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Automatic Computer Vision System to Detect the Accumulation of Vehicles and Control the Traffic

[1]Mokhtar H. Mohamed, [2]Ali M. Allam
[1] Department of Computer and Information Systems, Sadat Academy, Egypt
[2] Department of Electronic and Communication Eng., Faculty of Engineering, Helwan University, Helwan, Egypt
[1, 2] Department of Basic and Applied Sciences, Unaizah Community College, Qassim University, Unaizah, 51911, PO 4394, Saudi Arabia

Abstract— The accumulationofvehicles problem inthe streets ofthe bigcities has become a phenomenon, especially in rush hours. This problem is annoyingthe citizens andofficials as like.To solvethisproblem by the traditional ways, werequiredalargenumberoftraffic policeequipped with many devices. The solutionbythismethod is effort consuming and costlyfinanciallyand the efficiencyislimited due to the dependenceonhuman. To overcome the human-based traffic control system, we propose a computer vision-based system for traffic monitoring based on vehicles detection and counting in a certain zone on the road. The proposed system will detects theaccumulationofvehicleson the streets and it controls the traffic light signs by closing or opening automatically. The system captures images in certain time interval for region of interest (RI) across the road. These images will be treated to construct a probabilistic atlas of the components of the background images, this atlas will be used as a prior information for the RI under surveillance. The Bayesian algorithm is modified by incorporating the prior information in clustering images into vehicles and background. After segmenting the surveillance zone images, the system counts the number of vehicles candidates in this region. If the number of vehicles increases a pre-defined threshold, the system will close the streets leading to this region in automatic style and then open after the end of the accumulation.

Keywords— vehicles detection, traffic surveillance, Classification, Bayesian method, communication

I. Introduction

Vehicles accumulation is one of the traffic problems which has become a phenomenon due to the increasing of the population growth especially in major capitals cities, especially in the rush hours. This problem is annoying the citizens and officials as like. So, traffic monitoring based on density of vehicles improve the traffic control system by measuring the density of vehicles on the road. To solve this problem by the traditional ways, it require a large number of traffic police equipped with devices. This solution effort consuming and costly financially and the efficiency is limited to dependence on human element.

Recently, most of the cities of the world have an Intelligent Transport Systems (ITS) which is equipped with electronics devices to communicate about the traffic condition with the moving vehicle and also monitor the traffic rules and regulation which is the need for the quick development of the social and economic. So, the vehicle detection system as a part of the ITS plays a key role to make the existing systems more efficient. It is not only help to reduce the number and severity of traffic crashes. Also it helps to reduce the traffic accumulation in urban environment by diverting traffic to less crowded alternative roads or close the leading roads. By this way, ITS is assisting travellers to reach their destination as early as possible with less energy consumption. ITS tries to extract the traffic information from images or videos, such as traffic flow, vehicle velocity and the number of vehicles inside the Region of Interest (ROI). Road engineering uses this information to improve efficiency of road utilization.

ITS faces many challenges because of because of the complicated background, multiple targets, environmental change and so on. All these challenges make the traffic video detection always difficulty to get ideal result. Most of the present detection algorithms are mainly based on machine vision, such as background subtraction, frame difference, edge detection method, optical flow method, motion vector method [1]. These algorithms have been designed to perform image segmentation and classify all pixels of the input image as pixels of vehicles, pixels of background [2, 3, 4]. The background modulation and subtraction is one of the most popular methods. Several adaptive background models have been proposed for the vehicle surveillance images segmentation [5, 6]. Different algorithms have been intended for the counting of vehicles when passing through so-called virtual loops. In [7], the statistical models have been applied to extract image features that allow us to classify each state of the pixel into three categories (road, vehicle head and body) and to recognize passing vehicles. The methods proposed in [8, 9] use the time-spatial frames analysis for the task of road traffic flow count. Also 3-D shape models have been proposed for the vehicles detection [10, 11].

Gaussian probability distribution model for each pixel in the image is proposed in [12, 13]. The pixel values are updated by the Gaussian probability distribution model from new image in the new image series. Then, each pixel (x,y) in the image is classified either be a part of the foreground (moving object or called blobs) or background according to adequate amount of information accumulated from the previous model.

Another method proposed by [14]. It detects vehicles in traffic supervision video streams labelled the vehicles from examples for detection process. The method is constructed from an adaptive background approximation and dividing the image into small none overlapped blocks for founding the candidate vehicles parts from these blocks. The Principal Component Analysis (PCA) is applied as a low-dimensional statistical approach to measure the two histograms of each candidate. Also, support vector machine (SVM) is considered for vehicle parts classification. Finally, all classified parts shaped and connected as a parallelogram to represent the parts shapes for matching process.

