Traffic Density Measurement by Automatic Detection of Vehicles Using Gradient Vectors from Aerial Images

Saman Ghaffarian, Ilgın Gökaşar

Abstract—This paper presents a new automatic vehicle detection method from very high resolution aerial images to measure traffic density. The proposed method starts by extracting road regions from image using road vector data. Then, the road image is divided into equal sections considering resolution of the images. Gradient vectors of the road image are computed from edge map of the corresponding image. Gradient vectors on the each boundary of the sections are divided where the gradient vectors significantly change their directions. Finally, number of vehicles in each section is carried out by calculating the standard deviation of the gradient vectors in each group and accepting the group as vehicle that has standard deviation above predefined threshold value. The proposed method was tested in four very high resolution aerial images acquired from Istanbul, Turkey which illustrate roads and vehicles with diverse characteristics. The results show the reliability of the proposed method in detecting vehicles by producing 86% overall F_1 accuracy value.

Keywords—Aerial images, intelligent transportation systems, traffic density measurement, vehicle detection.

I. INTRODUCTION

THE location and movement of the vehicles are necessary for monitoring traffic flow on road/street networks. Currently, the traffic statistics are measured based on location depended methods such as loop inductions and Remote Traffic Microwave Sensors (RTMSs); however, traffic density is an area-based measurement. On the other hand, remote sensing provides geo-information by acquiring signals for large areas from a distance. Recently, developments in remote sensing technologies enable gathering information of very large area like cities at a time as images. These images enable mapping very large areas. Moreover, very high spatial resolution remote sensing imagery produce images with spatial resolution below one meter. Consequently, extracting information within the roads/streets such as vehicles in addition to road/street network features becomes possible.

In recent years several studies have been conducted to detect vehicles from aerial images. Reference [1] used edge map that produced by Canny edge detector, and match contours considering edge results to generate an on-line learning model. Then, [2] used Canny edge detection results to compose a car model with regard to the size and shape of an average car. Reference [3] developed a simple and fast

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method. However, their proposed method only considers perfect rectangular shaped vehicles, which causes several failures in final results. Further, [4] developed a Bayesian Network model for complex models using several features such as vehicle boundaries, shadow and windshield. Another Model-based method was proposed by [5] utilizing radiometric features along with geometric features of the vehicles. His developed method fails where the vehicles were not modeled due to lack of radiometric and/or geometric information.

Reference [6] developed a method which starts by extracting road regions using color histogram. Then, a dynamic thresholding is performed for sophisticated blobs extraction technique to detect vehicles from previously extracted road regions. Further, [7] utilized fusion of the density and symmetry properties of blob-like cars along with mean-shift algorithm to achieve efficient extraction of road regions. Reference [8] used fuzzy set and optimization based classification method to detect and classify the vehicles. Besides, high resolution satellite images were used in a framework to detect cars by [9]. They utilized geometric, spectral and color distribution properties of cars in an extended image descriptor method.

Recently, by developing Unmanned Aircraft Vehicles (UAVs) some studies have been conducted to detect vehicles from these images [10], [11]. Besides, [12] developed a method using Digital Elevation Model (DEM) to initially extract the roads. Then final vehicles are detected based on region growing and Histogram of oriented Gradients (HoG) integration method. Their proposed method was detected approximately 70% of the vehicles. In addition, [13] boosted the machine learning-based classification method using HoG and Haar-like features and Local Binary Patterns (LBP) so as to efficiently detect vehicles. In a different study, [14] proposed a method based on a machine learning algorithm and a Digital Surface Model (DSM). Then, [15] used adaptive boosting technique in their developed method.

Most of the past studies start their methodology with extracting road regions from the image, which leads to some errors in final vehicle detection results. In addition, nowadays all the cities have Geographical Information Systems (GIS) databases which include road vector map data sets. Therefore, to improve the accuracy of the vehicle detection results, road regions are extracted considering vector map data. Moreover, diversity of the colors of the vehicles in the image leads to method failures in detecting vehicles in past studies. Thus, in

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this study, color of the vehicles is only used to generate Gradient vectors map, which is not consider the variousity of the color combinations within image. After extracting road regions and generating gradient vectors map, the image is divided into equal sections considering resolution of the image, which is 30 cm in this study, and small car length. Eventually, vehicles are detected and counted on the section boundaries by calculating complexity of the gradient vectors on the boundary lines.

