Road identification and refinement on multispectral imagery based on angular texture signature

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Keywords: road extraction, multi-spectral imagery, image segmentation, shape descriptor, texture

ABSTRACT: The misclassification of roads and parking lots is one of the major difficulties in automating road network extraction from high resolution remotely-sensed imagery, especially in urban areas. This paper proposes a new integrated approach to road identification on high resolution multi-spectral imagery. The input images are first segmented using a traditional $k$-means clustering on normalized digital numbers. The road cluster is then automatically identified using a fuzzy logic classifier. A number of shape descriptors of angular texture signature are introduced for a road class refinement, i.e. to separate the roads from the buildings and parking lots that have been misclassified as roads. Intensive experiments have shown that the proposed methodology is effective in automating the separation of roads from buildings and parking lots on high resolution multi-spectral imagery.

1 INTRODUCTION

During the last two decades, substantial work has been completed for automatic road extraction from remotely-sensed imagery in the photogrammetric and computer vision communities. Accordingly, dozens of different strategies or algorithms have been proposed in the existing literature [Mena, 2003; Baltsavias, 2004]. Most of the existing road extraction methods for multi-spectral imagery (MSI) rely heavily on automatic and reliable classification of the 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 classification method or an unsupervised method is used. The main difficulty lies in the high misclassification between roads and parking lots, and between roads and some building roof materials.

Road and parking lot surfaces use the same construction materials and thus will have similar spectral signatures, which make it very difficult to automatically separate them from a remotely-sensed image. Introducing other information (e.g. height data from Lidar, clues from detected vehicles) does not measurably improve the situation due to the fact that roads and parking lots are usually at the same level and both will usually be occupied by vehicles. Research on the classification of roads and parking lots is quite recent partly due to the fact that road network extraction in urban areas becomes more feasible with the availability of high resolution remotely-sensed imagery.

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. The vehicles are extracted by a pixel-based classification method. It is assumed that a region with a nearly squared shape and large area has a high possibility of being a parking lot. The output from this step is used to improve the detected road segments from a Hough transform. Based on image classification results from pan-sharpened imagery, Zhang and Wang (2004) apply a directional
texture detector to deal with large parking lots and buildings which are misclassified as road networks. The directional texture detector measures the pixel grey value variance along the central lines in each of four directions (horizontal and vertical) of an operation window. 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. 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. A Self-Organized Road Map (SORM) was developed by Doucette et al. (2001) for extracting road networks from classified imagery. Doucette et al. (2004) presented a novel methodology for fully automated road centerline extraction that exploits the spectral content from high resolution multispectral images. The key elements of the proposed methodology include the Anti-parallel-edge Centerline Extraction (ACE) algorithm, SORM, and a Self-Supervised Road Classification (SSRC).

In this paper, we propose a new approach to effectively identify the parking lots/buildings from the road cluster resulting from a spectral clustering. The new approach is based on a number of shape descriptors of the Angular Texture Signature (ATS) in combination with a fuzzy classifier. This paper is organized into five sections. First, a brief description of the framework we used for the road identification on multi-spectral imagery is given in Section 2. Then the three main steps, image segmentation using spectral clustering, automatic road cluster identification, and road class refinement, are discussed in detail in Section 3, 4 and 5 respectively. Section 6 summarizes our research and concludes the paper.

2 OVERVIEW

The proposed approach starts with 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 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 signatures of road pavement materials and the corresponding normalized digital numbers on each multi-spectral band. Finally, we define a number of shape descriptors for the Angular Texture Signature. These measures are used to reduce the misclassifications between the roads and parking lots/buildings. The whole process is unsupervised and fully automated.

![Figure 1. Overview of road identification and refinement on multi-spectral imagery.](image-url)
3 IMAGE SEGMENTATION

There are a number of methods for image segmentation, ranging from edge-based approaches to region-based algorithms. In our research, the $k$-means algorithm is applied because of its simplicity and efficiency. All the four bands of an Ikonos image are used in the spectral clustering and the number of clusters is set to six for all the cases. Figure 2 shows a typical output of the $k$-means algorithm from our Ikonos MS imagery. From Figure 2, we can see that the classification process is able to find the road cluster from other land coverage clusters on multi-spectral imagery. The major problem, however, is the huge misclassification between the roads and parking lots/buildings, which motivates us to find a way to separate the roads from the parking lots/building in the road cluster.

