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Semi-Automatic Verification of Two Brazilian GIS Databases

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Abstract. This paper presents a successful approach for GIS database quality control, called WiPKA-QS, applied for the verification of different Brazilian GIS datasets. The knowledge-based system GeoAIDA/InterIMAGE was used to perform this analysis. Two different experiments were implemented: one aiming at identifying changes on a road network, and the other, at identifying land-cover changes in the State of Rio de Janeiro. The architecture, main features as well as an overview of the interpretation strategy implemented in the GeoAIDA/InterIMAGE platform is presented, as well as the explicit knowledge, interpretation model defined for each experiment. Specific operators were used to identify relevant features used on the verification process. The knowledge model implemented in each experiment was defined in such a way that the consistency of the GIS input data could be confirmed or questioned, depending on the features extracted from the input images. Using that information, much of the time spent by a human specialist to update GIS data can be saved, because only the geodata likely to have changed need be verified. The results obtained in the experiments show the potential of this approach.

Keywords: remote sensing, automation, change detection, GIS, quality control.

1. Introduction

Remote sensing technology delivers the most important subsidies for the identification and monitoring of change on the surface of the Earth, effectively supporting the investigation of the interactions among the environment and agricultural or urban planning activities (Ehlers et al. 2002).

Presently, however, the lack of efficient automatic image interpretation tools makes it difficult to achieve the goals of many land cover monitoring applications. The large amount of time spent from the acquisition of an image to its classification results in insufficient time to substantiate critical decisions that may avoid or diminish the effects of environmental degradation or unplanned urban expansion. A specific aspect of the problem has to do with the large time spent on the update of GIS data, usually performed manually by specialized photo-interpreters.

Although there is already a relatively small number of commercial software for automatic or semi-automatic image interpretation, currently most remote sensing data analysis techniques require intense human intervention. Even when such analysis is performed with the aid of software tools, the automatically delivered results usually require careful scrutiny by a human specialist for the identification and rectification of inconsistencies (Bückner et. al 2002). There is, consequently, a strong demand for the development of robust techniques for automatic information extraction and interpretation of remote sensing data (Carrion et. al 2002).

A rather successful approach for automatic image interpretation is based on the explicit modeling, on a high level computational environment, of the human interpreter's knowledge concerning the interpretation problem (Bückner et al. 2002; Schiewe et al. 2001). Human expert's knowledge is organized in a knowledge base, used as an input of the automated interpretation processes – enhancing the productivity and accuracy and reducing the subjectivity of the interpretation process.

In many applications the interpretation process of remote sensing data benefits from GIS technology, often used in the definition public policies related to urban and environmental planning. Together with up-to-date remote sensing imagery, GIS data can be used in large scale for monitoring of different environmental issues, such as forest devastation, and non-planned urban expansion. The WiPKA-QS project has already successfully implemented this approach for GIS data update using high-resolution imagery of Germany.

In this paper we present the results of applying the WiPKA-QS approach to verify GIS data using imagery of the State of Rio de Janeiro, Brazil. Two different experiments were performed: one aims at identifying changes in land-use maps, and the other, at identifying changes in a road network.

The architecture and most relevant features of the knowledge-based image interpretation system used in the experiments are presented, as well as the knowledge models designed for each experiment. The specific operators used for road extraction and classification, and texture analysis for land-cover detection are also presented.

In the remainder of this paper we describe the WiPKA-QS project (Section 2). The basic characteristics of the GeoAIDA/InterIMAGE Framework are presented in Section 3. The operators used in the experiments performed are described in Section 4, and in Section 5, the experiments' results, followed by the conclusions and directions for future work, in Section 6.

2. WiPKA-QS Description

The WiPKA-QS Project, initiated in the year 2000, aims at the automated verification of the German topographic reference dataset ATKIS[1]. ATKIS is a trademark of the Working Committee of the Surveying Authorities of the States of the Federal Republic of Germany (AdV). The dataset has a geometric accuracy of 3m.

The project WiPKA-QS was initiated by the German Federal Agency for Cartography and Geodesy (BKG) together with the Institute of Photogrammetry und GeoInformation (IPI) and the Institute of Information Processing (TNT), both at the Leibniz Universität Hannover. The first version of WiPKA-QS was installed at BKG in 2003 (Busch et al. 2004). Since 2003 the system has been permanently enhanced. In this section the workflow of WiPKA-QS is described.

