Advanced Traffic Monitoring

Transumo

WWW.ATMO.TUDELFT.NL

Deliverable	**DIID-2c**
Deliverable type	International paper
Title	***Detection of Incidents and Events in Urban Networks***
Author(s)	Thomas, T., and Van Berkum, E.C.
Date	2008
Source	CD-rom: Proceedings in European ITS congress, Geneva
Name subproject	**Recognition and Classification of Regular and Non-regular Network Conditions**
Organisation	University of Twente
Leader subproject	Prof. dr. ir. E.C. (Eric) van Berkum

Transumo project number	**VM04 031**
Project name	Advanced Traffic Monitoring (ATMO)
Project leader	Dr. ir. Hans van Lint. Delft University of Technology Faculty of Civil Engineering and Geosciences Department of Transport & Planning

Transumo

The ATMO project is made possible with support of Transumo.

Transumo (TRANsition SUstainable MObility) is a Dutch platform for over 150 companies, governments and knowledge institutes that cooperate in the development of knowledge with regard to sustainable mobility.

Transumo aims to contribute to a transition from the current inefficient mobility system towards a system that facilitates a stronger position in economic competition, as well as ample attention for people and environment. The research and knowledge development activities of Transumo have started in 2005 en will continue at least until 2009. Currently over 20 projects are conducted within Transumo.

More information is available via www.transumo.nl.

Detection of Incidents and Events in Urban Networks

T. Thomas University of Twente, Enschede, the Netherlands, t.thomas@utwente.nl
E.C. van Berkum University of Twente Enschede, the Netherlands , and
Goudappel Coffeng, Deventer, the Netherlands, .evberkum@utwente.nl

1. INTRODUCTION

Although there is a large variation in traffic flow patterns, we can distinguish two main types: recurrent and non-recurrent patterns. A recurrent pattern repeats itself with a known period and is therefore predictable. An example is the rush hour peak, but also the peak in travel demand which is caused by a weekly event, like a professional football match. Non recurrent patterns are caused by single events and incidents. Although these are relatively rare, they often have a very negative impact on the traffic situation (e.g. Smith et al. 2003). An important issue for policy makers therefore has been to reduce these negative effects.

Much effort has gone into the development of incident detection algorithms (e.g. Browne et al. 2005, Koppelman & Lin 1996) which form a crucial part of incident management. These algorithms use real-time measurements of volume, occupancy and / or speed to detect incidents. There are several types of detection algorithms. Some of them are based on neural networks (e.g. Liu et al. 2004, Ritchie & Cheu 1993). In other algorithms an incident is declared when the data fulfill certain pre-selected criteria. In time-serie algorithms for example an incident is detected when the measurements differ significantly from the predictions (e.g. Stephanedes et al. 1992, Dudek et al. 1974). With the McMaster algorithm different traffic situations (e.g. incidents) are distinguished based on the location of measurements in the occupancy – flow volume diagram (e.g. Hall et al. 1993). Finally, in decision structure algorithms incidents are detected when measurements exceed thresholds in a decision tree (e.g. Ash 1997, Payne & Tignor 1978).

In The Netherlands a decision structure algorithm has been developed for the Dutch motorways which appears to be quite successful (Knibbe et al. 2005). Complementary, in this paper we introduce a prediction scheme for recurrent events and an incident detection algorithm based on data from a Dutch city. For our detection algorithm we only use volume data. In section 2 we describe the data and in section 3 we introduce our incident detection method. In section 4 we describe the prediction method for recurrent events. In section 5 we analyse the incidents which we detected with our detection method. We discuss our results in section 5.

2. DATA

The study area for this research consists of the urban network of the Dutch city of Almelo. Traffic data were collected at about 20 intersections from September 2004 till 2005. Vehicles were detected by means of inductive loop detectors. These data were processed into volume measurements per link. In most cases measurements were provided in 5-minute intervals, which means that each daily time-series or volume profile contains 288 volumes.

