A Hybrid Fusion Strategy for Spatial Change Detection

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Abstract: - Monitoring of changes in topographic urban geospatial databases is one of the main requirements of urban planners, urban decision-makers and managers. In this paper, an attempt has been made to design and develop of automatic solution for spatial change detection of objects. The approach presented here takes advantage of hybrid fusion of descriptive and logical information. That is, descriptive fusion to exploit the multi-level characteristics of the objects and logic fusion for enhancing the learning abilities of the object recognition in change detection process. The potential of the proposed methodology was evaluated based on a 1:2000 scale digital map of the city of Qom in Iran by using 1:10000 aerial photos and a pan-sharpened Quickbird scene. Visual inspection of the obtained results demonstrates the high capability of the proposed method.

Key-Words: - Automatic Change Detection, Descriptive and Logical Information Fusion, Fuzzy Reasoning, Neural Network, Neuro-fuzzy, Quickbird Imagery

1 Introduction

In recent years, significant attention has focused on multi-sensor data fusion to increase the capabilities of intelligent machines and systems [0]. Data fusion techniques combine data from multiple sensors and related information to achieve more specific inferences than could be achieved by using a single and independent sensor. Due to this, information fusion became an area of intense research activity in the past few years [0, 0, 0, 0, 0].

Data fusion covers a wide domain and it is difficult to provide a precise definition. Several definitions can be found in the literature [0, 0, 0, 0]. Among them, a comprehensive definition presented by Dasarthy is: "Data fusion deals with the synergistic combination of information made available by various knowledge sources such as sensors, in order to provide a better understanding of a given scene" [00].

Data fusion involves combining data to estimate or predict the state of some aspect of the universe. Often the objective is to estimate or predict the physical state of entities: their identity, attributes, activity, location and motion over some past, current, or future time period. If the job is to estimate the state of people (or any other sentient beings), it may be important to estimate or predict the informational and perceptual states of individuals and groups and the interaction of these with physical states.

The concept of multi-sensor data fusion is not new. As humans and animals have evolved, they have developed the ability to use multiple senses to help them survive. For example, assessing the quality of an edible substance may not be possible using only the sense of vision; the combination of sight, touch, smell, and taste is far more effective. Similarly, when vision is limited by obstacles, the sense of hearing can provide advanced warning of impending dangers. Thus, multi-sensory data fusion is naturally performed by animals and humans to assess more accurately the surrounding environment and to identify threats, thereby improving their chances of survival. While the concept of data fusion is not new, the emergence of new sensors, advanced processing techniques, and improved processing hardware have made real-time fusion of data increasingly viable [0].

The information fusion may play a key role in geospatial information related topics. For example, in multi-agent systems, fusion of information perceived through sensors of each agent from its surrounding environment can lead to a better computational model.

One of the important issues concerning information fusion is to determine how to fuse the information or data. Depending on the stage at which fusion takes place, it is often divided into three categories, namely, data level, feature level and decision level [00, 0]. In data level fusion, the combination mechanism works directly on the data obtained from the outputs of sensors. Feature level fusion, on the other hand, works on features extracted from the source data or the features which are available form different other sources of information. Decision level fusion works at an even higher level, and merges the interpretations of different objects obtained from different source of information.

The objective of this paper is to discuss the concept and application of descriptive and logical information in the geospatial domain. To demonstrate the capabilities of these concepts to solve the spatio-temporal problems, a case study on change detection in urban geospatial databases have been done.

2 Descriptive Fusion

The most important descriptors for perceiving the behaviour of the objects in computer vision are three attributes of structural, textural and spectral information (STS). Texture, as regards the pixel intensity variation with respect to the neighbouring pixels and spectral as regards the pixel intensity value in the multi spectral space and the third information content is the 3D geometric (structural) parameters in the corresponding object space. These STS descriptors are important elements for a comprehensive recognition process and they need to be fed simultaneously into the recognition engine.

Although STS descriptors are effective tools for recognition of different objects, in practice, the main problem is their inability to reliably and realistically fuse these conditions for decision making. There are several schemes for the fusion of different descriptors [0]. Fuzzy reasoning is one of these methods by which the parameters that influence the decision making process can be fused using a human like reasoning strategy. This is achieved by defining the so called linguistic variables, linguistic labels and membership functions. The fuzzy reasoning process is then realized using the fuzzy if-then rules that enable the linguistic statements to be treated mathematically.

A single fuzzy IF-THEN rule can be formulated according to:

$$\text{IF } x \text{ is } A \text{ THEN } y \text{ is } B$$

A and B are linguistic labels defined by fuzzy sets on the range of all possible values of x and y, respectively.

