Radar Based Traffic Incident Detection using Support Vector Classification for Road Safety

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Abstract

This research presents the usage of Support Vector Classification (SVC) to classify incident of vehicles driving in the opposite traffic lane by using data collected from traffic radar. First, we develop a data collection program for gathering traffic data from a traffic radar sensor remotely located in Prachinburi province, Thailand. The gathered data are used in training and verifying our proposed SVC model. Secondly, we develop an Automatic Incident Detection (AID) program with SVC algorithm to detect desired incidents such as driving in an opposite lane. Our research is tested in 6 different environments such as the time of day and the average speed. In the results, we found that it can classify thepattern of driving in the opposite traffic lane, TTD is 1.616 seconds, DR is 99.85 percent and FAR is 1.74 percent. From the result, our proposed work with SVC algorithm can be efficiently applied to classify road incidentsfrom the data collected from traffic radar.

Keyword: Road Incident Detection, Microwave Traffic Radar, Support Vector Classification, SVC, Road Safety.

1. INTRODUCTION

Road accidents have caused a great deal of the people's loss of lives and properties in Thailand. Last year, there are approximately 61,114 road accidents which approximately injure about 22,257 casualties and kill 8,660 lives. When the economic loss is considered, it is estimated that road accidentscausearound 185,444 million Baht per year [1]. The main factors that cause the road accidents are from the driver's behavior such as negligence, failure to study the route before travelling, and failure to respect traffic rules. These factors are calculated to be 88.6 percent of road accidents [2]. In some case that roads are very curvy and very steep, it increases the risk and could easily cause accidents, and can be fatal. The road authoritieshaveattempted to install such a detection and warning system by using traffic radar in the areas of narrow roads, steep roads, and curvy roads to warn and to enforce the traffic laws. Recently, there are several methods to reduce vehicle accident for example. The Automatic Incident Detection (AID) can detect occurs of traffic incidents by identifying the abnormal changes of traffic flow parameters such as velocity, traffic flow, occupancy, headway, etc, which were gotten by traffic monitoring equipment (induction loops, infrared detector, camera detector, etc). The performance of AID is greatly restricted by the number of monitoring sensor, available fund, algorithms used to confirm an accident, weather, traffic flow and so on. Manual incident detection methods including motorist report, department of transportation or public works crews report, closed-circuit television surveillance and aerial surveillance. The disadvantage of manual detection methods is that one has to witness an incident when it occurs. Moreover, when it comes to the motorist report, the accuracy of information relies on the expression of the people who call for help and incident position is hard to confirm, besides, operators of transportation department have to filter and confirm reports, which is exhausting. With the development of location technologies, more and more people apply themselves to the research of using Global Positioning System

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(GPS) and Mobile Phone Positioning System (MPPS) to gain traffic flow parameters or location of vehicles.

Therefore, the objective of this research is to classify incident of vehicles driving in the opposite traffic lane by using data collected from traffic radar.We use our research work with Universal Medium Range Radar (UMRR) from Smartmicro Company. The experiments results have shown that our system using Support Vector Classification (SVC) is able to accurately detect the traffic violation of driving in a wrong lane, and it could be deployed in the traffic detection and warning system for traffic authority enforcement.

2. LITERATURE REVIEW

Researcher reviewed several previous studies that related with our research both same and different techniques for studying the traffic incident detection system.

According to the study of Roe H, this study found that the microwave has an important role for control and management of road traffic. Moreover, this technique helps to increase the safety for drivers. [3]

Wassantachat T. *et al* studied about the effectiveness of texture features in describing the traffic density, and propose a real-time VLD based on on-line SVM classifier and a background modeling technique (OSVM-BG) to estimate the traffic density information probabilistically and automatically. The system uses feedback from background modeling to train and update its SVM kernel to self-adapt to various lighting environments. Experimental results show that the system outperforms an existing algorithm and achieves an average accuracy of 89.43% under various illumination changes, weather conditions and especially changing static shadows in daytime. [4]

Ma Y. *et al* developed a framework for highway incident detection using vehicle kinetics. This framework uses an in-vehicle intelligent module, based on a support vector machine (SVM), to determine the vehicle's travel experiences with autonomously generated kinetics data. Roadside infrastructure agents (also known as RSUs: roadside units) detect the incident by compiling travel experiences from several vehicles and comparing the aggregated results with the pre-selected threshold values. The results of this study showed no significant differences in the detection performance between the original network and a new network that the VII-SVM system has not seen before. [5]

