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Study on Incident Detection System Using Fuzzy Logic

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Abstract

This paper presents the potential application of fuzzy logic to the automatic incident detection system. While the conventional incident detection algorithms are based on a binary decision process, the algorithm using fuzzy logic can incorporate ambiguity which occurs in determining incidents. Since collecting good amount of data to construct data base for incidents is pretty expensive, a traffic simulator called FRESIM is used to simulate traffic condition in a freeway. Incident data are obtained by changing input parameters of the simulator and the fuzzy algorithm generates fuzzy rule for determining normal and incident traffic conditions. In this paper, various steps are described to test the algorithm and its results are summarized.

Keywords: incident detection system, ITS(Intelligent Transport Systems), fuzzy logic, traffic simulator

1. Introduction

In recent years, tremendous efforts have been made to improve road traffic condition by providing transportation system with intelligence. Basically it aims at higher safety and efficiency by means of full utilization of information and communication technologies. These programs are conducted under the name of ITS (Intelligent Transport Systems) in several countries[1-2]. Automatic incident detection is one of key issues in traffic management areas.

Traffic incident reduces traffic capacity and increases queue length, which results in slower traffic and additional accidents. An incident, especially in freeway, poses more serious problems when it is not properly managed immediately. Therefore, early detection can save lives and reduce economical as well as environmental losses. In addition, occurrence of incident can be informed to travelers by means of VMS(variable message sign), radio and other roadway-vehicle communication methods so that they can choose alternative route to reduce traveling time.

There are several algorithms for incident detection as shown in Table 1. The vital shortcoming of the conventional algorithms in Table 1 is that the thresholds for triggering alarm are preestablished and it is inadequate to manage various conditions.

Table 1. Comparisons of the incident detection algorithm

Categories	Algorithm	Principle
comparative	• California Algorithm • APID Algorithm	Algorithm trigger an alarm when parameter exceed the thresholds.
Statistical	• Standard Normal Deviate	An alarm is triggered when observed data significantly differs form estimated values.
Time series	• Time Series ARIMA Algorithm • Low-Pass Filtering	Processed data is typically compared to predetermined threshold.
Traffic and theoretical model	• Dynamic Algorithm • The Modified McMaster Algorithm	Actual traffic parameters are compared to those predicted by model.

In this paper, we propose an incident detection algorithm based on fuzzy logic[3] to accommodate the following properties: (1) It is unnecessary to predetermined the thresholds for an incident. (2) Robustness and adaptiveness of fuzzy logic can be utilized via learning. (3) It is easy to achieve good balance between incident detection rate and false alarm rate.

This paper is organized as follows. In the next section, we explain data generation which is used to find fuzzy rule for incidents. Section 3 describes input and output of inference system and generation of fuzzy rules. Section 4 presents simulation results and conclusion is followed.

2. Data generation for analysis

It is not easy to obtain reliable traffic data with a limited number of observations. As common practice in traffic engineering, we use a simulator called FRESIM to generate traffic data. Traffic data consisting of normal and abnormal (incident) is used to construct fuzzy rules for incident detection system.

2.1 Simulation setup

To run traffic simulation using FRESIM, we assume that it is performed in a freeway with 3 lanes as shown in Fig 1.

Traffic moves from left to right with various amount of traffic volumes. Time period is set to 60 seconds and simulation runs for 19 periods. The maximum traffic volume is 2400 veh/hr/lane and minimum is 1333 veh/hr/lane with an interval of 167 veh/hr/lane. Trucks and buses occupy 3-5% of the total traffic volume.

An incident occurs at middle of each link which is marked as star in the sixth period and lasts for 5 periods. Detectors are placed in the small rectangles with solid line and data of link(1,2) indicates the number of vehicles passing that area.

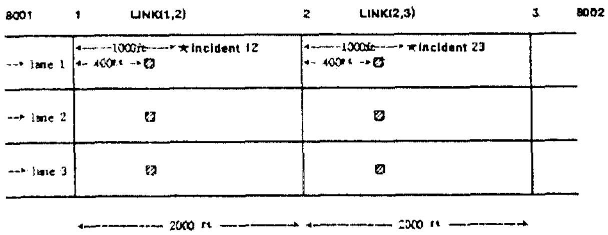

Fig 1. Geometric structure for simulation

2.2 Validation of simulated data

Since we use simulated data using FRESIM instead of real traffic data, it is necessary to confirm its validity. Incident data generated by FRESIM are shown in Fig. 2 - Fig. 5. Solid line and dotted line represent the data obtained at the link(1,2) and link(2,3), respectively. There are changes in occupancy and speed when incident occurs. As indicated in Fig. 2 - Fig. 5, incident at the link(1,2) has significant deviations in both occupancy and speed while changes at the link(2,3) are negligible. Because incident in Fig. 4 and 5 occurs at the upstream side of link detector, data from two links show similarities with time delay. The location of an incident can be inferred using two adjacent link data which is either occupancy or speed.

