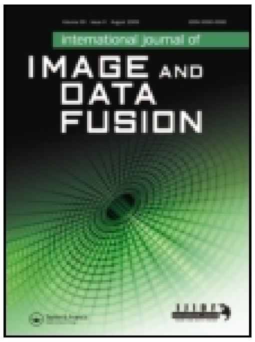

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Multi-source remote sensing data fusion: status and trends

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With the fast development of remote sensor technologies, e.g. the appearance of Very High Resolution (VHR) optical sensors, SAR, LiDAR, etc., mounted on either airborne or spaceborne platforms, multi-source remote sensing data fusion techniques are emerging due to the demand for new methods and algorithms. The general fusion techniques have been well developed and applied in various fields ranging from satellite earth observation to computer vision, medical image processing, defence security and so on. Despite the fast development, the techniques remain challenging for multi-source data fusion within varying spatial and temporal resolutions. This article reviews current techniques of multi-source remote sensing data fusion and discusses their future trends and challenges through the concept of hierarchical classification, i.e., pixel/data level, feature level and decision level. This article concentrates on discussing optical panchromatic and multi-spectral data fusing methods. So far, the pixel level fusion methods have mainly focused on optical data fusion; high-level fusion includes feature level and decision level fusion of multi-source data, such as synthetic aperture radar, optical images, LiDAR and other types of data. Finally, this article summarises several trends tending to broaden the application of multi-source data fusion.

Keywords: data fusion; multi-source remote sensing data; LiDAR; SAR

1. Introduction

Data fusion, as a general and popular multi-discipline approach, combines data from multiple sources to improve the potential values and interpretation performances of the source data, and to produce a high-quality visible representation of the data. Fusion techniques are useful for a variety of applications, ranging from object detection, recognition, identification and classification, to object tracking, change detection, decision making, etc. It has been successfully applied in the space and earth observation domains, computer vision, medical image analysis and defence security, etc.

Remote sensing data fusion, as one of the most commonly used techniques, aims to integrate the information acquired with different spatial and spectral resolutions from sensors mounted on satellites, aircraft and ground platforms to produce fused data that contains more detailed information than each of the sources.

Research on data fusion has a long history in the remote sensing community because fusion products are the basis for many applications. Researchers and practitioners have

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made great efforts to develop advanced fusion approaches and techniques to improve performance and accuracy. Fusing remotely sensed data, especially multi-source data, however, remains challenging due to many causes, such as the various requirements, the complexity of the landscape, the temporal and spectral variations within the input data set and accurate data co-registration.

In general, remote sensing fusion techniques can be classified into three different levels: the pixel/data level, the feature level and the decision level (Pohl and van Genderen 1998).

Pixel level fusion is the combination of raw data from multiple sources into single resolution data, which are expected to be more informative and synthetic than either of the input data or reveal the changes between data sets acquired at different times.

Feature level fusion extracts various features, e.g. edges, corners, lines, texture parameters, etc., from different data sources and then combines them into one or more feature maps that may be used instead of the original data for further processing. This is particularly important when the number of available spectral bands becomes so large that it is impossible to analyse each band separately. Methods applied to extract features usually depend on the characteristics of the individual source data, and therefore may be different if the data sets used are heterogeneous. Typically, in image processing, such fusion requires a precise (pixel-level) registration of the available images. Feature maps thus obtained are then used as input to pre-processing for image segmentation or change detection.

Decision level fusion combines the results from multiple algorithms to yield a final fused decision. When the results from different algorithms are expressed as confidences (or scores) rather than decisions, it is called soft fusion; otherwise, it is called hard fusion. Methods of decision fusion include voting methods, statistical methods and fuzzy logic-based methods.

The above categorisation does not encompass all possible fusion methods, since input and output of data fusion may be different at different levels of processing. In practical operations, the applied fusion procedure is often a combination of the three levels mentioned previously.

The objective of this article is to review current multi-source remote sensing data fusion techniques, and present some perspectives on the current status. This article is organised as follows: Section 1 gives an overview of the definition, classification and application of data fusion; Section 2 reviews the current status of multi-source remote sensing data fusion from pixel level pan-sharpening to high-level fusion; Section 3 addresses and highlights some future trends for new sensor data fusion and finally Section 4 presents some conclusions and comments.

2. Current status

In this section, we address the current status of fusion methods at pixel level and at high level. Since the pixel level fusion methods are mainly applied to optical images, we will concentrate on the methods of fusing optical panchromatic (PAN) and multi-spectral (MS) images. High-level fusion includes feature level and decision level fusion of multi-source data, such as synthetic aperture radar (SAR), optical images, LiDAR, geographic information systems (GIS) data and ground data.

2.1 *Pixel level fusion*

The purpose of pixel level fusion of optical images is mainly to improve spatial resolution, enhance structural and textural details and retain the spectral fidelity of the original MS data simultaneously. For this reason, it is also called pan-sharpening. For multi-temporal data, the purpose of pixel level fusion is to highlight the informative changes between different times, using either the same or different sensors. Although there is a trend to apply fusion techniques for change detection and change analysis, it is beyond the scope of this review.

So far, many pixel-level fusion methods for remote sensing images have been presented where the structural and textural details of the MS image are enhanced by adopting the higher resolution. The algorithms for pixel-level fusion of remote sensing images can be divided into three categories: the component substitution (CS) fusion technique (Chavez *et al.* 1991, Shettigara 1992, Pellemans *et al.* 1993, Aiazzi *et al.* 2007), modulation-based fusion techniques (Zhang 1999, Liu 2000, Gangkofner *et al.* 2008) and multi-resolution analysis (MRA)-based fusion techniques (Aiazzi *et al.* 2002, Amolins *et al.* 2007) (Figure 1).

