

DATA INTEGRATION RELATED TO SENSORS, DATA AND MODELS

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Commission VI, WG VI/4

KEY WORDS: Fusion, Spectral Information, Spatial Resolution, Region Growing, Change Detection, Potential Evaluation

ABSTRACT

Data integration or fusion refers to the acquisition, processing and synergistic combination of information provided by various source of data. The scope of this article is to describe three typical applications of data integration in photogrammetry and remote sensing. The first study case refers to the evaluation of the potential of different image fusion techniques on integration of two satellite images with different spatial and spectral resolution. The second one considers the problem of the object extraction in outdoor situations and the solution which proposed base on a feature level fusion. The third one presents the characteristics of a decision level fusion strategy for construction of an automatic system for detection of changes between available sensor information and corresponding digital vector map. Each study case presents also the results achieved by the proposed techniques applied to real data.

1. INTRODUCTION

In recent years, there has been a growing interest in the use of multiple source of information to increase the capabilities of intelligent machines and systems (Varshney, 1997; Hall and Llinas, 1997). Due to this, information fusion becomes an area of intense research activity in the past few years (Varshney, 1997; Llinas, and Walts, 1990; Abidi and Gonzalez, 1992; Clark and Yuille, 1990; Luo and Kay, 1995; Hall and Llinas, 1997). Information fusion is a process of combining evidence from different information sources in order to make a better judgment. It plays an important role in many application domains. No single source of information can provide the absolute solution when detection and recognition problems become more complex and computationally expensive. However, complementary information can be derived from multiple sources (Samadzadegan, 2002).

One of the important issues concerning information fusion is to determine how to integrate (fuse) the information or data. Depending on the stage at which fusion takes place, it is often divided into three categories, namely, pixel level, feature level and decision level (Abidi and Gonzalez, 1992; Hall and Llinas, 1997). In pixel level fusion, the combination mechanism works directly on the pixels obtained at the sensors' outputs. Feature level fusion, on the other hand, works on image features extracted from the source images or the features which are available from different source of information. Decision level fusion works at an even higher level, and merges the interpretations of different objects obtained from different source of information.

Several data fusion algorithms have been developed and applied, individually and in combination, providing users with various levels of informational detail in photogrammetry and remote sensing (Anderson, 1987; Burt, 1992; Carper *et al.*,

1990; Chavez *et al.*, 1991; Kathleen and Philip, 1994; Rockinger, 1996; Sharma, 1999). The choice of a suitable fusion level depends on the available information type: when the sensors are alike, one can opt for fusion at the pixel-level to take all data into account. When sensors or information are very different, decision-level fusion is more suitable and is also computationally more efficient. Feature-level fusion is the proper level when the features as found by the processing of the different sensors can be appropriately associated.

The application of the fusion approach shows successes with techniques ranging from expert systems to probabilistic techniques. As there is no simple rule for selecting the proper fusion technique, a wide range of techniques has potential applicability. The process of selecting optimum algorithm for fusion is complicated by the fact that data analysis seeks to combine incomplete and missing data in a complex environment in real time. In this paper three typical applications of these techniques are described.

2. DATA FUSION IN PIXEL / IMAGE LEVEL

Image fusion (i.e. fusion in pixel/image level) refers to the synergistic combination of different sources of sensory information into one representational format. We use the term image fusion to denote a process generating a single image which contains a more accurate description of the scene than any of the individual source images. This fused image should be more useful for human visual or machine perception. The different images to be fused can come from different sensors of the same basic type or they may come from different types of sensors (Figure 1). The sensors used for image fusion need to be accurately co-aligned so that their images will be in spatial registration.

