

IMPROVING CARTOGRAPHIC ROAD DATABASES BY IMAGE ANALYSIS

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ABSTRACT:

The extraction of road networks from aerial images is one of the current challenges in digital photogrammetry and computer vision. In this paper, we present our system for 3D road network reconstruction from aerial images using knowledge-based image analysis. In contrast to other approaches, the developed system integrates processing of color image data and information from digital spatial databases, extracts and fuses multiple object cues, takes into account context information, employs existing knowledge, rules and models, and treats each road subclass accordingly. The key of the system is the use of knowledge as much as possible to increase success rate and reliability of the results, working in 2D images and 3D object space, and use of 2D and 3D interaction when needed. Another advantage of the developed system is that it can correctly and reliably handle problematic areas caused by shadows and occlusions. This work is part of a project to improve and update the 1:25,000 vector maps of Switzerland. The system has been implemented as a standalone software package. We tested the system on a number of images in different landscapes. In this paper we present the results of our system in recent benchmark tests conducted independently by our project partner in Switzerland, and test results with black and white images in a test site in Belgium.

1. INTRODUCTION

The extraction of roads from digital images has drawn considerable attention lately. The existing approaches cover a wide variety of strategies, using different resolution aerial or satellite images. Overviews can be found in Gruen et al. (1995, 1997), Foerstner and Pluemer (1997) and Baltsavias et al. (2001). Semi-automatic schemes require human interaction to provide interactively some information to control the extraction. Roads are then extracted by profile matching (Airault et al., 1996; Vosselman and de Gunst, 1997), cooperative algorithms (McKeown et al., 1988), and dynamic programming or LSB-Snakes (Gruen and Li, 1997). Automatic methods usually extract reliable hypotheses for road segments through edge and line detection and then establish connections between road segments to form road networks (Wang and Trinder, 2000). Contextual information is taken into account to guide the extraction of roads (Ruskone, 1996). Roads can be detected in multi resolution images (Baumgartner and Hinz, 2000). The use of existing road data for road updating is reported in Agouris et al. (2001). The existing approaches show individually that the use of road models and varying strategies for different types of scenes are promising. However, most methods are based on relatively simplistic road models, and make only insufficient use of a priori information, thus they are very sensitive to disturbances like cars, shadows or occlusions, and do not always provide good quality results. Furthermore, most approaches work in single 2D images, thus neglecting valuable information inherent in 3D processing.

In this paper, we present a knowledge-based system for automatic extraction of 3D roads from stereo aerial images which integrates processing of colour image data and existing digital spatial databases. The system has been developed within the project ATOMI (Automated reconstruction of Topographic Objects from aerial images using vectorized Map Information), in cooperation with the Swiss Federal Office of Topography (L+T), with aims to improve road centerlines from digitized

1:25,000 topographic maps by fitting them to the real landscape, improving the planimetric accuracy to 1m and providing height information with 1-2m accuracy. The details of ATOMI can be found in Eidenbenz et al. (2000). We currently use 1:16,000 scale color imagery, with 30cm focal length, and 60%/20% forward/side overlap, scanned with 14 microns at a Zeiss SCAI. The other input data include: a nationwide DTM with 25m grid spacing and accuracy of 2-3/5-7m in lowland/Alps, the vectorized map data (VEC25) of 1:25,000 scale, and the raster map with its 6 different layers. The VEC25 data have a RMS error of ca. 5-7.5m and a maximum one of ca. 12.5m, including generalization effects. They are topologically correct, but due to their partly automated extraction from maps, some errors exist. In addition, DSM data in the working area was generated from stereo images using MATCH-T of Inpho with 2m grid spacing.

2. GENERAL STRATEGY

Our road network reconstruction system makes full use of available information about the scene and contains a set of image analysis tools. The management of different information and the selection of image analysis tools are controlled by a knowledge-based system. We give a brief description of our strategy in this section, for more details, we refer to Zhang and Baltsavias (2000).