In 2006, the Data Fusion Committee of the IEEE Geoscience and Remote Sensing Society conducted a survey of eight pan-sharpening algorithms contributed by participants worldwide. The best algorithm was identified through both visual and quantitative assessment (Alparone *et al.* 2007). In May 2008, IEEE Transactions on Geoscience and Remote Sensing published a special issue on data fusion, which included several new developments in image fusion methods (Gamba and Chanussot 2008).

2.1.1 *CS fusion techniques*

The CS fusion techniques consist of three steps. First, forward transform is applied to the MS bands after they have been registered to the PAN band. Second, one component of the new data space similar to the PAN band is replaced with the higher resolution band. Third, the fused results are constructed by means of inverse transform to the original space.

The typical algorithm of the CS fusion technique is the intensity-hue-saturation (IHS) transform (Carper *et al.* 1990, Chavez *et al.* 1991, Shettigara 1992), which uses the high-resolution PAN image to replace the intensity component and obtains the fused image by applying an inverse IHS transform. The original algorithm is suitable for exactly three MS band fusion but has been generalised (GIHS) to support fusion of near-infrared (NIR) images (Tu *et al.* 2004). Although the PAN image is usually histogram-matched before CS, significant radiometric changes still occur in most images. To develop an image fusion method preserving the characteristics, the high-resolution image has to sharpen the MS image without adding new grey level information to its spectral components. This is a non-trivial task for IHS-based fusion techniques, since the colour and spatial information have to be separated to allow an adaptive enhancement of the spatial information content by employing the spatial information achievable from higher resolution PAN images. Various attempts have been made to reduce the spectral distortion by using specific algorithms, such as a genetic algorithm or the spectral response characteristics of the sensors. In this way, the optimal weights of the MS bands in synthesising the intensity component and the injection gains could be achieved for single sensor data (Choi 2006, Garzelli and Nencini 2006, Gonzáles-Audícana *et al.* 2006, Aiazzi *et al.* 2007). For multi-source PAN and MS data, however, there is usually a significant inconsistency between the spectrum coverage of the PAN image and MS images (Andreja and Krištof 2006). A more practical method is then an IHS transform coupled with Fourier domain

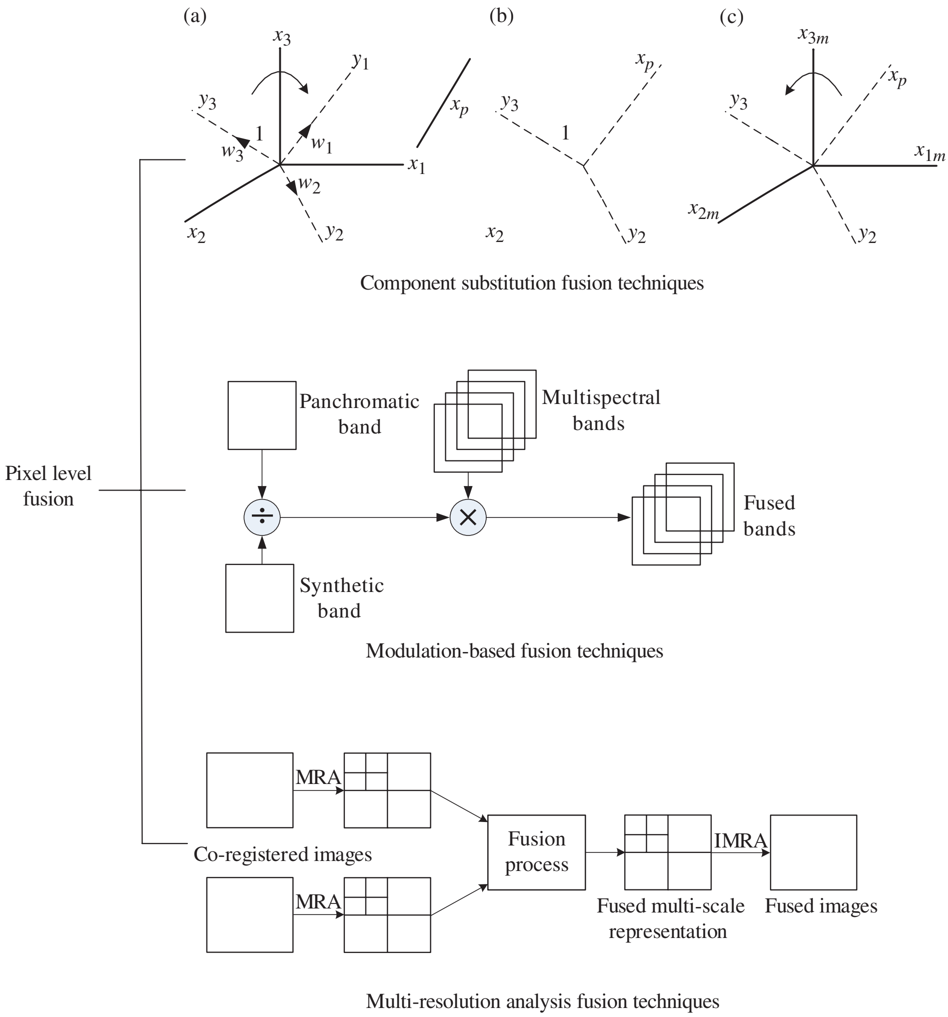

Figure 1. Three categories of pixel level image fusion.

filtering of both the PAN image and the intensity component of the original MS image (Ehlers 2004, Ling *et al.* 2007).

