AN INCIDENT DETECTION METHOD CONSIDERING METEOROLOGICAL FACTOR WITH FUZZY LOGIC

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ARTICLE INFO

***Article history*:**
Received: 28.09.15.
Received in revised form: 09.03.16.
Accepted: 17.03.16.

Keywords:
Automatic incident detection
Meteorological factor
Fuzzy logic
Learning vector quantization (LVQ)

Abstract:

To improve the performance of automatic incident detection algorithm under extreme weather conditions, this paper introduces an innovative method to quantify the relationship between multiple weather parameters and the occurrence of traffic incident as the meteorological influencing factor, and combines the factor with traffic parameters to improve the effect of detection. The new algorithm consists of two modules: meteorological influencing factor module and incident detection module. The meteorological influencing factor module based on fuzzy logic is designed to determine the factor. On the basis of learning vector quantization (LVQ) neural network, the new incident detection module uses the factor and traffic parameters to detect incidents. The algorithm is tested with data collected from a typical freeway in Chongqing, China. Also, the performance of the algorithm is evaluated by the common criteria of detection rate (DR), false alarm rate (FAR) and mean time to detection (MTTD). The experiments conducted on the field data study the influence of different algorithm architectures exerted on the detection performance. In addition, comparative experiments are performed. The experimental results have demonstrated that the proposed algorithm has higher DR, lower FAR than the contrast algorithms, and the proposed algorithm has a better potential for the application of freeway automatic incident detection.

1 Introduction

With a rapid increase in metropolitan and other urbanization activities, freeway incidents are major cause of undesirable congestion and mobility loss. They require to be detected in time to prevent serious accumulation of congestion, traffic delay, and possible second traffic accidents. To solve this

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problem, a variety of automatic incident detection (AID) algorithms are developed. In the early years, algorithms such as pattern recognition [1] and time-series [2] were applied. Also, the California algorithm [3], regarded as the most notable one by some researchers, was still used for benchmarking of new algorithm designs. Recently, more advanced approaches were tested; these included partial least squares regression [4], combinations of algorithms [5], artificial neural network [6], spatio-temporal clustering [7], wavelet-based incident detection algorithm [8] and genetic adaptive detection algorithm [9]. Owing to the better performance of Bayesian approaches [10] and support vector machine (SVM) [11] with field data, we also use them as contrast algorithms in our experiments.

These AID algorithms usually adopt various methods to distinguish traffic flow status based on data from inductive loop detectors and have achieved some certain effects in a real detection system. However, the changeable meteorological variables not only significantly affect traffic characteristics, but also deteriorate the performance of real-time incident detection as well. Furthermore, in a real time application, a foul weather may cause problems such as low detection rates, high error rates and poor robustness. Therefore, the researchers concerned about the impact of weather condition on traffic mainly focus on the relationship between weather variation and the traffic flow characteristics [12-14], and the influence of the weather on the occurrence of traffic incident [15-16]. There are few research papers/studies about the impact of the weather condition on the AID algorithm performance. In 2012, Duan presented an information fusion method for detecting traffic incidents, in which weather condition was utilized as a part of information source [17]. However, it could not illustrate how to analyze and quantify the relationship between multiple weather variables and incidents in the algorithm. Nevertheless, this topic is meaningful and few research studies/papers have been done so far to our knowledge.

To solve these problems, this paper attempts to develop a new algorithm that would consider the impact of different weather conditions on traffic incident detection. Firstly, we present a new method to quantify the relationship between the multiple weather variables and the occurrence of traffic incident, as the factor α . Then, an approach which combines the factor α with traffic parameters for freeway incident detection by learning vector quantization (LVQ) is proposed. We conduct comparative experiments to evaluate the performance of the algorithm with the field data. Results show that the algorithm can improve the detection effect under changeable weather conditions, and all evaluating indices of the algorithm are thus encouraging.

The remainder of this paper is organized as follows. Section 2 introduces the proposed algorithm considering the meteorological influencing factor α with fuzzy logic. In Section 3, the new algorithm is tested with flied data sets, including the incident data, traffic parameters and meteorological data, to study influences which various LVQ network architectures exert on detection performance. Then Section 4 compares the proposed algorithm with the contrast algorithms to further illustrate its performance. Finally, the conclusions are drawn and future research directions are recommended in the Section 5.

