AN INCIDENT DETECTION TECHNIQUE USING A DISCRETE CHOICE MODEL

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Abstract: In this research, a logit-based incident detection algorithm for urban streets is developed. Incidents, temporary events that reduce the capacity of roadway segments and cause delays, are a major cause of urban roadway congestion. The performance of the proposed algorithm, California algorithm, and Neural Network technique were evaluated on the basis of their operating characteristic curves. The evaluation results revealed that the proposed algorithm could identify incidents more effectively than other models. Detection rate(DR) and False alarm rate(FAR) of the proposed model are 96.3%, and 5.3% respectively, and At all levels of DR and FAR, the proposed algorithm is superior to the California algorithm and Neural Network. Test results with the proposed algorithm show that the area of uncertainty decreases when incident index is applied. The distribution curves of the proposed algorithm are almost separated so that most of the incident could be detected accurately.

Key Words: Incident Detection, Discrete Choice Model, Logit Model

1. INTRODUCTION

Urban roadway congestion is a daily phenomenon in Seoul metropolitan city. Incidents, temporary events that reduce the capacity of roadway segments and cause delays are a major cause of urban roadway congestion. Recently there has been a great deal of interest in increasing the efficiency of existing roadways through the development of Advanced Traveler Information Systems (ATIS). The rapid and automatic detection of incidents will be a key part of ATIS.

Incident management programs, in general, consider the four stages of an incident: detection, response, clearance, and recovery stage. The time saved by an incident management program depends on how well the four stages of an incident are managed. In incident detection stage, a traffic condition that is not normal for the time period or the location is noted. Most major incidents are detected within 15 minutes but minor incident could not be recognized for an hour or more.

Currently, incidents are detected by detectors that are placed on the roadway, telephone calls from motorists, or reports from enforcement and service patrols. Among those detection methods, the automatic detection of incidents based on detector-based algorithms is highly useful and successful way in ATIS. In freeway incident detection research, various techniques such as time series, pattern recognition, filtering techniques, and neural networks have been used and some of these have been implemented. All of the research use detector data to recognize incident traffic patterns. These techniques, however, are in the early stages of development for the surface streets. In this research, a detector-based incident detection algorithm for urban streets was developed.

2. LITERATURE REVIEW

Automatic incident detection algorithms have generally been based on spot speed and occupancy measurements, usually obtained from inductive loops. Early algorithms, such as California algorithm, endeavored to detect the shock waves due to the incidents by looking for special and temporal discontinuities in flow and occupancy. Another incident detection algorithm used time series statistical procedures to take into account the variation in measurements under non-incident conditions. Recently several studies are conducted to test the feasibility of applying neural network or fuzzy techniques for urban network incident detection. The algorithms so far described are suitable for freeway traffic flows. For arterial network flows, however, the incident detection techniques are in the early stages of development(1). The characteristics of incident detection algorithms are summarized in table 1.

Table 1. Characteristics of incident detection techniques

Techniques	Characteristics	Data
California Algorithm	- Incident detect based on Occupation variation. - Detection rate and false alarm rate varied by threshold value. - Simple and generally applied.	- Occupation rate
Smoothing Technique	- Can be used with other method. - Get ride of unusual data. - Much unusual case let as a incident	- Occupation rate - Speed - Volume, etc
All purpose of Incident Detection Algorithm	- Using variance of occupation rate and Volume between time and place. - Using occupation rate and Volume data simultaneously.	- Occupation rate - Volume, etc
Neural network Algorithm	- Using artificial Neural network notion - Not formalized incident detection technique - Can be used with other method.	- Occupation rate - Speed - Volume, etc
Fuzzy Algorithm	- Use Fuzzy determination technique - Can be use to estimate incident occurrence place and severity - Can be used with other method.	- Occupation rate - Speed - Volume, etc

3. ALGORITHM DESCRIPTION

Current detection algorithms are usually based on the data gathered from inductive loop detectors. The statistical nature of traffic data is critical to identify incidents(7). The traffic variable chosen in the incident detection process reflects its own variability so that the variable is distributed with a certain mean and variance on a respective traffic condition. The distribution curves of a variable, e.g. spot speed can be drawn as figure 1. The curves represent the distributions of the selected variable (e.g. spot speed) on normal and incident conditions. The difference in means between normal and incident conditions is recognizable in the real world. However, a large area of uncertainty exists on the region where the two distribution curves are overlapped as shown in figure 1. The area of uncertainty can be included any category of traffic condition with a confidence level in the incident detection process. When the area of uncertainty is decreasing, the accuracy of detecting incidents increases. Thus, a major feature of a detection algorithm is to find appropriate decision variables to minimize the region of uncertainty in the incident detection process.

