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Graph-supported verification of road databases☆

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Abstract

The verification of existing data is an important task in order to ensure a high level of data quality, such as is needed in geographic information systems (GIS). Today, this work is carried out manually by an operator, who compares vector data from databases with remotely sensed imagery. In this paper, 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 optimise the whole process in terms of reliability and efficiency is presented. The main goal is to call the operator's attention only to parts of the network, where the automated process did not find sufficient evidence of a road. The road extraction is supported by the use of prior knowledge on the global level (whether the road is situated in rural, urban or forest areas), and 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 optimised road network. If rejected roads are part of these connections, they are checked again using a more tolerant parameter control. A detailed performance analysis of results shows the applicability of the proposed method for quality control of topographic road databases.

Keywords: GIS; database verification; knowledge-based image analysis; road network extraction; parameter settings; quality control; reliability; performance analysis

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 the context of this paper, quality is understood to comprise completeness, positional accuracy and the correctness of the attributes for each object, and the temporal correctness.

The aim of a project carried out in conjunction with the German Federal Agency for Cartography and Geodesy (BKG) and the Institute of Communication Theory and Signal Processing, University of Hannover (TNT) is to increase the efficiency of the verifi-

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cation 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 1:25,000.

Today, quality control is done completely manually, i.e. a human operator compares the road objects from the database with an up-to-date orthoimage. In the project, an automation of this process is intended. The main idea is to carry out an automatic road extraction in the images. Road attributes and context information from the database are used in order to support and optimise the extraction process. Currently, panchromatic orthoimages with a ground resolution of 0.4 m are used, since such imagery is readily available for the whole country. If the road extraction algorithm finds evidence for a road object from the database, this road is accepted; otherwise, it is rejected. 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 10×12 km^2 near Frankfurt/Main, Germany, and first results were presented in Willrich (2002).

In the work at hand, an improvement of the approach is presented. In the previous system, the road extraction algorithm was optimised in order to minimize the number of false positives (FP). Therefore, the control of the parameters is very strict and some correct roads are rejected (false negatives (FN)). Moreover, the road objects are verified individually, i.e. a topological examination does not take place. If two automatically accepted roads are for instance linked by a rejected one, this latter one is not considered further, although this situation may constitute a contradiction in terms of the function of a road, namely to connect different places.

A new approach is introduced to enhance the reliability of the overall system by involving a graph-based optimisation of the verification process. Cases occurring due to topological conflicts are solved by an examination of the respective rejected roads, using a more tolerant parameter control.

In the next sections, a short overview on related approaches is given and afterwards the previous approach for road verification is described. The mentioned drawbacks of this approach are explained in more detail. In Section 4, the consequences from these drawbacks are analysed and an enhancement of the previous system is introduced, including some results from the new algorithm. Finally, conclusions and an outlook of further work are given.

2. Related work on knowledge-based road extraction

This work deals with verifying a given road database by comparison to automatically extracted features from aerial imagery. Therefore, knowledge from the existing spatial database may be incorporated. The used knowledge consists of information about the road objects themselves and knowledge about local and global context.

Every road extraction algorithm is based on an appropriate object model. Generic road models have the disadvantage that road 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, for example a road network in urban areas is much denser 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 occlusions by buildings in urban areas than in rural ones.

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 optimise the road extraction and exclude other objects. Additionally, global contextual knowledge is incorporated from the database. Although the objects in the database are modelled in a small scale (1:100,000), 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 just 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 (cf. Baltsavias, 2002; Zhang and Baltsavias, 2002), the topographic database VEC25, consisting of road objects digitised from maps 1:25,000, 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 optimise road extraction.

In summary, a large number of road extraction algorithms has 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 colour, 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 the goal of this work 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, for example at BKG.

3. Road verification

The system for automated road verification includes three modules: An Automatic Pre-Processing module, the Main Automatic Processing module and an Interactive Post-Processing module (cf. Fig. 1). 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, such as road width. Moreover, the knowledge about the global context contained in the ATKIS DLMBasis is obtained. As a seamless image database is not available, the ATKIS objects are clipped at the border of the orthoimage to be processed.

