ADVANCED CLASSIFICATION TECHNIQUES: A REVIEW

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ABSTRACT:

This paper will present a review of the recent activity related with the image classification techniques. We have used the terms of reference of the working group VII/4 for a rough classification of this activity. Sometimes it is difficult to compare different approaches because really different input data sets are used. A proposal to use a common data set with a very precise land use map is presented to overcome this problem.

1. INTRODUCTION

For years, many efforts have been made to develop automated procedures for land use map production using remote sensing image data. However, the situation is still characterised by a considerable operation gap. This gap is even higher since high resolution digital imagery is available. Usual image analysis procedures have had considerable difficulties dealing with the information content of high resolution imagery. Users are moving from pixel oriented classifiers to object oriented analysis systems in order to manage properly the rich information present in those images. Looking for more information is a complementary way of improving the classification results, in parallel to improve image analysis tools.

Analysts looking for land use classification started working with one image using some kind of statistical pixel by pixel classifier with poor or not at all ancillary information. Now the same analysts work with many images, covering the vegetation phenological evolution along the year season, manages different resolution images from different active and passive sensors, works with hierarchical objects having spatial and contextual relationship with their neighbours, combining it with some complementary input as topographic and meteorological data on a Geographic Information System environment.

Nevertheless many questions are still open and we only need to look to the topics concern by the papers presented to this Conference, and also to recent Symposia, or presented recently to Remote Sensing magazines. Without trying to be exhaustive:

- The synergism between classification approaches: pixel wise classification, context analysis, texture analysis. The right use of segmentation procedures to build objects from pixels components.

- Advanced and practical methodologies of Computer Assisted Interpretation (CAI) and Analysis of remotely sensed data, and the use of Knowledge Systems in order to infer generalized evidence using Data Mining techniques on huge amounts of data.

- A wise utilisation of information coming from different sensors. The right classifiers for hyperspectral data. The right classifiers for polarimetric, interferometric and multiband SAR data sets. Multitemporal analysis in order to manage the seasonal evolution of phenomena.

We would like to present next some specific details on each of these topics.

2. PER-PIXEL VS. OBJECT CLASSIFICATION, TEXTURE AND CONTEXT ANALYSIS

Very high resolution satellite imagery offers an unseen level of spatial detail which is appropriate for visual interpretation and mapping purposes. On the other hand, difficulties arise when the images has to be classified. The classic per-pixel multispectral classification results in a disgusting salt and pepper effect on complex environment, reducing the land use maps readability.

Different approaches have been tested but two are basically followed:

- A segmentation pre-process to build objects and then classify objects.

- A per-pixel classification and a post-processing land use parcel building aggregating land cover pixels.

A variety of different classification outputs can be derived from the application of a suite of classifiers to the same data set. The derived classifications may differ greatly in accuracy, on both a per-class and overall basis. By combining the outputs of a set of classifiers it is possible to derive a classification that is more accurate than any of the individual classifications used. See, for instance: (Briem, 2002), (Ji, 1997), (Liu, 2002), (Steele, 2000).

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Land cover and land use classification from high spatial resolution and low spectral resolution images can be done using standard classification techniques. The low spectral resolution can be compensated by the use of texture features, which become meaningful at high spatial resolution. See, for instance: (Zhou, 2003), (Michelet, 2004), (Warner 2005), (Trias-Sanz, 2005).

Image segmentation is usually performed as a pre-processing step for many image understanding applications, for example in some land-cover and land-use classification systems. A segmentation algorithm is used with the expectation that it will divide the image into semantically significant regions, or objects, to be recognized by further processing steps. It is however well known that semantically significant regions are found in an image at different scales of analysis. For a high resolution aerial image, for example, at coarse scales we may find fields, while at finer scales we may find individual trees or plants. Parameters and thresholds in a typical single-scale segmentation algorithm must be tuned to the correct scale of analysis. However, it is often not possible to determine the correct scale of analysis in advance, because different kinds of images require different scales of analysis, and furthermore in many cases significant objects appear at different scales of analysis in the same image.

