spectral vectors with same wavelength from the multispectral and fused images respectively. 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 in image vectors (Carvalho et al. 2000). Averaging over the whole image yields global measurement of spectral distortion.

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.

For the description of spectral and textural difference or color heterogeneity the sum of the standard deviations of spectral values in each layer weighted with the weights w_c for each layer are used:

$$h_c = \sum_c w_c \cdot \sigma_c \tag{5}$$

The shape criterion again consists of two subcriteria for smoothness and compactness based on the following equation.

$$h_{shape} = w_{cmpt} \cdot h_{cmpt} + \left(1 - w_{cmpt}\right) \cdot h_{smooth} \tag{6}$$

The overall fusion value f is computed based on the spectral heterogeneity h_c and the shape heterogeneity h_{shape} as follows:

$$f = w \cdot h_c + \left(1 - w\right) \cdot h_{shape} \tag{7}$$

The weight parameter w, allows adapting the heterogeneity definition to the application. The scale parameter is the stop criterion for optimization process. Prior to the merging of

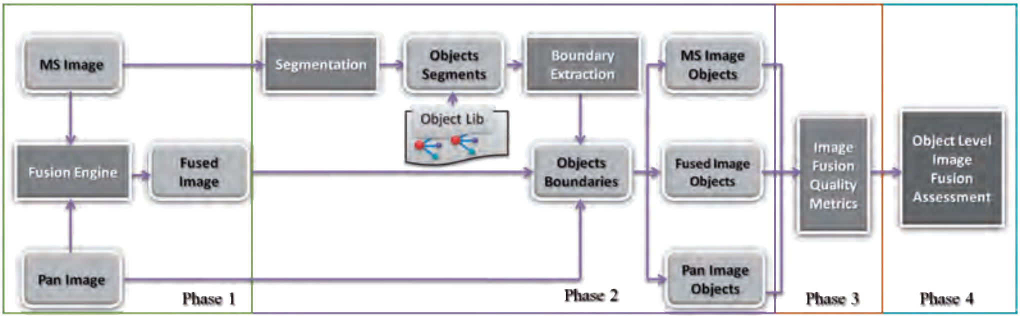


Fig. 1: Flowchart of proposed object level fusion quality assessment.

two adjacent objects, the resulting increase of heterogeneity *f* is calculated. If this resulting increase exceeds a threshold t determined by the scale parameter, $t = \Psi$ (scale parameter), then no further fusion will take place and the segmentation will stop. The larger the scale parameter, the more objects can be fused and the larger the objects grow. Details are to be found in (Benz et al. 2004).

As we are looking for meaningful image objects, the initial multi-spectral image was selected as a reference image to extract image segments. Multi spectral image contains the lowest level of textural information and objects extracted from this image are identical or integration of some smaller objects in panchromatic and pan-sharpen images.

By performing image segmentation on source multi-spectral image, objects pulled out and boundaries of extracted image objects can be determined. These boundaries are projected to panchromatic image and produced fused image, and corresponding image objects are generated. By the time, considering object libraries, type of each image object, can be determined.

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.

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

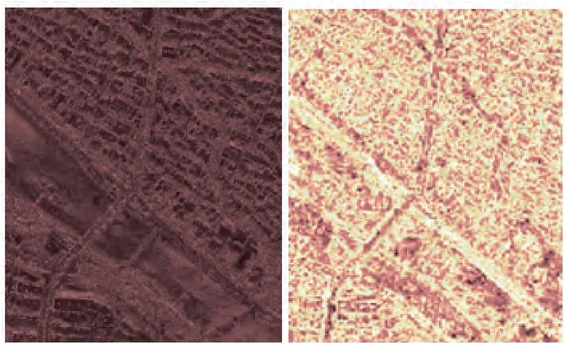
Proposed strategy is implemented and evaluated for quality assessment of high-resolution QuickBird image data over an urban area. The original panchromatic QuickBird has 0.61m pixel while the original multi spectral image has 2.4m pixel spatial resolution. Fused Quickbird images generated based on wavelet based image fusion technique resulted in new images with 0.61 meter spatial resolution and three *B1*, *B2*, *B3* (R,G,B) spectral bands (Zheng et al. 2011). All three images of data set are presented in Fig. 2.

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,

a. Pan Image b. MS Image c. Fused Image

Fig. 2: QuickBird Data set.



a. Pixel level SAM b. Pixel level UQI

Fig. 3: Pixel level behavior of IFQM through data set.

based on Equation (4). To represent disparity of achieved SAM values, they are represented as pixels intensity values. Achieved image is depicted in Fig. 3a. By averaging the whole computed SAM indices yields global measurement of spectral distortion, and is presented in Tab. 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 Tab. 1. Additionally, 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. The mean of pan-sharpen three spectral bands is computed and compared to panchromatic image to evaluate the result of fusion process with respect to initial panchromatic image (P-I). 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. 3b.

