Photogrammetrie • Fernerkundung • Geoinformation 5/2008, S. 363–373, 8 figs., 4 tab.

De-generalization of Japanese Road Data Using Satellite Imagery[1]

HIDENORI FUJIMURA, Tsukuba; MARCEL ZIEMS & CHRISTIAN HEIPKE, Hannover

Keywords: Reversal of cartographic generalization, roads, gray value profiles, supervised classification, support vector machine, experimental test

Summary: This paper focuses on the elimination of displacement due to cartographic generalization inherent in road data of the Japanese national topographic dataset NTIS. Panchromatic satellite imagery from ALOS PRISM is used for this task. The developed method is based on histogram analysis of gray value profiles parallel to the roads. The true-position candidate is selected using a supervised classification of the histograms based on support vector machines. Experiments with the Japanese NTIS road database show, that the proposed method reverses the displacement of approximately 50 % of the road features, while a further 20 % of the road features are validated as being located in the true position. Further experiments with the German ATKIS road database also yield very good results, which shows that the proposed method can be transferred across different geographic regions.

Zusammenfassung: *De-Generalisierung japanischer Straßendaten mit Hilfe von Satellitenbildern.* Dieser Artikel beschäftigt sich mit der Bestimmung und Berücksichtigung von Verschiebungen durch kartographische Generalisierung für Straßendaten der japanischen topographischen Datenbasis NTIS mit Hilfe panchromatischer Satellitenbilder von ALOS PRISM. Die entwickelte Methode beruht auf einer Histogrammanalyse von Grauwertprofilen parallel zu den Straßen. Die tatsächliche Lage der Straße im Bild wird durch eine überwachte Klassifikation der Histogramme mittels einer Support Vector Machine bestimmt. Untersuchungen mit der japanischen NTIS Straßendatenbank haben ergeben, dass die vorgeschlagene Methode für ca. 50 % der Straßen eine korrekte Verschiebung der Daten bestimmen kann, dazu kommen ca. 20 %, für die keine Verschiebung notwendig ist. Weitere Experimente mit ATKIS Daten zeigen ebenfalls gute Ergebnisse und demonstrieren die Übertragbarkeit in andere geographische Räume.

1 Introduction

In many countries digital landscape models (DLM) of the national mapping agencies provide a fundamental positional reference for a multitude of tasks related to geospatial information. The quality of this positional information is thus of prime importance. The DLM have usually been set up based on the requirements of a topographic map of similar content. Recently, independent sources of positional information, such as the Global Positioning System (GPS), which inherently has a very high geometric accuracy, have gained in popularity and are being used today for many applications such as car navigation. In order to provide the user of a DLM with the possibility to overlay his GPS data with the DLM and derive meaningful conclusions, both need to be at the same level of geometric accuracy. To fulfill this requirement, it is essential in many cases to enhance the geometric accuracy of the existing DLM.

[1] This work has been carried out while the first author was a visiting scientist at the Institute of Photogrammetry and GeoInformation, Leibniz Universität Hannover. A prior version of this paper is published in the proceedings of the 2008 ISPRS Congress, held in Beijing in July 2008.

1432-8364/08/2008/363 $ 2.75

The Geographical Survey Institute (GSI), the national mapping agency of Japan, had digitized its topographic map data at a scale of 1 : 25 000 to generate a printing quality image database (SATO et al. 1995). The original drawings of the topographic maps were scanned and stored in raster form. After this raster-based system had been realized, all the data were vectorized and stored in vector form into a topographic map information system named NTIS (OHNO et al. 2002). As a result, both the raster data and the NTIS still contain generalization effects which stem from the topographic map.

According to the specification of the Japanese topographic map 1 : 25 000 in paper form, the geometrical accuracy of NTIS features is defined to be 12.5 m in general. The geometrical accuracy is allowed to be degraded down to 25 m in case of cartographic generalization. For the reasons explained above, the geometrical accuracy of the NTIS data needs to be improved.

For the task of removing cartographic generalization effects, information of additional data sources is necessary. For urban areas, confiation with existing larger scale vectors is possible and will achieve a high level of automation. Currently, the GSI investigates methods to merge these heterogeneous vector datasets.

This paper focuses on the automatic reversal of generalization in rural areas. For these regions topographic data with larger scale are rarely available. Hence, satellite imagery is used for comparison with the database information. For this project up-to-date imagery of the Advanced Land Observing Satellite (ALOS) acquired with the Panchromatic Remote-sensing Instrument for Stereo Mapping (PRISM) was used.