(a)　　　　　　　　　　(b)　　　　　　　　　　(c)
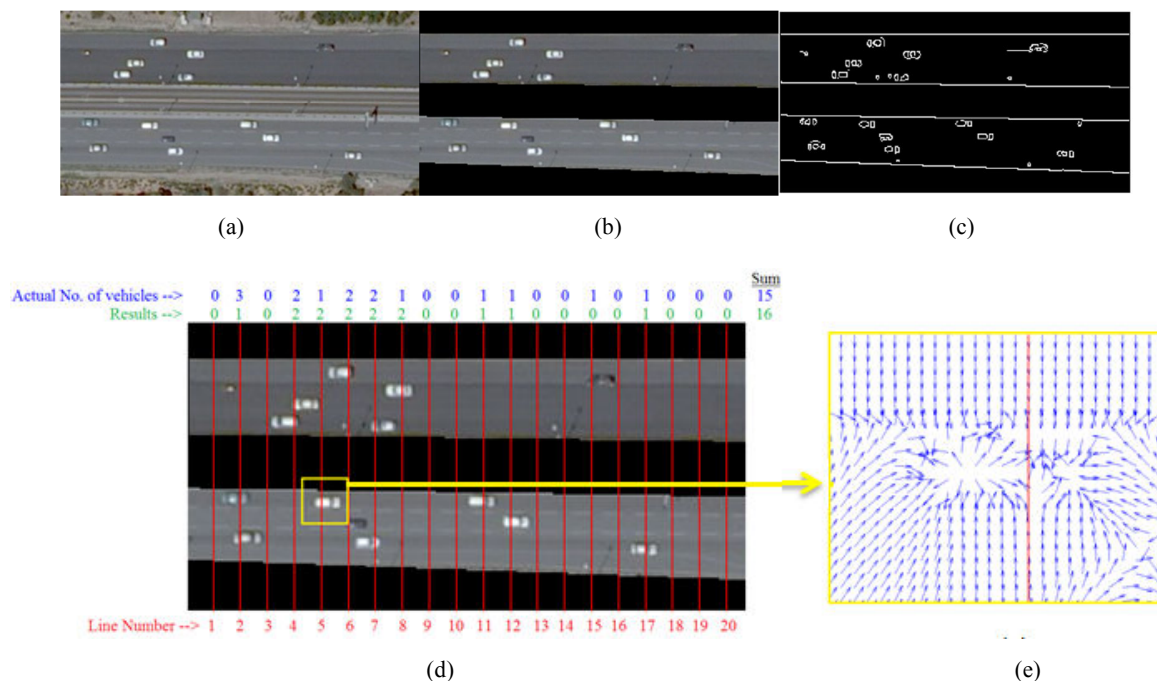

(d)　　　　　　　　　　　　　　　　(e)

Fig. 1 Steps of the proposed method, (a) original Image, (b) ROI image, (c) edge map, (d) divided image with corresponding line number and developed vehicle detection results for each division, (e) generated Gradient vectors map for denoted region for test image #1

II. METHODOLOGY

The proposed traffic density measurement by automatic detection of vehicles from aerial images has five main steps as follows:

A. Region of Interest (ROI) and Road Extraction

Almost all of the road databases in big cities such as Istanbul are generated and stored as coordinated vector data for traffic and transportation engineering, urban planning and other applications. Therefore, in this study, road vector maps are used to extract ROI and road regions from aerial images as first step (Fig. 1 (b)).

B. Edge Detection and Gradient Vectors Map Generation

Due to have regular and noiseless gradient vectors, the gradient vectors of the images calculated from edge detection results. Edge map of the image are computed using Canny edge detector [16] as one of the well-known and popular edge detection methods in image processing applications (Fig. 1 (c)). Canny edge detection starts by smoothing the image using Gaussian Filtering which leads to reduce image details such as noises. Then compute gradient magnitude and direction at each pixel. To determine edge pixels the gradient magnitude at a pixel considered and when its magnitude is larger than those at its two neighbors in the gradient direction marks as edge pixel. Otherwise, mark as non-edge pixel. Finally a hysteresis thresholding is implemented to remove the weak edges. Two threshold values are also existed in the method to control the density of the edges considering sigma (variation) and length of the weak edges.