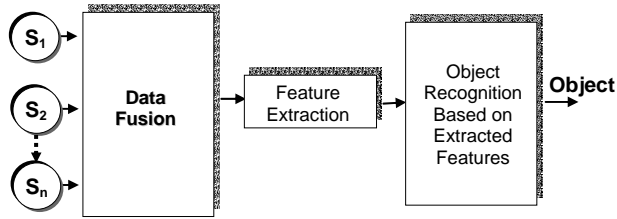


Figure 1. Pixel/Image Level Fusion

2.1. Case Study – Fusion of a high spatial image with a high spectral resolution images

Many image fusion methods have been proposed for fusing multi-sensor data in order to produce multispectral images having the highest spatial resolution available within the data set (Anderson, 1987; Burt, 1992; Carper and *et. al.*, 1990; Chavez and *et. al.*, 1991; Kathleen and Philip, 1994; Rockinger, 1996). However, a few comparison research works have been done in current literature to evaluate the quality of the fused image from different fusion methodologies in photogrammetry and remote sensing. With respect to the design idea of these techniques, we classified the proposed strategies to eight classes of IHS, PCA, DWT, SIDWT, Contrast pyramid, Min/Max Selection and Average Pyramid (Samadzadegan, 2003).

2.2. Experiments and Results

To evaluate the potential of different image fusion techniques, we applied the above methodologies to fuse IRS-1C and ASTER images. The original panchromatic IRS-1C has 5m pixels while the original multispectral ASTER images have 15m pixels (Figure 2). The ASTER original bands were B₁, B₂, B₃. These data sets were chosen for the high spatial resolution of the panchromatic (5 meters) data, the relatively high spectral resolution of the multispectral data, and the low spatial resolution ratio of three to one (3:1).

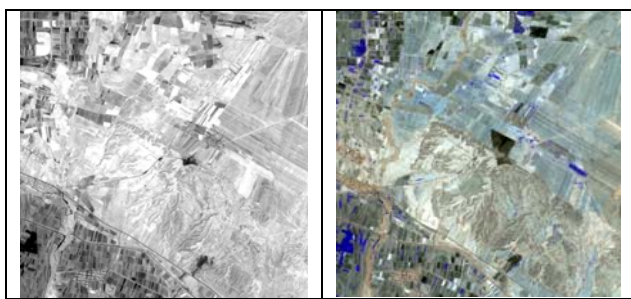


Figure 2. Panchromatic IRS-1C image (left), and ASTER original bands of B₁, B₂, B₃ in RGB format.

Because there is not available any ASTER (multispectral) image at 5m resolution to compare with, the evaluation of the potential of the different fusion methods is not easy. To solve this problem, we applied the merging method to an inferior level of resolution, that is to say, on a IRS-1C panchromatic image at 15m resolution and a ASTER multispectral image at 45m resolution. The result of the image fusion method was a fused multispectral image at 15m resolution which can be compared with original ASTER image at 15m. After the

application of the data fusion techniques, each merged image was analyzed statistically, graphically, and for increased photointerpretive potential as compared with the original multispectral images.

To quantify the statistical behaviour of different methods, we computed the correlation between the different solutions and the reference intensity and spectral image (Figure 3 and Figure 4).

$$C = \frac{\sum_{i=1}^n [(g_{si} - \bar{g}_s) \cdot (g_{Ti} - \bar{g}_T) / (n-1)]}{\sqrt{\sum_{i=1}^n [(g_{si} - \bar{g}_s)^2] / (n-1) \cdot \sum_{i=1}^n [(g_{Ti} - \bar{g}_T)^2] / (n-1)}}$$

where, \bar{g}_s and \bar{g}_T state for the mean value of the corresponding data set.

Each of the image fusion techniques analysed here enhanced the spatial resolution of the original multispectral ASTER image and in most cases; the spatial enhancement provided can be of more benefit than that of a relatively low spatial resolution of multispectral ASTER image. However, as DWFT has no dyadic decimation at each decomposition level, its representation is both aliasing free and translation invariant. Experimental results show that SIDWT outperforms methods based on IHS, PCA and DWT, especially when the source images are not perfectly registered.

