FLEXSYS

Motion-based Traffic Analysis and Incident Detection

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.1 Introduction

Intelligent transportation system (ITS) to monitor dynamic traffic phenomena becomes more important in applications. Formulating dynamic traffic phenomena, which describes traffic situations to adapt the requirement of dynamic traffic assignment models and ITS applications, is a valuable research area.

Traffic surveillance using monitoring cameras has been widely applied in current traffic management. For over a decade, video based traffic flow analysis has been actively investigated, while the spatial and temporal nature of video sequences offer a richer source of traffic information than can be achieved by conventional point based detection systems such as inductive loops.

Based on traffic analysis, detection and prediction of different traffic incidents can be archived, such as accident, jam, etc. Traffic congestion, for example, is a road condition characterized by slower speeds, longer trip times, and increased queueing. A period of extreme traffic congestion is colloquially known as a traffic jam. Traffic accidents are abnormal events in traffic scenes.

There are quite some ITS available in the literature for traffic flow analysis. In the following sections, some state-of-art methods will be briefly presented.

.2 Traffic flow modelling based traffic analysis and incident detection

Mathematical description of traffic flow has been a lively subject of research. The traffic flow theory is a new science, which has addressed questions related to understanding traffic processes and to optimizing these processes through proper design and control [5].

This has resulted in a broad scope of models describing different aspects of traffic flow operations, either by considering the time-space behavior of drivers in microscopic models and mesoscopic models, or from the viewpoint of the collective vehicular flow in macroscopic models. The first attempts to give a mathematical theory of traffic flow dated back to the 1950s. Due to the complexity of the traffic flow system, analytical approaches may not provide the desired results, therefore, traffic flow models designed to characterize the behavior of the complex traffic flow system have become an essential tool for traffic flow analysis and experimentations.

During the past fifty years, a wide range of traffic flow theories and models have been developed, the models can be classified according to :

- Scale of the independent variables (continuous, discrete, semi-discrete).
- Representation of the processes (deterministic, stochastic).
- Level of detail (microscopic with high detail, mesoscopic with medium detail, macroscopic with low detail).

Based on level-of-detail which the vehicular flow is described, in the literature, researchers formulate the problem in mainly three ways, corresponding to the three main scales of observation in physics as follows, in which modelling accuracy, applicability, generalisability and model calibration and validations are general issues addressed.

- Submicroscopic and microscopic scale: every vehicle is considered as an individual, formulated by an equation, which is usually an ordinary differential equation (ODE).
- Mesoscopic (kinetic) scale: vehicles and driver behavior are not distinguished nor described individually, but rather in more aggregate-terms, the behavior rules are described at an individual level.

- Macroscopic scale: in analogy with fluid dynamics models, the rules of fluid dynamics are applied to traffic flow, formulated as a system of partial differential equations (PDE) for some gross quantities of interest, e.g the density of vehicles or their mean velocity.

At the microscopic scale, car-following models were used starting from the 1960's, these models are based on supposed mechanism describing the process of one vehicle following another. The dynamic equation of the car-following model can be written as

$$\ddot{x}_n = f(v_n, \Delta x_n, \Delta v_n) \tag{1}$$

where the function f represents the response to the stimulus received by the n-th vehicle, $\ddot{x}_n$ is acceleration or deceleration of the n-th vehicle. The stimulus may be composed of the velocity v_n of vehicle, the relative velocity $\Delta v_n = v_{n+1} - v_n$, and the headway $\Delta x_n = x_{n+1} - x_n$.

Bando et al [1] proposed an extension of car-following model called the optimal velocity model in 1995 and Xue [17] further developed it, which is governed by a second order differential equation and can describe the traffic-free flow and jam. Komatsu and Sasa [9] developed the modified Korteweg-deVries equation from the optimal velocity model to describe traffic jams in terms of a kink density wave.

Up to now we still do not have a satisfactory and general theory to be applied in real flow conditions. This is because traffic phenomena are complex and nonlinear, depending on the interactions of a large number of vehicles. Moreover, vehicles do not interact simply following the laws of mechanics, but also due to the reactions of human drivers.

.3 Vehicle tracking based traffic analysis and incident detection

Large amounts of methods for traffic analysis are proposed based on vehicle tracking in traffic. There are three main steps included: vehicle detection, vehicle tracking and traffic parameter evaluation [16]. They normally employ a vehicle segmentation and tracking framework. First, a potential vehicle is segmented from the scene using motion as well as other cues, or through background subtraction. Once segmentation is performed, the objects/vehicles are tracked between frames using different methods.

Vehicle tracking can yield traditional traffic information, such as lane changes and vehicle trajectories. Averaging trajectories over space and time, the traditional traffic parameters are more stable than corresponding measurements from point detectors which can only average over time. Traffic parameters are often calculated based on the numbers and instantaneous speeds of tracked vehicles.

Vehicle tracking strategies in the literature can be classified into four main categories[3, 6]: region based, active contour based, model based, and feature based.

Region-based tracking methods are dependent on the variation of the image region corresponding to the moving object[4]. They work well for scenes containing few vehicles, but can not handle the occlusion between vehicles.

Active contour-based methods represent the outline of moving objects as contours, which are updated dynamically in successive images [10]. Peterfreund [12] employed the "Snakes" to extract contours of vehicles for tracking. Those methods provide more efficient descriptions of objects than region-based methods and have been successfully applied to practice. But objects occlusion and automatic initialization of tracking are difficult to handle and tracking precision is limited by a lack of precision in the location of the contour.