Validity of data can be claimed from the fact that data at the link(1,2) in Fig. 2 and 3 are close to those at the link(2,3) in Fig. 4 and 5. It means the data generated by simulation is consistent.

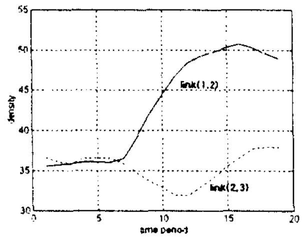

Fig 2. Plot of occupancy when incident occurs at link(1,2)

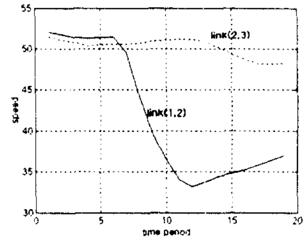

Fig 3. Plot of speed when incident occurs at link(1,2)

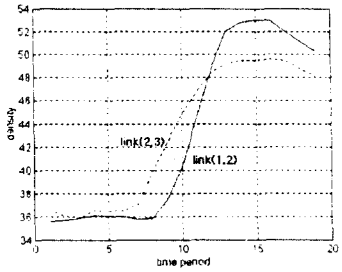

Fig 4. Plot of occupancy when incident occurs at link(2,3)

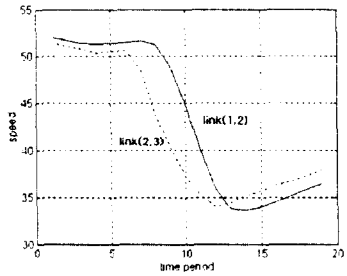

Fig 5. Plot of speed when incident occurs at link(2,3)

2.3 Selection of input data

Time series of traffic occupancy and speed are observed to determine an incident. However, occupancy or speed itself does not convey much information unless its deviation with respect to time is not considered. It is therefore the difference of occupancy or speed is a better choice for the input variable of the incident detection system. The differences of occupancy and speed as illustrated in Fig. 6 and 7 are derived from Fig 4 and 5, respectively.

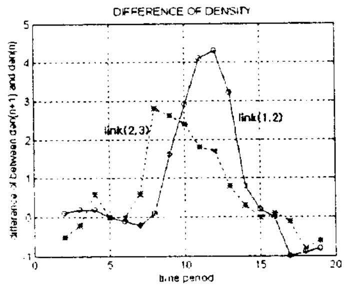

Fig 6. Differences of occupancy when incident occurs at link(2,3)

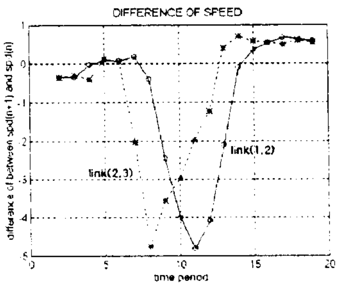

Fig 7. Differences of occupancy when incident occurs at link(2,3)

3. Design of Fuzzy Incident Detection System

3.1 Input and output

As it is explained in the previous section, time difference of occupancy or speed is more suitable for the input of incident detection system

$$Z(n) = X(n+1) - X(n) \quad (1)$$

where X(n) is either occupancy or speed and n represents time. Fuzzy membership function of the input is shown in Fig. 8 where Z(n) consists of three regions.

The output of incident detection system is either *"incident occurs at link(1,2)"*, *"incident occurs at link(2,3)"*, or *"no incident."*

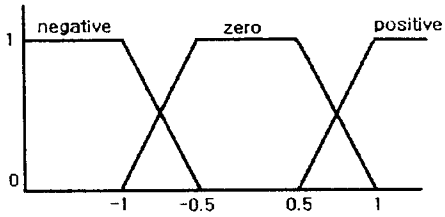

Fig 8. fuzzy membership function for system input

3.2 Fuzzy Rule

By careful inspection, we can find that the incident at link(2,3) can be observed when one of the following conditions are satisfied:

$\Delta d(1,2)=P \cap \Delta d(2,3)=P \cap \Delta s(1,2)=N \cap \Delta s(2,3)=N$
$\Delta d(1,2)=P \cap \Delta d(2,3)=P \cap \Delta s(1,2)=N \cap \Delta s(2,3)=Z$
$\Delta d(1,2)=Z \cap \Delta d(2,3)=P \cap \Delta s(1,2)=N \cap \Delta s(2,3)=N$
$\Delta d(1,2)=Z \cap \Delta d(2,3)=P \cap \Delta s(1,2)=N \cap \Delta s(2,3)=Z$

where Δd, Δs are time difference of occupancy and speed, respectively and P, N, and Z stand for positive, negative and zero. Similar rules for incident at link(1,2) can be obtained and fuzzy rules are obtained when those rules are converted to the well known IF-THEN structure.

