MULTI-HIERARCHICAL QUALITY ASSESSMENT OF GEOSPATIAL DATA

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ABSTRACT:

In this paper we describe the analysis framework system GEOAIDA with view of an application for a versatile and efficient quality assessment of geodata. GEOAIDA allows to develop image analysis strategies for complex object class definitions being provided by different GIS databases. The image analysis strategy and GIS data model can be expressed in tree-like semantic networks. The multi-hierarchical architecture allows multiple combinations of image analysis tools for a multifaceted use. A practical application is the semiautomatic quality assessment of MGCP data by using IKONOS imagery. For the comparision of MGCP and image content, information about different object classes is extracted from the image. The landcover objects are detected by color texture classification combined with structural analyzing methods. Roads are detected by a line based extraction algorithm combined with color texture classification results. The MGCP database itself is used as prior knowledge to perform the image analysis.

1 INTRODUCTION

Many applications of administration, economy and leisure activities are based on spatially referenced data. The advantages of database technology compared to analog means have led to the construction and enhancement of consistent object-based digital landscape models (DLM) by national and international organizations. Commonly, the production and update of these geodata is realized by different instances. Apart from the data themselves, information about their quality and about the consequence of possible errors and the risk associated with these errors is required by most applications. Along these requirements we have developed a system for semiautomatic quality assessment of existing geospatial data. The necessary reference information is derived from up-to-date digital images via automatic image analysis. The task of the system is to reduce the manual effort to a minimum. To compensate limitations of the automatic components human interaction is focused on those objects, for which no reliable verification result can be achieved within the automatic process.

1.1 Background

Our project objective since 2000 is the quality assessment of the German ATKIS (Authoritative Topographic-Cartographic Information System), as a major interest of BKG (German Federal Agency for Cartography and Geodesy) described in (Busch et al., 2004), (Gerke, 2006), (Müller, 2007) and (Gerke and Heipke, 2008). Based on the developed system, the project called WiPKA-QS was expanded in 2006 to the most important object classes of the MGCP (Multinational Geospatial Co-production Program) database. The AGeoBw (Geoinformation Office of the German Federal Armed Forces) has the task to produce a large contingent of this global database. The data are acquired by different commercial companies. Therefore, a final quality assessment ensures quality of the data.

With a view on automatic quality assessment some semiautomatic solutions are described in the literature, e.g. (Klang, 1998) presents a system for an enhancement of the Swedish road database by detecting inconsistencies between database and satellite imagery. This approach was extended in relation to the task of the National Topographic Database of Geomatics Canada (Fortier et al., 2001) and the ability to use high resolution aerial imagery. The project called Automated reconstruction of Topographic Objects from aerial images using vectorized Map Information (ATOMI) of Switzerland (Zhang, 2003) applies a more complex analysis strategy regarding the considered object model and the used data sources. The results of the mentioned approaches prove the functionality of different image analysis strategies with specific premises, e.g. properties of imagery and DLM databases. Our current task is characterized by variable input data and heterogeneous environmental conditions, which demand different strategies. Consequently, one major request for the assessment system is to provide a higher flexibility by developing a strategy for a rapid adaptation of the image analysis tools.

Within WiPKA-QS, the knowledge-based image interpretation system GEOAIDA (Geo Automatic Image Data Analyzer) (Liedtke et al., 2001), (Pahl, 2003) is used to perform image analysis. The analysis strategy is modeled efficiently using a tree-like hierarchical representation. As a drawback of this system some general restrictions regarding practicable image analysis and quality assessment strategies have to be accepted. Therefore, we have enhanced the system to also handle complex strategies with several sub-strategies in a new multi-hierarchical approach.

In section 2 a new multi-hierarchical approach is presented. In the following section we show how this allows to build a flexible, easy configurable and powerful quality assessment system for area and line classes. The functionality of this approach is demonstrated for a concrete example of MGCP in a coastal region of Northern Africa. Quality assessment results are shown in section 4. Finally, in section 5 a conclusion is given and future applications for the presented multi-hierarchical approach and quality assessment system are presented.