Formulating the rules is more a question of the expertise of an operator than of a detailed technical modelling approach. Given the rules and inputs, the degree of membership to each of the fuzzy sets has to be determined. This step, which is the first step of fuzzy inference, is called fuzzification of input variables. The fuzzy AND or OR operators combine the membership values of the inputs in each rule (step 2) which results in one number (so-called firing strength of inputs) for the antecedent of that rule. Step 3 is the implication of the antecedent to the consequent. Implication is a process of shaping the consequent. The firing strength is used to truncate and scale the output fuzzy set. Implication is carried out for all rules and the next step (step 4) is to aggregate the output fuzzy sets over all rules. Inputs of aggregation are the truncated output functions returned by the implication process for each rule. The result of the aggregation process is one fuzzy set for each output variable. What remains in the final step is to defuzzify the fuzzy set and to produce a crisp output. The mostly applied defuzzification method is to calculate the centre of gravity which determines the centre of the area under the aggregated output function.

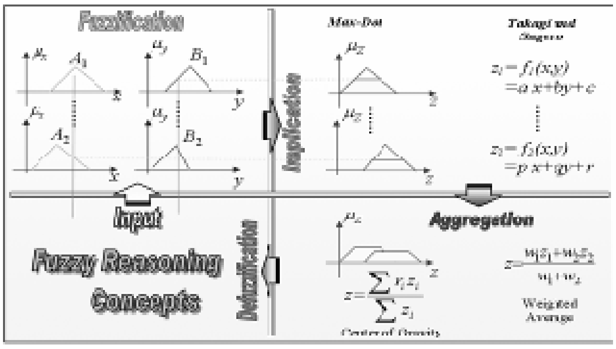

Fig.1: Overall flow of a fuzzy inference process

Figure 1 illustrates the main steps of fuzzy inference with input, fuzzification, implication, aggregation and defuzzification. Graphically indicated are two proposals dealing with the implication and aggregation steps. The Max-Dot approach proposed by Mamdani [**Error! Reference source not found.**] and the TSK approach [0] are widely used strategies of fuzzy inference.

3 Logic Fusion

The fuzzy reasoning process introduced in Section 2 utilizes human expertise by storing its essential components in the knowledge base and performs fuzzy reasoning to infer the overall recognition results. Defining the extractable feature characteristics of objects of the real world is a nontrivial problem and there is a need of adaptability to tune the membership functions and rules depending on the complexity of the application. Learning based on a given input-output data set is a very well known feature of neural networks. On-going research is focusing on building neural network based fuzzy inference systems (for a comprehensive review of neuro-fuzzy systems cf. 0]). An integrated neuro-fuzzy reasoning system will possess the advantages of both neural networks (learning from examples, optimization by taking advantage of desired input-output data sets) and fuzzy systems (meaningful representations, encoding knowledge, fuzzy if-then rules and fuzzy reasoning).

Roger Jang has proposed a class of adaptive networks which are functionally equivalent to fuzzy inference systems and called this architecture ANFIS, standing for Adaptive Network based Fuzzy Inference System [0, 0]. The adaptive network is a multilayer feed forward network combined with a back-propagation gradient-descent-type learning algorithm [0, 0, 0]. In this learning scheme, the error at the output layer is propagated backward to adjust the network parameters in order to minimize the output errors. To achieve a desired input-output mapping, training data are used to update the parameters.

4 Case Study: Automatic Spatial Change Detection of Urban Geospatial Database

High rates of urban change, in particular in the developing countries, call for an efficient and fast technique for mapping the changes for updating the existing topographic urban geospatial databases [0, 0]. However, in practice most of the processes for analyzing the spatial changes are manual operations like on-screen change detection that are time consuming and expert dependent.[0,0]. The availability of the new generation of commercial high resolution satellite imageries have opened a new era in the problem of automatic change detection and consequently the topographic urban geospatial databases updating. Therefore, automatic change detection has been an area of major interest in remote sensing and GIS for the last few years [0, 0, 0].

To model the human capabilities in object perception and recognition for detection of spatial changes, it seems that in a comprehensive solution: (a) All available descriptive information components of an object (such as structural information, textural information and spectral responses) must be simultaneously used; (b) A fuzzy formulation for the object definition should be devised; (c) Learning capabilities to modify the defects accompanied by the objects definition needs to be considered. This will enhance the recognition potentials when encountering new and undefined objects [0, 0].

In this paper a system that integrates all above features in a total and comprehensive automatic geospatial database change detection solution is shown. The approach presented here uses the 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 2).

