Fusing moving average model and stationary wavelet decomposition for automatic incident detection: case study of Tokyo Expressway

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Abstract: Traffic congestion is a growing problem in urban areas all over the world. The transport sector has been in full swing event study on intelligent transportation system for automatic detection. The functionality of automatic incident detection on expressways is a primary objective of advanced traffic management system. In order to save lives and prevent secondary incidents, accurate and prompt incident detection is necessary. This paper presents a methodology that integrates moving average (MA) model with stationary wavelet decomposition for automatic incident detection, in which parameters of layer coefficient are extracted from the difference between the upstream and downstream occupancy. Unlike other wavelet-based method presented before, firstly it smooths the raw data with MA model. Then it uses stationary wavelet to decompose, which can achieve accurate reconstruction of the signal, and does not shift the signal transfer coefficients. Thus, it can detect the incidents more accurately. The threshold to trigger incident alarm is also adjusted according to normal traffic condition with congestion. The methodology is validated with real data from Tokyo Expressway ultrasonic sensors. Experimental results show that it is accurate and effective, and that it can differentiate traffic accident from other condition such as recurring traffic congestion.

Key words: automatic incident detection; moving average model; stationary wavelet decomposition; Tokyo Expressway

1 Introduction

Traffic congestion is a growing problem in urban areas all over the world. Han et al. (2007) analyzed that much of congestion is caused by incidents, which refer to non-recurring events such as accidents, break-
downs, debris, spilled loads, inclement weather, temporary maintenance and construction activities, as well as other unusual or special events that disrupt the normal flow of traffic. During an incident, the normal capacity of the road is restricted and queues and delays often occur. Every year expressways accidents and obstructions result in traffic congestion, environmental pollution, and damages in property, personal injury, and fatalities. Accurate and prompt incident detection is crucial to the response to such emergencies in order to save lives, prevent secondary incidents, and restore normal operations in a timely fashion. A study (Charles 2007) revealed the increasing contribution of incidents to expressway congestion and other problems has generated strong interest in the development of efficient and effective automatic incident detection (AID) methods in the past few decades. Nowadays the functionality of AID on the expressways is a primary objective of advanced traffic management system (ATMS), which is an integral component of a country's intelligent transportation system (ITS).

The objective of this paper is to propose and validate a methodology to detect incident on expressway fusing moving average model and stationary wavelet decomposition. The data is acquired from Tokyo Metropolitan Expressway ultrasonic sensors. In the field data there are some missing data caused by communication delay as well as shockwave, which may cause false alarm. So the developed methodology should be robust with these noises consisting in real data. To solve this problem, a MA model is applied to smooth the raw data first. Then wavelet decomposition is applied on the velocity and occupancy data. Road traffic flow under normal circumstances has certain inertia, but when an event occurs, the traffic flow state changes and reflects in the performance of the traffic parameters. Wavelet analysis has good performance, ideal frequency and local characteristics in the analysis of transient data. Unlike other wavelet-based method presented before, in this paper stationary wavelet decomposition is applied, in which the transfer coefficient of the signal does not shift and thus can detect the time of incident more accurately. The proposed methodology is tested with Tokyo Metropolitan Expressway traffic sensors data.

This paper is organized as follows: Section 2 provides the literature review for incident detection algorithms. Section 3 provides an introduction to discrete wavelet transform and stationary wavelet transform. The ultrasonic sensors data of Tokyo Metropolitan Expressway used in this study is introduced in Section 4. Then the proposed AID methodology for expressway is described in Section 5, followed by its testing and validation results with the field data in Section 6. Finally, the conclusion and discussion are presented in Section 7.

2 Literature review

Since the 1970s, a number of automatic incident detection systems have been developed (Cook and Cleveland 1974; Bowers et al. 1995; Dia and Rose 1997; Cheu et al. 2004; Crabtree and Stamatiadis 2007; Jeong et al. 2011; Kadali et al. 2014). AID systems involve two main components, detection technology and incident detection algorithm. The traffic detection technology provides the traffic information necessary for detecting an incident while the incident detection algorithm interprets that information and ascertains the presence or absence of incidents. The performance of AID system is evaluated by three main criteria (Chung and Rosalion 1999; Jiang et al. 2001).

2.1 Performance evaluation criteria

The parameters are detection rate (DR), false alarm rate (FAR), and mean time to detect (MTTD).