After detecting edges, corresponding gradient vectors of the edge map is generated for each pixel as gradient magnitude and direction in order to be used in further steps of the proposed method.

C. ROI Division

Spatial resolution illustrates the size of each pixel of the image on the ground. Furthermore, average length of the vehicles (cars) in the cities considered as 5 meters. However, experiments on the images and results demonstrated that one meter change in this approximate value does not have significant effects on the final results but, it should be defined between 4-6 meters to obtain appropriate results. Thus, considering spatial resolution and average length of a vehicle the ROI image is divided into equal parts with a width equal to predefined vehicle length value (Fig. 1 (d)).

D. Vehicle Detection and Counting

The complexity of the gradient vectors is used to make decision whether there is/are vehicle on the boundary line of each section of the ROI or not. To do so, firstly pixels on the corresponding boundary line of the section are grouped and divided where the gradient vectors considerably change their direction. This step uses a threshold value divide pixel or pixel

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groups where the change in direction and magnitude of the gradient vectors on the line is above threshold value. Then each group is considered as an object and the standard deviation of each object (pixel group with gradient values) are calculated. Finally, an object/group is accepted as vehicle when the standard deviation of the gradients of the object is above the threshold value for standard deviation. As it can be seen from Fig. 1 (e) gradient vectors generally on a regular basis unless there is a vehicle in that part of the image.

E. Traffic Density Measurement

Traffic density is computed as unit of vehicle per km or mile. Furthermore, as we know the spatial resolution of the image, the approximate length of the ROI of road image can be estimated. Thus, after counting the vehicles on the ROI a simple unit transformation is conducted to compute traffic density as vehicle/km unit (Table I).

III. RESULTS AND DISCUSSIONS

A. Study Area

The proposed method was tested on four aerial images with 30 centimeters spatial resolution, and three bands (RGB) which were acquired from Istanbul, Turkey. The test images and vehicle detection results are provided and illustrated in Fig. 2.
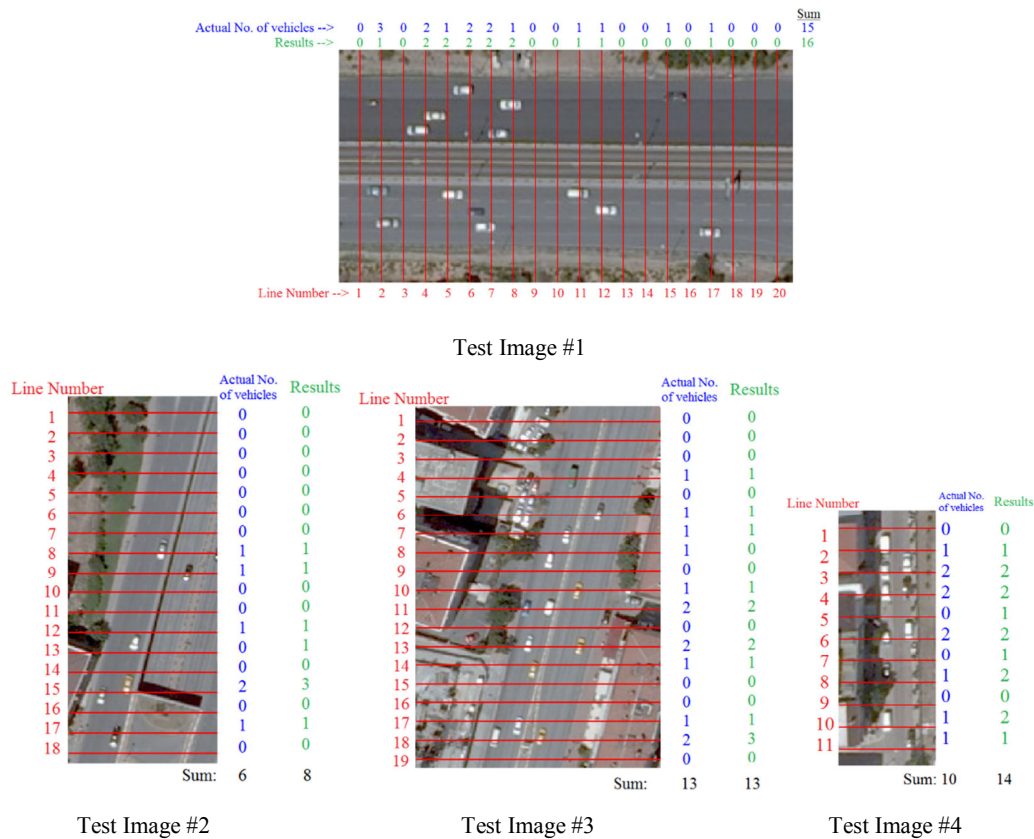

