SEMI-AUTOMATIC ROAD DETECTION FROM SATELLITE IMAGERY

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ABSTRACT

In this work, we present a semi-automatic road extraction scheme to detect roads from low resolution satellite imagery. In our approach, we used the à trous algorithm to locate and identify roads. Principle component analysis (PCA) is used to combine the detail coefficients. After detecting possible road pixels, we used a graph searching algorithm to draw a final complete road network. We found that our approach leads to an effective method to form the basis of a road detection approach.

Keywords: Road detection, à trous algorithm, graph searching, Principle component analysis

1. INTRODUCTION

Linear feature extraction from aerial or satellite images has been an active area in the field of computer vision. There are various kinds of features that can be extracted from aerial imagery, such as roads, buildings, lakes, rivers, etc. Road detection from satellites imagery has received significant attention because it is very practical in many applications, especially in geographical information systems (GIS), remote sensing and photogrammetry. One of the major expectations is in the use of updating urban/rural maps, such as road network for car navigation system.

An interesting problem in remote sensing is how to extract the information of the roads and remove all the other irrelevant information. This problem has been extensively studied. In the past two decades, there are a number of road extraction methods have been developed. For example, Fischler presented two types of detectors type 1, few false alarms, and type 2, few false detection, where their results are combined and applying F* algorithm. The shortest path of road seed candidates is linked using a dynamic programming algorithm [1]. An optimal convolution filters for the identification of wide line features is described in Petrou [2]. Another approach by Tupin [3], two local line detectors and a method to combine the information from these detectors to get road segments is presented. The real roads are identified using a Markov random field (MRF) algorithm. A technique that combined template matching and support vector machine for road identification from the high-resolution aerial images was proposed in Mei [4]. A semi-automatic approach searches for an optimal path between a few given points proposed by Grun and Li [5]. These points are connected using dynamic programming.

In this paper we make use of the fact that different characteristics of objects such as roads can be best detected in different scales. This scale depends on the characteristic scale contained in the object to be detected. Optimal processing of an image thus requires the representation of an image at different scales. In order to detect roads in an image, it is necessary to perform and combine information of road detection at multiple scales. Therefore, it can improve the robustness of road detection.

In our approach, we present a road detection method for use with low-resolution satellite imagery, the width of roads typically ranges from one pixel to five pixels, using à trous algorithm. Two different resolutions of the same image are used, a coarse one with 5x5 mask, and a fine one with 3x3mask. To combine the detail coefficients on different scales, the principle component analysis is used. After detecting possible road pixels, we used a graph searching algorithm to draw a complete road network. In the following section, we discuss our approach for road detection. Some experimental results and conclusion will be provided.

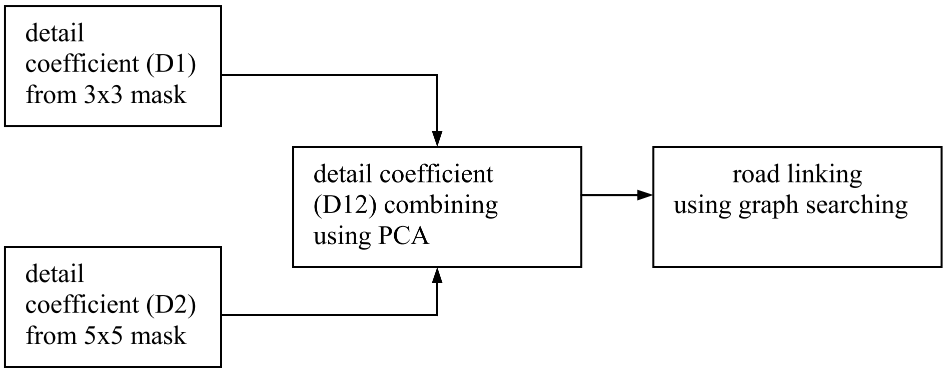


Figure 1. Flow chart of the semi-automatic of road detection algorithm

2. À TROUS ALGORITHM

In the past decades, the wavelet transform (WT) is a powerful and remarkable tool, which is used for handling fundamental problem in science and engineering. It is an alternative way to represent a signal. Instead of transforming a pure time description into a pure frequency description, it is carried out to represent a signal in the term of time- frequency description. Due to the downsampling in the filter bank algorithm, a wavelet transform is not translation invariant. In order to overcome this drawback, the undecimated wavelet transform (à trous algorithm) was used for road detection. It gets rid of the downsampling step, causing all subbands to have the same size as the original data set. It consists of a bandpass and a lowpass filter. The bandpass filter is the dilated by two mother wavelet samples and the lowpass filter is à trous [6]. The lowpass filter *f* is said to be an à trous if it satisfies

$$f = \delta(k)/\sqrt{2}. \tag{1}$$

This algorithm performs successive convolutions with a filter obtained from an auxiliary function named scaling function. It is extensible to the two dimensional space, which can lead to a convolution with a mask 3x3 pixels for the wavelet related to linear interpolation. The coefficients of the mask are:

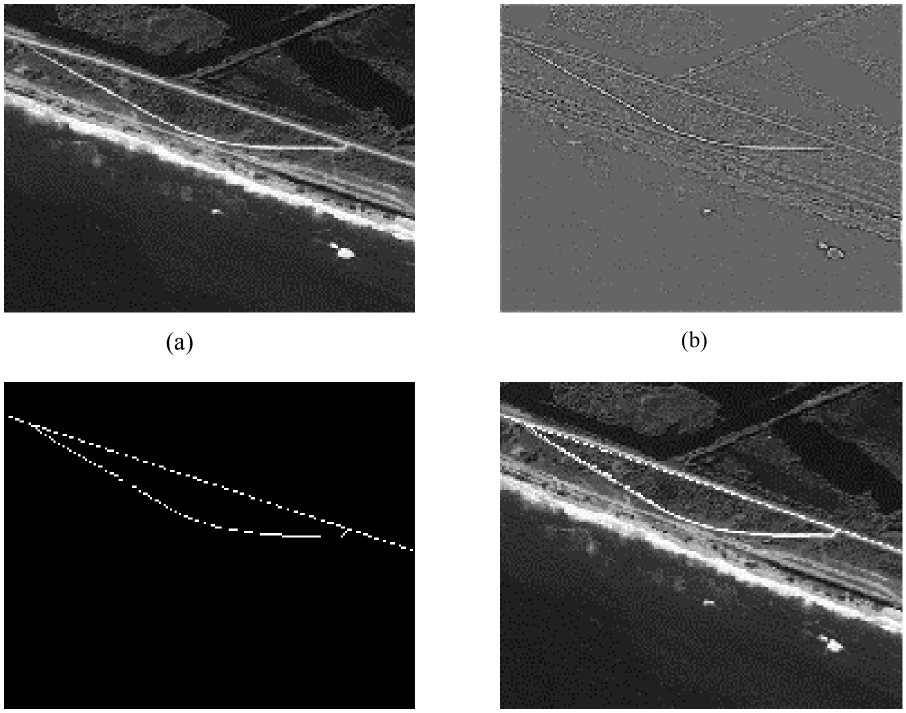
$$\begin{pmatrix} \frac{1}{16} & \frac{1}{8} & \frac{1}{16} \\ \frac{1}{8} & \frac{1}{4} & \frac{1}{8} \\ \frac{1}{16} & \frac{1}{8} & \frac{1}{16} \end{pmatrix} \tag{2}$$

In addition, we also use a scaling function, which has a B_3 cubic spline profile. The use of a cubic spline leads to a convolution with a mask of 5x5 [7]:

$$\begin{pmatrix} \frac{1}{256} & \frac{1}{64} & \frac{3}{128} & \frac{1}{64} & \frac{1}{256} \\ \frac{1}{64} & \frac{1}{16} & \frac{3}{32} & \frac{1}{16} & \frac{1}{64} \\ \frac{3}{128} & \frac{3}{32} & \frac{9}{64} & \frac{3}{32} & \frac{3}{128} \\ \frac{1}{64} & \frac{1}{16} & \frac{3}{32} & \frac{1}{16} & \frac{1}{64} \\ \frac{1}{256} & \frac{1}{64} & \frac{3}{128} & \frac{1}{64} & \frac{1}{256} \end{pmatrix}. \tag{3}$$

3. ROAD DETECTION

The principle component analysis (PCA) is known as Hotelling Transform. It is based upon the eigenvalue decomposition of the covariance matrix of any image. According to Tseng [8], pixel-level fusion, image fusion, serves to increase the useful information in an image such that the performance of image-processing task such as segmentation and feature extraction can be improved. In this paper, principle component analysis (PCA) is used to combine the detail coefficients. In our road detection approach, figure 1 gives an overview of the proposed procedure. First, we perform the convolution between the satellite imagery with two masks 3x3(W1) and 5x5(W2). Applied the à trous algorithm to the images, it provides a smoothing effect in each scale. After smoothing the images, the detail coefficients (D1 and D2), possible road pixels, are computed as the difference between the low passed images (O1 and O2) and the satellite imagery (X),



(a) (b)

(c) (d)

Figure 2. Results of experiments (a) original image (b) detail coefficients after combining with PCA (c) final result after using graph searching algorithm (d) superimpose result

$$O1{,}2=\sum_{i=-m}^{m}\sum_{j=-n}^{n}W1{,}2_{ij}\quad X_{ij}, \tag{4}$$

$$D1{,}2=X-O1{,}2. \tag{5}$$

Next, we have to merge the detail coefficients of roads detection using the Principle component analysis (PCA) and labeled the results as D12. For K vector samples of an image, the mean vector can be found from [9],

$$M_D=\frac{1}{K}\sum_{k=1}^{K}D1{,}2_k. \tag{6}$$

The covariance matrix can be obtained from,

$$C_D=\frac{1}{K}\sum_{k=1}^{K}D1{,}2_k\,D1{,}2^T{}_k-M_D M^T{}_D\ . \tag{7}$$

The combination of the detail coefficients is

$$D12=A(X-M_D). \tag{8}$$

where A is a matrix whose rows are formed from the eigenvectors of C_D. We used the first row of the eigenvector that corresponds to the largest eigenvalue.

4. EXPERIMENTAL RESULT

The experiment of road detection is shown in figure 2. After detecting possible road pixels by using à trous algorithm and PCA (figure 2b), we used a graph searching algorithm [10] to identify roads. To create a complete road network, a user selects a start and stop point with a mouse and the road is found between these two pixels (figure 2c). Figure 2d is the superimpose result. Our algorithm was implemented in MATLAB, running on a 1.6GHz Intel Celeron processor, with 256MB RAM. Typical execution time for a 256 X 256 image is about 10 seconds. Most of the running time is dedicated to the graph searching algorithm process.

5. CONCLUSION

In this paper, we proposed a semi-automatic road extraction scheme to detect roads from satellite imagery. The final complete road network is conducted in a semi-automatic way by graph-searching algorithm. We found that our approach leads to an effective and useful method to form the basis of a road detection approach. Also our approach is general and can be applied to other images.

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7. REFFERENCES

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