The DR is the ratio of number of detected incidents to the recorded number of incidents in the data set. It is given as a percentage.

The algorithms examine incidents at every discrete time interval such as 20 s, 30 s and 1 min. The FAR is the ratio of incorrect detection interval to the total number of intervals to which the algorithm was applied. It is usually expressed as percentage per section (between the upstream and downstream detector stations).

\[ \text{FAR} = \frac{N_i}{N_t} \times 100\% \]

where \( N_i \) is the number of incorrect detection interval;
$N_i$ is the total number of intervals to which the algorithm was applied.

The time to detection is the time difference between the time the incident was detected by the algorithm and the actual time the incident occurred. The MTID is the average time to detection over $n$ incidents.

2.2 Detection technology

A number of technologies are available for traffic management which are also used to detect incidents. These technologies include: inductive loop detectors use magnetic or inductive loops embedded in the pavement to detect the presence of a vehicle, the most common detectors; microwave radar, infrared, ultrasonic detection, non-intrusive detectors, mounted on a structure above the roadway. Microwave performs well in all weather, while others are sensitive to environmental effects; video image detection processing images from camera is sensitive to light and has been expensive, but costs are dropping; vehicle probes, Li and McDonald (2005) described that the installation of electronic toll tags in an increasing proportion of the vehicle fleet provided an opportunity to use probe vehicles as sensors to measure speeds and travel time.

Automatic number plate recognition technology can be used alternatively; mobile phone location is similar in concept to vehicle probes but using triangulation to monitor vehicle travel speeds, hence it is able to detect incidents (Cheu et al. 2002).

As reported before, inductive loop detectors embedded in the pavement are typically used to obtain traffic data. The data comprises speed, flow and occupancy and is typically provided in 20 s cycles. Data of this type would form the input to an incident detection algorithm, which would raise a flag to indicate the presence of an incident.

2.3 Incident detection algorithms

A lot of research and development work has focused on automatic incident detection algorithms. These AID algorithms can be classified into the following categories.

(1) Comparison algorithms

Comparison algorithms compare the current traffic conditions such as volume and occupancy to preset thresholds and decide whether or not an incident has occurred. Examples of the comparison algorithms include the California algorithm, California #7 algorithm, California #8 algorithm, and other modified or improved pattern recognition algorithms.

The California algorithm (Payne et al. 1976) compares occupancies at neighboring detectors in the same time interval, and occupancies at different time intervals in the same detector. Occupancies are 1 min values updated every 20 s or 30 s. $O(i, t)$ stands for average occupancy of section $i$ at time $t$ (min). Then the decision rule detects an incident when the value at the left-hand side of each criterion below exceeds the corresponding threshold at time $t$.

$$O_1 = O(i, t) - O(i + 1, t) \geq T_1$$
$$O_2 = \frac{O(i, t) - O(i + 1, t)}{O(i, t)} \geq T_2$$
$$O_3 = \frac{O(i + 1, t - 2) - O(i + 1, t)}{O(i + 1, t - 2)} \geq T_3$$

where $O_1$ is the difference between the share of upstream and the share of downstream; $O_2$ is the relative difference between the share of upstream and the share of downstream; $O_3$ is the relative difference between the adjacent downstream shares in two minutes; $T_1$, $T_2$, and $T_3$ are the test thresholds. Schematic of California algorithm is shown in Fig. 1.

![Fig. 1 Schematic of California algorithm](image)

An ARRB and VicRoads AID algorithm is also developed based on speed, occupancy and flow measurements in 20 s time slice (Luk 1989). The traffic parameters are measured by a dual inductive loop system, with stations located 500 m apart.

(2) Statistical algorithms

Statistical algorithms compare the observed traffic data with the predicted traffic data and decide whether or not an accident has occurred based on statistical
significance. Examples of the statistical algorithms include the standard normal deviation algorithm and the Bayesian algorithm (Levin and Krause 1978).

### (3) Time-series algorithms

Time-series algorithms (Ahmed and Cook 1982a) compute the short-term forecasting values based on observed values and statistical forecasting of traffic data. Significant deviations between observed and forecasting values are attributed to incidents. Examples of the time-series algorithms include the double exponential smoothing algorithm, the detector logic with smoothing algorithm and the autoregressive integrated moving average algorithm etc (Ahmed and Cook 1982b).

