2011 18th IEEE International Conference on Image Processing

REAL-TIME TRAFFIC ANALYSIS AT NIGHT-TIME

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ABSTRACT

This paper presents a video-based approach to traffic analysis and monitoring in night light conditions. In this kind of scenarios the headlights of the vehicles are the main features of the image taken from an urban or inter-urban traffic camera. The body of the vehicles is very low contrasted and many of the algorithms used in day-time decrease their performance. In our algorithm, we detect car headlights, and using this information, we obtain the three main magnitudes used in traffic monitoring: number of vehicles per time unit, i.e. *intensity*, *mean speed*, and *occupancy*. Extensive evaluations show that the system exhibits an excellent performance with real-time video sequences from cameras of the Traffic Authority of the city of Valencia, Spain.

Index Terms— Video Surveillance, Traffic Analysis, Counting, Night-time, Vehicles, Occupancy

1. INTRODUCTION

Intelligent transportation systems use three fundamental parameters to optimize traffic flow: *intensity*, also refered in the literature as density (number of vehicles to cross a line per time unit), *occupancy* (average fraction of time a vehicle is over a line o loop) and *mean speed* (mean of the speed of the vehicles crossing). These three magnitudes are periodically obtained and sent to a traffic control center with a predetermined cadence (usually a value from 30 s to 2 min), named *evaluation period*. Traditionally, inductive loop sensors have provided this information with more o less accuracy. However, most modern cities have a big number of video cameras already installed. Video cameras are quite useful because they provide a very good visual human-operated way to know what is happening, i.e. congestion or other traffic state, queue length, what type of incidents, trajectories of the vehicles, weather conditions, etc. These days, there is a big effort to incorporate extra functionalities to video cameras, so that it is possible to obtain automatically the same information supplied by the inductive loop sensors. Recent advances in computer vision and the increase of computational power, has allowed to develop many video-based traffic analysis systems, but mainly in day-time conditions. The images obtained in day-time conditions and night-time conditions are very different. In day-time, the body of the vehicles has enough contrast to be detected with many algorithms like background subtraction, edge detection, neural nets, etc. But at night the body of the vehicle is less contrasted, and when it appears in the scene, the main image changes are due to its headlights, which appear as very bright small areas. An additional problem is that the illuminated area in front of the vehicle affects severely the measurements if day-light algorithms are used. Night-time is also important in traffic control because the number of vehicles in the cities or on the road in the evening in winter is important and it is very rare that the cities have cameras with night vision in infrared-thermal spectrum or even infrared lamps. Therefore, it is interesting to develop specific algorithms that meet the specific necessities of the night conditions but using the already deployed visible-spectrum cameras. The algorithm proposed in this paper is fast enough to run at real-time and has been evaluated with video sequences provided by the Traffic Authority of the city of Valencia (one million people approximately). The city has about eight hundred cameras deployed, working 24 hours per day, at 25 images per second, allowing us to extensively evaluate the performance of the algorithm during night-time. Figure 1 shows some scenarios used in this paper.

Fig. 1. Scenarios with the indication of the loops of the lanes under analysis.

2. PREVIOUS WORK

Video-based traffic analysis is a very active topic in computer vision for intelligent transportation systems. Surveys on this topic can be found in [1, 2]. In [3], a method for accu-

This work was funded by the Spanish Government project MARTA under the CENIT program and CICYT contract TEC2009-09146.

rately counting the number of vehicles in the case of multiple-vehicle occlusions is presented. In this work, it is assumed that the vehicles are segmented from the background. Then, a deformable model is geometrically fitted on the occluded vehicles and a contour description model is utilized. Although these two techniques report very interesting results, they can't be used at night-time because in many images the body of the vehicle hasn't enough contrast to be detected properly from the background. In [4], corner feature points detected on foreground regions are used to detect and track the vehicles. It also uses 3D perspective mapping from the scene to the image to properly distinguish features belonging to the same vehicle and count them. This work provides results for day light conditions only. A statistical analysis approach based on traffic flow regions is presented in [5]. The interesting idea of this work is that traffic flow is estimated without detecting individual vehicles. However, no results are presented for night conditions. An example that detects parked vehicles at nights using corner features is presented in [6]. Another example of a work that counts vehicles regardless of the day-night condition can be found in [7]. The performance decreases from 98 % to 91% during the night. In this work, the camera position is perpendicular to the direction of the traffic flow (lateral view of the vehicles) and 1 o 2 meters above the ground. Although the results of this work are promising, it requires specific video cameras to be installed. In our work, we do not require the installation of additional infrastructure and use the existing monitor cameras installed on many street poles at junctions, see Fig 1. In [8] a night-time system for detection and classification is presented. This work combines headlight detection with an appearance-based classifier that reduces false positives. Although the results are very promising, the algorithm requires to detect two headlights per vehicle, therefore one-headlight vehicles, such as motorcycles, will be missed, and it does not work for rear views of the vehicles.