According to the study of Rufu H. *et al,* the researchers proposed a new method of incident detection was based on an in-car terminal which consisted of Global Positioning System (GPS) module, Global System for Mobile communications (GSM) module and control module as well as some optional parts such as airbag sensors, mobile phone positioning system (MPPS) module, etc. When a driver or vehicle discovered the freeway incident and initiated an alarm report the incident location information located by GPS, MPPS or both would be automatically send to a transport management center (TMC), then the TMC would confirm the accident with a closed-circuit television (CCTV) or other approaches. [6]

The study on An Innovation-Based Approach to Timely and Robust Automatic Highway Incident Detection by Schober M, Wehlan H, and Meier J [7] reported timely and accurate detection of traffic incidents is of crucial importance for highway management and warning systems. This study was using algorithms of traffic State Estimation (SE) combined with Automatic Incident Detection (AID) on the basis of local measurements (e.g. inductive loop data, radar data, etc.). It is evident that faults and inaccuracies in the process of measuring traffic data affect the quality of SE and AID significantly. Especially faults in measuring the traffic volume occur frequently. They cause false alarms or they hinder these systems to detect dangerous incidents. In this article we apply methods of technical fault diagnosis to design an AID. Therein, a vector-based innovation of an Extended Kalman filter (EKF) is used for distinguishing traffic incidents from flawed data and from other disturbances on traffic flow. Also it is used for timely detection of traffic incidents. For reasons of a robust application in real-world scenarios with flawed data, some modifications are discussed and their positive effects on the innovation-based approach are presented.

The study on Traffic incident detection based on artificial neural network by Qi W presented a detection method based on Artificial Neural Network for designing AID algorithm based on testing facilities, simulation results show that BP algorithm has the advantages of high detection rate, low false alarm rate and short detection time after comparing with traditional algorithm. [8]

Refer to the study of Ohe, I., Kawashima, H., Kojima, M., and Kaneko, Y., this study presented the changes in traffic average in case of traffic incidents have certain patterns different from the normal case. Their research tried to detect traffic incidents immediately and automatically by using neural networks, which use one minute average traffic data as input, and decide whether an incident has occurred or not. [9]

Hi-ri-o-tappa, K., Likitkhajorn, C., Poolsawat, A., and Thajchayapong, S. [10] proposed a traffic incident detection system that can report the occurrence of traffic incidents, which occur between detectors. Based on the previously proposed dynamic time warping algorithm, this incident detection system monitors and assesses changes at upstream and downstream sites. Then, if the upstream-downstream changes are associated with traffic incidents, the system raised an alarm and report CCTV images on site, which are sent to traffic operators to further response. Performance evaluations are conducted using real-world traffic data where it is shown that the incident detection algorithm used in the proposed system achieves 94% detection rate and low false alarm rate.

According to reviewed previous studies, we found that most of researches focus on system for detecting road accidents when the incidence already occurred. However, there are lacks of research that try to develop the early detection system to detect the incidents of vehicle running in the opposite traffic lane that main cause of car accidents and early warn the driver before car accident will be occurred.

3. PROPOSED WORK

In this research, we conduct the study of traffic incident detection by using SVC to classify the vehicles driving from the opposite lanes. The traffic data collected using the microwave radar sensor on March 24, 2014, April 5, 2014, and April 8, 2014, on Highway 304, at Bu Phram Sub-district, Nadi District, Prachinburi Province. In Figure 1, it shows the installation of the microwave radar sensor above the traffic lane to collect vehicle data. The sensor is installed on the road in the mountain area that has only two lanes available, and it is very curvy and steep, and it has a lot of traffic; therefore, this area often has a lot of incidents.

