Vehicle Counting with an Embedded Traffic Data System using an Optical Transient Sensor

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Abstract—**In this paper a sensor system for traffic data acquisition is presented. The embedded system, comprising a motion-sensitive optical sensor and a low-cost, low-power DSP, is capable of detecting, counting and measuring the velocity of passing vehicles. The detection is based on monitoring of the optical sensor output within configurable regions of interest in the sensor's field-of-view. In particular in this work we focus on the evaluation of the applied vehicle counting algorithm. The verification of the acquired data is based on manually annotated traffic data of 360 minutes length, containing a total of about 7000 vehicles. The counting error is determined for short (3 minutes) and long (60 minutes) time intervals. The calculated error of 99,2% of the short time intervals and 100% of the long time intervals analyzed, remain within commonly recognized margins of 10% and 3% of detection error respectively.**

I. Introduction

Ever increasing traffic volume has driven various efforts of applying known technologies to the development of novel traffic monitoring systems [7, 8, 9, 10]. These technologies comprise pavement invasive sensors like induction loops and non-invasive sensors like ultra-sound, infrared, microwave-radar or video based systems [1]. The main task of these detectors is to provide fairly accurate measurements of vehicle speeds and traffic volumes, in order to optimize the traffic flow.

Radar and ultra-sound systems have the advantage to be nearly independent of weather conditions and ambient light; however they are subject to stringent restrictions concerning their mounting position. Furthermore each of these systems can service one lane only. In contrast, video systems can be mounted at a side view position and a single sensor is able to monitor several lanes simultaneously. The main disadvantages of video based systems are the huge digital processing power [2, 3] needed to extract the essential information from the video image data and the sensitivity to inevitably varying lighting conditions.

The traffic monitoring system presented here uses a novel asynchronous optical transient sensor [4]. Applied in the context of traffic data acquisition, the sensor features almost all advantages of video-based systems without exhibiting the above mentioned drawbacks. By performing focal-plane analog signal preprocessing, a substantial data rate reduction is achieved, as compared to traditional frame-based image sensors, by completely suppressing redundant information in the image data. Consequently the subsequent digital signal processing can be accomplished by a low-performance, low-cost DSP. Additionally, the sensor exhibits a dynamic range of 6 decades of illumination, hence is largely insensitive to lighting conditions.

The presented system is capable of detecting, counting and measuring the speed of vehicles on up to 4 lanes simultaneously.

This paper concentrates on the evaluation of the vehicle counting algorithm implemented in the embedded system. For this purpose, the counting results delivered by the system are compared to ground-truth data extracted from the corresponding video stream by human interaction.

A comprehensive treatise on speed estimation algorithms employed in similar systems can be found in [5].

II. Embedded System and Test site

A. Sensor System

The embedded sensor system consists of the optical sensor and a DSP with Ethernet connectivity.

The sensor comprises 64×64 pixel performing on-chip detection and extraction of moving edges. Each of the autonomously operating pixels signals temporal contrast by generating asynchronous 'address events' (AEs). An address event consists of the signaling pixels' address, polarity (i.e. sign of change from bright to dark or dark to bright) and the time of event generation and thus is a most concise description of the dynamic contents of a scene. While the pixel reacts to illumination changes within microseconds, the DSP allocates time-stamps to the events with one millisecond time resolution, which is sufficient for vehicle detection and speed computation [4, 5].

For signal processing, a simple low-cost and low-power fixed-point DSP (Analog Devices Blackfin®) is used. The incoming address event stream is processed to detect vehicles and determine a series of vehicle properties (speed, length, time gap, vehicle class). The results are transmitted over Ethernet to a data receiver for post-processing or storage. More details about the sensor and the setup of the embedded system can be found in [4, 5].

B. Test installation

For nearly two years, we have been working with the local highway authority in operating a series of test sites

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allowing us to evaluate our traffic data systems in long-term field tests. All test sites feature uninterrupted power supply and broad-band network connectivity, thus allowing permanent access to the systems.

