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Road Extraction from High Resolution Image with Deep Convolution Network – A Case Study of GF-2 Image

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Abstract: Recently, with the development of remote sensing and computer techniques, automatic and accurate road extraction is becoming feasible for practical usage. Nowadays, accurate extraction of road information from satellite data has become one of the most popular topics in both remotes sensing and transportation fields. It is very usefull for appliying this technique for fast map updating, construction supervision, and so on. However, as there are usually huge informations provided by remote sensing data, an efficient method to refine the big data is important in corresponding applications. We apply the the deep convolution network to perform an image segmentation approach, as a solution for extraction road network from high resolution images. In order to taking advantage of deep learning, we study the methods of generating representative traing and testing datasets, and develop semi-superised skill to enhance the data scale. The extraction on the satellite images that affected by color distortion is also studied, in order to make the method more robust for more applicational fields. The GF-2 satellite data is used for experiments, as its images may show optical distortion in small pieces. Experiments in this paper showed that, the proposed solution successfully identifies road networks from complex situations with a total accuracy of more than 80% in discriminable areas.

Keywords: big data handling; road extraction; deep convolution network; remote sensing imagery

1. Introduction

In remote sensing applications, the road network extraction plays an important role in traffic management, navigation, map updating and city planning. Remote sensing images have the unique advantages of in providing large scale informations, which is very suitable for analyzing road networks efficiently [1-2]. Accuracte road informantions from high spatial-resolution images are urgently required in recent years. In the past few decades, great efforts have been made for extracting and updating the road network [3-8].

The road network have standard geometrical morphology, but generally speaking, it is not easy to extract road network precisely from remote sensing images. The reason is that the road network presented in real scenes is usually covered by many kinds of ground objects, like vehicles, tress, and shadows. Therefore, the shape and color of roads are usually diverse in different areas. In recent years, different methods have benn developed. The state-of-art methods could be divided into 3 typical categories: 1) outline or borders extraction; 2) object detection/classification; 3) image segmentation [9-11]. This paper focuses on the third category, i.e., the image scene is divided into road area and background area. If desired, the road ares can be further segmented, for example, according to the paved materials. This method aims to label each pixel with an ownership probability of different classes, which is a challenging work. Recently, with the development of calculation power (GPU) and the big data concept, deep convolutional neural network (DCNN) has been widely used in image studies [12-13]. It is believed that DCNN methods have revolutionized computer vision area with remarkable achievements. On the other hand, in current era of big data, although various images could be easily achieved from the network for free, which actually supports the use of DCNN, these images consist of huge information incluing both the valuable and useless ones for our specific research. Consequently, the first problem that should be solved is to effectively refine and enhanced the datasets to make them more suitable for our study.

GaoFen-2 (GF-2) is one of China’s civilian optical satellite products, with the resolution of better than 1m. Due to the excellent spatial resolution of GF-2 image, it could be widely used in various fileds including the road uptate. But the reason we choose GF-2 is not for its high spatial resolution, but is because GF-2 has an obvious problem in radiance calibration, which has been found in previous studies. We aim to develop road extraction method that are feasible even in color distortion cases, which maybe helpful to expand the apllicational areas of GF-2 images.

Inspired by the big data theory and deep learning technique, this paper proposes a solution for using the GF-2 images to extract road networks. Firstly, semi-superised method is applied to gererate labeled data. The benchmark road is automatic produced and then manually revised according to the road design and construction specifications that made by transportation industry. The data with color distortion is also regarded as on of the road type. Following that, the DCNN model with deep layers was trained to learning the various road characters. The DCNN will distinct multi-type roads from complex situations.

2. The Proposed Methods

2.1. The Problem and Task Description

As mentioned before, we use GF-2 data in this paper. GF-2 satelliete was launched on August 19, 2014, which is the first optical remote sensing satellite in China with a spatial resolution of being superior to 1m for panchromatic and 4m for multispectral. Since the first image and transmit data was started, GF-2 has supported various studies such as the civil land observation, land and resources monitor, map update and et al. Table 1 shows the detailed parameters of the GF-2 satellite[14].

Table 1. Parameters of GF-2.

