AN INTEGRATED APPROACH TO EXTRACTING URBAN ROAD NETWORKS FROM HIGH RESOLUTION MULTI-SPECTRAL IMAGERY

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ABSTRACT

Automated road network extraction from remotely sensed imagery can be a promising approach to efficient road databases creation, refinement and updating. However, due to the extreme complexity of an urban scene, road extraction in urban areas is challenging. This paper presents a new integrated approach to extract urban road networks from high spatial-resolution multi-spectral imagery. The proposed approach begins with an image segmentation using a traditional *k*-means clustering algorithm. The road cluster is automatically identified by using a fuzzy classifier based on a set of predefined membership functions for road surfaces and on the corresponding normalized digital numbers in each multi-spectral band. A number of shape descriptors for the adapted Angular Texture Signature are defined and used to reduce the misclassifications between roads and other spectrally similar objects, such as parking lots, buildings and crop fields. An iterative and localized Radon transform has been developed to extract the centrelines of the road segments from the refined road cluster. The detected road segments are further grouped to form the final road network. Experiments on Ikonos MS and Quickbird MS imagery have shown that the proposed methodology is effective in automating the road network extraction from multi-spectral imagery in urban or suburban areas.

INTRODUCTION

An accurate and up-to-date road database is essential for many Geographical Information System (GIS) applications, such as urban planning, transportation management, vehicle navigation, emergency response, etc. Rapidly changing urban environments accelerate the need for frequent updates or revisions of road network databases. However, due to the extreme complexity of an urban scene (iv), automated urban road network extraction is one of the most challenging research topics in the field of photogrammetry and computer vision.

On the other hand, although dozens of different algorithms have been proposed for automatic road network extraction from remotely-sensed imagery during the last three decades (i), little research has been conducted on multi-spectral imagery (MSI) (ii). This situation is now changing with the increasing availability of high spatial resolution MSI, which has an advantage over panchromatic imagery as it enhances the capability to discriminate road surface material from most of the other types of landscape materials. This could be very helpful in a road identification step. With the emergence of new advanced data fusion technologies, it is now even possible to extract road networks from Pan-sharpened MSI in urban areas (iii).

This paper presents a new integrated approach to extract urban road networks from high spatial-resolution MSI. The remaining of this paper is organized as follows. A brief discussion on the image characteristics of road network on MSI is presented in the next section. The proposed methodology for road network extraction from high resolution MSI is detailed in the third section followed by an evaluation of our results. Finally some conclusions and outlooks are made.

ROAD NETWORK MODELS

The difficulties in automated road network extraction from remotely-sensed imagery lie in the fact that the image characteristics of road feature vary a lot according to sensor type, spectral and spatial resolution, ground characteristics, etc. Even in the same image, different roads often appear differently. In urban residential areas, with high resolution remotely-sensed image, the situation becomes even worse (iv). High resolution image enables a more accurate localization of the road sides as well as its extraction as surface element. But it generates a higher complexity of the image and an increase of artifacts such as vehicles, trees along the road, occlusions, etc (v). Finally, in the real world, a road network is too complex to be well modelled mathematically.

As Xiong (vi) stated, the studies of road image characteristics, their changes with respect to geographic background, image types, image resolutions, development of mathematical models to represent these characteristics, are critical in order to make substantive progress in this area. The author further pointed out that, practically, a road recognition algorithm can consider a limited set of characteristics, and when these characteristics change beyond a limit, the algorithm may fail. Similar remarks have been made by Auclair-Fortier *et al* (vii): in order to appropriately detect roads, understanding how a road's physical characteristics influence its visual characteristics is primordial. These visual characteristics are used to identify roads in a given image.

The general physical characteristics of a road in a remotely sensed image have been presented by Bajcsy and Tavakoli (viii) and revisited by Auclair-Fortier *et al* (iv). These characteristics include four types: (1) spectral properties (e.g. surface characteristics); (2) geometric properties (e.g. width, curvature); (3) topological properties (e.g. links, networking); and (4) contextual properties (e.g. the type of road).

