Graph Supported Automated Verification of Road Databases Using Aerial Imagery

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Abstract
The verification of existing data is an important task in order to ensure a high level of data quality in Geographic Information Systems (GIS). Today this work is carried out mostly manually by an operator, who compares vector data from databases with remotely sensed imagery. In this paper we present a system for automated road data verification using digital image processing for the extraction of roads from aerial imagery and topological analysis in order to optimize the whole process in terms of reliability and efficiency. The main goal is to call the operator's attention only to parts of the network where the automated process did not find evidence for a road. The road extraction is supported by the use of knowledge on the global level (whether the road is situated in rural, urban or forest areas), and the information on the road geometry and its attributes. The road extraction is executed twice: Firstly with a strict parameter control ensuring the minimization of false positives and a subsequent evaluation which denotes roads from the database being accepted or rejected. In a second step a graph-based search algorithm detects connections which are missing for an optimized road network. If rejected roads are part of these connections they are checked again using a more tolerant parameter control. Results of tests show the applicability of the proposed method for quality control of topographic road databases.

1 Introduction
Geographic Information Systems (GIS) are used in many facets of our daily life. A majority – estimated to be about 80% – of the decisions from public authorities and private industry are made using spatial data. The more this kind of data is used the more important the question regarding its quality becomes. In our context quality is understood to comprise completeness, positional accuracy and the correctness of the attributes for each object, and the temporal correctness.

The aim of our work is to increase the efficiency of the verification of road objects contained in the ATKIS DLMBasis. ATKIS stands for Authoritative Topographic Cartographic Information System and represents the German national geo-spatial core database. The DLMBasis (basic digital landscape model) contains the data of the highest resolution approximately equivalent to a topographic map 1:25000[1].

Today such quality control is done completely manually: A human operator compares the road objects from the database with an up-to-date orthoimage. In our work we want to automate this process: The main idea is to carry out an automatic road extraction in the images around the road objects which are given in the database. Road attributes and context information from the database are used in order to support and optimize the extraction process. Currently, we restrict ourselves to panchromatic ortho-images with a ground resolution of $0.4m^2$, since such imagery is readily available for the whole country. If the road extraction algorithm finds evidence for a road in the neighborhood of a road object from the database, this road is accepted, and rejected otherwise. In the following step a human operator can focus on the rejected roads only, resulting in significant time savings as compared to the traditional process. The designed system has been tested with 30 orthoimages covering an area of 10 x 12 km^2 near Frankfurt/Main, Germany, results were presented in Willrich (2002).

In this paper we want to focus on an improvement of the approach. In the current system the road

[1] The project is carried out in conjunction with the German Federal Agency for Cartography and Geodesy (BKG) and the Institute of Communication Theory and Signal Processing (TNT), University of Hannover

extraction algorithm is optimized in order to minimize the number of false positives. Therefore the control of the parameters is very strict and many correct roads are rejected (false negatives). Moreover, the road objects are verified individually, i.e. a topologic examination doesn't take place. If two automatically accepted roads are for instance linked by a rejected one, this latter one is not considered further, although such a situation may constitute a contradiction in terms of the function of a road, namely to connect different places. A new approach is introduced aiming at enhancing the reliability of the overall system. This new approach mainly involves a graph-based optimization of the verification. If a situation appears to be a conflict from the viewpoint of topology the respective rejected roads are examinated again, using a more tolerant parameter control.

In the next chapters we first give a short overview on related approaches and then describe our approach for road verification, give results and explain some drawbacks more in detail. In chapter 4, the consequences from of these drawbacks are analysed and an enhancement of the current system is introduced, including some preliminary results of the new algorithm. Finally, we give some conclusions and an outlook to further work.

2 Related Work on Knowledge-Based Road Extraction

Our work deals with verifying a given road database by comparison to automatically extracted features from aerial imagery. We are therefore able to use knowledge from the existing spatial database. The used knowledge consists of information about the road objects themselves and of knowledge about local and global context.

