SEMIAUTOMATIC QUALITY CONTROL OF TOPOGRAPHIC REFERENCE DATASETS

C. Becker [a], U. Breitkopf [b], T. Büschenfeld [a], A. Busch [c], D. Grünreich [c], C. Heipke [b], P. Helmholz [b,*], S. Müller [b], J. Ostermann [a], M. Pahl [a], K. Vogt [a], M. Ziems [b]

[a]TNT - Institut für Informationsverarbeitung, Leibniz Universität Hannover, Appelstr. 9a, 30167 Hannover, Germany
(becker, bfeld, osterman, pahl, vogt)@tnt.uni-hannover.de,
[b]IPI - Institut für Photogrammetrie und GeoInformation, Leibniz Universität Hannover, Nienburger Str. 1, 30167 Hannover, Germany
(breitkopf, heipke, helmholz, mueller, ziems)@ipi.uni-hannover.de,
[c]BKG - Bundesamt für Kartographie und Geodäsie, Richard-Strauss-Allee 11, 60598 Frankfurt, Germany
(andreas.busch,dietmar.gruenreich)@bkg.bund.de

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ABSTRACT:

The usefulness and acceptance of spatial information systems are mainly dependent on the quality of the underlying geodata. This paper describes a system for semiautomatic quality control of existing geospatial data via automatic image analysis using aerial images, high-resolution satellite imagery (IKONOS and RapidEye) and low-resolution satellite imagery (Disaster Monitoring Constellation, DMC) with mono- and multi-temporal approaches focusing on objects which cover most of the area of the topographic dataset. The goal of the developed system is to reduce the manual efforts to a minimum. We shortly review the system design and then we focus on the automatic components and their integration in a semiautomatic workflow for verification and update. A prototype of the system has been in use for several years. From the experience gained during this time we give a detailed report on the system performance in its application as well as an evaluation of the results.

1 INTRODUCTION

Today, many public and private decisions rely on geospatial information. Geospatial data are stored and managed in Geoinformation Systems (GIS). In order for a GIS to be generally accepted, the underlying data need to be consistent and up-to-date. As a consequence, quality control has become increasingly important. In the European Norm DIN EN ISO 8402 (1995), quality is defined as the "Totality of characteristics of an entity that bear on its ability to satisfy stated and implied needs". In the context of GIS this means that the data model must represent the real world with sufficient detail and without any contradictions (quality of the model). Secondly, the data must conform to the model specification (quality of the data). There are four important measures for quality of geodata: consistency, completeness, correctness, and accuracy (Joos, 2000). Only the consistency can be checked without any comparison of the data to the real world. The other three quality measures can be derived by comparing the GIS data to the real world, as it is represented in aerial or satellite images. We call this step verification or quality assessment. In the last step of quality control, the actual update, the GIS data are changed to conform with the real world as represented in the images (a more detailed discussion of the related terminology is described in (Gerke and Heipke, 2008)). In order to reduce the amount of manual work required for quality control, a high degree of automation is desirable.

In this paper, we describe a system for the quality control of GIS called WiPKA-QS (Wissensbasierter Photogrammetrisch-Kartographischer Arbeitsplatz zur Qualitätssicherung - Knowledge-based photogrammetric-cartographic workstation for quality control). 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 Institut für Informationsverarbeitung (TNT), both at the Leibniz Universität Hannover. The first version of WiPKA-QS was installed at BKG in 2003 (Busch et al., 2004). Since that time the system has been permanently enhanced. This paper gives an up-to-date overview about this system. After introducing the strategy and the workflow in section 2, section 3 describes the used GIS and image data. Section 4 deals with the components of the systems. An evaluation using different sets of image data and GIS is presented in section 5. The paper concludes with a summery and an outlook.

2 STRATEGY AND WORKFLOW

Strategy The goal of WiPKA-QS is an efficient quality control of GIS data with respect to the aforementioned quality measures completeness, correctness and accuracy. Verification and update are realized in combination with an automated indication of changes in the landscape compared to current GIS data. In WiPKA-QS we verify and update GIS data automatically comparing them with the real world in terms of remote sensing images.