Due to the importance of the road network for the users, and because the road network forms a geometric frame for all other features, this research aims at a reversal of feature displacement inherent in NTIS road features. For this task, an analysis based on histograms of profiles parallel to the road in the image data is suggested. The geometrical position and shape of each NTIS road feature is considered as prior information.

The aim of the work is to develop a new method which can be used at GSI to process the whole NTIS database of Japan as automatically as possible in a time frame of approximately 12 months. This paper reports on results achieved for the described task. Japanese as well as German datasets were processed in order to demonstrate that the algorithm can be transferred across different regions in the world.

2 Related Work

In this section, a selection of existing approaches for updating and verification of existing road databases with a practical background is described. There are two aspects of major interest for us: Firstly, the way other authors incorporate existing prior information, secondly, the used road model and the subsequent handling of road features that do not conform to the model. The second aspect refers to the robustness with respect to practicability and a large-sized versatility which are more important for this project than a complete automation.

In early work BORDES et al. (1995) suggested to guide road extraction for the BDTopo of the French Institut Géographique National (IGN) by information from the less detailed BDCarto. The accuracy of the result is evaluated using a matching strategy between the two datasets. WIEDEMANN & MAYER (1996) check roads which are available in a database by investigating the gray value profiles perpendicular to the road axes.

A semi-automatic system for an enhancement of the Swedish road database based on a comparison with satellite imagery of SPOT and Landsat was described in (KLANG 1998). The approach detects the position of road junctions by different template matching methods in the image within a tolerance radius around the given position. Based on this result the nodes are used as seed points for an active contour model which is applied to every road feature of the database. Finally, a comparison of the extraction result and the corresponding database object provides the human operator with a number of potential objects for the updating process. Thus, the extracted roads are not automatically included in the database. The system was extended in relation to the task of the National Topographic Database of Geomatics Canada (Fortier et al. 2001). The enhanced quality of the extracted junctions was used to include the detected roads directly in the database and make the whole system fully automatic.

Another relevant project in our context is the Automated reconstruction of Topographic Objects from aerial images using vectorized Map Information (ATOMI) of Switzerland (Zhang 2004). The approach makes extensive use of prior knowledge derived from the existing database, i. e. geometries and attributes as well as topological information of the given road network. Additionally, context information about local background objects is used to define an adaptive road model for urban and rural areas. The automatic analysis is realized using stereo color aerial images combined with DSM information. The road model is based on gray value gradients but uses also aspects of area classification to consider shadow and occlusion by context objects.

The WiPKA-QS project deals with the automatic quality control of the German authoritative topographic reference data set ATKIS-DLM and the MGCP (Multinational Geospatial Coproduction Program) dataset using aerial or satellite imagery (Gerke et al. 2004). Following the same main strategy as (Klang 1998), only road features with high evidence for correctness are processed automatically. The used road model is mainly gradient based and is adapted by use of prior knowledge from the database similar to Zhang (2004). WiPKA-QS allows for a speedup of about a factor of 3 as compared to manual quality control (Busch et al. 2004). More recent work in this project deals with analyzing histograms of road profiles to improve the performance (Ziems et al. 2007).

The use of active contour models e. g. (Grün, Li 1997) seems also to be applicable for this task. Snakes are deformable objects and thus can adapt naturally to road features in image space. In general, however, snakes suffer from the need for a good initialization and thus require a relatively high number of seed points. Butenuth (2007, 2008) showed that the network topology can be used instead of accurate seed points and can overcome many limitations of traditional snakes. A precision improvement of the Japanese 1:25 000 vector data using snakes was already investigated (Uetaki et al. 2006). The algorithm achieves good performance in suburban and rural areas, but it is rather slow and needs high-resolution aerial imagery which is very costly.

3 Data Sources

3.1 *Japanese NTIS/ALOS PRISM*

As mentioned above the road data of the NTIS have a positional accuracy of 12.5 m. In case of cartographic generalization, the positional accuracy can degrade down to 25 m. An important property of the NTIS road features is that most of them are straight. Fig. 1 shows the number of polygon points for each road feature in our test site. As can be seen, nearly 50 % of the road features are represented with only two points. From experience we know that this is a consequence of the fact that also the actual roads in object space in a typical Ja-

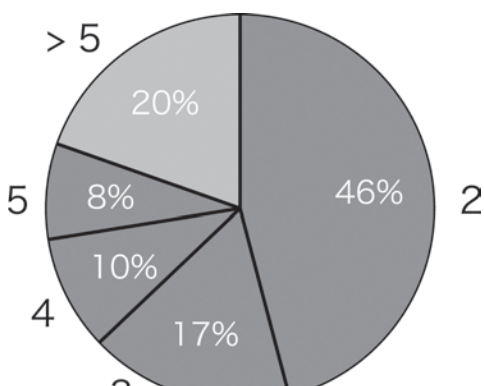

Fig. 1: Number of points in each road features in our test site (50.8 km^2, rural area).