2 A new algorithm with meteorological influencing factor

There are two important models in this new algorithm: (1) meteorological influencing factor model based on fuzzy logic and (2) LVQ network based on an incident detection model. In the meteorological influencing factor module, typical meteorological parameters are used to quantify the relationship between the weather condition and the occurrence of traffic incident as a factor α by fuzzy logic. Then, a new approach based on LVQ to detect incidents with the factor and traffic parameters, is proposed in an incident detection model.

2.1 Meteorological influencing factor based on fuzzy logic

During the past decades, considerable research studies were dedicated to reveal the impact of various weather conditions on the occurrence of traffic incident by rainfall and visibility. Several researchers concluded that the average frequency of accidents during rain hours is significantly more than the average frequency at other time [15]. Some studies found that increased rates of incidents are associated with low visibility [16]. From the literature review, we found that: (1) these analyses focused mostly on the relationship between one kind of meteorological parameters and the occurrence of incident; (2) previous studies would not clearly quantify and analyze the impact of multivariable meteorological parameters on traffic incident.

With above findings in mind, we propose a new method to quantify the relationship between multivariable meteorological parameters and the occurrence of incident in this model. Considering that rainfall and visibility are significantly related to the occurrence of incident, these parameters are used as the meteorological variables in this paper. Furthermore, a method based on fuzzy logic determines the meteorological influencing factor which reflects the influence of multivariable parameters on the occurrence of traffic incident.

2.1.1 Fuzzy logic

Fuzzy logic was first introduced by L. A. Zadeh in his fuzzy set theory in 1965. It provides a many-valued logic which deals with approximate reasoning rather than with fixed and exact ones. Fuzzy modelling has the characteristics of simplicity and natural structure [18, 19]. The structure of a fuzzy logic system is presented in Fig. 1, and the four steps for determining the factor α will be introduced in the following section.

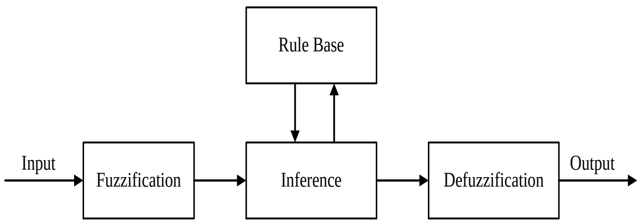

Figure 1. Structure of a fuzzy logic system.

2.1.2 Meteorological influencing factor

(1) Fuzzy variables and membership functions

There are two major meteorological parameters in this model: hourly visibility and six-hour rainfall. When analyzing the relationship between meteorological parameters and the occurrence of incident, the incident frequency is used to describe the influence of different weather conditions on traffic incidents. The incident frequency (IF) is determined by the following equation:

$$IF = \frac{number\ of\ incidents\ in\ this\ measured\ value}{times\ of\ the\ measured\ value\ in\ sample} \times 100\% . \quad (1)$$

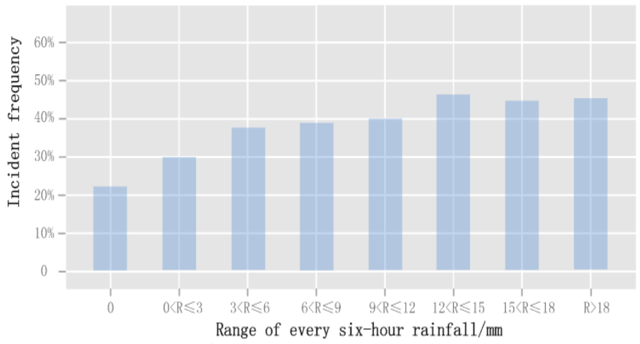

Figure 2. Six-hour rainfall with the incident frequency.