Every road extraction algorithm is based on an appropriate object model. Generic road models have the disadvantage that its radiometric and geometric properties also fit to other linear objects like rivers or railways. If the model parameters are chosen too rigorously, one may exclude rivers or railways but also some roads. One possibility to overcome this problem is to incorporate additional knowledge about the object itself, and on the so called local and global context (Baumgartner et al., 1997). Local context defines the interrelationship between single objects. In aerial imagery roads may be occluded by buildings or trees. If this knowledge is considered and if appropriate object extraction algorithms exist, one may benefit from local context and derive a better extraction result. For example, Hinz and Baumgartner (2000) use objects found in urban areas such as road markings, cars or buildings to enhance the road extraction in these regions. Butenuth et al. (2003) use extracted rows of trees in rural areas to close gaps between extracted road sections.

Global context defines the environment in which the object is situated. In certain environments objects have certain properties, e.g. a road network in urban areas is much more dense than in rural areas and single road segments are often shorter. Moreover the global context influences the appearance of the object in aerial imagery: For instance there are much more occlusion by buildings in urban areas than in rural areas.

Bordes et al. (1997) use a nation-wide road database to derive geometry (e.g. curvature and length) and semantic information (type of road and number of lanes) of road objects to optimize the road extraction and to exclude other objects. Additionally, global contextual knowledge is incorporated from the database. Although the objects in the database are modeled in a small scale (1:100000) the information is sufficient to be used for road extraction at a larger scale.

In (Wallace et al., 2002) another approach is applied. As the underlying system is designed to extract more linear object classes than roads, it first carries out a linear object extraction and then classifies these objects according to additional knowledge, derived from a database.

In the Swiss ATOMI-project (c.f. e.g. Zhang and Baltsavias 2002, Baltsavias 2002) the topographic database Vec25, consisting of road objects digitized from maps 1:25000 is being de-generalized and thus geometrically refined by extracting roads automatically from aerial imagery. Object information and global context knowledge from the database as well as local context knowledge obtained from object extraction algorithms is used to optimize road extraction.

In summary, it can be said that a large number of road extraction algorithms have been suggested in the literature. Recently, trends can be observed to using more prior knowledge in the form of object models, context, topology, and more diverse input images such as color, near infrared and – especially in urban areas – also height layers. Nevertheless, virtually none of the algorithms has found its way into practice, perhaps with exception of the work carried out in ATOMI. It is our goal to design and implement a reliable quality control module for road databases, incorporating the latest research findings from image analysis and being useful for practical applications, e.g. at BKG.

3 Road Verification

Our system for automated road verification includes three modules: an Automatic Pre-Processing module, the Main Automatic Processing module and an Interactive Post-Processing module (c.f. Fig.1).