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 Tab. 2. 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 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

Tab. 1: Pixel level results of SAM.

Metric	Min/Max	Mean	STD
SAM	0/26	2.05	1.44

Tab. 2: Pixel level results of UQI.

Bands	Min/Max	Mean	STD
R-R	0/.98	0.60	0.26
G-G	0/.98	0.60	0.27
B-B	0/.98	0.55	0.24
P-I	0/.96	0.72	0.25

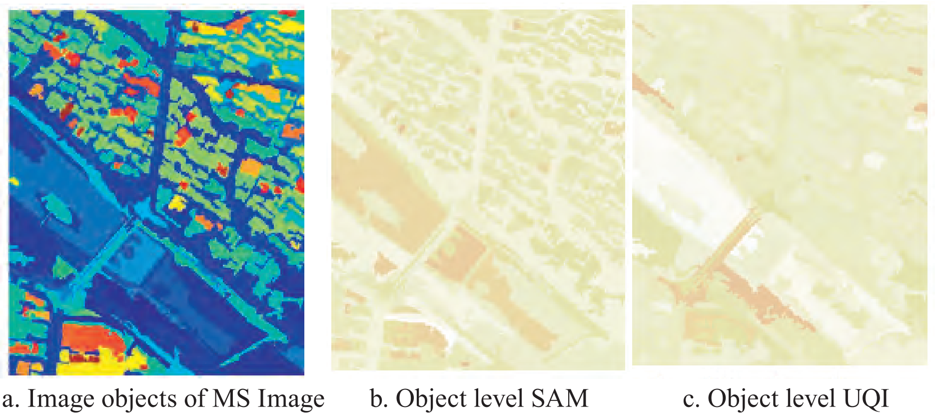
applying pixel level fusion quality assessment, it is clear that fusion function does not behave uniformly towards whole image.

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 0–3 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 capability of object level fusion quality assessment for lessening these limitations.

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. For implementation of segmentation, eCognition software system that provides multi resolution object-oriented image analysis is applied (Benz et al. 2004). 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. 4a. By implementing image segmentation, 108 different 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



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

Fig. 4: Extracted Image objects and Object level behavior of IFQM through data set.

Tab. 3: Object level results of SAM.

Metric	Min/Max	Mean	STD
SAM	.51/3.31	1.71	0.31

Tab. 4: Object level results of UQI.

Bands	Min/Max	Mean	STD
R-R	.60/.97	0.80	0.07
G-G	.62/.96	0.80	0.06
B-B	.56/.95	0.77	0.07
P-I	.25/.96	0.80	0.13

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. 4b. 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 (2). Average amount of achieved UQI value for all three pan-sharpen image band with respect to bands of multi spectral image are assigned as pixel intensity values and illustrated in Fig. 4c.

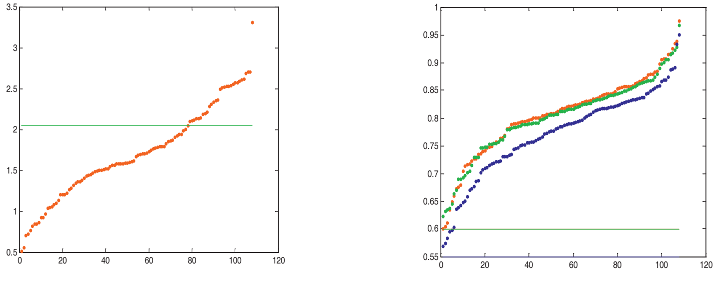
The same as pixel level assessments, the achieved amount of metrics in each individual segment with the Min, Max, Mean and STD values of all segments are determined. Achieved results of both SAM index and UQI are presented in Tabs. 3 and 4.

Tabs. 3 and 4 shows dissimilar statistical behavior of quality index in different image objects for both situation of UQI (mono modal metric) and SAM (multi modal metric).

To assess object level fusion quality, the final results for each metric in all 108 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. 5b). The quality metric values achieved traditionally are also plotted. Graphs depicted in Fig. 5 present image regions number (horizontal axis) versus resulted quality metric values of each region (vertical axis).

The figure clearly shows that the achieved quality in different image objects have a wide range of alteration in comparison with the achieved traditional value. The range of these variations is too large to be ignored. The UQI metric appears to behave differently not only in different image regions but also in different bands of images. Moreover, depicted diagrams insist on the claim of different fusion quality over different image object with different paternal behavior. It also bolds the fact that it is not justified to ignore these variations and have a uniform view over the whole image data set while assessing image fusion quality.

In our experiments, the quality of objects categorized in three levels, high quality, mean quality objects and low quality objects (Fig. 6). Fig. 7 shows the frequency of image objects pixels to the value of their image quality metrics of SAM and UQI in the test area.



a. SAM b. UQI (R-R)

Fig. 5: Behavior of Object based IFQMs.