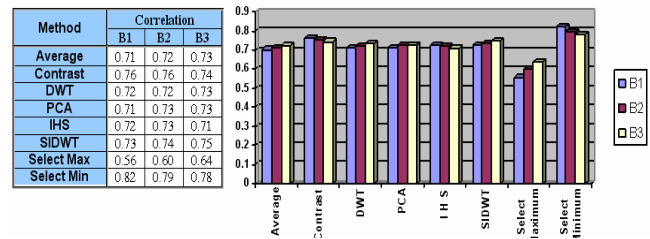


Figure 3. The spectral correlation of the output of different fusion techniques with the B₁, B₂, B₃ of original ASTER bands.

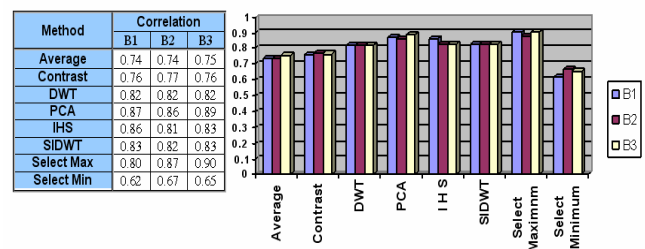


Figure 4. The intensity correlation of the output of different fusion techniques with the original panchromatic IRS-1C band.

3. DATA FUSION IN FEATURE LEVEL

Since one of the essential goals of fusion is to preserve the image features in the sensor images, a logical extension of image fusion is to transform the images into a representation that decomposes the images into “features” such as edges, and perform fusion in this domain. Such a decomposition or transformation can be obtained in terms of basis functions that capture the particular image features. Researchers have shown

that fusion techniques that operate on such features in the transform domain yield subjectively better fused images than pixel_based techniques (Morales *et. al.*, 1995; Burt, 1992; Hu and Acton, 1994). The need to preserve image features in the fused image imposes certain requirements for the transform domain representation to satisfy.

Data fusion in feature level is performed by using the extracted features from each sensor and the identity declaration based on this extracted features (Figure 5). The identity declaration process includes techniques such as knowledge-based approaches (expert system, fuzzy logic), or training-based approaches (such as discriminant analysis, neural networks, Bayesian technique, *k* nearest neighbours, centre mobile algorithms).

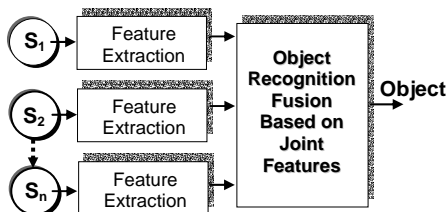


Figure 5. Feature Level Fusion

3.1. Case Study – Region Growing

Three dimensional object extraction has been an area of major interest in photogrammetry for quite a long time (Brunn and Weidner, 1997; Fischer *et. al.*, 1998; Fua and Hanson, 1988; Grün *et. al.*, 1995; Haala and Brenner, 1999). However, most of the existing methods for automatic object extraction employ parametric methods and hence object’s fuzziness behaviour is basically neglected. These methods, thus, do not take into account the extraction complexities and may fail to reach a satisfied reliability level in complex situations. In this section a feature level fusion approach for 3D object extraction is formulated which takes into account simultaneously relief variation of the object as well as its corresponding radiometric behavior in image space.

The proposed method is implemented based on the following strategy: (a) for a more reliable extraction of objects, the underlying 3D digital surface model is generated, (b) morphological operators are then applied to delimit the individual 3D objects, (c) This 3D structural information layer is accurately fused to corresponding 2D regions in image space by a rigorous geometric registration process, (d) the textural information and the size of the regions on image space as well as the roughness values for the relief variations in object space are simultaneously analyzed to modify the initially generated 2D regions.

Because of the fuzzy behavior associated with the texture, size and relief attributes, the region analysis is performed by a fuzzy based 2D region growing approach. Thus, the proposed object extraction methodology takes advantage of all object’s potential information content, inherent in image and object spaces, using a fuzzy logic reasoning strategy (Figure 6).