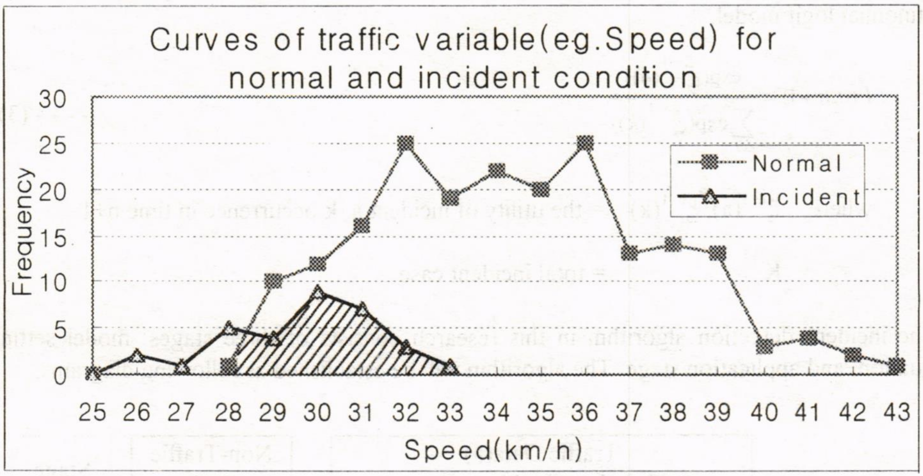

Figure 1. Distribution Curves of spot speed for normal and incident conditions

The algorithm developed in this research attempts to recognize incident patterns by using incident index. The incident index, that represents the probability of occurring incidents, is estimated by multinomial logit model(3). In the algorithm, incidents are reported when the probability of incident occurrence is larger than that of normal condition on the roadway section. The incident index in the equations can be expressed as the utility of the Discrete Choice Model. Such a notion can be shown as follows.

The incident index for incident type "a", P(a, n+1), can be expresses as equation (1).

$$P(a, n+1) = P(\xi^{n+1}(a) \geq \xi^{n+1}(k), \quad k \quad K, a \neq k) \qquad \text{- - - - (1)}$$

where, P(a, n+1) = the probability of occurring incident "a" in time n+1
$\xi^{n+1}(a)$, $\xi^{n+1}(k)$ = the utility of incident a, k
k = incident type
K = Total incident case

The utility of incident, $\xi^{n+1}(a)$, is affected by traffic conditions such as turning volumes and speeds. The utility, therefore, can be restated as equation (2).

$$\xi^{n+1}(a) = \sum_j \sum_i a^a_{j,i} \bullet occ^{n+1}_{i,j} + \sum_j \sum_i b^a_{j,i} \bullet occ^n_{i,j} + \sum_j \sum_i c^a_{j,i} \bullet q^n_{i,j} + \sum_j \sum_i d^a_{j,i} \bullet q^{n-1}_{i,j} + \varepsilon_a \qquad \text{- - - - (2)}$$

where, $a^a_{ij} \cdot b^a_{ij} \cdot c^a_{ij} \cdot d^a_{ij}$ = parameter of independent variables

$occ^{N+1}_{ij} \cdot occ^{N}_{ij}$ = occupancy rate on the section j lane i at analysis time interval n+1 and n

$q^{N}_{ij} \cdot q^{N-1}_{ij}$ = traffic volume on the section j lane i at analysis time interval n and n-1

ε_a = error term

When error term ε_a and ε_k is assumed to be a gumbel distribution, multinomial logit model can be used to estimate the incident index, the probability of incident occurrence. Equation (3) expresses incident a occurrence probability at analysis time interval n+1 in the multinomial logit model.

$$P(a,n+1) = \frac{\exp(\xi^{n+1}(a))}{\sum_{k \in K} \exp(\xi^{n+1}(k))} \quad \text{- - - - (3)}$$

where, $\xi^{n+1}(a), \xi^{n+1}(k)$ = the utility of incident a, k occurrence in time n+1

K = total incident case

The incident detection algorithm in this research consists of three stages: model setting, evaluation, and application stage. The algorithm will be established as following diagrams.