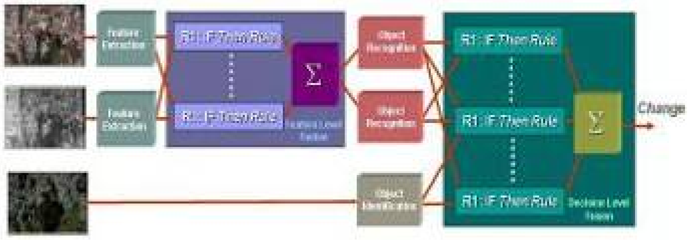

Fig.2: Proposed Feature and Decision Level Fusion

The proposed automatic spatial change detection process utilizes two types of the data sets. In the first category, (raster aerial) and satellite images are used as data sources for generating a Digital Surface Model (using stereo digitized aerial photographs), textural information (using both image and satellite images) and spectral information (using satellite image). Aerial images, because of their geometric stability, provide metric information, and satellite imagery, due to their wealth of spectral information, generate spectral data. The second type of the data sets is the topographic urban geospatial databases (i.e. 3D digital map vector data). These data sets provide reference information, whereas the aerial and the satellite images serve to generate the most recent information and changes. To facilitate the automatic change detection operations, the input data is pre-processed. The change detection process is divided in object identification, object extraction, object recognition and change detection phases.

These phases generate two different data sets. The first data sets are the objects that are detected and recognized using structural, textural and spectral components. The second data are the detected objects from the map data set. It is now possible to compare the two sets of detected objects. This is achieved by transferring the detected and recognized objects from the image space into their corresponding map positions. One of the following situations may occur:

Case1. The detected object in the image space matches the detected object in the map space.

Case2. The detected object in the image does not match the corresponding object on the map.

Case3. There is no object on the map for the corresponding position of the object which is detected in the image space.

Case4. There is no object in the image space for the corresponding position of the object which is detected on the map.

In the first case the object on the map is flagged as unchanged. In the second case the object is marked with a flag showing that a change has been occurred and thus the old object must be replaced by its modified version. In the third case, a flag implies that a new object exists on the corresponding position and should be added to the old GIS data set. The final change detection analysis is performed for those objects on the map for which no object exists on the image. This implies that the old object no longer exists on the object space and consequently should be removed from the corresponding layer in the GIS data set.

The proposed automatic change detection methodology was tested on a 1:2000 scale digital map and a pan-sharpen Quickbird scene of the city of Qom, Iran. The maps have been produced in 1999 from 1:10000 aerial photographs by the National Cartographic Centre (NCC) of Iran. The satellite imagery was acquired on Jan 17th 2005. During these six years between the generated digital map data and the Quickbird image acquisition, some changes have occurred in the city. For the two object classes of building and tree, Liguestic variables, Labels (Table 1) and the preliminary membership functions for the STS components are defined based on the knowledge of an experienced photogrammetric operator.

Table 1: Linguistic variables and labels

Type		**Linguistic Variable**	**Linguistic Labels**
Input	*Structural*	Height	*Very Low, Low, Medium, Tall, Very Tall*
		Area	*Very Small, Small, Medium, Large, Very Large*
		Relief	*Very Irregular, Irregular, Regular, Very Regular*
		Shape	*Non Stretched, Stretched, Very Stretched*
	Textural	Roughness	*Very Irregular, Irregular, Regular, Very Regular*
	Spectral	Colour	*Light Green, Medium Green, Deep Green*
Output	*Object*	Building	*False, Probably False, Probably True, True*
		Tree	*False, Probably False, Probably True, True*

Since the spectral information of our data set was limited to the visible range of electromagnetic spectrum, the linguistic variables were defined for three spectral bands of red, green and blue (RGB) and subsequently the membership functions were constructed for the normalized RGB components (Figure 3).

It should be noted, however, that, for our particular image data, only the green color maintained its discriminate character for recognition of trees against buildings. Buildings may have any arbitrary color and hence spectral attributes in the visible electromagnetic range for this object class could not contribute to the recognition process. Based on the membership functions and the human perception from the chromaticity diagram [0, 0], the corresponding fuzzy rules were generated.

As membership functions can initially not be defined with sufficient confidence, they are tuned and modified by the learning potentials of the neuro-fuzzy technique. For the initial training operations of the system, 200 samples as learning data set and 50 samples as the checking data set were selected. The more samples are used the more comprehensive the membership functions would be defined and hence more reliability for the recognition process. To test the adaptation potentials of the recognition process for the modification of the membership functions, 200 samples were selected so that a great variety of viewing appearances for the building and tree object classes are covered. Based on these preliminary training operations the adjusted membership functions were determined. These functions are presented in Figure 3.

To assess the capabilities, reliability and efficiency of the proposed automatic change detection method, a portion of an urban area is selected. The selected area i shows a significant complexity as regards the proximity of the objects.

The results of our automatic spatial change detection strategy are presented in Figure 4. The visual inspection of the obtained results demonstrates the high capability of our strategy.

