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Hybrid Fuzzy Logic-Genetic Algorithm Technique for Automated Detection of Traffic Incidents on Freeways

Dipti Srinivasan, *Member, IEEE,* Ruey Long Cheu, and Young Peng Poh

Abstract-- **Incident detection has become an important and sophisticated task in today's complex engineering environment, and is one of the key functions of modern traffic management systems. The incidents, depending on their severity, affect the traffic pattern on expressways and cause congestion. This paper presents a hybrid AI approach for immediate and automatic detection of traffic incidents on expressways. Specifically, a hybrid combination of fuzzy logic and genetic algorithm (GA) has been applied to automatically detect incidents on a traffic network. The flexible and robust nature of the developed fuzzy controller allows it to model functions of arbitrary complexity while at the same time being inherently highly tolerant of imprecise data. The maximizing capabilities of genetic algorithm, on the other hand, enable the fuzzy design parameters to be optimized to achieve optimal performance. A cascaded framework of 11 fuzzy controllers takes in traffic indices such as occupancy and volume to detect incidents along an expressway in California. The results obtained from this hybrid model demonstrate the superiority of this approach when compared with two commonly used conventional incident detection algorithms.**

***Index Terms*—Incident detection, fuzzy logic, genetic algorithms.**

I. INTRODUCTION

Automated incident detection (AID) has become an important and sophisticated task in today's complex engineering environment, spanning areas from air navigation, traffic networks to power systems and computers. Incidents on urban expressways include accidents, disabled vehicles, spilled loads, maintenance, detector malfunctions and other activities that disrupt normal traffic flow and cause delay to motorists and deteriorate road safety conditions. For more effective traffic management systems, an automated incident detection algorithm that is reliable and quick in detecting incidents is essential. Early detection of incidents is vital for formulating effective response strategies and provision of real-time information to motorists.

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This paper attempts to provide an AI-based solution to the above problem in the general framework for developing expressway AID systems. Two types of artificial intelligence techniques have been applied. First, fuzzy logic is used to implement an AID model. Second, genetic algorithm (GA) is used for optimizing the unknown fuzzy variables. The framework developed in this paper could serve as the basis for developing an adaptive AID model for future real-time applications.

A. The Operation Framework of Expressway AID Systems

In general, an automatic incident detection (AID) system has three basic operating components: (1) detectors (typically inductive loop detectors or video image processing systems) that sense vehicle movements; (2) signal processing units that calculate and transmit traffic data at every 30-second interval; and (3) an AID model that detects abnormal traffic flow and gives incident alarm. Detectors are placed in individual lanes at the boundary of each section of an expressway as shown in Fig. 1. These sections are normally 500 m to 1000 m in length. The collected traffic flow characteristics are typically the volume, occupancy and average speed. They are used as inputs to the AID model.

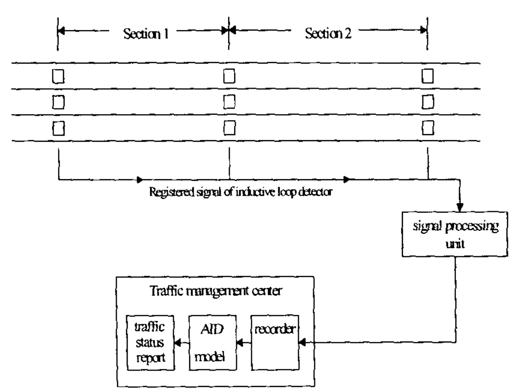

Fig. 1. The Operation Framework of An AID System

The commonly used performance measures of an AID model are detection rate (DR) and false alarm rate (FAR) and the mean-time-to-detect (MTTD). They are defined by:

$$\text{DR} = \frac{\text{no. of detected incidents}}{\text{total no. of incidents}} \text{ x } 100\% \quad (1)$$

$$\text{FAR} = \frac{\text{no. of false alarm cases}}{\text{total no. of input patterns}} \text{ x } 100\% \quad (2)$$

$$\text{MTTD} = \frac{1}{n}\sum_{i=1}^{n}(t_{detected} - t_{on-set}) \quad (3)$$

Here, $t_{detected}$ is the time interval between the onset of an incident and the instant when the alarm is triggered, t_{on-set} is the time when the incident actually occurs, and n is the number of detected incidents. It is worth mentioning here that normally the false alarm rate increases when one tries to increase the detection rate. Therefore, a challenge is to maintain a high detection rate and at the same time minimize the false alarm rate. One approach is to apply a persistence test to reduce the false alarms caused by random traffic fluctuations. With the persistence test, an incident alarm triggers only after a number of consecutive intervals of incident patterns have been observed.

