

Automatic Traffic Accident Detection Based on the Internet of Things and Support Vector Machine

GuoJun Liang

Zhuhai Technician College, Zhuhai 519100, China
E-mail: Gorgen@163.com

Abstract

Recent years, the transportation efficiency and related issues have become one of the main focuses of the global world. Along this line, intelligent transportation systems (ITS) based on Internet of Things (IoT) has become a common solution to many transportation problems, such as traffic prediction, road status evaluation, traffic accident detection, etc. In this paper, we focus on the traffic accident detection in the IoT platform. Specifically, we propose an overall framework of intelligent transportation. Then, for traffic accident detection, we proposed a Support Vector Machine (SVM) modified by Ant Colony Algorithm (ACA) as the solution. We conduct experiments on real world traffic data to predict 7 types of traffic accidents. The results show that our proposed method is effective and efficient.

Keywords: *Intelligent transportation, traffic accident detection, The Internet of Things (IoT), Support Vector Machine (SVM)*

1. Introduction

Recent years, the transportation efficiency and related issues have become one of the main focuses of the global world [1-2]. However, the high speed movement of adaptive vehicles nodes leads to the frequent and massive change of the network topology and the no uniform distribution of the topology, and thus the quality of wireless channel cannot be guaranteed. Therefore, the transportation intelligence requires more stable and reliable method of data collection as well as accurate and real time analysis of collected transportation data.

Intelligent transportation systems (ITS) [3] are the best solution to above issues. Data collection is based on Internet of Things (IoT) technology [4], which refers to the interconnection of computing devices and sensors using RFID technology and wireless communication within existing Internet infrastructure. Currently, IoT have been applied in more and more fields, such as agriculture [5], environment monitoring [6], transport logistics [7], etc. In this work, we propose an intelligent transportation framework based on IoT and cloud computing infrastructure [8].

Specifically, we focus on the automatic incident detection application in the framework. According to the statistics results from [9], there are approximately 1.3 million people died and 20-50 millions injured in traffic accidents. Therefore, the security issue of transportation has been a significant problem. In order to improve the traffic status, reduce the traffic accidents and increase the transportation efficiency, we need to evaluate the security status of the traffic using accurate data and appropriate methods.

Existing possible models of traffic prediction include ARMA model [10], grey model [11], BP neural network [12], and Support Vector Machine (SVM) [13], etc. However, even though ARMA is relative simple and easy to implement, it is only suitable for linear prediction and the accuracy is not satisfactory [14]. As for grey model, the data samples are relatively small and the modeling process is simple; however, it cannot preserve good accuracy with volatile data [15]. Based on the principle of minimizing empirical risks, BP

neural network has some limitations such as local minimum and weak generalization, and therefore the prediction accuracy is still not good enough [16]. Considering that SVM is suitable for finding the global best solution to deal with the small sample issue, non-linear and high-dimensional problems, in this paper, we utilize SVM model to detect traffic accident. However, the parameter selection of SVM is crucial for learning accuracy and generalization ability. Accordingly, we propose to utilize Ant Colony Algorithm (ACA) algorithm [17] for parameter selection of SVM.

To remain of this paper is organized as follows. Section 2 provides some related work. In Section 3, we present the overall framework of intelligent transportation based on IoT, and in section 4, we focus on the traffic accident detection problem and propose the solution model. Empirical experiments are conducted in Section 5. Finally, the paper is concluded in Section 6.

2. Related Work

Many efforts have been made on intelligent transportation. For example, Xiang, *et al.*, [18] studied the optimization of accuracy rate for traffic safety early warning mechanism. Zhao, *et al.*, [19] discussed the mobile phone location and its impact on intelligent transportation. Taniguchi, *et al.*, [20] presented the intelligent transport systems in city logistics field. Wang, *et al.*, [21] investigated the parallel control and management for intelligent transportation systems. Xiao, *et al.*, [22] leverages IoT for intelligent traffic monitoring system.