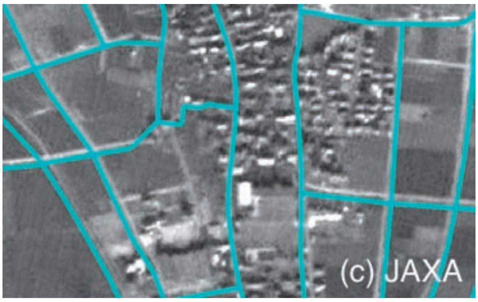

Fig. 2: Typical differences of ALOS PRISM imagery and NTIS road features (light blue).

panese rural area are mostly straight, and not a result of simplification as part of the cartographic generalization.

Fig. 2 shows an ALOS PRISM image superimposed with NTIS road features. ALOS PRISM is a 2.5 m resolution panchromatic sensor with a ground coverage of 35 x 35 km^2. An ortho-rectified image is used in our study. The horizontal positional accuracy of the georeferenced images is said to be around 2.5 m (Mizuta et al. 2007). Clear differences in geometry due to feature displacement can be observed in Fig. 2.

3.2 *German ATKIS/IKONOS*

To check the transferability of the developed method on the one hand and to gain an additional option to evaluate on the other hand, a second set of data sources was considered in our work. This set consists of IKONOS ortho-rectified images and a road database, which is derived from the Digital Landscape Model (DLM) of the German Authorative Topographic Cartographic Information System (ATKIS). The main difference to the first set (NTIS and ALOS PRISM) is that ATKIS DLM road features have a geometric accuracy of 3 m and have not been subject to cartographic generalization. Consequently, there is no direct demand for detecting a shift of ATKIS DLM road features. However, the quality of the proposed algorithm can be measured, because we can utilize the validated database information for external evaluation. This second dataset is also aimed at investigating the applicability of the proposed method to images of a higher resolution.

The available IKONOS scenes consist of one panchromatic and four spectral bands. For our investigation, pan-sharpened images with a ground resolution of 1 m were used. The imagery contains three different German regions called Hildesheim, Weiterstadt and Ulm. The images show dissimilarities in seasonal date and terrain type.

4 Methods

4.1 *Model Selection*

There are two main decisions to be taken in order to solve the stated problem: (a) a model for cartographic generalization of the road features and (b) a model for roads to be extracted from images must be selected. Both models can also be combined, e. g. in a snakes-based approach. Although snakes have a number of attractive properties (see above), they were judged to be too complicated and too slow for our aims, and the fact that snakes can deform during processing was though not to be necessary in rural Japan.

Observing the fact that most roads of interest are straight, we use a shift perpendicular to the road direction to model cartographic generalization. This model is local and very simple, which makes it attractive from a practical point of view. In some cases, however, it will not be sufficiently detailed, and the topology at nodes will in general be destroyed, as different edges will be shifted in different directions. Since road topology is one of the major points to be preserved, a post-processing step was designed: the one-dimensional shifts of all edges incident to a node are considered to derive the final two-dimensional node shift. The shifted nodes are then topologically connected in the same way as before. While there may be extreme cases were edges start crossing each other due to erroneously large shifts, in most cases the topology does not change, when applying the described method.

The second issue is the extraction of road features from the image. As was discussed in section 2 a number of approaches have been suggested for this task, many of them use prior database knowledge (the road feature position, direction, length, width etc.) and consider the road to be a line. While we also use the information from the database, we suggest an alternative method and model for road feature extraction. We look at different gray value profiles parallel to the database road feature in a buffer of a certain width, this width being related to the geometric accuracy of the database and the amount of potential cartographic generalization. Given an appropriate distance between the profiles one of them describes the road, while the others lie to the left and to the right of the road and contain gray values of the road neighborhood. Our task then is to select the profile belonging to the road; the problem can be solved by classifying all profiles into the two classes *road* and *non-road*.