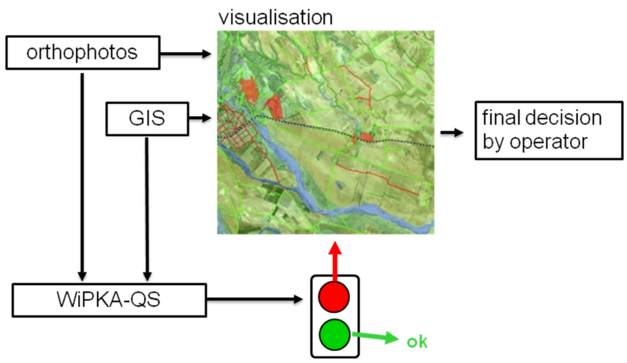

Figure 1: Workflow of WiPKA-QS

Workflow Input data into the system WiPKA-QS are orthophotos and a GIS. The system verifies and updates the objects using automatic image analysis tools (see section 4.3) integrated into a knowledge-based image interpretation system (see section 4.2) including all necessary pre-processing and post-processing steps (see 4.1). The results of the automatic procedures of WiPKA-QS are passed to the human operator. These results consist of verification and update information about each GIS object attached

Country	GIS	Imagery	Objects of Interest
Brazil	Local thematic data	IKONOS pan, Landsat 5+7	residential, forest, industrial, agriculture
Germany	ATKIS	Aerial pan. RGB 0.4m, IKONOS pan. ms. 1m	roads, residential, industrial, forest, agriculture (cropland/grassland)
	CLC	RapidEye ms. 5m, DMC ms. 32m	residential, industrial, forest, agriculture (cropland/grassland)
Japan	NTIS	ALOS PRISM, pan 2.5m	roads
Kosovo	Self generated	IKONOS pan. ms. 1m	roads
Netherlands	NWB	Aerial RGB 0.5m	roads
North Africa (Algeria, Tunisia)	MGCP	IKONOS pan. ms. 1m	roads, residential, industrial, forest, agriculture
Saudi Arabia	Local cadastral data	Aerial RGB 0.1m	roads, residential, vegetation, desert
Switzerland	Self generated	Aerial RGB 0.5m	roads
USA	Self generated	DOQQ, pan. 1m, SAR 2.5m	roads

Table 1: Data already processed with WIPKA-QS
(pan: pan-sharpend, ms: multispectral)

to the initial GIS data that was used as input for the system. In case the verification of an object is successful the system labels this object as accepted (green); otherwise the object is labelled as rejected (red). For all rejected objects the final decision is taken by a human operator. He decides if the automatic rejection of a GIS object is correct, and if so he edits the GIS object. Additionally the human operator receives update information about the scene, i.e. objects not contained in the database.

Thus, WIPKA-QS is a semi-automatic system. Its workflow is sketched in Figure 1.

3 DATA

The system WIPKA-QS can handle different sources of image data as well as GIS types. An overview about the data already processed with WIPKA-QS is given in Table 1.

In this paper we focus on four datasets covering a wide range of images with different resolutions, and three different kinds of GIS to verify the objects of interest namely residential areas, forest, industrial areas, agriculture areas and roads. The sets are shown in Table 2.

GIS data We used a national GIS dataset, a European GIS dataset and an international GIS dataset - more specifically the German Authoritative Topographic Cartographic Information System (ATKIS), data from the European CORINE Land Cover (CLC) and the international Multinational Geospatial Co-production Program (MGCP).

ATKIS is a trademark of the Working Committee of the Surveying Authorities of the States of the Federal Republic of Germany (AdV). The geodata for ATKIS is collected by every of the sixteen federal states of Germany. Among other sources ATKIS data are collected using aerial photography with a resolution of 20cm or 40cm supported by ground truth data, and set to be used in scale between 1:10.000 and 1:25.000. Objects of interest are point, line and area based objects listed at (AdV, 1997) with a minimum mapping unit of 0.1 ha to 1 ha. The traditional update cycle is 5 years, however an update of objects with high relevance is to be completed in 3 (e.g. roads), 6 (e.g. airports) or 12 (e.g. wind power stations) months. The geometry accuracy is 3m.