1.2 GEOAIDA

To build a powerful, highly flexible and easy configurable quality assessment system we use the knowledge-based image interpretation system GEOAIDA. Thus, we first give a short overview of how the system works.

Figure 1 shows the design of GEOAIDA. Input data is processed by the system control to obtain a description of the given scene as output.

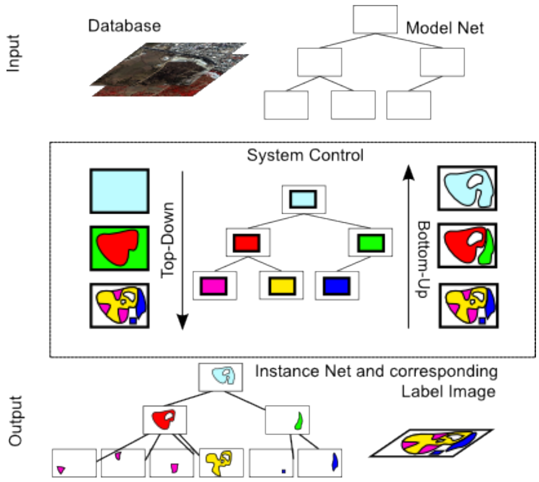

Figure 1: GEOAIDA Design

1.2.1 GEOAIDA Input

Database The database provides all input information available for the scene interpretation. This includes images of different sensors, like optical images, laserscans, or SAR data, as well as GIS information. GEOAIDA itself is not limited to any kind of input data – restrictions are only imposed by the attached external image processing operators, which work on their dedicated input data. Internally, GEOAIDA manages two dimensional regions which are assigned to nodes of the instance net.

Model Net The *a priori* knowledge about the scene under investigation is stored in a model net. The nodes of the net are ordered strictly hierarchical, i.e. each node has exactly one parent node. Thus, it can be represented as a tree structure. The topmost node is the scene node. Attributes can be assigned to each node. Common attributes are *name*, *class* and the associated *top-down* and *bottom-up* operators. *Top-down* and *bottom-up* operators are external image processing operators with a common interface (Liedtke et al., 2001).

A *top-down* operator is capable of detecting objects of its node class in the given input data. For each detected object a hypothesis node is generated. The *bottom-up* operator investigates the relationship between the sub-nodes and groups them into objects of the node class. These objects are then represented by instance nodes. *Top-down* and *bottom-up* operators can also be configured according to additional attributes, that are operator specific. Hypothesis and instance nodes are symbolic descriptions of objects. Geometrical position and form are defined in corresponding label images.

1.2.2 System Control The main task of GEOAIDA itself is system control. The analysis is accomplished in two major steps. First a *top-down* pass through the model net, calling the attached image processing operators to generate hypotheses about the objects in the scene. According to the model net these hypotheses are structured in the hypothesis net. The second step is a *bottom-up* progression through the model net. During this pass an instance net is generated from the hypothesis nodes on the basis of object properties like size or structural relationship between complementary hypotheses.

The structure of the model net and attached *top-down* and *bottom-up* operators define the performed analysis strategy. Although how this is done highly depends on the specific analysis task, a general assignment of objectives can often be observed: On the one hand, leaf nodes of the model net process image data in a top-down-operation. Top-down operations use knowledge and algorithms to segment specific object classes in the image. On the other hand, nodes other than leaf nodes tend to deal with more abstract object class relations. Their top-down-operators often trigger various complementary or competing hypotheses, based on prior knowledge and image processing. When performing the bottom-up-operation, results from the hypotheses are evaluated.

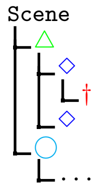

Figure 2: Example for information availability in the instance net

1.2.3 GEOAIDA output The output of the GEOAIDA analysis is an instance net, which describes all verified objects of the scene. The ordering of the nodes is strictly hierarchical, i.e. the footprint of child nodes is always completely represented in the parent node. Furthermore, all nodes of the same hierarchic level are disjunct. Thus, it is possible to describe the position of all objects of an instance tree in a two dimensional label image.