Other CS based methods, such as principal component analysis (PCA) transform fusion methods (Chavez *et al.* 1991, Shettigara 1992) and Gram–Schmidt (GS) spectral sharpening (Laben and Brower 2000), also suffer from challenges on spectral preserving, and specific algorithms have also been developed to reduce the spectral distortion (Aiazzi *et al.* 2007, Shah *et al.* 2008) but these are less frequently used in operational work.

2.1.2 *Modulation-based fusion techniques*

The modulation-based fusion techniques utilise the idea that the spatial details are modulated into the MS images by multiplying the MS images by the ratio of the PAN image to the synthetic image, which is generally a lower resolution version of the PAN image. This fusion method is expressed as (1):

$$\text{fusion}_i = \frac{\text{pan}}{\text{Syn}_p} \times \text{mul}_i \tag{1}$$

where fusion_i is the fused ith band, mul_i is the lower resolution MS ith band, Syn_p is the synthetic band and pan is the higher resolution PAN band.

The typical modulation-based fusion algorithms include Brovey, Smoothing Filter-based Intensity Modulation (SFIM), high-pass spatial filter (HPF) and synthetic variable ratio (SVR) fusion algorithms. For the Brovey transform fusion algorithm (Vrabel 2000), the synthetic image is the average of the blue, green and red bands:

$$\text{Syn}_p = \frac{1}{3}(\text{R} + \text{B} + \text{G}) \tag{2}$$

For the SFIM fusion algorithm, Liu (2000) pointed out that by using a ratio between a higher resolution image and its low-pass filtered (with a smoothing filter) image, spatial details can be modulated to a co-registered lower resolution MS image without altering its spectral properties and contrast. This technique can improve spatial resolution for either colour composites or an individual band. The synthetic image is the local mean of the panchromatic image with a 3×3-, 5×5- or 7×7-sized window smoothing filter kernel, which can be expressed as follows:

$$\text{Syn}_p = \frac{1}{n}\sum_{1}^{n} \text{pan}, \quad n = k \times k \text{ neighbourhood} \tag{3}$$

For the HPF method (Chavez *et al*. 1991), the higher spatial resolution data applies a small high-pass spatial filter. The results of this small HPF contain the high-frequency component that is mostly related to spatial information. Results from the HPF method are added pixel-wise to the lower spatial resolution, i.e. the higher spectral resolution data set. This process can be transformed into Equation (2), while the synthetic image Syn_p can be expressed as follows:

$$\text{Syn}_p = \text{LPH(pan) LPH, Low-Pass Filter} \tag{4}$$

Gangkofner *et al*. (2008) optimise the HPF addition technique whose improvements are standardisation of the HPF parameters over a wide range of image resolution ratios and the controlled trade-off between resulting image sharpness and spectral properties.

Zhang (1999) presents the SVR merging method, which is calculated by means of Equation (1). The synthetic image is the grey value of the high-resolution synthetic PAN image formulated by the following equation:

$$\text{Syn}_p = \sum \varphi_i \, \text{mul}_i \tag{5}$$

The SVR method can directly derive parameters φ_i by means of the following equation:

$$\text{pan} = \sum \varphi_i \, \text{mul}_i + \varepsilon \tag{6}$$

To reduce colour distortion, the parameters φ_i are calculated directly by means of multiple regression analysis to identify the best fit between grey values of individual image bands.

In general, the performances of the modulation-based fusion techniques, especially their spectral preservation quality, are determined mainly by the accurate estimation of the components of the MS bands related to the PAN image at higher resolution. To achieve this, most algorithms assume that the spectrum response of the PAN image can be linearly simulated, and thus can be estimated by a weighted summation of the MS images. This performs well on single sensor data but when applied to multi-source data poor results are sometimes obtained because the spectrum coverage and the gains and offsets are usually different. However, with high-resolution images, the ground objects of the neighbouring pixels become more heterogeneous and thus the grey values become more difficult to predict and interpolate, making estimation of the spatial distribution of these components extremely difficult. This is especially the case if the resolution ratio between the PAN and MS images becomes small, like for instance for the SPOT5 and the Landsat ETM+ MS band, where the ratio is approximately 1:12.

2.1.3 *MRA fusion techniques*

The MRA-based fusion techniques (Amolins *et al*. 2007) adopt multi-scale decomposition methods such as multi-scale wavelets (Núñez *et al*. 1999), Laplacian pyramids (Aiazzi *et al*. 2002) or bi-dimensional empirical mode decomposition (BEMD; Liu *et al*. 2007) to decompose MS and PAN images with different levels. They derive spatial details that are imported into finer scales of the MS images. They highlight relationships between PAN and MS images in coarser scales and enhance spatial details.

MRA-based fusion techniques consist of three main steps: (1) MRA: wavelet multi-resolution decomposition; (2) fusion: replacement of approximation coefficients of PAN by those of the MS band; and (3) IMRA inverse multi-resolution transform.