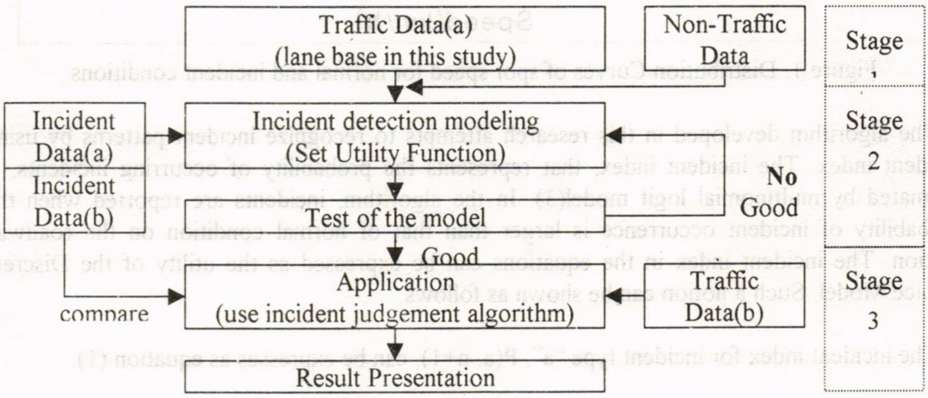

Figure 2. Incident Detection Diagram Using Logit Model

The proposed model employed a multinomial logit model since the error term is assumed to be a Gumbel distribution. The model was programmed by LIMDEP(6) and the coefficients of the utility function were estimated by maximum likelihood method. The incident detection algorithm is summarized as follows;

- step1 : collect traffic data (normal and incident conditions), and estimate coefficients of the utility function.
- step 2 : estimate utilities, $\xi^{n+1}(a)$, $\xi^{n+1}(k)$, for various traffic conditions (eq. 2).
- step 3 : estimate incident index, P(a, n+1), by equation 3.
- step 4 : select P(a, n+1) = max{P(k, n+1| k K)}, and identify incident.

4. EVALUATION

4.1 Design of Experiment

4.1.1 Network Representation and Data Collection

A typical signalized arterial that consists of an incident and a signalized crosswalk was selected to evaluate the proposed model. The test network was transformed into a NETSIM(2) network that is composed of 4 external nodes and 12 pseudo internal nodes. Incidents were designed to occur at pseudo nodes. Loop detectors were emulated at stop lines of the intersection and crosswalk, respectively. To test the feasibility of the proposed model, it is necessary to obtain traffic data on normal and incident conditions in the real world. However, gathering incident data in the real world is extremely difficult unless the data collection system is well constructed. In this study, the traffic data on normal and incident conditions were collected by NETSIM. The test network and signal data are illustrated in figures 3 and 4.