In this paper we show data from one of the sites where vehicles are viewed from the front (i.e. vehicles are approaching the sensor). At this location the highway has four lanes per traffic flow direction and features a wide speed range (stand-still congestion up to 180 km/h measured during night time) and very high traffic volume at rush hours (up to 1800 vehicles/hour/lane).

C. Detection and Counting Algorithm

Vehicle detection is based on monitoring the address event rate in predefined regions-of-interest (ROI). The AE rate is accumulated over 100 milliseconds and continuously compared against a threshold. If the threshold is exceeded, vehicle detection is assumed and address events from the respective lane are recorded. At the time the address-event rate under-runs the threshold the vehicle is assumed to have passed, data buffering is stopped and different algorithms processing the acquired data are started. Figure 1 shows the address event rate over time from a single ROI where five vehicles are passing. The detection threshold is marked as a red line. Every peak that exceeds and subsequently under-runs the threshold is regarded as one vehicle.

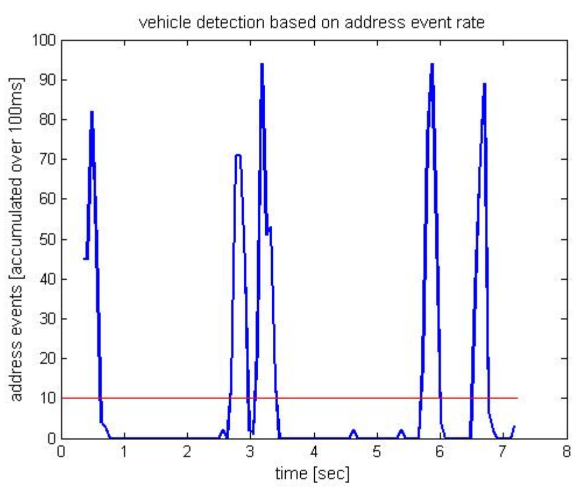


Figure 1: Detecting vehicles based on address event rate in region-of-interest. Start and stop time of vehicles are determined by using a simple threshold.

This simple method is robust with regard to missing vehicles but tends to detect false positives:

- Tall vehicles overlap neighboring lanes due to geometry/perspective.
- Front and back sections of one vehicle may be detected as independent vehicles.
- Shadows are cast by large vehicles on neighboring lanes, leading to erroneous double counts.

These false positives are removed in a second step by processing the buffered AE data.

Imposing a minimum number of address-events per detected vehicle suppresses double counts from overlaps, which generally show a much lower event count.

Front and back boundaries of vehicles are always easily detectable, independent of the vehicle's color and contrast to the road surface. The detection of leading and trailing edges is eased by prominent features like bumpers and head-/tail-lights, etc. and the always present ground shadows. However, the featureless middle section of certain vehicles causes a distinct minimum in the instantaneous AE rate which leads to unintended double detection. An imposed minimum distance between two consecutive detections, depending on the viewing angle and typical vehicle length, reduces those false counts.

To cope with the third shortcoming, a shadow cancellation algorithm was implemented. Upon vehicle detection, an AE histogram is accumulated, summing up AEs over the full sensor width at the region-of-interest's length. The histogram is filled until activity in the ROI under-runs the threshold. Shadow cancellation is based on the evaluation of the histogram's shape. Figure 2(a) shows a video frame and a histogram of two vehicles driving side by side on two lanes. They generate two distinguishable peaks on their respective lanes, separated by a clear local minimum. In contrast, a vehicle, when casting a shadow on a neighboring lane, generates only one local maximum in the histogram. A shadow appears as a shoulder without a local minimum (Figure 2(b)). The reason for this behavior is …..

D. Additional Derived Traffic Parameters

Other parameters important for traffic statistics such as the vehicle time gap and the lane occupancy are derived from begin and end of the vehicle detection (exceeding and under-run of detection threshold).

