Reducing Light Change Effects in Automatic Road Detection

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Abstract

Automatic road extraction from aerial images can be very helpful in traffic control and vehicle guidance systems. Most of the road detection approaches are based on image segmentation algorithms. Color-based segmentation is very sensitive to light changes and consequently the change of weather condition affects the recognition rate of road detection systems. In order to reduce the light change effects, a novel Otsu thresholding-based approach for automatic road detection is proposed. Otsu method calculates the optimum threshold value, which efficiently separates the two classes of road parts and non-road parts, so that their inter-class variance is maximal. Conducted experiments confirm the performance of the proposed method for detection of roads in different lighting conditions whilst the experimental images are taken from different geographical areas.

Keywords: *Automatic road detection, Edge detection, Morphological operators, Otsu thresholding method*

1. Introduction

Aerial and satellite images are important sources of information for different fields including geographical applications, weather forecasting, city design and so on.Road detection or in other words, road extraction is one of the most useful applications of aerial images where the road detection can be considered as the first step in the sequence of road extraction process (Figure 1). The geographical information of the roads is used in urban mapping, urban planning, land management and traffic control.

Nowadays, highly accurate road boundaries and vehicle detection are often needed in traffic analysis [1]. The traditional way of traffic analysis relies on manual vehicle counting from aerial images that is a tedious, expensive, inaccurate and time-consuming task, and has to be performed manually [2]. Therefore, the process of road detection and traffic control must become automated with the help of current computer technologies.

Automatic road detection in the digital images has been a major research direction in computer vision field for more than two decades [1]. Variety of approaches have been investigated for road extraction from aerial images. For instance, geometrically constrained template matching [3], active contours or snakes [3-5], fuzzy sets and morphological operators [6-8], semantic networks and genetic algorithm [9], object based approaches [10] and model based approaches [11] are some of the methods, which are used for road extraction.

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An investigation in the road detection research reports, like [2] and [12-19] shows that most of the road detection methods make some assumptions about the characteristics of the road, i.e.:

- roads are elongated,
- road surfaces are usually uniform and homogeneous,
- and there is enough contrast between a road and its neighboring areas.

According to the introduced assumptions, image segmentation is an essential issue in road detection [7], [20] as it is used in the different fields of computer vision such as object detection and object navigation [21] [22]. In the literature, a large number of algorithms for image segmentation have been proposed. Some examples of the approaches for image segmentation include employing thresholding techniques, region growing, split and merge algorithms, watersheds and Markov random field-based models.

Most of the reported studies for road detection employ the color-based features in order to segment the road parts. For instance, [23] uses a back-propagation neural network algorithm for road detection from satellite images for the classification process and classifies each pixel into road and background classes. His work is based on using spectral information by moving a 3×3 window around each pixel, which is extracted as nine red, nine green and nine blue values, after normalizing the RGB values between 0 and 1 for forming input parameters. In addition to previous work, [24] uses RGB color of each pixel as a neural network input feature vector. The work done in [20] uses color-based features for road detection. Instead of other geometry constrains, an adaptive fuzzy decision is also introduced as the clustering method to detect a road in a more effective way.

The disadvantages of color assumptions used in road detection ([8][10][20][24]) and threshold-based segmentations are:

- lack of validation samples for color detection threshold,
- some assumptions are pre-defined and fixed such as color thresholding whereas image road features vary considerably,
- road surfaces are built from various materials that cause change in road color,
- road surfaces may not have enough contrast with neighboring areas due to the road texture and also lighting conditions which depends strongly on weather conditions,
- and different weather conditions, change of lighting conditions and different road textures change the roads color (used in [8][10] [20][24]), so these decrease the accuracy of road detection systems.

In this paper, we investigate a new road detection method based on Otsu thresholding to resolve the discussed problems. The method has a low process runtime, which is able to detect a road in different lighting conditions. The main contribution of the paper is employing Otsu thresholding method in order to segment the road part by an optimum threshold value. The basic idea of Otsu automatic thresholding is to automatically select an optimal gray-level threshold value for separating objects of interest in an image from the background based on their gray-level distribution. According to the characteristics of the Otsu thresholding, it is expected that the experimental results of the proposed method can show that it can work with a low runtime overhead and with an acceptable recognition rate in different lighting conditions.