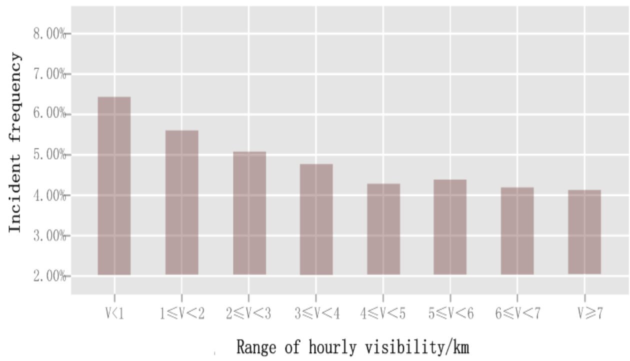

Figure 3. Hourly visibility with incident frequency.

In the Fig. 2 and Fig. 3, it is clear that different meteorological parameters have evident influence on the frequency of traffic incidents. IF increases along with the rainfall, and it reduces with an increase in visibility. In order to determine the function members in fuzzy logic model, it is divided into three different regions. They are determined by different influence levels of rainfall and visibility so that rainfall is divided into *Small*, *Medium* and *Large*, and visibility is divided into *Low*, *Medium* and *High*. Corresponding fuzzy sets of rainfall are $U^R = \{U_1^R, U_2^R, U_3^R\}$ and the universe is $u_R = [0, r_{\max}]$. Then the fuzzy sets of visibility are $U^V = \{U_1^V, U_2^V, U_3^V\}$ and the universe is $u_V = [0, v_{\max}]$ ($r_{\max}$ and $v_{\max}$ is the historical maximum value). The influence of meteorological parameters exerted on incidents is divided into three levels which are *Little*, *Medium* and *Serious*, and fuzzy sets are $U^\alpha = \{U_1^\alpha, U_2^\alpha, U_3^\alpha\}$.

Conventional approaches have sought to subjectively define the membership function by studying the existing system. In this paper, we propose the method that compared the expected incident frequency in a fuzzy model with the real incident frequency in Fig. 2 or Fig. 3, and make the expected incident frequency consistent with the actual situation by adjusting the ranges of fuzzy sets.

For example, R_{fuzzy} is the expected incident frequency in rainfall, which can be expressed as:

$$R_{fuzzy} = U_1^R W_1^R + U_2^R W_2^R + U_3^R W_3^R \,, \tag{2}$$

where, W_1^R , W_2^R and W_3^R are the average incident frequency of the range of U_1^R , U_2^R and U_3^R , respectively.

Different lines of R_{fuzzy} are drawn through continuous testing to adjust the ranges of U_1^R , U_2^R and U_3^R . By comparing R_{fuzzy} and the real incident frequency in Fig. 2, the optimal R_{fuzzy} line which has the minimal difference with the real incident frequency is selected. Fig. 4 depicts and compares the expected incident frequency with real incident frequency in rainfall. Besides, triangular and trapezoidal functions are selected to describe fuzzy set considering the W_2^J liner distribution in universe of rainfall and visibility. According to Fig. 4, fuzzy sets of rainfall are determined where W_1^J is 0.28, W_1^J is 0.37 and W_3^J is 0.49 in this paper. The member function for rainfall is illustrated in Fig. 5 and then the member function of visibility is determined by using the same method also presented in Fig. 5.

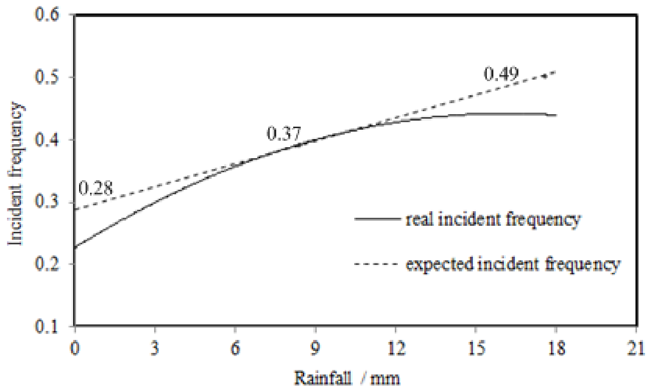

Figure 4. Real incident frequency and expected incident frequency in rainfall.