There are some existing efforts on traffic accidents detection. For example, Wang, *et al.*, [23] established a state temporal association model for urban traffic based on IoT sensor technology, and perform real-time streaming guide and forecasting in order to keep track on the city's traffic flow. Zhao, *et al.*, [24] conducted research on road traffic safety using systems approach. Kamijo, *et al.*, [25] developed an algorithm, referred to as spatio-temporal Markov random field, for traffic images at intersections. Wang, *et al.*, [26] introduced an automatic alarm device for traffic accidents.

3. Overall framework

The overall framework of intelligent transportation based on IoT is shown in Figure 1, where the front end is built upon sensor technology of IoT, and the back end is supported by cloud computing technology. We have four layers in the overall framework.

Application Layer: interface between network layer and applications and services for intelligent transportation, including analysis, integration, sharing and management of all information collected from lower layers. The most common applications in intelligent transportation include traffic forecasting, traffic planning and traffic computing, *etc.* In this work, we focus on the incident detection application.

Datacenter Layer: data storage of the whole framework built upon cloud computing technology, providing data storing, querying, analyzing, mining and understanding of massive sensor data. This layer is responsible for automatic dynamic node provision and resource assignment, in order to satisfy the on-demand requirements and deliver high quality services.

Network Layer: responsible for information transmission and communication. This layer is built upon existing Internet with the combination of cables, mobile 2G/3G/4G network, Wi-Fi, Bluetooth, *etc.* The goal is to achieve interconnection and collaboration among heterogeneous networks, and transfer the collected data from lower layer to upper layer.

Perception Layer: responsible for intelligent perception, including collecting transportation data through variable IoT sensor devices, such as the vehicle type, traffic flow and road congestion status. This layer provides all data from IoT devices to upper layers.

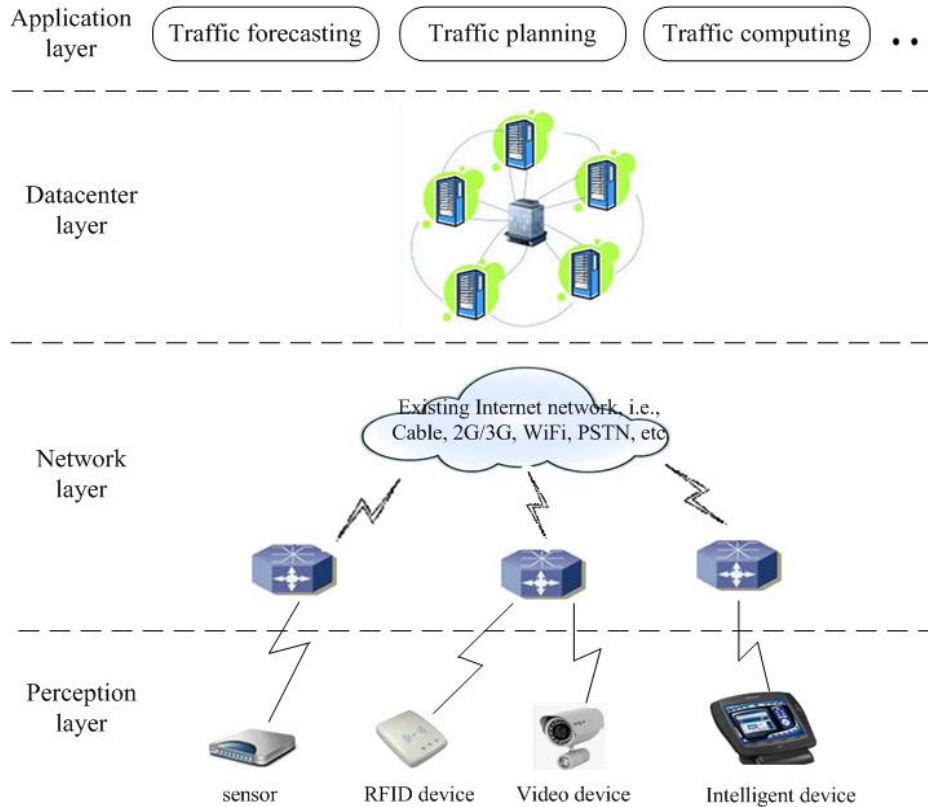


Figure 1. Framework of Intelligent Transportation based on IoT

Based on above framework, we focus on the traffic accident detection problem. We utilize the high sensitive giant magneto resistive sensor as the IoT sensor nodes to monitor the vehicles, as shown in Figure 2. Detected information is transferred to the Transmit-Receive Unit (TRU) for information integration. Specifically, (1) we detect the existence of vehicles by the sudden changes of the magnetic field within the region; (2) we capture the sound signals such as collision and brake sound; (3) we use to two different sensors to detect the direction of vehicles.