Fig. 2 Test images and the result of the proposed automatic vehicle detection and density measurment method

B. Accuracy Assessment Strategy

The results of the proposed method are evaluated using three standard assessment equations which are used in [17], [18] as:

$$precision = \frac{TP}{TP + FP} \qquad (1)$$

$$recall = \frac{TP}{TP + FN} \qquad (2)$$

$$F_1 = \frac{2 * precision * recall}{precision + recall} \qquad (3)$$

where TP is the sum of True Positive, FP is the sum of False Positive, and FN is the sum of False Negatives.

C. Results and Discussions

Fig. 2 illustrates the proposed vehicle detection results by providing actual number of vehicles for each section on the road and the corresponding results of the developed method.

As it can be seen in Table I, overall accuracies of the developed method in precision, recall ratios are 79.5% and 95%, respectively. The precision ratio is ranging between 71% and 92%, and the recall ratio is ranging between 86% and 100%. Throughout four selected images, all resulted in F_1 score above 80% which shows efficiency of the proposed method in detecting vehicles from very high resolution aerial images. The images were specially selected to show the street

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and roads ranging from street in the city to a highway. However the results demonstrate the reliability of the developed method in all kind of roads and streets in detecting vehicles. In addition, overall precision ratio is 79.5%. Considering the complexity and various characteristics in the test images such as including trees and shadow regions, this is a good result.

According to numerical results in Table I, the lowest precision accuracy value (71%) belongs to test image #4, which it because of entering trees and building shadows into the street regions that leads to be detected as vehicles on the street. Furthermore, in the cases that the boundary line of the sections in the image are located near the vehicles, they can be affected from the gradient vectors or actually, the gradient vectors are influenced by the near vehicles, which it causes to be detected as vehicles. This leads to producing poor precision ratio 75% by test image #2. Besides, test images #1 and #3 demonstrate the robustness of the developed method in detecting vehicles by producing 80% and 92% precision ratio, respectively.

In all test images, the recall ratio is above 86% with two 100% values, which show that our method detect vehicles without producing many FNs. It can be also seen in Table I which only 3 FNs were produced for all test images that demonstrates efficiency of our proposed method.

TABLE I
NUMERICAL RESULTS OF THE PROPOSED AUTOMATIC VEHICLE DETECTION AND TRAFFIC DENSITY MEASUREMENT METHOD

Image	Traffic density (veh./km)	TP	FP	FN	Precision (%)	Recall (%)	F_1 score (%)
#1	172	12	3	2	80	86	83
#2	85	6	2	0	75	100	86
#3	131	12	1	1	92	92	92
#4	237	10	4	0	71	100	83
Overall		40	10	3	79.5	95	86

IV. CONCLUSION

In this study, a method is proposed for automated detection of vehicles and traffic density measurement using very high resolution aerial images. The proposed method is based on gradient vectors of the image. This method shows that

Gradient vectors are a reliable and robust source to detect vehicles by calculating their complexity. Furthermore, results shows that using shadow and tree detection methods to discard the effect of objects like them can increase the accuracy values of the method.

Experimental results on four selected images from very high resolution aerial images demonstrate the efficiency of the developed method in such environmental conditions, diverse road and vehicle characteristics. The important exclusivity of the proposed method is its independency from color combinations of the vehicles, and diversity of the roads which can range from city streets to highways.

Besides, the proposed method works fully automated; however, in future some developments can be done to increase the efficiency of the method in such circumstances that objects other than vehicles are on the road. Furthermore, the proposed density measurement method due to using the direct image size to estimate ROI (road) length it is not a good choice to calculate the length of the curved road and in future it will need to develop new techniques for this step of the proposed method.

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