Earlier studies (Garguet-Duport *et al*. 1996, Yocky 1996) adopting discrete wavelet transform (DWT) maintain more spectral characteristics of the MS imagery than do the CS fusion schemes (e.g. IHS and PCA). They, however, introduce artefacts in the fused image. Núñez *et al*. (1999) present the additive wavelet fusion algorithm (AWL) by using the 'a trous' algorithm, which allows the use of a dyadic wavelet to merge non-dyadic data in a simple and efficient scheme. To improve the spectral quality, the high-pass details are injected proportionally to the low-pass MS components in such a way that the fused MS pixel vector is proportional to that before fusion. Liu *et al*. (2007) proposed a fusion method using the BEMD to produce a certain level of intrinsic mode functions (IMF) and residual images of the original PAN and MS images based purely on spatial relationships between the extrema of the image. By injecting all IMF images from the PAN image into the residue of the corresponding MS image, the fusion image can be reconstructed. The method performs well on spectral preservation, even on very small resolution ratio multi-source data. Aiazzi *et al*. (2002) presented the generalised Laplacian pyramid and context-based decision (GLP-CBD) fusion algorithm, which exploits MRA, achieved through GLP, with the spatial frequency response of the analysis filters matching a model of the modulation transfer function (MTF) of the MS instrument. The injection model uses a decision based on locally thresholding the correlation coefficient (CC) between the resampled MS band and the low-pass approximation of the PAN. Otazu *et al*. (2005) introduced sensors' spectral responses and ground spectral features into fusion technology on the basis of MRA. Other authors utilise the regularisation method to optimise the fusion results so as to satisfy the higher resolution MS image model (Aanæs *et al*. 2008). Wald (2002) and Ranchin *et al*. (2003) introduce the 'Amélioration de la Résolution

Spatiale par Injection de Structures' (ARSIS, improving spatial resolution by structure injection) concept based on the assumption that the missing information is linked to the high frequencies of the data sets to be fused. The basis of the ARSIS concept is a multi-scale technique to inject the high-spatial information into the MS images. Zhang *et al.* (2008) generalised this idea and proposed a new model quantifying the mathematical relationship between the fused higher MS images and the original MS image, the spatial details being extracted from the high-resolution PAN image and the adopted fusion strategies.

Due to the increasing complexity of high resolution and multi-source data fusion, it is now more difficult to categorise the various pan-sharpening techniques into these three classes. A mixture of the above-mentioned techniques has been developed with the merit of the CS-based method of maximising spatial improvement and the merit of the MRA-based methods of minimising spectral distortion. For instance, some algorithms combine wavelet transform and IHS transform (Chibani and Houacine 2002, González-Audícana *et al.* 2004, Zhang and Hong 2005) or PCA transform (González-Audícana *et al.* 2004, Shah *et al.* 2008). These hybrid schemes use wavelets to extract the detail information from one image and standard image transformations to inject it into another image, or propose improvements in the method of injecting information (e.g. Garzelli and Nencini 2005, Otazu *et al.* 2005). These efforts have shown that improved results on multi-source images have been achieved and seem to be promising.

2.2 *High-level fusion*

2.2.1 *Fusion of optical images and SAR*

An undesirable property when applying the available pixel-level fusion techniques to the fusion of SAR and optical images is that either spectral features of the optical imagery or the microwave backscattering information is destroyed, or both of them simultaneously. Therefore, it is necessary to develop a specifically tailored SAR-optical image fusion technique, which can fully utilise those two types of image sources. Up to now, classifier combination has been an effective measure, which not only chooses the basic classifier corresponding to the SAR and optical imagery, respectively, but also integrates fusion results from different basic classifiers.

Early high-level multi-sensor fusion methods (Hall and James 1997) have been applied to land use classification. Solberg *et al.* (1994) presented a framework for the fusion of remotely sensed data based on a Bayesian formulation. The method is suitable for land use classification based on the fusion of remotely sensed images of the same scene captured at different dates and from multiple sources. Model performance is evaluated by fusing Landsat TM images and ERS-1 SAR images for land use classification.

Theory and approaches adopted for multi-source fusion include Bayesian decision theory (Mascarenhas *et al.* 1996), Shafer's theory of evidence (Lee *et al.* 1987), a statistical approach (Benediktsson *et al.* 1990, Stein 2005) and neural networks (Benediktsson *et al.* 1990, Bruzzone 1999). Lee *et al.* (1987) utilised two methods for combining the information from multiple sources of remote sensing image data and spatial data in general. One is a probabilistic scheme that uses a global membership function (similar to a joint posterior probability) and is derived from available data sources. The other is an evidential calculus based upon Dempster's orthogonal sum combination rule. Benediktsson *et al.* (1990) introduced reliability measures to rank the quality of the data sources in statistical classification methods. The data sources are then weighted according to these rankings in the statistical multi-source classification. Neural network learning procedures and statistical classification methods are applied and compared empirically in the classification of multi-source remote sensing and geographic data. Bruzzone (1999) proposed a data fusion approach to the classification of multi-source and multi-temporal remote sensing images, which is based on the application of Bayes rule for minimum error to the 'compound' classification of pairs of multi-source images acquired at two different dates.

In the recent literature, the remote sensing data fusion community has proposed high-level multi-source fusion methods based on Markov random field (MRF; Solberg *et al.* 1996), support vector machines (SVM) (Waske and Benediktsson 2007, Waske and van der Linden 2008), and the decision fusion approach for multi-temporal classification (Jeon 1999). Solberg *et al.* (1996) proposed a general model for multi-source classification of remotely sensed data based on MRF. A specific model for fusion of optical images, SAR images and GIS field data are presented in detail and tested. Waske and Benediktsson (2007) presented a scheme for the decision fusion of different outputs, while each data source is treated separately and classified by an SVM. Instead of fusing the final classification outputs (i.e. land cover classes), the original outputs of each SVM discriminant function are used in the subsequent fusion process. Waske and van der Linden (2008) presented a strategy for the joint classification of multiple segmentation levels from multi-sensor imagery using SAR and optical data.