Authors in [15] used an estimated background to detect moving objects and updated the background for luminance changes. This method requires an initial background without any foreground objects. The background information is updated by occupies during a considerable time in the whole process of detection. In [16] authors used edge information and set up an optical flow model to detect vehicles and [17] performed the segmentation using a neural network, based on local-oriented coding and entropy analysis.

In this paper, we discussed an effective way to detect automatically the accumulation of vehicles in certain region. The system using computer vision technique and fixed or mobile cameras. A communication system is used to remotely control the traffic lights. This integrated system working efficiently all the day and night. The system depends on monochrome cameras to cover a specific region of the street and in the influential area. Then capturing some images of this area during free of vehicles and under different imaging conditions of day, night, dust and rain whenever possible. These images will be treated to construct a probabilistic atlas of the components of the background images. This atlas will be used as a prior information for the background area under surveillance (ROI). The Bayesian algorithm is modified by incorporating the prior information in clustering images into vehicles and background. After classifying the ROI images, the system count the number of vehicles in this region. According to the threshold number of vehicles inside the ROI, the system will control the traffic of the leading roads to this region in an automatic manner for the traffic light systems. The rest of the paper is organized as follows: vehicle detection and classification approaches are discussed in section 2. In section 3 we illustrate the proposed communication system. Section 4 illustrates the proposed method results. Finally conclusions are summed up in section 5.

II. PROPOSED CLASSIFICATION METHOD

The proposed method depends on the prior information about the nature of the ROI. It uses a priori information of the background and foreground pixels to construct two separate models for background and foreground classes of the ROI.

We use Parzen window as a non-parametric technique to estimate the PDF of the data set. We tend to use nonparametric statistical modelling since it learns arbitrary PDFs via data-driven strategies [18]. The posterior probability of any class pixels will be calculated by computing the value of the PDF at this pixels and multiply it by the prior probability of each class. The classifier gives its decision after applying the Bayes maximum rules over the posterior probabilities:

$$P(w_c \mid \bar{s}) = \frac{p(\bar{s} \mid w_c)P(w_c)}{\sum_c p(\bar{s} \mid w_c)P(w_c)} \quad (1)$$

where w_c is the c th class, $\bar{s}$ is feature vector, $P(w_c \mid \bar{s})$ is the posteriori probability, $P(\bar{s} \mid w_c)$ is the Probability Density Function (PDF) of the data set, and $P(w_c)$ is the class a priori probability. Since the denominator term in (1) does not depend on an of the classes, it can be discarded to get the Bayes classifier as

$$P(w_c \mid \bar{s}) \propto p(\bar{s} \mid w_c)P(w_c) \quad (2)$$

From (2), the right hand side contains two terms, the value of probability density function at the classified pixel, and the priori probability of presenting any class in the given ROI.

Parzen window technique [18] is used to estimate the PDFs of $p(\bar{s} \mid w_c)$. The training data set has 3 dimensions feature vector $\bar{s} = \{i, x, y\}$, where i is the difference between pixel intensity and the average intensity of the corresponding image. (x, y) are the Cartesian coordinates of the pixel. So, the PDF will be denoted as.$p(i, x, y \mid w_c)$

Due to the fact that, we do not know the specific form of the data set PDFs, so we utilize Parzen window technique to estimate it. The Parzen-window estimation is defined mathematically as

$$P(\bar{s}) = \frac{1}{n}\sum_{j=1}^{n} \frac{1}{h_n^{\,d}} K\left(\frac{\bar{s} - \bar{s}_j}{h_n}\right), \quad (3)$$

where $K(\bar{s})$ is the window function or kernel in the d-dimensional space such that

$$\int_{\Re^d} K(\bar{s})d\bar{s} = 1, \quad (4)$$

and $h_n > 0$ is the window width or bandwidth parameter that corresponds to the width of the kernel. The Gaussian PDF is a popular kernel for Parzen-window density estimation, being infinitely differentiable and thereby lending the same property to the Parzen-window PDF estimate $P(\bar{s})$. So the Parzen-window with a Gaussian kernel becomes

$$P(\bar{s}) = \frac{1}{n}\sum_{j=1}^{n} \frac{1}{(h\sqrt{2\pi})^{d}} exp\left(-\frac{1}{2}\left(\frac{\bar{s} - \bar{s}_j}{h}\right)^2\right), \quad (5)$$

where h is the standard deviation of the Gaussian PDF along each dimension. In this work, we use (5) to estimate $p(\bar{s}|w_c)$in (2). So the final form of Bayes classifier in (2) will has the following form,

$$P(w_c|\bar{s}) \propto \frac{1}{n}\sum_{j=1}^{n}\frac{1}{h^d}\exp\left(-\frac{1}{2}\left(\frac{\bar{s}-\bar{s}_j}{h}\right)^2\right)P(w_c). \tag{6}$$