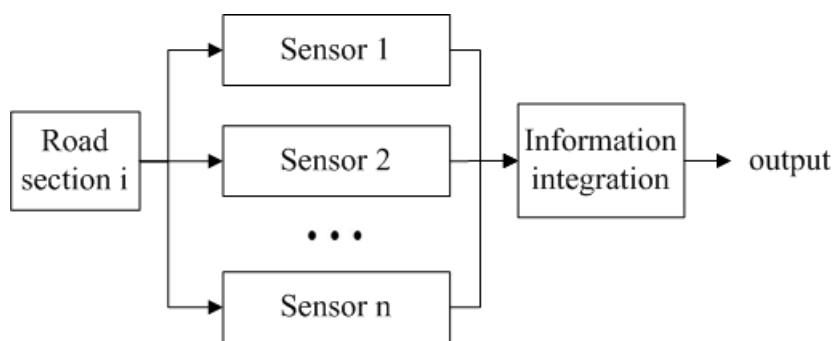


Figure 2. Sensor Components

4. Traffic Accident Detection

In this section, we focus on the traffic accident detection problem. Using the data collected from the above IoT based framework, we build a SVM based model for traffic accident detection. The general idea is to collect the historical data stream of transportation traffic, and perform the model fitting on the history data, and then conduct prediction on future traffic data to estimate possible accidents and give alerts.

4.1. Support Vector Machine (SVM)

In statistical theory, there are two kinds of risks in learning machines: experience risk and expected risk. Experience risk refers to the fitting precision compared to the existing sample data, which occurs in the model building phase; the expected risk refers to the fitting precision compared to the unseen data during the training time. When the size of samples is very large and there are no outliers in the sample dataset, the difference between experience risk and expected risk is small. In contrary, when the sample size is normal and there are outliers in the dataset, the generalization of the training model cannot be guaranteed. In this case, SVM utilizing the idea of structural risk minimization inductive principle [27] is suitable for solving the problem. Indeed, SVM have been successfully applied in classification, function approximation and time-series prediction fields [5-7].

As illustrated in Figure 3, there are two groups of samples, denoted as solid and hollow points respectively. H is the separating hyper plane, and H_1, H_2 are the nearest planes for both two groups, and the space between them is called margin. The goal of SVM is to maximize the margin, and the vectors nearest the optimal hyper plane are called support vectors.

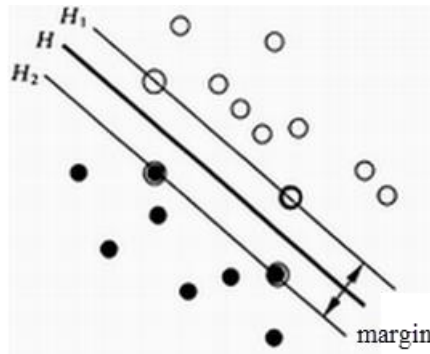


Figure 3. Illustration of SVM

Suppose the sample size is l , and therefore the training data can be represented as:

$$D = \{(x_i, y_i) \mid i = 1, 2, \dots, l\}, x_i \in E, y_i \in R \quad (1)$$

The linear regression form is:

$$f(x) = ax + b \quad (2)$$

The loss function is:

$$L(y, f(x, \delta)) = L(|y - f(x, \delta)|_\varepsilon) \quad (3)$$

where

$$|y - f(x, \delta)|_\varepsilon = \begin{cases} 0, & \text{if } |y - f(x, \delta)| \leq \varepsilon; \\ |y - f(x, \delta)| - \varepsilon, & \text{otherwise.} \end{cases} \quad (4)$$