In WiPKA-QS, GIS data is automatically verified by comparing them with the real world – in terms of remote sensing imagery. Currently, in the BKG application, pan-sharpened IKONOS data consisting of orthorectified images with a red, blue, green and infrared channel with a resolution of 1m is utilized. In the experiments reported later in this paper, data of lower spatial resolution is used: ALOS imagery with 10m resolution and LADSAT imagery with 30m resolution.

The WiPKA-QS system consists of two components – an interactive GIS component and an automated knowledge-based image analysis component. Furthermore, the interactive GIS component is divided into a pre-processing step and a post-processing step, respectively before and after the image analysis component.

[1] Amtlich Topographisch-Kartographisches Informationssystem (Authoritative Topographic Cartographic Information System).

First of all, in the pre-processing step, the necessary sources for the verification system are defined. These are the GIS dataset, corresponding remote sensing imagery, and a semantic network that corresponds to the knowledge model for image analysis application.

In the automated knowledge-based image analysis component, the verification system compares the GIS objects of interest with the image data, in order to collect evidence for the acceptance or rejection of these objects. The GIS objects of interest for the BKG application are objects which cover large areas (e.g. settlement, industrial area, cropland, pasture and forest) or objects where many changes may arise (like roads). The workflow of WiPKA-QS is sketched in Figure 1.

Currently, the verification of GIS is still far away from being carried out completely automatically. Therefore, the final decision about the rejection of objects is made by a human operator - an interactive post-processing step is necessary. The results of the automatic procedures are passed to the human operator in the form of a traffic light diagnostics. Rejected objects (red) are visualized for further editing, whereas it is not necessary for the human operator to take a look at accepted (green) objects.

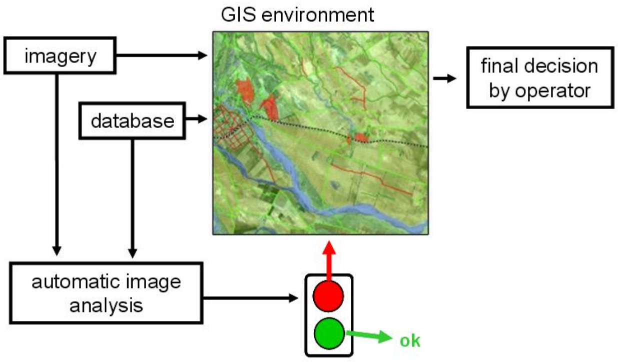

Figure 1. Workflow of WiPKA-QS

3. Knowledge-Based Image Analysis Component

The core of the automated procedures in the image analysis component of WiPKA-QS is the knowledge-based image interpretation system GeoAIDA (Bückner et al. 2002) and various methods for feature extraction.

GeoAIDA has been developed at the TNT Institute of the Leibniz Hannover University, Germany. Its interpretation engine is currently being extended through the InterIMAGE Project, leaded by the Computer Vision Lab of the Catholic University of Rio de Janeiro (PUC-Rio) and by the Brazilian Space Research Institute (INPE). As a work in progress, a new graphical user interface, knowledge extraction functionality and image processing operators are planned to be included in InterIMAGE in the near future.

3.1 Interpretation Strategy

In GeoAIDA/InterIMAGE explicit knowledge about the objects expected to be found in a scene is structured in a semantic network, defined by the user through the system’s graphic user interface (GUI).

A semantic network contains nodes and edges, whereat nodes represent concepts and edges represent the relations between the concepts. In each concept node, information necessary for the analysis, such as the image processing operator specialized in the search of occurrences of the concept, is defined. During the analysis, guided by the semantic network, the system controls the execution of the operators and generates a network of instances, each instance defining a geographic region associated to a specific concept.

Interpretation of remote sensing data means to transform input data into a structural and pictorial description that represents the result of the analysis. In GeoAIDA/InterIMAGE, the result of the interpretation contains a structural description of the result (an instance network) and thematic maps. The final and all intermediate results, in terms of region descriptions, are stored in XML format, and can be used for further external examinations.

The analysis process performed by GeoAIDA/InterIMAGE has two steps: a bottom-up step and a top-down step. The top-down step is model driven and generates a network of hypothesis based on the semantic network. The grouping of hypothesis and their verification or falsification is a task of the data driven bottom-up analysis. The final instance network results from the bottom-up analysis.

In each network node the user defines the information necessary for the execution of each processing step, that is, the image processing operator and respective parameters to be used in the top-down step (top-down operator), and the decision rules to be used in the bottom-up step.

