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Automatic Vehicle Speed Estimation Method for Unmanned Aerial Vehicle Images

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Abstract. *This paper presents a solution to solve the detection and estimating the speed problem for road vehicles in images acquired by means of unmanned aerial vehicles (UAVs). UAV photographing which can conveniently take vehicles picture and save time for setting up fixed cameras have become an important part of the intelligent transportation system (ITS). UAV images are characterized by a very high spatial resolution (order of a few centimeters), and consequently by an extremely high level of details which call for appropriate automatic analysis methods. The proposed method starts with the hue, saturation, and value (HSV) color space transformation in order to reduce the influence of light change, and uses the saturation features to remove shadows in the aerial images. Then, it performs a temporal difference process to separate moving objects (vehicles) and backgrounds. The last step of our method is focused on finding out the centroid of vehicles and the moving distance expressed in pixels, and in the end the road lane is used as a scale to estimate the speed of vehicles. The experimental results show that this method performs well in 20 meters to 40 meters in height, and the vehicle speed calculation error is less than 3.47%.*
Keywords: Unmanned aerial vehicle (UAV), Speed estimation, HSV color space, Temporal difference

1. **Introduction.** In the recent years, the increase in vehicle population has resulted in serious traffic congestion in the urban roads all over the world. Traffic congestion reduces the efficiency of the traffic system and increases the travel time, a high level of road traffic is strictly result in car accidents and pollution problems as well. The direct traditional approach to reduce congestion is the expansion of infrastructure. However, infrastructure expansion is of limited scope because of its high expense and large space requirement. A relatively recent alternate approach to tackle this situation is to go for better management of the existing infrastructure such as by using Intelligent Transportation System (ITS) applications. Modern technologies are applied to ITS to improve the efficiency of traffic.

ITS includes various applications such as Advanced Traveler Information System (ATIS), Advanced Public Transportation System (APTS) and Route Guidance System (RGS), which can provide useful information to the road users regarding congestion, accidents, delays, etc. [1]. If the traffic information is obtained from the ITS, the traffic management unit can easily plan alternative routes or increase manpower to divert traffic. In addition, the driver can also use this information to change the route or choose to avoid traffic spikes, reduce traffic congestion or fatigue driving condition [2, 3, 4, 5, 6].

Traditionally, many kinds of fixed ground sensors, such as induction loops, bridge sensors, stationary cameras, and radar sensors, are applied to gather traffic information [7, 8]. By using these fixed ground sensors, the traffic flow, vehicle density, and driving speed, parking situation are partially acquired. However, these methods fail to provide a complete overview of the traffic situation, which is very important for ITS to make exhaustive decision.

Remote sensing images captured by satellites [8, 10] or airplanes precisely meet the demand for gathering an overview of traffic situations, on the other hand because of shooting down from the top, the problem of big vehicle partially covering small one that results in the vehicle detection error with the traditional stationary cameras can be avoided. Due to these advantages, remote sensing images have been widely applied for monitoring vehicles [9, 10]. Compared with satellite images, aerial images are more attractive for traffic monitoring because: First, aerial images have useful high spatial resolution ranging from 0.1 to 0.5 m [11, 12]. Because of this, vehicles, even small cars, can be clearly identified in aerial images. Second, aerial images are easier to acquire [13]. Third, aerial images are convenient especially in emergency situations which need to arrive and monitor specific roads timely. Today, local administrations have exploited aerial image technologies to detect vehicles and generate ITS management information [14].