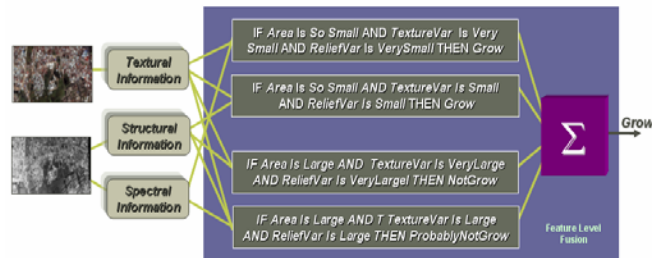


Figure 6. General structure of region growing strategy.

3.2. Experiments and Results

To assess the capabilities of the proposed object extraction method a sample pair of scanned colour aerial photographs of an urban area in the city of Engen (Germany) was selected (Figure 7). The selected area was suitable for the evaluation of the proposed strategy because the required complexities (e.g. proximities of different objects: building, car and tree) were available in the image. The test was conducted for boundary extraction of three different objects: buildings, trees and cars.

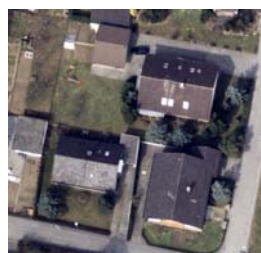


Figure 7. The image patch used for the OE evaluation.

The process was initiated with automatic DSM generation. The overall view of the generated DSM is given in Figure 8.

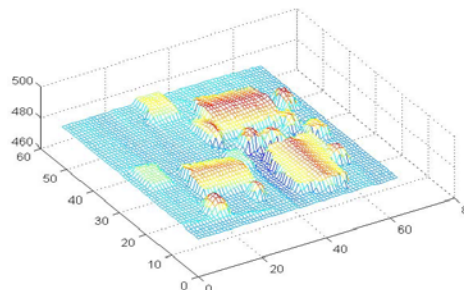


Figure 8. The automatically generated DSM for the image patch.

By generating the DSM of the area, in the next step, based on morphological operators, all of the 3D candidate regions are extracted. Figure 9 shows the initial segmented, refined and the extracted boundaries after the clean-up operation. As Figure 9 shows due to the high proximity of the objects (i.e. building, car and tree), these features are not distinct as individual 3D objects.

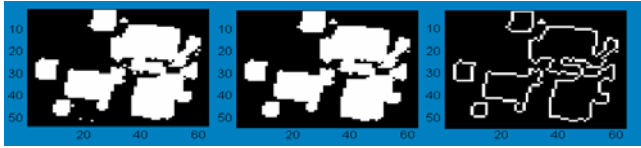


Figure 9. Initial 3D Regions, 3D Regions after refinement, Boundary of 3D Regions.

This defect is compensated by incorporating the relevant information in image space. The corresponding areas in image space for the 3D object are determined by the inverse solution of collinearity condition equations (Figure 10).



Figure 10. The Superimposed boundaries of the extracted objects in image space.

Figure 11 presents the final extracted regions in image spaces. As this figure shows our feature level fusion strategy has successfully identified the presence of sub-regions within the initial regions and hence the 2D regions are subdivided accordingly to separate segments.

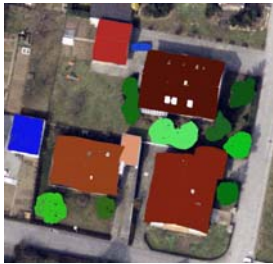


Figure 11. Final extracted regions in image space

4. DATA FUSION IN DECISION LEVEL

The decision level fusion is performed by using the identity declaration provided by each source of information. The fusion of the identity declaration is then made by using *Identity based methods* such as MAP and Dempster-Shafer methods (Shefer, 1976) or *Knowledge based method* such as Expert knowledge Neural network and Fuzzy logic methods (Lin and Lee, 1996).

It is Important to note that decision level fusion use: (1) feature extraction, transforming the raw signal provided by the sensor into a reduced vector of features describing parsimoniously the original information, and (2) identity declaration or object recognition that assigns a quality class to the measured produce based on the feature extraction process (Figure 12).