The volume measurements were inspected and invalid data were rejected after which the volume profiles were analysed is detail (Weijermars et al. 2007, Thomas et al. 2007a). From these analyses we concluded that the noise (i.e. variations in successive traffic counts which are uncorrelated and therefore unpredictable) can be approximated by a Poisson distribution and that 10 minute time lags are most suitable for volume predictions. In Thomas et al. (2007b) we presented a scheme for volume predictions. We applied this scheme on a sample of 48 intersection links (with on average more than 100 profiles equally distributed over different weekdays), and we showed that the accuracy of our short term predictions was about 5%. In this study we use the same sample (with 10 minute time lags) to compare the measured volumes with the expected volumes from the short term predictions. From this comparison we will be able to detect incidents.

3. DETECTION OF OUTLIERS

When traffic accidents, road works, or other unique events occur, traffic volumes can differ significantly from the average. Most of these events are unexpected and can have a large impact on traffic circulation. Here we introduce a 3 plus 4-sigma clipping method which is quite effective in identifying these so called outliers in real time. The idea of this method is simple. We compare the actual volume measurement q^{obs} with the prediction q^{pred}. When the absolute difference between the two exceeds 4 times the standard deviation of the noise, we call the measurement an outlier. The noise can be approximated by a Poisson distribution with standard deviation equal to the square root of the prediction (for details we refer to Thomas et al. 2007a).

We found that the fraction of detected 4 sigma outliers is about 0.2% of all measurements. Although it is a small fraction, it is still significant. We know that in most 10 minute intervals volumes are much larger than 10 vehicles. For these volumes the Poissonean noise can be approximated by a Gaussian distribution. Given a Gaussian distribution we can calculate the probability that a noisy measurement is misidentified as an outlier. This probability is $6.3*10^{-5}$ and therefore about 30 times smaller than the real fraction of detected outliers. In other words, the probability that a detected outlier is in fact not an outlier is only 3%.

If we would use a detection limit of 3 sigma, we would find a much higher fraction of false alarms, i.e. 30% or more. This detection limit is therefore not suitable. However, the probability that two successive measurements are both misidentified as outliers is only $7.3*10^{-6}$ (0.0027 * 0.0027), while the number of successive detections is of the same order as that of (single) 4 sigma detections. In other words, the probability that two successive false alarms occur is very small (< 1%) for the 3 sigma detection limit. With the double 3-sigma criterion we can identify outlying events that are not very extreme, but that have longer timescales (20 minutes or more).

In fig. 1 we show two examples of outlying events. The dotted lines are time-series of two observed daily profiles. The solid lines are the predictions with a 10 minute time horizon (for details we refer to Thomas et al. 2007b). In the top panel a small amount of extra traffic is generated by an event. In this case the outliers only can be detected by the 3-sigma limit (open symbols). In the bottom panel a significant peak is detected by the 4-sigma limit (filled symbols). Note that only 17% of all daily profiles contain one or more outliers between 6h and 24h. All the other profiles (83%) have regular shapes during the day period (between 6h and 24h).

In the literature (e.g. Stephanedes et al. 1992) the following measures are used for evaluating an incident algorithm: detection rate (DR), false alarm rate (FAR) and mean time to detect (MTTD). It was shown that our detection method is quite successful with the chosen thresholds. We have shown that the false alarm rate is only a few percent, while from visual inspection we conclude that we probably detect all large incidents (i.e. accidents) and most small incidents (for example those that are caused by a blockade of a truck). Unfortunately, we cannot verify this with information from the police or by visual information from cameras. The mean time to detect lies between 10 and 20 minutes. However, with smaller time-lags in our time-series (i.e. 5 minutes) we probably can reduce the detection time to 5 minutes for large incidents without significantly changing the detection and false alarm rate.

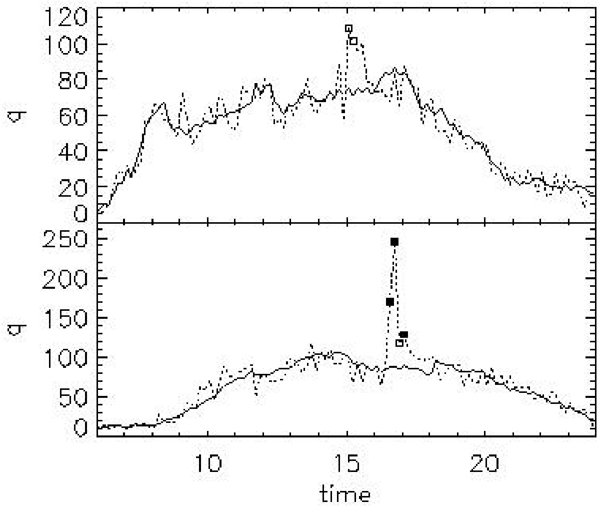

Fig. 1 Two examples of outlying events in volume time-series (dotted lines) compared to predictions (solid lines)