B. Incident Detection Algorithms

Research in automated incident detection techniques started in early 1970s with the implementation of interstate freeway systems. In the early years, techniques such as decision tree for pattern recognition [1], time series [2] and Kalman filters [3] were applied. The three main incident detection algorithms are briefly described below.

California algorithms

The California algorithms consist of a family of 11 algorithms with variations of binary decision trees for incident detection [1]. Each decision tree detects incidents based on a discontinuity in occupancy values between two adjacent detector stations on a freeway. One of the better-known algorithms, the California algorithm #8, uses a five-minute roll-wave suppression logic that helps reduce false alarms due to shock waves from downstream. The four input features and five threshold values in the algorithm are calibrated with historic incident data before application [4].

The main advantage of California Algorithms is that their decision logic is easy to understand. The main unique advantage of the California algorithm #8 is a low false alarm rate. However, the main disadvantage of California algorithm #8 is that it uses only occupancy-related variables as inputs. Volume related data is never taken into account.

McMaster algorithms

The McMaster algorithms are based on catastrophe theory [5]. In this algorithm, traffic conditions are classified into four regimes in the station-specific 30-second volume-occupancy space, obtained from the fast lane. The recognition of congestion is based on the regime that current traffic inputs fall in.

McMaster algorithm has some distinct advantages in comparison to California algorithm #8". In this algorithm, malfunction of a downstream detector does not affect incident detection unlike in California algorithm #8. It uses volume as an input in identifying possible incidents, unlike California algorithm #8, which takes only occupancy inputs into account. The mean time to detect an incident is 30 seconds faster than in California algorithm #8. McMaster algorithm takes recurring congestion into account in identifying incidents, leading possibly to a lower false alarm rate.

The main disadvantage of McMaster algorithm is that only data from the fast lane is evaluated. A longer incident detection time is taken for an incident occurring on the shoulder or right-most travel lane, which is detected only after it affects the traffic flow in the fast lane.

Minnesota algorithm

The Minnesota algorithm [6] depends on the occupancy values as input and operates on 30-second intervals. Specifically, one-minute average occupancy across all lanes, at the upstream and downstream stations is used as inputs. Its detection concept is based on comparing the average spatial occupancy differences before and after an incident.

The Minnesota algorithm has two main disadvantages. First, it uses only occupancy values as input and ignores volume values. During low-volume conditions, the lack of volume as input may lead to many false alarms. Second, the detection time is extended to three minutes as the algorithm uses occupancy values from the past six time intervals.

C. AI Based Models

Current AID techniques are still limited by their low transferability and adaptability. The basic AID model usually performs poorer (i.e., lower DR, higher FAR) when there is significant change in its application environment.

The growing interest in artificial intelligence (**AI**) techniques have presented new opportunities to provide solutions to increasing challenges of the future. AI-based techniques such as neural networks, fuzzy logic and genetic algorithms (GAs) [7-9] are highly adaptive and can devise solutions to problems where traditional methods cannot be effectively applied. AI based techniques have shown great potential in the development of automated incident detection algorithms [4, 14, 15] with the promise to give high incident detection rates and low false alarm rates. Fig. 2 illustrates the automated incident detection process using AI techniques.