The Main Automatic module consists of the *Process Control Component* and the *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

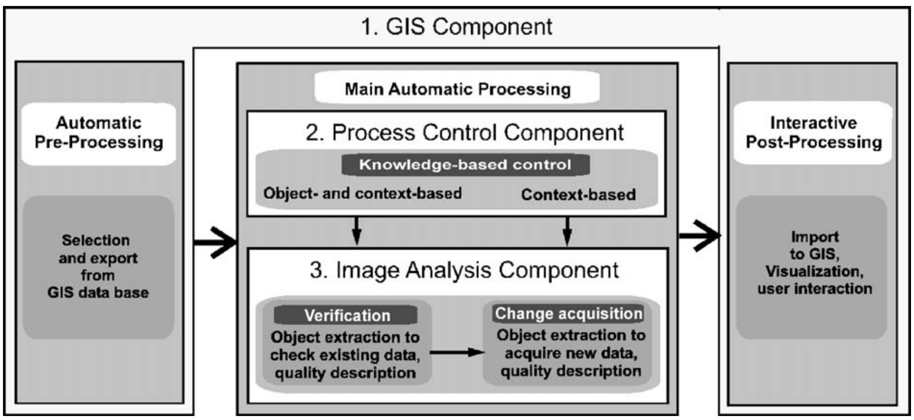


Fig. 1. System overview.

acquisition module. Finally, the *GIS Component* is used again to support interactive post-editing. In the following, we focus on 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 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 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 and, additionally, the nominal accuracy of the ATKIS road objects being ± 3 m is considered. If the road width 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.

In this system, the road extraction algorithm as introduced by Wiedemann (Wiedemann, 2002; Wiedemann and Ebner, 2000) is currently used. This approach models roads as linear objects in aerial or satellite imagery with a resolution of about 1–2 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 this case, panchromatic imagery is used, 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 (line is darker than the background). The reason is that according to a lot of experiment 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. The decision whether the extracted and evaluated lines should be grouped into one road object is made corresponding to a collinearity criterion (allowing a maximum gap length and a maximum direction difference). To support the object-wise road extraction, two small vectors (seed vectors) are inserted denoting the direction of the ATKIS object.

All significant and important parameters for road extraction can be set individually. The described road extraction software was adapted to the given tasks, especially by applying individual parameters for the given context areas and the extraction for each road object separately.

After the road extraction has been finished, each road object from the ATKIS DLMBasis is evaluated (cf. 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 analysed. This step is motivated by the fact that lines could be often found in the image domain, but due to large gaps, caused for example by occlusion, a grouping of these lines to one road did not occur. 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*; otherwise, it is *rejected*. The results of this evaluation are presented to the human operator in a so-called traffic-light solution (Förstner, 1996).

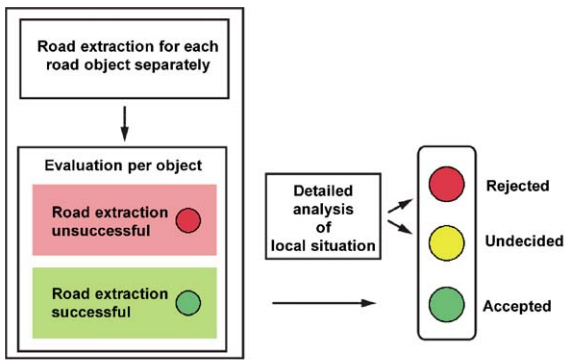


Fig. 2. Overview on the verification process (previous system).

3.2. 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 FPs 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 FNs is relatively high. An analysis of FN errors has shown that about 60% of these errors occurred because the contrast settings have led to a non-detection of lines. Another 30% FN errors were related to too large gaps between detected lines and the remaining 10% occurred because of the not considered radiometric model (step model).

Another drawback of the previous approach concerns road topology. Road networks are mostly optimised in order to link places in the scene efficiently in terms of travel time and distance. Therefore, the incorporation of road network topology is an important aspect for our task. Nevertheless, in the previous Verification module, every road is checked without taking into account adjacent road objects.

4. Topology-supported road verification

Looking at the described drawbacks of the previous system, it is clear that a minimization of FPs and FNs in one passage of road extraction is not feasible. The reliability of the Verification process (minimization of FPs) should be maintained, while the majority of correct roads should be found in the given imagery (minimization of FNs). It is reasonable to combine the solution of this problem with a deeper look into the topology and, therefore, overcome the drawback of the system.

A similar problem was treated already more than two decades ago in Fischler et al. (1981). There, two automatic road extraction operators were introduced to extract roads from aerial or satellite imagery. Operator *type I* was designed to reliably detect roads, i.e. the number of FPs was minimized, but a number of roads are not extracted. Operator *type II* extracted most roads, but also found instances of other objects. The task was to combine the results of these two algorithms in order to find an optimized road network; a graph-based approach was introduced. The output of *type I* operator was considered being a reliable foundation of the road network as the number of FPs was supposed to be very low. Missing links between these objects were closed by taking *type II* roads.

The solution presented in the subsequent text follows these ideas.

4.1. Verification approach

Firstly, the given ATKIS DLMBasis is evaluated by applying the described road extraction algorithm with a very strict parameter control in order to reach a minimum number of FPs. As explained above, this will lead to a relatively high number of *rejected* roads (FNs).