The top-down operators have the task of creating concept hypotheses, defining regions on the image associated to the concepts of the semantic network. This task is performed recursively from the upper to the lower nodes. For this purpose any (external) classifying operator can be used in the analysis process. The regions hypotheses can be defined by means of consistency measurements. If the contemplation of texture, for instance, allows only a few possible hypotheses for a particular region, no further investigation of other concept hypotheses is performed for that region.

When the top-down analysis reaches the leaf nodes, analysis changes from model-driven interpretation to data-driven interpretation (bottom-up). The decision rules for the bottom-up step are defined in a particular stack based language that provides functions for deciding between spatially concurrent hypotheses generated in the top-down step.

4. Image-Analysis Operators

The core of every automated procedure is based on image analysis algorithms. In this section we discuss operators for the verification of line objects (e.g. roads) as well as polygonal objects (e.g. urban, forest, field and bare soil), used in the experiments reported in Section 5.

4.1. Road Verification Module

The road verification module is designed to check the existence and positional accuracy of roads from a given GIS database. Two special operators are used for the task. The first operator extracts relevant information from the image; the second operator compares the extraction result with the database. Both operators will be described in the following sections.

4.1.2. Road Extraction Operator

The operator is based on the road extraction algorithm, presented in (Wiedemann and Ebner 2000), which models roads as linear objects in single channel imagery with a resolution of 1 to 2m. The underlying line extractor is introduced in (Steger 1998). The approach is restricted to the open landscape area since a homogeneous surrounding of the road is a precondition. The initially extracted lines are evaluated through fuzzy rules concerning their attributes, such as length, straightness, constancy in width and in grey value. Final step is the grouping of the individual lines in order to derive topologically connected and geometrically optimal paths. The decision whether extracted and evaluated lines are grouped into one road object is based on a collinearity criterion, allowing for a maximum gap length and a maximum direction difference.

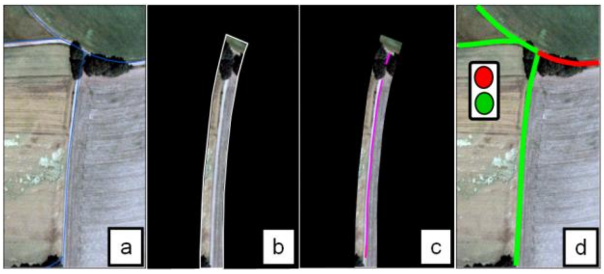

Figure 2. Road verification process: a) imagery and GIS road data; b) Generated buffer for the single road object; c) Result of the line extraction algorithm; d) Traffic light decision for the GIS road data.

The line-based road extraction algorithm is executed for each road object individually. Thus, in each case a region of interest is defined, depending on the geometric description from the database. More precisely, a buffer around the vector representing the road axis is defined, and the buffer width complies with the overall requested geometric accuracy of the GIS and the road width attribute in the database. If the width value fails a plausibility test or is not available at all, a predefined value is taken. Subsequently, the road extraction algorithm is executed with appropriate parameter settings in the image domain of the buffer. The geometric and radiometric parameters are initially selected based on the knowledge about the given context region. Varying contrast situations, based on differences in the illumination of the imagery, are compensated by an automatic parameter training module. This training module is executed independently from the road extraction operator. Hence, the module refines the radiometric properties from the existing GIS road network in the respective scene. Based on the assumption that the majority of the GIS roads are correct, a rank filter is used to avoid inadequate parameter settings, which are refined from incorrect roads (Ziems et al. 2007). Consequently, the extraction algorithm is processed with a scene, context and object dependent parameter selection. Figure 2 depicts the main extraction process.

4.1.3. Road Verification Operator

The road verification operator is designed to check if the roads from the database keep a predefined positional accuracy as well as to detect commission errors (a road from the database does not exist in the reference image). The road verification operator compares geometry, shape and attributes of the corresponding road objects. If the calculated evidence for the correctness of the database road is high enough, the GIS information is assumed to be correct, i.e. it is accepted, and otherwise it is rejected and marked for manual checking. For the assessment topological relations to other extracted objects, e.g. local context objects like rows of trees or shadowed areas can be considered too. A geometric-topologic relationship model allows combining evidences from different extraction methods. For further information concerning the verification operator refer to Gerke (2006).