### (4) Catastrophe theory algorithms

Catastrophe theory algorithms (Persaud and Hall 1989) such as the McMaster algorithm (Aultman-Hall et al. 1991; Persaud et al. 1990) detect incidents from sudden discrete changes that occur in a single variable of interest while other related variables such as speed, flow, and occupancy are exhibiting a smooth and continuous change.

### (5) Other algorithms

These algorithms include wavelet theory, neural network algorithms (Jin et al. 2002), fuzzy set algorithms and video image processing. Wavelet theory was applied to traffic incident detection because of its superior ability of denoising and extracting new features through the transformation (Ghosh-Dastidar and Adeli 2003; Jeong et al. 2006a; Manjunath and Ravikumar 2010; Jeong et al. 2011). Luo et al. (2010) proposed a wavelet-based expressway incident detection algorithm with adaptive threshold parameters.

## 3 Introduction to discrete wavelet transform and stationary wavelet transform

### 3.1 Decomposition and reconstruction of discrete wavelet

Discrete wavelet decomposition generally uses the Mallat algorithm. Since the wavelet transform is defined for infinite-length signals, the finite-length signals must be extended before they can be transformed (Li et al. 2003). Then after the wavelet decomposition with the low-pass and high-pass filter and down-sampling (\( \downarrow 2 \)), the coefficients are transferred as a low frequency signal and a high frequency signal, which ensure that the amount of data signal after the wavelet decomposition remains unchanged (Karim and Adeli 2002). In reconstruction, firstly the approximation coefficients and detail coefficients are up-sampled (\( \uparrow 2 \)) and filtered, and then pass low-pass and high-pass reconstruction filters respectively to recover to approximation coefficients \( |a_j| \) (or the original signal \( f(t) \)) of previous level. Low and high frequency filters used in decomposition filter are named \( h \) and \( g \).

The discrete wavelet decomposition and reconstruction process is shown in Fig. 2 (Jeong et al. 2006b).

![Decomposition and reconstruction of discrete wavelet](image)

### 3.2 Decomposition and reconstruction of stationary wavelet

The classical discrete wavelet transform (DWT) suffers a drawback that it is not a time-invariant transform. It means that even with periodic signal extension the DWT of a translated version of a signal \( X \) is not, in general, the translated version of the DWT of \( X \). Stationary wavelet transform (SWT) algorithm is derived from DWT but does not have this deficiency. SWT for a given approximation coefficient \( |a_j| \) (or the original signal \( f(t) \)) of previous level can be obtained by convolving the signal with the appropriate filters as in the DWT case but without down-sampling. Then the approximation and detail coefficients at level \( j \) are both size \( N \), which is the signal length. The discrete wavelet decomposition and reconstruction process is shown in Fig. 3.

![Decomposition and reconstruction of stationary wavelet](image)
The general step $j$ convolves the approximation coefficients at level $j$ with up-sampled versions of the appropriate original filters to produce approximation and detail coefficients.

4 Data collection and analysis

The methodology presented in this paper was developed using data collected from ultrasonic sensors on the following site.

4.1 Site description

The site selected is Shibuya Line (Route 3) of Tokyo Metropolitan Expressway (Fig. 4). Tokyo Metropolitan Expressway has a total route of 301.3 km in service and a daily average traffic volume of 1.114 million vehicles.

Table 1 below shows the traffic flow statistics of the Tokyo Metropolitan Expressway from April 1st, 2010 to March 31st, 2011.

<table>
<thead>
<tr>
<th>Category</th>
<th>Tokyo routes</th>
<th>Kanagawa routes</th>
<th>Saitama routes</th>
<th>Total</th>
</tr>
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<tbody>
<tr>
<td>Total for FY 2010</td>
<td>295329</td>
<td>94994</td>
<td>16240</td>
<td>406562</td>
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<tr>
<td>Weekday average</td>
<td>830</td>
<td>269</td>
<td>46</td>
<td>1144</td>
</tr>
<tr>
<td>Holiday average</td>
<td>717</td>
<td>226</td>
<td>40</td>
<td>982</td>
</tr>
<tr>
<td>Daily average</td>
<td>809</td>
<td>260</td>
<td>44</td>
<td>1114</td>
</tr>
<tr>
<td>Ordinary vehicles</td>
<td>266664</td>
<td>83352</td>
<td>15674</td>
<td>365690</td>
</tr>
<tr>
<td>Average</td>
<td>65.6%</td>
<td>20.5%</td>
<td>3.9%</td>
<td>89.9%</td>
</tr>
<tr>
<td>Vehicle type</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ordinary vehicles</td>
<td>28665</td>
<td>11642</td>
<td>566</td>
<td>40873</td>
</tr>
<tr>
<td>Large vehicles</td>
<td>7.1%</td>
<td>2.9%</td>
<td>0.1%</td>
<td>10.1%</td>
</tr>
</tbody>
</table>