In this way we turn the feature extraction into a classification problem and after defining an appropriate feature space we can thus use classification algorithms of remote sensing and pattern recognition. We selected the support vector machine (SVM) classifier, as it has proven to be a very successful algorithm (e. g. Vapnik 1998, see also Mallet et al. 2008). The open-source SVM library LIBSVM (Chang & Lin 2001) was used for all computations. Instead of outputting the label of the class, the SVM is set to output the estimated confidence to belong to the class (see Wu et al. 2004 for details).

When looking at the gray value profile we define a road as follows: (a) the road has a profile histogram which is dissimilar to those of all its neighbors, while the neighboring histograms share some similarity among each other. Note, that while we thus require a certain degree of internal homogeneity of the left and the right neighborhood, the two neighborhoods do not need to be similar; (b) the road surface is homogeneous, thus gray values of the road profile are similar and the average can be coded with a low entropy. Also, the average is assumed to be different from that of the surroundings. While this definition is generally satisfied in rural areas, it is not valid in urban scenes, where the profile histogram of a road may be rather inhomogeneous due to various disturbances (vehicles, shadows etc.), and the neighborhoods may also be inhomogeneous, e. g. due to different buildings. However, as our algorithm should primarily work in rural areas, these limitations are less relevant for our work.

4.2 *Pre-Processing*

A major prerequisite of the suggested approach is that the database information is used to define the approximate position and shape of every road feature in the image. The NTIS database contains a number of short connected road features which belong to one and the same straight road. In a first step these short features are linked based on their direction. The reason is that the histograms, which are generated from such short features, are not representative and thus not reliable enough. Our experience has shown that we need road features with a length of at least 60 pixels.

In the NTIS database we used for evaluation, such short features make up 28% of the road features and as mentioned most of them are linked to longer roads. In the test area in Germany only 5% of the road features are subject to preprocessing.

4.3 *Road Detection by Histogram Classification*

Overview

Fig. 3 shows the idea of histogram analysis of the proposed algorithm. The different profiles and the related histograms of a short part of a road feature can be seen, the actual road shows a shift of 7.5 m to the left of the database road depicted at a shift value of 0. The main algorithm is described in the following:

1. Create candidates for road features in approximate positions by use of database

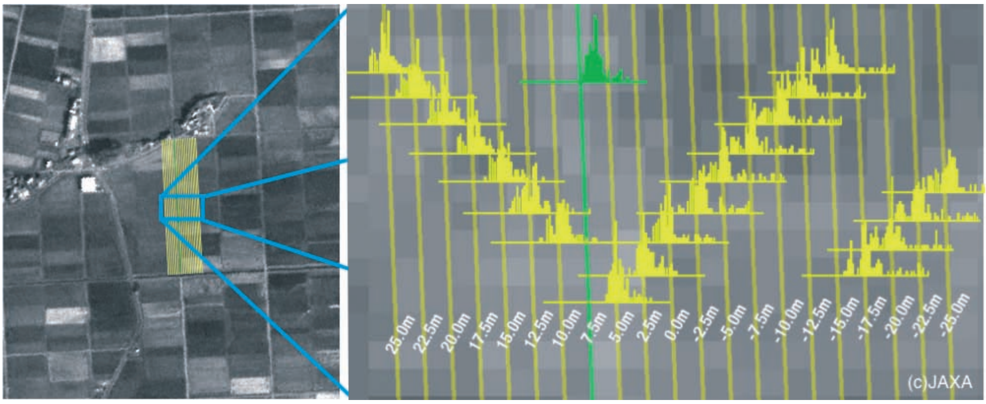

Fig. 3: Idea underlying the proposed algorithm: for one road feature (left), the different profiles and the resulting gray value histograms are depicted. As can be seen the green histogram representing the road is distinctly different from the neighboring histograms. As compared to the position of the database road at shift = 0, the road feature in the image is located 7.5 m to the left.

information. Candidates are generated in a buffer parallel to the line connecting the start and the end point of the database road. The range of possible shifts is determined according to the accuracy specification of the database and potential displacements due to generalization. In this work, the range is set to -30 m to 30 m because the limit of the feature displacement is 25 m (see above). We included a 5 m margin on either side because we need some background area to separate roads from the background. The step size of the shift is determined considering the precision of data sources. In our work, the step size is 2.5 m or one pixel. Therefore, we obtain 25 candidates for each given road feature.