In order to exploit the connection character of roads, the presented procedure is embedded in a two-stage graph-based approach, which leads to a reduction of false alarms in the verification. In the first phase, the road extraction is applied using a strict parameter control, leading to a relatively low degree of false-positive road extraction, but also a high number of roads will be rejected, although being correct. For the second phase, the latter objects are examined regarding their connection function inside the road network. It is assumed that accepted roads from the first phase are connected via a shortest path in the network. All rejected roads from the first phase fulfilling important network connection tasks are checked again in a second phase, but with a more tolerant parameter setting for the road extraction operator. Consequently, the verification operator takes global information of the whole road network into account while the extraction operator is restricted to a single road object.

4.2 Textural Analysis Operator

The textural analysis uses a segmentation algorithm initially described in Gimel'farb (1996), and later extended to use a multiresolution technique to segment images. This classification algorithm has to learn the properties of the classes with manually created training regions for the classes.

The learning steps are: (a) learning of texture with the training areas in four subsampling resolution levels resulting in four parameter files; (b) segmentation of the input image in all resolution levels based on the parameter files; (c) evaluation of the segmentation for each class in all resolutions; and (d) calculation of an evaluation matrix.

As a result of the learning process, four parameter files and an evaluation matrix are derived. The texture analysis operator begins with the lowest resolution and processes the higher resolutions level by level. It uses the parameters derived from the training areas.

The steps of the top-down texture operator are: (a) analysis of the input image in all resolution levels using the parameter files; (b) calculation of a resulting segmentation using the segmentations in the different resolution levels and the evaluation matrix.

The learning step determines the resolution level on which a class gains significant signatures. From the evaluation matrix, we derive in which resolution level a texture can be differentiated. The resolution with the best separation characteristics may differ from one class to another. The classification of inhabited areas is, for example, significantly better in the lower resolutions and therefore preferably used.

The learning step is a crucial part for the effectiveness and correctness of the derived results. This step is preferably done by a human operator, who manually defines training areas for the desired classes by use of a developed training tool. The automatic generation of training areas by the use of GIS data is also possible. The training areas for the desired classes can be taken from the regions of a GIS and be used to train the classifier. This has to be done for a few areas, whereas the resulting classification definitions can be used for similar images, e.g. the complete set of images of a flight. Since the fully automatic derivation of training areas sometimes leads to training areas containing a mixture of classes, the separability of the classes is not as good as it is with manually defined areas.

5. Experiments and Results

Two different experiments, using Brazilian GIS databases were carried out in this work: one to verify road changes, form a database produced by IBGE (Brazilian National Geography and Statistics Institute), and the other to verify land-cover changes in GIS data, from a database of the IPP (Pereira Passos Municipal Urban Institute, an agency from the Rio de Janeiro City Administration). Both GIS datasets cover areas inside the State of Rio the Janeiro, and they are at least two years older than the images used in the verification process.

5.1. Road Verification

The goal of the first experiment was to detect road changes in a given GIS dataset using ALOS imagery with 10m resolution. Only the spectral bands from the visible part of the electromagnetic spectrum were used. The GIS data covered a biological reserve area, in the northwest of Rio de Janeiro State.

The semantic network was designed so as to detect different types of roads, with different widths. A top-down operator, with the functionality described in Section 4.1.1, was attached to each leaf node of the network. The generated road hypotheses were subsequently compared with the input GIS data, at the bottom-up interpretation step, through the procedure described in Section 4.1.2.

If a GIS road can be validated by a set of hypotheses, a flag associated to the road object is set to signalize that the GIS road is unchanged. If the validation procedure result is inconclusive, the system will set a flag that indicates a change occurred, and that the GIS road could not be detected (inconclusively).

In Figure 3 the results obtained for road verification on the IBGE's dataset are depicted, for a small area within the study region. It is possible to observe that some roads could not be verified due to the resolution of the available imagery, which was too low (10m) to identify properly small roads.