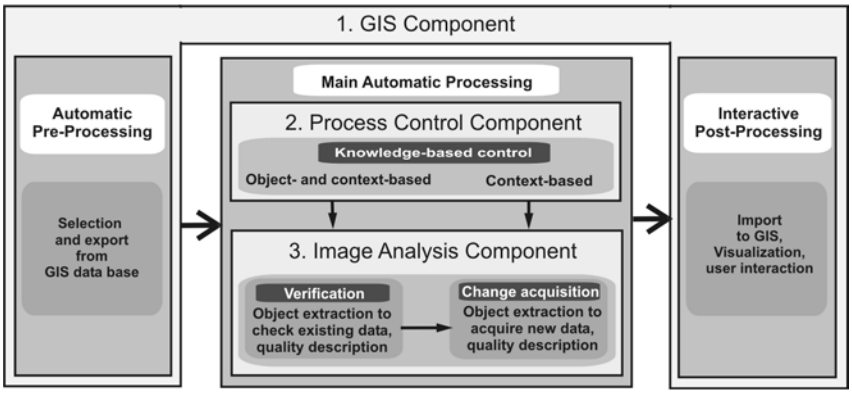

Figure 1. System overview

In the Automatic Pre-Processing phase the *GIS Component* exports the road objects to be verified from the database, including their geometric descriptions and attributes, e.g. road width. Moreover, the knowledge about the global context contained in the ATKIS DLMBasis is obtained. The Main Automatic module consists of the *Process Control Component* and an *Image Analysis Component.* The *Process Control Component* is a communication layer between the GIS and the *Image Analysis Component:* It makes the information from the database available for object extraction in an appropriate manner. The *Image Analysis Component* itself consists of the Verification and the Change acquisition module. Finally the *GIS Component* is used again to support interactive post editing. In the following we deal in more detail with the enhancement of the Verification module. A description of the whole implemented system is given in (Willrich, 2002).

3.1 The Verification Module

The Verification module is designed to check the positional accuracy of the roads from the database as well as to detect commission errors (a road from the database does not exist in the reference orthoimage). In order to solve this task a region of interest is defined for each road object from the database, depending on its geometric description. More precisely, a buffer around the vector representing the road axis is defined, the buffer width complies with the corresponding attribute given in the ATKIS database. If this value fails a plausibility test or is not available at all, a predefined value is taken. This step is followed by a selection of an appropriate road extraction algorithm to be executed in the image domain of the buffer. The selection includes an optimized control of the parameters considering the knowledge on the given context region.

We are currently using the road extraction algorithm as introduced by Wiedemann (Wiedemann, 2002; Wiedemann and Ebner, 2000). This approach models roads as linear objects in aerial or satellite imagery with a resolution of about 1 to 2 m. The underlying line extractor is the one introduced by Steger (1998). The initially extracted lines are evaluated by fuzzy values according to attributes like length, straightness, constancy in width and constancy in gray values. The evaluation is followed by a fusion of lines originating from different channels. In our case we are using panchromatic imagery, but the line extractor is applied twice: Firstly, using a bright line model (line is brighter than the background) and secondly using a dark line model. The reason is that according to our own experiences roads in images often fit to one of those models. The last step in road extraction as applied in the Verification module is the grouping of the single lines in order to derive a topologically correct and geometrically optimal path between seed points according to some predefined criteria. Seed points are the endpoints of lines having reached a certain minimum value in the evaluation phase. The decision if extracted and evaluated lines are grouped into one road object is made corresponding to a collinearity criterion (allowing a maximum gap length and a maximum direction difference). All significant and important parameters for road extraction can be set individually. We adapted the described road extraction software to our specific tasks, especially by applying individual parameters for the given context areas and the extraction for each road object separately.

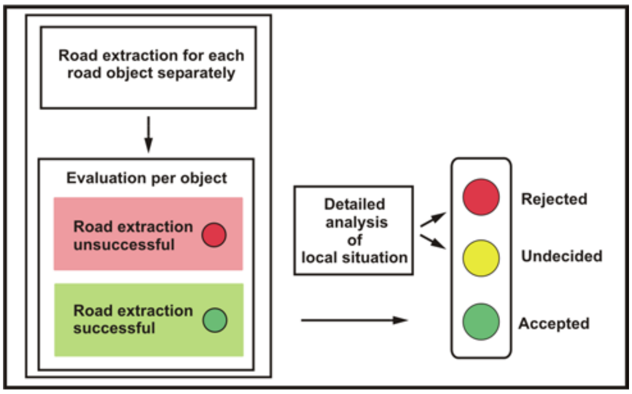

Figure 2. Overview on the verification process

After the road extraction, each road object from the ATKIS DLMBasis is evaluated (c.f. Fig. 2). If the road extraction algorithm was successful, i.e. the grouping algorithm found a valid road, the road is denoted as *accepted*. Otherwise the local situation is to be further analyzed. This step is motivated by the fact, that often lines close to a road could be found in the image domain, but due to large gaps caused e.g. by occlusion a grouping of these lines to one road did not happen. In order to differentiate these cases from situations where the initial line extraction failed, the quality measures *completeness* and *root mean square error* (Wiedemann et al., 1998) of the initially extracted lines are calculated in comparison to the ATKIS DLMBasis road object. If one of these quality measures is above a given threshold, the ATKIS road is denoted as *undecided,* and *rejected* otherwise. The results of this evaluation are presented to the human operator in a so called traffic-light solution (Förstner, 1996).