The initial knowledge base is established by the information extracted from the existing spatial data and road design rules. This information is formed in object-oriented multiple object layers, i.e. roads are divided into various subclasses according to road type, land cover and terrain relief. It provides a global description of road network topology, and the local geometry for a road subclass. Therefore, we avoid developing a general road model; instead a specific model can be assigned to each road segment. This model provides the initial 2D location of a road in the scene, as well as road attributes, such as road class, presence of road marks, and possible geometry (width, length,

horizontal and vertical curvature, land cover and so on). A road segment is processed with an appropriate method corresponding to its model, certain features and cues are extracted from images, and roads are derived by a proper combination of cues. The knowledge base is then automatically updated and refined using information gained from previous extraction of roads. The processing proceeds from the easiest subclasses to the most difficult ones. Since neither 2D nor 3D procedures alone are sufficient to solve the problem of road extraction, we make the transition from 2D image space to 3D object space as early as possible, and extract the road network with the mutual interaction between features of these spaces.

3. CUE EXTRACTION

When a road segment from VEC25 is selected, the system focuses on the image regions around the road. The regions are defined using the position of the road segment and the maximal error of VEC25. Then, according to the road attributes a set of image processing tools is activated to extract features and cues. 3D straight edge generation is a crucial component of our procedure. We are interested in 3D straight edges because the correct roadsides are among them. The 3D information of straight edges is determined from the correspondences of edge segments between stereo images. With color images, a multispectral image classification method is implemented to find road regions. We also exploit additional cues such as road marks to support road extraction.

3.1 3D straight edge extraction

The edge segments are extracted by the Canny operator in stereo images. The correspondences of edge segments across images are determined by our developed structural matching method that exploits edge rich attributes and edge geometrical structure information. The edge rich attributes include the geometrical description of the edge and the photometrical information in the regions right beside the edge. The epipolar constraint is applied to reduce the search space. The similarity measure for an edge pair is computed by comparing the edge attributes. The similarity measure is then used as a prior information in structural matching. The locally consistent matching is achieved through structural matching with probability relaxation. We refer to Zhang and Baltsavias (2000) and Zhang et al. (2001b) for the detailed matching strategy and qualitative performance evaluation.

The 3D position of each edge pixel is computed by the well-known photogrammetric forward intersection. In order to find the corresponding pixels, we examined following three methods. In Figure 1, we represent edge pixels as small rectangles, and the straight edge segment l in solid black lines.

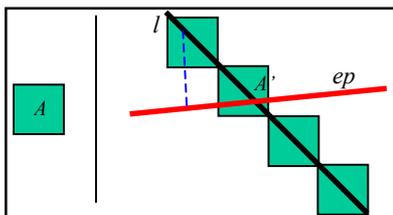


Figure 1. Pixel correspondence for 3D computation

For pixel A in left image, its epipolar line ep (shown in red line) in right image can be computed using orientation parameters.

The correspondence of A should be on the pixel chain, and close to the intersection of ep with l , A' . In the first method we take a window centred on A' , and obtain the candidate matches for A from the edge pixels on the chain and inside the window. We then compute the orthogonal distances from the candidates to ep (the dashed line), and take the pixel with the smallest distance as the correspondence of A .

The above method works fine except in the case shown in Figure 2, where edge pixels A , B and C are aligned parallel to base line, consequently their epipolar lines are totally identical. Therefore the method may find a same point as correspondence for A , B and C , resulting a zigzag chain in object space. We apply a “pixel grouping” method (method 2) to improve solution in this case. That is, we take pixel A , B and C in a group, and only find the correspondence and compute the 3D position for the group center. The pixel grouping procedure is applied to the edges in left and right images if necessary.

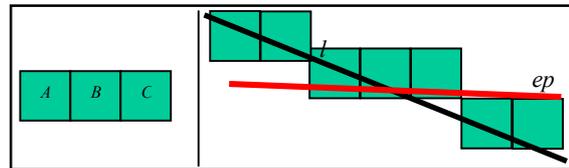


Figure 2. Pixel grouping for 3D computation

Another method (method 3) to compute 3D position is directly from the fitted straight edge segments. We select along the straight edge segment in left image points at an interval of 1 pixel. Then, for each point we take the intersection of ep with the corresponding straight edge segment in right image as its correspondence.