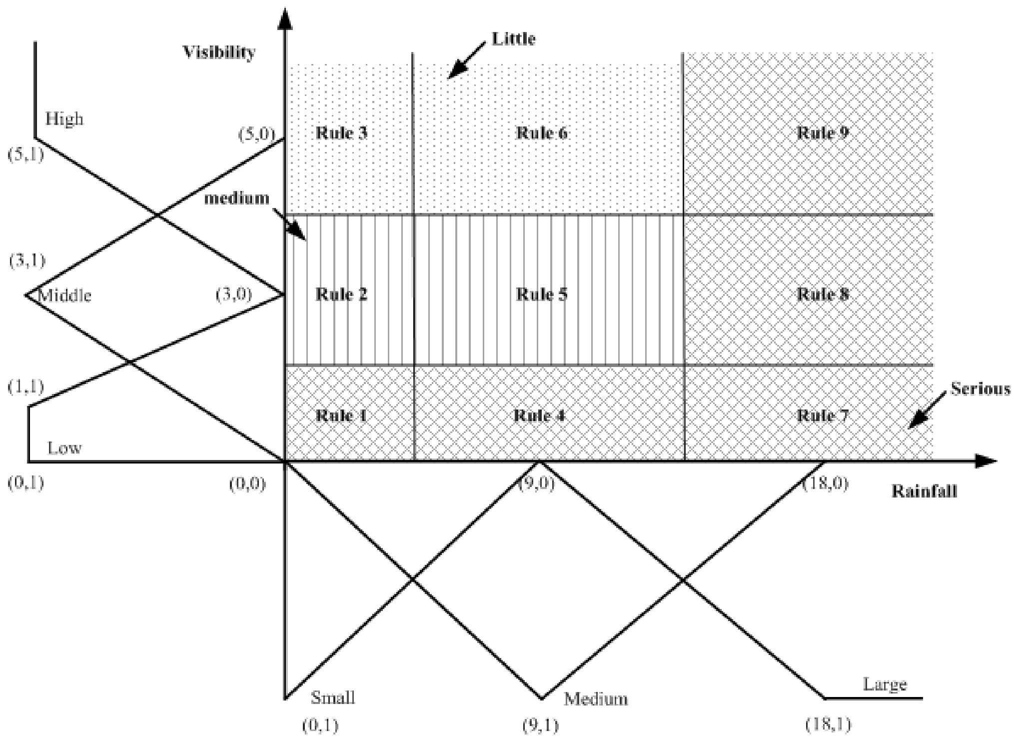

Figure 5. Membership and rules for meteorological influencing factor.

(2) Rule base

The relationship between inputs (i.e. U^R and U^V) and output (U^α) is described by rule base comprised of a set of rules. As illustrated in Fig. 5, rainfall and visibility denote X and Y, and nine rules are divided by X and Y. For example, when X is Small and Y is Low, the influence of meteorological parameters on incident denotes Serious. Using IF-THEN form, rule base is described in Table 1.

Table 1. Meteorological influencing factor model rule base

Number of rules	Rules
1	IF U^R is U_1^R and U^V is U_1^V, THEN U^α is U_3^α
2	IF U^R is U_1^R and U^V is U_2^V, THEN U^α is U_2^α
3	IF U^R is U_1^R and U^V is U_3^V, THEN U^α is U_1^α
4	IF U^R is U_2^R and U^V is U_1^V, THEN U^α is U_3^α
5	IF U^R is U_2^R and U^V is U_2^V, THEN U^α is U_2^α
6	IF U^R is U_2^R and U^V is U_3^V, THEN U^α is U_1^α
7	IF U^R is U_3^R and U^V is U_1^V, THEN U^α is U_3^α
8	IF U^R is U_3^R and U^V is U_2^V, THEN U^α is U_3^α
9	IF U^R is U_3^R and U^V is U_3^V, THEN U^α is U_3^α

(3) Inference method

The inputs can be defined as x and y. And then n (i.e. one to four) rules is chosen with the certain x and y. Due to the relationship which is described as "and" between U^R and U^V in rule base, Mamdani Reasoning [20] is used as the inference method to determine the selected rule. The membership degree of each rule is computed as follows:

$$\mu(\mathrm{A}_i) = \min(\mu(x), \mu(\mathrm{y})), \qquad (3)$$

where, $\mu(\mathrm{A}_i)$ is the membership degree of i rule, $\mu(x)$ is the membership degree of U^R and $\mu(\mathrm{y})$ is the membership degree of U^V.