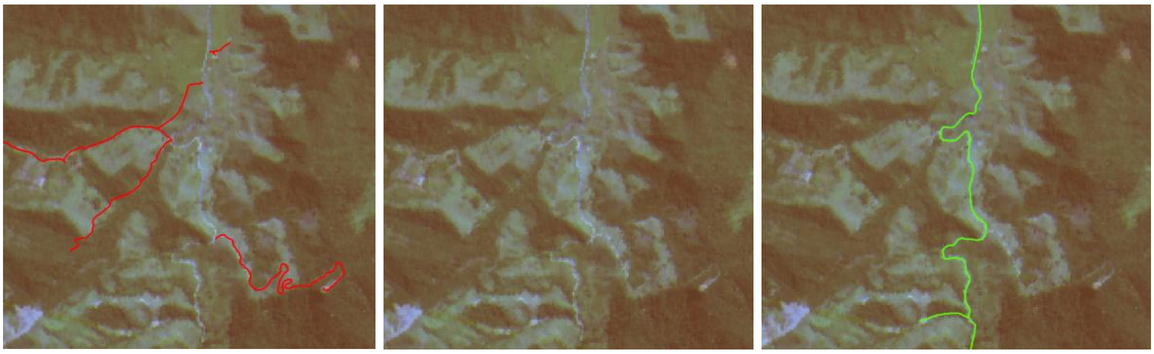

Figure 3: Road verification experiment: rejected GIS road data (right); input image (center); accepted GIS road data (left).

5.2 Land-cover usage verification

The goal of the second experiment was to detect land-cover changes in a GIS dataset, using LANDSAT imagery (30m resolution). The semantic network was designed so as to detect four different types of land-cover classes: urban (red), field (light green), forest (dark green) and bare soil (yellow). Only the spectral bands from the visible part of the electromagnetic spectrum were used.

Each land-cover polygon from the GIS dataset was initially defined as a hypothesis of the corresponding land-cover class. The multi-resolution texture analysis top-down operator (Section 4.2) was then called to process the image segment within the original polygon, trying to find hypotheses of any land-cover class. Subsequently, in the bottom-up step, a decision rule is used to judge the original hypothesis based on the ratio of the land-cover classes automatically found within the original polygon. If less than a certain percentage of the original hypothesis area (as defined in the GIS database) is covered by the original land-cover class (as detected automatically by the top-down operator), a flag associated to the original land cover polygon is set, indicating that its class has probably changed.

Figure 4 shows the results obtained for a small area within the study region.

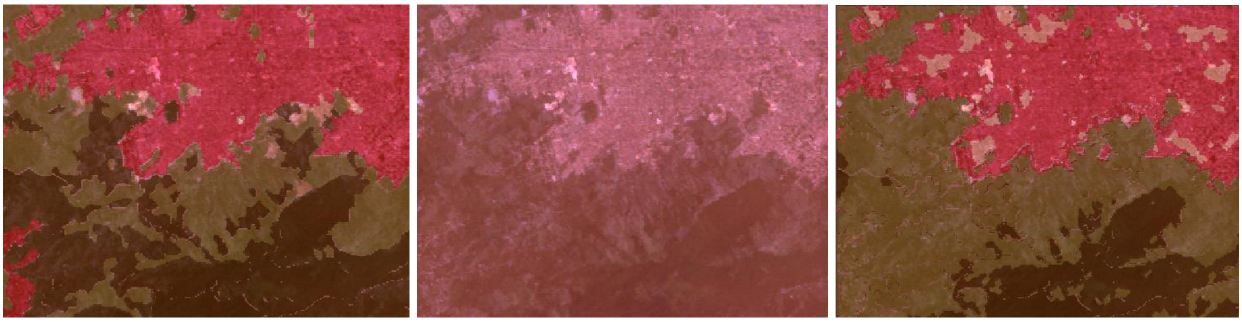

Figure 4: Land-cover verification experiment: original GIS land-cover data (right); input image (center); textural analysis result – urban: red; field: light green; forest: dark green; and bare soil: beige (left).

6. Conclusions

This paper presented a successful approach for GIS database quality control, called WiPKA-QS, applied for the verification of different Brazilian GIS datasets.

Experimental results demonstrate the potential of WIPKA-QS to update Brazilian GIS datasets. In the road verification experiment the main roads could be properly verified, but some of the small roads could not detect automatically due to the resolution of the imagery used.

In the land-cover verification experiment, which was based on textural analysis, the devised application was successful in finding the correct land use classes and validating the GIS dataset. Some errors, though, were observed in transition regions, such as sparsely populated areas, where most confusion between the field and urban classes occurred.

This quality control approach can save much of the time spent with the updating process of GIS data, usually performed manually, by trained specialists. The specialists can focus on the objects rejected from system; saving most of the time spend on visual verification of the whole data set. In this way, the experiments performed indicate a promising approach for semi-automatic GIS data update.

For the continuation of this work, we are considering to execute the experiments with higher resolution imagery (from the IKONOS or Quickbird sensor systems). In the case of the land-cover update application, we are also considering a running the experiments on a dataset with a larger number of classes.

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