AUTOMATED ROAD NETWORK EXTRACTION FROM HIGH RESOLUTION MULTI-SPECTRAL IMAGERY

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ABSTRACT

In this paper, a new approach to road network extraction from multi-spectral (MS) imagery is presented. The proposed approach begins with an image segmentation using a spectral clustering algorithm. This step focuses on the exploitation of the spectral information for feature extraction. The road cluster(s) is automatically identified using a fuzzy classifier based on a set of predefined membership functions for road surfaces and the corresponding normalized digital numbers in each multi-spectral band. A number of shape descriptors from the refined Angular Texture Signature are defined and used to reduce the misclassifications between roads and other spectrally similar objects such as parking lots, buildings or crop fields. An iterative and localized Radon transform is then performed on the classified and refined road pixels to extract road centerline segments. The detected road segments are further grouped to form the final road network, which is evaluated against a reference dataset. Our experiments on Ikonos MS, Quickbird MS, and color aerial imagery show that the proposed approach is effective in automating road network extraction from high resolution multi-spectral imagery. Results from two different evaluation schemes also indicated that the proposed approach has achieves a performance comparable to other methods.

INTRODUCTION

Roads are probably the most important topographic object class and it is of paramount interest to have very short updation cycles for road networks (Bentabet *et al.*, 2003). It is also very important to keep the road network database up-to-date for many Geographical Information System (GIS) applications (e.g. urban planning, vehicle navigation, traffic management, emergency handling, etc). Traditionally, photogrammetric and remote sensing imagery has been considered the primary data source for topographic mapping (Heipke *et al.*, 2004). However, manual updation of road databases is very tedious and time-consuming. Automated road network extraction from remotely sensed imagery can be used to simplify the creation and updating of road databases and make the process more efficient.

According to Baltsavias (2004) and other literature (Klang, 1998; Fillin and Doytsher, 2000; Auclair-Fortier *et al.* 2001), image-based road database updating may include the following four processes: (1) Extraction of new roads; (2) Elimination of roads which no longer exist; (3) Updating roads which have changed; and (4) Improvement and refinement of existing non-changed roads, which can involve an increased degree of detail, better geometric accuracy, further attributes and possibly also the third dimension (Heipke *et al.*, 2004).

The realization of the above four processes requires an efficient, robust and accurate extraction of a new version of the road network from remotely sensed imagery. Substantial work has been completed for automated road extraction from remotely sensed imagery in the photogrammetric and computer vision communities during the last three decades. Dozens of different strategies or algorithms are proposed in the existing literature (Auclair-Fortier *et al.*, 2000; Mena, 2003; Baltsavias, 2004; Quackenbush, 2004). However, there is little research on road network extraction from multi-spectral imagery (MSI) (Doucette *et al.*, 2001; 2004). This situation is now changing due to the increasing availability of high spatial resolution MSI. MSI has a great advantage over panchromatic or other grey-level imagery as it enhances the capability to discriminate road surface material from most other types of landscape materials. For example, the multi-spectral data usually includes a NIR band that is a powerful discriminator of vegetation and man-made surfaces. This could be very helpful in a road identification step. With the emergence of advanced data fusion technologies, it is now even possible to extract road networks from Pan-sharpened MSI in urban areas (e.g., Zhang and Wang, 2004).

However, many issues still need to be researched in the extraction of road networks from MSI, especially from

high resolution MSI. For example, most of the existing road extraction methods for MSI rely on an automated and reliable classification of road surfaces (e.g., Doucette *et al.*, 1999, 2001; Amini, *et al.*, 2002, Song and Civco, 2004). Unfortunately, the classification accuracy of roads is far from satisfactory whether a supervised or an unsupervised classification method is used. The main difficulty lies in the high misclassification between roads and other spectrally similar objects, such as parking lots, buildings or crop fields. Another issue involves the extraction of road centerlines, i.e. how can we accurately and robustly extract road centerlines from classified imagery?