We applied the above three methods in different cases, and compared the results with manually extracted 3D edge segments. This is done by matching the computed 3D edge positions with the reference data, and calculating the coordinate differences. Table 1 summarises the RMS errors from a comparison for a vertical edge (case 1) and an edge with 20 degree difference in direction to the base line (case 2). The three methods deliver similar results for case 1, while improvements are obvious for case 2 using method 2 and method 3, especially in Z direction. Furthermore, we observed in experiments that the results from method 3 in case 2 are more smooth.

		dx	dy	dz
case 1	method 1	0.136755	0.011757	0.085529
	method 2	0.136355	0.011684	0.085155
	method 3	0.136420	0.011729	0.097824
case 2	method 1	0.056595	0.122870	0.610071
	method 2	0.052046	0.113061	0.437204
	method 3	0.055884	0.122865	0.452631

Table 1. Evaluation of 3 methods for 3D computation (unit: m)

After the 3D computation for edge pixels, a 3D straight edge segment is then fitted to the 3D edge pixels.

3.2 Image Classification for Road Region Detection

ISODATA (Jain and Dubes, 1988) is employed in our system to classify the color images and separate road regions from other objects. The algorithm automatically classifies the image data

into desired clusters. It recursively generates a new partition by assigning each pattern to its closest cluster center and merges and splits existing clusters or removes small or outlier clusters. The success of image classification also depends on the data used. As we are concerned with road surfaces and shadows (especially shadows on road surfaces), our purpose is to separate them from other objects in the image, and we do not pay much attention to separate other objects. The original RGB color image is transformed into different color spaces, and the following 3 bands are selected for image classification:

- 1) The first component of principal component transformed image
- 2) a band calculated with R and G bands in RGB space as $(G-R)/(G+R)$
- 3) S band from HSI color space

With this classification, we avoid using a hard threshold for image segmentation, and 5 classes are determined. They correspond to road regions, green objects, shadow areas, dark roofs and red roofs (if available).

3.3 DSM and DTM Analysis

The DTM or DSM has been used in our system to reduce search space for straight edge matching. They are also used to verify if a 3D straight edge or a region is on the ground. Because a DSM ideally models the man-made objects as well as the terrain, subtracting the DTM from the DSM results in a so-called normalized DSM (nDSM) which enables the separation of above-ground objects (buildings and trees) and ground objects (roads, etc.). Since in ATOMI, the DTM data is not very precise, we propose to extract above-ground objects directly from the DSM data, thus avoid introducing errors from the DTM data. This is achieved by a multiple height bin method (Baltsavias et al., 1995) to generate nDSM from the DSM data. By combining the information of nDSM with image classification data, our system creates redundancy to confirm the existence of roads. Furthermore, it is also used to correct errors in classification data and in occlusion areas to compensate the missing information in classification data.

3.4 Road mark and zebra crossing extraction

Road marks and zebra crossings are good indications of the existence of roads. They are usually found on main roads and roads in urban areas. Both of them have distinct color (usually white or yellow). Generally, road marks give the road direction and often the road centerline, while the zebra crossings define the local road width. Thus, they can be used to guide the road extraction process or verify the extraction results. In addition, in many cases the correct road centerlines can be even derived directly from present road marks and/or zebra crossings. This is especially useful when the roadsides are occluded or not well defined, such as in cities or city centers.

Since road marks are usually white, the image is first segmented by thresholding in R, G, B bands. The road marks are then extracted using an image line model and the geometrical description of each road mark is obtained. The shape of a image line can be presented as a second order polynomial (Busch, 1994); it is fitted to the grey values as a function of the pixel's row and column coordinates. We can compute the line local direction α using this model. We then get the profile in the direction perpendicular to α . The profile can be described as a parabola, from which the precise position of each line point is obtained. The detected line points with similar direction and second directional derivative are linked. The details of the

algorithm and implementation can be found in Zhang et al. (2001a). Straight lines are obtained by least squares fitting. The 3D lines are generated by our developed structural matching method. The 3D lines are then evaluated using knowledge. Only those on the ground (as defined by the nDSM data), belonging to road region (as determined by the classification) and in the buffer defined by VEC25 are kept as detected road marks.

Zebra crossings are composed of several thin stripes. Using color information, the image is first segmented. Morphological closing is applied to bridge the gaps between zebra stripes. We then obtain several clusters by connected labeling. Only the clusters with a certain size are kept, while the small ones are discarded. Then, the shape of the cluster is analyzed. The rectangle-like clusters are selected as zebra crossings. The center, the short and long axes of the detected zebra crossings are computed using spatial moments.