2.2.2 *Fusion of LiDAR data and images*

A LiDAR sensor delivers 3D point clouds with the intensities of the returned signals. In some cases, multiple pulses or full waveform signals can be provided by certain hardware systems (Wagner *et al.* 2006). Similar to aerial or satellite optical imagery, extensive post-processing is required to extract accurate terrain or semantic information from the LiDAR point cloud. Although the shape of topographic objects can be easily recognised by humans in 3D point clouds or optical imagery, this is not a straightforward task for computer algorithms.

The fusion of LiDAR data and imagery has been widely explored for a variety of applications, ranging from Digital Surface Model (DSM)/Digital Elevation Model (DEM) generation, 3D object extraction and modelling to land cover mapping.

One of the most important applications of fusing LiDAR data and aerial images is in the generation of highly accurate DSM and DEM. Traditionally, methods for DSM/DEM generation were based on aerial/satellite stereo-image matching techniques. If the image matching is reliable, the image-derived DSM may have a better quality than the DSM generated from LiDAR data. This is because the ground resolution of the aerial image is generally higher than the point spacing of the LiDAR data and the images preserve the edge and corner information better than the LiDAR data. On the other hand, image matching in the area of homogeneous texture inherently becomes very difficult, resulting in great difficulties for high accurate DSM/DEM generation for plain area, where LiDAR can be used for direct accurate range data acquisition and interpolation, providing fine topographic details. In the current state-of-the-art, it seems that the DEM/DSM derived from either only LiDAR data or only images is not satisfactory for various applications requiring high-quality urban DEM/DSM.

Hong *et al*. (2009) proposed a fusion method by combining the LiDAR points with the object points derived from image matching. The proposed method includes three steps: (1) registration of the image and LiDAR data using the LiDAR data as control information; (2) image matching using the LiDAR data as the initial ground approximation and (3) robust interpolation of the LiDAR points and the object points resulted from image matching into a grid. If image matching is robust and reliable, points derived from the image can retain higher point density and better representation of the point and linear features of the terrain than the LiDAR points. Another important application of fusing LiDAR data and aerial images is object recognition and 3D shape reconstruction.

Mapping of ground objects, especially man-made structures, has been an important task in photogrammetry and remote sensing applications. Compared to optical imagery, LiDAR has both advantages and disadvantages with respect to automatic object extraction (Rottensteiner 2003). On the one hand, LiDAR data provide better opportunities for deriving the geometrical properties of surfaces for discriminating different objects, especially man-made objects; on the other hand, LiDAR can provide only limited information on the reflectance or absorption properties of the object surfaces. Optical images deliver MS information and object boundaries are usually better extracted from optical imagery than from LiDAR data, especially in the presence of height discontinuities. Given the pros and cons of LiDAR and aerial imagery, it has been suggested that these data be fused to improve the degree of automation and the robustness of automatic object extraction (Rottensteiner 2003). Therefore, buildings and road extraction and reconstruction have received particular attention.

Zabuawala *et al*. (2009) proposed an automated and accurate building footprint extraction method based on the fusion of LiDAR data and aerial images. The proposed algorithm starts with initial building footprint extraction from a LiDAR point cloud based on an iterative morphological filtering approach. This initial segmentation result, although inaccurate and which can only indicate locations of buildings within a limited accuracy, can be refined by fusing LiDAR data and the corresponding colour aerial images and generating a combined gradient surface, and then applying the watershed algorithm initialised by the LiDAR segmentation to find ridge lines on the surface. Various techniques for building reconstruction from LiDAR and image data were compared (Kaartinen *et al*. 2005). Based on an international test carried out by European spatial data research (EuroSDR; www.eurosdr.net) it was concluded that LiDAR-based techniques in general have a higher degree of automation and produce a better height accuracy (Maas 1999, Rottensteiner 2003, Sampath and Shan 2007). The planimetric accuracy of 3D models generated from aerial imagery, however, especially the building outlines, was higher. Again, due to the complementary properties of these data sources, the fusion of aerial imagery and LiDAR data has been proposed, either to improve planar segmentation (Khoshelham 2005) or to improve the geometrical quality of the building outlines (Rottensteiner *et al*. 2004).

Fusion of these two data sources for road extraction has also been investigated recently. Using LiDAR point cloud data combined with imagery, it is possible to extract both simple and complex bridges (or flyover) from complex landscape contexts (Sithole 2005). Hu *et al*. (2004) use a Hough transform to detect and extract grid road networks from filtered LiDAR data, while colour imagery is used to classify and exclude vegetated regions during the network construction process. Due to the fact that roads are usually among the lowest objects in a scene, their appearances in imagery are more frequently disturbed by shadows of higher objects such as trees and buildings. On the contrary, roads in airborne LiDAR data are less frequently disturbed by higher objects due to LiDAR's higher penetrability into vegetation and its smaller field of view. Considering these complementary clues, Zhu *et al.* (2004) detected most road objects without shadows from high-resolution colour image data, then used LiDAR data to identify and connect roads across shadowed regions.