3.2 Results

The system was tested in an area of 10 x 12 km^2 near Frankfurt/Main containing some 10000 road objects. The employed images have been resampled from the original resolution of 0.42m to 1.68m in order to fulfill the requirements of the road extraction algorithm. The three differentiated context classes rural, urban and forest as well as the object-related information were automatically selected from the ATKIS DLMBasis.

Context reg.	accepted [%]	rejected [%]	undecided [%]
Rural	79	17	4
Urban	58	34	8
Forest	60	34	6

Table 1. Verification result for test area (covering 120 km^2)

low contrast [%]	large gap [%]	step-model [%]
57	30	13

Table 2. Examination of 100 existing roads in rural area being denoted as *undecided* or *rejected* after automatic road extraction

Table 1 shows the results of the whole test area, listed by context area and evaluation result. The high rejection-rate of 34% for both urban and forest areas can be explained by the road model and the appearance of roads in the given image data. In dense urban areas the used road extraction algorithm is known to be insufficient because occlusions and disturbances from e.g. buildings or cars are not modeled. The results for forest areas are plausible as even a human operator often cannot verify a road in optical images in these locations. Only very wide roads like highways can be automatically extracted.

Rejection of existing roads in rural context is mainly caused by low contrast conditions (57%, c.f. Table 2), by large gaps between extracted lines (30%) or an incorrect radiometric road model (13%): The line extraction algorithm does not take into account a step-model for lines, where the road is brighter than one adjacent area but darker than the one on the other side.

3.3 Drawbacks of this Approach

The main goal of the whole system is to support the human operator in the evaluation of the road objects contained in the ATKIS DLMBasis database. One important aspect regarding the Verification module is to reliably denote the roads which can doubtlessly be found in image data and therefore be ignored by the operator in the further process. In other words the number of false positives must be minimized, because they would lead to an *acceptance* of the respective road, although not enough evidence can be found in image data. Therefore, the parameter control during the road extraction has to be very strict. In the used algorithm this relates mainly to the contrast parameters and the length of gaps which can be bridged in the grouping phase. As a consequence of this strict parameter control, the number of false negatives is relatively high. This is confirmed by the reports from independent checks of the obtained results: About 12% of roads a human operator would accept were denoted *rejected* by the system, another 5 % were denoted *undecided*.

Another drawback of the given approach concerns road topology. Road networks are optimized in order to link places in the scene efficiently in terms of travel time and distance. In the current Verification module every road is checked without taking into account adjacent road objects. This fact leads to cases as demonstrated later in Figure 4 (left): It shows a verified road network in the context class rural where many roads have been *accepted* but if these accepted objects are linked the result does not appear to be a proper road network.

4 Topology Supported Road Verification

Looking at the described results and drawbacks of the current system it is clear, that a minimization of false positives and false negatives in one passage of road extraction is not feasible. The reliability of the verification process (minimization of false positives) should be maintained while the majority of roads existing in both the database and the orthoimage should be found in the given imagery (minimization of false negatives). It stands to reason to combine the solution of this problem with a deeper look to topology and therefore overcome the drawback of the current system regarding the non-consideration of the given road network.

A similar problem was treated in (Fischler et al., 1981). Here two automatic road extraction operators are introduced to extract roads from aerial or satellite imagery. Operator *type I* is designed to reliably detect roads, i.e. the number of false positives is minimized, but a number of roads are not extracted. Operator *type II* does extract most roads, but also finds instances of other objects. The task is to combine the results of these two algorithms in order to find an optimized road network. A graph based approach is introduced. The output of *type I* operator is considered being a reliable foundation of the road network as the number of false positives is supposed to be very low. Missing links between these objects are then closed by taking *type II* roads as most roads. Our solution presented in the following follows these ideas.