Road objects from the database which have been successfully verified in the first evaluation step are further called *accepted I* and *rejected I* otherwise. The detailed analysis of the local situation (cf. Fig. 2) is skipped, as unreliable extracted roads are not of interest here.

In order to ensure the reliability of the whole approach, a plausibility test after the first evaluation phase is carried out. If the percentage of *accepted I* objects is below a given threshold (here 50%), it is assumed 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 issued for the whole area being analysed.

In the absence of 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 (cf. Section 4.1.2).

Fig. 3 gives an overview of the enhanced verification process.

It should be pointed out that the application of the tolerant parameters for the whole scene right from the beginning may lead to an unacceptable high number of FPs. Only the support by means of topological considerations allows to apply a more tolerant parameter control.

4.1.1. Detecting gaps in the road network

The approach on road verification enhancement is based on the assumption that a road network connects any two points (called *start-nodes* below) in a way that travel time and distance are minimized. In the absence of knowledge about travel time, just distance is considered. In other words, the shortest path between two *start-nodes* is searched, based on the ATKIS DLMBasis road database. Although it is not sure whether the network given in the database is fully correct, it can be used to formulate such connection hypotheses.

Firstly, a graph has to be defined, which suits the 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, *start-nodes* are selected. In order to avoid isolated *rejected I* roads, a *start-node* must have at least one adjacent *accepted I* road. To minimize the computing time, a *start-node* should have at least one adjacent *rejected I* road.

The next step consists in finding the shortest path between *start-nodes*. For this purpose, the A*-Algorithm (Duda and Hart, 1973) is applied. 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.

The 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.

4.1.2. Second examination of selected objects

According to the results from the evaluation of rejected roads (cf. Section 3.2), the thresholds for the contrast conditions and the gap length to be bridged automatically are adapted. After the second extraction phase, each appropriate road object is evaluated again. Similarly to the first evaluation step (see Section 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.

In Fig. 4, an example is given. The left image shows an orthoimage, in the right image the *accepted I* roads are displayed in white, the *accepted II* roads in dashed-white and the *rejected* objects in black. As ATKIS objects lying in settlement areas are not considered, those regions are masked out. The finally *accepted* network is much denser than the road object

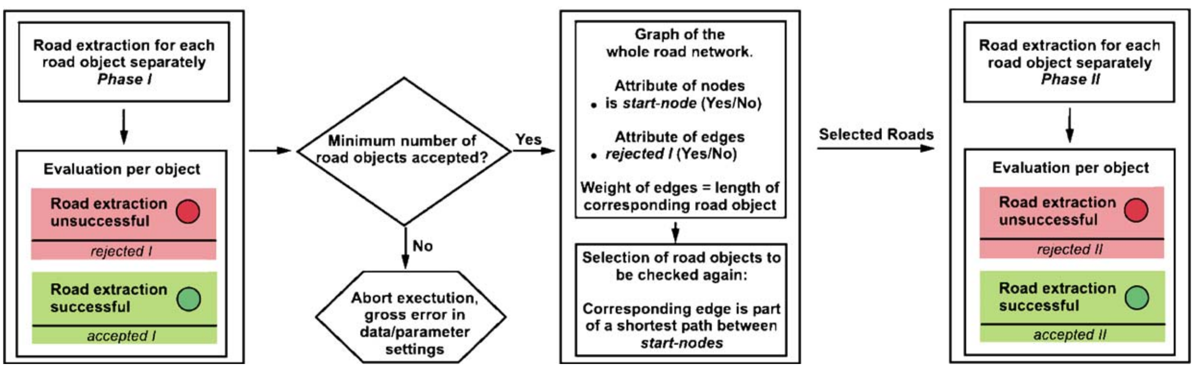


Fig. 3. Overview on the topology-based verification process.