![Figure 2. A typical output of the $k$-means algorithm from Ikonos MS imagery: (a) true color composite ortho-image; (b) segmented image with the road cluster shown in red.](image)

4 AUTOMATIC ROAD CLUSTER IDENTIFICATION

To automate the whole process, we need to find a way to automatically identify the road cluster in the classified image. Thanks to the discriminating capability of the multi-spectral imagery, the road cluster does have its own signature in the final means of each cluster.

Generally speaking, the road surface has relatively higher reflectance in the blue, green, and red bands, while it has a relatively lower reflectance in the near infrared band. The problem is how to model these spectral signatures mathematically. In our research, the mean-standard deviation normalization is applied for each band in the classified clusters and the final means are used to automatically find the road cluster.

A fuzzy logic classification is applied to identify the road cluster. We used the Gaussian membership functions for all four bands. The cluster which has the highest combined road membership is labeled as the road cluster. The combined road membership is the multiplication of the road memberships from each band. The identified road cluster in Figure 2(b) is shown in red.

A number of different Ikonos MS ortho-images have been tested. The results are identical to human visual inspection ones and are quite robust. The tested images were captured in different years and are covering different areas.

5 ROAD CLASS REFINEMENT

As mentioned above, the road cluster resulting from the classification is a mix of roads, parking lots and buildings. Further refinement is needed to remove the non-road regions before we can perform a road network formation. In this research, the road class refinement is achieved by an advanced application of the Angular Texture Signature and its new derived shape descriptors.

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5.1 Basic angular texture signature

A texture measure is described in [Gibson, 2003] and defined as follows. At each pixel \( p \) of a panchromatic image, \( T(\alpha, w, p) \) is defined as the variance from the mean for a rectangular set of pixels of width \( w \) around the point \( p \) whose principal axis lies at an angle \( \alpha \) from the horizontal. This measure is computed for a set of angles \( \alpha_0, ..., \alpha_n \). Figure 3(a) shows the templates for a single point. At the point \( p \), the Angular Texture Signature (ATS) is defined as the set of values \{ \( T(\alpha_0, w, p), T(\alpha_1, w, p), ..., T(\alpha_n, w, p) \) \}.

The graph of an Angular Texture Signature for a single point \( p \) is shown in Figure 3 (b). The local minima on this graph correspond to the most likely directions of the road at \( p \) (e.g. direction 4 and 13 in Figure 3). At each pixel \( p \), the number \( k \) and location of the strong local minima are computed from the Angular Texture Signature. For example, the signature shown in Figure 3 (b) has three minima that are significant (i.e. less than 250 in this case). We refer to the number \( k \) of minima as the degree of the pixel. The texture measures that are usually used in road detection are: the degree of the pixel and the direction of the minimum.

![Image showing texture computation](image)

Figure 3. Texture is computed over a set of rectangular regions about pixel (a) and the graph of the Angular Texture Signature for a single pixel (b). The image used is a subset of an Ikonos MS-red image. The size of the rectangular regions is 5 by 20 pixels.

To simplify the computation, we define the ATS based only on the road pixels. We compute the ATS on the binary image of our road cluster, where the road pixels are white and their surrounding pixels are black. Furthermore, instead of calculating the variance, we use the mean value only. Four new shape descriptors of ATS are defined in the following sections, which are suitable for identifying parking lots from roads.

5.2 Shape descriptors of angular texture signature

There are some interesting links between the shape of the ATS polygon and the corresponding pixel types. To form the ATS polygon, instead of plotting the ATS values for each direction along a horizontal line, we plot the ATS values around the pixel under consideration with the corresponding directions and link the last point to the first point. The resulting polygon is called the ATS polygon. Figure 4 shows the calculated ATS for some interesting pixels with the ATS polygons shown in blue. The pixels under consideration are marked with a red cross.