Feature-based methods extract elements (features) from objects in scene, cluster them into high-level features, and then match the features between images[3]. The methods can adapt successfully and rapidly, allow tracking of multiple objects. However, the recognition rate of vehicles using 2D features is lows and stability is poor.

Model-based methods localize and recognize vehicles by matching a projected model to the image data [6]. Hu et al [6] proposed a framework for a traffic accident prediction scheme using 3-D model based vehicle tracking. They match the 3-D vehicle models with the captured video sequences. Neural network algorithm is applied to learn activity patterns from moving trajectories obtained by this tracking. According to its motion history, the future activity of vehicle is predicted and the probability of an accident is estimated.

Recent evaluations found the commercial video image processing systems had problems with congestion, high flow, occlusion, camera vibration due to wind, lighting transitions and long shadows linking vehicles together. The need for traffic surveillance under all conditions has led to research in more advanced video-based vehicle detection.

Keen and Hoose [8] presented a project which combined low-level sensor based information with high level system knowledge in order to achieve a consistent and robust automatic incident detection system. The first part of the system detects and tracks individual vehicles moving along highway. The information of the trajectory of every vehicle can be aggregated both spatially and temporally and then analyzed to indicate valid traffic incidents. The second part of the system generates a qualitative description of the traffic directly from the video image without individual vehicles being identified. The scene is described in terms of where there are no vehicles, moving vehicles and stationary vehicles. The two approaches are complementary in many aspects for final detection of incident.

Based on local analysis of the behavior of each vehicle, Kamijo et al [7] proposed a traffic event detection system. The system learns various event patterns of behavior of each vehicle in the Hidden Markov model (HMM) chains, and identifies current event using the output from the vehicle tracking.

It is known that video detection methods are unable to remain robust at all times because of different weather and lighting conditions. Ploetner and Trivedi [13] developed an integrated multi-modal system and framework for vehicle detection, tracking, and event detection. Feature extraction and data fusion techniques are investigated, and complementing video cameras with other sensing modalities is used to improve robustness.

.4 Motion field analysis for incident detection

As we know, an efficient traffic management system needs accurate traffic condition information. As explained before, most existing vision systems for monitoring road traffic rely on vehicle tracking.

One main disadvantage of the tracking based systems is that their accuracy relies on the quality of the segmentation and the tracking performance. Depending on the lighting conditions, speed of the traffic, and object occlusion, the segmentation and the tracking can become unstable [14]. Furthermore, segmentation cannot be performed reliably on low resolution images where the vehicles only span a few pixels. Tracking algorithms also have problems when there are many objects in the scene, which is typically the case for highways scenes with congestion. On the other hand, inspection of the traffic condition in the entire road is more interested for monitoring traffic.

In the literature, some interesting methods depending on estimation of motion vectors for traffic analysis have been proposed, thus avoiding the difficulties of vehicle segmentation and tracking. Porikli and Li [14] used a Gaussian Mixture Hidden Markov Model (HMM) framework to build the traffic event model. The parameters from HMM can be learned through a training process from feature vectors extracted from compressed video. The classification of five traffic patterns (including congestion) is performed by selecting the category corresponding to the proposed model of largest likelihood.

Chan and Vasconcelos [2] modelled the entire motion field as a dynamic spatio-temporal texture, which is an auto-regressive stochastic process. Traffic congestion is classified using nearest neighbors classifier or a support vector machine [15] based on the Kull-Leibler kernel [11].

Instead of using statistic models and classifiers, we propose in the following to design certain descriptors to capture directly the variability of the motion field of traffic without the need for tracking individual components/vehicles.

.4.1 Proposed Method

Dense motion estimation is first of all obtained using different algorithms, such as Horn-Schunck and Lucas-Kanade methods, which computes the optical flow based on assumption that the intensity does not change in two successive images. The motion from the video sequence is therefore abstracted and represented as motion vectors.

In general, traffic incident and congestion are characterized by two important properties: speed and density of traffic. We therefore propose the following measurements regarded as descriptors which could indicate different traffic condition, especially accident.

Mean Motion Flow: It is defined as average motion in scene of moving vehicles. Traffic jam normally causes slow traffic flow. We denote it as S.

Acceleration: Rapid velocity variation is a useful descriptor of a traffic accident. A traffic accident normally causes rapid change to vehicle speeds. Hence, we use the variation rate of vehicle speed for accident detection. We denote it as $\dot{S}$.

Based on the above two terms, one activity measure based on motion of vehicles can be defined as follows:

$$M = (p_1 + p_2\dot{S})S \tag{2}$$

where p_1 and p_2 are positive constants to balance S and $\dot{S}$.

It can indicate different traffic incidents as detecting abnormal event.

Density of moving vehicles and its rate: Here we refer to density of moving vehicles as the normalized area of moving vehicles over the selected road. *Area* means the number of pixels, i.e. the pixel with an optical flow higher than a given threshold. High density of moving vehicles in a scene indicates heavy traffic. When vehicle moves normally, the variation rate of the density is small, while the accidents/incidents cause rapid change to the density. We denote by A the density, and by $\dot{A}$ the variation rate of the density.

Keeping in mind that the above descriptors are different from traditional traffic parameters based on vehicles as defined in the following.

Flow rate is defined as

$$q = n/T \tag{3}$$

where n is the number of vehicles detected, T is the time interval.