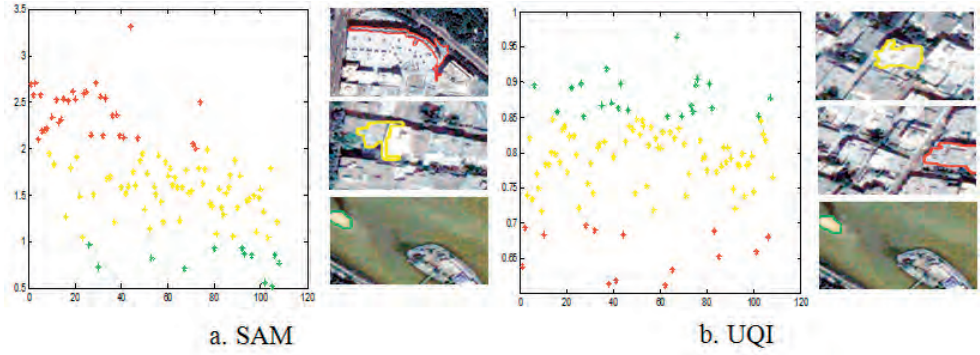


Fig. 6: Categorization of fusion quality in test area. a) SAM quality levels and three object samples for each level. b) UQI quality levels and three objects samples for each level.

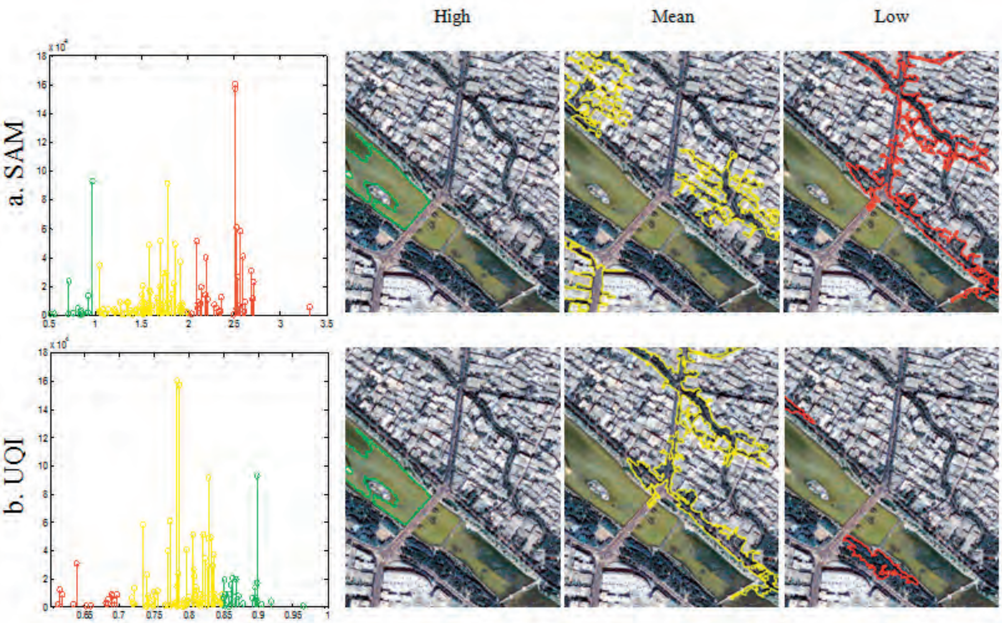


Fig. 7: Frequency of image objects pixels to the value of their image quality metrics of a) SAM and b) UQI in the test area and three largest objects for each level.

Conducted experiments and the obtained results show that fusion process does not behave uniformly towards the whole image. Having said that, it is not reliable to evaluate fusion quality of a pan-sharpen image just by a single value.

Although debated quality assessment metrics are apparently observed to be successful, in conformance with previously studied researches, using a pixel level strategy inevitably leads to evaluating image as a whole. This takes us just to a hazy general evaluation of the image regardless of the quality of fusion concerning each object.

As in most applications, the processing is mainly focused on specific types of objects, using an object level strategy, image fusion could be more selectively and reliably evaluated due to the reduction of image space into target objects. For example, using an object library, it might be possible to provide the capability of assessing fusion quality for a specific object such as building, vegetation, etc.

In patch wise or locally computed metrics such as UQI, although it seems that a local patch wise strategy using a traditional pixel level is obtained, they fail to represent a local evaluation. This can be viewed in two angles. First, they miss to evaluate locally as patches are acquired in a routine manner, regardless of the regional relations between pixels and corresponding objects. Second, the averaging of the computed evaluation values of each patch results in a general value for whole image but no local assessment.

As shown in Fig. 6, it is observed that different image quality metrics show more behavioural conformity to each other when computed through an object level strategy rather than pixel level traditional one.

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. Besides, the quality of fusion process can be evaluated by the proposed method while all spectral bands of images are applied or for comparing different image fusion strategies, in future studies.

This means they evaluate global fusion quality in image paying no attention to available textural diversities in different objects which dictate different fusion behavior.

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