AUTOMATIC ROAD EXTRACTION BASED ON LOCAL HISTOGRAM AND SUPPORT VECTOR DATA DESCRIPTION CLASSIFIER FROM VERY HIGH RESOLUTION DIGITAL AERIAL IMAGERY

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1. INTRODUCTION

The increasing availability of very high resolution satellite and aerial imaging sensors requires the availability of suitable automatic interpretation algorithm and system to extract cartographic features, especially in rapidly changing urban areas. Roads are one of the most important cartographic features. Extraction of roads from remotely sensed imagery is not only meaningful for cartography and topography [1], but also significant for various applications such as Geographic Information System (GIS) updating and automated vehicle navigation [2]. Many strategies, methodologies and algorithms for road extraction have been presented since the 1970s, which have achieved varying degrees of success. Mena has presented a detailed review for this topic [3].

2. METHOD

In this paper, an automatic road extraction approach from very high resolution aerial imagery based on local histogram calculated from image tiles and support vector data description (SVDD) classifier was proposed. SVDD is a relatively new SVM-like one-class classifier proposed by Tax et al. [4], in which a hypersphere shape discriminative boundary is generated to distinguish the class of interested and the background class. The spectral digital numbers (DNs) of pixels in a moving window of image were accumulated into histogram, and features come from concatenated histograms with all bands were inputted into the classifier. The classes of pixels were then determined. In this paper, a 13×13 pixel window was taken as the image tile to calculate the histogram, and the original DNs with 256 quantization were discretized into 16 levels, hence, 48 features were formed in the feature space for the image with three bands. The idea of histogram-based image classification using SVM algorithm can be found in Chapelle et al. [5]. Because the SVDD is a supervised classifier, the samples are required to train the classification model. In this paper, we manually selected some regions of interest (ROI) from graphic user interface (GUI) that represent road samples, and rearranged them into histogram form. A distinct advantage of one-class classifier like SVDD is that only samples of class to be classified are required; background samples such as non-roads for this study are not needed. The collection of samples from images are usually time-consuming for most remote sensing classification tasks, and the reduced requirement of samples will undoubtedly facilitates the road extraction. Due to the variety of roads, one road sample is not sufficient to describe all roads in a complicated scene; therefore, multiple samples are used to represent different roads. Each sample is used to discriminate all pixels in the image into road and non-road, and multiple samples will make multiple road maps. We eliminate the partial of road maps according to the radius of hypersphere calculated from the SVDD training process and combine the rest ones into final road map.

3. DATA

The data used in this paper is acquired by a Zeiss Imaging's DMC camera with a size of 12428×7780 pixels. The spatial resolution is about 0.2 meters per pixel. The image has three bands, and it is quantified in 8 bits. The image covers the urban area of Denver, Colorado, United States of America. Different scenes, subsetted from this data, that contain various kinds of roads from highway scene to complex overpasses were employed to perform experiments.

Because the spatial resolution of this image is very high, the roads are shown in details. The roads are not linear features as in TM or SPOT imagery, but the ribbon shaped objects and the widths vary with different roads. In addition, the roads in the image are not homogenous regions anymore, lane marks and vehicles are shown clearly, and the existence of overpasses and parking lots will definitely have negative impact on road extraction.

4. RESULTS

Two sub-image subsetted from the DMC data were used to evaluate the effectiveness of the proposed approach. In figure 1(a), a sub-image of highway scene was presented. The extraction of the slip road and internal road should be involved besides the main highway, and the spectral variation of different roads will increase the difficulty of road extraction. The selected road samples included some lane marks, but vehicles pixels were excluded. To increase the accuracy and robustness of road extraction, seven regions of interest selected manually from different areas were taken as road samples to represent different kinds of roads. Red boxes in figure 1(a) gave the positions of selected samples. The shapes of samples were rectangular but the sizes were not fixed, just determined by interactive operations.

Figure 1 (a)

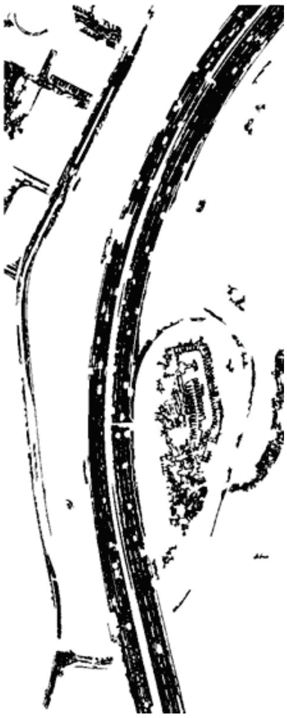

Figure 1 (b)

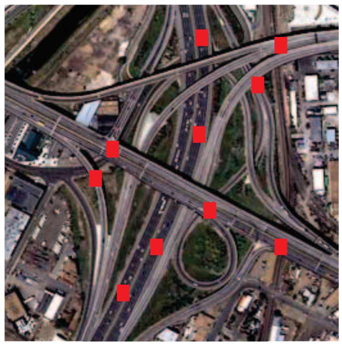

Figure 2 (a)

Figure 2 (b)

Table 1 Extraction accuracy measured by total accuracy, kappa, commission error and omission error

Scene	Total Accuracy (%)	Kappa	Commission Error (%)	Omission Error (%)
Scene 1	83.58	0.54	23.91	43.20
Scene 2	80.50	0.56	32.33	26.18

A complex scene is presented in figure 2(a). Overpass dominates this image, and internal roads, slip roads are connected to the highway. To extract the various roads in this scene, we utilized ten samples shown in red boxes in figure 2(a) to represent different roads conditions. After selecting the road samples, we rearranged samples from original spectral description into local histogram description calculated in square windows, and inputted them into an SVDD one-class classifier. Each sample will generate an independent thematic road map, but only the ones that fulfill some criterion will be used to combine into the final road map. The radius of hypersphere obtained in the training process was employed as the criterion in this paper. The black pixels in figure 1(b) and 2(b) presented the extracted roads, and other white pixels meant non-roads. Because only the road class was the focus of study, we used commission error and omission error of road class to estimate the accuracy and effectiveness for proposed road extraction approach. Meanwhile, total accuracy and kappa coefficient were presented in Table 1 as well.

From final road maps in figure 1(b) and 2(b), the visual effect of extracted roads were fairly good, especially considering that the proposed approach was automatic except the initial sample selection. All of the roads were recognized and most roads pixels were classified correctly. The pixels covered by vehicles and lane marking lines did not extracted, but they were not roads spectrally. Some pixels of parking lots were misclassified since there were no significant differences between the roads and parking lots from spectrum. Any classification based approaches only utilizing purely spectral features do not have ability to solve these problems, especially for classification of very high spatial resolution imagery. One feasible solution was using some techniques like mathematical morphology to process the classified map, but we did not perform any post-processing step to save executing time. Finally, according to table 1 that measured the two experiments quantitatively, approximate 28% of commission error and 35% of omission error can be achieved.

5. CONCLUSION

An automatic road extraction approach utilizing local histogram description and SVDD classifier is developed in this paper. For the test cases presented, this approach is feasible and effective. For very complicated scene, it still demonstrates good robustness. Except for classification process, no time-consuming calculations are involved in this approach; therefore, it has potential to deploy into operational road extraction systems.

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