Gruen and Li presented a similar but more programmable road model (ix; x). The properties in their generic road model include: (1) good contrast to its adjacent areas; (2) homogenous in grey values along a road; (3) smooth and without small wiggles; (4) continuous and narrow; (5) having upper bound in local curvature; (6) without significant change in the width.

The limitations of these road models are that most of these properties are derived based on the assumption that the image is noise-free. In a real image, however, particularly in urban area, roads are subject to a lot of "noise" or artifacts and are not necessary satisfying some of the above conditions.

In this research, instead of developing a generic road network model, which does not exist due to the complexity of the real road network and the variety of imaging sensors and imaging conditions, we are interested in developing a road network model which can describe the image characteristics of a road on high resolution multi-spectral imagery.

Spectral properties

Although it depends on the pavement materials used, in general, on multi-spectral imagery, assuming we have red, green, blue, and NIR bands, roads usually have relatively high reflectivity in the red, green and blue bands, while relatively lower reflectivity in the NIR band. Due to the variety of sensing conditions and road conditions, the reflectivity values (or the digital numbers) are hardly to be compared directly. In this research, we use normalized digital numbers to segment the input image and then identify the road cluster(s).

As mentioned above, in a real image, roads are subject to a lot of "noises" and artifacts. It is almost impossible to model all these "noises" and incorporate them in a road network extraction process. In this research, we assume that all these situations will result in a misclassification in the image classification step and will be treated in the road centreline extraction and road network formation steps by using less noise-sensitive approaches.

Spatial properties

Spatially a road extends along the road direction continuous and narrow. In low-resolution images (>4m), roads may appear as lines. In high-resolution images, roads appear as elongated regions with parallel borders (vii). This property can be used to separate roads from many other spectrally similar objects, such as parking lots, buildings, crop fields as these non-road objects usually occupy a large and wide area.

Geometric properties

A road usually goes smoothly without small wiggles (x). It usually has an upper bound in local curvature, which follows from smooth traffic flow requirement (x). It does not significantly change in width (viii; x). These geometric properties justify extracting road primitives locally and then linking them to form a road network.

Topological properties

Roads are built to link certain places together and neighboring roads are connected to form networks (viii). This property is usually used in the road network formation step, particularly when bridging gaps.

Contextual properties

The type of road is one of the contextual properties which can be used in road network extraction. In the real world, roads have different classes, such as highway, driveway, pathway, etc. Therefore knowing the types of the roads under consideration can be a helpful hint in determining the parameters used, e.g. the width of a search window. This information can also be used to verify the extracted roads' properties, e.g. the road width.

METHODS

In this research, a framework for road network extraction from multi-spectral imagery has been proposed. The first step involves an image segmentation using the *k*-means algorithm (Figure 1). This step mainly concerns the exploitation of the spectral information as much as possible for the feature extraction. The road cluster is then identified automatically using a fuzzy classifier based on a set of predefined membership functions for road surfaces. These membership functions are established based on 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, and crop fields. An iterative and localized Radon transform is developed for the road centreline extraction from the classified and refined images. The road centreline segments are then grouped into a road network. The whole process is unsupervised and fully automated.