	Band Number	Spectral Range (μm)	Resolution(m)	Swath width (km)
Panchromatic	1	0.45-0.90	1	45
Multispectral	2	0.45-0.52	4	
	3	0.52-0.59		
	4	0.63-0.69		
	5	0.77-0.89		

A disadvantage of GF-2 is that its images are sometimes affected by optical distortion. Acuarlly, it is a common problem by many high resolution optical satellite. But in GF-2, obvious radiometric distortion is a very noticeable problem when identifying road network. Figure 1 shows a tipical condition of this problem, we can find that the road surface gives abnormal spectra reflectivity. The road are paved with asphalt and concrete, shown with different color. But in figure 1, we cannot differentiates them because the color of a same asphalt road is turned from dark grey into bright white. The problem is more likely to happen when the nearby objects have some certain reflectances, which may affected the satellite sensors.

This paper aims to hanld this probem mainly bye the following ways. Firstly, inspired by the basic idea of big data, we try to use data of large scale and various informations, in oder to gain different conditions as many an possible. Secondly, we use DCNN methods with very deep layers to learn the abstract features from these conditions. Morever, data enhancement and perturbations is applied to further generating enough data and avoid overfitting

(a) **(b)**

Figure 1. The optical distortion on road network of GF-2 image: (a) An aera with abnormally whitten road network in certer location; (b) magnified detail of (a) .

2.2. Producting dataset by semi-surprised method

For deep learning algorithm, pixel-level labelled dataset is very crucial for model training, but for remote sensing dataset, manually drawing region with clear boundary is a very time-consuming work. Nowadays, with the development of web-map services, rich information about the roads could be easily obtained from the network for free. For example, as one of the most popular web-maps, the Open Street Map (OSM) has been widely used in providing road information including the road level, road name and roay type. In this case, by combing the OSM's road vectors and the satellite images, it will obviously decrease the time cost in producing the road labels. More importly, through this way, it could also help to improve the accuracy of the labels that produced by different person. The main workload is to registrate the road network and satellite images to a relative coordinate, which can be performed by typical Geographic Information System (GIS) softwares. After that, we need to furture improve the label accuracy, because in some areas the map may outdated. One can ues the open social platforms or free map sever API to search the ground place/road names of assigned coordinate ranges, providing suspected locations. And finilly, we inspect and manually drawing the final road regions. The metrial of road can be set according to the color of road surface. For the specific case like figure1, the road surface will be labeled as a "other case" , in order to distinguish from normal situations.

After labeling the images, a following pre-preprocessing and data cleaning are required to produce the training datasets for build the model. That is, since the original image scene usually covers hundreds of square kilometers. The computer cannot handle such large data at the same time. In order to generate train/test dataset, the original dataset the image should be firt clipped into several small ones accrodign to the specific computer settings. The following procedure of data cleaning is to remove the images with none or few road segments in it. This process is also very cucrial, because the images having roads usually make up only a small proportion, if most training image have no roads on them, the DCNN algorithms will tend to classify most pixels as background.

2.3. Road segmentation by DCNN

There are different DCNN methods can be used, like Unet, DeepLab, Segnet, and so on[15-17]. In this paper, we chose deeplab since it can applied with very deep layers. In order to match such a large DCNN layers, data enhancement is a necessary process. Usually, the image rotation and mirror, is processed to extend the training datsets by times. We can also randomly set the clipping origin of subsetion 2.2, and from the view of computer, this procedure will produce different shape of objects.

2.4. Post-processings and Refining

Many researchers aim to fine an end-to-end way for image segmentation, but for practical applications of road verification from complex satellite data, it is desirable to apply modified approach. For example, using morphology algorithm to combine the broken network structures, filtering out spots and burrs. To make the extracted road regional more realistic, the extracted road segments are processed through several morphological algorithms to fill the holes, smooth the edges, connect the road segment and finally achieve the coarse center lines of road segments.

1) Order the initial center lines by giving a start pixel and divide the lines into several parts according to the branch points;

2) For each segments of the lines, a group of straight line approximations can be obtained after giving an interval [18], which is 50 in this paper.

$$y_i = \begin{cases} a_{i,1}x_i + b_{i,1}, & x_{i,1} < x_i \le x_{i,2} \\ a_{i,2}x_i + b_{i,2}, & x_{i,2} < x_i \le x_{i,3} \\ \ldots & \\ a_{i,M}x_i + b_{i,M}, & x_{i,M} < x_i \le x_{i,M+1} \end{cases} \tag{1}$$

where xi and yi are the coordinates of the certain line segment; M is the number of sub-segments that divided by the given interval; ai,M and bi,M are the coefficients of the approximated line function for M th sub-segment.