In the current literature, it is possible to find several vehicle detection techniques considering both low and high resolution images. For instance, Zhao and Nevatia [15] present a system to detect passenger cars from aerial images taken along roads, where cars appear as small objects. Moon et al. [16] perform an end-to-end analysis of a simple model-based vehicle detection algorithm for aerial images of parking lots. Schlosser et al. [17], by using an adaptive 3-D model, introduce an automatic approach to detect vehicles in monocular high-resolution aerial images. Wang [18] proposes a vehicle detection algorithm based on an improved shape matching algorithm. In [19] the authors present a novel technique to detect vehicles on high- way based on a gray scale morphological algorithm combined with a road layer to improve the performance. In [20] the authors exploit a combination of a boosting technique and the histogram of oriented gradient (HOG) features to make the method faster. Moranduzzo et al. [21], by using a feature extraction process based on scalar invariant feature transform and a support vector machine classifier, represent a one key point-one car method in car detection and calculated the number of cars through final key points identified. Chen et al. [22] presents an algorithm for vehicle detection in high-resolution aerial images through a fast sparse representation classification method and a multi-order feature descriptor that contain information about texture, color, and high-order context. Overall, UAVs have demonstrated to be a rapid, efficient, cost-effective acquisition system to collect sequences of remote sensing data. For their capacity to acquire extremely high resolution images over specific areas, UAVs are a suitable technology to monitor the traffic in urban scenarios.

Comparatively, in the literature, it is possible to find only very few paper which deal with the estimation of vehicle speed from aerial images. Yamazaki et al. [23] suggests deriving the speed of cars by exploiting the shadow of cars. In [24] the authors explore the use of a set of invariant features (i.e. SIFT features) to locate the vehicles and to estimate their speed in two successive UAV images. The problem of vehicle speed estimation from remote sensing images is less debated mainly because of two reasons [24].Until a short time ago, there were only few devices which allow the acquisition of sequences of images over the same area and the identification of the spatial position of the vehicle in low resolution images is rough, thus an estimation of the vehicle velocity is inaccurate. With the advent of extremely high resolution images, the determination of the precise spatial position of the objects in two different times became feasible; therefore the vehicle speed estimation problem has started to be taken into consideration.

In this paper, we propose a method to detect vehicles and estimate the vehicle speed for aerial images acquired by means of the UAV sensor. The road lane is used as a scale for the purpose of reducing the error influences in UVA flight altitude pressure. Temporal difference method is used to separate moving objects (vehicles) and backgrounds. By finding out the centroid of vehicles and calculate the moving distance expressed in pixels, speed of vehicles are estimated more accurately.

This paper is organized as follows: Section 2 describes the proposed methods to detect the moving vehicles and estimate the speed. In Section 3, we present the estimation results obtained on a real case. Section 4 is devoted to the conclusions of this paper and to future developments.

2. Proposed Method.

2.1. Image Preprocessing.

The image processing algorithms used in this paper include foreground extraction, color space conversion, image binarization, edge detection, morphology, horizontal projection and region of interest (ROI). The procedure of each method is discussed in more detail in the following text.

We use the method of temporal difference [14], which is not affected by the motion of the UAV camera, and not resulted in judging moving object failure, for the foreground extraction. By using this method, we can obtain the moving object information more completely.

In order to reduce the influence of light intensity, this paper converts the RGB color space form of images to the HSV color space ones, and uses the saturation features to remove shadows in the images.

For the purpose of reducing the number of scattered areas of the images, the morphology operation [1] methods are adopted to enhance the binary images. Firstly, we set the structuring element (SE)'s size and shape, then we make the small binarization areas composite or deleted according to the morphological algorithms. The basic morphological algorithms include: dilation and erosion; opening and closing, which are derived from the combination of the first two algorithms (dilation and erosion).

The procedure of horizontal projection [20] is projecting the object in the image of the vertical axis firstly, and then summing up all of the pixels along the column. Horizontal projection is used in this paper to determine how much percentage of the whole image the lane occupies in vertical axis, and further to determine the range of each lane and set the ROI. The lane horizontal projection result is shown in Figure 1 (a), in which there are eight extremes with large numerical variation. It is obvious that the values between the lane positions vary regularly. For example, positions (row 198, 268 and 333) represent the fast lane marking and lane separation line with almost the same width of vertical distances (70 and 65). We use this regularity feature to map the lane centerline and the lane region for later processing. Figure 1 (b) illustrates the corresponding binary image of the lane.