Mean speed : is the average speed of vehicles present in a segment of roadway or during a designed time period,

$$\bar{S} = \frac{n}{\sum_{i=1}^{n} S_i^{-1}} \tag{4}$$

where S_i stands for speed of each vehicle.

Density is defined as

$$D = q/\bar{S} \tag{5}$$

Based on the above proposed descriptors, we can analyze traffic flow for different traffic situation, such as light traffic, normal traffic and jam.

.4.2 Experiments on video sequence CamZoomError

The video sequence CamZoomError is analyzed as follows. For the frame 1-1000, the two different descriptors, Mean motion flow S and Acceleration $\dot{S}$, are measured and shown in Fig. 1. Activity measure defined in Eq. 2 is shown in Fig. 2, together with density of moving vehicles A. Observing the evolution of the density of moving vehicles and activity measure, one can notice that the traffic flow first grows and then goes down until frame ♯100. From there, traffic flow grows till frame ♯265, then goes down till frame ♯400, and climbs up till around frame ♯680, and so on. Based on video sequence, this evolution is quite consistent with real traffic situation.

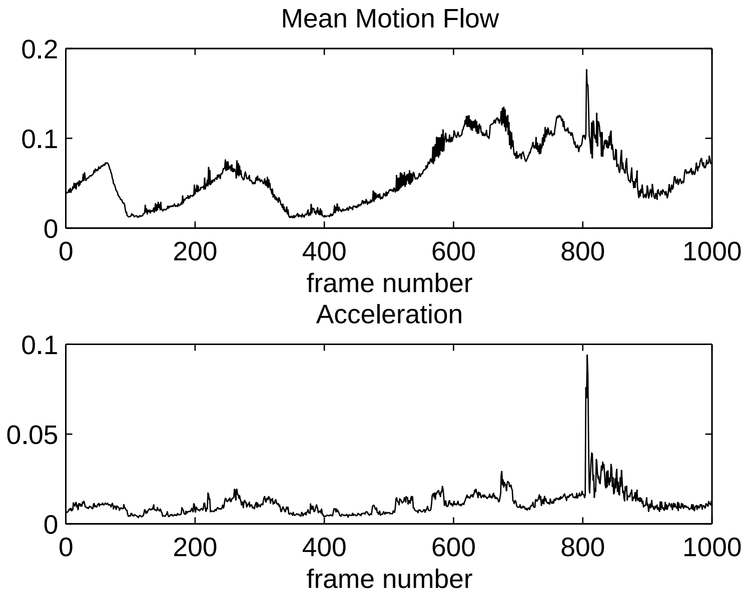


Figure 1: Traffic descriptors: frame 1-1000.

In general, the density of moving vehicles A can be regarded as one indicator for traffic situation. If A is high, the traffic is heavy, if A is low, the traffic is light. We define three traffic status: light, normal and heavy. A threshold is set to 0.3 in this experiment to distinguish light traffic from other traffic status. The last figure in Fig. 2 shows the analysis result.

We can see that there are parts of frames where A oscillates, i.e. value of A changes quickly, which makes the traffic indicator jump from one status to another quickly. Such quick change is not due to normal traffic change. From the video sequence, it has been discovered that those correspond to camera shaking (frames from ♯135 to ♯390, frames from ♯513 to ♯537, frame from ♯810 to ♯1000), etc.) [1]

In order to reduce the influence due to camera shaking and improve accuracy of traffic analysis, a 7-point moving average method is used to smooth the density of moving vehicles A. The

[1] The issue of camera stabilization will be tackled later on in this project.

analysis result using the smoothed A as the indicator is illustrated in Fig. 3. It is obvious that the performance is much more improved compared with the previous one in Fig. 2.

On the other hand, we notice that there exists a big peak in the activity measure M at around frame ♯810, which is also indicated in Fig. 1, A varies abruptly. Sudden change of M in video sequence is caused by certain change in the scene, which can be generated by traffic accident, or by the acquisition system. We refer to such event as a kind of traffic incident. In reality, from video sequence, we find that camera makes right shift at frame ♯808 plus shaking.

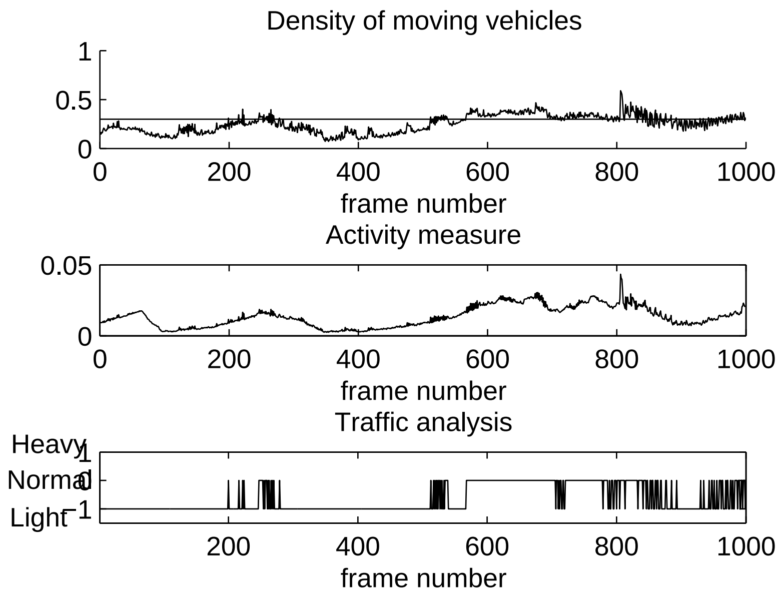


Figure 2: Traffic analysis.

