Remote sensing image fusion in the context of Digital Earth

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Abstract. The increase in the number of operational Earth observation satellites gives remote sensing image fusion a new boost. As a powerful tool to integrate images from different sensors it enables multi-scale, multi-temporal and multi-source information extraction. Image fusion aims at providing results that cannot be obtained from a single data source alone. Instead it enables feature and information mining of higher reliability and availability. The process required to prepare remote sensing images for image fusion comprises most of the necessary steps to feed the database of Digital Earth. The virtual representation of the planet uses data and information that is referenced and corrected to suit interpretation and decision-making. The same pre-requisite is valid for image fusion, the outcome of which can directly flow into a geographical information system. The assessment and description of the quality of the results remains critical. Depending on the application and information to be extracted from multi-source images different approaches are necessary. This paper describes the process of image fusion based on a fusion and classification experiment, explains the necessary quality measures involved and shows with this example which criteria have to be considered if the results of image fusion are going to be used in Digital Earth.

1. Introduction
The vision on Digital Earth (DE) for the next decade published in the a position paper from the International Society for Digital Earth in 2012 [1], comprises three important interest areas, namely
(1) Dynamic information flow of social and environmental interactions
(2) Establishing DE as a framework
(3) Raising awareness of the concept of DE
These aspects were raised from a European perspective but I believe that they play an equally important role around the world. Having this vision in mind, this paper intends to highlight contributions to DE 2020 coming from Earth observation and advanced remote sensing image exploitation in particular.

The choice of remote sensing image data has increased tremendously during the last decades. Sensors covering various parts of the electromagnetic spectrum provide multi-spectral, multi-temporal, multi-polarization, multi-look and multi-resolution imagery. Our view on the Earth has become more detailed and precise with the effect that remote sensing image users face new challenges, handling larger volumes of data with increased resolution that requires more accurate image processing and information extraction. Along with this development new image fusion techniques have emerged that enable the user to adapt the fusion process to local context and sensor characteristics, both being a requirement for reliable information extraction.

Image fusion is a powerful tool to obtain data and information from complementary, multi-sensor images. It enables to enhance image content so that information can be derived that cannot be obtained from a single sensor alone [2]. Many researchers have dedicated their time in the past twenty years to explore techniques, applications and limitations of remote sensing image fusion. Some

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concentrated on the development of new techniques, such as adapted component substitutions methods [3], further developments of wavelet approaches [4], or the implementation of new algorithms [5]. Others focused on the comparison of performance of image fusion approaches, looking at qualities and accuracies achieved [6]. In addition, many case studies were published to show the effectiveness of image fusion for many different applications that are also relevant for DE in the future, using globally relevant examples, e.g. forest monitoring [7], urban change detection [8] or natural hazard characterization [9], just to name a few.

With this effort of the remote sensing research community we have arrived at a stage where it is possible to integrate image fusion in an operational environment. This is shown by more and more modules appearing within widely used commercial software packages (e.g. ENVI, ERDAS, PCI). The next step is a general framework to compile the scientific achievements and provide a “Fusion Atlas” to the user community. This is in particular relevant for remote sensing image fusion because the application of multi-sensor image fusion for different applications requires a broad range of experiences and knowledge. To obtain reliable and accurate results the user needs to be aware of sensors’ characteristics, their particular imaging technology, radiometric and geometric specialties, the actual fusion technique and its implications on the image content as well as the application the resulting fused image is going to be used for. At the end each product needs to come with precise ancillary data, i.e. a description of the processing performed on the original image plus the parameters describing the quality of the information including an accuracy statement that can be read by other users. All these aspects are pre-requisites for a successful concept of Digital Earth.

Due to the nature of fused images they are very suitable for further use in a geographic information system (GIS) and the combination with other layers of information on the area of interest. This paper uses an image fusion experiment to illustrate the need for a framework and emphasizes the importance of ancillary data to contribute to DE. The following section explains the performed image fusion. Section three describes the land use classification carried out on the fused images. In the last section (four) the findings are analysed and put in the perspective of DE’s vision for the next decade.

2. Image fusion experiment

The image fusion experiment for this paper was performed on Razaksat imagery acquired over an area of the Malaysian peninsular in South East Asia. This Malaysian satellite and its image characteristics have been described in detail in [10]. The study site, already published in another research paper of the author [11], covers a complex industrial site at the west coast of the peninsular Malaysia, north of the cultural heritage city of Melaka.