3) A group tragedy, which is inspired by [19], is finally adopted to further improve the results iteratively. To put it simply, for each three neighbor line segments, if these segments share the same direction up to a tolerance τ, they will be regarded as the same line and a new line approximation will be made for all the points in these segments.

$$Collinear(k_{i-1}, k_i, k_{i+1}) < \tau \tag{2}$$

where ki-1, ki, ki+1 indicate the directions of three neighbor line segments; τ is the threshold value for collinear detection.

4) Iteratively check the current lines through 3) and finish modification.

3. Results and Disscussion

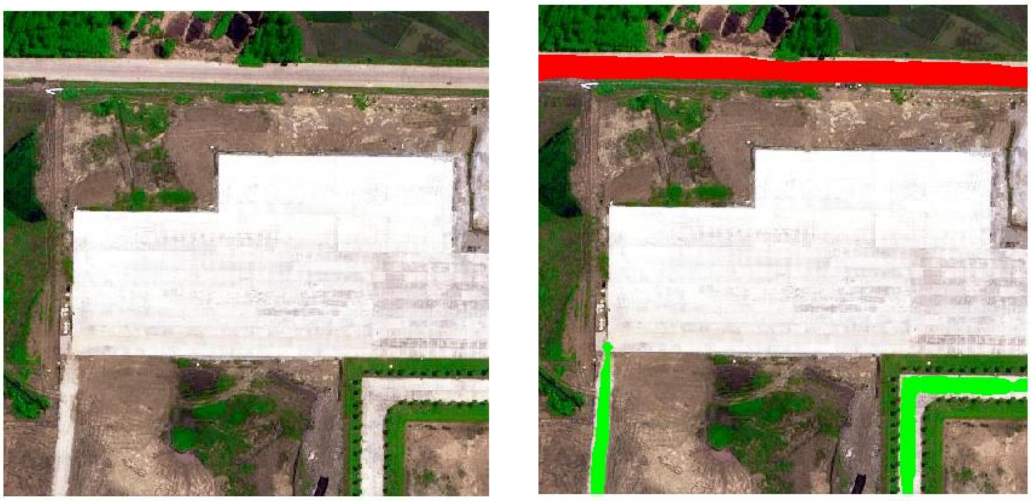
In our experiments, the GF-2 data of different locations and seasons are used for experimental test. The multi-spectral image bands are fused with panchromatic bands to produce the images with the spatial resolution of 1m. The original image scene is divided into 256*256 size images, producing thousands of images of for training and testing. The label consists of three parts: centerline, width, and material. There are there materials, including asphalt, concrete, and others. The label details have been checked manually, in order to guarantee the authenticity of the data.

Figure 2 shows the results in the country area. There is optical decade in this location, and we can see that the roof in the center is excessive bright in the scene while the vegetations in the top right corner are turned to be grey color. But as shown in Fig.(b), the proposed method extracts road segment successfully.

Figure3 gives the classification results when different matrials represents in the same image scope. It can be found that there are three road segments with two different pavements, asphalt and concrete, respectively. The asphalt material is labeled as red and concrete is represent as green. There is a parking lot in the center of this image, paved with concrete. The parking lot is not extracted, implying that the proposed method judge the object not only by colors, but also utilizes the shape informations. In this image, we can see that the asphalt road is not precisely in dark color, due to the optical distortion, but the road segment is also extracted correctly.

(**a**) (**b**).

Figure 2. Road extraction result: (a) Input image; (b) Output results.



(**a**) (**b**).

Figure 3. Road extraction result: (a) Input image; (b) Output results.

4. Discussion

However, there are still lots of further work need to be improved: 1) the method should be continuely tested with various areas for widely usage; 2) accurate and smoothness approximation for curve lines should be further studied

5. Conclusions

This paper transposes DCNN to remote sensing road detection. Semi-supervised labelling method is studied to provide the applicability for wide range of different area. DCNN is used as tools for feature extraction, and the precise road boundary is achieved by pos-processing and the final results will be more consistent with the real situation. That is, a much straighter and smoother road region could be provided, which steps further to practical application.According to the experiments, a total correctness of approximately 80% can be obtained through our proposed method.

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