There may be only a small area containing the valuable data information throughout the whole image, processing the whole image needs lots of time, and even results in serious misjudgment caused by the noise interference in regions where include no valuable information. Therefore, we only choose a specific region of the image as the ROI. Figure 2 shows the ROI results for the screen size of 960*540 pixels. To capture the vehicles through the screen, we use the results of the horizontal projection of the location of the road marking to set an ROI. The detailed approach is as follows: the Y direction of ROI is set to the horizontal projection of the road center line plus and minus the lane width; the X direction one is fixed to subtract 10 percent of the left and right sides of the deformation region of the image. The ROI region marked by a red line is showed in Figure 2, and it is only 27.85 percent of the original image in the size of 768*188 pixels. Through setting the ROI, we can remove the serious deformation regions simultaneously to achieve a higher accuracy.

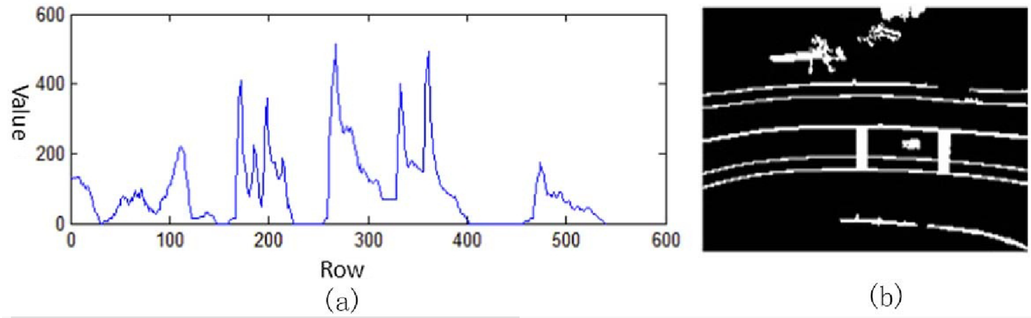

Figure 1. Horizontal projection results. (a) Horizontal projection of the lane. (b) Binary image of the lane

2.2. **Feature Extraction.** Feature extraction, mainly used to distinguish between different objects in the image, has three common characteristics: color, size and texture. In this paper, we use the size and the length/width ratio of moving an object to focus on a vehicle. The vehicle centroid calculated result is shown in Figure 3. Firstly, continuous

Figure 2. ROI result

image subtraction method is used to obtain the foreground image. Then, we capture the ROI region and binarize the image in order to restrict the areas where detecting vehicles thus reduce the probability of false alarms. By using the morphology to remove noise and repair images, we can get more complete foreground image. The third step of our procedure is focused on how to label the areas which are connected with each other as one object in the foreground image by using connected component labeling (CCL) algorithm. At the end of the procedure, the centroid of each vehicle, which can be used for calculating the vehicle speed, is additionally found out in the ROI.

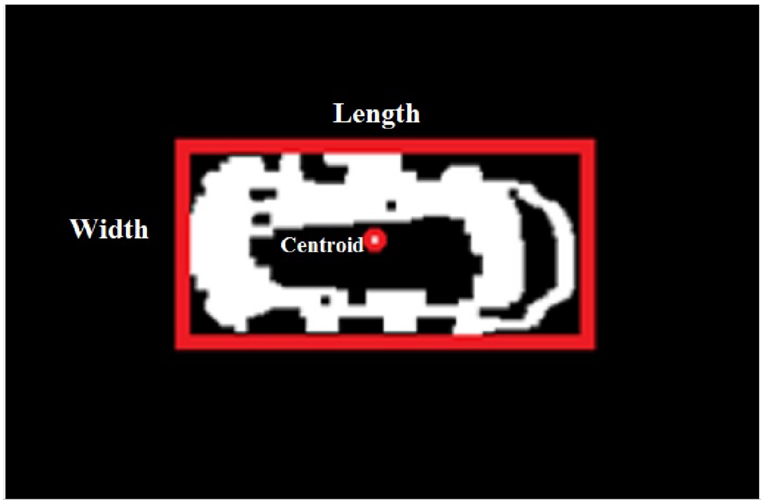

FIGURE 3. Vehicle centroid

2.3. **Moving Object Classification.** Since there are other kinds of moving objects such as human and animals which are not our interests for vehicle detection, we should carry out the moving object classification first to exclude the non-vehicle moving objects before the vehicle speed estimation.