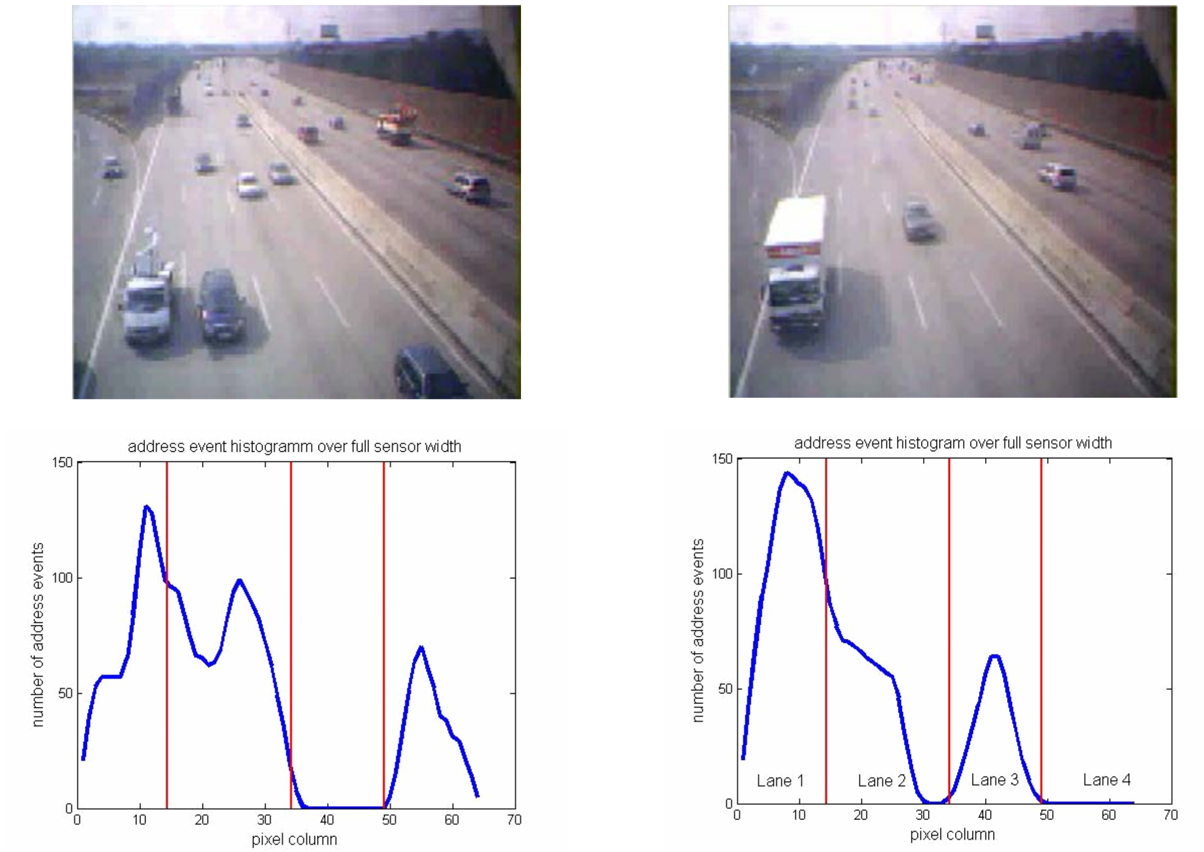
The time gap between vehicles is calculated and stored from the detection end to the start of the consecutive vehicle detection for each single vehicle with a resolution of one millisecond. Average time gaps for one minute intervals are derived for each lane.

The lane occupancy is the percentage of the time a ROI was occupied by a vehicle detection during a fixed time interval. It is calculated from the sum of the vehicle time gaps $T_{\Sigma gaps}$ observed in this observation interval as $(1 - T_{\Sigma gaps}/T_{interval})$.

Vehicle speed is derived from buffered AE data using two independent speed estimation algorithms reported in [5] and [12].