The model can be formulated as follows:

$$\begin{aligned} \min_{\omega, b, \xi_i, \xi_i^*} & \frac{1}{2} \|\omega\|^2 + c \sum_{i=1}^l (\xi_i + \xi_i^*) \\ \text{s.t. } & y_i - (\omega\phi(x_i) + b) \leq \varepsilon + \xi_i, \\ & (\omega\phi(x_i) + b) - y_i \leq \varepsilon + \xi_i^*, \\ & \xi_i, \xi_i^* \geq 0, i = 1, 2, \dots, l. \end{aligned} \quad (5)$$

In above equation, the objective function controls the generalization capability, and the constraint conditions are used to reduce the experience risk. $c(c > 0)$ Is the penalty parameter, used to control the balance between sample errors and the generalization ability, and ξ_i^*, ξ_i are slack variables.

Transform Equation (5) into the solution of $\omega = \sum_{i=1}^l (\alpha_i^* - \alpha_i)x_i$, where α_i^*, α_i are the Lagrange multipliers:

$$\begin{aligned} \min \omega(\alpha, \alpha^*) &= \frac{1}{2} (\alpha_i - \alpha_i^*)^T K(x_i, x_j) (\alpha_j - \alpha_j^*) + \\ & \varepsilon \sum_{i=1}^l (\alpha_i + \alpha_i^*) + \sum_{i=1}^l y_i (\alpha_i - \alpha_i^*) \end{aligned} \quad (6)$$

Where $\sum_{i=1}^l (\alpha_i - \alpha_i^*) = 0$, $0 \leq \alpha_i^*, \alpha_i \leq C, i = 1, 2, \dots, l$, and $K(x_i, x_j)$ is the kernel function.

Therefore, the SVM function can be simplified as:

$$f(x) = \sum_{i=1}^l (\alpha_i^* - \alpha_i) K(x_i - x) + b \quad (7)$$

Where the RBF kernel function [28] is used, that is,

$$K(x, x_i) = \exp\left(-\frac{|x - x_i|^2}{2\sigma^2}\right) \quad (8)$$

Where σ is the width of the kernel.

4.2. ACA

ACA is a swarm intelligence algorithm for optimization problems [29]. There are two major steps of ACA: state transition and pheromone update. Let τ_{ij} be the amount of pheromone between cities i and j , and initialized as $\tau_{ij}(0) = B$, where B is a constant. At iteration t , the transfer probability of ant k from i to j is calculated as:

$$p_{ij}^k(t) = \begin{cases} \frac{(\tau_{ij}(t))^\alpha (\eta_{ij}(t))^\beta}{\sum_{u \in allowed_k} (\tau_{iu}(t))^\alpha (\eta_{iu}(t))^\beta}, & \text{if } j \in allowed_k; \\ 0, & \text{otherwise.} \end{cases} \quad (9)$$

Where $allowed_k$ denotes the set of qualified cities for next step, α is the heuristic of pheromone indicating the importance of path, β is the heuristic of path. $\eta_{ij}(t) = 1/d_{ij}$ is the expect of ant moving form i to j , where d_{ij} is the distance

between cities.

After each ant moves a step or finishes the traversal of all n cities, the pheromone is updated as follows:

$$\tau_{ij}(t+n) = (1-\rho) \cdot \tau_{ij}(t) + \Delta\tau_{ij}(t), \quad (10)$$

Where $\rho \in (0,1)$ is the evaporation coefficient of pheromone,

$$\Delta\tau_{ij}(t) = \sum_{k=1}^m \Delta\tau_{ij}^k(t)$$

and , where

$$\Delta\tau_{ij}^k = \begin{cases} \frac{Q}{L_k}, & \text{if ant } k \text{ passes } (i,j); \\ 0, & \text{otherwise.} \end{cases} \quad (11)$$

4.3. SVM Improved by ACA

In this section, we design an improved SVM model for detecting accidents based on ACA.