4.1 Enhanced Verification Approach

We propose first to evaluate the given ATKIS DLMBasis by applying the described road extraction algorithm with a very strict parameter control in order to reach a minimum number of false positives. As shown in the chapters above this will lead to a relatively high number of *rejected* roads (false negatives).

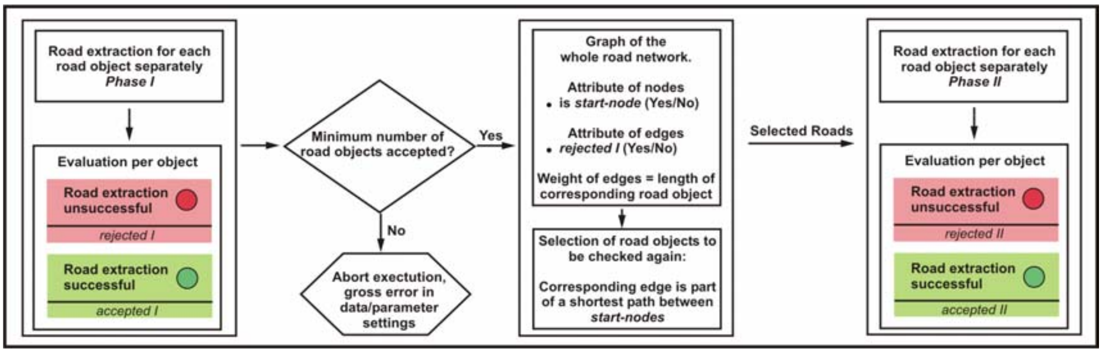

Figure 3. Overview on the enhanced verification process

We further call road objects from the database which have been successfully verified in the first evaluation step *accepted I* and *rejected I* otherwise. As we are just interested in reliably extracted roads, the detailed analysis of the local situation (c.f. Fig. 2) is skipped.

In order to ensure the reliability of the whole approach we carry out a plausibility test after the first evaluation phase. If the percentage of *accepted I* objects is below a given threshold (here: 50%) we assume that this is either caused by gross errors in the data (database or image data) or by very bad conditions for automatic road extraction. Therefore, the execution of the further process is stopped and a warning is raised for the whole area being analysed.

In the absence of such a warning the graph of the given ATKIS road network is built up, considering the results of the first evaluation step. Non-verified road objects are chosen according to several criteria (refer to section 4.1.1). A second evaluation of these selected objects is then executed using more tolerant parameters for road extraction (c.f. section 4.1.2). Figure 3 gives an overview on the enhanced verification process.

4.1.1 Detecting Gaps in the Road Network

Our approach on road verification enhancement is based on the fact that a road network connects any two points (called *start-nodes* below) in a way that travel time and distance are minimized (see above). In the absence of knowledge about travel time, we restrict ourselves to considering distance. In other words we search for the shortest path between two *start-nodes*, based on the ATKIS DLMBasis road database. Although we do not know if the network given in the database is fully correct, we can use it to formulate such connection hypotheses.

First we have to define a graph, which suits our requirements. In the ATKIS DLMBasis the topology of the road network is implicitly given as adjacent road objects share the same node points. Therefore, it is rather simple to derive a valid graph description from the road database. Next, we select *start-nodes*. In order to avoid isolated *rejected I* roads we require a *start-node* to have at least one adjacent *accepted I* road. To minimize the computing time, we also require a *start-node* to have at least one adjacent *rejected I* road.

The next step consists in finding the shortest path between *start-nodes*. For this purpose we apply the A*-Algorithm (Duda and Hart, 1973). The edges of the given graph are weighted with the length of the corresponding road object. Therefore the shortest path between two *start-nodes* equals the shortest road connection. All *rejected I* objects which are part of those shortest road connections are subsequently checked again.

This described procedure has the following effect: All *rejected I* objects which are on both sides directly connected to *accepted I* objects are chosen for the second examination. Moreover, if a combination of several road objects connects adjacent *start-nodes* in the way that the total length of the connection is shorter than the connections given by *accepted I* objects, all *rejected I* roads being part of this shortest connection are also chosen for the second examination phase.

