Self-speed and Headway Measurement in Highway Traffic from Onboard Video Footage

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ABSTRACT

We present a method to automatically collect data about distance and speed of vehicles ahead of a car participating in highway traffic. The method should support the registration of traffic in front of a driving car over long periods of time in order to be able to detect over-persistent congestion (OPC) situations. The method requires no specialized devices; it is based on a simple video stream from any (low-cost) camera mounted near the front window of a car. The data is used to fine-tune traffic flow models in order to determine the conditions for the emergence and the dissipation of traffic jams more accurately. The paper deals with the performance of the vehicle tracking method itself and presents a criterion for over-persistent traffic jams applied to the data. The outlook towards a driver's advisory system to reduce traffic congestion (and thus time loss and environmental load) is discussed as well.

Keywords

Collecting traffic statistics, car detection, speed measurement, reduction of traffic congestion.

1. INTRODUCTION

In densely populated regions (such as in the western part of the Netherlands), infrastructural expansion of motorized traffic is almost no longer an option. Instead, several types of regulations are being considered to flatten rush-hour peaks and to create financial penalties on car drivers using certain roads at certain times. To optimize the traffic flow, information provision systems through road panels or radio, telephone and internet channels can advice the driver and/or update the car navigation device. Research is rapidly progressing toward intelligent vehicles, based on onboard observation equipment and automatic information exchange among nearby cars [Kim 2007, Guenthner 2008, Doman 2010, Sun 2006]. We are still far away from automatic driving, and much of the efficiency of the road capacity usage depends heavily on the individual car drivers and their conduct in various traffic situations. Individual driving styles can be modeled and evaluated using traffic flow models [Fellendorf 2000, Hoogendoorn 2010]. It has been reported that traffic congestions are reduced or avoided when car drivers receive particular guidance or when adaptive cruise control is implemented [Driel 2010]. To obtain better understanding of car driving behavior and to reveal critical situations we propose to collect and analyze speed and distance data taken from a car participating in high-way traffic over long periods of time. The acquired information will be different from and complementary to what is measured customary at counting points stationary to the road, and thus have the potential to validate and enrich traffic flow models.

2. OVER-PERSISTENT CONGESTIONS

One factor that affects the life time of traffic congestions significantly is the outflow of vehicles at the downstream front of jams. In [Kesting 2008] it has been demonstrated in simulation runs that an increase of acceleration combined with a decrease of headway time is positively correlated to the maximum capacity for freeways.

To model the car driver's behavior we have made use of the intelligent-driver model or IDM [Treiber 2006]. The IDM is a microscopic traffic flow model that can accommodate simple human driving schemes as well as ACC algorithms and other driving assistance principles by setting a number of parameters.

Using the IDM, we have simulated a number of of single-lane traffic situations, representing jam forming and dissipation and studied the evolvement of traffic for differing settings of (*e.g.*) T and $a_{\max}$. In the scenario we have initialized two clusters of cars. The first consists of 200 cars driving in a platoon fashion at low speed, v_i = 10Km/h at t = 0. The length of the cluster is approximately 3.1Km. In the simulation, the foremost car is assigned a constant acceleration of 1.3m/s^2 beginning at t >300s, until car 1 reaches v=120Km/h, which takes about 24s. The remaining 199 cars are followers according to the IDIM.

The distance between the clusters is shrinking until $t \cong$ 750s, when car 201 gets close to the tail of cluster 1 and needs to reduce its speed from 120 to approximately 65Km/h. At that point in time car 200 has v = 50Km/h and appears to quickly accelerate towards v* as did all cars in cluster 1 before. For t > 770s all 400 cars have merged into a single cluster and have reached an equilibrium state at a speed near v*. The duration of merging process is about 40s.

An over-persistent congestion (OPC) has been produced in the simulation by modifying the parameters of the IDM. Two effects are then obvious. Car 200 has reached a speed of 105Km/h at t = 861s, which is 95s later than it did in condition B. This delay triggers another effect on cluster 2. Car 201, leading cluster 2, reaches car 200 while the latter is still at its low speed of 10Km/h. After about 1 minute car 200 starts to accelerate, dragging cluster 2 behind it. A strip of about 60 low-speed cars propagates to the tail of cluster 2 in about 300s. It can be concluded that (unnecessary) slow and small acceleration contributes to the emergence and lifetime of traffic jams and causes delay for traffic behind. Similar observations were made by [Treiber 2003].

To be able to predict (and then to conquer) OCPs reliably, it is necessary to improve the car following model. To do so we need empirical statistics about the acceleration function $a(s, v, \Delta v)$. Collecting data a, v and s as a function of t over long durations would serve that purpose.

3. COLLECTING LONG-DURATION DATA FROM VIDEO FOOTAGE

The most common way to register traffic flow is by using stationary measurement points such as induction loops. However, the resulting data would not yield sufficient information about the behavior of individual car drivers. Video data from a helicopter as obtained in [Hoogendoorn 2006] could provide some clues. High-statistics information from onboard cameras are very suited to correctly model the behavior of car drivers when they leave traffic jams, either by adapting the parameters of equation (1) or by extending equation (1) with empirically-based terms.