Formulate the problem as follows:

$$\min f(x) = f(x_1, x_2, \dots, x_m), \quad (12)$$

Where x_i is each feasible solution, and $x_i = [c, \varepsilon, \sigma^2]$, where the parameters are obtained from SVM. The smaller $f(x)$ is, the better the location is. The objective function is:

$$\begin{aligned} \min F &= \sum_{i=0}^l (y_i - y_i')^2 \\ \text{s.t. } &c_l \leq c \leq c_h, \\ &\varepsilon_l \leq \varepsilon \leq \varepsilon_h, \\ &\sigma_l^2 \leq \sigma^2 \leq \sigma_h^2. \end{aligned} \quad (13)$$

Where y_i is the observed value and y_i' is the predicted value using SVM.

Let the i -th ant at time t corresponding to a feasible solution, notated as $x_i(t)$. The procedure of ACA search can be summarized as follows.

Step 1: find the current best location of ants based on the objective function, notated as x^* , and the ant is called leader ant.

Step 2: other than x^* , divide the remaining ants into two parts. For the worse part, perform location movement guided by the leader ant; for the other part, perform location movement adjusted by pheromone update [30].

Step 3: the leader ant performs local search as follows:

$$\begin{aligned} x_{imp}(t) &= x^*(t) + \alpha * step, p > 0.5; \\ x_{imp}(t) &= x^*(t) - \alpha * step, p \leq 0.5. \end{aligned} \quad (14)$$

Where P is the random number. If $x_{imp}(t)$ is better than $x^*(t)$, replace $x^*(t)$ with $x_{imp}(t)$. The pheromone is updated by:

$$\tau(x_{imp}(t)) = \tau(x^*(t)) + K[f(x^*(t)) - f(x_{imp}(t))] \quad (15)$$

Step 4: after each iteration of search, perform global pheromone update, as shown in

Equation (10).

5. Experiment

We collect the transportation data of Qingdao as the training data, and perform data analysis using Mat lab. The sampling frequency of the sound signal is 22 kHz, audio sample size is 8 bits, and sampling frequency of magnetic field signal is 128 kHz. There are 7 detected accidents in our experiment settings: vehicle-vehicle collision, vehicle-people collision, vehicles on blaze, traffic jam, and road occupied by crowd gathering, abnormal traffic infrastructure, and poor road conditions.

The efficiency of accident detection is evaluated by three metrics.

False Alarm Rate (FAR): refers to the ratio of error alerts to all detected events,

$$FAR = \frac{num_{fa}}{num_{de}} \times 100\% \quad (16)$$

Where num_{fa} is the number of false alerts, and num_{de} is the number of all detect events.

Detection Rate (DR): refers to the ratio of detected events to the real world accidents,

$$DR = \frac{num_{de}}{num_{re}} \times 100\% \quad (17)$$

Where num_{re} is the number of real world accidents.

Average Time to Detect (ATD): refers to the time average between detected and happened,

$$ATD = \frac{1}{n} \sum_{i=1}^n [HT(i) - DT(i)] \quad (18)$$

Where $HT(i)$ is the actually happened time, $DT(i)$ is detected time, and n is the number of detected events.

We compare the results of IoT based platform and traditional sensor method in Table 1, where the IoT based method is denoted with -IoT, and the traditional sensor method is denoted with -SEN. The ATD is measured by minutes. Note that here we use the basic SVM model for platform comparison. We can observe that our IoT based method outperforms the traditional sensor based method. This shows that IoT platform is quite promising in data collection and perception.

Table 1. Accident Detection Results Comparison of IoT Framework and Traditional Method

Accident type	DR-IoT	DR-SEN	FAR-IoT	FAR-SEN	ATD-IoT	IoT-SEN
vehicle-vehicle collision	96.67%	88.14%	3.04%	6.25%	0.58	0.65
vehicle-people collision	89.33%	70.95%	5.51%	7.78%	1.09	2.98
vehicles on blaze	99.26%	95.17%	0.02%	0.60%	0.32	0.43
traffic jam	99.83%	90.11%	0.02%	0.89%	0.48	0.87
Road occupied by crowd	90.21%	63.32%	4.19%	6.88%	2.53	3.02

gathering						
abnormal traffic infrastructure	95.48%	80.92%	1.76%	2.94%	0.77	1.85
and poor road condition	99.15%	83.28%	1.58%	2.13%	1.16	2.08

Also, we compare the results of SVM based detection model (notated as -SVM) and proposed detection model (notated as -OUR) in Table 2. Note that here both models are based on IoT platform. We can observe that our proposed modified model based on ACA outperforms the basic SVM model.