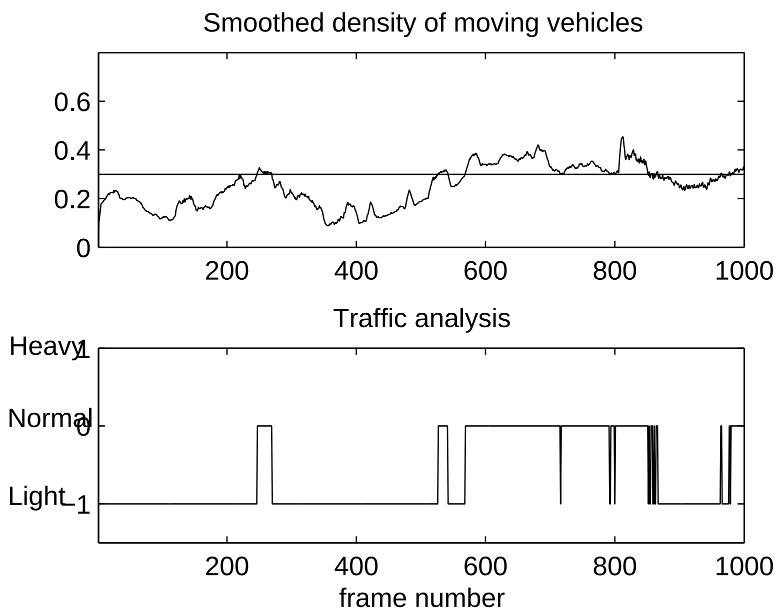
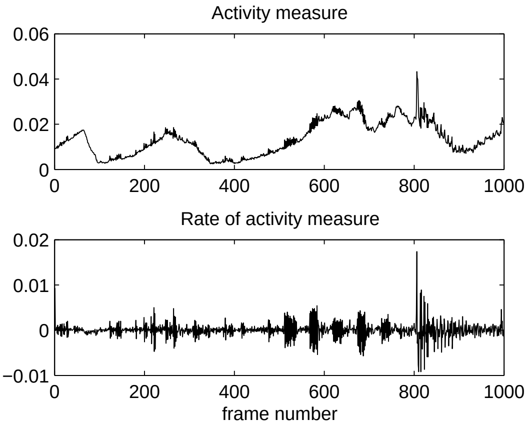


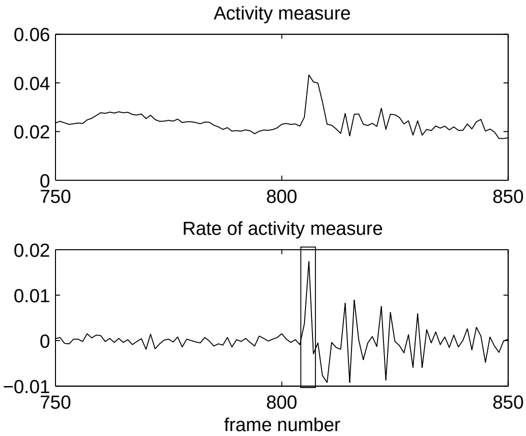
Figure 3: Traffic analysis with the smoothed density A as the indicator.

This incident can be located from the video sequence by calculating the rate of activity measure $\dot{M}$, i.e. the variance of activity measure, as shown in Fig. 4 (a). Then the incident can be singled out by setting a threshold on $\dot{M}$ (0.01 is chosen here), as illustrated in details in Fig. 4 (b).

Once there exists an incident which is indicated by a big change in activity measure, the traffic indicator A normally could not determine correctly the traffic status as shown in Fig. 2.



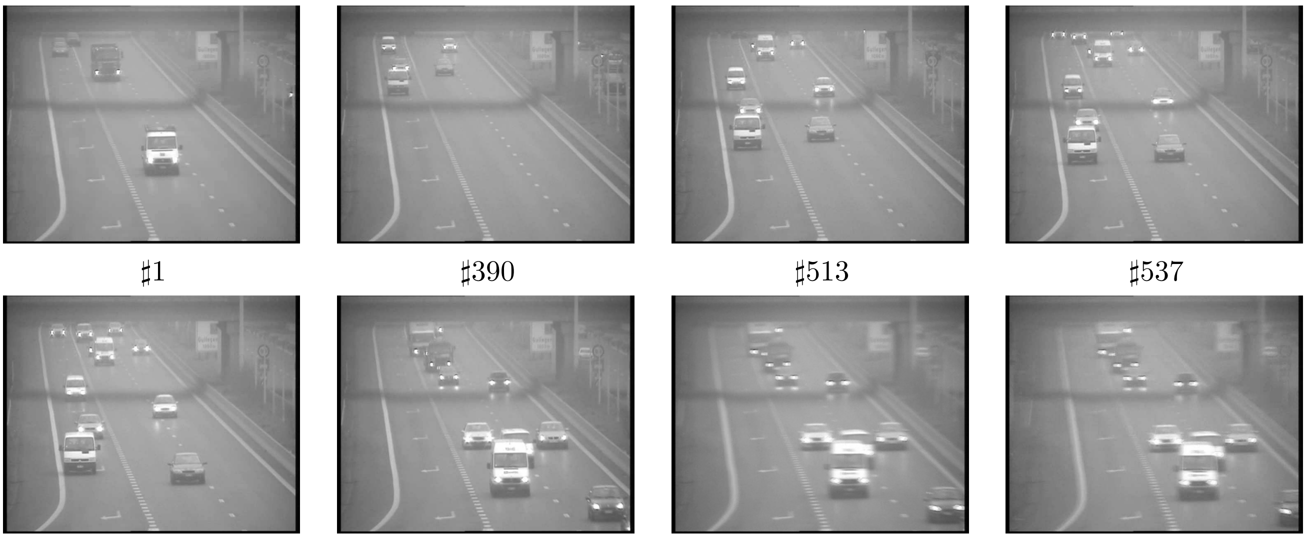
(a)