Fusing LiDAR data and optical imagery for land cover mapping has been a more recent research topic. Laser scanning data offer the potential to discriminate different land use/land cover types and even the structure of the upper canopy from its height differences (Morsdorf *et al.* 2004). This is an important improvement for classification methods based on spectral and structural characteristics. Park *et al.* (2001) fused LiDAR data and colour digital photography for land cover classification, and the results showed that the fusion of multi-source imageries could improve accuracy and create more consistent recognition of land cover patterns. When multiple pulses or even the full waveform of the returned signal are provided, the vertical structure and components of the land cover, e.g. vegetation, can be analysed, because the system can frequently penetrate leaves of deciduous trees and receive the returned signals reflected by leaves, branches and trunks, as well as the ground. With this method, plant communities can be narrowly defined, i.e. plant communities at a low hierarchical level of classification in the Braun–Blanquet system (Verrelst *et al.* 2009). Wang *et al.* (2007) proposed an effective forest boundary delineation method using both aerial images and LiDAR data. The combination of curvature features, GVI, J-value segmentation (JSEG) segmentation results and the Gabor wavelet texture features leads to automatic and accurate forest area detection and obtains spatially contiguous forest boundaries. Wulder and Seemann (2003) proposed a forest inventory height update method through the integration of LiDAR data with segmented Landsat images. St-Onge *et al.* (2008) combined digital stereo-photogrammetry and LiDAR techniques and created hybrid photo-LiDAR canopy height models (CHMs) for effective canopy height mapping. To model forest growth, models combining hyperspectral, LiDAR, SAR and field data are proposed and will be used to estimate leaf area index (LAI) dynamics, tree heights and above ground biomass (Patenaude *et al.* 2008).

2.2.3 *Fusion of optical images and GIS data*

GIS data, such as topography, land use, road and census data, may be combined with remotely sensed data to improve the accuracy of image classification, object recognition, change detection and 3D reconstructions. Previous research has shown that the fusion of remote sensing and GIS has played a critical role in map updating (Weis *et al.* 2005, Yang and Zhang 2005, Yang *et al.* 2008, Aydöner and Maktav 2009). The integration of remote sensing and GIS is emerging as a new research field.

However, the different nature and content of remote sensing imagery and GIS data prevent a direct comparison. Therefore, the integration of data from different applications has to concern the differences in the object model and semantics of the objects themselves (Fonseca *et al.* 2002, Weis *et al.* 2005). Images are usually composed of a raster of pixels representing the intensities in the RGB-domain; whereas GIS data contains artificial objects with label forms, representing the objects or region affiliations. Pixel values may not correspond to objects, but represent radiometric properties. To incorporate GIS data as auxiliary or reference information in training area selection and post-processing of the classification result, a simple and feasible way to use the auxiliary data as additional bands is required. However, if the classification method requires GIS data to be used as statistical characteristic in the classification procedure, the additional band method may not be used because most auxiliary data do not meet the requirements of statistical characteristics (Li *et al*. 2000). Therefore, in the latter case, the two sources of data must be unified into object level and fused. Due to the differences of characteristic levels of information and semantics between the two different data sources, the comparison of image data and GIS data cannot take place on the pixel level, but has to be accomplished on a level where aggregation of low-level image objects to meaningful objects has taken place (Weis *et al*. 2005). The object-oriented classification and change detection approach provides an opportunity to integrate these two different data sources in a seamless way since an inherent characteristic of this method is the aggregation of the image pixels to semantically meaningful polygon objects and thus can be overlaid and analysed with vector format GIS data. To date, object-oriented classification is available in some commercial software packages, e.g. Definiens Company's eCognition object-oriented image analysis software.

To combine segmented objects or primitives from remote sensing images and GIS data at feature level or decision level, traditional pattern recognition methods can be used and have demonstrated their potential capabilities, e.g. knowledge-based techniques (Amarsaikhan and Douglas 2004), neural network and statistical approaches (Benediktsson and Kanellopoulos 1999, Chanussot *et al*. 1999), fuzzy set theories (Fauvel *et al*. 2006), Bayesian techniques (Mohammad-Djafari 2003) and Dempster-Shafer based method (Le Hégarat-Mascle *et al*. 1997, Tupin *et al*. 1999). One of the main challenges concerns the knowledge modelling (Fabre and Dherete 2003). Valuable work has been accomplished in this field; in cartographic updating, Weis *et al*. (2005) made use of a knowledge-based approach to model the objects that are expected to be found and implemented the combination of GIS data and aerial images. The results show that an automatic interpretation can be achieved using GIS information. To improve the performance of land use classification, Li *et al*. (2000) used data mining techniques to discover knowledge from a GIS database and a remote sensing image. In their method, to resolve the problem of spectral confusion, they present an approach to combine inductive learning with the Bayesian method, which has significantly improved the accuracy of classification.

However, difficulties still exist in data integration due to the differences in data types, data structures, spatial resolution and geometric characteristics. The integration of data from different application fields has to concern the differences in the object models and semantics of the objects themselves (Fonseca *et al*. 2002, Lu and Weng 2007). At the same time, understanding and modelling the uncertainty and inconsistency of the different information interpreted from various data sources at different scales or with different accuracies, and their influences on the fused results, also remain key scientific questions.

2.2.4 *Data fusion of satellite, aerial and close-range images*

Due to the development of multi-view and multi-resolution earth observation systems, data fusion of satellite, aerial and close-range images is necessary for some specific applications, such as environmental monitoring, road mapping, archaeology, building detection and reconstruction, etc. Moreover, the cross-sensor platforms could be satellites, aircraft, Unmanned Aerial Vehicles (UAVs) and vehicles; the surveillance range is hundreds of kilometres or some kilometres for site monitoring.