E. Test data recording

The AE data stream of about three hours of traffic data was recorded at a timing resolution of 1 millisecond by the embedded system. In parallel, a 5 frames-ps video stream



(a) (b)

Figure 2 Video frames of the test data and corresponding address event histograms

was recorded by a webcam at a resolution of 320×200 pixel and synchronized to the AE data using the AE inherent time stamps. Figure 3 shows raw address event data and the corresponding video frame of a scene recorded at the test site.

Figure 3: Video frame and rendering of AE data

The recording times for the test data sequences were chosen to contain a representative mix of different vehicle's speeds, traffic volume and lane occupancy. In case of bright sunshine where shadow cancellation is required shadows vary greatly depending on time of day and therefore test sequences have been recorded at different times (e.g. one sequence in the morning and one in the afternoon).

Table 1: Test data sequences

Time of day	**Length** min:sec	**Average** veh./hour/lane	**Light conditions**
06:42	33:22	1291	overcast
09:30	30:13	1018	overcast, rainy
09:42	26:44	956	sunny
10:43	30:36	836	overcast
10:52	27:24	904	heavy rain
11:30	20:52	776	overcast
15:08	19:39	720	sunny
total	**188:50**		

By human inspection, timestamp, lane and vehicle type were determined and linked to the raw address-event data stream. Three hours worth of video stream containing several thousands vehicles were processed and analyzed this way.

Table 1 contains a list of the recorded and annotated test sequences.

III. Results and Discussion

A. Vehicle Counting

Figure 4 shows a typical result of the vehicle counting accumulated over all four lanes over the course of four days. The data is shown in 2 minutes resolution, scaled to one hour intervals. As city inbound traffic flow is monitored, traffic peaks on weekdays at around 7am. On Saturday there is no pronounced peak whereas a traffic peak is found in the evening hours caused by people returning from weekend vacation.

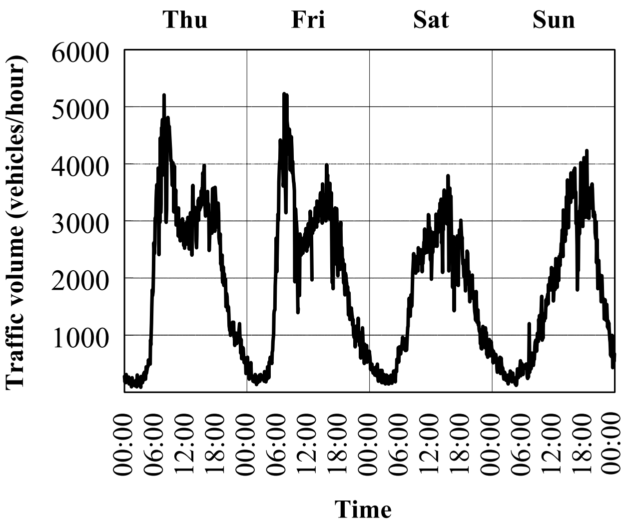


Figure 4: Vehicle quantity traffic data acquisition results accumulated over four lanes given in 2 minutes time intervals.

Figure 5 shows a typical result for the average lane occupancy evolution for the same days as presented in Figure 4. The data is resolved for the single lanes with lane number 1 being the right (slow) lane and lane number 4 being the left (fast) lane. Lane occupancy is basically following the traffic volume development. The strongest modulation of the lane occupancy is found on lane four which is used frequently only during peak times. Heavy usage of lane 1 on weekday mornings indicate frequent truck traffic in this time, whereas peaks on lane 3 and 4 on Sunday evening indicate the traffic generated by (fast) passenger cars.

B. Evaluation of Counting Precision

For the evaluation of the traffic data acquisition precision, in accordance with "Technische Lieferbedingungen für Streckenstationen (TLS)" [13], the official German norm for traffic data acquisition equipment suppliers, the data were evaluated over "short" and "long" time intervals and the total vehicle quantity per lane and interval were compared against a reliable reference quantity Q. The difference ΔQ between reference and system under test is then related to the vehicle quantity to define the counting error $\Delta Q/Q$ in percent.