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2. Proposed Method

In this paper, a new automatic road detection approach is presented. The method is applied to a set of high-resolution aerial images. Due to the unique characteristics of the aerial images that are taken in different areas with variation of lighting, the approach contains a sequence of image processing and machine vision techniques. First, for enhancing edges and smoothing non-edge pixels, a nonlinear filter is employed as a preprocessing step. Then an Otsu thresholding method is used to distinguish the road and the surrounding area by finding the optimum threshold value. After finding the approximate area of the road, edges are detected using Canny edge detector and then the segmentation result is improved by using morphological operations. Finally, the road boundaries are detected by using the edges length and a heuristic operator. This section is continued by describing the proposed algorithm steps.

2.1 Removing image inequality

In first step, a nonlinear filter is employed to modify image surface roughness by removing roughness in non-edge parts while keeping edges in road parts. First, eight derivatives of each pixel is calculated in all directions for combining and adding to the pixel value. Figure 2 shows the pixel at (n, m) and its eight neighbors. Equation (1) computes the derivative of pixel neighbors. In this equation, I_i represents the gray level of i*th* neighbors of the pixel at (n, m). After calculating derivatives in all directions, these values are multiplied by the coefficient δ and are added to the pixel value (equation (2)). As shown in equation (2), the proposed filter includes three parameters (K، α عکع δ). [illegible] ۰.۲، ۲.۵ عکع 1.25 respectively based on empirical experiments.

$$\delta_i = I_i - I(n,m) \tag{1}$$

$$I(n,m) = I(n,m) + \delta\{\frac{\delta_1}{1+\left|\frac{\delta_1}{K}\right|^{\alpha}} + \ldots + \frac{\delta_8}{1+\left|\frac{\delta_8}{K}\right|^{\alpha}}\} \tag{2}$$

As mentioned above, the filter removes non-edge surface roughness while keeping the real edges in the road segments. Based on discussed equations, if derived value in the edge pixel is larger than parameter K, then the absolute operand is greater than one.When a large value is assigned to $\left|\frac{\delta_1}{K}\right|^{\alpha}$, it can change only a little of an edge pixel intensity value. Therefore, the filter has no effect on the edge pixels. On the other hand, as the absolute value of $\left|\frac{\delta_1}{K}\right|^{\alpha}$ is smaller than one for non-edge pixels, it can be ignored. Thus, equation (2) in limit case is a Laplace filter for non-edge pixels and acts as a smoothing filter for edge pixels. In addition, this nonlinear filter can be applied on the image for more times. Figure 3 shows what happens in the edge and non-edge areas, when the filter is employed on an image more than once. The images obtained after each iteration are displayed in Figure 3.

As Figure 3a shows, non-road areas that are essential for this project are quite non-uniform and in some parts the non-road area intensity is the same as the road. Thus,

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transformation is needed for converting these regions to uniform regions. It is not possible to use a smoothing transformation because it causes loss of road edges that are useful for this application. Figure 3b shows that this filter can smooth the non-edge surfaces by a little.By repeating the filter on the image, in Figure 3c and 3d, smoothness of non-edge pixels is more evident.

2.2 Image segmentation and improvement

Image intensity-based machine vision approaches are the most common methods to find the probable areas of road from aerial images [1]. The luminance of road pixels is usually close to the others, so it is possible to find an appropriate threshold value and segment the road in aerial images.The parameters and threshold value used in each method are selected experimentally, which are sensitive to image acquisition conditions and lighting of the area when the images are taken.

In this paper, in order to separate the road region from the background automatically, we apply Otsu [25] method to the aerial images. In other words, Otsu's method is used to perform histogram-based image thresholding automatically, that assumes that the image to be verged contains two classes of pixels by using a bimodal histogram.

This method calculates the optimum threshold value that efficiently separates these two classes, so that their inter-class variance is maximal [26]. The advantage of the proposed method comparing to the similar approaches is the low sensitivity of the method to light changes, so that it yields the same segmentation area in different lighting condition.

Figure 4a and 4b show two example images verged by Otsu method. After segmentation using Otsu method, a morphological operator is used to improve the segmentation areas (see figure 4c and 4d).