As the resolution of images from spaceborne, airborne or ground-based platforms ranges from coarse to fine, data fusion using those images reflects the specific properties of the individual sensors at that resolution. For satellite images, automatic high-resolution satellite image geo-referencing can be implemented by fusing existing digital orthophotos derived from aerial images. Studying and monitoring environments in urban areas require highly accurate satellite images. However, this kind of application involves an accurate geo-referencing processing of the images to a given geodetic reference system. Taking advantage of the existing digital orthophoto-maps and photo-planes derived from aerial photogrammetry, Gianinetto and Scaioni (2003) proposed a methodology for automatic high-resolution satellite image geo-referencing.

Fusion of aerial images and vehicle-borne sensor data can be applied for improved semantic mapping. Ground-based data are obtained by a mobile vehicle equipped with a calibrated or omni-directional camera, differential Global Positioning System (GPS), terrestrial laser scanning, etc. This semantic information is used for local and global segmentation of an aerial image. After matching with features detected in an aerial image, the data are used as input to a region- and boundary-based segmentation algorithm for building detection and 3D reconstruction in the aerial image. Persson *et al.* (2008) investigated the use of semantic information to link ground level occupancy maps and aerial images. The result is a map where the semantic information has been extended beyond the range of the sensors, which predicts where the mobile device can find buildings.

Much research work has been undertaken for the integration of range sensors and digital photogrammetry for cultural heritage applications (Guidi *et al.* 2003, Beraldin 2004). Range sensors can generate dense 3D point cloud data to create high-resolution geometric models, whereas digital photogrammetry is more suitable for producing high-resolution textured 3D object models, and it can also orient and locate edges and linear surface features in order to bridge gaps in the laser scanner data (Alshawabkeh and Haala 2004). In many cases, fusion or integration of both surveying techniques are regarded only as the application of digital images to the range-based 3D model and/or the production of orthophotos. Guarnieri *et al.* (2004) report the study of merging close-range photogrammetry and terrestrial laser scanning to produce a unique detailed 3D model of a complex historical building. A proper modelling procedure has been developed in order to exploit the surveying capabilities offered by both techniques more effectively.

3. Trends and challenges

Multi-source data fusion is an evolving technology, which fuses data from multiple heterogeneous sensors in order to acquire enhanced information for decision making. Applications of data fusion tend to cross many disciplines, including environmental monitoring, ecological modelling, automatic target detection and classification, battlefield surveillance, global awareness, etc. For specific purposes, ancillary and terrestrial data, such as laser scanner data, GIS data, distributed web-sensor data, field survey, meteorological data and economic census data, may be combined with remote sensing data to improve the performance of data fusion. Several trends have been emerging, tending to broaden the applications of multi-source data fusion.

3.1 *New methods for pixel-level multi-source high-resolution image fusion*

The developments in remote sensing imaging technologies include providing much higher resolutions for PAN and MS images, SAR images, and more recently the airborne

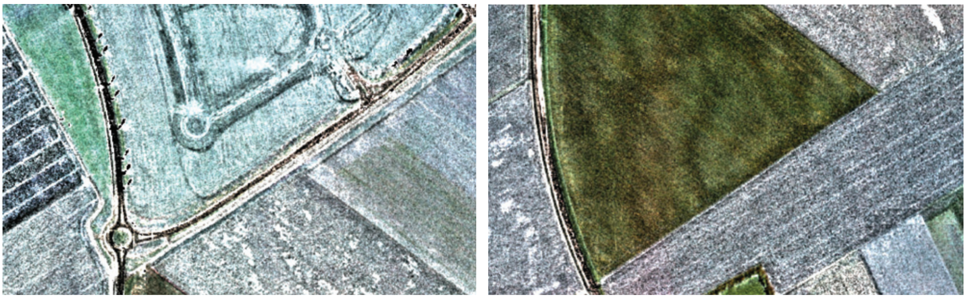

Figure 2. (a) Block-regression based SAR and optical image fusion; (b) two segments of an image fusing an airborne multispectral image (~3 m) and an AeS-1 airborne SAR image (~1.5 m), of Munich, Germany.

intensity images interpolated from LiDAR footprint reflectance. For instance, currently the highest resolution for an optical satellite image is 0.41 m (GeoEye-1), and 1 m for a satellite SAR image (TerraSAR-X and COSMO-SkyMed). For the fusion of optical images, a high image resolution corresponds with a large spectral discrepancy between neighbour pixels. For example, for a pair of PAN and MS images with very high resolution, one pixel in the MS image corresponds to several pixels from variant spectral features observable in the PAN band. The resolution transition from low to high or very high therefore leads to new demands for pan-sharpening techniques. Thus, one of the trends for pan-sharpening techniques is to develop new methods for dealing with high-resolution images. For the fusion of SAR and optical images, or LiDAR intensity images, however, higher resolution leads to more difficulties in co-registration of these images.

Specifically, for the fusion of SAR and optical images or LiDAR intensity images, the main purpose has changed significantly in recent years. The improvement of spatial or structure information enhancement is being paid more attention than preserving spectral information. For instance, Zhang *et al*. (in press) present a pixel-level fusion technique based on block-regression, aimed at fusing higher resolution airborne SAR and optical images. Those fusion results are shown in Figure 2.