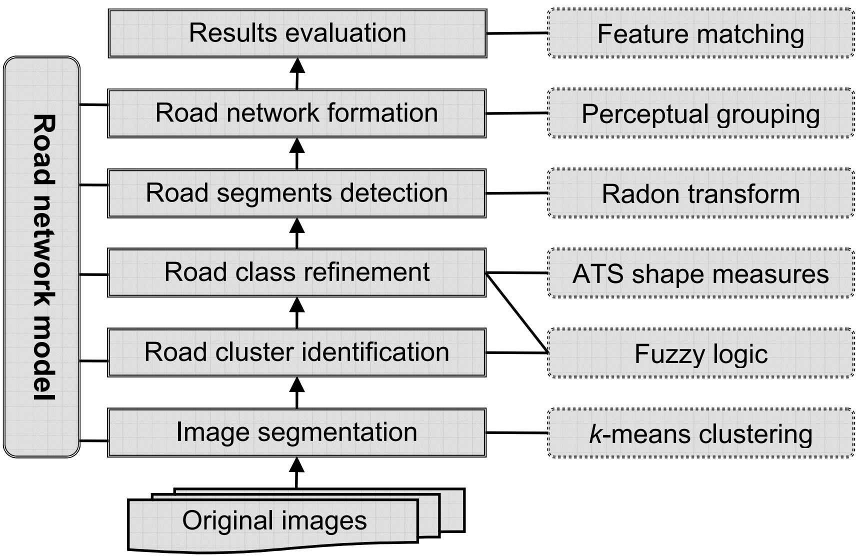

Figure 1: Proposed framework for road network extraction from multi-spectral imagery

Image segmentation

Image classification plays an important role in the automated road network extraction from remotely-sensed imagery, especially from high resolution multi-spectral imagery. The choice of image classification methods is also important and will affect the whole process. In our research, the *k*-means algorithm is applied because of its simplicity and efficiency. All the bands of an input image are used in the spectral clustering. Although any number from five to seven works well for most of our test images, six is selected as the number of clusters for all the cases in this research.

Figure 2 and Figure 3 depict typical outputs of the *k*-means algorithm from Ikonos MS imagery and QuickBird MS imagery respectively. We can see clearly that the algorithm is able to separate the road surfaces successfully from the other landscape types. However there is a huge misclassification between the roads and other spectrally-similar objects, e.g. the upper-left corner of the Ikonos test image shown in Figure 2 and the centre portion of the Quickbird test image shown in Figure 3 which are parking lots.

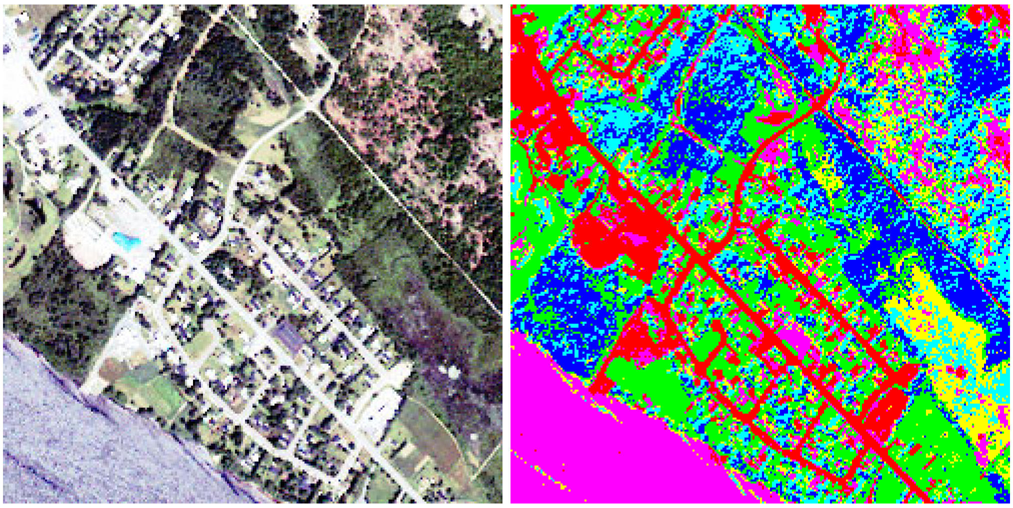

Figure 2: A typical output of the k-means algorithm from Ikonos MS imagery: (left) original true color composite ortho-image; (right) segmented image with the road cluster shown in red