2.1. Pre-processing

The data set available for this experiment forms a simple case for image fusion because the image is acquired by one sensor, the medium-size aperture camera (MAC) providing five bands: one high resolution panchromatic (PAN) and four multispectral (MS) bands. In the meantime, fusion of PAN with MS is a standard method, called pansharpening [12]. It has been investigated intensively in the past and led to the implementation of commercial software as mentioned before. In order to perform pixel-based fusion the images have to be co-registered and geometrically corrected. To avoid multiple resampling which always induces a deterioration of the image content an intelligent system would model the geometric correction process and integrate the fusion approach with one time resampling (see also [13]). In the present case the data fed into the fusion process is radiometrically and geometrically corrected and geocoded to the Universal Transverse Mercator coordinate system, Zone 48N, WGS-84.

2.2. Image fusion

The actual fusion process is performed on a subset of the scene obtained of the region (figure 1). This subset was chosen to demonstrate classification issues using a ‘real-life example’ even though it is disturbed by a cloud.
Out of the large variety of experiments performed on this data set the paper concentrates on the description of two particular pansharpening methods, namely Fuzego™ and Ehlers fusion. Fuzego™ (hereafter called Fuzego) is a newly developed brand based on the University of New Brunswick (UNB) pansharp algorithm. It fuses image data from all satellite or airborne sensors. It automatically adjusts to each individual data set without manual input requirements [14]. The Ehlers algorithm is based on a combination of Intensity Hue Saturation (IHS) component substitution and the Fast Fourier Transform. It has shown a very good performance in the past ([6]) and allows pansharpening while preserving a high spectral quality which is a pre-requisite for multispectral image classification.

Figure 1 displays the results of the two different techniques, each performed twice: first with emphasis on spectral and second with the focus on spatial enhancement. In figure 1(a) Fuzego was applied without choosing extra spatial enhancement; figure 1(b) contains the result of Ehlers fusion focusing on spectral preservation. Figures 1(c) and (d) contain spatial enhancement focused results, for Fuzego and Ehlers, respectively. Looking at the Petroleum storage facilities, pipelines and roads the differences between the results become obvious. The influence of these different approaches will become even more obvious when looking at the classification results that are discussed in the next section.

2.3. Classification

For multispectral image classification two supervised methods were chosen using the same classes that were identified in a previous study [11]: 1. The classic Maximum Likelihood (ML) Classifier and 2. the advanced Support Vector Machine (SVM) classification. Both approaches have their advantages and disadvantages that are widely discussed in the literature (e.g. [15]). For the training of the classifier training samples of eight classes were taken using Google Earth and field data as ground truth. For both classifiers the same training samples were used. In order to evaluate the classification
results a set of ground truth samples were created based on a well distributed set of regions of interest. Figure 2 shows the classification results.

Figure 2. Fuzego classified fused images using ML and SVM classifiers: (a) Fuzego spectral ML, (b) Fuzego spatial ML, (c) Fuzego spectral SVM and (d) Fuzego spatial SVM

On the left side figures 2(a) and (c) show the ML and SVM classification results on the Fuzego images without extra spatial enhancement, respectively. Figures 2(b) and (d) are the classified Fuzego fused images with emphasis on spatial enhancement. The differences of the fusion method applied are immediately obvious when focusing on analyzing the petroleum storage containers and the construction leading to the pier. These features become more distinct when using a spatial enhancement focus even for the classification. The advantage of using an advanced classification algorithm such as SVM becomes apparent when looking at the influence of the cloud and its shadow and the small containers at the bottom right corner of the images. It is not possible to state if the SVM performs mature in comparison to the ML classifier by visual analysis.

The qualitative evaluation is confirmed by the quantitative assessment summarized in table 1. It has to be pointed out that the values listed in table 1 cannot be read as absolute values. The approach in this experiment allows a relative quality assessment for the two fusion techniques and the two classifiers applied. Based on the ground truth samples chosen from regions of interest and the calculation of the confusion matrix the best overall accuracy is achieved by the SVM classifier on the Fuzego fused image with spatial enhancement. It is very interesting to point out that the Fuzego algorithm without spatial enhancement performs excellent even using the simple ML classifier. The use of SVM classification only increases the overall accuracy by about 2%. This is different for the Fuzego spatially enhanced image. There the ML classifier fails (38.98%) in comparison to the SVM method (94.58%).

| Image classified   | Overall accuracy ML [%] | Overall accuracy SVM [%] |
|--------------------|-------------------------|--------------------------|
| Original           | 84.51                   | 89.37                    |
| Fuzego spectral    | 92.59                   | 94.57                    |
| Fuzego spatial     | 38.98                   | 94.58                    |
| Ehlers spectral    | 56.12                   | 86.70                    |
| Ehlers spatial     | 65.14                   | 89.70                    |
The effects of the choice of fusion and classification method becomes even more interesting when looking at figure 3 which contains the comparison of results of the SVM classification of the Ehlers fused images in figure 3(a) – spectral and (b) – spatial emphasis with the Fuzego fused images in figure 3(c) – spectral and (d) – spatial focus.