4. EVENT PREDICTIONS

When large events take place traffic flows are influenced by the large number of visitors that attend these events. At certain locations this will result in a significant increase of traffic just before the event has started and after the event has finished. In Almelo most of these peaks occur when the local professional football team Heracles plays their home matches. In this section we analyse the event related patterns in more detail.

We selected 11 days on which Heracles played their home match, starting at 20.00h. At 26 links we could detect extra traffic due to the football match. For these links we determined the average (over 11 days) difference profile between observations and predictions. In fig. 2 we show some examples of these difference profiles. The time plotted on the x-ordinate is relative to the start of the event (left panel) and to the end of the event (right panel). The volumes show well defined peaks, although the data is quite noisy. This is the result of our choice to use 5 minute time-series. Only with 5 minute time-series is it possible to resolve the peaks which show very short time-scales. This is especially true for the departure peaks.

The observed patterns in fig. 2 can be approximated by a Gaussian fit (solid lines). According to these fits the peak intensity occurs on average slightly more than 35 minutes before the start time and slightly less than 25 minutes after the end time. In addition, the typical width (standard deviation) of the arrival peak is about 15 minutes, while that of the departure peak is even smaller (less than 10 minutes). As might be expected it takes longer for all visitors to arrive at the event than it takes for them to depart.

In fig. 3 we show 3 examples of volume profiles (dotted lines) during which a football match took place. The links in the example serve traffic from the stadium and they show a clear peak after the match (around 22.00h). The predictions are shown by the solid lines. Most peaks in the sample are predicted quite well (e.g. see upper panel), although in many cases the observations show a tail which is absent in the prediction. This tail is caused by people that don’t leave immediately after the match. A significant fraction of peaks however cannot be predicted accurately. In some cases is the peak shifted with respect to the prediction (second panel). This situation occurs for example when the match does not start at the planned time. Variable start and end times cannot be predicted. However, when they are immediately communicated with the traffic centre prediction might be improved. Finally, volumes can vary significantly between matches, which can lead to wrong predictions (bottom panel). Because visitor numbers are rather constant, we suggest that these variations are related to changes in distribution (i.e. the origins from which the visitors arrive) or modal split (which probably depends on the weather).

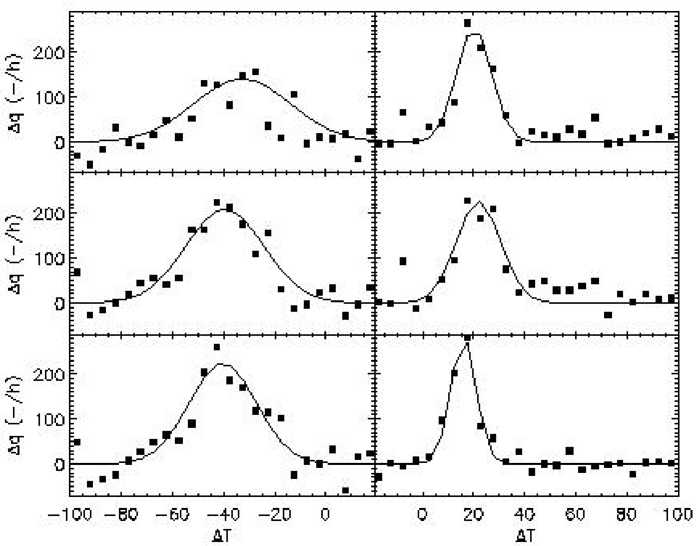

Fig. 2 Event related volume patterns before the start of the event (left) and after the end of the event (right) at different intersection links