Some representative work in extracting road networks from MSI has been conducted by Doucette *et al.* (1999, 2001, 2004). Doucette *et al.* (1999) performed a principal component analysis on Hyperspectral Digital Imagery Collection Experiment (HYDICE) imagery and then used a maximum likelihood classification to generate a classified layer. This classified layer was combined with coarse GIS data in a neural network in order to extract linear features. The GIS data provided approximate location information for the extraction and speeded up convergence while minimizing user input. Doucette *et al.* (2004) presents a novel methodology for fully automated road centerline extraction that exploits the spectral content from high resolution multi-spectral images. Preliminary detection of candidate road centerline components is performed with Anti-parallel-edge Centerline Extraction (ACE). This is followed by constructing a road vector topology with a fuzzy grouping model that links nodes from a self-organized mapping of the ACE components. Following topology construction, a Self-Supervised Road Classification (SSRC) feedback loop is implemented to automate the process of training sample selection and refinement for a road class, as well as deriving practical spectral definitions for non-road classes. SSRC demonstrates a potential to provide dramatic improvement in road extraction results by exploiting the spectral content. Road centerline extraction results are presented for three 1m color infrared suburban scenes which show significant improvement following SSRC.

Due to the inability of the discriminatory of spectral information, there is a trend to incorporate the spatial information in image classification or to refine the spectral road class by integrating the spatial information. Gao and Wu (2004), for example, used a spatial filter to refine the road class resulting from an image classification of their input Ikonos MS images. The refinement was achieved by removing noisy pixels, such as the building pixels, using the spatial filter based on the assumption that all of the small size components are not actual road pixels. The road segments are then joined and thinned to form a road network. Similarly, in (Tarku *et al.*, 2004), the coarse road class is obtained by thresholding the original panchromatic image. Refinement is achieved by removing the false road pixels based on a connected component analysis. Small components, dense components, and irregular components are less likely to be road-based components. They are identified and removed from the road class. In (Hu *et al.*, 2004), the vehicle clue is used to verify a parking area in combination with a morphologic operation, which is applied to the classified image to detect big open areas. It is assumed that a region with a nearly square shape and large area has a high possibility of being a parking lot. Based on image classification results from pan-sharpened imagery, Zhang and Wang (2004) apply a segment filtering algorithm to deal with large parking lots and buildings which are misclassified as road networks. Basically, a directional texture detector is developed to distinguish different types of objects according to their textures in different directions. The work demonstrates that it is possible to extract urban objects from pan-sharpened imagery. However, the separation of parking lots and buildings from road networks is not satisfactory. There are many artifacts introduced by the directional texture detector. Song and Civco (2004) used two shape measures, namely smoothness and compactness, to further reduce the misclassification between roads and other spectrally similar objects from a support vector machine (SVM) classifier. The two shape measures were derived by the commercial software eCognition©. Experiments on Ikonos MS imagery showed that the SVM classifier has a slightly better performance than the traditional maximum likelihood classifier in terms of overall classification accuracy. By combining the spectral information and shape measures they were able to remove most of the false-road objects in the road group.

For road centerline extraction from classified imagery, Doucette *et al.* (1999; 2001) presented a self-organizing road map (SORM) approach to road centerline delineation from classified imagery. The SORM is essentially a spatial clustering technique adapted to identify and link elongated regions. This technique is independent from a conventional edge definition and can meaningfully exploit multi-spectral imagery. However, the positional accuracy of the extracted lines is low because the lines are created by linking the cluster centers and these centers are sensitive to any noisy pixels (e.g. misclassified road pixels). Line-fitting techniques can also be applied but they are only suitable for finding a single line in an image. This is not the case in road network extraction. Mathematical morphology operations are also used to find the line skeletons in a binary image (e.g., Karathanassi *et al.*, 1999; Amini *et al.*, 2002). However, these methods have issues with spikes in the resulting skeletons, which are usually determined at a pixel level. The Hough transformation was used by Hu *et al.* (2004) in their integrated processing of high resolution imagery and LIDAR data for the automatic extraction of a grid structured urban road network. To reduce the influence of multiple peaks in the transform space, the Hough transform was applied iteratively. For each step of the transform, only one maximum response in the Hough space was detected and then the extracted stripe pixels were removed from the binary image.

This paper presents our work on automated road network extraction from high resolution MSI. The proposed methodology is discussed in the next section and the evaluation of our method is summarized in the third section. The final section of the paper outlines our conclusions and the direction of future research.