In this paper, the length and width of the connected area are considered as an important basis in moving object classification. The classification rule is: we first determine whether the moving objects width (see Figure 3) is more than one-fourth of the lane width, which is calculated from the horizontal projection method, to verify a vehicle. Then the aspect ratio of the vehicle is used to determine the vehicles category. The procedure of determining the vehicle category is: If the aspect ratio is between 1.5 and 3 times, it will be regarded as a vehicle, this range represents small vehicles (locomotives, bicycles, etc.) and medium-sized vehicles (minivans, cars, Recreational cars, etc.). Vehicles, whose width is greater than half the width of the lane and the aspect ratio is more than 3.5 times, is regarded as large vehicles (including buses, big trucks, etc.), the objects that do not meet the above conditions are determined as non-vehicle moving objects. This method eliminates most of the blurring factors caused by the UVA swaying or road trees and other non-vehicle moving objects effects.

2.4. **Vehicle Speed Calculation.** In the current literatures the speed is calculated mostly through the coordinate plane transformation, which must first set up a reference point in the real world, and then judge the reference point position in the image and enter their relative position in the real world information, through the three-dimensional coordinates transformation, calculate how long distance the vehicle has moved in the image, and according to the speed formula, calculate the speed of the vehicle. However, because of the time-consuming parameters, and thus losing the importance of the use of UAV mobility and convenience, this paper proposes a more convenient and rapid calculation method, which uses the lane width as a scale to calculate the actual moving distance.

The proposed method firstly determines whether the moving object is the estimating target according to the classification rule illustrated in section 2.3. If we focus on one estimating object, we calculate the centroid of the target to define the object position in the image (see Figure 3). Compared the positions of vehicle centroids in two consecutive frames (In the experiment, we choose the time interval for 0.5 seconds.), the moving distance of the vehicle can be estimated (in pixels). Moreover, since we can detect the actual lane width (in kilometers) with some sensors, the actual distance (in kilometers) represented by per-pixel can be calculated from horizontal projection method mentioned in section 2.1 by using the lane width as the scale. The vehicle moving distance (in pixels) is multiplied by the actual distance (in kilometers) about per-pixel and then we calculate the actual vehicle moving distance. If the distance is divided by the time interval (0.5 seconds), we can estimate the speed of vehicles.

3. **Experimental Results.** In this section, we show results obtained by using the proposed technique on a sequence of images acquired over different altitudes. In the end of this section, we actually drive a vehicle to test the accuracy of the speed estimation method. To illustrate speeds are estimated more accurately on our proposed method, we proposed the experimental results on traditional method in the same experimental condition as well.

FIGURE 4. Mobile phone APP interface

3.1. **Experimental Platform and Environmental Parameters.** In order to validate our methodology, we tested the whole vehicle speed calculation process on a real scene. We acquired such scene using a UAV equipped with imaging sensors shooting the visible range. The UAV used in the experiment is: DJI PHANTON2 Vision +, whose GPS positioning function can effectively reduce the requirements for manipulation technology. We also can monitor the current UAV speed, height, and the camera's photographic images and other information in the mobile phone APP interface (see Fig.4). The images were acquired over the Baoshan road in Changhua city (Taiwan) on November 22, 2016, at 12:00 A.M. The images are characterized by three channels (RGB). All the acquired images have sizes of 1920 * 1080 pixels and 30 frames per second (FPS), but in order to enhance the calculating speed we reduce the resolution to 960 * 540 pixels. The experimental development platform is MATLAB 2016b. We capture one image every 15 frames, that is to say we capture two images per second for processing. The images were taken at altitudes of 20m, 30m and 40m respectively, in order to test the results of this method at different heights.