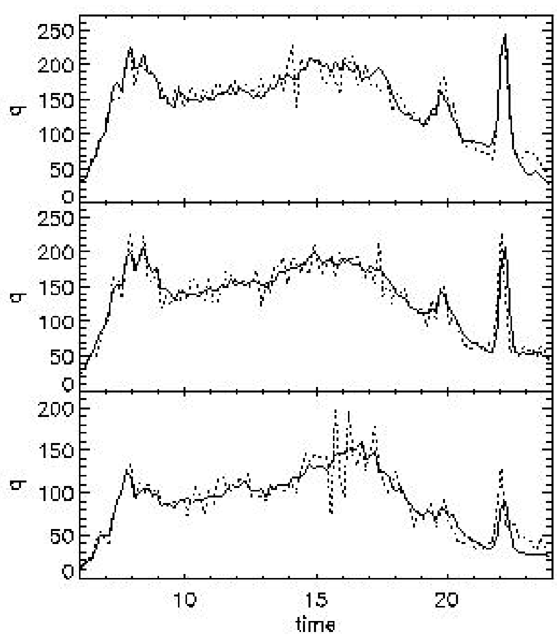

Fig. 3 Observed time-series (dotted lines) and predictions (solid lines) for links that served traffic after a football match

5. INCIDENTS

Apart from events and road works, unexpected deviations in volumes are almost always the result of incidents. An incident can be viewed as a negative outlier of a flow, i.e. an outlier for which the observed volume lies below the expected volume. In our sample we selected more than 200 of these outliers. This corresponds with about 2 incidents per day on the whole network. Some of the incidents are small and can be caused for example by a blockade of a truck. Other incidents are large and those are often caused by accidents. In fig. 4 we show examples of small incidents (left panel) and large incidents (right panel). The incidents are detected by both the 3-sigma (open symbols) and 4-sigma (solid symbols) clipping method.

According to the figure, incidents generate a typical pattern (dotted line). A dip in volume with respect to the prediction (solid line) is followed by an excess of traffic (caused by the dispersion of queued traffic). We call the duration of the dip the incident period ($T_{incident}$) and that of the excess in traffic the recovery period ($T_{recover}$). We find that the incident period is 20 minutes or less for small incidents. The recovery period lies typically between the 20 and 40 minutes (twice the incident period). Note that we cannot detect periods less than 20 minutes because of the limited resolution of the time-series. Incident periods of large incidents lie typically between 60 and 90 minutes and recovery periods are of the same length. The depth of the dip is more variable. In the upper right panel was the minimum volume during the accident close to 0, which could be due to a temporary closure of the road. The accident in the bottom right panel was less extreme. In that case was the minimum volume about 50% of the expected volume.

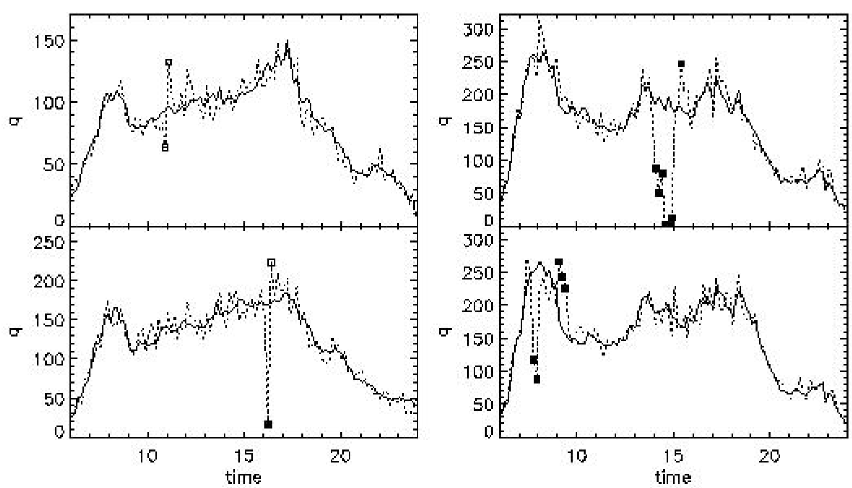

Fig. 4 Examples of small incidents (left) and large incidents (right) in volume time-series (dotted lines) compared to predictions (solid lines)

