

# An Algorithm for Incident Detection Using Artificial Neural Networks

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**Abstract**—Vehicular accidents cause tragic loss of lives and traffic congestion to the transportation system. Therefore, prompt detection of traffic incidents offers tremendous benefits of minimizing congestion and reducing secondary accidents. Most incident management systems use inductive loop detectors for incident detection. Inductive loops are the most commonly used traffic detectors and they collect data such as vehicle speed at a point. However, the implemented algorithms using loop detectors showed mixed success. I think that the changes in average traffic speed in case of traffic incidents have certain patterns that are different from the normal conditions. In this paper, I try to automatically detect traffic incidents using artificial neural networks and traffic condition information of the traffic information center. In the field tests, the new model performed better than existing methods.

## I. INTRODUCTION

It is known that reducing the initial action time by 5 minutes in the event of a traffic accident reduces the mortality rate from 90% to 50%. Therefore, if an incident management system is systematically and quickly processed, it will be possible to reduce traffic accident deaths and to deal with injured persons properly. Approximately 60% of the delays on urban freeways are associated with incidents [1]. Therefore, accurate and prompt detection of incidents offers tremendous benefits of saving lives and minimizing delay.

Traffic incidents occur frequently on roadways, resulting in congestion and delay. One traffic incident management strategy is to disseminate accurate incident information to travelers (e.g., through car navigation systems), who can then make more informed travel decisions. Another approach is to actively redirect traffic in a road network to avoid incident-induced congestion. In both approaches, accurate and prompt incident detection is required.

This research is concerned with detecting the beginning of accidents, stalls, and other incidents that cause traffic disruptions on roadways and require the emergency response of an ambulance, police. Most of the existing incident detection algorithms are based on a loop detector. The basic premise of this research is that it may be possible to replace the inductive loop data currently used for incident detection by traffic data obtained from a traffic information center.

The paper begins with a description of the incident detection methods used by existing systems. Problems with the

current systems are discussed, and a new method is presented that was developed to detect traffic incidents under real road conditions. A more extended evaluation of the proposed system and algorithms is then performed for road segments in the cities of South Korea. Finally, the main conclusions of the evaluations are presented.

## II. BACKGROUND

### A. Related work

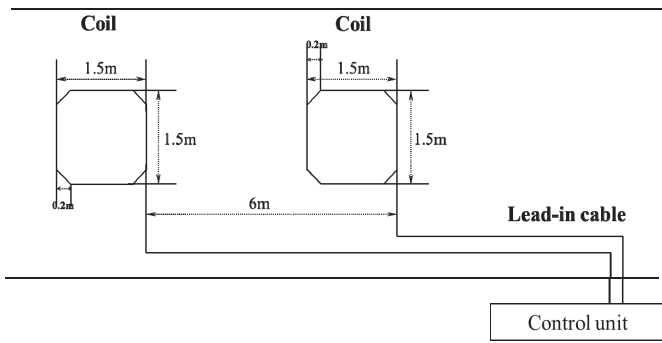
Incident detection algorithms currently in use have been primarily developed for inductive loop detector. The principle components of an inductive loop detector system include one or more turns of insulated loop wire wound in a slot sawed in the pavement of a roadway, a lead-in cable from a curbside pull box to a controller cabinet, and a detector-electronic unit housed in the controller cabinet. Fig. 1 shows a simple schematic of an inductive loop detector system.

Since its introduction in the nineteen sixties, the loop detector has been the popular form of detection system, and most traffic surveillance applications depend on it. A set of double-loop detectors is generally used for detecting traffic incident [2]. However, double-loop speeds that are computed using digital outputs typically have errors between 3% and 5% for ordinary vehicles such as cars and pickups [3].

Generally, incident detection algorithms are divided into five categories: comparative, statistical, traffic-model-based, artificial intelligence-based, and mixed models [4].

Statistical algorithm models perform short-term prediction of traffic variables. If the predicted value deviates enough from the observed value, then an incident alarm is declared. One of the earliest approaches is called the standard normal deviate model, which uses the deviation from standardized values of a traffic control depending on the mean and standard deviation of the data [5].