2.3 Edge detection

Edges occurring in a digital image provide important information about the objects existing in the image. In other words, edges are the boundaries between the image objects and also the boundaries between an object and its background in the image. A pixel is classified as an edge pixel when the magnitude of the derivative of the image intensity function is relatively higher than the same function value at the neighborhood of that pixel [27].

A number of methods for edge detection are available in the literature such as Sobel, Prewitt, Canny, Susan, Laplacian, Gaussian and Kirsch detectors [28][29]. The Sobel, Prewitt and Kirsch detectors are simple for implementation but they are usually highly sensitive to noise and are consequently inaccurate. In order to reduce the undesirable negative effects of noise, the Gaussian edge detectors try to smooth the image before performing edge detection [28]. The Canny detector, which is a Gaussian edge detector, is one of the most popular edge detectors in the literature.

After segmenting the aerial image using Otsu thresholding method, Canny edge detector is used to detect image edges. Figure 5 shows the output images after applying the Canny edge detector on images in Figure 4c and Figure 4d. As one can see in Figure 5, the results of the edge detection operator are very precise. After finding probable edge of the road, a heuristic operator is employed to remove non-road edges.As the roads are elongated in aerial images, the number of pixels associated with the non-road edges is low. Therefore, removing the edges which are with the number of pixels less than a defined threshold is a good heuristic operator.

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Many of the road detection methods, after edge detection step, try to detect lines using Hough transform and consider them as roads. Because the Hough line detection algorithm has high running time, the proposed heuristic algorithm reduces search space and running time. Low runtime of the algorithm makes it suitable for real-time applications.

3. Experiments and results

The proposed method is applied to experimental images taken from Google Earth software [30] in order to analyze its performance for road detection. The aerial images for the experiments are from different geographical areas, which are taken in different time of day with different sun light conditions. Figure 6 shows the experimental results obtained by applying the proposed method on the selected images.

As one can see in Figure 6, some failures happen where some parts are not detected as the road and some parts of the non-road area are detected as a road. At the stage of improving the image segmentation, a simple morphological method is employed in order to reduce execution time. Although in stage of improving the image segmentation, it is possible to achieve the best results by using the erosion linear element structure with angles from 0 to 180 degrees, it is not used due to time complexity. The use of erosion by linear element is not reasonable in real-time applications because achieving less computing time is more important and economical than more accurate detection rate. Thus, future research can involve the usage of image erosion with linear elements, while reducing the time complexity by modifying and improving the proposed method for aerial urban images.

As it is mentioned earlier, due to the reason that the aerial images are taken in different lighting conditions of different areas, the applications designed to work with such images have to be invariant to lighting changes. The Otsu's method is expected to be able to adapt itself to the light changes by selecting the best threshold value in each aerial image. So, in order to watch how the proposed method act with an aerial image taken in different light conditions, the experiments have been conducted to see the output images after applying the proposed method on the images which are taken from an area in different times of a day. The experiments show that Otsu thresholding method is not sensitive to light changes and in different lighting and weather conditions correctly detects the road area (Figure 7). In Figure 7, three images with different light conditions and the corresponding output results of segmentation by applying the proposed method are shown.

Results of various experiments show that the proposed method compared to the other research reports in road detection like [8][10][20][24] has lower execution time and also is more stable against changes in lighting conditions. The running time of about 68 milliseconds for the images with the size of 800×600 pixels provides the proposed method with being applicable for real-time applications.

4. Conclusion

This paper proposes a new method for automatic suburban road detection in aerial images. Although most of the previous methods for road detection are based on using color and texture of the road, they have a big disadvantage, i.e. the light change effects on recognition rate of the classifier and also the fact that the threshold value for

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segmentation must be set manually. In contrary, this paper tries to segment a road from the background using Otsu Thresholding method, which is invariant to lighting conditions that are strongly dependent on the area of the road and the time of capturing the aerial images. Furthermore, due to the setting of the threshold value automatically, the proposed method can be employed in real-time applications.

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Figure 1. Color image from Google Earth used in this research.

I_2	I_3	I_4
I_1	$I_{n,m}$	I_5
I_8	I_7	I_6

Figure 2. Pixel (n, m) and 3×3 neighborhood.