(b)

Figure 4: Incident indication.

Some frames from 1-1000 are displayed in Fig. 5, corresponding to above analysis.



♯1 ♯390 ♯513 ♯537

♯568 ♯808 ♯809 ♯811

Figure 5: Some frames.

For frame 1001-2000, the Mean motion flow S and Acceleration $\dot{S}$ are measured and shown in Fig. 6. The activity measure M and density measure A are displayed in Fig. 7, they both are quite consistent to show the traffic evolution. The traffic status is illustrated in the last figure of Fig. 7. Some frames are displayed in Fig. 10 to show traffic situation.

The first part of density measure A evolution looks simple, contains some oscillations. On the other hand, there exists a big peak in activity measure around frame ♯1325, followed by an oscillatory part up to frame ♯1600, accordingly the traffic indicator starts to jump between normal and light traffic.

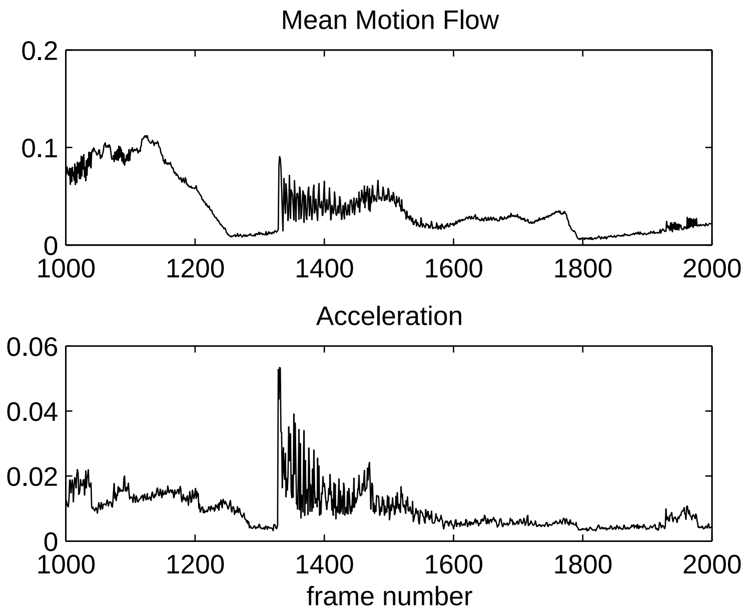


Figure 6: Traffic descriptors: frame 1001-2000

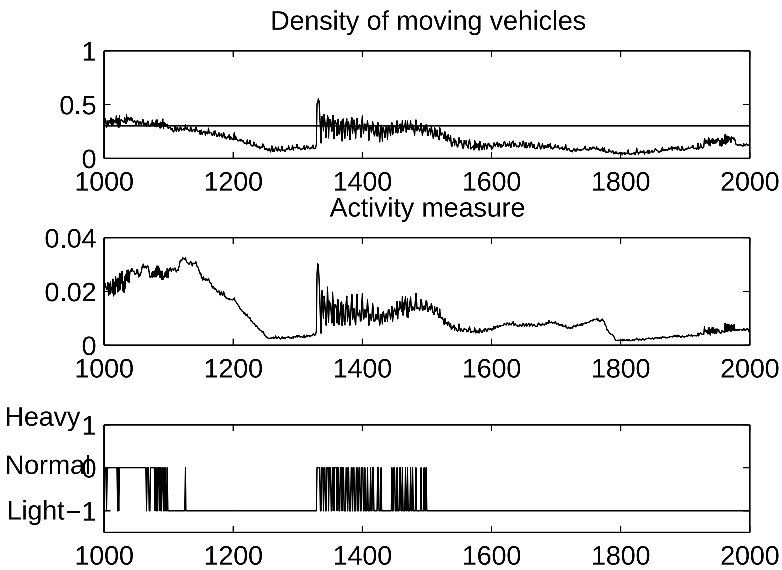


Figure 7: Traffic analysis.

The analysis result using the smoothed A as the indicator is illustrated in Fig. 8. It is clear that the influence of oscillatory parts of A for traffic analysis is much more reduced.