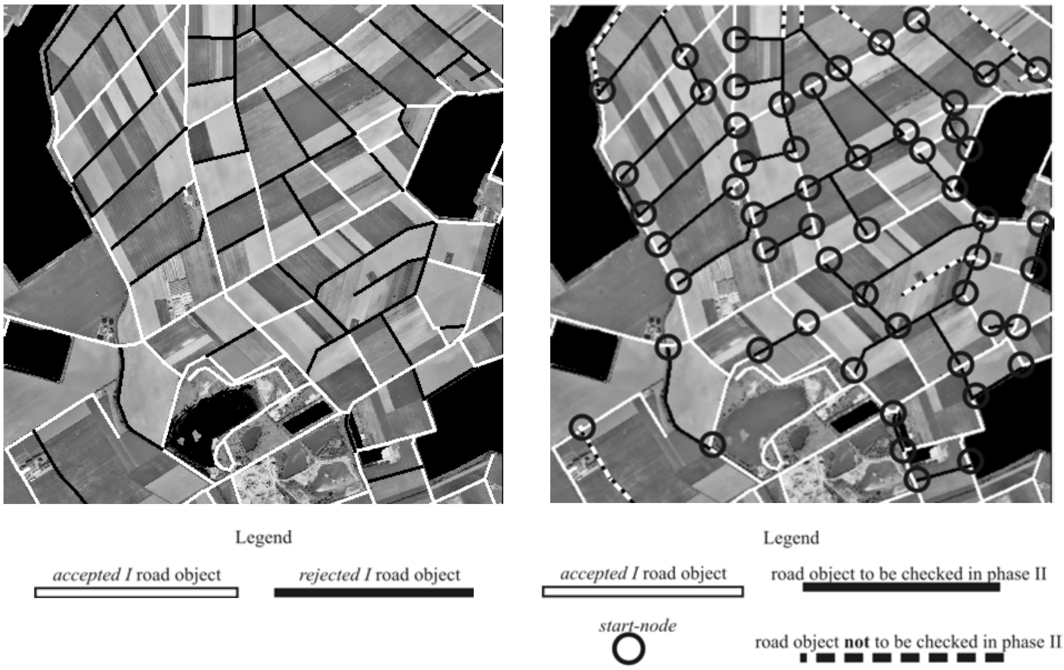

Figure 4. Example for finding rejected roads to be checked again.

In Fig. 4 an example is given: Superimposed to the orthoimage the *accepted I* roads are highlighted in white and *rejected I* roads in black (left image). In the right image all *start-nodes* are emphasized and the *rejected I* road objects which are part of shortest paths between *start-nodes* are printed in black. These objects are chosen to be checked again. The dashed line shows *rejected I* objects not fulfilling the requirements to be checked again.

4.1.2 Second Examination of Selected Objects

According to the results from the evaluation of rejected roads (c.f. Table 2) we adapted the thresholds for the contrast conditions and the gap length to be bridged automatically. After the second extraction phase each appropriate road object is evaluated again. Similar to the first evaluation step (see chapter 3.1) the objects are denoted *accepted II* if the road extraction algorithm could extract a valid road in the corresponding buffer and *rejected II* otherwise.

4.2 Results

We tested the introduced approach for two test-areas, covering an area of 8 km^2 and containing 432 road objects in rural context only. Because of the lack of local context knowledge in urban and forest areas and the mentioned problems of the used road extraction algorithm in those regions it seems not very meaningful to apply the new approach to urban and forest areas.

In Fig. 5 an orthoimage is shown, results for the first and second evaluation phase are superimposed. Roads which have been *accepted* are shown in white, *rejected* roads are black. From 172 objects 111 have been *accepted* in the first phase, the analysis of the topology led to 52 road objects out of 61 *rejected I* roads to be checked again (left image). The right image shows the results after the second evaluation phase. About 65% of the roads checked a second time have been *accepted*, finally about 84% of the roads have been *accepted* in the domain of this image (c.f. Table 3, image 1).