Combination of the original model net with the instance net and the corresponding label image leads to a *hierarchical map*. Opening and closing branches of the model or instance net changes the level of detail in the hierarchical map.

2 NEW APPROACH

A GEOAIDA analysis is controlled by using a single model net. For a simple structure of the analysis, the tree-like structure of the model net is essential.

Often a complex analysis task can hardly be expressed by using a simple strategy, though. Instead, an analysis task might be composed of several sub-analyses. Subsequently, these have to be combined in some way.

Performing several analyses is possible in GEOAIDA by expressing two or more diverse (sub-)analyses in one large model net. Each sub-analysis is represented by a separate branch. This limits the possibility for combining analysis results: While in the top-down process each node only receives information about its parent node (and from input data), in the bottom-up process only information provided by the direct child nodes is available.

In the example in figure 2, the node marked with △ can only access results from its child nodes (◇). Information from nodes underneath (†) is hidden, as well as results from nodes in disjunct branches (◯).

Hence, a new approach to deal with diverse analyses was developed. This approach uses existing results as starting point for further analysis. Each of them being the result of a hierarchical analysis, processing several GEOAIDA results leads to a multi-hierarchical analysis.

2.1 Multi-Hierarchical Analyzis

As described in the preceding section a complex analysis can sometimes be hardly expressed conveniently in a single model

```
Scene
├△
│ ├†
│ │ └†
│ └†
└○
  └◇
```

Figure 3: Example for selection in model net

net. Hence, we first split up the complex analysis in multiple independent sub-analyses. For each (sub-)analysis a conventional GEOAIDA-analysis is performed. Finally, the hierarchical maps from these analyses are evaluated by an *additional* GEOAIDA analysis. In this way, the analysis and modeling abilities of GEOAIDA can be utilized for a multi-hierarchical approach.

The additional GEOAIDA analysis evaluates the hierarchical maps arising from the miscellaneous analyses. As described in section 1.2.3 a hierarchical map consists in fact of three parts: model net and instance net together with the corresponding label image. The label image and instance net are used to access analysis results for each point on the surface at different levels of detail. The model net describes the structure of the instance net.

To define the strategy for the evaluation, again a model net is used:

```
Scene
└Multi-Hierarchical Interaction
  └...
```

The *top-down* operator of the node *Multi-Hierarchical Interaction* performs two steps:

Selection step In each hierarchical map, several interpretations for each point in the scene are provided. For each level of detail one result is maintained. Hence, it is necessary to determine in advance which level of detail shall be used.

For every hierarchical map nodes in its *model net* are selected. Those can be determined by arbitrary key-value pairs (e.g. a specific name). A node can only be selected if no other node in its path to the top node (Scene) is selected.

In the example in figure 3, node ◇ can only be selected if node ○ is not selected. If node △ is selected, all nodes marked with † cannot be selected.

When performing the evaluation analysis, nodes in the *instance net* are selected automatically according to the selection in the model net (identified via the class attribute). This leads to a simplified corresponding label image. Due to the used selection scheme, for each pixel at most one level of detail is used. This procedure is performed for each hierarchical map, one for each analysis.

Merge step All simplified maps are merged into a final map. In this map all region boundaries from all simplified maps are contained. Thus, any given region from one analysis is divided into one or more sub-regions, depending on the objects in the other simplified maps. The object class of each region is a tuple, containing all object attributes, including class ids, from each simplified map.

Using this segmentation, the following nodes can evaluate the tuples of object attributes, depending on the application. Moreover, they may access the hierarchical maps of all given analysis results. After this evaluation, the bottom-up-operator in the node *Multi-Hierarchical Interaction* can recombine evaluation results. The recombination strategy has to be designed according to the application.

3 AN EXAMPLE: AUTOMATIC QUALITY CONTROL OF MGCP DATA

To demonstrate applications of GEOAIDA with the multi-hierarchical approach, a region dependent model net for the task of quality assessment is constructed in the following. In this context a short overview of the data source and the used image analysis tools, separated for landcover and line objects, is given.