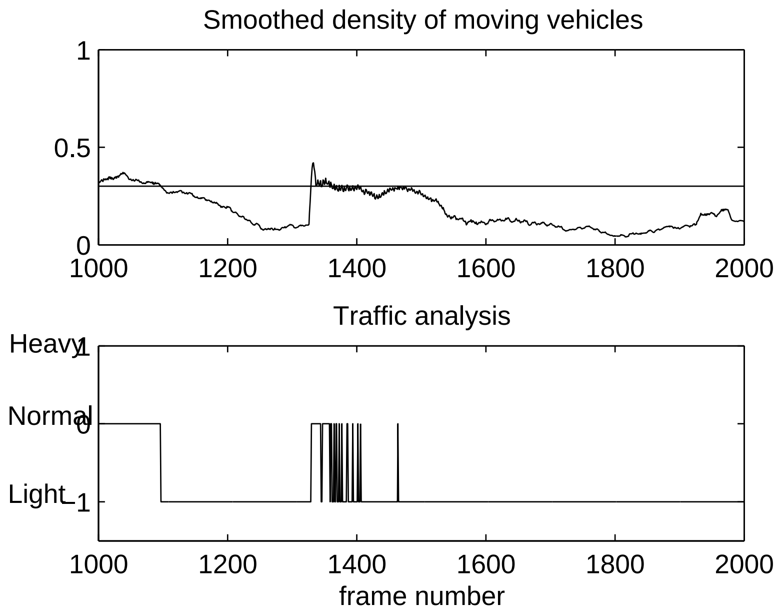
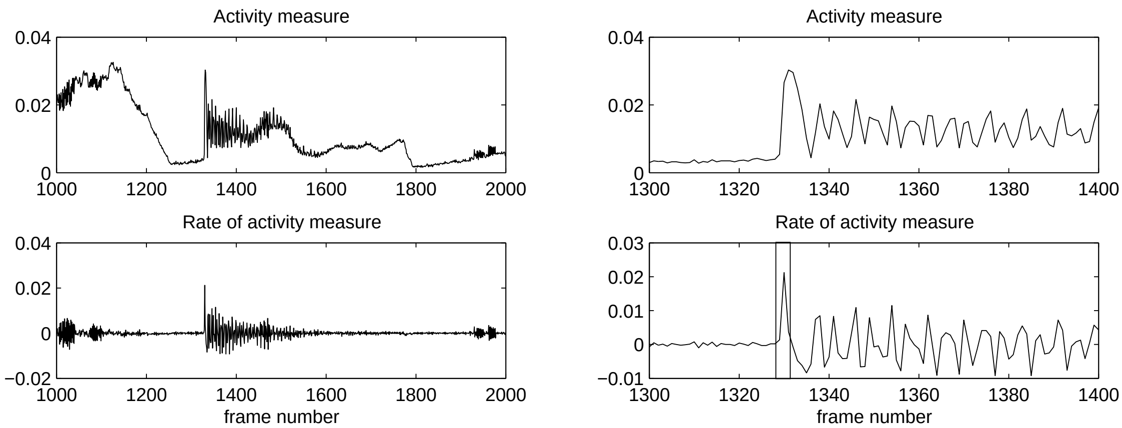


Figure 8: Traffic analysis with the smoothed density A as the indicator.

Fig. 9 explains how to single out this incident from the sequence. The rate of activity measure $\dot{M}$ is calculated and the high peak can be picked up by thresholding as explained before. As shown in Fig. 9 (b), the incident appears at frame ♯1325. In reality, we find that video sequence images become suddenly blurred from frame ♯1325, camera makes shift and starts shaking (shaking becomes smaller gradually). As illustrated, this incident can be detected.



(a) (b)

Figure 9: Incident indication.

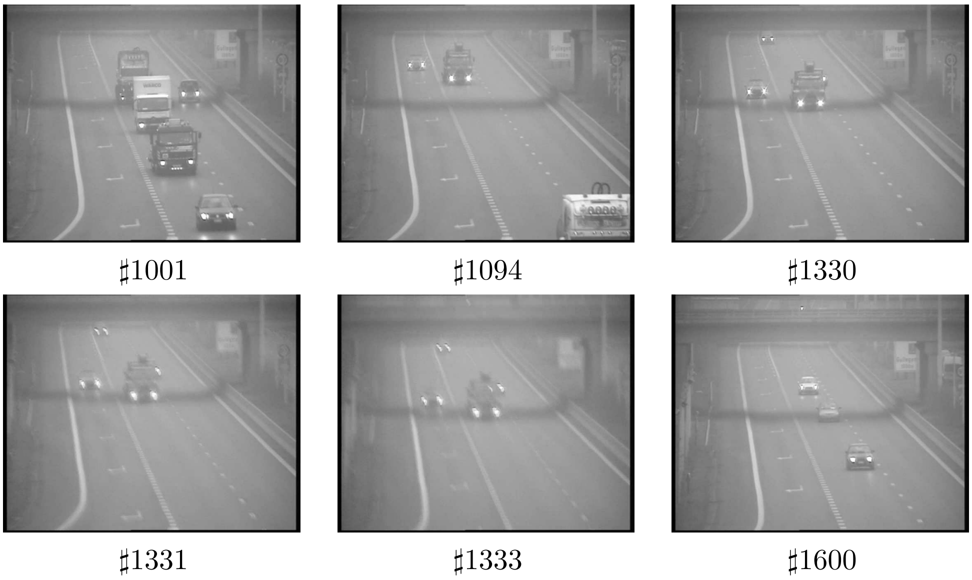


Figure 10: Some frames.

Similar analysis goes to frame 2001-3500, Fig. 11 illustrates the evolution of the two descriptors, activity measure M and density of moving vehicles A are shown in Fig. 12.