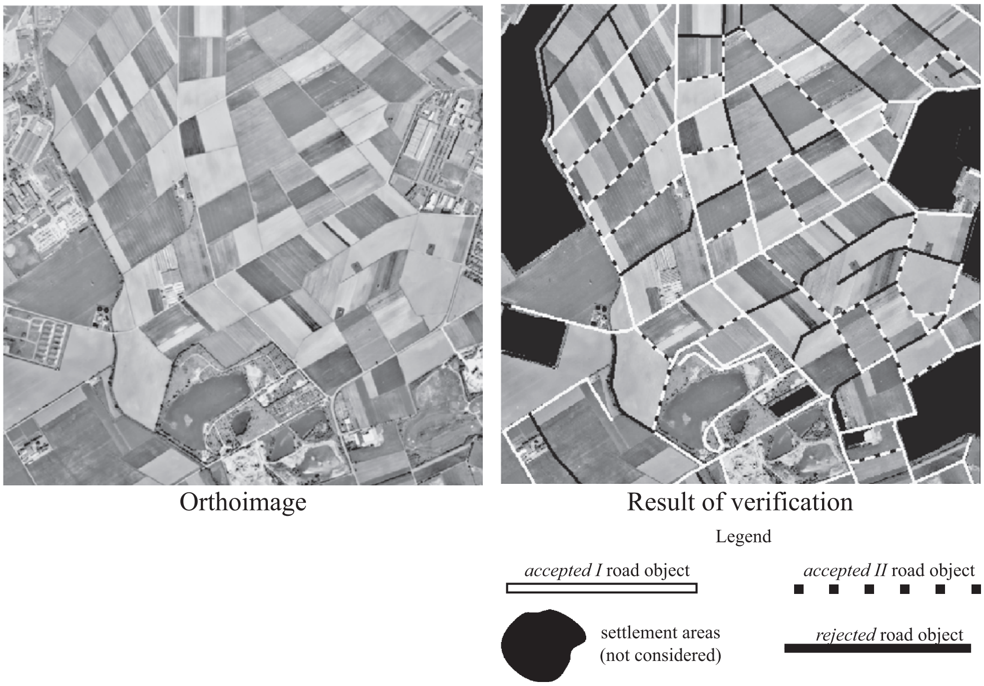


Fig. 4. Example for the current approach.

being *accepted* in phase I. A more detailed analysis of results is given in Section 4.2.

4.2. Results from the current system and discussion

The introduced approach has been tested with 10 orthoimages, covering an area of 40 km^2 and containing 2356 road objects in rural context. All roads together have a length of 374 km. Because of the lack of local context knowledge in urban and forest areas, it does not seem very meaningful to apply the new approach to urban and forest areas. In Table 1, the overall results are shown.

The number of *accepted* roads increased from about 57% after phase I to about 70% after phase II. An interesting question is now how reliable this result is. Two major errors are possible: (a) a road is *accepted* although it is not correct (FP) and (b) an object is *rejected* although it is correct (FN). As was stated earlier, the number of occurrences of error (a) is an indicator for the reliability and the smaller the number of errors (b), the more efficient the whole approach becomes. In order to evaluate the approach, a reference dataset has been created, containing only correct road objects. These correct objects are chosen according to the ATKIS object description. Here, a nominal accuracy of ± 3 m for the position of road objects is prescribed. All road objects from the database having at least one section, which does not maintain these values (in comparison to the orthoimage) is not denoted as correct. The generated dataset serves to determine the number of FPs and FNs. Additionally, the topology-based approach is to be compared with the previous approach. Furthermore, the differences between the results from the strict and

Table 1
Overall result

Road objects (#)	2356
Accepted I [#] (%)	1352 (57.4%)
Rejected I [#] (%)	1004 (42.6%)
Objects selected for second check [#]	550
Accepted II [#] (%)	307 (55.8%)
Rejected II [#] (%)	243 (44.2%)
Accepted total [#] (%)	1659 (70.4%)
Rejected total [#] (%)	697 (29.6%)

the more tolerant parameter control for the road extraction are analysed. Therefore, FPs and FNs are calculated for the results of three analyses per orthoimage: (1) without topology enhancement and with strict parameters, (2) without topology enhancement and with tolerant parameters, (3) with topology enhancement, applying the strict parameters in phase I and the more tolerant parameters in phase II.

4.2.1. Analysis of false positive errors

Label errors, i.e. road objects from the database belong to another object class in reality (such as river), do not appear in the dataset. Therefore, all FP errors are related to cases where the geometrical accuracy is not maintained by the ATKIS object or where no road can be found in the image at all (commission errors not identified). In Table 2, an overview of the FPs is given.

The number of FPs resulting from the topological approach is smaller than the number of FPs, if the more tolerant parameter control is applied for all objects, but higher if just the strict parameters are applied. The FP errors are divided into four classes (examples and the reason for these wrong decisions are given below): (1) The ATKIS road object is not situated inside the predefined tolerance of ± 3 m, but the system has *accepted* the object as it was found inside the buffer. (2) The ATKIS road object is very short and wrong, but the system has found a valid road. (3) Interfering objects like trees or fences get a good evaluation score and are therefore used for the road extraction. (4) The wrong ATKIS road object lies parallel to plough furrows or path of tractors, respectively; these are extracted. The number of these classification errors are given in Table 3.

The first kind of errors (ATKIS object outside tolerance but *accepted*) are related to the fact that the ATKIS DLMBasis contains the centreline of the roads and has a nominal accuracy of ± 3 m. The buffer for the automatic line extraction algorithm must contain the whole potential road, i.e. $\pm$(3 m + 0.5*road width) on each side of the centreline.