3.1 Data Source

The goal of our example is the evaluation of the MGCP database by comparison with current IKONOS imagery in the coastal region of Northern Africa. The region is characterized by agricultural use in flat terrain, forest or thicket in rolling terrain and numerous shared settlements. The vegetation is influenced by arid climate conditions and systematic irrigation. Considered landcover objects are settlement, grassland, forest, cropland, thicket, desert and, as an example for the linear GIS data, the road network.

The available MGCP dataset was acquired independently by use of available local paper maps and manual digitizing based on those IKONOS imagery, which is also available for the quality assessment. The IKONOS imagery consists of one panchromatic and four spectral bands. For the considered region pan-sharpened images with a ground resolution of 1m were used.

3.2 MGCP Model Net

The following model net, representing the given MGCP data, is constructed to prepare the database information for a later comparison with the image analysis results:

```
MGCP representation
├Settlement
│ ├Settlement overlaid with Industry
│ └Settlement without Industry
├Forest
│ └Roads in Forest
├Cropland
│ └Roads in Cropland
├Grassland
│ ├Grassland overlaid with Industry
│ ├Grassland without Industry
│ └Roads in Grassland
├Thicket
│ └Roads in Thicket
└Desert
  └Roads in Desert
```

The harmonization of the considered database objects with their expected image representation requires the removal of the typical superimposition effects. More precisely, the roads are transferred from line into area objects while neighboring area objects are reduced. Furthermore, some of the MGCP landcover classes are subdivided to take their different characteristics in the imagery into consideration, e.g. grassland with and without industrial facilities. The knowledge about the characteristics is also refined from the MGCP database i.e. from object attributes and from so called activity area classes.

3.3 Landcover Classes

3.3.1 Area Image Analysis

Several image processing algorithms are combined to achieve a landcover classification, depending on the expected area class combination and available image data.

To cover the object classes settlement, industrial, forest, desert and grassland which are typically homogenously textured, a supervised texture classification based on Gibbs Random Fields (Gimel'farb, 1999) is used. The cropland object class is a collection representing several agricultural areas, though. These areas can significantly differ in their appearances. Thus, several approaches for segmentation have to be used.

In the regions we cover in our work the majority of cropland contains field structures and plantations. Currently, the already mentioned texture classification is used also in these areas.

```
Scene △
├Settlement
├Forest
├Cropland △
│├Plantation
│└Fields
├Grassland
├Thicket
└Desert
```

The bottom-up operators in nodes Scene and Cropland (△) combine results from their child nodes. Too small regions are considered as irrelevant and are excluded.

3.3.2 Landcover Verification Module For quality assessment of area classes it is necessary to compare the description provided by a given MGCP scene with a scene description derived from satellite imagery. Differences are then regarded as possible errors in the MGCP dataset.

A reliable image classification is the key for our procedure. Nevertheless, even with a perfect image classification developing an assessment system is non-trivial. It has to handle different scenarios:

Inconsistencies in region description If a (sub-)region changed or a region was classified incorrectly when captured for MGCP, this results in inconsistent region descriptions. Not all inconsistencies are errors for the purpose of the MGCP specifications. Depending on the specifications such inconsistencies have to be ignored regarding the required minimum mapping unit.

Moreover, Landcover Features include only a subset of object classes. Other object classes are called Activity Area Features, e.g. Processing Facility or Harbor. They always overlap one or several Landcover Area Features. If this is the case, in images often only the Activity Area Feature can be detected. Hence, a sub-region being covered by such a feature cannot be judged from image analysis and is excluded from verification.

Wrong boundaries In this scenario, the descriptions for a given region are mostly the same, but the boundary differs. This happens when the boundary was not captured correctly in the database or the region boundary changed after data capture. These errors might affect only a small sub-region of a region. Nevertheless, they have to be detected according to the MGCP extraction rules. If the region boundary is hard to locate, the situation is less clear. This is especially a problem when there is a soft transition in the image between regions.