An analysis of the finally *rejected* roads shows that several causes may lead to the *rejection*: a) The contrast is very weak; in some cases even a human operator could not decide whether a road exists at this point or not, b) Lines are not extracted due to the missing step-model implementation, c) Roads are hidden by dense rows of trees. Often, also parts of roads are not extracted due to one of the mentioned reasons. In these cases the resulting gap is too large to be bridged automatically, even in the tolerant second examination phase.

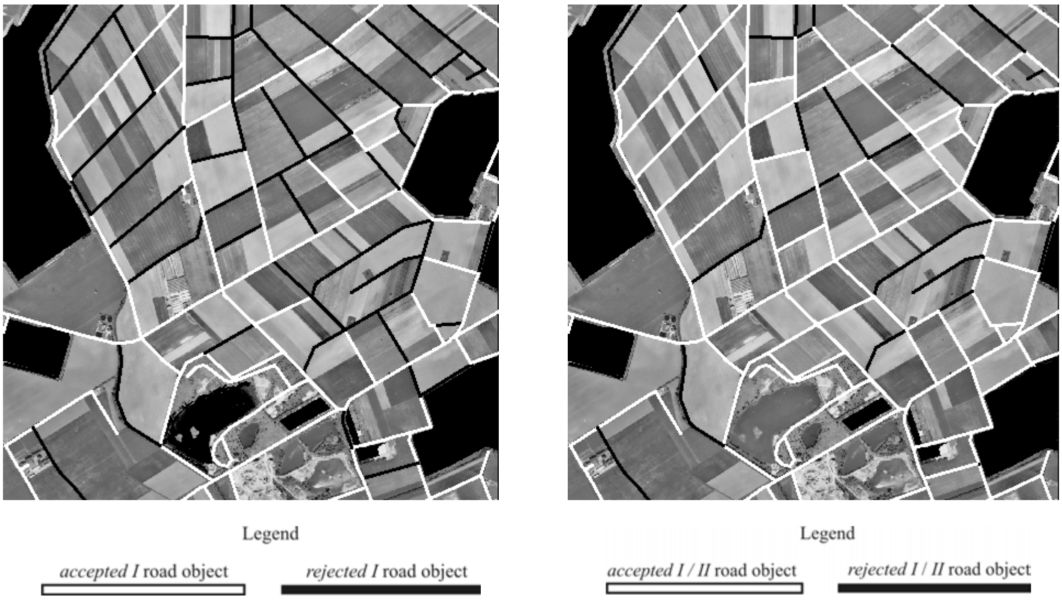

Figure 5. Results of Image No. 1 after phase I (left) and II (right)

Image No.	road objects #	*accepted I [%] (#)*	*rejected I [%] (#)*	chosen objects for second check #	*accepted II [%] (#)*	*rejected II [%] (#)*	***accepted total [%] (#)***	***rejected total [%] (#)***
1	172	64,5 (111)	35,5 (61)	52	65,4 (34)	34,6 (18)	**84,3 (145)**	**15,7 (27)**
2	256	84,8 (217)	15,2 (39)	29	79,3 (23)	20,7 (6)	**93,8 (240)**	**6,2 (16)**

Table 3. Verification result from the new approach, applied to rural context area

In Table 3 statistical results are given for the verification of two scenes, Image No. 1 refers to the example shown in Fig. 5.