Table 2
Overview of FP errors

Image no.	1	2	3	4	5	6	7	8	9	10	Sum	Comment
Just strict parameters	8 (2.8%)	0	1 (0.6%)	0	2 (0.7%)	1 (0.5%)	5 (2.7%)	3 (1.3%)	0	0	20 (0.85%)	Previous approach
Just tolerant parameters	16 (5.5%)	3 (1.4%)	4 (2.3%)	0	6 (2.1%)	3 (1.5%)	9 (4.9%)	13 (5.8%)	4 (1.3%)	1 (0.3%)	58 (2.46%)	
Topology	13 (4.5%)	0	3 (1.7%)	0	3 (1%)	1 (0.5%)	7 (3.8%)	9 (4.0%)	0	0	36 (1.53%)	Current approach

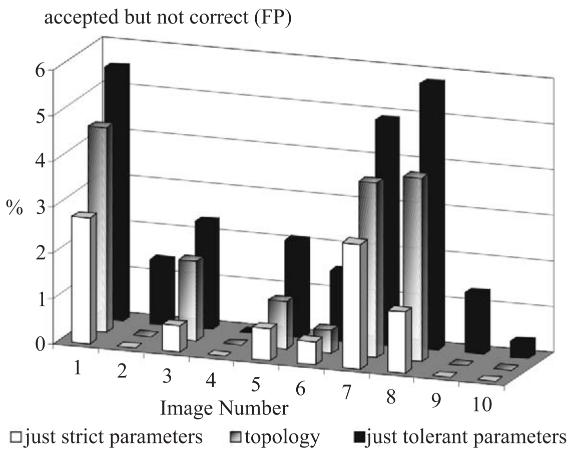


Table 3
Absolute number of classified FP errors

Type of error	ATKIS object outside tolerance	ATKIS object very short	Interfering objects	Plough furrow/path of tractor	Comment
Just strict parameters	15	1	1	3	Previous approach
Just tolerant parameters	27	7	14	10	
Topology	22	2	4	8	Current approach

Inside this buffer often some parallel line-shaped objects like ditches or shoulders are situated, which are extracted as lines. As a differentiation between the real road centreline and such parallel lines is not implemented, the system has to *accept* all extracted roads in this buffer. In other words, the current system can not check whether the nominal accuracy of ± 3 m is maintained; and thus, objects which are found inside the buffer with a radius of $\pm (3\ \mathrm{m} + 0.5{*}\mathrm{road\ width})$ are *accepted*. In Fig. 5, such a situation is shown: the upper left image shows the orthoimage, the upper right shows the same image with the ATKIS object superimposed in black. Obviously, the geometric accuracy of ± 3 m is not maintained in this case, but the buffer being broader than this value contains the road (lower left image). The result of the road extraction is given in the lower right image. As the extracted road connects the first and last vertex of the road from the ATKIS DLMBasis, this object is *accepted*. This first class of FP errors is

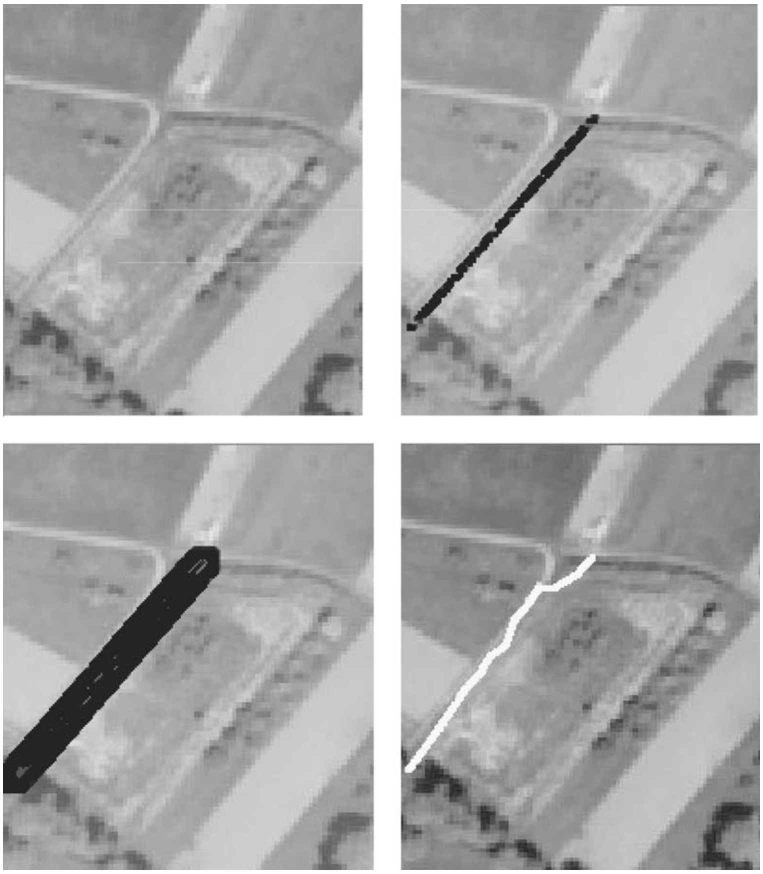


Fig. 5. Example of FP errors due to the buffer width being too large.