Thus, an assessment system has to be configurable, taking local and global aspects of errors into account and has to deal with sometimes arbitrary boundaries and generalizations. Moreover, easy and comprehensive configuration of the system is a major objective.

GEOAIDA's tree-like model net allows easy configuration but not all described quality assessment scenarios can be handled in a single GEOAIDA analysis. While errors regarding inconsistencies of (sub-)regions can be handled, dealing with boundary decisions was not possible prior to our new developments. Boundary decisions have to take neighborhoods into account. This information is only available after an image analysis is finished, making area quality assessment an application for the multi-hierarchy approach.

As described in section 2.1 results from GEOAIDA analyses are post-processed in an additional analysis. Input results are generated with the nets for landcover classes and MGCP. The approach used for landcover verification can be visualized by an exemplary semantic net:

```
Quality Assessment Scene
└Merge Scene Descriptions △
 ├Correct ○
 └Might be Defect
  ├Grassland-Cropland ◇
  ├Grassland-Settlement ◇
  └Defect †
```

This example can be read like a decision tree. In node △ both scene descriptions are transformed into a single label image (section 2.1): First, each hierarchical map is transformed into a simplified label image by selecting nodes in the model net. Selection has to be done with respect to a corresponding level of detail of image processing and MGCP. In the succeeding merging step a new label image is created, containing the region boundaries from both descriptions. Each region in this image contains one area feature from MGCP and image analysis.

Those regions are now handled independently. Conflicts can be determined by specifying attributes in the nodes. Hence, it is possible to distinguish different forms of object class relations:

- Regions belonging to the same object class are correct (○).
- All other regions might be wrong in the database and are handled depending on the scenario:
  - Inconsistencies in region description, but errors have to be ignored due to minimum mapping restrictions.
  - Wrong boundaries. Boundary decisions can now be handled depending on the classes being involved (◇). For deriving decisions for those regions the image analysis results are considered. Thus, neighborhood conditions can be taken into account.

  All other class combinations are regarded as wrong (†).

After handling all regions, they are recombined to regions according to the MGCP regions. This is done in the bottom-up operation in node △. Results from the different sub-regions are weighted and a final result is calculated for each MGCP region, leading to verification or rejection.

3.4 Road Network

For the quality assessment of the MGCP road network we primarily use a single road extraction algorithm as top-down operator. A multifaceted usage of the single algorithm is achieved by adapted parameter sets, which are selected based on the design of the semantic net architecture. The comparison of the extraction result and the existing database is carried out by two different modules for the two discrete tasks of verification and update. These components are described in the following.

3.4.1 Road Extraction The road extraction algorithm, presented in (Wiedemann and Ebner, 2000) and (Wiedemann, 2002) models roads as linear objects in aerial or satellite imagery with a resolution of about 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 by fuzzy values according to attributes, such as length, straightness, constancy in width and in gray value. The 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. All significant parameters for road extraction can be set individually, thus being adaptable for specific tasks and varying road models.

The selection of specific parameter settings is based on knowledge, which can be expressed in the semantic net, e.g. the definition of different context regions. For the coastal region of Northern Africa a semantic net based on the local conditions was defined:

```
Scene
└Settlement †
└Forest
└Cropland
└Grassland
│ └Grassland overlaid with Industry †
│ └Grassland without Industry
└Thicket
└Desert
```

On the first level a Top-Down operator separates the IKONOS scene along appropriate context regions based on the available information of given MGCP database. The marked nodes (†) for settlement and industry are not used for the road extraction process.