2. Calculate the histogram of line pixels belonging to each candidate profile. Road width attributes are considered when available by defining the width of the region for which the histogram is calculated.
3. Calculate a feature vector for each candidate profile, as explained below, from the histograms.
4. Determine for a small number of road features the shifts manually and use these features to train the support vector machine classifier used in this study.
5. Classify all histograms using the SVM.
6. Choose the actual road features from the output of SVM.

Feature Vector

The feature vector consists of a number of features which were chosen to differentiate the road from the surroundings. All features are calculated from the normalized histogram $H_s(g)$ where s is the shift and g is the gray value. The components of the feature vector are:

1. 'Sum of similarity of histograms (SSH)' between one histogram s and all other histograms t in the neighborhood. The histogram similarity is expressed using the Bhattacharyya distance BC (H_1,H_2) (Bhattacharyya, 1943; Fukunaga 1990):

$$SSH(s) = \sum_{t=-S}^{S} (1 - \delta_{s,t})\, BC;$$

$$BC = \sum_{g \in G} \sqrt{H_s(g) \cdot H_t(g)} \tag{1}$$

where δ denotes the Dirac function. Fig. 4 explains the idea of SSH, an example is shown Fig. 5: In a typical rural Japanese landscape, the SSH steeply decreases from around 20 to less than 10 when the histogram $H_s(g)$ describes a road feature.

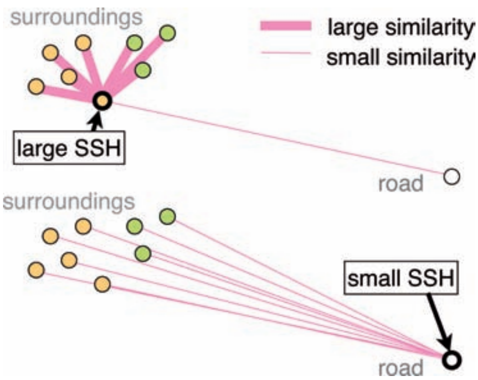

Fig. 4: Explanation of SSH: histograms with many similar partners have a large SSH while seldom histograms (such as those of road features) have a small SSH.

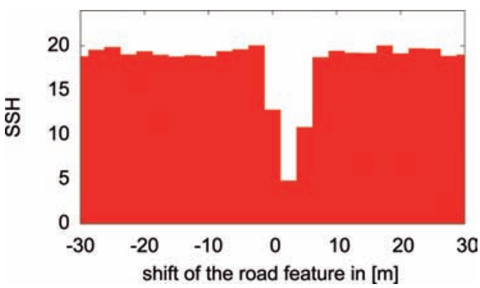

Fig. 5: A plot of SSH, a road is situated at a shift of 2.5 m.

2. Average brightness M(s) along the profile:

$$M(s) = \sum_{g \in G} g \cdot H_s(g) \quad (2)$$

This feature is chosen due to the fact that the average gray value of the road and the surroundings are assumed to be different. The average was normalized by dividing it by 256, as the radiometric resolution of the image was 8 bit.

3. Entropy of the histogram:

$$E(s) = -\sum_{g \in G} H_s(g) \cdot \log H_s(g) \quad (3)$$

This feature is chosen to include information about the texture. If the area is homogeneous as a road is assumed to be, the entropy will be low. The entropy was normalized by dividing it by 8 (the maximum entropy given the radiometric resolution of 8 bit).

4. Normalized rank, i. e. the index of the value in the sorted list of values for all 25 candidates, of the SSH. All rank values were normalized by dividing the actual rank by the number of candidate profiles.
5. Normalized rank of average gray value.
6. Normalized rank of the entropy.

We added the normalized rank of the first three feature vector components, because, according to our experience rank features significantly help in separating the two classes.

Consequently, six features are used for every available spectral band, i. e. in case of the PRISM imagery, these six features were taken into account, while for the IKONOS imagery with four spectral bands 24 features are used for classification. By normalizing all feature values to a range between 0 and 1, numerical problems in the following classification are minimized.