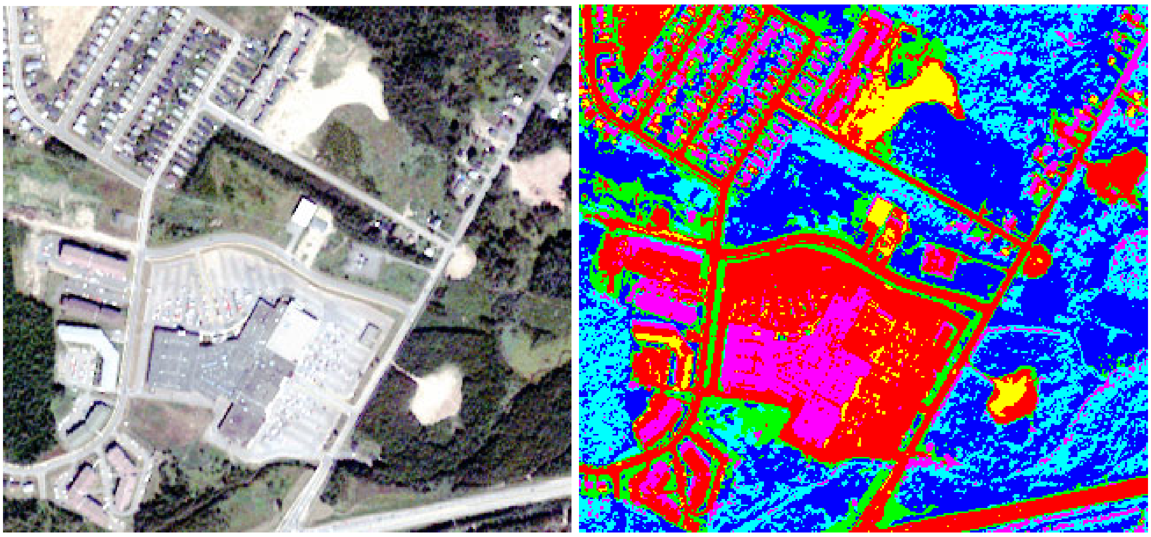

Figure 3: A typical output of the k-means algorithm from a Quickbird MS image (left) original true color composite ortho-image; (right) segmented image with the road cluster shown as red

Road class refinement

The road cluster resulting from the classification is a mix of roads, parking lots, buildings and other spectrally similar objects. Further refinement is needed to remove the non-road regions before we can perform a road centerline extraction and a 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 (xi). The justification of this approach is, from our observation, that the main difference between the roads and other spectrally similar objects is that the roads usually appear as elongate regions while the others are usually open areas. Figure 4 is the outputs of the road class refinement from the two previous test images.

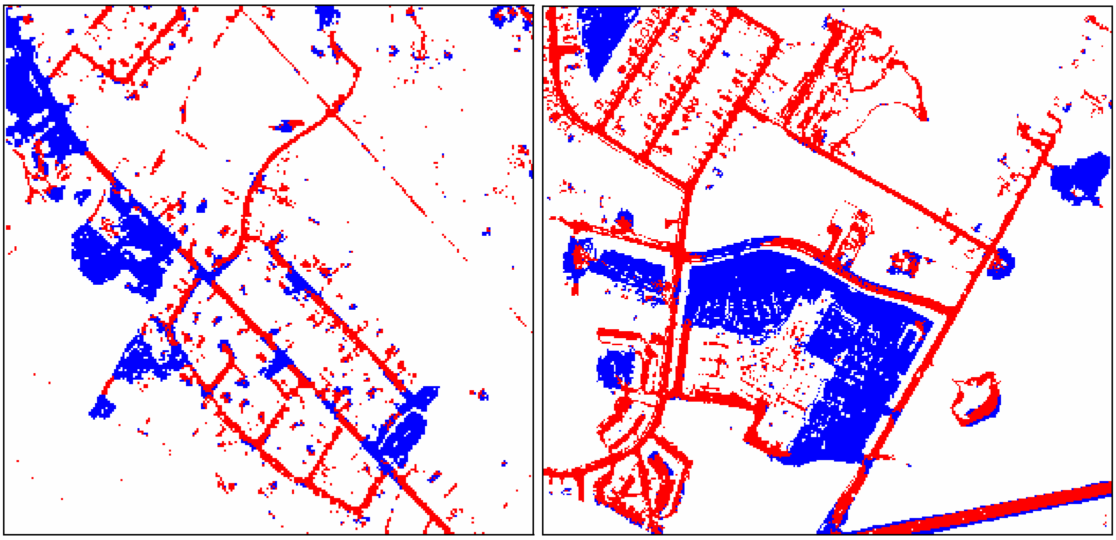

Figure 4: Road class refinement: road pixels shown in red and non-road pixels shown in blue for the Ikonos test image (left) and the Quickbird test image (right)