We define the following new shape descriptors for ATS:
1. **Mean**

The mean of the ATS is defined as the mean ATS value for all directions. It tells us how many object pixels surround the current pixel. A pixel on a parking lot or building will have a larger ATS-mean than a road pixel. Figure 5 (a) confirms this assumption.

2. **Compactness**

The compactness of the ATS is defined as the compactness of the ATS polygon using equation 4. It tells us whether the shape of the ATS polygon looks like a circle. A circle-like ATS polygon usually means that a pixel is on a parking lot or a building (Figure 4 (b) and (d)). It can be seen clearly in Figure 5 (b) that the parking lots and buildings have very large compactness values.

\[
\text{ATS Compactness} = \frac{4 \cdot \pi \cdot A}{P^2} 
\]

where \(A\) and \(P\) are the area and perimeter of the ATS polygon respectively.

3. **Eccentricity**

The eccentricity of the ATS is defined as the discrepancy between the origin point of the ATS polygon (i.e. the point under consideration) and the centroid of the ATS polygon. If a pixel lies at the corner of a parking lot or building, the eccentricity will be relatively larger than those closer to the center of the feature (Figure 6(a)). Experiments have shown that the boundary problem could be reduced greatly by introducing the ATS-Eccentricity in the detection of parking lots.

4. **Direction**

The direction of the ATS is redefined as the direction of the symmetric maximum direction, *i.e.* if the direction \(n_i\) gives a maximum and one of the directions \((n_{i-1}, n_i, n_{i+1})\) is also a local maximum.
then the direction \( n_i \) will be identified as a symmetric maximum direction and will be used as the direction of the ATS. Among all the symmetric maximum directions we select the one that has the largest combination ATS value (i.e. the sum of the direction pairs) as the ATS direction of this pixel. The new defined ATS-direction is more meaningful than the original one and more useful in the road network formation process. This is evident in Figure 6 (b), which shows the coded ATS-direction (1 to 9, same codes than in Figure 3 (a)) of the test image. The directions of the road pixels are more consistent comparing with the basic ATS-direction.

5.3 Road class refinement using the angular texture signature

We use a fuzzy logic classification to separate the roads and parking lots/buildings based on the ATS shape descriptors defined in the previous section. Figure 7 (a) shows the road membership for each pixel. Figure 7 (b) is the result after thresholding Figure 7 (a) at a membership of 0.1. Figure 8 is the output for another Ikonos MS test image.

From Figures 7 and 8, we can see clearly that the proposed approach is able to identify the parking lots/buildings effectively. Most of the parking lots have been successfully identified and completely separated from the road networks. However, there are some false alarms, which will
harm the road network topology. One problem is that certain roads, which are closely adjacent to parking lots/buildings, were misclassified as parking lots. The other problem is that some road intersections were misclassified as parking lots. One of the possible solutions to these two problems is to integrate the information from the ATS-direction. It is evident that the ATS-direction for roads (even at the road intersections) gives a consistent clue for road formation.

6 CONCLUSIONS

Due to poor image classification accuracy, little research work has been done in road extraction from multi-spectral imagery. This paper proposed a new road identification approach which integrates a traditional unsupervised classification, a fuzzy logic classification and the Angular Texture Signature. A number of shape descriptors have been proposed from the Angular Texture Signature. They have been used successfully to separate road pixels from parking lot/building pixels. Substantial experiments have shown that the proposed methodology is robust and can be applied to improve the image classification quality for the purpose of feature extraction.

We are currently working on reducing the misclassification of the roads that are closely adjacent to parking lots/buildings and those within a major road intersection. Applying the proposed approach to aerial color imagery and other very high resolution ($\leq$ 1 m) multi-spectral imagery including pan-sharpened imagery will also be included in our future work.

ACKNOWLEDGEMENTS

We would like to acknowledge the Canadian NCE GEOIDE research program for their financial support of the project “Automating photogrammetric processing and data fusion of very high resolution satellite imagery with LIDAR, iFSAR and maps for fast, low-cost and precise 3D urban mapping” and the City of Fredericton, NB, Canada for providing the satellite images.
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