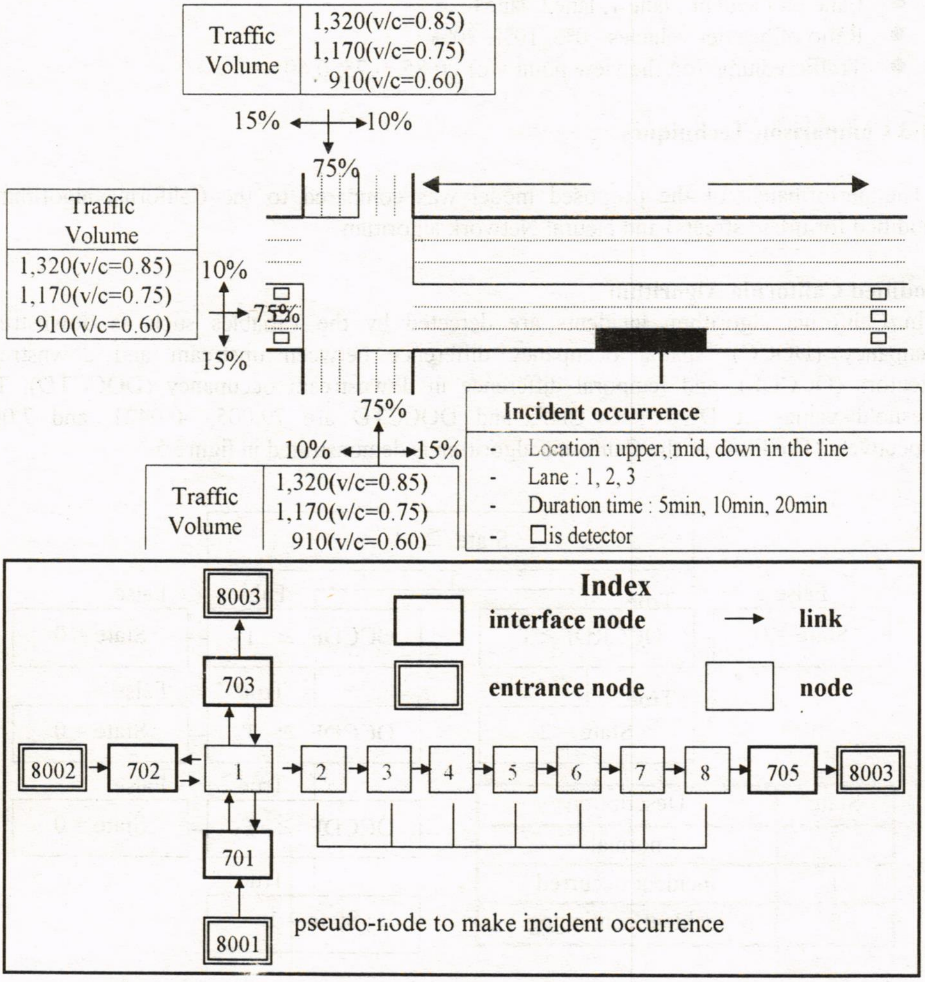

Figure 3. Simulation Network and it's Presentation for NETSIM

Phase	# 1	# 2	# 3	# 4	Cycle (offset)
Movement / green time (yellow time)	17(3)	37(3)	17(3)	37(3)	120sec (30sec)

Figure 4. Signal Timing Plan

4.1.2 Incident Scenarios

An incident was assumed to occur at a pseudo node on mid-block link. The incident scenario and network conditions are summarized as follows:

- Incident duration: 5min, 10min, 20min
- Location of incident occurrence : upper, mid, lower- section of the mid-block link
- Lane on incident : lane 1, lane2, lane3
- Ratio of heavier vehicles : 0%, 10%, 20%
- Traffic volume (on the view point v/c) : 0.85, 0.75, 0.60

4.1.3 Comparison Techniques

The performance of the proposed model was compared to the California algorithm#7 (modified for urban streets) and Neural Network algorithm.

Modified California Algorithm

In California algorithm, incidents are detected by the variables such as downstream occupancy (DOCC), spatial occupancy difference between upstream and downstream detectors (OCCDF), and temporal difference in downstream occupancy (DOCCTD). The threshold values of DOCC, OCCDF, and DOCCTD are 79.005, -0.0421, and 7.060, respectively. The Flow of the California algorithm is demonstrated in figure 5.

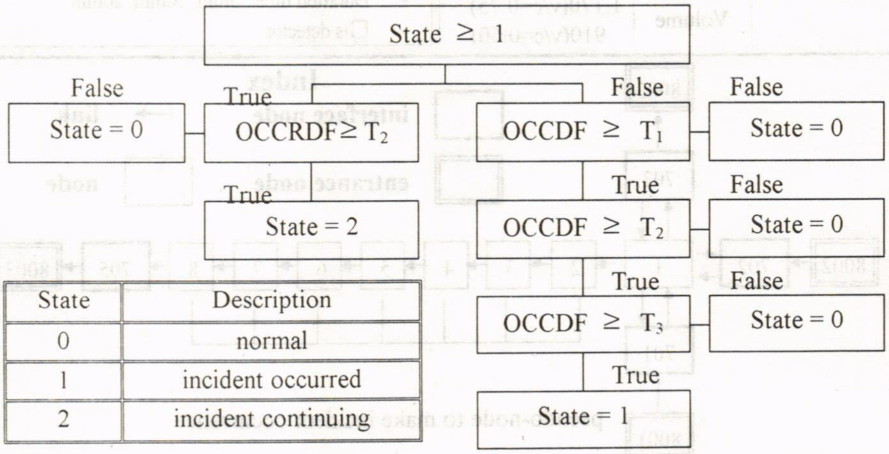

Figure 5. Algorithm flow of Occupancy Difference Method

Neural Network Algorithm

Neural Network Algorithm(4,5) on this study is multi-layer feed-forward model, as shown in figure 6, which is generally used among Neural Network. In particular, the back-propagation method specifies what changes to make to the weights so that the difference of the actual and the desired network output is reduced. The transition function to generate output value from neuron is the sigmoid function that most generally used. The architecture of Neural Network on this study is shown in figure 6.