In Table 1, the output of fuzzy set U^α can be described as three results (i.e. Z_1, Z_2 and Z_3), which present Little, Medium and Serious, respectively. The max reasoning method is used to determine the degree of the result, which is written as:

$$\mu(\mathrm{Z}_m) = \max(\mu(\mathrm{A}_i), \mu(\mathrm{A}_j)...) \quad m \in [1,2,3], \qquad (4)$$

where, Z_m is the membership degree of the selected rule with same consequence, $\mu(\mathrm{A}_i)$ and $\mu(\mathrm{A}_j)$ are the membership degrees and m is the number of possible result.

(4) Defuzzification method

In the last step of this model, a crisp value reflecting the influence of meteorological conditions on the occurrence of incident is determined by the fuzzy result. Let α denote the meteorological influencing factor. The complete factor α is constructed as:

$$\alpha = \mu(\mathrm{Z}_1) + \mu(\mathrm{Z}_2) + \mu(\mathrm{Z}_3). \qquad (5)$$

2.2 A new AID algorithm with meteorological factor

The approach based on LVQ neural network which is used to combine the factor α with traffic parameters for incident detection is proposed in this model. Compared with other classification methods [21-22], LVQ is widely used in the data fusion and it has been proved to be an efficient classification method [23-24]. Thus, we propose the approach to detect the freeway incidents with the factor α and traffic variables based on LVQ neural networks in this model.

2.2.1 LVQ neural network

LVQ, put forward originally by Kohonen [25], is an effective method for classification. As Fig. 6 illustrated, a LVQ network contains an input layer, a Kohonen layer and an output layer. The input layer fully connecting with Kohonen layer contains one node for each input feature. And the Kohonen layer partially connecting with output layer learns and performs the classification. Then in the output layer each class is represented by one node.

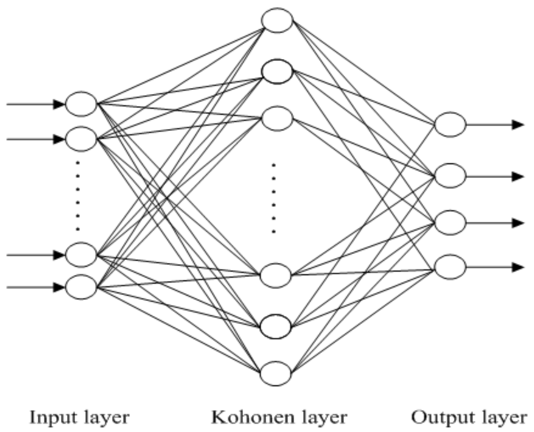

Figure 6. LVQ structure.

The LVQ algorithm combines competitive learning with supervised learning. Let input vector of the first layer be given by x, weight vector of which is w. The Euclidean distance from x to w is calculated in the Kohonen layer by the formula:

$$\| D(w,x) \| = \left\{ \sum_{i=1}^{N} (w_i - x_i) \right\}^{1/2} . \tag{6}$$

As the competitive learning, the winning neuron will be the one whose weight vector w_c is nearest to the input vector x, where c is the index of the weight vector:

$$\| x_i - w_c \| = \min\{\| x_i - w \|\} . \tag{7}$$

Under supervised learning, the classes compete among themselves in order to find the most similar class to the input vector so that the winner will be the one with less Euclidean distance. Only the winner class will modify its weights with a reinforced learning algorithm, either positive or negative, depending on whether the classification is correct or not. Thus, if the winner class belongs to the same class as the input vector (the classification has been correct), it will increase the weight and move slightly closer to the input vector. The following equation presents the basic learning process:

$$w_c(t+1) = w_c(t) + \eta(t)[x(t) - w_c(t)] , \tag{8}$$

where, $w_c(t+1)$ and $w_c(t)$ are the weight vector at time $t+1$ and t, respectively. $x(t)$ is the input vector and $\eta(t)$ is the learning rate, being $0 < \eta(t) < 1$. It is recommended that $\eta(t)$ should initially be rather smaller than 0.1 and $\eta(t)$ continues decreasing according to the following equation:

$$\eta(t+1) = \eta(t) - \frac{\eta(0) - \mu}{N} , \tag{9}$$

where, μ is a given threshold, N is the number of classes [25].