Set	GIS	Imagery	Location	km^2/ objects	Objects of Interest
1	ATKIS	Aerial (2000-06-17)	Germany	56 / 5299	residential, forest, industrial, agriculture, roads
2	ATKIS	IKONOS (2003-06-24)	Germany	85/ 3247	residential, forest, industrial, agriculture, roads
3	MGCP	IKONOS (2008-04-24)	North Africa	170 / 2943	residential, forest, industrial, agriculture, thicket, roads
4	CLC	RapidEye (2009-08-20), DMC (2009-04-24, 2009-08-24)	Germany	328 / 3803	residential, forest, industrial, cropland, grassland

Table 2: Sets with GIS and Imagery

Images	Bands	Resolution
Aerial	R, G, B	0.4 m
IKONOS	NIR, R, G, B	1 m
RapidEye	NIR, RE, R, G, B	5 m
DMC	NIR, R, G	32 m

Table 3: Overview of Image Data

The European CLC dataset is managed and coordinated by the European Environment Agency (EEA), assisted by the European Topic Centre for Land Use and Spatial Information (ETC-LUSI). In Germany the UBA (Umweltbundesamt – Federal Environmental Agency) is the national reference centre (NRC), acts as the contact point for the EEA and is responsible for the management and coordination of CLC which is derived from the ATKIS dataset (Arnold, 2009). The data model was set up to be used in the scale of 1:100.000; its minimum mapping unit is 25 ha for new polygons and 5 ha for changes on existing polygons.

The international MGCP is a coalition of 28 countries around the world participating in the production of a global high-resolution GIS, established and maintained by the United States National Geospatial-Intelligence Agency (NGA). The production of the MGCP dataset is still work in process and is scheduled to be completed by December 31, 2011. The MGCP dataset is set up to be used globally at the 1:50 000 or 1:100 000 scales. All data collected will reflect 25 meter accuracy.

Image data All used images are orthorectified. Detailed information is given in Table 3. The DMC images mentioned in this table are images of the Disaster Monitoring Constellation operated by the company DMC International Imaging (DMCii). To describe the bands available from the different data sources the common abbreviations are used (red: *R*, green: *G*, blue: *B*, near infrared: *NIR*, red edge: *RE*).

4 COMPONENTS OF THE SYSTEM

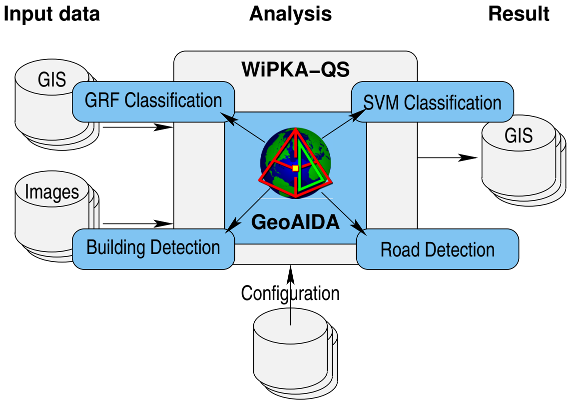

Figure 2: Components of WIPKA-QS

As circumstances change over the years, mainly due to technical progress the whole system consists of components which can easily be adapted to altering constraints. Figure 2 shows how the data ist processed by WIPKA-QS. On the left side we see the input data, i.e. there are GIS data to be verified and updated and some image data which is used to accomplish this task. As a result of the process we obtain updated GIS data. This might be some attributes added to the original GIS data or new GIS data. In the middle of figure 2 we see components of the WIPKA-QS system. It is divided into the controling interface which is seen by the user, the framework for the image interpretation called GEOAIDA, and a number of operators doing the image processing, here 'Gibbs Random Field (GRF) Classification', 'Support Vector Machine (SVM) Classification', 'Building Detection' and 'Road Detection'.