Instead of video data one could use alternative ways to collect position and distance data. Position (and thus speed) information could be obtained from GPS data and distance to the car ahead could be obtained from radar sensing. However, we are aiming at a method to obtain the information with minimal intervention using a simple device which can easily be mounted and demounted from a car. The idea is that information should be gathered from a number of cars over longer durations, *e.g.* 1 to 4 weeks, where the operation of the device should be either absent or minimal. Also, there should not be the necessity of a technical installation involving the connection to existing devices in the car (such as its navigation system or ACC). The device should be simply mountable into any car and require not more from the driver than its switching on or off. A video camera with built-in hard drive is one option. Another option would be a webcam (perhaps attached to the front window) connected to a data storage system, provided that the devices do not cause any disturbance to the driver.

The method that we developed starts from pixel data coming from any simple webcam or video camera fixed inside the car near the lower edge of the wind shield, where the camera is aimed nearly horizontally into the forward driving direction. The video data is analyzed frame by frame. As a first step we search, in the frame, for brightness drops on the road in the positive z-direction, which is the driving direction of our car, corresponding to the positive y-direction in the pixel plane. If in addition the brightness of the darker pixel is below a certain limit we have possibly detected the lower part or shadow from a car ahead. The threshold for brightness drop was defined as a fraction of the average brightness of the road surface, which was calculated for each frame individually. We did not make use from color information. Treating dark regions as hints of vehicles was recently applied successfully in the framework presented by [Nieto 2011]. The method works in daylight conditions but also during night conditions with street light illumination. Depending on the threshold settings of the brightness drop, the darkness criterion etc, candidate regions are detected on and outside of the road.

4. IMPLEMENTATION DETAILS

The input to the software are video recordings made by a low-cost camera with a resolution of 720 times 576 at 25 frames per second. Video recordings with practically unlimited duration without interruption can be obtained. The only non-standard provision is electric power supply from the car's 12V battery. We used a simple 12V DC to 230V AC converter to power the camera over long time periods as to be independent from the camera's battery pack.

Fig. 1. Result of single-frame analysis with different settings of darkness criterion and brightness drop-down. Candidate cars have been marked red; white lane markers marked blue; the assumed horizon is represented by the green line (bottom).

The speed and distance extraction method has been implemented in C++ on the Visual Studio platform [Microsoft 2012] using the OpenCv library of real-time computer vision algorithms [OpenCV 2012]. OpenCV supports the import of video films and accessing and editing of individual video frames, as well as outputting of (annotated and/or modified) video files.

Criteria have been introduced to define whether a dark region is positioned on or beyond the road surface and by requiring a minimal size of the region in horizontal direction. When bright lane markings are visible the algorithm can be focused on the area bounded by them. However, the most important criterion for a dark region to be associated with a driving car ahead is temporal coherence.

5. RESULTS

We have collected video footage from a dozen of journeys, ranging in duration from 1 to 13 hours. The algorithm extracts the right speed and distance under various daylight conditions. However, strong against-light or a snowy road surface prohibit the detections.

As explained above, *v* is computed from the maximally populated bin occurring in the past 250 consecutive velocity histograms, representing 10 seconds. The fraction of speed values that actually occurred in such bins is plotted as well and floats around 20%. An example of the self-speed histogram at a particular point in time is shown in Fig. 4.

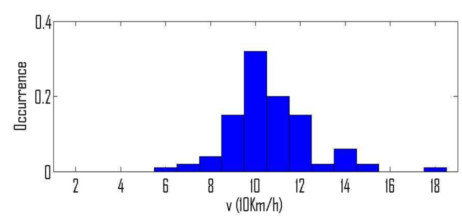

Fig. 2. Distribution of measurements of self-velocity at one point in time.

When this fraction gets low (*e.g.* smaller than 5%) then the speed measurement is no longer reliable. This occurs *e.g.* at t = 270s. The speed v is not strongly influenced by short interruptions of information from white markings, as the averaging over 250 frames acts as a low-pass filter for v. The evolvement of the velocity probability histogram over time is shown in Figure 3.

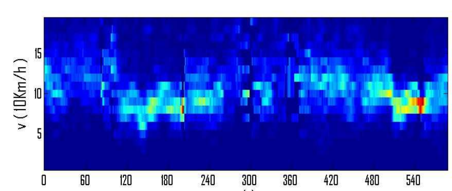

Fig. 3. Velocity probability as a function of time. Bright and red color signify high probability, blue/dark signifies no or few occurring velocities .

Based on our desktop implementation in C++ we could achieve a throughput of the data with more 25fps, that is the program would run in real time. Since much of the computation can be handled in separate independent pieces, GPU-enhanced processing could certainly be considered.

6. CONCLUSIONS

An initial evaluation revealed that the method works satisfactory under good and reasonable light conditions. Short interruptions of data can be compensated by low-pass filtering, but against-light, snow or darkness prevent the algorithm from working correctly. Several ways of improvement are suggested in the literature. One we are working on is to detect optical flow from any road surface. Two or three frames taken some 5ms apart in time at reasonable resolution would be sufficient to compute self-speed. It is not necessary to take frames every 5ms, but to have three frames once very second. A common high-speed camera would probably be overkill and counter effective when it would be difficult to mount and to operate.

The speed and distance values as a function of time are suited to study the driving behavior in various conditions. The data provides information about the occurrence of situations potentially compatible with OCPs.

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