3.2. **Results and Analysis.** Several speed estimated results captured from each experiment in different altitudes are displayed in Figure 5 for the actual driving speed of 40km/h. We proposed three speeds estimated results in different altitude.

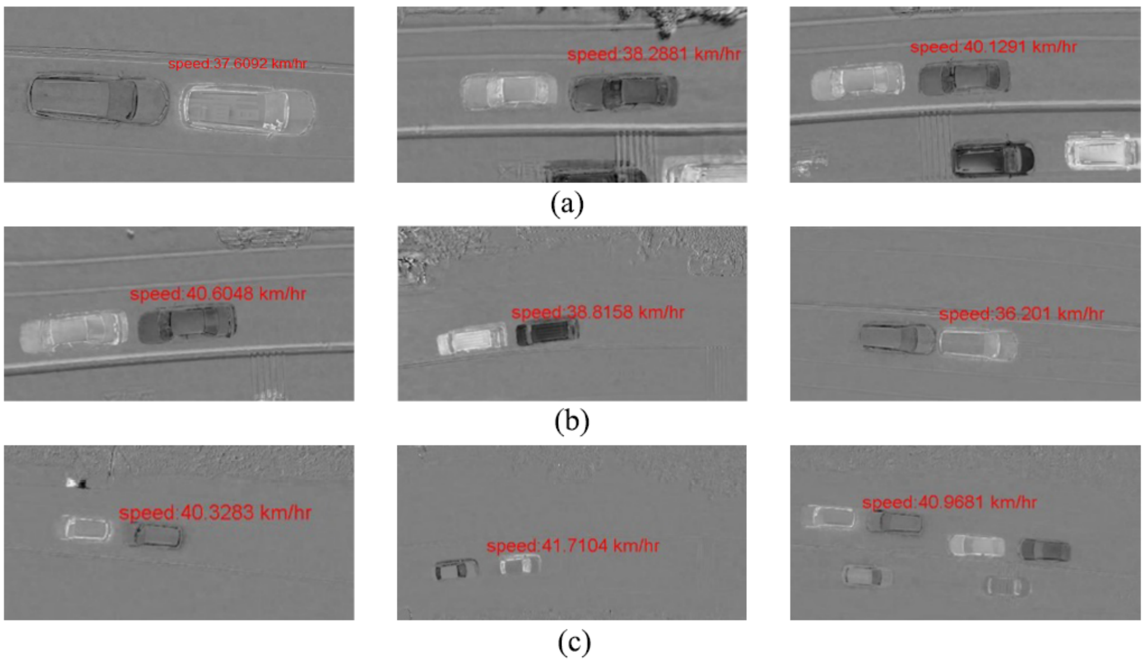

FIGURE 5. The proposed speed estimated results of (a) 20 meters, (b) 30 meters and (c) 40 meters.

From the estimated accuracy analysis results (Table 1), the average relative errors at the altitude of 20 meters and 30 meters are 3.52% and 4.65% respectively, the least average relative error 2.25% appears at the altitude of 40 meters. Integrating the above analyzed results, we got the total average relative error of 3.47%.

To illustrate speeds of vehicles are estimated more accurately with our proposed method, the comparison results with the traditional speed estimated method which use the UVA flight height as the scale to calculate the actual moving distance per-pixel are proposed in Figure 6, and the accuracy analysis is reported in Table 2. In traditional method, the moving distance about per-pixel is estimated according to the different flight height measurements which is susceptible to air pressure, because of this, the estimation error is very large. The total average relative error on traditional method is 11.77%.