Mixed models are those methods that combine different types of approaches. One of the most well-known mixed models is the Minnesota algorithm, which is a combination of statistical and comparative types of algorithms [6]. Ki and Lee presented a video incident detection method that uses several existing traffic monitoring cameras [7]. Michalopoulos and Jacobson built an autoscope video-detection system to detect incidents [8].



(a)



(b)

Fig. 1. Photograph of the inductive loop detector. (a) Configuration of an inductive loop detector. (b) Vehicle passes over the loop coils

On the contrary, only a few researchers have investigated the detection of incidents using traffic condition information (e.g. link travel speed) of the traffic information center. Ki and Heo suggested a model for incident detection using Two-way Probe Car System, which was developed as a mobile sensor for measuring vehicular speeds in South Korea [9].

*B. Problem of false alarms and detection rate*

In general, there are trade-offs to be considered between the false alarm rate (FAR) and the detection rate (DR) in automatic incident detection (AID) systems. In the case of roadway AID, for desired levels of DR, FAR's have been unacceptably high for operational purposes. In the case of roadway operations in which detection algorithms continuously verify the existence of incidents for numerous vehicle detection stations simultaneously, lowering FARs may actually demand huge emergency response deployment.

The high occurrence of false alarms in AID systems can be attributed to several factors. There are situations in which traffic may exhibit incident-like patterns when in fact there is no incident, such as in the presence of compression waves, roadway bottlenecks, equipment malfunction, and so on.

*C. Korea traffic information system*

As shown in Fig. 2, Korea traffic information system (KTIS) is an in-vehicle advanced traveler information system that operates in South Korea. It is designed to provide origin-destination shortest-time route guidance to a vehicle based on an on-board static (fixed) data-base of average network link travel times by time of day, combined with real-time information on traffic conditions provided by radio frequency communications with a central traffic information center (CTIC).



Fig. 2. Photograph of the KTIC

Probe car system (PCS) is a means of collecting traffic condition information and then broadcasting related traveler information and various alerts back to vehicles. The wireless media is based on PCS technology operating at 5.725 GHz in South Korea, and the communication standards are based on the wireless LAN family of standards. Under the PCS concept, vehicles will be equipped with a PCS radio, a highly accurate on-board positioning system, and an appropriately configured on-board computer to facilitate communications, support various applications, and provide an interface for the driver. This equipment is collectively referred to as the On-Board Equipment. Vehicles communicate with Roadside equipment (RSE), which is linked to the specialized PCS network. RSEs are positioned at major signaled intersections and along major arterial roads.

III. INCIDENT DETECTION ALGORITHM

*A. New incident detection model*

In this paper, a new algorithm is suggested to detect traffic incident using the link travel speed data of KTIC. The proposed algorithm uses neural networks. With capabilities of learning, self-adaptation, and fault tolerance, the Artificial Neural Networks (ANNs) approach has demonstrated good performance in many pattern classification applications. In addition to the extracted features, a three-layered ANN model

for incident detection was developed (Fig. 3). The proposed model showed improved performance in incident detection.

According to the investigation, an incident is likely to create congestion in the upstream road section and reduce flow in the downstream road section; this leads to a high velocity difference between two traffic states. The new ANN model used this feature for incident detection.