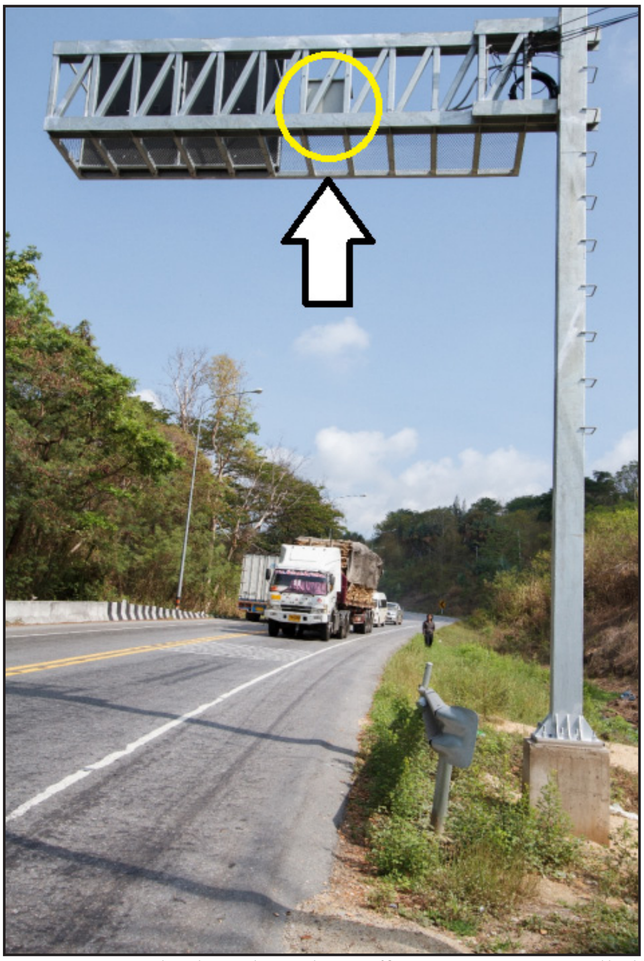

Figure 1. *Display how the radar traffic equipment is installed.*

3.1 Collection of TrafficInformation

In our study, we collect traffic data from the microwave radar sensor, Universal Medium Range Radar (UMRR) of

Smartmicro Company as shown in Figure 2 [11]. The radar sensor collects traffic information at a constant interval, and then transmits it over the Internet using TCP/IP protocol to a computer server as shown in Figure 3. The computer server is installed with the software for data analysis and incident classification as they are proposed in this work. The data obtained from UMRR are in the packet format, as shown in Figure 4, including 4 bytes of headers, 4 bytes of message id, 8 bytes of data payload and 4 bytes of timestamp. In each time interval, the data are obtained as shown in Figure 5, and decoded as the vehicle position, speed, and size as shown in Table 1 [12].

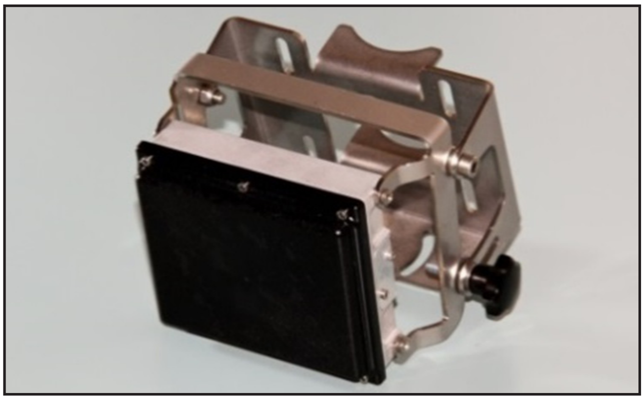

Figure 2. *Display of the radar traffic equipment (UMRR)*

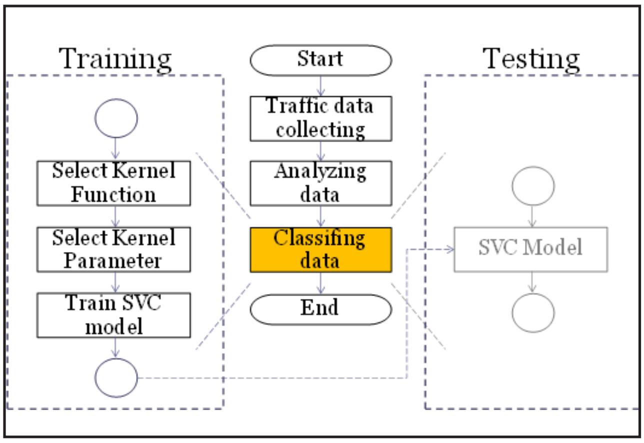

Figure 3. *Display of the system block diagram*

3.2. SVC Modeling and Verification

The decoded data obtained from UMRR have been divided into two parts, namely, the training set and the testing set as shown in the block diagram in Figure 6 [13-15]. The training set was used to train and create a SVC model that is tuned to classify the vehicles driving in the opposite lane from other vehicles. The training set was obtained on March 24, 2014. The testing set was used to verify the accuracy of the SVC model. The testing set was obtained on April 5, 2014 and April 8, 2014. The training set and testing set as shown in Table 2.