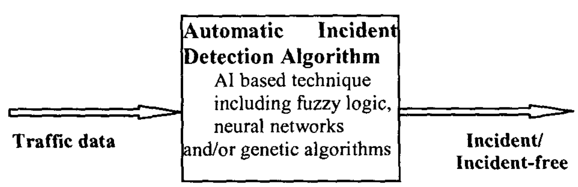

Fig. 2: Traffic data processing for automated incident detection

Most of the recent work on AI application for incident detection has centered on developing artificial neural network (ANN) models [4, 10, 11, 14, 15] for this problem. The ANN model developed in [14] was a multi-layer feed-forward network, with one hidden layer. The inputs to the neural network were 30-second occupancy and volume from time t to t-4 intervals at the upstream station as well as the same traffic measures from t to t-2 intervals at the downstream station. The results showed that this model had higher DR, lower FAR and shorter MTTD than California algorithm #8.

The application of ANNs in incident detection has been extended not only to various network designs, but also to the general requirements during system implementation. These requirements include (1) high detection rate (DR), acceptable low false alarm rate (FAR) and shorter detection time; (2) high transferability between sites and adaptability to local conditions.

II REVIEW OF FUZZY LOGIC AND GENETIC ALGORITHM

A. Fuzzy logic

Fuzzy Logic is a human inference oriented AI technique that incorporates the uncertainty and abstract nature inherent in human decision-making into intelligent control systems. It captures the approximate and qualitative boundary conditions of system variables by fuzzy sets with membership functions. A fuzzy system implements functions in near-human terms, i.e. **IF-THEN** linguistic rules, with reasoning by fuzzy logic[7].

Fuzzy sets equations

The difference between classical and fuzzy set theory is that classical theory only allows crisp, binary values 1 or 0 (true or false) whereas fuzzy logic, allows partial set memberships. The degree to which an element x belongs to a fuzzy set A is characterized by its degree of membership, $\mu_A(x) \rightarrow [0,1]$. The three basic fuzzy operators AND, OR and NOT, are:

Union of two sets: $A \cup B$, corresponds to the OR operation.

$$\mu_{A \cup B}(x) = \max(\mu_A(x), \mu_B(x)) \quad (4)$$

Intersection of two sets: $A \cap B$, corresponds to AND operation.

$$\mu_{A \cap B}(x) = \min(\mu_A(x), \mu_B(x)) \quad (5)$$

Complement of a set: $\bar{A}$, corresponds to the NOT operation.

$$\mu_{\bar{A}}(x) = 1 - \mu_A(x) \quad (6)$$

Fuzzy control rules

A fuzzy controller consists of a set of control rules and each rule is a linguistic statement about the control action to be taken for a process condition given by the following rule structure:

IF <condition> **THEN** <control action>

The <condition> is termed as the antecedent and the <control action> is the consequence. In linguistic approximation by fuzzy logic, each of these terms is represented by a preference fuzzy membership function to establish a value in the interval [0,1].

Fuzzification , rule base and defuzzification

The fuzzification of a crisp value to a fuzzy terminology is characterized by a scaling factor and a quantisation process. After quantisation [7], a degree-of-membership function is then applied to derive its degree-of-membership in each of the fuzzy linguistic sets. Typically, a Gaussian membership function is given as:

$$\mu(x) = e^{\left(\frac{-|x-\alpha|^{\beta}}{\sigma}\right)} \quad (7)$$

After the input variables are fuzzified, they are usually fed into a 2-dimensional fuzzy decision table to derive the output variable. Using the look-up table, fuzzy control actions are computed using the min-max functions in a fuzzy control system [7]. The min operation is performed on the antecedents of the rule followed by the max operation on the consequences to determine the final control actions. The control actions are used in the defuzzification process where a crisp executable value is computed.

There are four major defuzzification rules; which consist of the maximizer technique, weighted average method, centroid method and the *Singleton method* [7]. The *Singleton* method represents each fuzzy output set as a single output value by using a weighted average to combine multiple output actions. It treats each output degree-of-membership function as a rectangle and hence reduces the computation considerably. Having obtained a single output value, it is then multiplied by an output scaling factor to obtain a corresponding crisp, executable control action.