Whereas errors in the long time interval should be very low, errors in the short time interval are inevitable due to small sample size and imperfect synchronization of test and reference system. Due to the small sample size in the short time interval (typically 10 to 100 vehicles), a single false detection can easily account for errors of the order of several percent. Also, for short intervals the probability increases that the test system attributes the detection to one interval and the reference system to another one. Thus, one such synchronization error accounts for two errors (one missing vehicle in one interval and one false detection in another).

Thresholds 3% and 10% are, according to [13], acceptable error margins for long (60 min) and short (3 min) time intervals respectively.

Our analysis was based on results from two lanes within 6 intervals of 60 minutes and 122 intervals of 3 minutes each. Table 2 gives an overview of the test data and counting precision. 100% of the long and 99.2% of the short time intervals analyzed remain within the error margins.

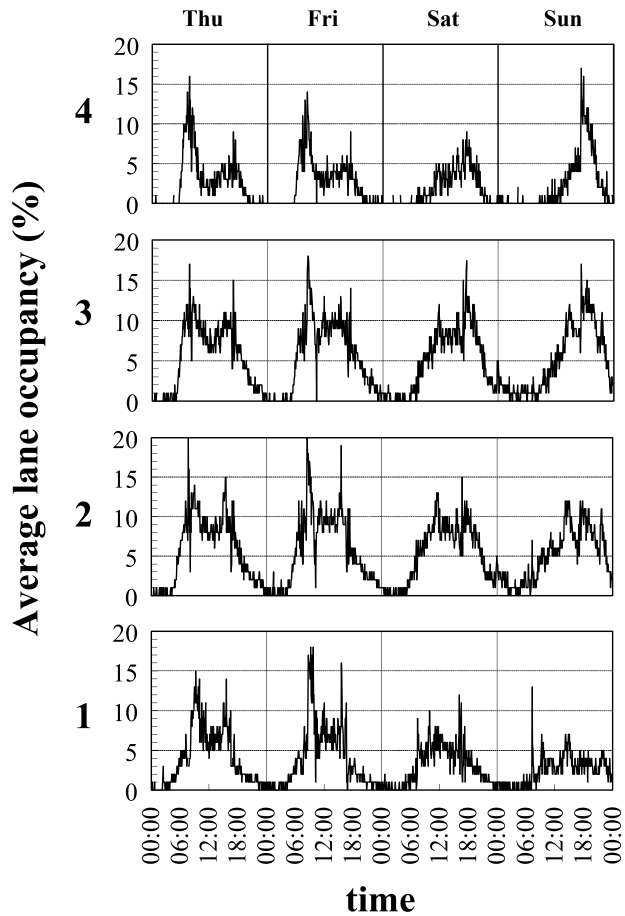


Figure 5: Lane occupancy traffic data acquisition results.

Table 2: Results of vehicle counting verification using manually annotated video.

Vehicles quantity Q	**7053**	
Truck quantity	20	
interval type	long term	short term
Interval duration	60 min	3 min
Accepted error $\Delta Q/Q$	<3%	<10%
Average Q per interval	1176	58
Number of Intervals	6	122
Compliant intervals	**100%**	**99.2%**

IV. Conclusion

An embedded vision system capable of detecting, counting, speed-measuring and classifying vehicles has been presented. The signal processing in the system strongly benefits from the sparse data delivered by the temporal contrast vision sensor. Several traffic parameters can be calculated in real time by a low-cost, low-power DSP. The focus of the paper lies on the evaluation of the counting algorithm based on manually annotated video sequences. The test data was acquired at a highway test site where one traffic flow direction is observed and processed with one vision sensor. The comparison of the reference data with the data acquired by the sensor system shows that the counting algorithm complies in 100% and 99.2% with the error margins of 3% and 10% for the long (60 min) and short (3 min) time intervals respectively.

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