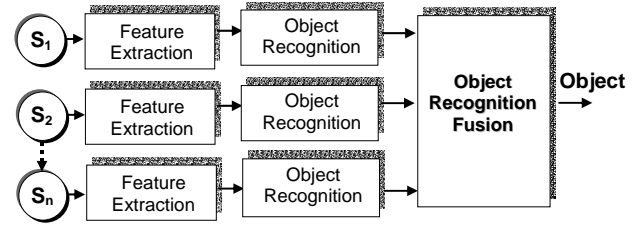


Figure 12. Object/Decision Level Fusion

4.1. Case Study – Automatic Change Detection

Monitoring of changes in topographic digital vector maps is one of the main requirements of urban planners, urban decision-makers and managers (Dowman, 1998; Armenakis et. al., 2002; Kim and Muller, 2002). However, in practice the processes for analysing the changes are the manual methods like on-screen change detection that are time consuming and expert dependent. The availability of the new generation commercial high resolution satellite imageries, due to their wealth of information content, have opened a new era in the problem of automatic change detection and consequently the digital vector maps updating. Therefore, automatic change detection has been an area of major interest in remote sensing and GIS for the last few years (Peled, 1993; Darvishzadeh, 2000; Dowman, 1998; Armenakis et. al., 2002; Kim and Muller, 2002; Schiewe 2002; Shi and Shibazaki, 2000).

Nevertheless, most of the existing methods for doing change detection process are basically optimized to use information of one sensor imagery and in addition, by employ parametric methods, object's fuzziness behaviour and the possibility for introducing training potentials are basically neglected. In this case, an attempt has been made to design a system that integrates all above features in a total and comprehensive automatic change detection solution. The approach presented here takes advantage of the concept of fusion in two levels of feature and decision. That is, information fusion to exploit the multi-level characteristics of the objects and logic fusion for enhancing the learning and hence recognition abilities of the system (Figure 13).

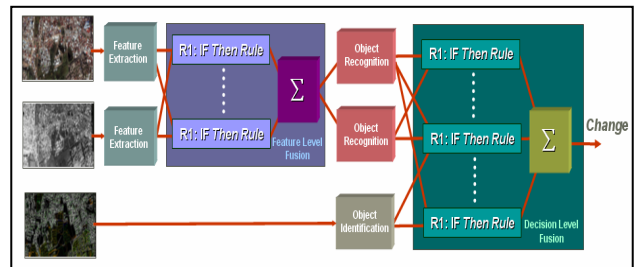


Figure 13. Decision Level Fusion

4.2. Experiments and Results

The proposed automatic change detection methodology was tested on a 1:1000 scale digital map and a pan-sharpen IKONOS scene of the city of Rasht, Iran (Figure 14). The maps have been produced in 1994 from 1:4000 aerial photographs by National Cartographic Centre (NCC) of Iran. The satellite

imagery was acquired on May 28th 2001. During these seven years time lapse between the generated digital map data and the IKONOS image acquisition, considerable changes have occurred in the city (See Figure 14).

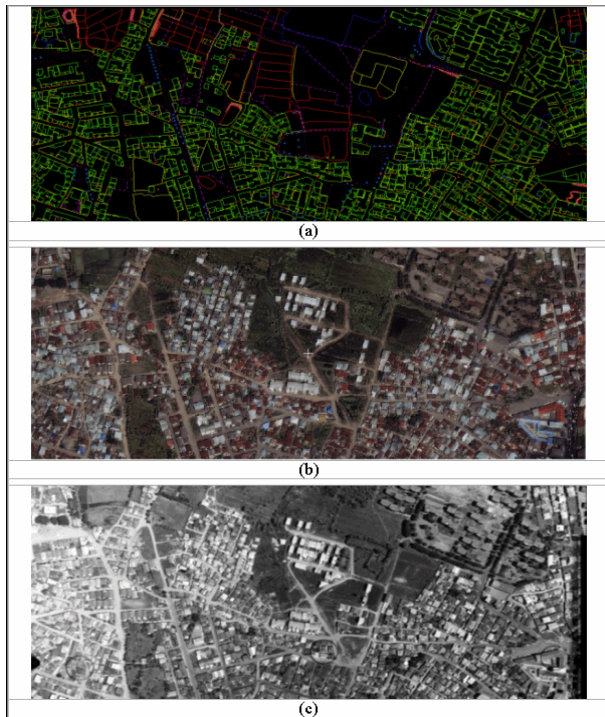


Figure 14. 1:1000 planimetric map of the city of Rasht (a), corresponding IKONOS Pan-sharpen (b), corresponding aerial photo (c).