Conversely, if the winner class is different from the input vector class (the classification has not been correct), it will decrease the weights and move slightly further from the input vector. In the same way, the learning process could be presented as follows:

$$w_c(t+1) = w_c(t) - \eta(t)[x(t) - w_c(t)] . \tag{10}$$

2.2.2 The proposed algorithm

The inputs of LVQ neural network include the meteorological influencing factor α and traffic variables (i.e. volume, occupancy and speed) which are collected both upstream and downstream. The output of the network is determined by a binary value (0 denotes that no incidents happen and 1 denotes that incidents happen).

The number of the input layer and the Kohonen layer are the keys to determine the detection performance in this algorithm [26]. In order to find the appropriate number of the input layer, we design three models with different detection periods which are from $t-2$ to t, from $t-1$ to t and single t, respectively. In the different models, the range of number of the Kohonen layer can be calculated by an empirical formula which is showed as follows:

$$n_2 = 2n_1 + 1, \tag{11}$$

where, n_1 is number of the input layer, n_2 is number of the Kohonen layer.

For obtaining the optimal number of Kohonen layer, we need to test the value by a trail-and-error approach around n_2 in the Section 3.3.

3 New algorithm performance

3.1 Data description

The selected section of Yuwu freeway in Chongqing, China, is a 2.2 km eastbound segment. Two microwave detectors are set upstream and downstream to collect the traffic parameters. Meteorological instruments have been installed along the road to monitor the meteorological conditions, and to make real meteorological data available.

Three data sets were utilized in this study, (1) the traffic measures were collected from the microwave detectors both upstream and downstream in different weather condition from February 1st, 2014 to September 30 th 2014; (2) incident data set was provided by Chongqing Expressway; (3) real-time meteorological data was recorded by the meteorological instrument which was the closest to test road. Both snow and hail rarely fell in Chongqing, so visibility and rainfall were used as the most important variables of meteorological parameters in this study.

A data set of 1656 instances was collected to verify the robust of the proposed algorithm in different weather condition. Each instance contains traffic and meteorological information. Then, we utilized the incident information data from Chongqing Expressway to determine whether an instance is an incident case or not. The traffic dataset consisted of 138 incidents and the rest of 1518 instances are incident-free. In addition, the data collection interval t is 5 minutes. The total data are divided into two parts as training and testing set as illustrated in Table 2.

Table 2. Training data and testing data

Category	Total number	Incident number	Incident-free number
Total	1656	138	1518
training	960	80	880
testing	696	58	638

3.2 Performance measures

Normally, the performance of an AID model is evaluated by three key indices, detection rate (DR), false alarm rate (FAR) and mean-time-detection (MTTD). DR, FAR and MTTD are defined as:

$$DR = \frac{number\ of\ detected\ incident\ case}{total\ number\ of\ incidents\ case\ in\ data\ set} \times 100\%, \tag{12}$$

$$FAR = \frac{number\ of\ false\ detected\ incident\ case}{total\ number\ of\ input\ instance} \times 100\%, \tag{13}$$

$$MTTD = \frac{1}{n}\sum_{i=1}^{n}(t_{detected} - t_{on\text{-}set}) \times 100\%. \tag{14}$$

3.3 New algorithm performance

To test the performance of the incident detection algorithm, experiments were done to search the LVQ network architecture with the best detection performance. In the experiments, we utilized three LVQ models with traffic measures in different length of time-series and the calculated factor α as the inputs. The traffic measures both upstream and downstream contained detection period from $t-2$ to t, from $t-1$ to t and single t, respectively. In order to determine the number of the Kohonen layer, we calculated the n_2 according to the Formula 11 and tested a series number around n_2 which were n_2-3, n_2-2, n_2-1, n_2, n_2+1, n_2+2 and n_2+3. The architectures of different models are shown in Table 3.