In an attempt to overcome this problem, in recent years there has been a trend toward multi-scale or hierarchical segmentation algorithms (Guigues, 2003), (Salembier, 2000). These analyze the image at several different scales at the same time. Their output is not a single partition, but a hierarchy of regions, or some other data structure that captures different partitions for different scales of analysis. As with classical, single-scale, segmentation algorithms, the need arises to evaluate the quality of a multi-scale segmentation against a reference, in order to compare different algorithms, and to select for an algorithm the parameters which are optimal for a given application. Most current segmentation evaluation methods (Segui, 2003) handle only single scale segmentations, that is, partitions of an image. They usually work by finding correspondences between points in the reference and points in the edges of the regions given by the segmentation. However, because multi-scale algorithms can deliver arbitrarily fine segmentations the concepts of “correspondence between reference points and segmentation edge points” and of “distance between segmentation edge and reference edge” cannot be easily transposed to the multi-scale case.

3. COMPUTED ASSISTED INTERPRETATION (CAI) AND THE USE OF KNOWLEDGE SYSTEMS

An increasing demand for detailed land use maps at regional or national (even continental) level must deal with the huge costs for expert image interpretation, necessary for the extraction of the usually long legend demanded for users. The uses of contextual classifiers on multitemporal images, combined with ancillary information managed in the framework of GIS, have provided some tools to manage the situation.

In some European countries environmental agencies ask for country land use maps with a minimum mapping unit of 1 to 5 ha and a legend 50 to 70 items long, covering both land cover and land use classes. There is not an automatic tool to produce this kind of products but there are some advances in order to get a very precise delineation of just a few low level land covers before interpreters should do a more detailed work inside these big parcels.

New classification algorithms like Artificial Immune System (AIS) present innovative approaches to the unsupervised classification of remote sensing images (Zhong 2006).

Spatial data mining, which is also considered as geographical knowledge discovery, is a branch of data mining that has attracted much attention in the recent researches. It puts emphasis on extraction of interesting and implicit knowledge such as the spatial pattern or other significant mode not explicitly stored in the spatial databases. The main idea of the research is to utilize spatial data mining techniques to find some interesting knowledge hidden in the spatial data. The extracted knowledge will be use to perform spatial prediction that could make the environmental monitoring task more efficient.

With the rapid development of computer techniques and the data collection and storage techniques, a large amount of spatial data was accumulated. Spatial Data Mining, or knowledge discovery in large spatial databases, is the process of extracting implicit knowledge, spatial relations, or other patterns not explicitly stored in spatial databases. There are many tasks in spatial data mining, such as Spatial Clustering, Spatial Characterization, Spatial Trend Detection, Spatial Classification etc. Also many methods can be used in spatial data mining processes. Decision tree, Bayesian Network, Neural Network, Spatial Analysis and Visualization etc are widely used methods in spatial data mining. They can be combined to complete a special mining task with each other corresponding to the difference of mining targets (Chen, 2005).

There has long been a research goal to produce maps from remotely sensed images in as automated manner as possible. For this goal to be achieved, automated strategies need to be developed that efficiently interpret the information content of highly complex images (Tompkinson, 2005). This investigation takes one approach to implementing the well known principles of top-down and bottom-up reasoning to reliably isolate the geometries of generic objects in the landscape for mapping purposes (Gamba, 2005).

4. A WISE UTILISATION OF INFORMATION COMING FROM DIFFERENT SENSORS

Almost all classifiers have a relatively good performance with medium resolution multitemporal images (like Landsat TM) and can classify vegetation classes looking for differences on plant phenology. More difficult is to combine SAR and optical images or work with spectral signatures of sensors providing more than 200 bands simultaneously.

The recent developments of the sensor technology resulted in the availability of remote sensing images characterized by very high spectral resolution (hyperspectral images). Nonetheless, the classification of hyperspectral images requires the definition of advanced methodologies capable of dealing with the complex problems induced by the small ratio between the number of training samples and the size of the input feature space. These problems result in poor estimates of classifier parameters and consequently in low labelling accuracy and unacceptable generalization properties.

One of the approaches used to analyse hyperspectral data are the Support Vector Machines. See for instance (Melgani, 2004) and (Bruzzone 2005) where different techniques for the semisupervised classification of hyperspectral data are compared.

There have been many approaches to the hyperspectral image segmentation problem, including neural networks (Muhammed, 2002), Markov chains (Mercier, 2003), supervised segmentation using parallepiped or maximum-likelihood classifiers and independent components analysis (Sha, 2002).

Hyperspectral image data contains - in contrast to multispectral image data - a huge amount of narrow bands. To process these large data, special classification algorithms, either for spectral unmixing or for material detection purposes, have been developed. Material detection algorithms like the Spectral Angle Mapper (SAM) calculate a deterministic value to express the spectral similarity of a pixel's spectra to a given reference. Unmixing approaches like the Mixture Tuned Matched Filtering determine for a measured spectrum the abundance fraction of a given reference spectrum. In both cases, the term "endmember" is used for the spectral reference definition. The determination of reference spectra as an endmember for material detection approaches like SAM could be carried out by measurements in situ with a field spectrometer or by a selection of pixels in the image data. The unsupervised image endmember definition is one of the procedures used (Greiwe, 2006).