Fuzzy logic is popular because it is conceptually easy to understand since it is based on natural language. It is tolerant of imprecise data and is therefore more robust as compared to conventional controllers. It can also model functions of arbitrary complexity and is very adaptive in nature. The disadvantages of using fuzzy logic are that it may be difficult obtaining good membership function graphs representing the actual control parameters to be modeled. The rule-base for the fuzzy decision table may be difficult to dictate and experience, or expert's knowledge rules may not always give the optimized solutions.

B. Genetic algorithms

Genetic algorithms (**GAs**) are search algorithms based on the mechanics of natural selection and Darwinian survival of the fittest. A GA uses coded strings (chromosomes) of binary numbers (genes) for the search process. Each chromosome is termed as an individual and a population of individuals is evolved from generation to generation with only the most suited individuals likely to survive and generate offspring, thereby transmitting their genetic material to the next generation. Three operators essentially perform GA, namely: reproduction, crossover and mutation[9].

Reproduction, crossover and mutation

The initial population size in genetic algorithms has substantial effect on the ultimate performance and efficiency in genetic search, ranging in size from 30 to 200. Reproduction occurs when new individuals are produced, whereby a new generation is formed by randomly selecting fittest individuals from an existing generation, to breed. The selection procedure, called the *roulette-wheel selection scheme* [9], generates a probability that the individuals with higher fitness values will be selected to reproduce within a fixed size population in each generation, resulting in individuals with higher fitness values in the new generation.

The crossover operator is used to produce offsprings that are different form their parents but inherit portions of their parents' genetic material. A selected chromosome is split into two or more parts (*multiple point crossover*) and recombined with another selected chromosome, which has also been split at the same crossover points to produce two new offsprings, which will replace weaker individuals in the population. Crossover operations provide and introduce new search spaces for further testing within the existing hyperplanes [9] into the new population.

Mutation in a chromosome is used to provide new genetic materials by randomly selecting bits (genes) to be mutated and subject them to inversion of values. The mutation operator contributes by discovering new or restoring lost genetic materials. Carrying out these three operators until a satisfactory result is found or maximum generation number is reached performs each GA generation.

Objective fitness function and coding schemes

The application of genetic algorithms to optimization problems depends on the choice of fitness function and coding schemes used to code the design parameters. The fitness function differs for individual problem and depends essentially on the factors to be optimized or minimized [12]. The coding of the parameter set typically involve binary coding but decimal coding is more efficient and flexible [9] with shorter chromosome length and reduced run-time of the GA. The formula for decimal coding is given as

$$C = C_{\min} + \frac{a_{p-1}b^{p-1} + \ldots\ldots + a_0 b^0}{b^p}(C_{\max} - C_{\min}) \qquad (8)$$

Features of genetic algorithms

Genetic algorithms are powerful because they consider a population of points in the search space simultaneously and permit the optimization of the whole parameter set. GAs use objective function to guide the search and are therefore more robust in achieving optimal solution. GAs use probabilistic rules to make decisions, and this has introduced intellectual capability in GAs.

III DESIGN OF AUTOMATED INCIDENT DETECTION ALGORITHM

This section deals with the design of the automated incident detection methodology developed to test incidents along an expressway in California and also covers some aspects of the computer simulations.

A. System overview and traffic data

The automated incident detection algorithm developed here adopts a macroscopic, section method which provides observation at two different adjacent sites, upstream and downstream, at several segments, along a stretch of expressway with data comparison between them and works with aggregated information. The INTRAS (Integrated Traffic Simulation) model was used to generate simulation detector data for the study[4].

B. The study site

An expressway section in the westbound direction of the SR-91 Riverside Freeway in Orange County, California, between the SR-57 and Interstate 5 Freeways, of approximately 5.0 miles in length, was selected as the study site. The entire site has eight detector stations and the spacing of the detector station varies from 0.34 to 1.02 miles.

C. AID Model implementation using fuzzy logic

The traffic indices chosen to be measured in the upstream and downstream portions of the expressway are the average occupancy and volume. Out of the 16 available occupancy and volume data at 30 seconds interval, only 12 of these are used as the input data. There are 35000 data vectors in each of the two test files, set1.dat and set2.dat, with each data vector consisting of 16 values.