![Figure 3](image-url)  
*Figure 3. Comparison of Fuzego and Ehlers fusion for Petroleum facility mapping using the SVM classifier: (a) Ehlers spectral, (b) Ehlers spatial, (c) Fuzego spectral and (d) Fuzego spatial*

The subset in figure 3 aims at showing the capability of the four different approaches to map petroleum facilities on the site. Even though the overall accuracy in table 1 has led to the conclusion that Fuzego spatial performed best this example shows that the facility infrastructures are much better mapped by the Ehlers spatial approach in combination with the SVM classifier. Therefore, we have to be very careful in defining processing flows and giving absolute quality measures. It is obvious that these vary depending on the land cover types and applications that we are looking for.

3. **Discussion and conclusion in the context of DE 2020**  
This paper describes an experiment using image fusion to increase multispectral image classification for land cover mapping. From the various processing flows implemented using two different pansharpening algorithms and two classifiers it was possible to show the manifold impacts and aspects to be considered if information is to be extracted as contribution to DE. Since the remote sensing images (original geocoded), the processed results (fused) as well as the information produced (classified) feed into a GIS it is very important to understand and describe the alteration that have happened to the original content. The user of the GIS needs adequate information regarding information content and quality in order to be able to use it. This is very important for a future implementation of a detailed digital representation of the Earth in all its complexity. Image fusion is very powerful in providing high quality information in a format that can directly be integrated in DE. A current effort intends to complete a framework (Fusion Atlas) and standardization (Fusion Approach Selection Tool – FAST) to make image fusion a part of DE in the near future.

**References**

[1] Craglia M, de Bie K, Jackson D, Pesaresi M, Remetey-Fülöpp G, Wang C, ANnoni A, Bian L, Campbell F, Ehlers M, van Genderen J, Goodchild M, Guo H, Lewis A, Simpson R, Skidmore A and Woodgate P 2012 Digital Earth 2020: towards the vision for the next
[2] Pohl C and Van Genderen J 1998 Multisensor image fusion: Concepts, methods and applications Int. J. RS 19 823-54
[3] Aiazzi B, Baronti S and Selva M Improving component substitution pansharpening through multivariate regression of MS+PAN data IEEE Trans. Geosc. RS 45 3230-39
[4] Amolins K, Zhang Y and Dare P 2007 Wavelet based image fusion techniques – An introduction, review and comparison ISPRS J. Photogr. RS 62 249-63
[5] Choi, J, Yeom J, Chang A, Byun Y and Kim Y 2013 Hybrid Pansharpening Algorithm for High Spatial Resolution Satellite Imagery to Improve Spatial Quality IEE Trans. Geosc. RS Letters 10 490-94
[6] Klonus S and Ehlers M 2009 Performance of evaluation methods in image fusion Proc. 12th Int. Conf. Information Fusion 1409-16
[7] Xin, Q, Olofsson P, Zhu Z, Tan B and Woodcock CE 2013 Toward near real-time monitoring of forest disturbance by fusion of MODIS and Landsat data RS Env. 135 234-47
[8] Deng JS, Wang K, Deng YH and Qi GJ 2008 PCA-based land-use change detection and analysis using multitemporal and multisensor satellite data Int. J. RS 29 4823-38
[9] Lu Z, Dzurisin D, Jung H-S, Zhang J and Zhang Y 2010 Radar image and data fusion for natural hazards characterisation Int. J. Image & Data Fusion 1 217-42
[10] Hashim M, El-Mahallawy M S, Reba M N M, AbasA A, Ahmad S, YapX Q, MarghanyM and ArshadA S 2013 Geometric and radiometric evaluation of Razaksat medium-sized aperture camera data Int. J. RS 34 3947-67
[11] Pohl C and Hashim M Increasing the potential of Razaksat images for map-updating in the Tropics 2013 ISDE8 IOP Earth & Env Sc, in press.
[12] Alparone L, Wald L, Chanussot J, Thomas C, Gamba P and Bruce L M 2007 Comparison of pansharpening algorithms: Outcome of the 2006 GRS-S Data-Fusion Contest IEEE Trans. Geosc. & RS 45 3012-21
[13] Toutin T 2011 State-of-the-art of geometric correction of remote sensing data: a data fusion perspective Int. J. Image & Data Fusion 2 3-35
[14] Fuzego homepage http://www.fuzego.com/ (last visited 24th July 2013)
[15] Colditz RR, Wehrmann T, Bachmann M, Steinnocher K, Schmidt M, Strunz G and Dech S 2006 Influence of image fusion approaches on classification accuracy: a case study Int. J. RS 27 3311-35