3. PROPOSED METHOD

3.1. Configuration

Since most vision systems used for traffic analysis try to emulate inductive loops, it is quite common to define virtual loops on the image where the *Intensity, Mean Speed* and *Occupancy* measurements must be taken. Figure 1 shows examples of virtual loops superimposed on the images. Although, in the example there is just one loop defined in each scenario, the common situation is that there is one loop per lane. Each scenario is calibrated so that is it possible to obtain how many pixels per meter there are in the place where the virtual loop is situated.

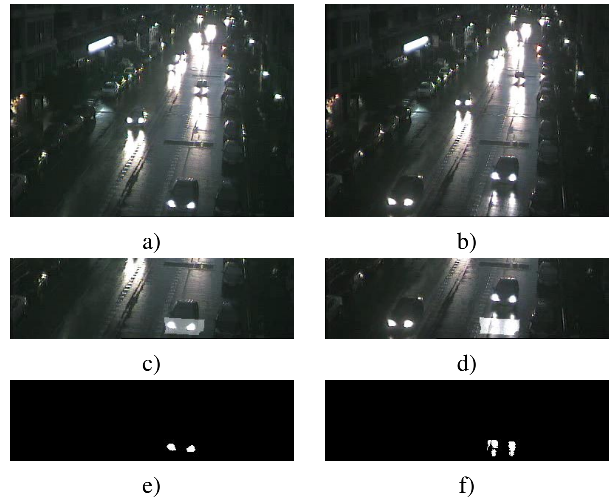

Fig. 2. Examples of headlight detection using the TopHat. In the left column there is a example of a true positive and on the right column there is an example of a false positive. e) and f) are the results of the TopHat.

3.2. Headlight detection

Headlights appear on the image as small regions with high contrast. A simple approach to detect headlights is by means of the morphological TopHat with a disk structuring element. The size of the disk must be greater than the headlight and smaller than other undesired bright structures. The analysis has to be conducted only in a small region (ROI) around the virtual loop as shown in Fig. 2.c. Although, this simple approach can detect most headlights, diffuse and specular reflections on the lane surface generate bright areas with similar appearance as the headlights inside the ROI and hence creating false positives (see Fig. 2.d). This example is specially challenging due to strong reflections on wet ground. In this paper we propose an alternative TopHat designed to deal with these situations.

One feature that can be used to distinguish between reflections and actual headlights is that reflections can usually be as narrow as the headlights but elongated in the direction of the lane (see Fig. 2.a-b) Therefore, a TopHat with a linear structuring element in the direction of the reflection would eliminate the reflections while keeping the headlights. The problem is that the direction of the camera respect to the street lanes and hence respect to the reflections, changes for each scenario. So we propose an alternative operator L which is independent of the camera orientation (see Fig 3 for a simplified graphical explanation), which is described next:

1. Instead of calculate one morphological opening with a disk, we obtain four openings, each one with a linear structuring element with 0, 45, 90 and 135 degrees orientation.

2. Compute the pixel-wise maximum of the four results.

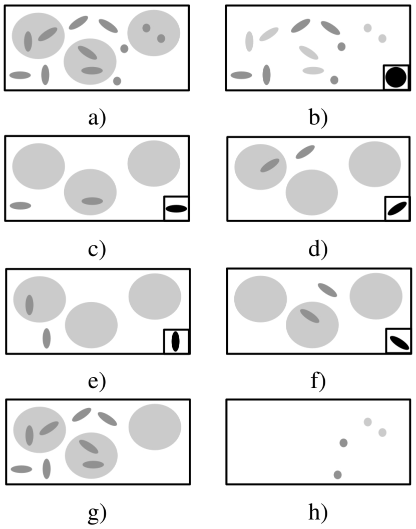

Fig. 3. Graphic to illustrate the operator steps 1-3 of L, and compare it with TopHat. a) source image. b) TopHat Result. c,d,e,f) Openings with linear structuring element. The structuring element used is in the bottom-right corner. g) pixel-wise maximum of openings. h) Residue (subtraction a - g); note that it does not contain elongated areas.

3. Compute the residue between the original image and the union of the apertures (similar to the TopHat operator).
4. Threshold with T
5. Opening with a squared structuring element of smaller size to clean small noisy areas smaller than the headlights.

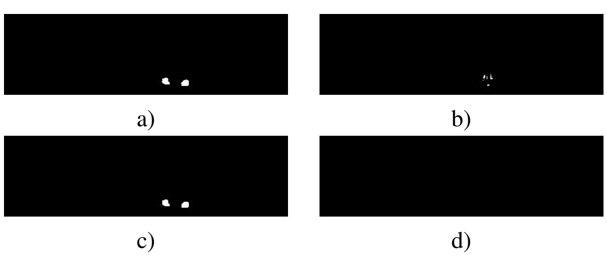

Fig. 4. Results of the operator L on the images of Fig 2: a) and b) steps 1-4. c) and d) result after cleaning (step 5).