Shift Estimation

For every considered profile the output of the SVM is the value describing the confidence that the considered profile stems from a road feature; an example can be seen in Fig. 6. According to experience the maximum with a confidence value higher than a pre-defined threshold is chosen to estimate the shift. The confidence value is also used to assess the reliability of the estimated shift: if the detected maximum confidence value is too small or side maxima exist near the

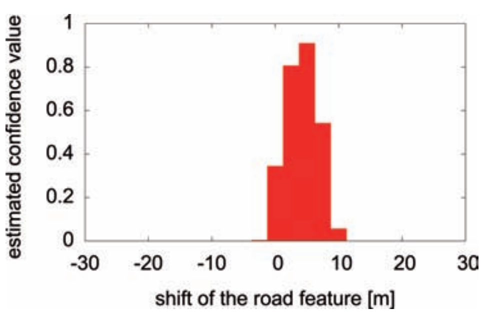

Fig. 6: Confidence values as a function of shift. In this example the computed shift is 5 m.

maximum, the shift estimation is labeled as unsuccessful. Possible reasons are that the cartographic generalization of the feature was more complex than a simple shift or that the assumed road model does not comply with the specific feature. In these cases, a human operator must interactively carry out the appropriate de-generalization of the road feature.

4.4 *Adaptation to Database Topology*

Because road features are shifted individually the (assumingly correct) topology of the road network from the database is in general destroyed. Since a correct topology is obviously of major interest, e. g. for routing applications, post-processing to recover the topology of the road network is required.

We consider each node individually and compute the node shift using a weighted least-squares approach with the shifts of all road features incident to that node as observations. The discrepancies between the different individual shifts are then minimized, taking into account that each shift only contains information about the shift direction orthogonal to the road feature. The weights we use correspond to the confidence values computed before. The resulting shift is then applied to the node. Subsequently, a Helmert transform is computed for each road feature between two nodes (for straight features, this is equivalent to connecting the two shifted nodes by a straight line). In this way the topology is preserved locally, and only in rare cases, e. g. if the sequence of roads changes due to extremely different shifts of two neighboring nodes, the topology changes globally. In the test examples, this case did not show up. Therefore, for the time being we accept this inconsistency for reasons of algorithmic simplicity.

5 Results and Discussion

For the evaluation of the proposed method, reference datasets were manually extracted from the images. These datasets were supposed to be correct. For the Japanese test area we generated the reference dataset ourselves, for the German test areas we used an independent dataset, obtained from the German Federal Agency for Cartography and Geodesy (BKG). This reference dataset was initially produced for evaluating the quality assessment system WiPKA-QS (GERKE et al. 2004).

5.1 *Japanese NTIS Data*

The necessary training data were collected in a small area of 4.5 km^2 in the image. The number of road features in the training set was 74. The trained model has a regression ratio of 99.4 %.

Fig. 7 shows our results for the area depicted in Fig. 2. For road features in green the shift has been validated by the human operator, for the red ones no reliable result could be computed or the human operator found it to be incorrect. In comparison with Fig. 2 we can see that most road features are moved to the correct position. Tab. 1 shows the statistics of the result for the test site. Only 21 % of the road features were found to be correct prior to the shift estimation. However, after applying the described algorithm, an additional 52 % of the road features could be corrected. Only the remaining 27 % of the road features have to be processed by a human operator.

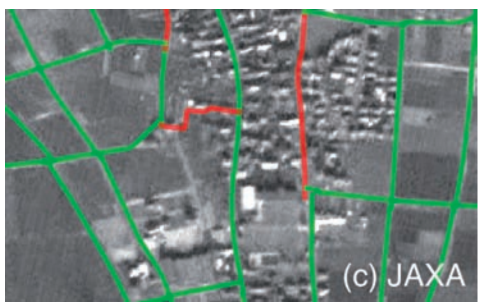

Fig. 7: Result for NTIS data (green: correct, red: incorrect).

Tab. 1: Result for Japanese NTIS/PRISM in selected rural area (50.8 km^2, 569 road features).

correct without shift	21 %
correct after shift reversal	52 %
incorrect	27 %

Tab. 2: Reliability of the results (here, only the correct features of the first test were considered).

system / human operator	correct shift
accepted	97.6%
rejected	2.4%

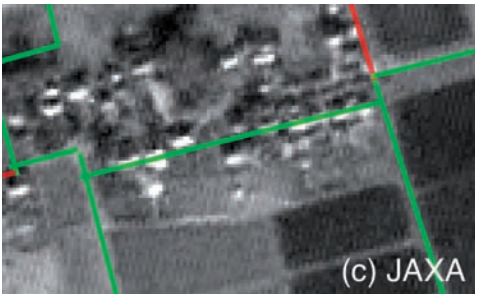

Fig. 8: false positive result: a row of buildings recognized as a road.

The reliability of the algorithm was checked in the following way: if a human operator could find a road feature at the place of the shifted road, the result was termed "accepted", otherwise it was termed "rejected". The result of this evaluation is shown in Tab. 2. Nearly 98 % of the detected road features comply with the decision of the human operator, thus the success rate of the developed method is very high.