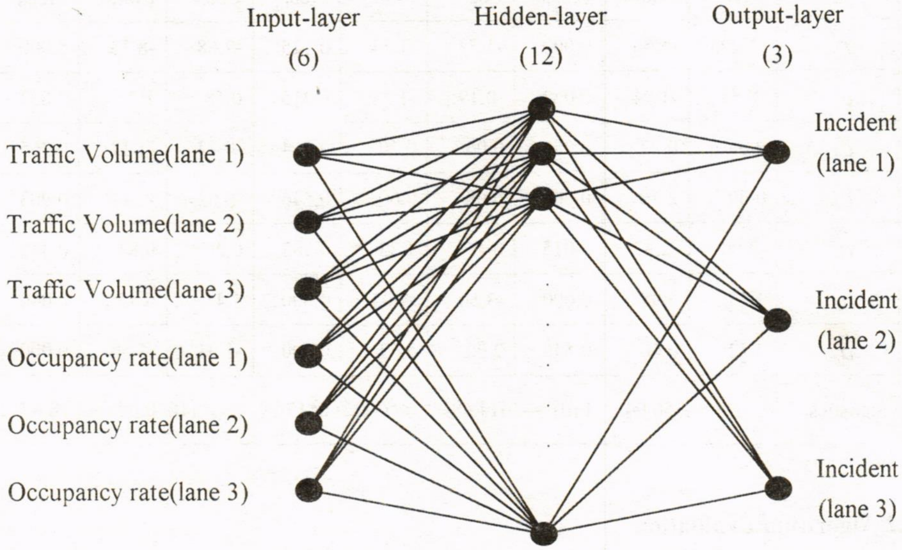

Figure 6. Structure of Neural Network Used in Comparison

4.2 Evaluation

4.2.1 Coefficient Estimation of the Proposed Model

The proposed incident detection model was tested on the cycle basis. The utility functions of the model were derived using 5min and 20min incident duration data sets. In this research, the general equation of the utility function was setup as follows.

$$\xi^{n+1}(a) = c^a_{d.1} \bullet q^{n+1}_{d.1} + c^a_{d.2} \bullet q^{n+1}_{d.2} + c^a_{d.3} \bullet q^{n+1}_{d.3} + a^a_{d.1} \bullet occ^{n+1}_{d.1} + a^a_{d.2} \bullet occ^{n+1}_{d.2} + a^a_{d.3} \bullet occ^{n+1}_{d.3} + \varepsilon^a \quad ---- (4)$$

where $\xi^{n+1}(a)$ = the utility of incident a, occurrence in time n+1

$q^{n+1}_{d.1} \cdot q^{n+1}_{d.2} \cdot q^{n+1}_{d.3}$ = traffic vol. on downstream lane1,2,3 at analysis time interval n+1

$occ^{n+1}_{d.1} \cdot occ^{n+1}_{d.2} \cdot occ^{n+1}_{d.3}$ = occupancy rate on downstream lane1,2,3 at analysis time interval n+1

$c^a_{d.1} \cdot c^a_{d.2} \cdot c^a_{d.3} \cdot a^a_{d.1} \cdot a^a_{d.2} \cdot a^a_{d.3} \cdot \varepsilon^a$ = coefficients

The coefficients of the utility functions and statistics are shown in table 2. T-test and X2-test test the reliability of coefficients for the proposed models. Most of coefficients are found to be reliable by t-test, and the models are significant by X^2-test

Table 2. Coefficients of the Utility Functions and Statistics

Variable	**Incident model 1**			**Incident model 2**			**Incident model 3**		
	Coe.	t-ratio	Prob|t|	Coe.	t-ratio	Prob|t|	Coe.	t-ratio	Prob|t|
ε^a	-17.03	-5.66	0.000	-1.72	-1.54	0.125	-7.68	-8.13	0.000
$c^a_{d,1}$	-0.78	-1.94	0.053	-0.19	-1.24	0.215	0.18	1.73	0.083
$c^a_{d,2}$	0.05	0.27	0.786	0.06	0.30	0.764	-0.12	-1.12	0.265
$c^a_{d,3}$	0.69	2.76	0.006	0.08	0.60	0.546	-0.02	-0.12	0.903
$a^a_{d,1}$	-2.00	-2.43	0.015	0.45	1.33	0.183	0.20	0.81	0.417
$a^a_{d,2}$	2.23	5.98	0.000	-3.50	-7.04	0.000	1.41	6.47	0.000
$a^a_{d,3}$	0.32	0.60	0.546	2.00	5.62	0.000	-1.94	-4.56	0.000
Statistics	L(β) = -356.04 L(0) = -3614.68 χ^2(18) = 6517.29 χ^2(18, 0.05) = 28.87								