PROPOSED METHODOLOGY

In this research, a framework for road network extraction from multi-spectral imagery has been proposed (Figure 1). The first step involves an image segmentation using the *k*-means algorithm. The main concern is the exploitation of the spectral information for the feature extraction. The road cluster is then automatically identified using a fuzzy classifier based on a set of predefined membership functions for road surfaces. These membership functions are established using the general spectral signature(s) of road pavement materials and the corresponding normalized digital numbers on each multi-spectral band. A number of shape descriptors are defined from the adapted Angular Texture Signature. These measures are used to reduce the misclassifications between the roads and other spectrally similar objects such as parking lots, buildings or crop fields. An iterative and localized Radon transform is developed for the road centerline extraction from the classified and refined images. The road centerline segments are then grouped into a road network, which is evaluated against a reference dataset.
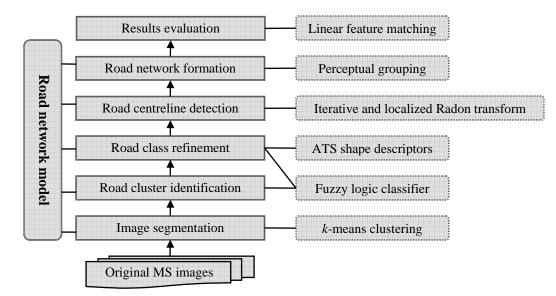

Figure 1. Proposed framework for road network extraction from multi-spectral imagery.

Image Classification

Image classification plays an important role in the automated road network extraction from remotely sensed imagery, especially from high resolution multi-spectral imagery. The task of road extraction addresses two issues: (1) identification and (2) delineation (Doucette *et al.*, 2001). Image classification can help automate the identification of road surfaces on the image. In our research, a spectral clustering is first applied on the input images and the road cluster(s) is then identified using a fuzzy logic classifier. For spectral clustering, the *k*-means algorithm is employed because of its simplicity and efficiency. The number of clusters is empirically set to six. Instead of using the digital numbers directly in the spectral clustering, we use the normalized digital numbers of each band based on a mean-standard deviation normalization method. A fuzzy logic classifier is defined to identify the road cluster(s) with the assumption that the road surface has a relatively higher reflectance in the blue, green, and red bands, while it has a relatively lower reflectance in the near infrared band.

Figure 2 and Figure 3 depict typical outputs of the *k*-means algorithm from Ikonos MS imagery and QuickBird MS imagery respectively. The identified road cluster is shown in red. We can see clearly that the algorithm is able to separate the road surfaces successfully from the other landscape types. However, there is a high misclassification between the roads and other spectrally-similar objects, e.g. the open rectangular areas at the upper-left corner of the Ikonos test image shown in Figure 2 and at the centre portion of the Quickbird test image shown in Figure 3 (both indicated by a black arrow).
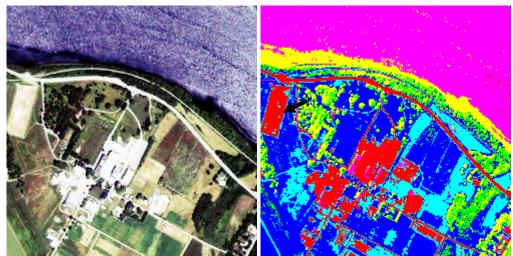
Figure 2. A typical output of the *k*-means algorithm from Ikonos MS imagery: (left) original true color composite ortho-image; (right) segmented image with the road cluster shown in red. The black arrow points to an example of misclassifying other spectrally similar objects as roads.

Figure 3. A typical output of the *k*-means algorithm from Quickbird MS imagery: (left) original true color composite ortho-image; (right) segmented image with the road cluster shown in red. The black arrow points to an example of misclassifying other spectrally similar objects as roads.

Road Class Refinement

The road class resulting from the classification is a mix of roads, parking lots, buildings and other spectrally similar objects. Further refinement is needed in order to remove the non-road regions before road centerline extraction and road network formation. In this research, the road class refinement is achieved by an advanced application of the Angular Texture Signature (ATS) and its derived shape descriptors. The justification of this approach lies in our observation that the main difference between roads and other spectrally similar objects is that the roads usually appear as elongate regions while the spectrally similar objects are usually open areas.