Because the line extraction algorithm is restricted to single colored imagery the operator is applied with different input data in parallel branches of the semantic net. Instead of the available pan-sharpened IKONOS channels R, G, B and IR only two channel combinations, i.e. NDVI and intensity of RGB are used. For the NDVI input image a dark line model (line is darker than the background) is defined to extract surfaced roads within dense vegetation areas. For the intensity input image also a bright line model (line is brighter than the background) can be defined. The designed semantic net is based on general knowledge about the considered region, e.g. cropland can appear dark and bright in view of roads and can contain dense vegetation, which leads to high contrast between road and local background in the NDVI image. However, in desert context, roads appear dark in the intensity image and show no contrast in the NDVI image. According to this region based knowledge the semantic net is shown for two context regions:

```
Scene
└Cropland
│ └bright line model (intensity image)
│ └dark line model (intensity image)
│ └dark line model (NDVI image)
└Desert
│ └dark line model (intensity image)
└...
```

All the nodes are further divided for two different aspects of the extraction process, i.e. road verification and road update, shown for the cropland node:

```
Scene
└Cropland
  └bright line model (intensity image)
    └road verification
    └road update
```

While line extraction for road update is carried out for the whole context region line extraction for road verification is done for each road object separately. More precisely, the line extraction uses the road object specific parameter road width, given in the MGCP database, within a buffer around the vector representing the road axis. The buffer width complies with the road width attribute and the nominal accuracy of the MGCP road objects being 25m.

In spite of optimizing the extraction process with the help of the constructed semantic net some parameters have to be tuned for every scene to achieve stable results. The reasons are the rather vague definition of the MGCP object classes as well as varying contrast situation based on differences in the illumination of the IKONOS imagery. To solve this task an automatic parameter training module was placed in front of the road extraction operator. This module makes use of the existing MGCP road network to refine the gray values of every road region and the related background regions beside the road from the image data. A histogram analysis based on these gray value distributions is carried out to estimate three scene dependent radiometric parameters for each final node of the semantic net:

- *Homogeneity* along the line object assumed to be a road. The line extraction operator requires pixels with similar gray values along the road centerline to form a line object.
- *Contrast* between road and local background. The line extractor requires a minimum difference of gray values across the road to detect a line object.
- *Global threshold* is defined as the upper (dark roads) or lower (bright roads) limit to generate a region of interest containing the roads.

The automatic parameter training is based on two assumptions: Firstly, the majority of the roads in the database are correct and have high positional accuracy - only some roads are incorrect or missing in the database. Secondly, the database contains a representative set of roads for the specific scene. A more detailed description and an evaluation of the automatic parameter training module is given in (Ziems et al., 2007).

Consequently, the road extraction operator is carried out at every leaf node with the three scene depended radiometric parameters in addition to a context, model and object specific parameter set.

3.4.2 Road Verification The Road Verification Module is designed to check whether 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 IKONOS image). As input data the analysis result of the road extraction (section 3.4.1) and the corresponding nodes of the semantic net, representing the MGCP data are used (section 3.2).

The road verification module 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 MGCP information is assumed to be correct, i.e. it is accepted, otherwise it is rejected and marked for manual checking. For the assessment, also topological relations to other extracted objects, e.g. local context objects like rows of trees can be considered to explain gaps. This functionality is not used for the coastal region of Northern Africa. For further information concerning the modeled road verification refer to (Gerke, 2006).

3.4.3 Road Update The Road Update Module is designed to check the completeness of the MGCP database regarding the road network. While update and verification are identical for landcover objects, the update of the road network requires an additional step. Missing roads are partially detected by the area verification module but usually roads generate no compact regions or sufficient coverage of a landcover object to detect this type of database defect within the area verification module.

For the update module the MGCP representation (section 3.2) is combined with the results of the color texture analysis (section 3.3) and the line based road extraction (section 3.4.1) as input data. The main strategy is divided in the following parts:

- *Part 1: The preparation of the color texture analysis result.* Since the road extraction operator is restricted to the open landscape, the MGCP regions settlement and industry are not considered in the road update module. In the open landscape the image pixels of surfaced roads are partially classified as settlement or industrial classes by color texture analysis. These pixels build up thin regions, which can be used to detect roads. To identify these regions the MGCP information is intersected with the classification result. The resulting regions are evaluated by simple shape descriptors to select elongated regions, which are assumed to be parts of roads. This step is used to prevent false alarms by noise or compact update regions, which are considered within the area verification module.
- *Part 2: Preparation of the line based road extraction result.* The results from the different road extraction leaf nodes are selected and fused. All extracted roads, which overlap with roads of the MGCP database, are ignored for the further analysis.
- *Combination of Part 1 and Part 2.* In our experience the Part 1 results show a weak point regarding the completeness but exhibit a high level of correctness. Thus, most roads are only partly detected. In contrast, the Part 2 results show high completeness, even if the image resolution and contrast conditions are suboptimal. As a drawback, the line based approach tends to extract smaller paths, walls and other line objects. These objects also correspond to the network character of the used road model and have to be eliminated. Therefore, the Part 1 result is used for an evaluation of the road candidates (Part 2) to reduce the overdetection rate. Consequently, the cover ratio for each road candidate is calculated. Based on empirical investigations minimum limits for the cover ratio and the number of pixels are defined.

Because the road update module provides no perfect result, the output geometries are only a suggestion of a probably missing road and need to be checked by a human operator.

4 RESULTS

For the evaluation of the proposed image analysis strategy, IKONOS scenes of coastal region in Northern Africa and the corresponding MGCP datasets are used. The datasets originate from the coordination phase of the MGCP data generation and constitute a manually generated reference dataset, produced by AGeoBw. According to the verification modules, a confusion matrix of decisions: human operator vs. automatic procedure, gives an idea about the efficiency and reliability of the used strategy. Additionally, the functionality of the road update module is exemplary demonstrated.

4.1 Area Verification

The matrix presented in table 1 shows the evaluation of the automatic quality assessment system for the landcover objects. The scenes contained 374 objects. 64.4% of those objects were stated to be correct by the system and the reference. 18.4% of the objects were correct according to the human operator, but the system could not confirm this. 13.2% of the objects were detected to be incorrect from both. According to the human operator, another 4.0% were incorrect objects while the system found them to be correct.

Reference \ System	Accepted	Rejected
Accepted	64.4%	18.4%
Rejected	4.0%	13.2%

Table 1: External Evaluation of Area Verification (374 objects)

From those results it appears that performing a totally automatic quality assessment is not feasible with the presented system. For 77.6% of the objects the system and the human operator reached identical results. Decisions for 22.4% of the objects diverged, though. Hence, we propose to use the system for a semi-automatic approach. When the result of the system is checked by a human operator only in those cases when the object is rejected from the system, an accuracy of 96.0% correctly evaluated objects could be achieved in the given scenes. At the same time, only 31.6% of the objects have to be evaluated by a human operator.

The high percentage of false objects (lower row of table 1) in the evaluated dataset is not representative for the general quality of the MGCP data because the used dataset was produced in the coordination phase.

4.2 Road Verification

Reference \ System	Accepted	Rejected
Accepted	58.8%	36.0%
Rejected	1.4%	3.8%

Table 2: External Evaluation of Road Verification (1117 objects)

Table 2 shows, that the chosen strategy for road verification allows to ignore nearly 60% of the road objects for manual quality assessment. The low number of critical mistakes (1.4%) shows the high reliability of the approach. The false negative decisions (36%) are due to the limitations of the used road model of the line extraction operator.

4.3 Road Update

Figure 4 shows interim and final results for a 5 x 5km cut out of an IKONOS scene in the open landscape (upper left). The MGCP road network is displayed in yellow (upper middle). Since, we found no missing roads in the dataset, for the test setup all roads are assumed to be missing. This scene is chosen as a complicated case for the line based algorithm because many line objects like forest aisles and sandy paths with high contrast and typical road width are visible in this scene. The light blue lines (upper right) are the result of the line based approach and illustrate the problems associated with an exclusive use of this approach in general. In the lower left of Figure 4 the classification result of the color texture analysis containing the landcover classes: cropland - brown, desert - yellow, grassland - light green, forest - dark green, settlement including the surfaced roads - blue; is shown. In the lower middle of Figure 4 the regions, which are evaluated as surfaced road parts are displayed. The final result (red lines) show the high completeness of the pure line based road extraction result and the high correctness of the area based classification.