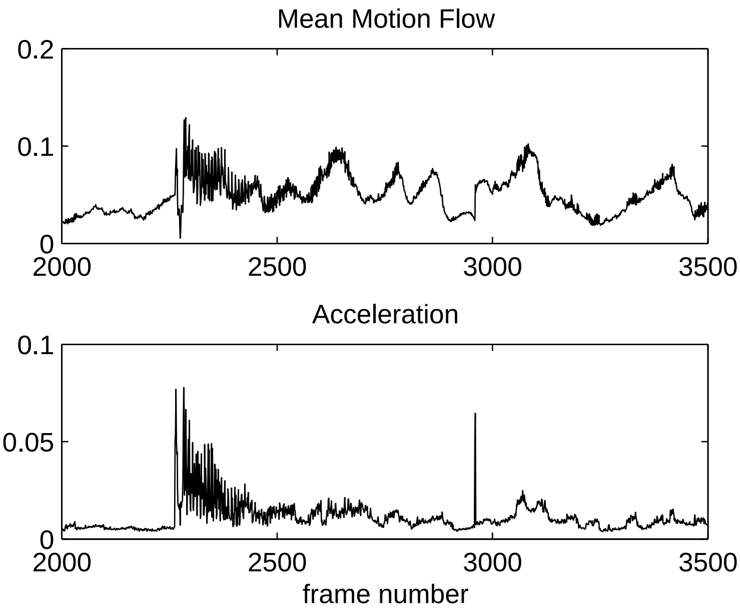


Figure 11: Traffic descriptors: frame 2001-3500.

From Fig. 12, M and A look consistent with each other. They show that the traffic is stable at the first part, and has a sudden change at frame ♯2265, followed by a heavy oscillatory part. As before, the oscillatory parts in the evolution of A result in incorrect traffic status indication at those parts.

The analysis result using the smoothed A as the indicator is shown in Fig. 13. It is obvious that the influence due to the incident and camera shaking is much more reduced and accuracy of traffic analysis is improved.

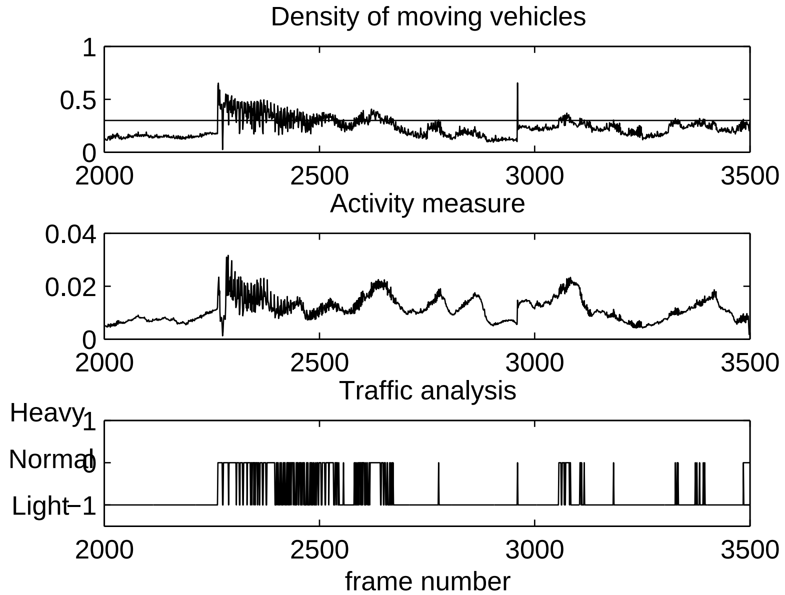


Figure 12: Traffic analysis.

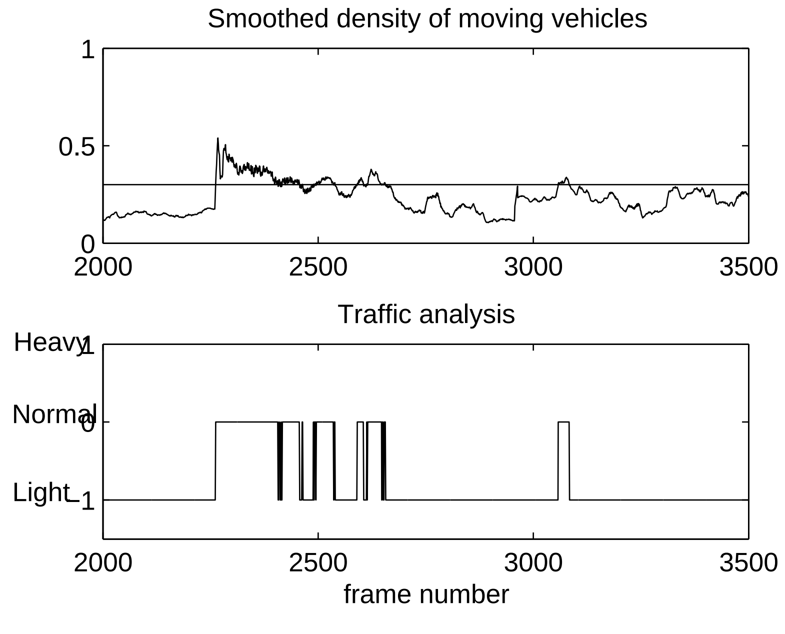


Figure 13: Traffic analysis with the smoothed density A as the indicator.

In Fig. 14, the rate of activity measure $\dot{M}$ is illustrated in order to determine and locate incident. A group of frames are singled out to indicate an incident–in reality, at frame ♯2265 the camera has error to show images and shakes.