In the examples above we discriminate between small and large incidents. We would like to quantify this rather qualitative difference by a certain strength parameter. We choose to define the strength by the equivalent width (*EW*), which we define for 10 minute time-series as

$$EW = 10\sum(q^{obs} - q^{pred}) / < q^{pred} > \qquad (1)$$

We defined the start time of the incident to be 10 minutes before the first detected outlier of that incident. We then estimated the equivalent width of the dip ($EW_{incident}$) during the incident period (between the start and end time of the dip), in which we chose $T_{incident}$ such that $EW_{incident}$ is minimal. After the incident period the recovery period starts. We chose the recovery period such that $EW_{recover}$ is maximal, but we demanded that $T_{incident} \leq T_{recover} \leq 2T_{incident}$. The equivalent width is a relative strength, i.e. relative to the mean expected volume ($<q^{pred}>$) over the whole period. The equivalent width is given in minutes and its length multiplied by the mean expected volume equals the amount of traffic that is missing (negative width) during the incident and the amount of extra traffic (positive width) during the recovery period. We therefore demanded that $EW_{incident} < 0$ and $EW_{recover} > 0$. With this demand we selected about 160 incidents.

In fig. 5 we show the equivalent widths of the incident and the recovery period. For small incidents there is no clear relation between both equivalent widths. In fact, in some cases is the amount of extra traffic during the recovery period even larger than the amount of missing traffic during the incident ($|EW_{recover}|>|EW_{incident}|$). These cases probably are not caused by a blockade or accident, reducing the number of true incidents even further, and they are shown by open symbols in fig. 5. For larger incidents ($|EW_{incident}| > 10$) there seems to be a correlation between the two equivalent widths. If we exclude the open symbols the average ratio between both equivalent widths (in absolute values) is about 0.4. In other words, 40% (on average) of the vehicles that have been blocked will follow their way, while 60% will take another route.

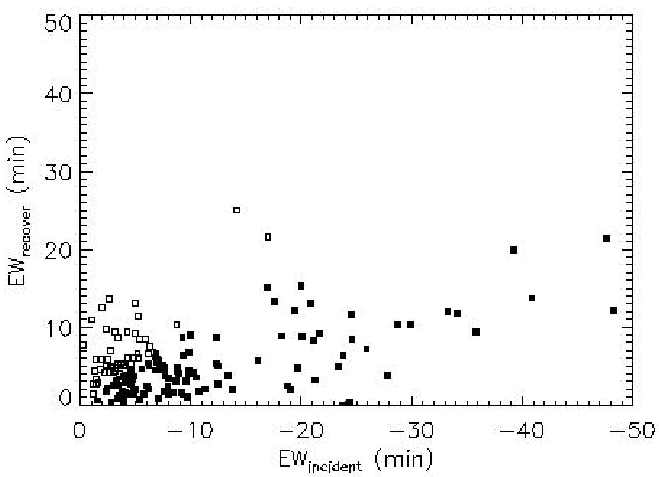

Fig 5: The equivalent widths during the incident and recovery period

6. DISCUSSION

We developed a prediction scheme for recurrent events and a detection scheme for incidents based on volume data which were collected at urban intersections in the Dutch city of Almelo.

Our detection method is based on an *n*-sigma clipping method which can detect outlying measurements in real-time. With our chosen thresholds ($n=4$ for a single outlier and $n=3$ for two successive outliers) we get a false alarm rate of only a few percent, while we probably identify all large incidents (e.g. accidents) and most small incidents (e.g. blockade by a vehicle). The detection time lies between the 10 and 20 minutes, but can be reduced when we reduce the time-lags of our time-series. We analysed the detected incidents and find that on average 40% of the missing volume during an incident disperses along the same link after the incident. In other words, about 60% of the traffic that would enter the location of the incident changes route.

Many algorithms use threshold values for detecting incidents. Some authors have pointed out that the choice of threshold values often is rather arbitrary (e.g. Ihler et al. 2006). Although we also choose thresholds, our algorithm is very successful for two reason. Our expected volumes are, contrary to some algorithms, robust predictions based on historical data of many days. More importantly however, the threshold is not arbitrary chosen, but depends on the random variation of the volumes, which can be described in an uniform way.

We presented a prediction scheme for recurrent events. We took the home-matches of the professional football team as a recurrent event. We selected 11 matches and found that the predictions of the event related volumes generally are quite good, although predictions may be complicated when the start and end times are not exactly known. Predictions could also deviate from the measured volumes due to variations in the distribution (i.e. the origins from which the visitors arrive) or modal split (which probably depends on the weather). A study of the area of Amsterdam (Houtriet 2007) shows that even traffic flows which are generated by large events can be predicted quite well.