A typical false-positive decision is shown in Fig. 8. A row of buildings is recognized as a road. We will try to detect this error in the future by using building data and by applying an additional evaluation step, in which shifts of topologically connected road features are considered simultaneously.

5.2 *German ATKIS Data*

As mentioned above the additional test with the German ATKIS data was carried out to demonstrate that the developed algorithm can be transferred from one geographic region of the world to another one. Because ATKIS data were not subject to cartographic generalization, a different outcome is expected. For a correct road feature from the database, the algorithm should choose the road candidate at a shift close to 0 with high confidence. Results with a large shift should be rejected and marked for interactive control.

The training data were generated from the reference dataset. The algorithm was tested with training data of various sizes to investigate the correlation between the training data size and the quality of the result. We processed roads and paths separately, because they are two separate features in the database and they can have a significantly different appearance in the image.

The upper half of Tab. 3 shows the evaluation for the complete Ulm test area (rolling terrain, spring season). Since the approach focuses on rural areas, settlement areas were not considered. The SVM was trained in a tile of $2 \times 2\,\mathrm{km}^2$ with 209 features in the reference dataset. Both, road and path features, were included in the training data. The result shows that the algorithm detects 69.4 % of the roads and 57.9 % of the paths at the correct position.

For comparison, the SVM was also trained using the whole reference dataset; the result of this control experiment is shown in the lower half of Tab. 3. As can be seen, no major difference appears when the size of the training data is changed. Thus, a small training set is enough for the proposed algorithm.

Tab. 4 shows the evaluation for the scenes Hildesheim (flat terrain acquired in winter) and Weiterstadt (rolling terrain, spring season). For training the Ulm data ($2 \times 2\,\mathrm{km}^2$) were used. The result is similar to the one for Ulm, which means that, at least in this case, the algorithm can successfully handle

Tab. 3: Evaluation for Ulm IKONOS scene (928 roads, 2886 paths).

training area	target feature	correct shift
$2 \times 2\,\mathrm{km}^2$	roads	69.4%
	paths	57.9%
complete scene	roads	66.8%
	paths	60.0%

Tab. 4: Evaluation for IKONOS scenes of Hildesheim (283 roads, 615 paths) and Weiterstadt (155 roads, 1366 paths).

test area	target feature	correct shift
Hildesheim	roads	81.6%
	paths	74.0%
Weiterstadt	roads	65.1%
	paths	49.4%

scene changes. This characteristic is obviously advantageous when large areas are to be processed, as is the case in national mapping agencies.

6 Conclusions and Future Work

This paper shows that in rural areas we can distinguish roads from their surroundings using histograms of profiles parallel to the road axes extracted from a geospatial database which had been subject to cartographic generalization. For 70% of the roads the generalization effects could be reversed assuming a shift perpendicular to the road as generalization model. The SVM was found to be an effective tool for classifying the profiles into road and non-road features. The algorithm is run feature-by-feature and thus is a local method. The simplicity of local methods is advantageous in practice, because the task can be distributed to computers across the organization.

Currently, the algorithm is implemented in JRuby and run on a 2 GHz Intel Core 2 Duo with 2 GB RAM on Mac OS X. The processing speed is 0.7 second per feature, which means that it takes less than 2 hours to process one map sheet. The speed enables the use of this algorithm in production. In the near future, the algorithm will be installed at GSI, in a first step as an operator-assisted utility to signalize any unacceptably large inconsistency between vector data and the image.

In future work we will enhance the classification by reducing potential correlations between the features in the feature vector, in particular for multispectral images, e. g. by using a principal component analysis as a further pre-processing step. We also note, that in general the effect of cartographic generalization does not only comprise parallel shift, though a parallel shift is dominant in the investigated dataset. The effect of other kind of generalization will be investigated, nevertheless, e. g. by revisiting the concept of network snakes. We will also implement constraints to ensure that shifts vary smoothly across neighboring features.

Acknowledgements

The stay of the first author at IPI was financially supported by the Japanese Ministry of Education, Culture, Sports, Science and Technology. We gratefully acknowledge this support. The authors would also like to thank Karsten Jacobsen for his kind help with the evaluation of the ALOS PRISM images, and GSI and BKG for providing the test data.

References

Bhattacharyya, A., 1943: On a measure of divergence between two statistical populations defined by probability distributions. – Bull. Calcutta Math. Soc. **35:** 99–109.