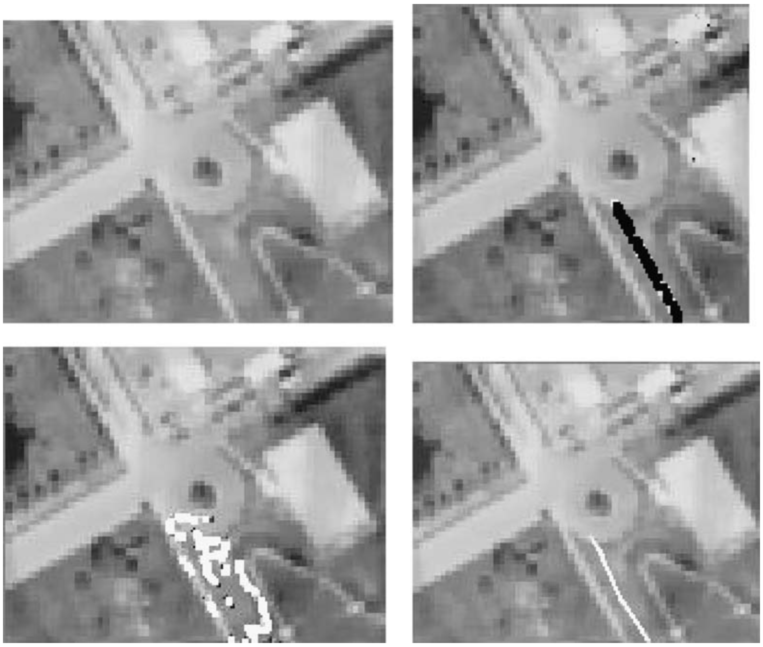


Fig. 6. Example of FP errors due to the problem with short objects.

more or less independent of the chosen parameter control.

The second class of FP errors (*acceptance* of short lines, though not correct) is related to the fact that the search for a connection between the first and the last vertex of the ATKIS road object (grouping of extracted lines) is supported by inserting a small vector (seed vector) pointing from the end vertices towards the respective next one. If no line between these vertices from the ATKIS object was extracted, the object is *rejected*. But, if small line segments are found in this area and the resulting gap between such segments and the artificial seed vectors from the ATKIS object is short enough for an automatic closing, this object is *accepted*. Typically, this error occurs mostly with the tolerant parameter control as the length of the maximum allowed gap, which is bridged automatically, is relatively small. In Fig. 6, an example is given: the upper left image shows the orthoimage, in the upper right image the ATKIS road object is shown, which does not maintain the geometrical accuracy of $\pm$ 3 m. The lower left image shows that a lot of small line segments have been extracted inside the buffer. As the gap between these segments is small enough to be bridged automatically, the object was successfully extracted (lower right image) and therefore the ATKIS object was *accepted*. This class of FP errors more often occurs with a tolerant parameter control. Even in the topology-supported verification, the number of FP errors of this class is as low as with a simple verification with strict parameter control. It is obvious that in this case the strategy followed in the topology-supported verification helps to reduce the number of FP errors. Due to the fact that those short objects are often situated at the border of the image (road objects are clipped), they will not be chosen for phase II.

The third class of FP errors can be explained by the inability of the used road extraction model to model local context (refer to Section 2). Objects like rows of trees or fences are not explicitly modelled and therefore may be incorporated into the grouping process, if the line extraction was successful.

Again, an example is given (refer to Fig. 7). The upper left image shows the orthoimage and on the upper right image the original ATKIS object is shown. In the lower part, the ATKIS object runs across a row of trees and does not maintain the maximum geometric tolerance. The line extraction algorithm finds lines on and beside the trees (lower