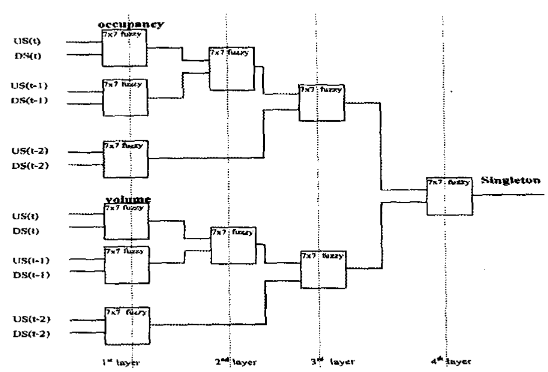

Fig.3: Block diagram of the AID model

The developed fuzzy algorithm resembles a *cascaded multiplexer design* and is divided into four different layers, simulating a *neural network* with an input layer, two hidden layers and an output layer (Fig. 3).

Fuzzification process

Each decision table takes in two inputs, upstream and downstream values of either occupancy or volume at the same time. Each input is fuzzified into 7 linguistic sets: ZO, PSZ, PS, PSM, PM, PMB, and PB with their corresponding degree-of-membership values. This results in a 7x7 decision table with 49 possible outputs and degrees-of-membership. Fig.3 shows the 12 data inputs at three different times; t, t-1 and t-2 are taken for each traffic index. To arrive at the output degree-of-membership, the AND operator is applied to the two antecedents to get the minimum value for the consequences, followed by applying the OR operator to get the maximum value among the consequences in each of the 7 sets. The 7 outputs from each of the seven sets from each fuzzy decision table in each layer are then fed accordingly as inputs into the subsequent layer of fuzzy decision tables (an example is shown in Fig. 4) and the process is repeated until it reaches the fourth and final layer. At this point, the Singleton method is applied to defuzzify the outputs of the fuzzy sets of the last table to produce a single output control action.

Decision table and membership functions

Each decision table has 49 values that can be tuned by genetic algorithm to obtain a "near-optimal" design. The membership functions for each of the seven fuzzy linguistic sets is either a triangular or Gaussian membership function to be determined by GA.

	ZO	PSZ	PS	PSM	PM	PMB	PB
ZO	ZO	PSZ	PSZ	PM	PMB	PB	PB
PSZ	ZO	ZO	PSZ	PS	PM	PMB	PB
PS	ZO	ZO	ZO	PSZ	PS	PM	PMB
DS PSM	ZO	ZO	ZO	ZO	PSZ	PS	PS
PM	ZO	ZO	ZO	ZO	ZO	PSZ	PSZ
PMB	ZO	ZO	ZO	ZO	ZO	ZO	PSZ
NB	ZO	ZO	ZO	ZO	ZO	PB	ZO

Fig.4: A typical decision table.

Defuzzification and crisp output value

The Singleton method is used for the defuzzification process where the average membership function value of each of the seven linguistic sets is taken and gives rise to one output. After de-normalization [9], a decimal output value between 0 and 1 will be obtained. A value above 0.5 (midlimit) gives a STATE of 1, corresponding to a detected incident; otherwise, a value below 0.5 gives a STATE of 0 corresponding to an incident-free interval.

D. Coding scheme using genetic algorithm

Genetic algorithm is used to fine-tune the 657 unknown fuzzy parameters to obtain optimal performance for the developed methodology and decimal coding is used for this process. Each chromosome used in the GA coding for this methodology has a total of 719 genes with values varying between 0 and 6 for a base number of 7.

Training by genetic algorithm

A random number generator with statistically uniform deviates generates the genes for the chromosome. These genes are input into a decoding algorithm to obtain the fuzzy parameters, which are subsequently fed into fuzzy set equations to arrive at the results for the automated incident detection algorithm. The process repeated for a certain number of generations, MAXGEN, called training by genetic algorithm (on-line GA).