From Figure 4, we can see clearly that the proposed approach is able to effectively identify the non-road but spectrally similar objects. Most of the parking lots have been successfully identified and completely separated 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, because this will harm the road network topology. Most of this type of misclassification occurs on the roads that are closely adjacent to parking lots, or are part of road intersections. Further improvement has to been made to reduce these misclassifications.

Road centreline 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 centrelines based on classified road pixels. Our literature review and preliminary experiments have shown that the Radon transform-based linear feature detector is one of the good choices in this aspect because of its robustness to noisy pixels (i.e. misclassified pixels), its positional accuracy, and its capability to estimate line width. In this research, an advanced technique is proposed to accurately estimate the line parameters and line width in the Radon domain (xii). An iterative and localized Radon transform is then developed to extract road centerlines from the classified remotely sensed imagery (xiii). It can find the road centrelines accurately and completely, and is able to find short, long, and even curvilinear lines. The input space is partitioned into a set of subset images called road component images. An iterative Radon transform is applied locally to each road component image. At each iteration, road centreline segments are detected based on an accurate estimation of the line parameters and line widths. Figure 5 shows the extracted road centrelines from our two test images. We can see that the extracted road centrelines are generally accurate and complete.

Road network formation

Road network formation enables the link of individual road segments into meaningful road lines and the building of the topological structure of the network so that the data is ready for a GIS. Generally, it includes tasks such as, bridging gaps between road segments, creating nodes for road intersections, removing overshooting or undershooting, and so on. Figure 6 illustrates the final road networks extracted from our two test images.

Figure 5: Road centreline extraction: extracted road centreline segments (red) overlaid on classified road pixels (black) from the Ikonos test image (left) and the Quickbird test image (right)

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

The major problem with the extracted road network from the Ikonos test image (Figure 6 left) is that there are some missed portions of the main road running from lower right to upper left. This is caused by the problem associated with our road class refinement algorithm. The missed roads are closely adjacent to the parking lots or other spectrally similar open areas and thus are removed as non-road pixels. False extractions are mainly due to the incompleteness of removing non-road pixels (e.g. the road lines on the left side 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. Missed roads are due to the problems associated with our road class refinement algorithm. The missed road close to the upper right corner is caused by the inadequateness of the spectral-based image segmentation as it has been classified into a non-road class (see Figure 2 [right]). False extractions are mainly from the boundaries of the parking lots or buildings.

RESULTS

The proposed road network extraction method has been applied to both Quickbird MS imagery and Ikonos MS imagery. In total, three subsets of an Ikonos MS image and three subsets of a Quickbird 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 the extracted road networks were quantitatively evaluated against the 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 8 meters with circular map accuracy standards. Table 1 summarizes the evaluation results from our test datasets.

Table 1: Evaluation results

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

The evaluation shows that the road extraction has a moderate success in terms of completeness and correctness. However, it has a good positional accuracy. This confirms our visual observations mentioned in the previous section.

CONCLUSIONS

As one of the image understanding tasks, road network extraction has been one of the most challenging research topics in both geomatics engineering and computer science communities for three decades. This research proposed an integrated approach to road network extraction from high resolution multi-spectral imagery in urban/suburban areas. The experimental results have shown that our method is able to extract the main road networks from high resolution multi-spectral imagery in urban/suburban areas.

Our future work includes further improvements in the road class refinement to reduce the misclassification of road pixels to non-road pixels, application of the proposed methods to even higher resolution remotely sensed imagery, such as colour aerial imagery, pan-sharpened satellite imagery, etc.

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