4. KNOWLEDGE-BASED ROAD RECONSTRUCTION: CUE COMBINATION

With the information from existing spatial data and image processing, the knowledge base is established according to the general strategy. The system then extracts roads by finding 3D parallel edges that belong to roadsides and link them in sequence. In case of shadows, occlusions caused by trees and buildings etc., a reasoning process is activated using the knowledge base. Thus, also the cases when only one or no side is visible can be often handled by the system. The main procedures are described below.

The system checks extracted edges to find 3D parallel edges. Only edges located in the buffer defined by VEC25, having a similar orientation to VEC25 segments and a certain slope are further processed. Since roads are on the ground, edges above ground are removed by checking with the DTM. By checking with the image classification results, a relation with the road region (in, outside, at the border) is attached to each edge. Two edges are considered as parallel if they have similar orientation in 3D space. The edges of a pair must overlap in the direction along the edges, and the distance between them must be within a certain range. The minimum and maximum distances depend on the road class defined in VEC25. The found 3D parallel edges are projected onto the images and evaluated using multiple knowledge. The region between the projected edges must belong to the class road as determined by the image classification. If road marks are presented on this road, the extracted road marks are used to confirm that the edge pair corresponds to correct roadsides.

For each found 3D parallel edge pair, the system tries to extend them as much as possible using 3D and 2D edge information. For each extension, a reasoning process (see below) is activated to guarantee that the extension area is road region and extended edges are roadsides.

The system also checks each individual 3D straight edge, if this edge does not belong to any 3D parallel pair. When one of the sides of the edge is road, the system hypothesizes its opposite side using the width from already found 3D parallel edges. Again the hypothesized area is checked using the accumulated knowledge. Compared with the visible 3D parallel edges, the system assigns a low reliability to the hypothesized parallel. If the single visible edge is close to an edge of a found 3D parallel pair and has similar orientation, its reliability is increased.

All found parallel edges are considered as Possible Road Sides that are Parallel (PRSP). They compose a weighted graph. The nodes of the graph are PRSPs, the arcs of the graph are the relations between PRSPs. Note that in occlusion areas, the arcs also represent the missing parts of a road between a pair of PRSPs. The width of two PRSPs should be similar. If there is no gap between two PRSPs, i.e. one PRSP shares points with another, and the linking angles between them in 3D space comply with VEC25, they are connected directly. In case of an existing gap, we first check the connecting angles between PRSPs and the gap. If the angles comply with the VEC25, the gap area is further evaluated using additional information, and we compute the possibility of the gap belonging to road. This is called reasoning process in our work. If the gap is not too long, and

- within the gap is a road region, or
- within the gap is a shadow or shadow mixed with road region, or
- the gap is caused by tree occlusion (determined from the image classification results and nDSM data), or
- within the gap is terrain as determined by the DSM, or
- road marks are extracted within the gap

Then, we consider the gap as possibly belonging to a road. Suppose N is the total number of pixels in the gap, and N_r , N_s are numbers of pixels of road and shadow respectively. N_g is the number of pixels of ground objects. The possibility of the gap belonging to a road is computed as $P_g = w_g * w_p$, where w_g and w_p are measures using height and image information respectively. They are given as

$$w_g = \frac{N_g}{N}, \quad w_p = \frac{N_r + N_s}{N} \quad (1)$$

The road is then found by searching the graph using a best-first method that maximizes the length while minimizing the curvature difference between the extracted road and VEC25 in a merit function. The function is defined as

$$(l_i + l_{gap} + l_j) * w_c \quad (2)$$

i and j are adjacent PRSPs, l_i and l_j are their lengths, l_{gap} is the gap length between i and j , w_c is a measure that is inversely related to the curvature difference between the curve formed by i , j and the corresponding curve on VEC25. The function defined in (2) gives high values to long curves that have similar curvature to VEC25.

For main roads, on which the system knows that road marks are present, the system also extracts roads using detected road marks and zebra crossings. The road marks are linked using a similar method as described in the previous paragraph. This procedure increases the effectiveness and reliability of our system. In complex areas, such as in city centers, the roadsides are usually occluded very much, and sometimes it is impossible to identify them. However, the road centerlines are successfully extracted by the system using road marks. In rural and suburban areas, the extracted road using road marks is used by the system to verify the extraction results using 3D parallel edges.