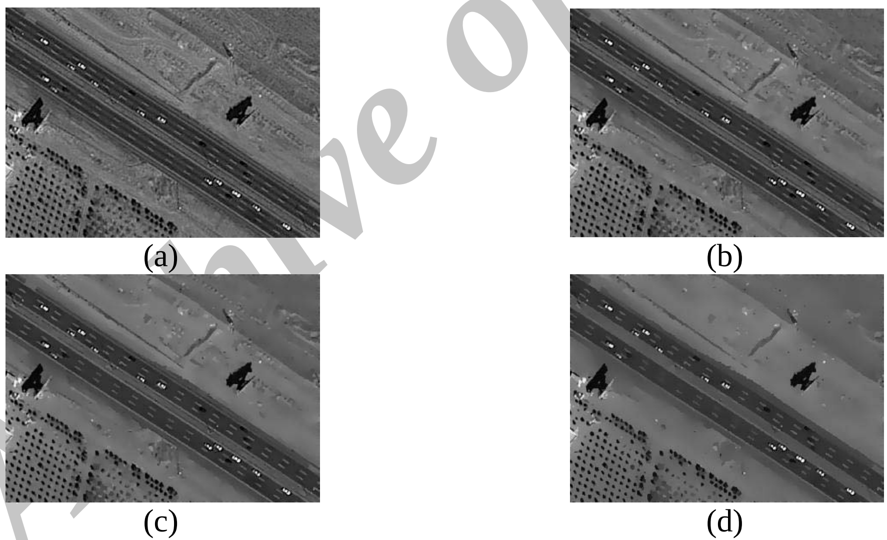

Figure 3. Results obtained from the nonlinear filter applied on the road image. (a) Original image (b) Filtered one time (c) Filtered twice (d) Filtered five times.

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(a) (b)

(c) (d)

Figure 4. Binary images verged by Otsu's method and improved it (blank pixels representing the road region pixels), (a) verged intensity image Figure 3b, (b) verged intensity image Figure 3d, (c) improved image Figure 4a, (d) improved image Figure 4b.

(a) (b)

Figure 5. Results from applying the Canny edge detector. (a) From image Figure 4c (b) from image Figure 4d.

Figure 6. Detection results using proposed method.

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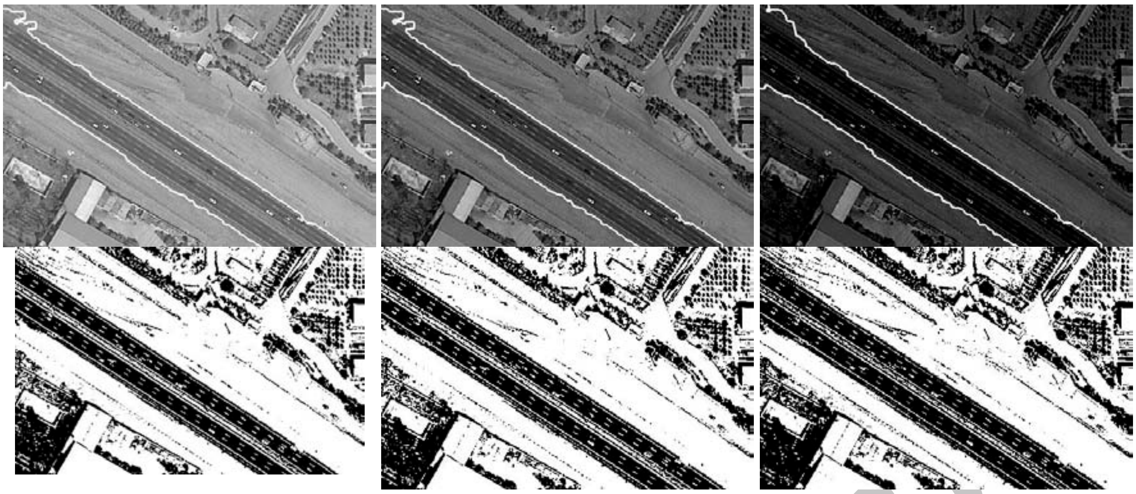

Figure 7. The correctly detected road areas in different lighting conditions using the proposed method.

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