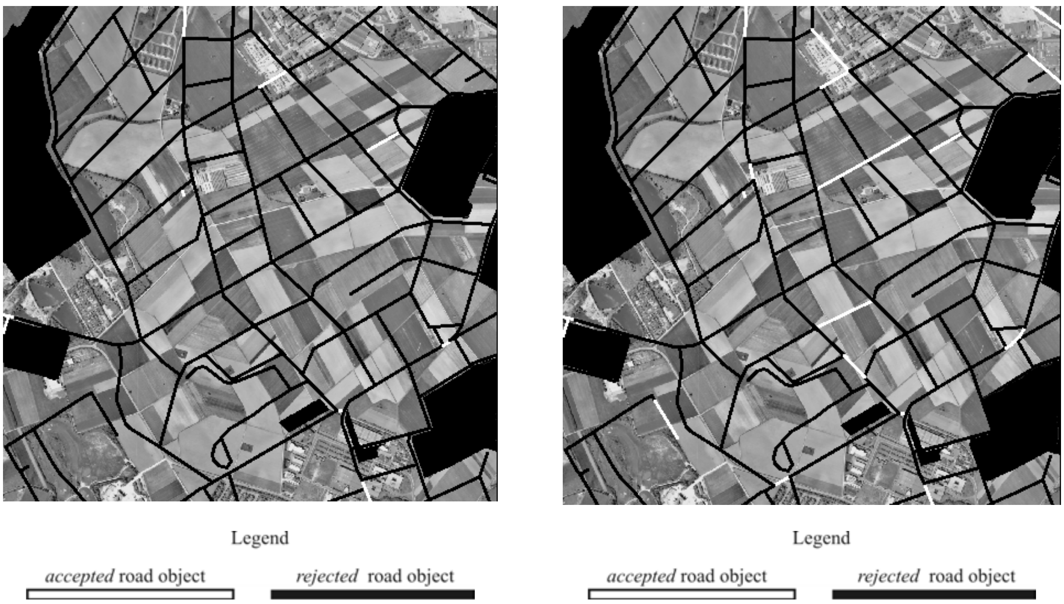

Figure 6. Results for parameter set I (left) and II (right), applied to rotated imagery

In order to test if the parameter control is properly chosen we tested the algorithm with the same parameter settings applied to rotated imagery. Ideally, the number of *accepted* roads should be zero for the parameter control of the first evaluation phase. In our example this is the case except for some objects lying accidentally in the area of a road or when line-fragments from other objects like buildings lead to a successfully grouping (c.f. Fig. 6, left). The more tolerant parameter control of the second evaluation phase leads to more *accepted* roads as the described linking of line fragments happens more often due to a larger allowed gap length (refer to the right image in Fig. 6). All cases where roads have been *accepted* can be explained by the contrast parameter and gap length settings. The results of this sensitivity test demonstrate the necessity for applying the suggested two-step procedure to road database quality control.

5 Conclusions and Outlook

In this paper we introduce a graph-based approach for road verification from aerial imagery. The background of this work is to design a system which supports a human operator in verifying an existing road database. Two main issues are of interest: Firstly, the automatic process has to be reliable, i.e. if a road from the database can not be found in the image data the system has to reject it. Secondly, the system has to be efficient, i.e. it should automatically extract as many correct road objects as possible.

A topology supported road verification is presented which combines the results of a very strict road extraction module (phase I) with the road extraction in the given imagery using a more tolerant parameter control (phase II). The first extraction phase satisfies the demand for a reliable system, the second one finds additional connections between reliably extracted roads. The choice of road objects to be checked in the second phase is based on an algorithm which tries to find the shortest connections between reliably extracted roads.

Results of a test-scene show the advantages of the approach compared to an algorithm which does not consider the network characteristics. The performance of the whole verification process is improved. One limitation concerns the road objects going beyond the image border or dead-end-roads: if these are *rejected* in the first phase they are not considered in the second phase. The underlying road extraction is not suitable for urban or forest areas. But the graph-based approach is independent of the used road extraction algorithm. If better algorithms become available for these regions in the future they can be integrated into the system. The use of local context in rural areas, e.g. the consideration of rows of trees as shown in Butenuth at al. (2003), will also lead to improvements.

Concerning the whole system the next step consists in the extraction of roads which are not yet contained in the database (Change acquisition). This module will be supported by using the final *accepted* roads as these constrain the search for additional road objects. In addition we currently investigate the use of planning data from road construction.

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