The basic ATS is defined as a set of variances computed in differently oriented rectangular sets of pixels around the pixel under consideration. It was used to extract roads on grey level images by Haverkamp (2002) and Gibson (2003). To make the ATS more meaningful, Zhang and Couloigner (2006a) introduced the concept of an ATS-polygon, which is a polygon formed by the angular texture measures plotted with their corresponding orientations. The shape of an ATS-polygon has been found to be relevant to pixel type. For example, a road pixel

usually has an elongate shape while a pixel within a parking lot has a circular shape. This information can be used to separate the road pixels from other spectrally similar non-road pixels. Four shape descriptors have been defined for the ATS-polygon. They are mean, compactness, eccentricity and direction. They are used to refine the road class resulting from the image classification step. Figure 4 shows the outputs of the road class refinement from the two previous test images.

From Figure 4, we can see that the proposed approach is able to effectively identify the non-road but spectrally similar objects (e.g. parking lots) and separate them from the road networks. However, we do have concerns about the relatively high false alarm rate, i.e., classifying real road pixels into non-road pixels. This will damage the road network topology. Most of this type of misclassification occurs for the roads that are closely adjacent to parking lots or are part of road intersections. Further improvement has to be made to reduce these misclassifications.
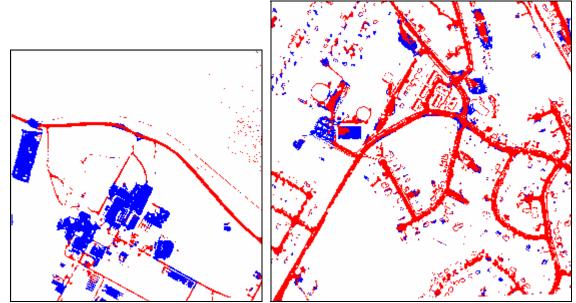

Figure 4. Road class refinement: road pixels are shown in red and non-road pixels are shown in blue for the Ikonos test image (left) and the Quickbird test image (right)

Road Centerline Extraction

The quality of the extracted road centerline from classified imagery usually determines the positional accuracy of the extracted road network. Therefore it is important to develop a method that can accurately locate road centerlines based on the classified road pixels. A review of the literature and preliminary experiments have shown that the Radon transform-based linear feature detector is a good choice because of its robustness to noisy pixels (i.e. misclassified pixels), its positional accuracy, and its capability to estimate line width.

However, there are many practical issues in using the Radon transform to extract road centerlines from classified imagery. Peak selection in the Radon domain is one of the main problems. A peak region-based approach is proposed in (Zhang and Couloigner, 2005a). The proposed approach can be used to accurately extract the centerline of a wide line. Based on the robust line parameter estimation, an iterative and localized Radon transform is then developed to extract road centerlines from the classified remotely sensed imagery. It finds the road centerlines accurately and completely, and is able to find short, long, and curvilinear lines. To localize the Radon transform, the input space is partitioned into a set of subset images called road component images using a gliding-box approach (Cheng, 1999). Other partitioning methods were tested (Zhang and Couloigner, 2005b) but the gliding-box approach was selected because it achieves acceptable quality with a much lower computational load. An iterative Radon transform is applied locally to each road component image. At each iteration, road centerline segments are detected based on an accurate estimation of the line parameters, including line widths. Figure 5 shows the extracted road centerlines from our two test images. We can see that the extracted road centerlines are generally accurate and complete.
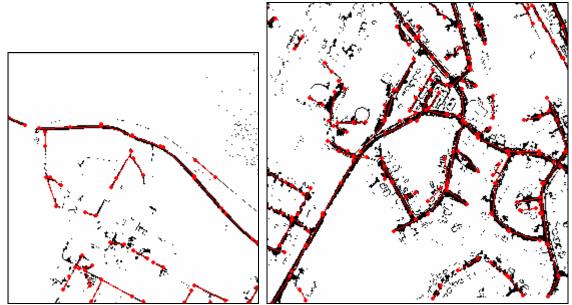
Figure 5. Road centerline extraction: extracted road centerline segments (red) overlaid on classified road pixels (black) from the Ikonos test image (left) and the Quickbird test image (right)