Table 3. New algorithm architecture in different time-series traffic measure

Model	Time-series of traffic measures	Number of neurons in input layer	Number of neurons in Kohonen layer	Network architecture
1	t	7	13	$7\times13\times1$
			14	$7\times14\times1$
			15	$7\times15\times1$
			16	$7\times16\times1$
			17	$7\times17\times1$
2	$t-1$ to t	13	25	$13\times25\times1$
			26	$13\times26\times1$
			27	$13\times27\times1$
			28	$13\times28\times1$
			29	$13\times29\times1$
3	$t-2$ to t	19	37	$19\times37\times1$
			38	$19\times38\times1$
			39	$19\times39\times1$
			40	$19\times40\times1$
			41	$19\times41\times1$

Three criteria (i.e. DR, FAR and MTTD) are taken into consideration to evaluate the performance of different architectures of the new algorithm. These criteria of different architectures are respectively indicated in Fig. 7. It is clear that the average of DR and FAR in the architectures with 13 inputs is superior to the architectures with 7 and 19 inputs. Therefore, the traffic measures with the detection period $t-1$ to t provided better/improving performance in detecting the traffic incidents. In Fig. 7, MTTD changed marginally in various architectures. Comparing the different coordinates, we found that the highest DR and lowest FAR correspond to the same architecture of $[13\times26\times1]$. Considering all three evaluating indices, the ultimate architecture of the model is determined as $[13\times26\times1]$.

Figure 7. DR, FAR, MTTD for different architectures.

4 Performance comparison

4.1 Performance comparison with California algorithm

California algorithm is one of the most representative incident detection algorithms in freeway. Detection measures including DR, FAR and MTTD in California algorithm are relatively satisfying, and the algorithm can easily be generalized. So many researchers tend to evaluate the new algorithm by comparing it with California algorithm. In this research, we compare the performance of the proposed algorithm with the widely-used California algorithm by using the same data set. This algorithm tests for an incidence using three equations applied to the occupancy from both adjacent detectors. A potential incident is declared when upstream occupancy increases sharply and the downstream one decreases, which reduces the calculated values from the three tests surpass preset thresholds. The three tests are defined as follows:

$$OCCDF = OCC(i,t) - OCC(i+1,t) \geq K_1 , \tag{15}$$

$$OCCRDF = \frac{OCC(i,t) - OCC(i+1,t)}{OCC(i,t)} \geq K_2 , \tag{16}$$

$$DOCCTD = \frac{OCC(i+1,t-1) - OCC(i+1,t)}{OCC(i+1,t-1)} \geq K_3 , \tag{17}$$

where, $OCC(i,t)$ and $OCC(i+1,t-1)$ are the upstream station occupancy within the period t and the downstream station occupancy within the period $t-1$. If $OCCDF$, $OCCRDF$, $DOCCTD$ exceed preset thresholds K_1, K_2 and K_3 in turn, an incident is indicated.

To get the best performance of California algorithm, and to obtain the appropriate trade-off between DR and FAR, more tests have to be performed to calibrate thresholds on the given data set. Table 4 shows testing results of California algorithm in different thresholds as well as the results of the proposed algorithm.

Table 4. Performance comparison: California algorithm vs the proposed algorithm

Algorithm	K_1	K_2	K_3	DR (%)	FAR (%)	MTTD (min)
California algorithm	0.15	0.40	0.20	65.51	0.09	2.76
	0.13	0.35	0.20	70.07	0.11	2.65
	0.11	0.26	0.18	74.14	0.14	2.61
	0.08	0.24	0.18	82.76	0.19	2.58
	0.06	0.18	0.18	89.55	0.26	2.52
	0.04	0.16	0.16	91.38	0.48	2.51
	0.03	0.14	0.14	91.38	1.11	2.49
Proposed algorithm	-	-	-	96.55	0.21	2.54