4.1 WIPKA-CONTROL

To adapt the system to constantly changing input data and output formats, we have developed a highly configurable GUI framework called WIPKA-CONTROL. WIPKA-CONTROL uses a configuration file to configure what should be done before and after the knowledge-based image interpretation. We call those tasks pre- and post-processors. Pre-processing can be used to carry out coordinate transformations, to adapt image resolution for specific image operators or to perform training for e.g. the SVM. The particular configuration of pre-processors is chosen accordingly to the available input data. Post-processors are responsible for the preparation of the raw results coming out of the knowledge-based image interpretation, e.g. labelling of the input data with the automatic verification results. All processing steps can be executed via a graphical user interface or run in batch mode.

4.2 GEOAIDA

To develop a powerful, highly flexible and easily configurable quality control system we use the knowledge-based image interpretation system GEOAIDA. Figure 3 shows the design of GEOAIDA (Liedtke et. al., 2001). The individual components are described in the following paragraphs.

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.

The *a priori* knowledge about the scene under investigation is stored in a *model net*. The nodes of the net are ordered strictly

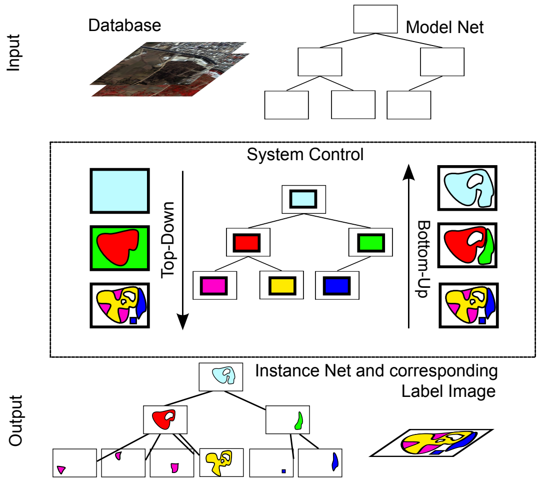

Figure 3: GEOAIDA Design

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.

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.

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 is carried out, 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 details highly depend 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.

4.3 Image Analysis

The automatic image analysis operators constitute the basis of our system. For different GIS data and remote sensing images appropriate operators have been developed and tested in the past. These operators consist of pixel-wise classification operators like the Gibbs Random Field classification and the Support Vector Machine as well as object extraction operators for roads and buildings. The operators developed in the project are described in the following paragraphs.

Gibbs Random Field Classification The Gibbs Random Field classification operator uses a supervised texture based segmentation algorithm described in (Gimelfarb, 1996). The algorithm was extended to a multiresolution technique. The classification algorithm has to learn the properties of the classes from training regions. The learning steps are:

- Learning of texture with the training areas in four subsampling resolution levels resulting in four parameter files.
- Segmentation of the input image in all resolution levels based on the parameter files.
- Evaluation of the segmentation for each class in all resolutions.
- Calculation of an evaluation matrix.

As a result of the learning process four parameter files and an evaluation matrix are derived. The segmentation is done by a top-down operator that begins with the lowest resolution and proceeds to the higher resolutions level by level. The steps of the top-down texture operator are:

- Segmentation of the input image in all resolution levels using the parameter files.
- 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. The resolution with the best separation characteristic may differ from one class to another; the classification of inhabited areas is, for example, significantly better suited for lower resolutions. The learning step is a crucial part for the efficiency and correctness of the derived results. This step is preferably done by a human operator, who manually defines training areas for the desired classes. Nevertheless the automatic generation of training areas by the use of GIS data is possible. This has to be done for a few areas and 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.

Support Vector Machine Classification The Support Vector Machine (SVM) (Vapnik, 1998) classifier can be divided into two main parts, the feature extraction and the classification by using an SVM.
Per channel features are extracted for each pixel within a local neighbourhood. Features used for this paper are the mean value and the variance of the gradient magnitude image. After extraction, feature vectors are passed to a SVM. The SVM (in (Burges, 1998) a comprehensive tutorial is given) is a *large margin classifier* that allows classification of non-linearly separable data by using kernel functions (Hofmann et al., 2008).

The application of the SVM classifier partly overlaps with that of the Gibbs Random Field classifier described before: it also offers a pixel-wise area classification. Thus, training and calculation of an evaluation matrix is done in an analogous manner.
A resolution pyramid is built up, too, for all available input channels. However, compared to the Gibbs Random Field classifier, features from different levels are processed simultaneously within the same feature vector.
The SVM classifier is also used for processing of multitemporal data as different epochs are considered as different channels.