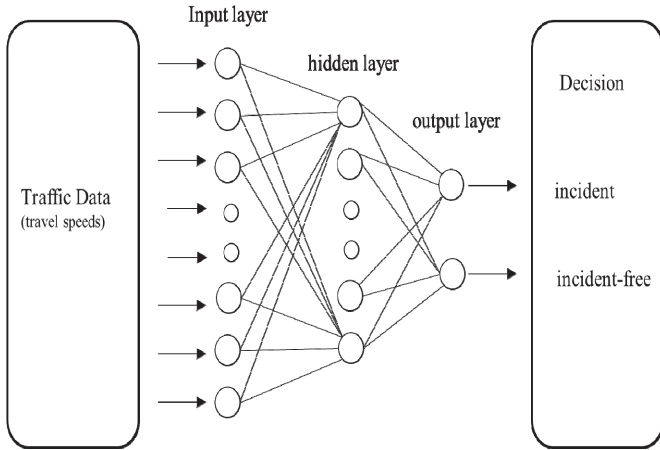


Fig. 3. Incident detection model using an ANN

**B. Feature extraction**

When an incident happens and is deemed to have a significant impact on traffic, the roadway can be divided into three segments. This leads to a high velocity difference between the three segments: (a) Segment 1, extending from the origin to the back of the queue; (b) Segment 2, containing the physical queue and the bottleneck (site of the incident) to the downstream destination, as illustrated in Fig. 4. The physical queue length changes over time, reaching the maximum when the incident is cleared if the approaching flow rate is lower than the service flow rate at the bottleneck.

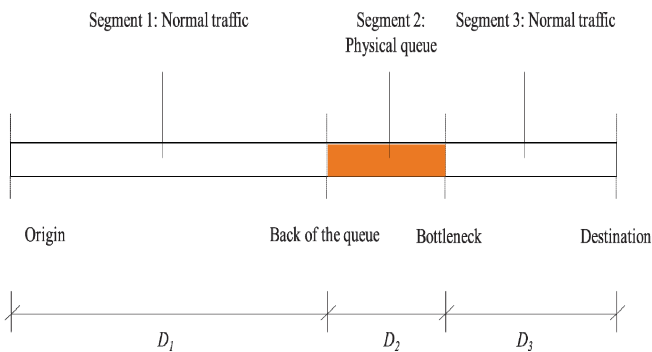


Fig. 4. Roadway segments under an incident

The new ANN model used this feature for incident detection. Table I shows the criteria for feature vectors suggested by analyzing the traffic data from the KTIC.

TABLE I. CRITERIA FOR FEATURE VECTORS

Input vector	1	2	3	4	5	6	7	8	9	10
Travel speed variation rate on road section under an incident (%)	-201 or less	-101 ~ -200	-51 ~ -100	-26 ~ -50	0 ~ -25	1 ~ 25	26 ~ 50	51 ~ 100	101 ~ 200	201 or more
Input vector	11	12	13	14	15	16	17	18	19	20
Travel speed variation rate on the upstream road section (%)	-201 or less	-101 ~ -200	-51 ~ -100	-26 ~ -50	0 ~ -25	1 ~ 25	26 ~ 50	51 ~ 100	101 ~ 200	201 or more
Input vector	21	22	23	24	25	26	27	28	29	30
Travel speed variation rate on the downstream road section (%)	-201 or less	-101 ~ -200	-51 ~ -100	-26 ~ -50	0 ~ -25	1 ~ 25	26 ~ 50	51 ~ 100	101 ~ 200	201 or more

**C. Data collection and performance measures**

Incident data were collected from the KTIS, a database containing a broad range of details for all traffic incidents that occur on roadways. For every incident, the incident response team collects details, including the incident location, as well as start time, clear time (the time the incident was completely taken care of), and the incident type. This study used the KTIS incident data collected from July to September, matching the time span of the travel time data.

The performance of the incident detection model is mainly evaluated using the detection rate (DR) and false alarm rate (FAR), which is defined as

$$DR = \frac{\text{total number of correct incident detections}}{\text{total number of incidents in data set}} \times 100\% \quad (1)$$

$$FAR = \frac{\text{number of test cases in which a false alarm occurs}}{\text{total number of test cases in data set}} \times 100\% \quad (2)$$

A good accident detection model should have a very high DR and a very low FAR. However, it is worth mentioning here that these objectives conflict with each other; normally, the FAR increases when one tries to boost the DR. Therefore, a challenge in this research is to maintain a high DR and at the same time minimize the FAR.

**IV. TEST AND EVALUATION**

**A. Experimental test**

As shown in Table 1, experimental tests were conducted at three sites in Seoul and Uiwang city. As shown in Table 1, the following three study segments were selected for the experimental test: Westbound Olympic expressway from the Dongjackro ramp to the Yeuido IC in Seoul city, with a length





of 3,022m; Westbound Gangbyeon expressway from the Hangangro ramp to the Daegunro ramp in Seoul city, with a length of 964m; Westbound Seoul outer circular highway from the Hagui JC to the Pyeongchon IC, with a length of 3,218m.