4. **Conclusions.** In this paper, we presented a method to detect vehicles and estimate the vehicle speed for aerial images acquired by means of a UAV sensor. The road lane is used as a scale for the purpose of reducing the error influences in UVA flight altitude pressure. Temporal difference method is used to separate moving objects (vehicles) and backgrounds. By finding out the centroid of vehicles and calculate the moving distance expressed in pixels, speed of vehicles are estimated more accurately. The experimental

Table 1. Speed estimated accuracy on proposed method

Altitude (meters)	Results (km/h)	Relative error(%)	Average relative error (%)	The total average relative error (%)
20	37.6092	5.98	3.52	3.47
	38.2881	4.28		
	40.1291	0.322		
30	40.6048	1.51	4.65	
	38.8158	2.96		
	36.201	9.49		
40	40.3283	0.08	2.25	
	41.7104	4.27		
	40.9681	2.42		

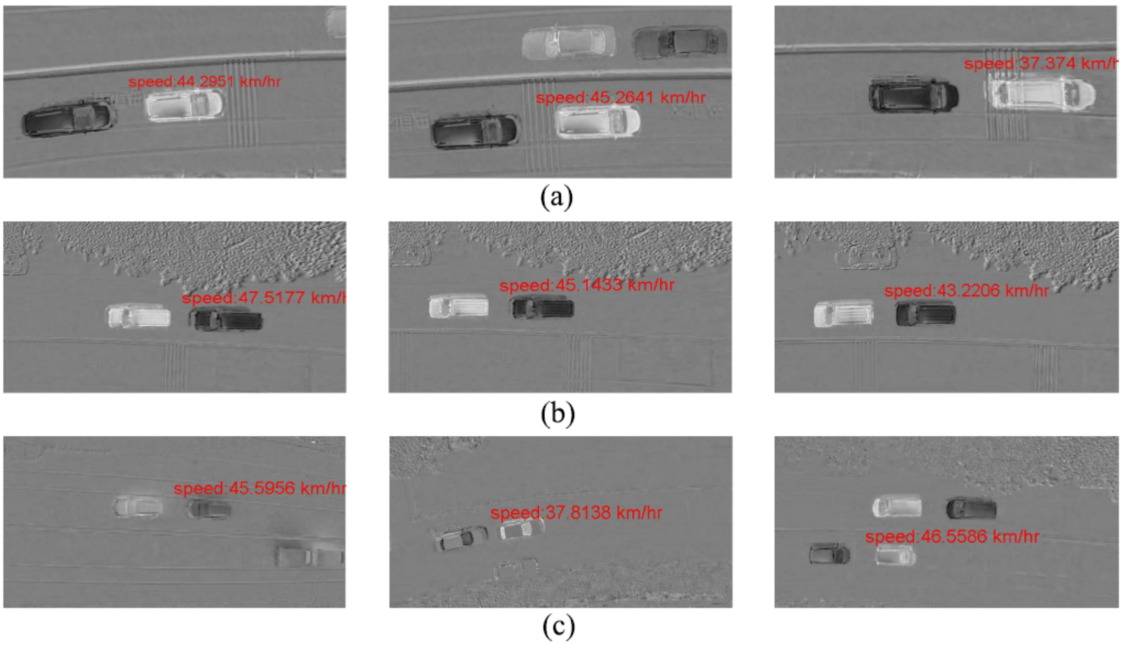

Figure 6. Traditional speed estimated results of (a) 20 meters, (b) 30 meters and (c) 40 meters.

Table 2. Speed estimated accuracy on traditional method

Altitude (meters)	Results (km/h)	Relative error(%)	Average relative error (%)	The total average relative error (%)
20	45.2641	13.16	10.15	11.77
	44.2951	10.73		
	37.374	6.57		
30	43.2206	8.05	13.23	
	45.1433	12.85		
	47.5177	18.80		
40	45.5956	13.98	11.94	
	46.5586	16.39		
	37.8138	5.44		

results prove that our method can achieve moving vehicle detection accuracy and the average relative error is less than 3.47%. The approach presented in this paper is able to quickly process real data, which will enable moving vehicles speed estimating to be performed automatically by UAVs, moreover, it is more convenient for planning and analysis of surrounding transportation for big event without taking time to set up a fixed camera or to mark a feature point on a road.

Future work realistic therefore focuses on the proposed technique works more accurately. Starting from this work, it is possible to identify several developments to make the method more stable for all possible altitude. Especially, the lane width calculating which is of main importance to correctly extract the differences could be improved to obtain better results even if the considered images are acquired with larger temporal difference.

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