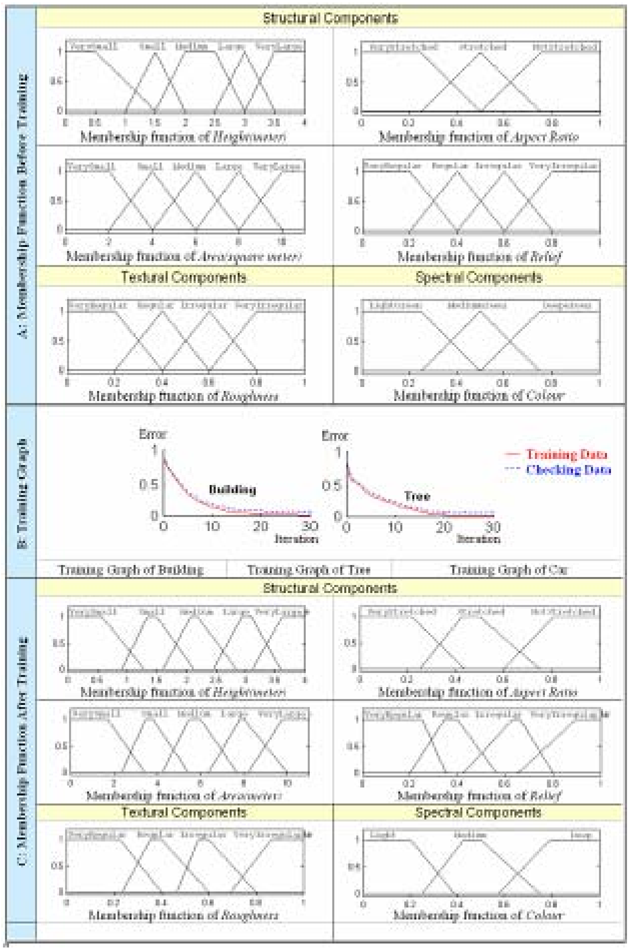

Fig. 3: Initial membership functions (A), training graphs (B), modified membership functions(C)

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A quantitative evaluation of the change detection result shows that five small buildings are not recognized, in particular, because they are fairly small and have not been properly considered within training.

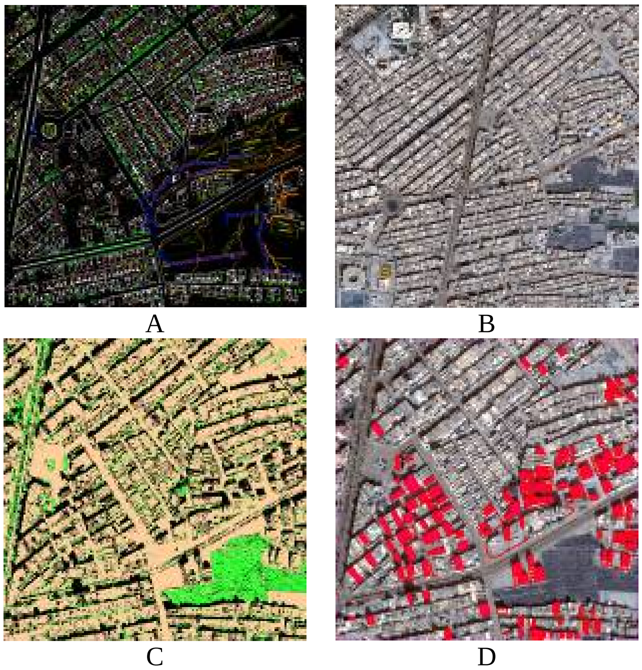

Fig. 4: 1:2000 planimetric map of the city of Qom (A), corresponding Quickbird Pan-sharpen Patch (B), Classified Objects from image (C), Result of proposed automatic change detection methodology in the test area (D)

5 Conclusion

The results obtained by applying our strategy on buildings and trees established the high capability of our proposed automatic change detection of these 3D objects which was constructed based on hybrid information fusion. The main feature of this strategy is not so much its individual modules that perform different tasks, but the methodology itself that governs the entire system. Our methodology is based on the premises: (1) Simultaneous fusion of all available information for the object extraction and recognition. In our example, these were three structural, spectral and textural components, but can be extended to include other descriptive attributes. (2) Because of the fuzzy state of the objects, a rigorous and crisp modeling approach for extraction and recognition problems should be avoided. (3) Due to the numerous varieties of the objects types and appearances, training potentials are a real necessity for automatic change detection method. (4) Within the general scope of the proposed methodology, individual modules such as matching operation, surface modeling, region growing, structural and textural analysis, etc. can be improved with the related algorithmic developments.

We believe that there are many potential fields in spatio-temporal modeling and analysis due to the integration nature of GIS analysis.

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