4.2 Data description

Data of Shibuya Line from March to August, 2010 is used including peak time (07:00-09:30 and 16:00-19:00) and off-peak time (09:30-16:00 and 19:00-07:00). The data characters are listed as follows: sampling period (1 min); loop detector intervals (300 m from the average); data channel (by lane, lane #1 and lane #2).

A data example of traffic flow ($Q$), velocity ($V$) and occupancy ($O$) on date 2010-03-17 (Wednesday) of lane #1 is shown in Fig. 6, where an accident occurred at 04:19 AM between upstream loop detector #03-02-14 and downstream loop detector #03-02-15.

5 Proposed methodology

This paper proposes a detection methodology combining stationary wavelet decomposition with MA model. Unlike other wavelet-based method presented before, it first smooths raw data with MA model, then uses stationary wavelet to decompose. The stationary wavelet has an advantage compared with other discrete wavelet, that it can achieve accurate reconstruction of the signal, and that the reconstructed signal does not shift. The following experiments show that it has good character of detecting incident. The threshold to trigger incident is determined by maximum of extraction of normal date data with recurring traffic congestion. More details are presented below.
5.1 Traffic parameters selection

This methodology also utilizes the phenomenon that the upstream traffic of occupancies will increase and downstream ones will decrease after the incident (Fig. 7). The situation was more complicated because there was traffic congestion before accident occurred. It is difficult to differentiate accident from recurring congestion in this situation. In real data there are also other situations such as the situation shown in Fig. 6. That is when the accident occurred very near to one detection station, the occupancy of it will be zero and the other station will not change too much.

In this methodology input is the difference of occupancies that upstream occupancy subtracts downstream occupancy.
5.2 Raw data preprocessor

It is obvious that the raw data contain noise which will cause false alarm of the detection. In this application, a MA model is applied to smooth raw data (Fig. 8). Experiment result shows that it can improve the detection rate of the methodology greatly.

5.3 Proposed methodology flow

The proposed methodology is described as follows.

Smooth raw data with MA model. 3-layer stationary decomposition of the smoothed difference between the upstream and downstream occupancy is carried out. Calculate the maximum of the highest detail layer coefficients of a normal day’s data with traffic congestion as $T$. Threshold equals $T$ plus $\Delta T$. $\Delta T$ is adjusted according to DR and FAR. If the value of a certain time’s highest detail layer coefficient is larger than threshold, incident alarm is triggered. The flowchart is shown in Fig. 9.

6 Results

Data of 2010-03-30 is shown as an example, in which the traffic condition is complicated. It contains traffic congestion and accident record of 11:04 AM between loop detectors 22 and 23 of lane #1. The smoothed differences of occupancies of three typical sections are shown in Fig. 10.

The 3-layer stationary decomposition result is shown in Fig. 11, in which the horizontal line stands for calculated threshold. Traffic incident can be accurately detected in this example.
Fig. 8 Raw and smoothed data of $Q$, $V$ and $O$ of detector #03-02-42 on 2010-03-30

Fig. 9 Flowchart of proposed methodology for expressway incident detection
7 Conclusions

This paper proposed a fusing of moving average model and stationary wavelet decomposition expressway automatic incident detection methodology, which utilizes smoothed difference between the upstream and downstream occupancies as input. This methodology is applied to loop data of Shibuya Line from March to August, 2010. Experiment result shows that it is accurate and effective. It can differentiate traffic accident from other conditions such as recurring traffic congestion in complicated traffic condition.

In experiments it also shows that the real traffic condition is much more complicated than a simulated one. Traffic accident’s type and happening time will also affect the result greatly. Next step more research will be carried out and the methodology will compare with other popular approaches such as California algorithm.

Acknowledgments

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Fig. 11 Comparison of wavelet decomposition results of three typical sections on 2010-03-30


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