Bordes, G., Giraudon, G. & Jamet, O., 1995: Road Extraction Guided by a Cartographic Database: Creating a Strategy. – In: IEEE Workshop on Context-based Vision: 30–37.

Busch, A., Gerke, M., Grünreich, D., Heipke, C., Liedtke, C.-E. & Müller, S., 2004: Automated verification of a topographic reference dataset: System design and practical results. – International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences **35** (B2): 735–740.

Butenuth, M., 2007: Segmentation of imagery using network snakes. – Photogrammetrie – Fernerkundung – Geoinformation **2007** (1): 7–16.

Butenuth, M., 2008: Topology-preserving network snakes. – International Archives of Photogrammetry, Remote Sensing and the Spatial Information Sciences **37** (B3): in print.

Chang, C.-C. & Lin, C.-J., 2001: LIBSVM: a library for support vector machines. –www.csie.ntu.edu.tw/~cjlin/libsvm.

Fortier, M.A., Ziou, D., Armenakis, C. & Wang, S., 2001: Automated correction and updating of road databases from high-resolution imagery. – Canadian Journal of Remote Sensing **27** (1): 76–89.

Fukunaga, K., 1990: Introduction to Statistical Pattern Recognition. – Academic Press, 2nd edition.

Gerke, M., Butenuth, M., Heipke, C. & Willrich, F., 2004: Graph supported verification of road databases. – ISPRS Journal of Photogrammetry and Remote Sensing **58** (3/4): 152–165.

Grün, A. & Li, H. H., 1997: Semiautomatic Linear Feature-Extraction by Dynamic-Programming and LSB-Snakes. – Photogrammetric Engineering & Remote Sensing **63** (8): 985–995.

Klang, D., 1998: Automatic detection of changes in road databases using satellite imagery. – International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences **32** (4): 293–298.

Mallet, C., Brétar, F. & Sörgel, U., 2008: Analysis of full-waveform lidar data for classification of urban areas. – Photogrammetrie – Fernerkundung – Geoinformation **2008** (5): 337–348.

Mizuta, Y., Sasagawa, A., Koido, K., Urabe, B. & Tanaka, H., 2007: Validation on application of ALOS/PRISM to topographic mapping (in Japanese). – Journal of the Geographical Survey Institute **111**: 119–124.

Ohno, H., Mizuta, Y., Nakaminami, K. & Ishii, T., 2002: The development of the new management system 'NTIS' for topographic map information. – Bulletin of the GSI **48**: 39–48.

Sato, E., Takita, Y., Ishii, H. & Takahashi, H., 1995: Computer aided map revision system for 1:25 000 topographic map (in Japanese). – Journal of the Geographical Survey Institute **82:** 16–25.

Uetaki, G., Uchimura, K. & Zhencheng, H., 2006: Refining positions of road map using network active shape models. – ISPJ Journal **47** (12): 3079–3089.

Vapnik, V. N., 1998: Statistical Learning Theory. – New York: Wiley.

Wiedemann, C. & Mayer, H., 1996: Automatic Verification of Roads in Digital Images Using Profiles. – Mustererkennung 1996. Proceedings des 18. DAGM-Symposiums. Springer, Heidelberg, Berlin, 609–618.

Wu, T.-F., Lin, C.-J. & Weng, R. C., 2004: Probability estimates for multiclass classification by pairwise coupling. – Journal of Machine Learning Research **5:** 975–1005.

Zhang, C., 2004: Towards an operational system for automated updating of road databases by integration of imagery and geodata. – ISPRS Journal of Photogrammetry and Remote Sensing **58** (3/4): 166–186.

Ziems, M., Gerke, M. & Heipke, C., 2007: Automatic road extraction from remote sensing imagery incorporating prior information and colour segmentation. – International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences **36** (3W49): 141–147.

Addresses of the Authors:

Hidenori Fujimura, Geographical Survey Institute (GSI), Kitasato-1, Tsukuba-shi, Ibaraki-ken, 305-0811 Japan, e-mail: hfu@gsi.go.jp

Dipl.-Ing. Marcel Ziems und Prof. Dr.-Ing. Christian Heipke, Institut für Photogrammetrie und GeoInformation (IPI), Leibniz Universität Hannover, Nienburger Str. 1, 30167 Hannover, Tel.: +49-511-762-2482, Fax: +49-511-762-2483, e-mail: ziems, heipke@ipi.uni-hannover.de

Manuskript eingereicht: April 2008
Angenommen: Juni 2008