In the United Kingdom, automatic incident detection systems are being integrated into adaptive traffic signal systems in urban areas (e.g. Ash 1997, Bowers et al. 1996). In the Netherlands, authorities like to include incident detection and event predictions into the management system of Dutch motorways (Taale et al. 2004). We suggest that our schemes might be included into traffic management systems of Dutch cities.

ACKNOWLEDGEMENTS
We want to thank Vialis and the municipality of Almelo for providing us the volume data in Almelo. This research is funded by Transumo.

REFERENCES
Ash, A. (1997) Incident detection in urban areas controlled by SCOOT. IEE Colloquium on Incident Detection and Management.
Bowers, D.J., Bretherton, R.D., Bowen, G.T. and G.T. Wall (1996) Traffic congestion incident detection. TRL Report 217, Transport Research Laboratory, UK.
Browne, R., Foo, S., Huynh, S., Abdulhai, B. and F. Hall (2005) AID CAAT: The automatic incident detection algorithm comparison and analysis tool. Transportation Research Board Annual Meeting, CD-Rom, Washington D.C.
Dudek, C.L, Messer, C.J. and N.B. Nuckles, N.B (1974) Incident detection on urban freeways. Transportation Research Record, 495 pp. 12-24.
Hall F.L., Shi, Y. and G. Atala (1993) On-line testing of the McMaster incident detection algorithm under recurrent congestion. Transportation Research Record (vol. 1394), pp. 1-7.
Houtriet, E. (2007) 'Monitoring Amsterdam Zuidoost: Het analyseren van VRI detectielus data', Msc thesis, University of Twente (in Dutch).
Ihler, A., Hutchins, J. and P. Smyth (2006) Adaptive event detection with time-varying Poisson processes. Proceedings of the 12th ACM SIGKDD international conference on Knowledge discovery and data mining, Philadelphia, USA.
Knibbe, W.J., Oostveen A., Bokma, H. and D. Poot-Geers (2005) A new incident detection scheme developed in The Netherlands. Proceedings of the 8th international IEEE conference on intilligent transportation systems, Vienna, Austria.

Koppelman, F.S. and W. Lin (1996) Development of an expressway incident detection algorithm for the ADVANCE area based on the California algorithm set. Path Project Report TRF-ID-311/312, The Transportation Center, Northwestern University, Evanston, USA.
Liu, W., Yin, X. and L. Guan (2004) Improved freeway incident detection using neural network based on pulse data of the loop detector. Proccedings of the 2004 IEEE International conference on networking, sensing & control, Taipei, Taiwan.
Payne, H.J. and S.C. Tignor (1978) Freeway incident-detection algorithms based on decision trees with states. Transportation Research Record, 682 pp. 30-37.
Ritchie, S.G. and R.L. Cheu (1993) Simulations of freeway incident detection using artificial neural networks. Transportation Research –C, 1 (vol. 3) pp. 203-217.
Smith B.L., Qin L. and R. Venkatanarayana (2003) Characterization of freeway capacity reduction resulting from traffic accidents. Journal of Transportation Engineering, 129 (vol. 4) pp. 362-368.
Stephanedes, Y.J., Chassiakos, A.P. and P.G. Michalopoulos (1992) Comparative performance evaluation of incident detection algorithms. Transportation Research Record, 1360 pp. 50-57.
Taale, H., Westerman, M., Stoelhorst, H. and D. Van Amelsfort (2004) Regional and sustainable traffic management in The Netherlands: methodology and applications. European Transport Conference 2004, Strasbourg, France.
Thomas T., Weijermars W.A.M and E.C. van Berkum (2007a) Periodic variations in urban traffic flows. European Journal of Transport and Infrastructure Research, submitted.
Thomas T., Weijermars W.A.M and E.C. van Berkum (2007b) Predictions of urban flow volumes. Transportation Research –C, submitted.
Weijermars, W.A.M., Thomas, T. and E.C. van Berkum (2007) Clustering of urban traffic patterns. Transactions on Intelligent Transportation Systems, submitted.