A new generation of SAR sensors will provide a lot of images in different frequencies, different polarizations, providing different image resolution and allowing interferometric processing. Many studies have been carried out on the potential of SAR data for the discrimination of different kinds of surfaces and objects. The approaches may vary according to the types and number of radar data and to the discriminating algorithms. Given the limited performance of the existing space borne Synthetic Aperture Radars, some approaches use single frequency, single co-polarization measurements and exploit their multi-temporality. Others refer to multi-frequency and/or multi-polarization data, as provided by experimental airborne systems.

SAR Polarimetry has been of primary interest to many researchers in the past two decades. It was essentially initiated by the AirSAR and SIR-C systems that provided fully polarimetric capabilities and allowed a leap forward in the field. The polarimetric data provided by the systems have been explored for many land applications, including forestry and agriculture. Classification is an important step towards the retrieval of bio-geophysical parameters (Pottier, 2005) and a classification scheme directly based on polarimetric SAR data is useful to understand the characteristics of the Earth surface, particularly for the physical assessment of scatterers. Processing of polarimetric data for classification purposes has been carried out by algorithms which span from Bayesian Maximum Likelihood to Fuzzy Logic and Neural Networks (Ferro-Famil, 2000), (Tran, 2004), (Ersahin, 2004), (Ersahin, 2004), (Skiver, 2005). Several target decomposition methods have recently developed to characterize the scatterers (Putignano, 2005).

An important objective of remote sensing is land-cover classification and mapping. Each object/land cover class may have their own characteristic spectral response in different spectral bands of the electromagnetic spectrum. This characteristic feature of land-cover classes is helpful in the identification and interpretation of classified products. However, experience from producing vegetation maps based on satellite images has shown that certain vegetation units are difficult to separate based on spectral information only. Depending on the topographic location, underlying geology, elevation, and vegetation complexity, a single spectral class may be representative for several quite different land-cover types. To minimize errors associated with the spectral classes representing more than one vegetation type, different types of ancillary digital information are needed to separate the vegetation classes from each other. The ancillary digital data are normally digital elevation models, field inventory data, digital topographic maps, land-cover layers or data layers extracted from other satellite derived products. (Solbø, 2005) demonstrates how SAR data can contribute to the separation of water bodies from coniferous forests.

An unsupervised oil slick detection technique is proposed by using Support Vector Machines into a wavelet decomposition of a SAR image. A specific kernel is developed to perform accurate segmentation of local sea surface wave spectrum by using both radiometric and texture information (Mercier, 2005).

The analysis of multitemporal data is one of the most important and challenging issues for the remote sensing community. (Melgani, 2003) propose an MRF-based approach that aims at improving both the accuracy and the reliability of the multitemporal classification process by means of a better exploitation of the temporal information. (Bachmann, 2003) develop a credit assignment approach to decision-based classifier fusion, which they apply to the problem of land-cover classification of multiseason airborne hyperspectral imagery. (Lombardo, 2003) devise a new fusion technique for a sequence of multitemporal single-channel SAR images of the same area covered by a single multiband optical image. (Bruzzone, 2004) uses backscattering temporal variability and long-term coherence information in a radial basis functions neural network classifier.

5. A CONTRIBUTION TO COMPARE CLASSIFICATION TECHNIQUES

In order to allow the comparison of different techniques for land use analysis a complex data set will be defined. It will include:

- multitemporal TM images
- multitemporal hyperspectral casi images
- multitemporal Digital Mapping Camera MS+Pan images
- multitemporal ENVISAT SAR images
- 15 x 15 m grid Digital Elevation Model
- Climatic maps

As a land cover map reference there is a map with a minimum map unit of 50 m^2 and 62 classes.

Registered users will be able to download this complete data set in order to test different classification techniques. The common reference would permit to compare results from different approaches.

6. CONCLUSIONS

Despite the long time spent developing the classification of remote sensing images new problems and new user demands have been accumulated to the existing ones:

- Existing classification techniques do not suit well to new sensors.
- Huge amount of data demand new approaches.
- A wise combination of image analysis techniques emulating the visual interpretation of humans beings.
- The need to move from the experimental to the operational applications

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