Road Detection For verification and update of the road network we primarily use a single road extraction algorithm as top-down operator. 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.

Each step of the extraction is controlled by parameters. According to this, the multifaceted usage of the single algorithm is achieved by adapted parameter sets. The selection of reasonable parameter sets is realized by two strategies. The first one concentrates on radiometric parameters, e.g. contrast, homogeneity and brightness. This group is sensitive to image exposure and to the reflectance properties of the surrounding surface. Therefore, the underlying training algorithm, which is described in (Ziems et al., 2007), uses radiometric properties of known GIS roads for local parameter adaption. The second parameter group is justified on the basis of global context information, which is introduced by the model net architecture in GEOAIDA. The instance nodes are controlled from the input GIS and the classification result. Thus, predefined parameter sets are applied for a number of possible context regions, e.g. desert, hilly rural area or scrubland. A more comprehensive description of this task is given in (Becker et. al., 2008).

The comparison of the extraction result and the existing database is carried out by separate bottom-up operators, the so called road verification module and road update module.

The *verification module* checks explicitly geometry, shape and attributes of each database road. If its calculated evidence for the correctness is high enough the GIS 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 are considered, see also (Gerke and Heipke, 2008).

The *update module* detects commission errors. For this purpose, each newly detected road candidate is validated by its relation to the already verified road network and other line objects in the database. Only if a plausible relation to the existing road network could be found the road candidate is forwarded to a human interpreter for possible introduction into the database.

Building Detection The building detection operator was developed to detect single buildings in the input images that are used within the system as an indication for settlement areas. The approach is divided into a low-level and a high-level image processing step. The low-level step includes image segmentation and post-processing: first, the input image is transformed to HSI and the intensity channel is taken as input for a region growing segmentation. The seed points are set in a regular grid, except for areas of vegetation and shadow.

	Gibbs Random Field	SVM	Roads	Buildings
Set 1	X	-	X	X
Set 2	X	-	X	-
Set 3	X	-	X	-
Set 4	-	X	-	-

Table 4: Datasets and used Image Analysis Operators

The segmentation result is post-processed to compensate effects like holes in the regions and to merge roof regions which are split into several parts. The regions are taken as building hypotheses in the following step.

The high-level step includes feature extraction and classification. First, implausible hypotheses are rejected by region area and colour. Afterwards, features are calculated for each hypothesis like:

- geometric features
  - object size: area, circumference
  - object form: roundness, compactness, length, angles
- radiometric features:
  - most frequent and mean hue
  - mean NDVI
- structural features
  - shadow
  - neighborhood

Furthermore, the main axes of the hypothesis are calculated. They define a hexagon describing the region's contour. The classification works as follows: First, all building hypotheses are assigned an evaluation value of 1. For each feature an expected value range is defined for valid building hypotheses. All features are considered sequentially and hypotheses with feature values outside the value range are multiplied with a weight less than 1. Hypotheses without neighbours get a reduction of 0.1 at the end. The final decision, if a building hypothesis is taken as a correct building is done by a thresholding. The building detection algorithm was developed for airborne imagery. Further details are available in (Müller and Zaum, 2005).

5 RESULTS

In this section confusion matrices for the verification process of the datasets defined in Table 2 are used to evaluate the system WIPKA-QS. Table 4 shows an overview of which image analysis operator was used in combination with which dataset.

The result of the verification process using set 1 is shown in Table 5. The efficiency is satisfying with about 72% (sum of left column, 67.9% + 3.8%), i.e. 72% of the objects of interest do not need to be inspected by the human operator because these objects were accepted automatically. On the other hand the system does only a somewhat disappointing job when detecting errors in the GIS. A rate of only 128 out of 331 errors, a reduction of the wrong objects in the GIS dataset by 39%, is not satisfying.

The confusion matrix in Table 6, showing the result of the verification process using set 2, is more satisfying. In this set the system does a reasonably good job: 178 out of 244 errors could be detected; so, the number of wrong objects of interest could be reduced by 73%. The efficiency is also satisfying with again about 72%, and even better compared to all other sets.