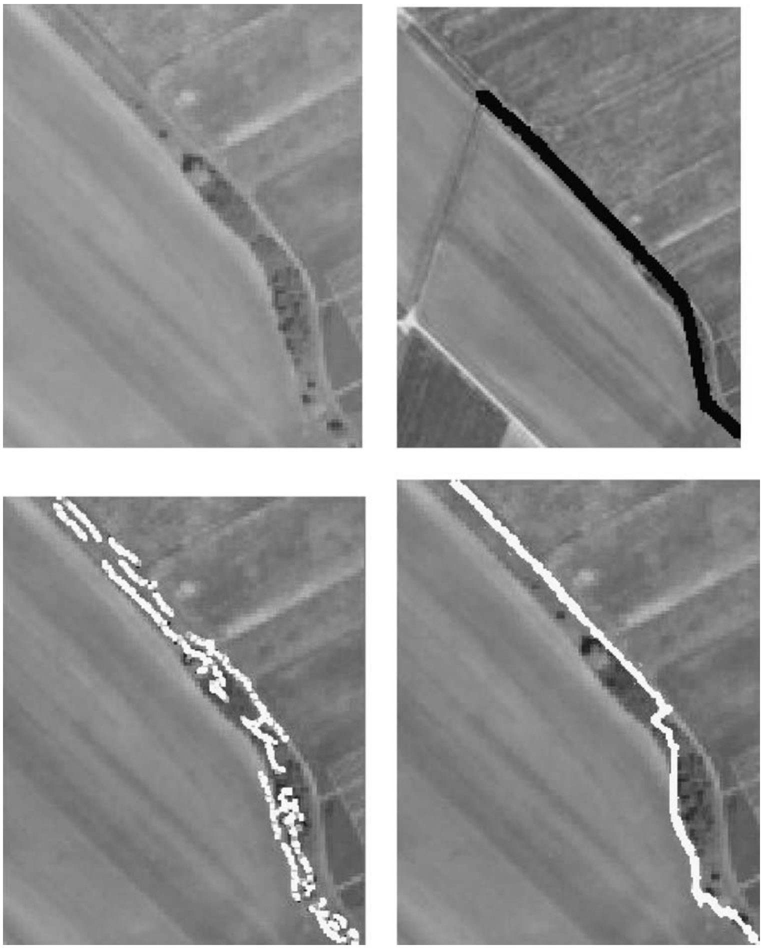


Fig. 7. Example of FP errors due to lack of local context modelling.

left image), which are connected in the grouping process (lower right image). In general, the extraction of row of trees supports the extraction of roads, as these are often placed besides each other (cf. e.g. Butenuth et al., 2003). In this case, the missing differentiation between these two object-classes in conjunction with the buffer width (see above) leads to an *acceptance* of the incorrect road. The FP errors assigned to this class also occur more often with the tolerant parameter control. Due to the strategy as applied in the topology-supported verification to exclude objects from an evaluation in phase II, which are not connected to *accepted I* objects on both sides, the number of FP errors is reduced compared to the simple approach with a tolerant parameter control.

The fourth type of FP errors is related to the fact, that sometimes the appearance of plough furrows or paths of tractors are similar to small roads (paths) between fields. If such structures are covered by the buffer around the ATKIS object and if their contrast values fit to the given control parameters, these paths are extracted as roads.

Fig. 8 gives an example. The ATKIS road has an offset larger than ± 3 m regarding the road, which can be seen in the image (upper right). The buffer of this object covers three small paths in the field, which have been extracted (lower left). Finally, a "road" could be extracted, thus leading to a FP error. These FP errors are a general problem of the approach, if low contrast thresholds are applied. On

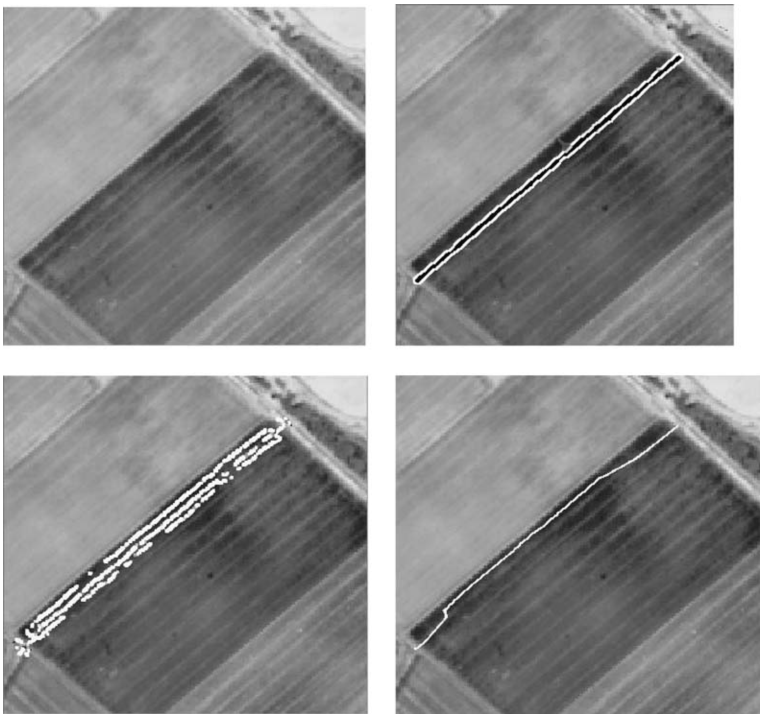


Fig. 8. Example of FP errors due to the extraction of plough furrows/path of tractor.

a field, such structures are extracted as lines and, as there are in general no disturbances like trees, the extraction result is likely to be labelled a road.