5. RESULTS

The described system is implemented as a standalone software package with a graphic user interface running on SGI platforms. The system reads color stereo imagery, old road databases and other input data, and outputs the extracted roads in 3D Arc/Info

Shapefile format that is readily imported in existing GIS software. The system has been tested using different datasets in various landscapes. Reports of the test results and the system performance can be found in Zhang et al. (2001a) and Zhang et al. (2001b). A recent benchmark test has been conducted independently by our project partner Swiss Federal Office of Topography with several stereopairs. We will show in this section some results of the benchmark test. Besides, we also tested our system on quite different image data provided by the National Geographic Institute (NGI), Belgium. The test results and performance evaluation will be given.

The benchmark test images were over Thun, Switzerland. The area fluctuates from 550m to 2200m. Almost all types of roads in Switzerland can be found in this area. The image data have the same specifications as described in Section 1. During the test, our system was only applied to extract roads in rural areas, while roads in urban and forest areas were not processed.

Figure 3 presents a portion of 3D road extraction and road network generation. The landscape of Figure 3 includes open rural and forest areas distributed with some houses. All the roads in this area are correctly extracted by our system. The details of automatic 3D road extraction and junction generation are presented in Figure 4, where the outdated roads from VEC25 are shown in yellow lines, and the extracted roads in pink lines. Figure 4a is an example of road extraction and junction generation in rural areas. Figure 4b shows a highway with 4 lanes, the system extracted the lane border lines and lane centerlines through road mark extraction.

Figure 5 presents some results from the Belgium site. The image data and the old road databases are provided by the National Geographic Institute, Belgium. The test area is generally flat. The image scale is around 20,000, and the camera focal length around 150mm. The image is black and white, and scanned using a PS1 scanner with 15 microns. As can be seen in Figure 6, the image does not have good quality, and many road-like lines are observed in the fields in the test site. A DTM in the test area is provided with 40m interval, the RMS error is around 10m. The RMS error in old road databases is around 9m, with maximum one around 25m. Some road attributes, e.g. road width, can be derived from the old databases. However, these parameters are too strict, they have to be relaxed for the test. We did not change anything in our system except in the image classification procedure. With black and white image, we only cluster a single band data to try to find road regions. Figure 5 shows a portion of the test results. The roads in rural area are correctly and reliably extracted by our system. In Figure 6, the details of road extraction and junction generation for this dataset is presented.

In order to evaluate the extraction results, we developed a method in previous paper to compare the extracted roads with the reference data. The method was applied to the datasets of Switzerland and Belgium. The reference data were measured by L+T and NGI at analytical plotters. The quality measures aim at assessing exhaustiveness as well as geometrical accuracy. To evaluate exhaustiveness, completeness and correctness are used. Completeness measures the amount of the reference data that is covered by the extracted roads, while correctness is the amount of correctly extracted roads covered by the reference data. The geometrical quality is assessed by mean and RMS of the distances between the extracted road and the reference data. The comparison results for Figure 3 and Figure 5 are listed in Table 2.

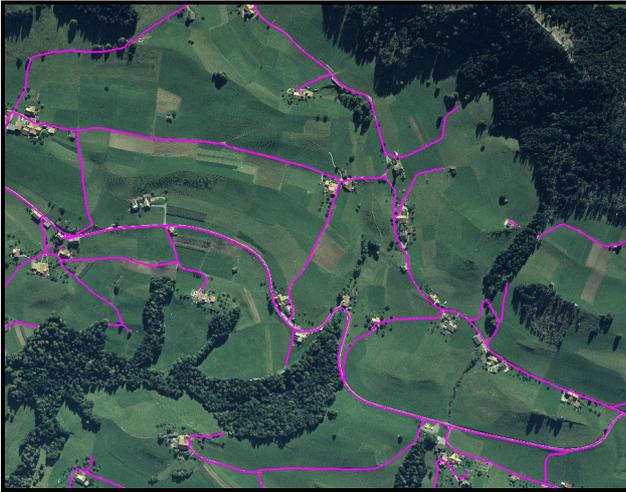


Figure 3. Extracted 3D roads and road network (the pink lines) in test site Thun, Switzerland



Figure 5. Extracted 3D roads and road network in test site in Belgium superimposed on image as pink lines