Respectively decreasing the value of K_1, K_2 and K_3 can greatly enhance the DR and MTTD, but, it yields high FAR. To obtain the best trade-off between DR and FAR, DR shown in Table 4 does not increase and FAR becomes terrible when K_1, K_2 and K_3 are less than 0.04, 0.16 and 0.16 respectively, and it gives FAR so large that it could not be accepted in any AID algorithm with a decrease in three thresholds. It is clear that comparing the best performance of California algorithm with the proposed algorithm, the latter has much better DR, 96.55 % compared to 91.38 %, a lower FAR, 0.21 % compared to 0.48 %, almost half of California algorithm. Besides, MTTD of the proposed algorithm is close to the compared algorithm, 2.54 compared with 2.51.

4.2 Performance comparison with SVM and Bayesian algorithms

The previous studies have shown that SVM algorithm and Bayesian are successful application for AID [7] [8]. In this paper, they are used as benchmarks for comparison. We utilize the same train data in Bayesian network and SVM. In addition, the threshold of posterior probability θ of the Bayesian is 0.6 according to Zhang's research. In another compared algorithm, v-SVM with radial basis function (RBF) kernel is selected as the suitable model in the SVM algorithm and the value of v is 0.2 [8]. Furthermore, SVM and Bayesian algorithms are conducted on the same test data in this study. The testing results are shown in Table 5.

The DR produced by the proposed algorithm is 96.55%. It is superior to the other DR produced by the SVM algorithm (94.57 %) and Bayesian algorithm (87.93 %). Both the proposed algorithm and the Bayesian algorithm have the low FAR. It is worth noting that the FAR of our algorithm presented here is 0.21 %, which is slightly lower than the value of Bayesian (0.27 %). The FAR of the SVM algorithm is not comparable to the rest algorithms, which is 0.45 %.

The MTTD of the Bayesian algorithm is 1.32 min quicker than the SVM algorithm and 0.44 min quicker than the proposed algorithm.

The experiments in this paper indicate that the proposed algorithm has excellent DR and FAR in comparison with the SVM algorithm and Bayesian algorithm. The MTTD is slightly inferior to Bayesian, and much better than SVM.

Table 5. Performance comparison: proposed algorithm vs SVM algorithm and Bayesian algorithm

Algorithm	Number of incidents	Number of detection	DR (%)	FAR (%)	MTTD (min)
Proposed algorithm	58	56/58	96.55	0.21	2.54
SVM algorithm	58	54/58	94.57	0.45	3.42
Bayesian algorithm	58	51/58	87.93	0.27	2.10

5 Conclusions

Due to the influence of weather conditions on the performance of traffic incident detection, this paper presents an incident detection method considering meteorological factors. The meteorological data (i.e. rainfall and visibility) and incident cases are used to quantify the relationship between weather and the occurrence of traffic incident based on fuzzy logic. Then, LVQ network is used to combine the meteorological factor with traffic parameters to detect whether an incident is happening or not. To test the detection performance in application, the algorithm is constructed on the basis of filed data. In addition, the outputs are measured by three indexes, namely DR, FAR and MTTD. The result showed that the proposed algorithm has a better performance on DR and FAR. Meanwhile, the proposed algorithm achieved a best performance in three indexes compared with SVM algorithm and Bayesian algorithms for the same experiment conditions.

Although these experiments have proved that the algorithm can effectively utilize meteorological data to strengthen the detection performance, there are still some problems and limits in its proper application and further works are still needed. As stated earlier, the performance of our algorithm is sensitive to the number of neurons in the Kohonen layer, this number should be well chosen for different data set which is worth studying. Meanwhile, due to the limits of experimental conditions, we could only use eight months off-line data to evaluate the performance and extensive testing of the algorithm by using different data sets collected from other freeway environmentalists, which is also important and will be conducted in our further works.

Acknowledgements

This work was supported by the National Natural Science Foundation of China (Grant No. 61573075), the Fundamental Research Funds for the Central Universities (Grant No. 106112014CDJZR178801), and the "151" Major Science and Technology Projects of Chongqing (Grant No. cstc2013jcsf-zdzxqqX0003).

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