3.3 Procedure

The block diagram for general fuzzy incident detection system is shown in Fig. 9. Function of each block is quite well known. It should be noted that the input of fuzzy inference system is a bit more complex than what we explained. In addition to the difference of occupancy or speed, traffic volume should be taken into account as an input of the system. Thus the input in Eq. (1) can be rewritten as

$$Z(n) = K\,(X(n+1)-X(n)) \quad (2)$$

where the value of K reflects the traffic volume.

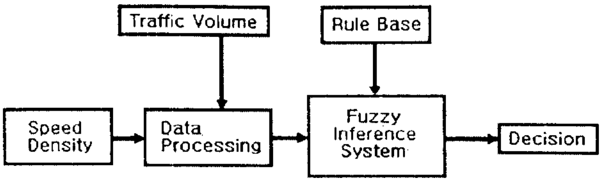

Fig 9. Block diagram of fuzzy incident detection system

4. Simulation result

We assume that an incident occurs at the link(1,2) or link(2,3) with three different traffic volume as follows:

incident #0: link(1,2) volume=1333-1400(veh/hr/lane)
incident #1: link(1,2) volume=1833-1900(veh/hr/lane)
incident #2: link(1,2) volume=2333-2400(veh/hr/lane)
incident #3: link(2,3) volume=1333-1400(veh/hr/lane)
incident #4: link(2,3) volume=1833-1900(veh/hr/lane)
incident #5: link(2,3) volume=2333-2400(veh/hr/lane)

Observation is made from period 1 to period 19 and incident occurs at time period 6 and lasts for 5 periods.

Simulation results are shown in Table 2 and 3, respectively. We assume that incident occurs at link(1,2) and link(2,3) with three different traffic volume.

Inspection of Table 2 reveals that the algorithm detects incident at period 8 or period 9. Its variance is due to the traffic volume. Obviously the smaller volume needs more time to detect. To reduce time to detection, we need to lessen the period interval. However it can increase false alarm rate. Therefore, it is desirable to find a period interval to achieve optimal trade off between false alarm rate and detection rate.

Degenerate performance is shown in Table 3 where an incident at link(2,3) is misinterpreted at period 13 for two larger traffic volume. False alarm occurs when an incident at link(2,3) is resolved and on the way back to the normal state.

From Table 2 and 3, we can find that it is easier to detect an incident at link(1,2) than one at link(2,3). It is quite self-evident that two adjacent detectors are the optimal pair to spot an incident which occurs between them.

Table 2. Simulation result when incident occurs at link(1,2)

time period	incident #0	incident #1	incident #2
5	normal	normal	normal
6	normal	normal	normal
7	normal	normal	normal
8	normal	inc 12	inc 12
9	inc 12	inc 12	inc 12
10	inc 12	inc 12	inc 12
11	inc 12	inc 12	inc 12
12	inc 12	normal	normal
13	normal	normal	normal
14	normal	normal	normal

Table 3. Simulation result when incident occurs at link(2,3)

time period	incident #3	incident #4	incident #5
5	normal	normal	normal
6	normal	normal	normal
7	normal	normal	inc 23
8	normal	inc 23	inc 23
9	normal	inc 23	inc 23
10	normal	inc 23	inc 23
11	inc 23	inc 23	inc 23
12	inc 23	inc 23	inc 23
13	normal	inc 12	inc 12
14	normal	normal	normal

5. Conclusion

In this paper, preliminary incident detection scheme using fuzzy logic is studied. There is room for ambiguity in determining the state of incidents using few traffic parameters. Fuzzy logic can provide robustness and adaptiveness and varying conditions are considered in the decision process.

Using freeway simulator, FRESIM, we generate traffic data, build fuzzy rules and finally obtain reasonable results.

Fuzzy incident detection system should be developed toward having with learning capability so that it can automatically adjust to varying traffic and environmental conditions.

Acknowledgment
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