Figures 4.a-b show the result of the previous steps 1-4 applied to the example images of Fig. 2. Note that in c) the headlights are detected correctly and we are able to eliminate the false positive.

A value of the threshold $T = 70$ has been used in our algorithm, although this is not very critical and similar results have been obtained using values in the range of 50 to 120. After the transformation L, connected components are extracted and those that are smaller than the expected size of the headlights are eliminated. The minimum size is obtained after calibration for each scenario. We do not take into account the number of detected headlights for a vehicle detection (1 or 2) so in our algorithm we allow the detection of the motorcycles.

Fig. 5. Reflection on the roof

3.3. Adding temporal coherence

Although the hit rate of our headlight detector is quite high, the whole process can be greatly improved by taking into account the temporal coherence. For example, in a typical scenario, with a camera situated on a street pole of 5 to 10 m high and situated 10 to 20 m from the virtual loop, and considering a speed from 0 to 130 km/h, one vehicle is on the loop in the image at least 5 to 10 frames. Another constraint is that after headlight detection there must be a time until the rest of the car crosses the loop. This time can be estimated using the speed of the vehicle. Figure 5 shows an example in which this constrain can eliminate a false positive caused by specular reflections on the car. To incorporate this knowledge to our system, we have created a finite automata. The rules of the automata are:

1. It is needed three consecutive frames with headlight detection to trigger the state *vehicle_detected*.
2. If there are two consecutive frames with no detection, the state changes to *end_of_vehicle_detected*.
3. The state *end_of_vehicle_detected* starts an inhibition time period inversely proportional to the speed of the vehicle. In this period, every headlight candidate detected is discarded.

3.4. Estimation of Mean Speed

Once the finite automata changes to the *vehicle_detected* state (a new vehicle is entering the loop), we estimate the displacement of the detected vehicle using the Lucas-Kanade method. The displacement is calculated between the current and previous frame. This procedure is repeated while we remain in the *vehicle_detected* state (all the frames from the same vehicle). Finally, all the estimated speeds are averaged to obtain a speed measurement per vehicle. It is important to mention that, in general, traffic control centers do not require speed measurements for each individual vehicle, and instead they only need an average speed measurement which integrates the speed of all vehicles that have crossed the loop during a suitable *evaluation period*. Therefore, all the individual vehicle speed values are accumulated and averaged, and this is the result that it is sent to the traffic control system.

3.5. Estimation of Occupancy

The third important measurement used for traffic planning is *occupancy*, defined as the average fraction of time that a vehicle is over the loop in a *evaluation period*. The problem of estimating *occupancy* at nights is that the rear part of the vehicles can't be extracted in a exact way due to the low contrast in many images. To avoid this problem, we assume a mean vehicle length of 5.25m. Since the speed of each vehicle (vel) has been estimated (section 3.4), we can obtain the approximated time that the vehicle is on the loop: $\Delta t = 5.25/vel$. From these values obtained for each vehicle, it is straightforward to calculate the *occupancy* measurement in the *evaluation period*.

4. RESULTS

The whole system has been implemented in C++ and it is able to process 20 lanes from 4 cameras simultaneously at 25 frames per second with a Intel Core 2 duo 2,53GHz. We evaluated the algorithm in 12 sequences provided by the Traffic Authority of the city of Valencia. Each sequence lasts one whole week, its spatial resolution is 384x288, and it is coded in Mpeg4 at 1.5 Mbits/s, yielding a total of 2016 hours of video. From all this huge amount of data we selected a representative sample of videos that contain different conditions such as: raining, tunnels, particularly dark illumination, variations in the camera tilt, high and low traffic intensity, rear view of cars, etc. In total, we gathered 165,000 frames with 653 vehicles. Table 1 shows the results of the vehicle counting process to compute *Intensity*. The *Mean Speed* accuracy obtained has an average error of 6%. The real mean *Occupancy* of the evaluated sequences is 5.35%, and the estimated value was 4.5%. A demo video can be seen at [9].

5. CONCLUSIONS AND ACKNOWLEDGEMENT

In this paper, we have presented a method to compute the three basic parameters used in traffic control, *Intensity, Mean Speed and Occupancy* in night-time using video. Our approach is accurate and has a negligible computational demand (we can process at least 20 lanes in real time at 25 frames/s). Our system reports results on real video sequences and incorporates temporal coherence to improve them. Also, the amount of evaluation data and the variety of acquisition conditions is probably one of the largest presented so far for night-time.

The authors thank the Traffic Authority of Valencia for providing the video sequences used in this research.

Condition	Ground Truth	FP+FN
Standard image quality	355	12
Poor image quality	179	28
Very rainy	53	16
Rear view	66	5
Total # of vehicles	653	61

Table 1. Evaluation of the vehicle counting

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