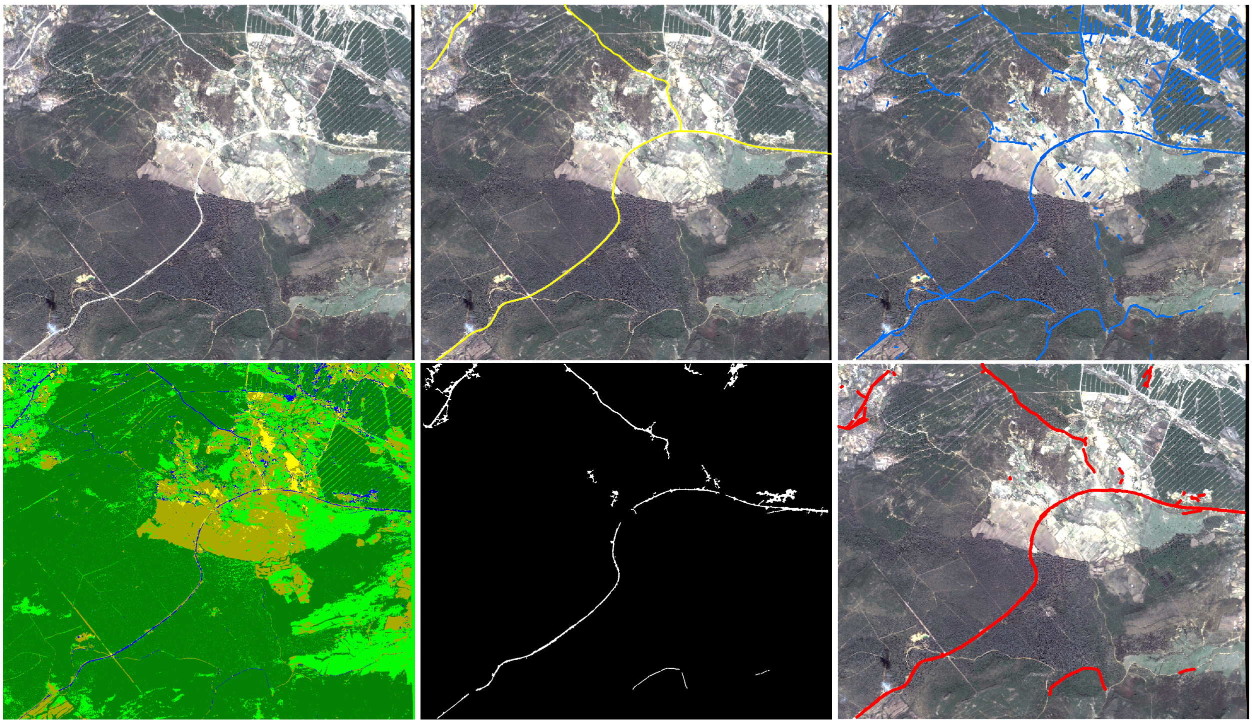

Figure 4: Road update interim and final results

5 CONCLUSIONS AND FUTURE WORK

A new approach for performing multi-hierarchical analysis of quality assessment of geospatial data was presented based on an enhanced version of our image interpretation system GEOAIDA, which can now handle multiple competing interpretations. It is now also possible to handle situations concerning boundary conflicts in a more flexible way. The automation rate for the MGCP quality assessment achieved approximately 60% using a regionally adapted model net.

In our future work we will introduce new image analysis operations to enhance the classification and reduce the rate of false positives. The multi-hierarchical development will be applied to multi-temporal and multi-sensor data. Regarding the road verification and update modules the model net will be enhanced by use of additional low-level top-down operators, which are based on complementary road models. Also, a final graph based net analysis will be developed to improve the results obtained so far. Additionally, it is planned to refine the training for the color texture classification from the MGCP road network in the local neighborhood.

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