4.2.2. Analysis of false negative errors

In Table 4, statistics for the FNs (correct, but *rejected*) are given. Compared to the simple verification with a strict parameter control, the number of FN errors decreases from approx. 40% to 27% in the topology-supported verification. A further decrease of about 10% is reached, if the verification is executed once with the tolerant parameter control. An analysis of these objects being *rejected* although they are correct shows that several causes may lead to the *rejection*: (a) the contrast is very weak, (b) lines are not extracted due to the missing step-model implementation, (c) roads are hidden by dense rows of trees and these rows have not been detected as lines. Often, parts of roads are also not extracted due to one of the above reasons. In these cases, the resulting gap is too large to be bridged automatically, even in the tolerant second examination phase. As expected, the number of FN errors achieved in the topology-based approach ranges between the two alternatives.

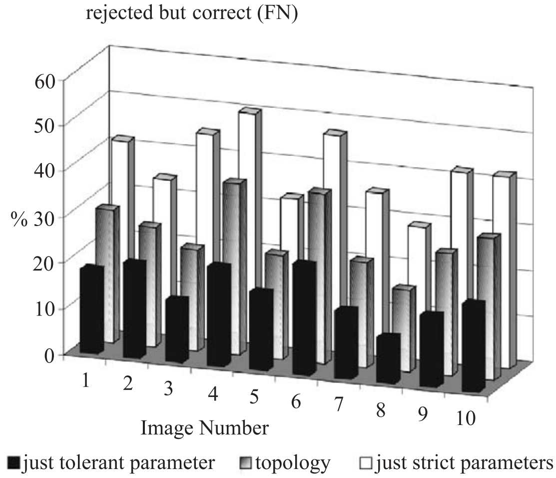
4.2.3. Discussion of results

Regarding the reliability and the efficiency of the whole system, the introduced topology approach makes a compromise between the simple approach applied with a more strict parameter control and a possible application of this simple method with more tolerant parameters.

What remains is the question whether the primary aims have been achieved by the topology-supported verification of ATKIS road data. Independently from the used parameter control or strategy, the used approach may cause FP errors, if a road object exceeds the nominal positional accuracy of ± 3 m but can be found inside the buffer considering the width of the road. FP errors, due to short objects or rows of trees, are minimized in the simple approach with strict parameter control applied and increase marginally in the topological verification. The FP errors related to plough furrows or paths of tractors respectively are minimized only in a verification

Table 4
Overview of FN errors

Image no.	1	2	3	4	5	6	7	8	9	10	Sum	Comment
Just strict parameters	120 (41.4%)	73 (34.0%)	77 (44.8%)	98 (50.3%)	93 (32.5%)	93 (47.2%)	65 (35.5%)	65 (29.0%)	127 (41.9%)	122 (41.9%)	933 (39.60%)	Previous approach
Just tolerant parameters	53 (18.3%)	44 (20.5%)	23 (13.4%)	42 (21.5%)	48 (16.8%)	47 (23.9%)	27 (14.8%)	22 (9.8%)	47 (15.5%)	55 (18.9%)	408 (17.32%)	
Topology	84 (29.0%)	56 (26.0%)	38 (22.1%)	73 (37.4%)	65 (22.7%)	73 (37.1%)	42 (23.0%)	40 (17.9%)	81 (26.7%)	90 (39.9%)	642 (27.25%)	Current approach



process where a strict parameter control is applied. It has to be investigated, if more strict contrast thresholds in phase II help to reduce the number of these FPs significantly. The number of FN errors decrease in the topology-based verification compared to the simple approach applied with a strict parameter control.

The proposed topology-supported approach for the verification of road objects contained in the ATKIS DLMBasis enables the operator to better adapt control parameters for the road extraction. The first phase focuses on reliability. In the subsequent phase II, the efficiency may be increased, keeping in mind that the number of FPs due to misinterpreted paths on fields becomes higher. This example shows a conceptual limitation of the system: as the verification is done per object, similar neighbouring objects are not detected and thus field structures are possibly misinterpreted as road.

5. Conclusions and outlook

In this paper, a graph-based approach for road verification from aerial imagery is introduced. 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 demonstrate 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. The analysis of the results shows that a further tuning of the parameters in order to decrease FP and FN errors is advisable.

Currently, we also investigate to which extent the parameters are scene independent, i.e. if the parameters related to radiometric properties can be transferred to other images. The underlying road extraction is not suitable for urban or forest areas. But the graph-based approach is independent on 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 et 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 new road objects. In addition, the use of planning data from road construction in order to support change acquisition is investigated.

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