4.2.2 Algorithm Evaluation

In this study, the performance of the proposed algorithm is compared to the California and Neural Network Algorithms. Test scenarios for the California and the proposed algorithm were setup on cycle basis. Incidents are reported based on the incident index (threshold: 0.5) for the proposed algorithm, DOCC, OCCDF, and DOCCTD for California algorithm (threshold: 79.005, -0.0421, 7.060) and weights for Neural Network. The incident index represents the probability of occurring incidents that is estimated by multinomial logit model(see equation 3). The results are evaluated by two MOEs(Measures of Efficiency).
Detection Rate(DR): DR = Detected Incidents / Total Incidents * 100%
False Alarm Rate(FAR): FAR = False Alarms / Total Alarms * 100%

Table 3 shows the incident detection process of the proposed algorithm results. The column represents sequential estimation process of the proposed model; the number of cycle, the condition of the network (normal = 0 or incident = 1,2,3), types of data collected (turn volume and occupancy), the utility, the incident index, and decision result. The shadowed area represents incident condition.

Table 4 represents the performance measure of the algorithms. Detection rate and False alarm rate of the proposed model are 96.3%, and 5.3% respectively. At all levels of DR and FAR, the proposed algorithm is superior to the California and Neural Network Algorithms.

Table 3. Proposed Algorithm Results(part of test)

Cycle	Incid-ent[1]	Traffic volume (vehicle/Cycle)			Occupancy rate (%)			Utility (Non Scale)			Probability (%)					Fit
		Lane1	Lane2	Lane3	lane1	Lane2	lane3	Lane1	lane2	Lane3	normal	Lane1	lane2	Lane3	**incident**	
14	0	10	10	7	3.6	4	2.9	-16.9	-9.04	-6.47	0.998	0.000	0.000	0.002	0.002	Ok
15	0	22	13	12	8.3	6.2	6.3	-26	-9.51	-7.33	0.999	0.000	0.000	0.001	0.001	Ok
16	1	8	21	12	2.7	8.9	4.8	2.069	-21.4	-5.2	0.112	0.887	0.000	0.001	**0.887**	Ok
17	1	0	27	8	0	10.8	2.8	14.89	-31.7	-1.23	0.000	1.000	0.000	0.000	**1.000**	Ok
18	1	2	24	9	0.5	9.3	3.3	9.666	-25.7	-3.53	0.000	1.000	0.000	0.000	**1.000**	Ok
19	1	2	21	14	1	8.5	5.9	11	-17.2	-9.37	0.000	1.000	0.000	0.000	**1.000**	Ok
20	1	2	17	8	0.7	7	2.9	2.95	-18.8	-5.11	0.050	0.950	0.000	0.000	**0.950**	Ok
21	0	18	14	9	7.7	5.3	3.6	-26.6	-11.5	-4.24	0.986	0.000	0.000	0.014	0.014	Ok
267	0	22	13	12	8.3	6.2	6.3	-26	-9.51	-7.33	0.999	0.000	0.000	0.001	0.001	Ok
268	2	16	5	19	6.8	1.9	7.4	-23.2	8.34	-16.1	0.000	0.000	1.000	0.000	**1.000**	Ok
269	2	15	8	16	6.5	2.9	5.7	-22	1.413	-11.9	0.196	0.000	0.804	0.000	**0.804**	Ok
270	2	12	3	19	4.3	1	6.7	-17.4	9.611	-17	0.000	0.000	1.000	0.000	**1.000**	Ok
271	2	10	5	16	3.5	2	6.5	-14	5.591	-15.9	0.004	0.000	0.996	0.000	**0.996**	Ok
272	2	11	5	14	4.3	1.8	5.3	-18.6	3.893	-13.5	0.020	0.000	0.980	0.000	**0.980**	Ok
273	0	11	13	7	4	5.3	2.8	-15.4	-13.6	-4.54	0.989	0.000	0.000	0.011	0.011	Ok
575	0	14	13	11	5.4	4.9	5	-18	-7.43	-8.64	0.999	0.000	0.001	0.000	0.001	Ok
576	3	9	15	1	3.6	6.8	0.3	-14.5	-24.1	1.9	0.130	0.000	0.000	0.870	**0.870**	Ok
577	3	15	19	2	5.4	8.8	0.8	-17.3	-30.1	4.7	0.009	0.000	0.000	0.991	**0.991**	Ok
578	3	11	19	1	4.1	7.8	0.3	-14.6	-27.5	3.304	0.035	0.000	0.000	0.965	**0.965**	Ok
579	3	9	15	4	4.2	6	1.4	-15.1	-18.5	-1.31	0.788	0.000	0.000	0.212	**0.212**	-
580	3	9	21	2	3.4	9.3	0.6	-7.45	-31.9	4.077	0.017	0.000	0.000	0.983	**0.983**	Ok
581	0	17	9	3	6.4	3.7	3	-27.9	-7.83	-5.17	0.994	0.000	0.000	0.006	0.006	Ok