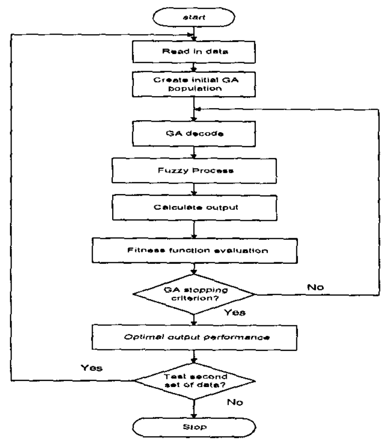

Fig.5 : On-line training by genetic algorithm

IV IMPLEMENTATION AND RESULTS

A. Performance measures

The performance measures evaluate the average detection rate, false alarm rate, false alarm interval, current performance and the average time-to-detect measures of the incident detection. The incident detection algorithm is designed such that the triggering of the fuzzy output pulse must come later than the actual output pulse rise in order an incident block be considered detected as in Fig.6.

The delay in detecting the actual incident from the fuzzy output is called the time-to-detect (TTD). The longest time to detect is the longest TTD while the average time to detect is the average TTD. Another factor to be considered is the current performance rate:

$$\text{Current performance} = \frac{100.0\text{x}\,(\text{DR} + \text{DV})}{\text{No of input\_output pair}} \qquad (9)$$

DR is incremented whenever the detected fuzzy output for an incidence corresponds to the actual target output. DV is incremented when the detected fuzzy output for incident-free condition corresponds to the actual target output.

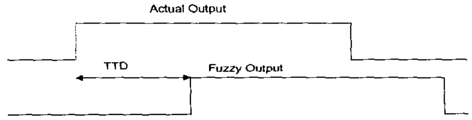

Fig.6: Block diagram showing the TTD calculation.

False alarm rate calculation

A false alarm interval occurs when the fuzzy output is triggered to indicate an incident when the actual target output is zero (no incident). A false alarm block rate that is 1% and below is within limits of acceptance.

Simulation Results

Detector outputs from the INTRAS simulation runs were grouped into two independent data sets (i.e. set1.dat and set2.dat). The traffic indices to be measured in the upstream and downstream portions of the expressway are the average occupancy and volume. For every set of traffic data, there are 5 occupancy values at upstream and 3 occupancy values at downstream at time-intervals of 30 seconds each. The same applies for the volume inputs, giving a total of 16 inputs per data set. The average detection rates, false alarm rates and the fitness values are given in Table 1 for the two sets of data.

Table 1: Simulation results

Data set	DR(%)	FAR(%)	FA(cases)	MTTD(sec)
Set1.dat	72.6	1.121	313	228
Set2.dat	73.7	1.104	309	240

The incident detection performance of the developed fuzzy-GA AID model was compared with an artificial neural network approach [14], and California, McMaster and Minnesota algorithms on a similar set of data. In case of California #8 and Minnesota algorithms, several sets of threshold values were obtained and used for calculating the detection rate (DR), false alarm rate (FAR) and time to detect (MTTD). The threshold set that gave the best performance were used for comparison of performance. The average DR from the ANN model [14] was 78%, while the FAR and MTTD were 1.503 sec and 206 sec respectively. The corresponding values from California #08 algorithm were 49%, 0.571 sec and 255 sec; while those from McMaster algorithm were 37%, 2.075 sec and 260 sec respectively.

The results obtained showed that the developed fuzzy-GA AID model performs generally better than the ANN approach for persistence tests 1-3 by giving a better detection rate and smaller time to detect. However, the false alarm rate is generally higher than the latter. The results also indicate that both these AI-based approaches are superior compared to non-AI algorithms.

V. CONCLUSION

This paper has presented the development of an automated incident detection (AID) model based on fuzzy logic and genetic algorithm. The model was developed using data from a freeway in the United States. The performance of this model was compared with three existing AID models. The simulation results have shown that the developed algorithm using a combination of fuzzy logic and genetic algorithm gives a high detection rate and a low alarm rate, and is very promising for expressway incident detection. Further work on this model will involve automatic tuning of fuzzy rules to obtain better detection rate.

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