3.2 *Higher level fusion methods*

The trend of fusion methods is to use high-level fusion approaches for precision improvement. High-level fusion methods, such as at feature level and decision level, are essential in order to use multi-features including spectral content, structural context and texture characteristics comprehensively. Combinations of multi-features can improve the accuracy of image classification and information extraction. The existing mathematical tools of high-level fusion methods include probability theory, evidence theory, fuzzy and possibility theory, neural networks, etc. One trend is the application of contemporary machine-learning techniques. SVM and ensemble learning, and other new developments in machine learning, are likely to be applied to high-level fusion shortly.

3.3 *Application-oriented assessment of image fusion and trends*

Application-oriented fusion techniques form a new sensor-oriented optical image fusion approach, designed and optimised according to the ideal imaging conditions. It is based on the idea that different fusion applications have different requirements, leading to distinct evaluation criteria. At present, the most common applications are classification and visual interpretation.

The current trend is to propose new optical image fusion techniques to satisfy application requirements such as change detection, de-clouding and enhancement of a specific feature. Application-oriented SAR and optical fusion techniques are among other developing methods for a variety of applications such as change detection, high-precision classification and specific feature enhancement and extraction.

3.4 *Fusion of multi-return/waveform LiDAR data and multi-source optical/SAR imagery for biophysical parameter estimation and ecological modelling*

With the recently delivered multi-return/waveform LiDAR systems, another trend with great potential is the application of this type of data fused with multi-source optical/SAR imagery for 3D biophysical parameter estimation and ecological modelling due to its high-penetration possibility.

Simulation of 3D complex vegetated ecosystems and their temporal changes usually requires extensive data and complex model parameterisation. The relationship between the signal recorded by a remote sensor and the vegetation canopy structure can be accurately characterised by physically based radiative transfer models (RTMs), such as the GeoSail model in the visible wavelength for optical sensors (Huemmrich 2001). Other models are proposed for modelling LiDAR and radar data (Sun and Ranson 1995, Sun and Ranson 2000), and have been used to retrieve the biophysical parameter independently. It is now believed that to recover the characteristics of canopy cover and retrieve the biophysical parameter, the best way may be by means of fusion of multi-sensor data (Dubayah *et al.* 2000, Guo *et al.* 2008). For example, roughness/texture measures derived from radar backscatter or shadow fraction in optical images could be combined with LiDAR to estimate the horizontal as well as vertical distribution of vegetation structure. Therefore, a general canopy model, which includes MS, radar and LiDAR with better biophysical parameter estimation, is expected.

Koetz *et al.* (2006, 2007) proposed a fused 3D RTM that is capable of representing the complex vegetation canopy structure as well as the involved physical processes of the LiDAR pulse interactions with vegetation. Consequently, the inversion of such an RTM presents a novel concept to retrieve forest biophysical parameters that exploits the full LiDAR/optical signal and underlying physical processes. The method has been successfully applied on the data acquired in a Swiss National Park and has demonstrated the feasibility and potential of RTM inversion to retrieve forest structure and biophysical parameters, such as fractional cover, LAI, maximum tree height, the vertical crown extension, etc.

Considering the latest developments in this research field, it is predictable that by the fusion of LiDAR, radar and optical imagery, the estimation of biophysical parameters can be improved using a general canopy model.

3.5 *Distributed web-sensor for data fusion*

New types of sensor hardware could drive the development of data fusion. The introduction of a distributed sensor network as a fusion data source is one of the most recent events in the data fusion community. A sensor network comprises a number of heterogeneous unmanned sensing platforms and a base station. Each sensor node is battery powered and equipped with integrated sensors, data processing capabilities and short-range radio communications. A data fusion node collects the results from multiple nodes. It fuses the results with its own data based on a decision criterion, and sends the fused data to another node/base station. The automated deployment of large numbers of sensing nodes and interpretations pose several new technical problems and challenges. Diverse applications exist for this technology including precision agriculture, livestock tracking, traffic monitoring and geophysical and environmental monitoring (Lamborn and Williams 2006).

Most current research in this field focuses on methods such as probabilistic models and Bayesian data fusion methods appropriate to describing and solving sensor in-network data fusion problems; for example, the distributed Bayesian algorithms for sensor networks are developed to estimate the temperature or humidity over an area. All of the information could be fused into satellite or airborne remote sensing images as quantitative and accurate terrestrial data. Therefore, the prospect of developing methods for remote sensing images and data fusion in sensor networks now offers a real possibility.

4. Conclusions

Developing effective methods for automatic fusion and interpretation of the multi-source, multi-temporal sensor data still is a challenging activity. It remains necessary due to the fast development of various sensor technologies, such as the VHR optical sensor, SAR and LiDAR sensors onboard airborne, spaceborne and terrestrial platforms.

The discontinuous and heterogeneous spectral and spatial characteristics of the multi-source VHR PAN and MS images require precise registration and new pan-sharpening techniques. These can simultaneously improve the spatial resolution and retain the spectral fidelity of original MS data during pixel-level fusion. Although several methods have been proposed, problems still exist in computation efficiency and effectiveness.

For high-level fusion, new feature extraction, knowledge representation and classifier combination methods have been investigated recently. Fusion of SAR and optical imagery has been applied to topography mapping, fused interferometric SAR and optical imagery to DEM extraction and fused optical and polarimetric SAR images for digital line graphics production. Fusion of LiDAR data and imagery has been widely adopted for a variety of applications, ranging from DSM and DEM generation, 3D object extraction and modelling, to land cover mapping.

In the next few years, we expect that especially high-level fusion techniques combining different data sources and different sensors, e.g. in a sensor network, will be widely used for quantitative modelling and inversion of the biophysical parameters and ecological modelling, in addition to map updating.

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