Road Network Formation

Road network formation enables individual road segments to be linked into meaningful road lines as well as the building of the network topological structure for use in a GIS. Generally, it includes tasks such as bridging gaps between road segments, creating nodes for road intersections, removing overshoots or undershoots, and so on. Figure 6 illustrates the final road networks extracted from our two test images.
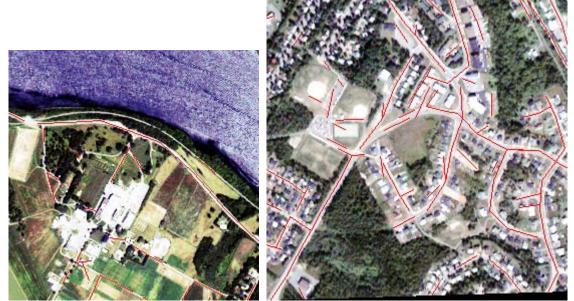

Figure 6. Road network formation: final road networks (red) overlaid on the original Ikonos test image (left) and the original Quickbird test image (right)

A major problem with the extracted road network from the Ikonos test image (Figure 6 left) is the missing portions of the main road running from the lower left to the centre. This problem is associated with our road class refinement algorithm. The missing road segments are closely adjacent to parking lots or other spectrally similar open areas and thus are classified as non-road pixels. False extractions are mainly due to the incompleteness of removing non-road pixels (e.g. the road lines at lower center of the image).

The result from the Quickbird test image (Figure 6 right) indicates that most of the roads have been extracted with a satisfactory accuracy. Missing roads are due to the problems associated with our road class refinement algorithm. The missing road close to the upper left corner is caused by the inadequateness of the spectral-based image segmentation as it was classified as non-road (see Figure 3 right). False extractions are mainly from the boundaries of the parking lots or buildings.

EVALUATION RESULTS

AutoMap Test Data

The proposed road network extraction method has been applied to both Quickbird and Ikonos MS imagery. These test data were provided through the Canadian Geoide AutoMap project. In total, three subsets of an Ikonos MS image and three subsets of a Quick-bird MS image have been tested. Both source images cover a portion of the City of Fredericton, NB, Canada. The National Road Network of Canada, Level 1 (NRNC1) was used as reference data and all of the extracted road networks were quantitatively evaluated against this reference data. The NRNC1 dataset was primarily produced with field driven Differential Global Positioning System (DGPS) technology and has a horizontal positional accuracy value of eight meters with circular map accuracy standards. The evaluation is achieved using the line segment matching approach described in (Zhang and Couloigner, 2006b) with a threshold distance of 5.0 pixels for the matching. Table 1 summarizes the evaluation results from our test datasets. Figure 7 shows the outputs from the evaluation of the extracted road networks shown in Figure 6. The evaluation shows that the road extraction has a moderate success in terms of completeness and correctness. However, it has good positional accuracy. This confirms our visual observations mentioned in the previous section.

Table 1. Evaluation results: AutoMap test data

Image set	Completeness (%)	Correctness (%)	RMSE (pixels)
Ikonos MS	0.49	0.37	0.90
Quickbird MS	0.50	0.49	1.07

Figure 7. Results evaluation for the Ikonos test image (left) and the Quickbird test image (right): Green – correct extraction, red – missed roads, blue – false extraction

EuroSDR Test Data

In 2004, the European Spatial Data Research (EuroSDR) Working Group "Automated extraction, refinement, and update of road databases from imagery and other data" initiated a unique program on assessing road network extraction methods. The main objectives of this program are (Mayer *et al.,* 2005):

- To thoroughly evaluate the current status of research including models, strategies, methods and used data;
- To test and compare existing semi- or fully automated methods using various data sets and high quality reference data;
- To identify weak points, and to propose strategies and methods that lead to an implementation of operational procedures for road extraction, update, and refinement.