Abstractly, naive Bayes is a conditional probability model: given a problem instance to be classified, represented by a vector $x = (x_1 \cdots\cdots x_n)$ representing some n features (dependent variables), it assigns to this instance probabilities $p(C_k|x_1 \cdots\cdots\cdots\cdots x_n)$ for each of K possible outcomes or classes.

The problem with the above formulation is that if the number of features n is large or if a feature can take on a large number of values, then basing such a model on probability tables is infeasible. We therefore reformulate the model to make it more tractable. Using Bayes' theorem, the conditional probability can be decomposed as

$$p(C_k|x) = \frac{p(C_k)p(x|C_k)}{p(x)} \qquad (7)$$

In plain English, using Bayesian probability terminology, the above equation can be written as

$$posterior = \frac{prior \times likeli\,hood}{evidence} (8)$$

In practice, there is interest only in the numerator of that fraction, because the denominator does not depend on C and the values of the features Fi are given, so that the denominator is effectively constant. The numerator is equivalent to the joint probability model

Bayesian updating is one viable approach, which takes advantage of a statistical model to combine the current observed data with prior knowledge, such as spatial constraints and smoothness level.Bayesian updating is statistical inference in which evidence or observations are used to update or to newly infer the probability that a hypothesis may be true. It uses aspects of the scientific method, which involves collecting evidence that is meant to be consistent or inconsistent with a given hypothesis. As evidence accumulates, the degree of belief in a hypothesis should change. With enough evidence, it should become very high or very low.

III. Proposed Communication Methods

Advances in mobile computing and wireless communication have offered new possibilities for Intelligent Transportation Systems (ITS), aiming at improving driving safety and traffic efficiency. By adding short-range wireless communication capabilities to vehicles, the devices form a mobile ad-hoc network, allowing cars to exchange information about road conditions. This is referred to in the literature as Vehicular Ad-hoc Networks (VANETs).

Long-Term Evolution (LTE) is the latest technology in wireless communication and categorized by its latency advantage compared with the previous wireless technologies [19]. The usage of LTE in GOOSE Vehicular Ad-hoc Networks (VANETs) will add several benefits as it will decrease the installation time for the communication environment. Using LTE in VANETs can be classified as Machine-2-Machine (M2M) communication, which is one of the biggest growing industries in the near future and it is a new breed to drive further enhancements of the LTE network.

A. LTE Latency

LTE network latency for data transmission is named as User plane (U-Plane) latency, which is defined as the one-way transit time between a packet being available at the IP layer in either the User Equipment/ Radio Access Network (UE/RAN) edge node or the availability of this packet at IP layer in the RAN edge node/UE [19].

The reason of the U-plane latency acquired due to the time taken within the data path within the LTE network.

B. Data-Path

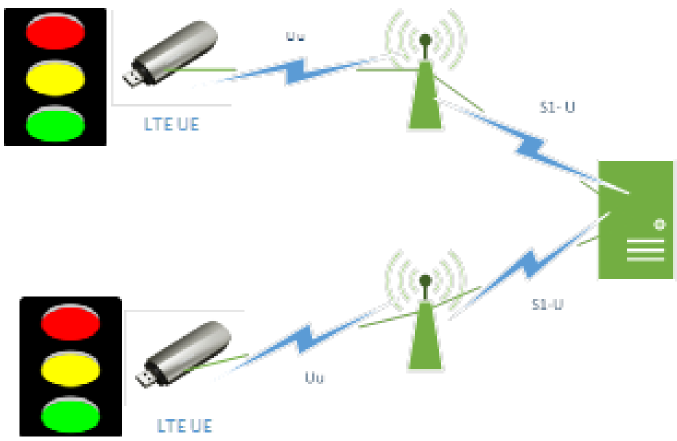

Fig. 1: show the equipment-2-equipment communication process, between two traffic lights signals.