The traffic condition information for feature extraction and for training and testing for the neural network were collected. Each database was divided into two parts, with 51% of the randomly selected sets of data constituting the training data. Testing data included the remaining 49% of the database. Therefore, out of 202 data sets, 104 were chosen as training data, and the remaining 98 constituted the testing data.

Information on actual incidents is available from the incident logs filed by the traffic management center operator daily. These logs report the time and location of each incident, its type, duration, severity, as well as the roadway condition and other incident-related information. The detection of incidents is mainly accomplished through observation of television monitors by on-duty traffic personnel, patrol reports, among others.

Incident logs from July to September were obtained for the selected roadway sections. There is a lag time between incident occurrence and reported times. This lag time varies depending on the types of incident. Major incidents such as multilane-blocking accidents usually have a short lag time, whereas minor incident logs such as shoulder disablements are likely to have a long lag time. Incident logs contain a number of false incident logs registered as test incidents. These false logs were examined and removed before the analysis.

TABLE II. TEST SITES AND CONDITIONS

Site characteristics	Photographs of the test sites
- Westbound Olympic expressway from the Dongjackro ramp to the Yeouido IC in Seoul city, with a length of 3,022m. - Five-lane segment	
- Westbound Gangbyeon expressway from the Hangangro ramp to the Daegunro ramp in Seoul city, with a length of 964m. - Four-lane segment	

- Westbound Seoul outer circular highway from the Hagui JC to the Pyeongchon IC, with a length of 3,218 m.

-Four-lane segment



B. Neural network architecture

A multilayer, feed-forward neural network model with one hidden layer was built (Fig. 5). There are 30, 14, and 2 nodes in the input, hidden, and output layers, respectively. At the input layer, the number of processing elements corresponds to the number of features obtained in the traffic condition information of the KTIC. The output nodes represent the incident detection results.

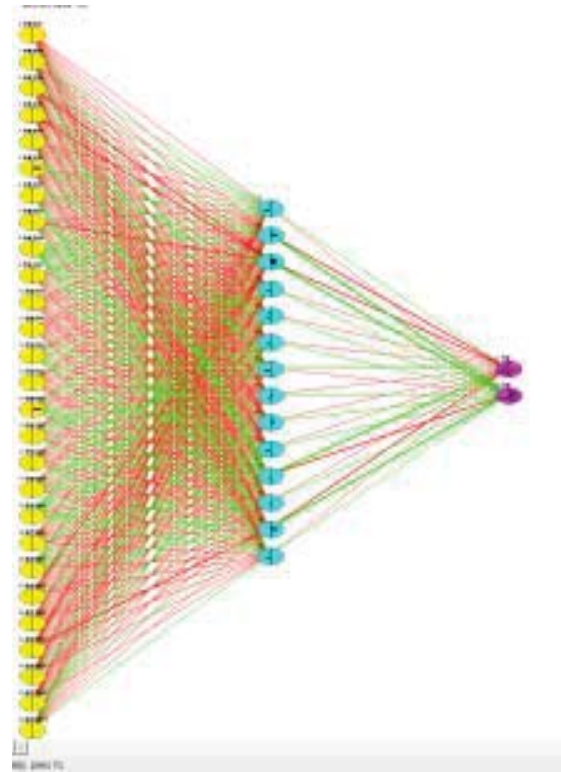


Fig. 5. Neural network architecture for incident detection

C. Training and testing

Several network parameters were carefully selected. The initial learning rate was 0.6, and the momentum term coefficient was 0.8. The threshold of error was 0.05. Before testing, training was conducted for 15 cycles with 104 sets of feature vectors. Fig. 6 shows the training errors of each experimental data according to the learning process.