Reference \ System	Accepted	Rejected
Accepted	3596 (67.9%)	1372 (25.9%)
Rejected	203 (3.8%)	128 (2.4%)

Table 5: Confusion Matrix for Set 1 (number and percentage of objects)

Reference \ System	Accepted	Rejected
Accepted	2280 (70.2%)	723 (22.3%)
Rejected	66 (2.0%)	178 (5.5%)

Table 6: Confusion Matrix for Set 2 (number and percentage of objects)

The result for the verification using the MGCP data of set 3 is shown in Table 7. The efficiency of the system for this set is satisfying, too, with 68%. Even when the efficiency of the system is a bit lower compared to sets 1 and 2, the system does a better job in detecting the errors. 62 out of 80 errors could be detected; so, the number of wrong objects of interest could be reduced by 78%.

In contrast to all other sets, a separation of the agriculture class into cropland and grassland is done in set 4, for this task we use multi-temporal image data. The result of this set is shown in Table 8. The efficiency of our system is satisfying again with about 75%. In addition, the system does a good job in detecting errors in the GIS, too. A rate of 55 out of 61 errors (a reduction of the number the wrong objects in the GIS by 90%) is even better than the results achieved for set 3.

Figure 4 shows an example for an error in the GIS, a false grassland object which could be automatically rejected by the system during the verification process. The RapidEye image shown on the left in the figure, was used in the SVM classification together with two DMC images from different dates. For comparison the orthophoto shown in the figure gives a better visual impression.

In total, the system WIPKA-QS is a reliable semi-automatic tool for the quality control of GIS datasets. As mentioned before, the main focus of our approach is the verification of the GIS objects. It is embedded in a semi-automatic workflow that uses the automatic tool to focus the attention of the human operator to possible errors in the GIS. Thus, time is saved largely due to the fact that the operator needs no longer to check any object that was accepted by the automatic module. This goal was achieved with our system with an efficiency of at least 68%.

However, given the fact that quality control is essentially carried out to remove errors in the data base, classification errors that cause errors in the GIS to remain undetected, i.e. the erroneous acceptance of a wrong object, are to be avoided. This goal could not be achieved in dataset 1, but in all other datasets. Between 73% and 90% of the errors could be detected successfully.

Reference \ System	Accepted	Rejected
Accepted	1984 (67.4%)	879 (29.9%)
Rejected	18 (0.6%)	62 (2.1%)

Table 7: Confusion Matrix for Set 3 (number and percentage of objects)

Reference \ System	Accepted	Rejected
Accepted	2836 (74.5%)	906 (23.6%)
Rejected	6 (0.2%)	55 (1.4%)

Table 8: Confusion Matrix for Set 4 (number and percentage of objects)

Figure 4: Example for a false grassland GIS object. Left: RapidEye image (© 2009 RapidEye AG, Germany. All rights reserved.), Right: Orthophoto (only used for visual interpretation, © GeoBasis-DE / BKG 2010).

6 CONCLUSIONS AND OUTLOOK

As the evaluation results show, the system WIPKA-QS is a useful tool for quality control of GIS datasets. The main goal of WIPKA-QS is the reduction of the amount of manual work required for the verification process.

The most salient land cover types can be automatically distinguished within the present system. Current tasks include to enhance the system for use of new images (Quickbird, TerraSAR-X) and to increase the overall degree of automation. Ongoing research focuses on new strategies to increase the functionality of the image analysis tools, described in section 4. In this manner we currently extend the road detection tool to deal with settlement area (Ziems et al., 2010).

In future we also plan to enhance the landcover classification by including a knowledge base of seasonal characteristics of different vegetation classes. First results for the discrimination of crop- and grassland objects could be achieved with the approach published in (Helmholz et. al., 2010). We also hope to be able to detect other object classes with similar features using this approach, e.g. vineyards. Additionally, WIPKA-QS should distinguish between different crop types using multi-temporal imagery in the future. First results can be found in (Müller et al., 2010). Another field of current work is the detection of plantations as important type of cultivation in some areas. Furthermore automation of the training of the applied image analysis operators is under development.

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