Note 1) if "incident = 0" then normal condition. if "incident = 1" then incident condition

Table 4. Performance Measures

Algorithm	Detection Rate	False Alarm Rate
Proposed Algorithm	96.3%	5.3%
Neural Network Algorithm [2)]	63.4%	2.6%
Occupancy Difference Method	40.0%	74.6%

Note 2) In Sarosh I Khan(1994). Incident detection using Neural Network Algorithm result in 55% Detection Rate and 1.8% False Alarm Rate.

The distribution curves of incident index of the proposed model are drawn as figure 7. The area of uncertainty is defined as the overlapped area of two curves. The distribution curves of the proposed algorithm in Figure 7 are almost separated, so that most of incidents could be detected accurately. It means that the incident index, which is estimated by the proposed algorithm, could be a more appropriate decision variable for identifying surface street incident.

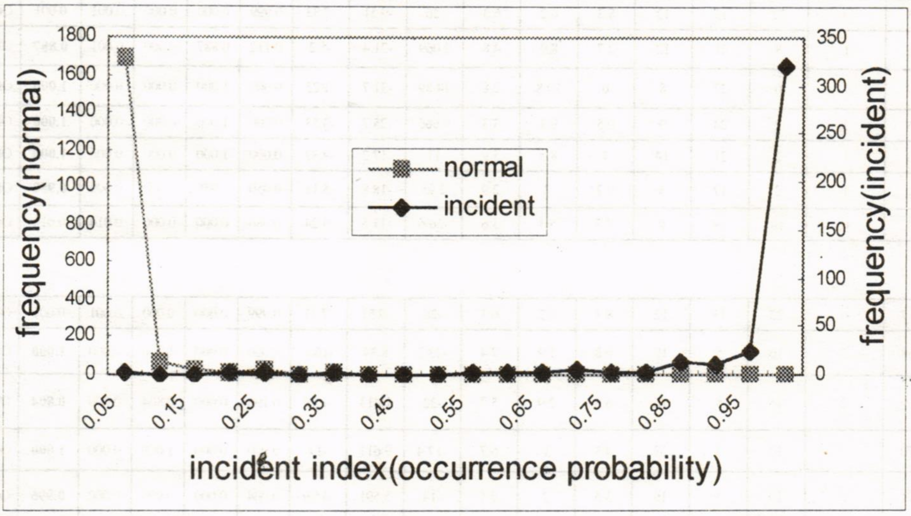

Figure 7. Distribution Curves of incident indices (Proposed Algorithm)

6. CONCLUSIONS

The performance of the proposed algorithm, California algorithm, and Neural Network algorithm were evaluated on the basis of their operating characteristic curves. The evaluation revealed that the proposed algorithm could identify incidents more effectively than other models. Detection rate and False alarm rate of the proposed model are 96.3%, and 5.3% respectively, and at all levels of DR and FAR, the proposed algorithm is superior to the California and Neural Network algorithms. Test results with the proposed algorithm show that the area of uncertainty decreases when incident index is applied. The distribution curves of the proposed algorithm are almost separated so that most of the incident could be detected accurately. The proposed algorithm, however, identifies incident more accurately than other algorithms, it is still restricted by data collecting process and location transferability. To overcome these problems, further research will be continued by the authors.

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