In total, eight images were provided for test purposes. The test images include three aerial images, two Leica ADS40 images, and three Ikonos images (Table 2). These images cover several rural or sub-urban areas in Europe. The extracted road networks are assessed against manually digitized ground truth using the same input images. The test participants are asked to send their results to a web-server which computed the evaluation results via a CGI script. In the first stage of the test, only the road centerlines have been evaluated. More details can be found in (Mayer *et al.* 2005). Table 3 shows a comparison of our method to the methods of other EuroSDR test participants, based on the same evaluation criteria and using the same images. The average evaluation measures are calculated based on the current available evaluation results for other test participants (see Mayer *et al.* 2005).

Table 2. Overview of the EuroSDR test data

Image set	Image size	Spatial resolution	Areas
Aerial1	4000 by 4000	0.5 m	suburban area in hilly terrain
Aerial2	4000 by 4000	0.5 m	rural scene with medium complexity in hilly terrain
Aerial3	4000 by 4000	0.5 m	rural scene with low complexity in hilly terrain
ADS40 1	5800 by 5765	0.2 m	rural areas with medium complexity in flat terrain
ADS40 2	4880 by 5290	0.2 m	rural areas with medium complexity in flat terrain
Ikonos1_sub1	1600 by 1600	1.0 m	urban/suburban area in hilly terrain
Ikonos3_sub1	1600 by 1600	1.0 m	rural scene with medium complexity in hilly terrain
Ikonos3_sub2	1600 by 1600	1.0 m	rural scene with medium complexity in hilly terrain

Table 3. Evaluation results: EuroSDR test data

Image set	Completeness (%)		Correctness (%)		RMSE (pixels)	
	Average	Ours	Average	Ours	Average	Ours
Aerial1	0.31	0.51	0.56	0.49	1.53	1.92
Aerial2	0.65	0.67	0.82	0.49	1.14	1.72
Aerial3	0.72	0.72	0.77	0.63	1.30	1.66
ADS40 1	-	0.56	-	0.48	-	2.80
ADS40 2	-	0.45	-	0.30	-	2.58
Ikonos1_sub1	0.30	0.59	0.70	0.43	1.21	1.66
Ikonos3_sub1	0.70	0.73	0.83	0.37	1.19	1.77
Ikonos3_sub2	0.73	0.70	0.89	0.34	1.30	1.18

Based on the evaluation report, our method achieves a similar or slightly higher completeness than the average of the test participants but a lower correctness and a slightly lower or similar positional accuracy.

Comparing the two evaluation results, our evaluation of the proposed road extraction method gives slightly different ratings than that of Mayer *et al*. (2005). Because the reference data of the EuroSDR test images are not accessible to us, and the details of the evaluation procedures are also unknown, we list the possible reasons for this evaluation discrepancy as follows.

- The two sets of test images are from different sensors. The Automap set is of Ikonos MS and Quickbird

MS, while the EuroSDR set is of aerial, ADS40, and pan-sharpened Ikonos MS with much higher spatial resolutions. The properties of road networks are different in different images.

- The two sets of test images are from different geographical areas. The Automap images are mostly set in urban/suburban areas, while the EuroSDR images are mostly set in rural or suburban areas. This might be one of the reasons why the quality from the latter set of images is better as urban areas are usually more difficult.
- Different parameter settings might be another reason. For example, the distance threshold used to define the matching of two lines will affect the evaluation results. The larger the threshold value used, the higher the completeness and correctness that will be achieved with a possible lower RMSE values.

CONCLUSIONS

As one of the image understanding tasks, road network extraction has been one of the most challenging research topics in both the Geomatics Engineering and Computer Science communities. This paper presents our work on automated road network extraction from high resolution multi-spectral imagery. Based on the evaluation results from both the Geoide AutoMap dataset and the EuroSDR dataset, the proposed methodology achieves a moderate success in automating the road networking extraction from high resolution multi-spectral imagery.

Future work will include the improvement of the ATS-based road class refinement in order to reduce the misclassification between roads and other spectrally similar non-road objects; the development of more complex road models to take into consideration large road intersections where the exit road from a main road usually has a large local curvature; and creation of an operational production chain from imagery to GIS databases through the integration of the quality assessment results into automated road map change detection and updation.

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