The obtained results by applying our proposed strategy on different kinds of objects from natural to man-made GIS objects established the high capability of our proposed automatic change detection strategy (See Figure 15). However, we are still far from reaching to a perfect solution for a fully automatic change detection system. Bearing in mind the general concepts presented above we may outline the future research works based on the following proposals:

- Implementation of a hybrid neuro-fuzzy approach by which recognition parameters as well as fuzzy rules are trained and modified.
- Algorithmic improvements should be investigated for individual modules govern the extraction, recognition and reconstruction phases.

5. Conclusion

Data fusion technology is still in its infancy, having undergone rapid growth that started in the late 1980s and has continued to the present. The described methods are among the most advanced techniques in the data fusion field; they have been selected to show, in quite different situations, the advantages that can be derived from the application of a data fusion approach.

In theory, the fusion process should be the most efficient by working at a pixel/image level. However, this level includes some practical limitations. First of all, it is rare that identical or commensurate sensors are used in a system. Secondly, this approach implies high memory capacity, and high-speed data processing that are currently not available. Feature and Decision level fusion techniques use less information with respect to the raw signal provided by each sensor; eventually, this transformation includes errors that will be transmitted to the fusion process. However, feature and decision level fusion techniques are well adapted to practical cases with different source of information and do not require high-speed data processing.

As a general conclusion concerning the different data fusion levels, one can state that all different fusion levels have their importance and their specific applicability domain. Based on these considerations, the optimum solution could be one or combination of different fusion levels.

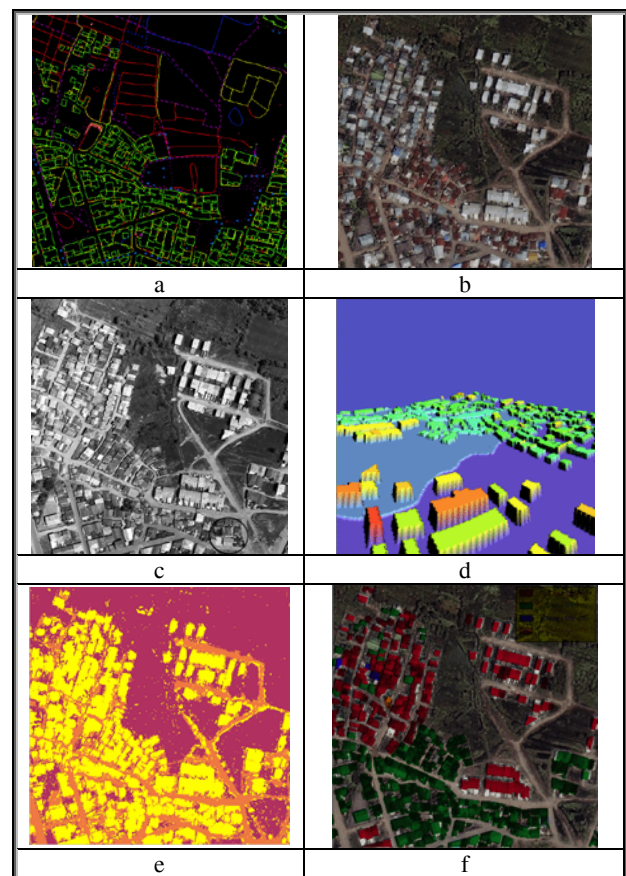


Figure 15. (a) 1:1000 planimetric map of the city of Rasht, (b) Corresponding IKONOS Pan-sharpen Patch, (c) Corresponding Aerial Patch, (d) Extracted 3D objects in test area, (e) Classified Objects and, (f) Final result of proposed automatic change detection methodology in the test area.

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