The data path within the LTE network from source to destination have to follow a specific path, in which the UE request grant from the evolved NodeB (eNB) requesting a resource to transmit its data, once the eNB provide the UE with the requested resource the UE will send its data to the eNB. After that, the eNB will forward directly the packet to the

Serving Gateway (SGW), which will route packet to its destination and forward it to the serving eNB. After that, the eNB will forward the packet to the destination UE. Table 1 below mention the time taken by each process within the data path, before applying our suggested adaptation.

TABLE 1 OVERALL LATENCY WITHIN LTE NETWORK [20]

Process	Time in ms
UL Resource assignment	8
UE UL Data transmission processing	4
eNB Processing time	3
S1-U	5
SGW Processing Time	2
S1-U	5
eNB Processing time	3
UE DL Processing Time	3
Total Latency	33

IV. RESULTS

The proposed algorithm was tested on many of images sequences captured at several various lighting and weather conditions. The summarized length of all tested sequences was about two days. The captured included day and night time scenes of the accumulation as well as free traffic flow. The proposed method was tested under various conditions such as clear weather or under dust storms. The size of experimental images was 654 x 304 pixels in greyscale mode. Fig. 2 shows an examples of the analysed images with the displayed boundaries of the ROI. The figure demonstrates the original ROI, the background mask, the binary background mask and the classified vehicles.

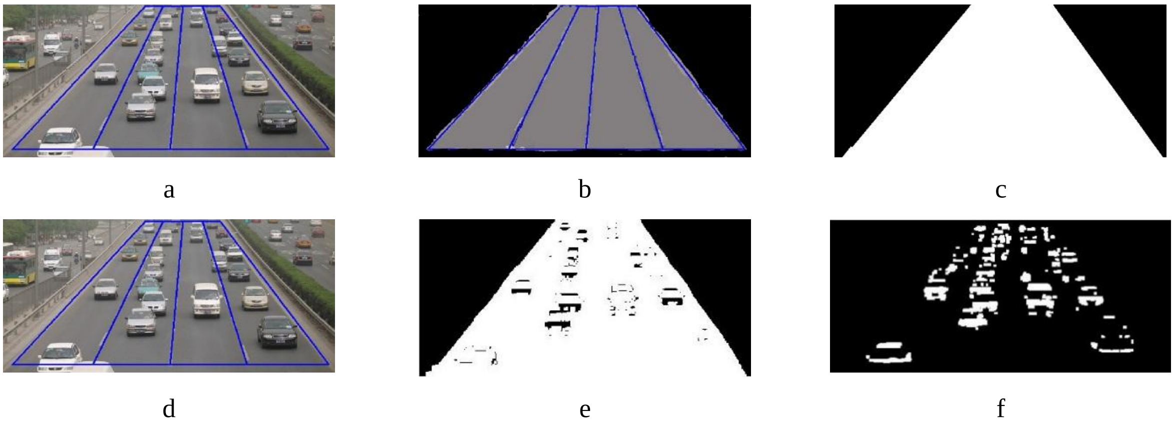

Fig. 2: Example of analysed image for a ROI. a) & d) are the original image, b) original image for the ROI background, c) binary mask for the ROI, f) classified vehicles.

The accuracy of the proposed method in vehicles detection was evaluated by the results verification for each image taken every 1 minute. Two types of errors were taken during evaluation. The first one is the false negative detection which mean a vehicle is presented in the captured image but not classified as a vehicle object in the processed image. The second one is false positive detection which mean a vehicle is not presented in the captured image but the method presents a vehicle object in the processed image in a detection zone. The registered error during the testing period was about 5 % of vehicles detection. But the final decision which controls the traffic flow according to a predefined threshold is 100 % acceptable.

The accuracy of our method is measured by the percentage of the area occupied by the classified vehicles and the area of the ROI as follows:

$$I = \frac{area\ occupied\ by\ classified\ \ vehicles}{area\ of\ ROI} \times 100 \tag{9}$$

According to the value of I and comparing with the predefined threshold T, a signal will be transmitted over the communication system in section 3 to the leading road open or close the traffic light.

V. CONCLUSION

In this paper, we have modelled the static background by a spatial distribution model called by Atlas. This distribution was constructed from the average of pre-captured images for the interested region. These images are obtaining without any moving image at the time of preparing to install cameras. Parzen window as a nonparametric technique is used to predict the distribution. The experimental results demonstrate that the proposed algorithm is feasible and promising for the applications in the vision-based vehicle detection. It fulfils the real-time requirement and provides the robust vehicle detection under different conditions like lighting transitions, traffic accumulation. A proposed communication system is used to transmit a control signal to the leading roads for open or close the traffic lights according to the number of vehicles occupies ROI.

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