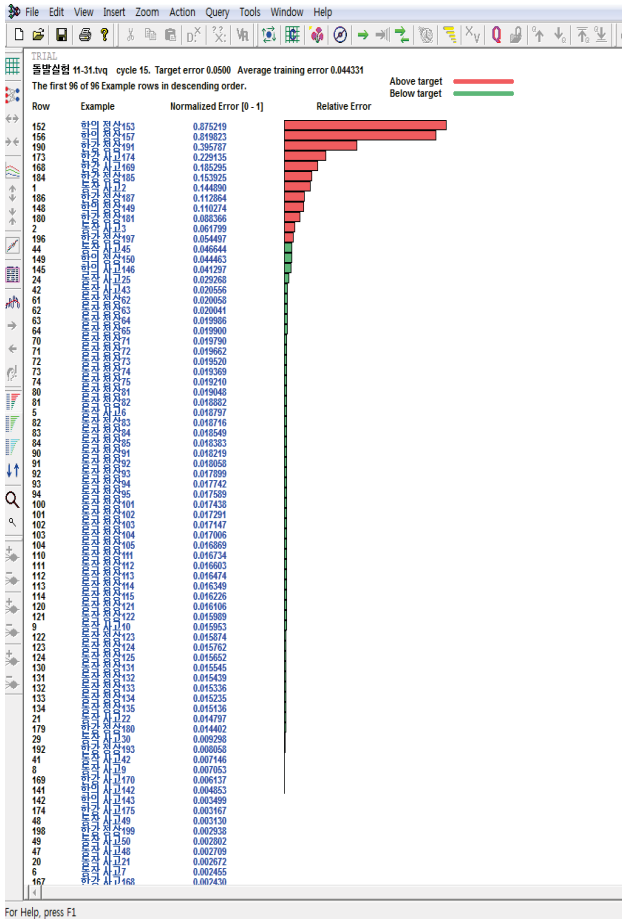


Fig. 6. Training errors of each experimental data

D. Test Results and Evaluation

Experimental tests were conducted in Seoul and Uiwang City. Among 44 incidents, 34 were correctly detected, but 10 were not detected; hence the DR was 77.3% and the FAR was 8.6%. New model excels in DR compared to existing freeway incident detection algorithms/systems. Most systems/algorithms with low FARs have DRs between 20% and 80% (1). As shown in Table □, the California #7a algorithm was reported to have DRs of between 19.47% and 45.81%, and the Speed-Based Incident Detection Algorithm (SBIDA) was reported to have DRs between 25.00% and 51.81% in (7). However, the proposed system achieves an excellent DR at 77.3% with a FAR of 8.6%. Accordingly, we conclude that the proposed model significantly improves incident detection efficiency.

TABLE III. COMPARISON OF THE INCIDENT DETECTION MODELS

Type	Incident detection model	DR(%)	FAR(%)
Incident detection algorithm in freeway	New model	77.6	8.6
	California #7a algorithm	19.47 ~45.81	0.08~0.34
	SBIDA	25.00 ~ 51.81	0.89~1.10
Accident detection algorithm at intersection	Vision-based Model (ARRS)	60	0.00496
	Sound-based Model (AIRS)	66.1	-

V. CONCLUSIONS

Because traffic incident management is critical in reducing the total delay to drivers in urban roadways, traffic planners continue to develop methods that can be used to reliably identify an incident. Interest in such methods has increased as transportation officials realize that prompt and reliable detection of incidents is critical to advanced traffic management systems for providing optimal control of freeways and arterial networks.

A new model for incident detection using ANN and traffic data has been presented in this paper. An incident is likely to create congestion in the upstream and reduce flow in the downstream station; this leads to a high velocity difference between the two stations. The new ANN model used this feature for incident detection.

The developed algorithm was assessed at test sites for evaluation. The proposed algorithm using ANN yielded a DR of 77.3% and a FAR of 8.6%. The DR of the new model using the neural network was 77.3%, which is higher than the DR (19.47~45.81%) of the California #7a algorithm, the DR (25%~51.8%) of the SBIDA, and the DR (60%) of the Vision-based model (ARRS: accident recording and reporting system). The evaluation revealed that the proposed model can identify incidents more effectively than some other models. This incident detection mechanism will be able to provide real-time crash warnings to the operators and drivers using PCS and so on.

The new model utilizes link travel speed information collected and provided by KTIC, eliminating additional costs. Therefore, the cost of the new model compares very favorably among those of the most commonly used traffic surveillance systems, including inductive loop sensors, microwave sensors, and video image-processing sensors.

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