Table 2. Accident Detection Results Comparison of Different Models

Accident type	DR-S VM	DR-O UR	FAR-S VM	FAR-O UR	ATD-S VM	IoT-O UR
vehicle-vehicle collision	96.67%	98.25%	3.04%	1.95%	0.58	0.48
vehicle-people collision	89.33%	90.88%	5.51%	3.67%	1.09	0.95
vehicles on blaze	99.26%	99.54%	0.02%	0.02%	0.32	0.28
traffic jam	99.83%	99.90%	0.02%	0.18%	0.48	0.33
Road occupied by crowd gathering	90.21%	92.04%	4.19%	3.11%	2.53	2.01
abnormal traffic infrastructure	95.48%	97.23%	1.76%	1.15%	0.77	0.44
and poor road condition	99.15%	99.84%	1.58%	1.02%	1.16	0.89

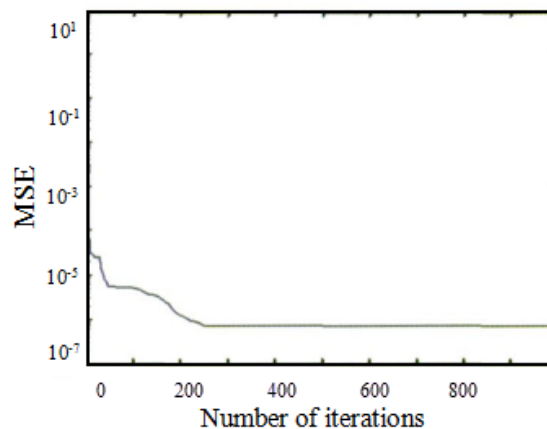


Figure 4. Convergence Curve of Basic SVM

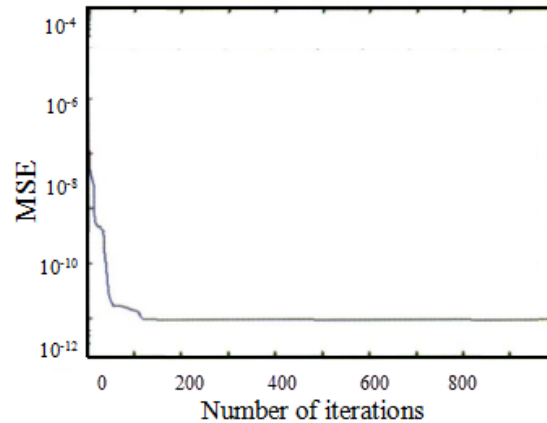


Figure 5. Convergence Curve of Modified SVM

Besides, we also test the efficiency of our modified SVM model. Figures 4 and 5 give the convergence curves for basic SVM model and the modified SVM in this work. We can see that our SVM modified by ACA can achieve faster convergence speed, and the mean square error (MSE) is lower compared to the basic SVM. Therefore, our algorithm is efficient.

6. Conclusion

In this work, we propose an overall framework of intelligent transportation based on IoT and cloud computing technology. Then we focus on the automatic accident detection problem, and propose a solution based on SVM model. Specifically, the data is collected by IoT based sensor platform, and integrated for further analysis. For the accident detection, in order to optimize the parameter selection of SVM modeling, we employ ACA algorithm for improvement. The experiments exhibit that our method is efficient.

However, there are still many other applications in intelligent transportation field, as shown in the application layer in Figure 1. In future works, we would like to explore other involved problems.

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Authors

GuoJun Liang, He received his M.Sc. in Electronics from University (2009). Now he is full lecturer of Electronics at Electronics Department, Zhuhai Technician College. Since 2014 he is deputy director of Electronics faculty. His current research interests include different aspects of Embedded System and Wireless Sensor Network.