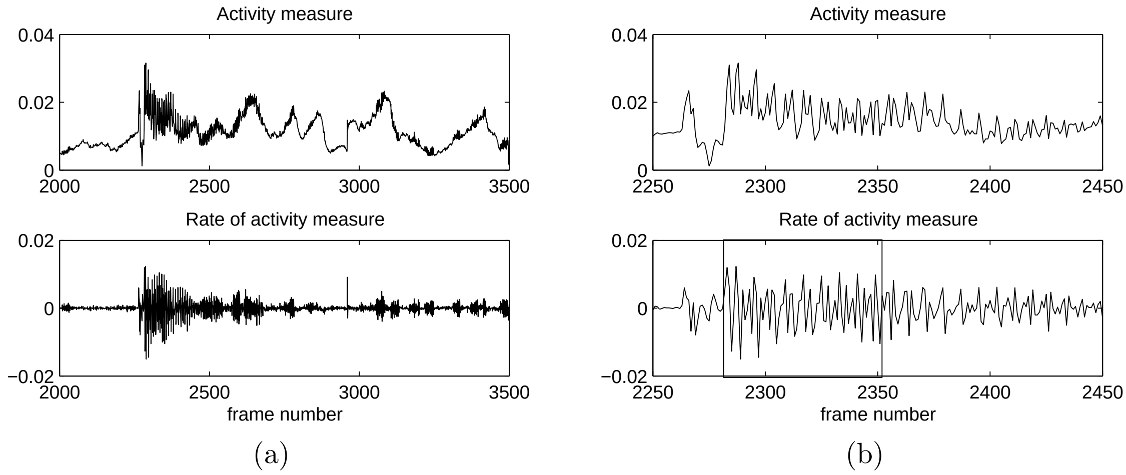


Figure 14: Incident indication.

Some frames from 2001 to 3000 are displayed as follows for reference of our analysis.

♯2265 ♯2266 ♯2280

Figure 15: Some frames.

Bibliography

[1] M. Bando, K. Hasebe, A. Nakayama, A. Shibata, and Y. Sugiyama. State-of-the-art of vehicular traffic flow modelling. *Phys. Rev.*, E 51(1035), 1995.

[2] A. B. Chan and N. Vasconcelos. Classification and retrieval of traffic video using auto-regressive stochastic processes. In *Proceedings of 2005 IEEE Intelligent Vehicles Symposium*, pages 771–776, 2005.

[3] B. Coifman, D. Beymer, P. McLauchlan, and J. Malik. A real-time computer vision system for vehicle tracking and traffic surveillance. *Transportation Research: Part C*, 6(4):271–288, 1998.

[4] S. Gupte, O. Masoud, R.F.K. Martin, and N.P. Papanikolopoulos. Detection and classification of vehicles. *IEEE Transactions on Intell. Transport. Syst.*, 3:37–47, 2002.

[5] S.P. Hoogendoorn and P.H.L. Bovy. State-of-the-art of vehicular traffic flow modelling. *Journal of Systems and Control Engineering*, 215(4):283–303, 2001.

[6] W. Hu, X. Xiao, D. Xie, T. Tan, and S. Maybank. Traffic accident prediction using 3-D model-based vehicle tracking. *IEEE Transactions on Vehicular Technology*, 53(3):677–694, 2004.

[7] S. Kamijo, Y. Matsushita, K. Ikeuchi, and M. Sakauchi. Traffic monitoring and accident detection at intersections. *IEEE Transactions on Intell. Transport. Syst.*, 1:108–118, 2000.

[8] K. Keen and N. Hoose. Invaid - integration of computer vision techniques for automatic incident detection. In *IEE Colloquium on Car and its Environment - What DRIVE and PROMETHEUS Have to Offer, No. 25*, pages 9/1–9/3, 1990.

[9] T. Komatasu and S. Sasa. State-of-the-art of vehicular traffic flow modelling. *Phys. Rev.*, E 52(5574), 1995.

[10] J. Malik and S. Russell. Traffic surveillance and detection technology development: New traffic sensor technology. Technical Report UCB-ITS-PRR-97-6, University of California, Berkeley, 1997.

[11] P. J. Moreno, P. Ho, and N. Vasconcelos. A kullback-leibler divergence based kernel for svm classification in multimedia applications. In *Advances in Neural Information Processing Systems*, Vancouver, Canada, 2003.

[12] N. Peterfreund. Robust tracking of position and velocity with kalman snakes. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 21:564–569, 1999.

[13] J. Ploetner and M. M. Trivedi. A multimodal framework for vehicle and traffic flow analysis. In *Proceeding of IEEE Intelligent Transportation Systems Conference*, pages 1507–1512, Toronto, Canada, September 17-20, 2006.

[14] F. Porikli and X. Li. Traffic congestion estimation using HMM models without vehicle tracking. In *In IEEE Intelligent Vehicle Symposium*, pages 188–193, 2004.

[15] V. Vapnik. *The Nature of Statistical Learning Theory*. Springer Verlag, 1995.

[16] J. M. Wang, Y. C. Chung, S. C. Lin, S. L. Chang, S. Cherng, and S. W. Chen. Vision-based traffic measurement system. In *Proceedings of the 17th International Conference on Pattern Recognition*, 2004.

[17] Y. Xue. Analysis of the stability and density waves for traffic flow. *Chinese Physics*, 11(11):1128–1134, 2002.