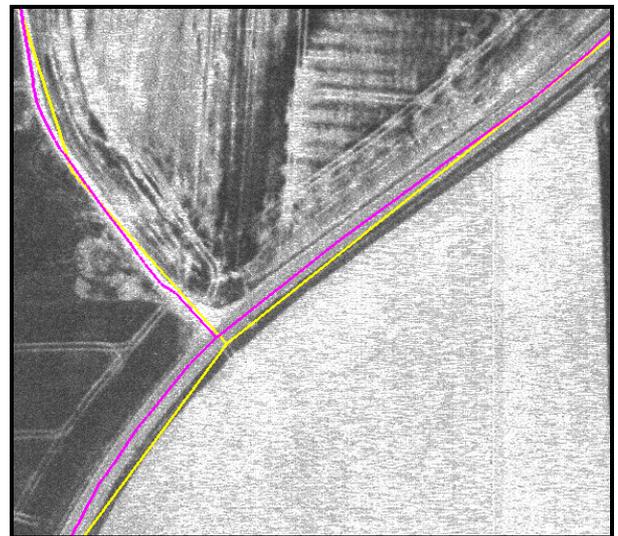


Figure 6. Details of road extraction and junction generation in Belgium dataset. Extracted roads are shown in pink lines and outdated roads in yellow lines

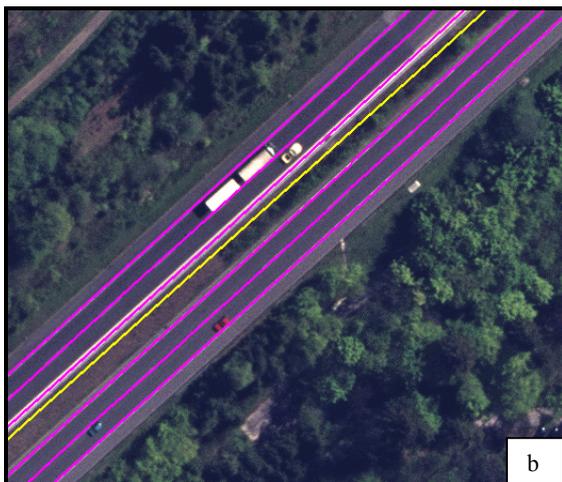


Figure 4. Details of road extraction in the test sites in Switzerland. The Extracted roads are shown in pink lines and outdated roads in yellow lines. a) Road extraction and junction generation, b) extracted lane border lines and lane centerlines on a highway

Quality Measures		Figure 3	Figure 5
Completeness		93%	97.6%
Correctness		96.3%	98.1%
Mean of difference	dx	-0.08	0.04
	dy	0.07	-0.11
	dz	0.19	0.27
RMS of difference	dx	0.45	0.57
	dy	0.31	0.72
	dz	0.62	0.89

Table 2. Quality evaluation (in m) of the reconstructed roads using manually measured reference data for the Swiss and Belgium datasets

6. DISCUSSION AND CONCLUSION

We presented a knowledge-based image analysis system for road extraction from stereo aerial images. The system has several advantages over other approaches. It uses existing

knowledge, image context, rules and models to restrict the search space, treats each road subclass differently, checks the plausibility of multiple possible hypotheses, therefore provides reliable results. The system contains a set of image processing tools to extract various cues about road existence, and fuses multiple cues and existing information sources. This fusion provides complementary and redundant information to account for errors and incomplete results. Working on stereo images, the system makes an early transition from image space to 3D object space. The road hypothesis is generated directly in object space. This not only enables us to apply more geometric criteria to create hypotheses, but also largely reduces the search space, and speeds up the process. The hypotheses are evaluated in images using accumulated knowledge. Whenever 3D features are incomplete or entirely missing, 2D information from stereo images is used to infer the missing features. By incorporating multiple knowledge, the problematic areas caused by shadows, occlusions etc. can be often handled. Based on the extracted roads the road junctions are generated, thus the system provides an up-to-date road network for practical uses. We also present in this paper the results of road extraction in benchmark tests conducted independently by our project partner, and the results on black and white image data provided by another national mapping agency. The quantitative analysis using accurate reference data is also presented. The comparison of the reconstructed roads with such data showed that more than 93% of the roads in rural areas are correctly and reliably extracted, and the achieved accuracy of the road centerlines is better than 1m both in planimetry and height. This indicates that the developed system can serve as an automatic tool to extract roads in rural areas for digital road data production. We are currently working on the derivation of reliability criteria for the extraction results. Our future work will concentrate on road extraction in cities and city centers.

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