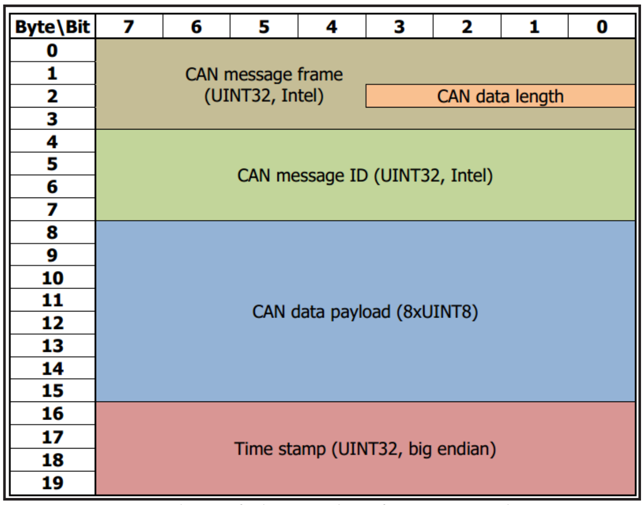

Figure 4. *Display of the packet format used to transmit UMRR data*

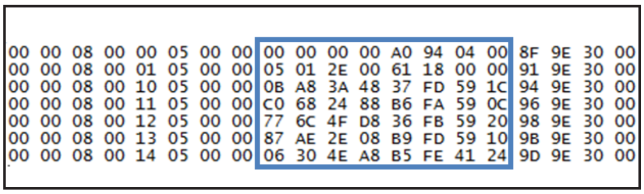

Figure 5. *Display of the data received from UMRR*

Table 1. *Data example obtained by decoding of UMRR data*

No.	ID	X Position (m)	Y Position (m)	X Speed (m/s)	Y Speed (m/s)	Length (m)
1	56	38.56	3.136	-41.4	-1.44	4.4
2	63	126.304	10.464	-55.8	-2.16	4.4
3	0	184.672	12.256	-56.52	-0.72	3.2
4	56	38.016	3.136	-41.4	-1.44	4.4
5	63	125.568	10.464	-55.8	-2.16	4.4

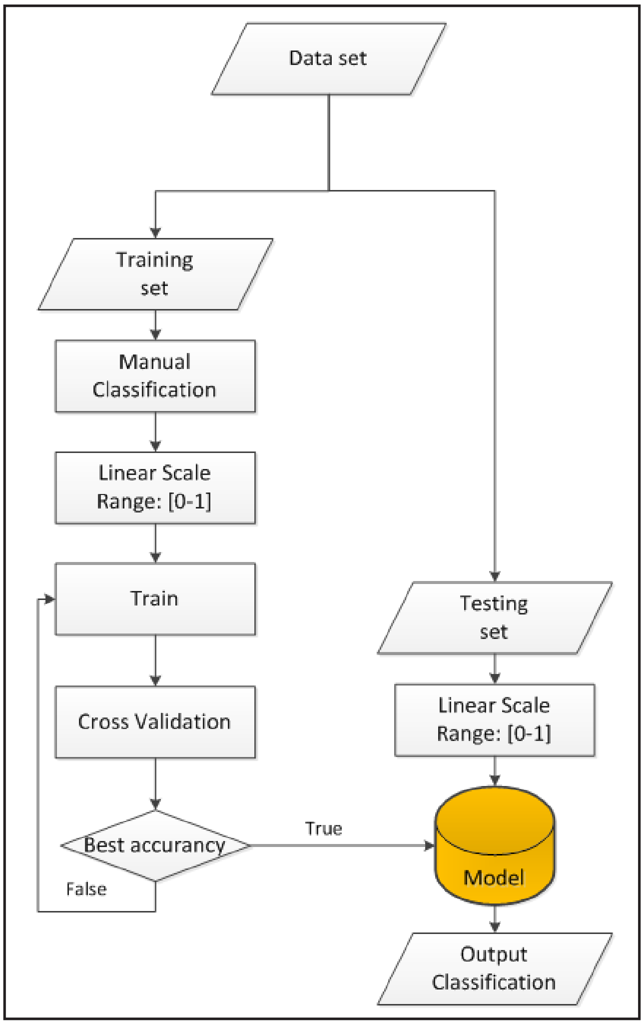

Figure 6. *Block Diagram for SVC modeling and classification*

Table 2. *Training set and testing set*

Set No.	Date	Initial Time	Stopping Time	Data Quantity (Units)	Type of data for SVC
1	24/3/2014	7:00:00	16:00:00	19,298	Training
2	5/4/2014	14:59:59	15:59:58	1,082,372	Testing
3	5/4/2014	20:00:00	21:00:00	1,352,412	Testing
4	5/4/2014	16:59:58	17:59:59	1,009,598	Testing
5	5/4/2014	21:30:01	22:30:02	2,018,639	Testing
6	8/4/2014	13:59:59	14:59:59	649,611	Testing
7	5/4/2014	22:59:58	23:59:58	644,350	Testing

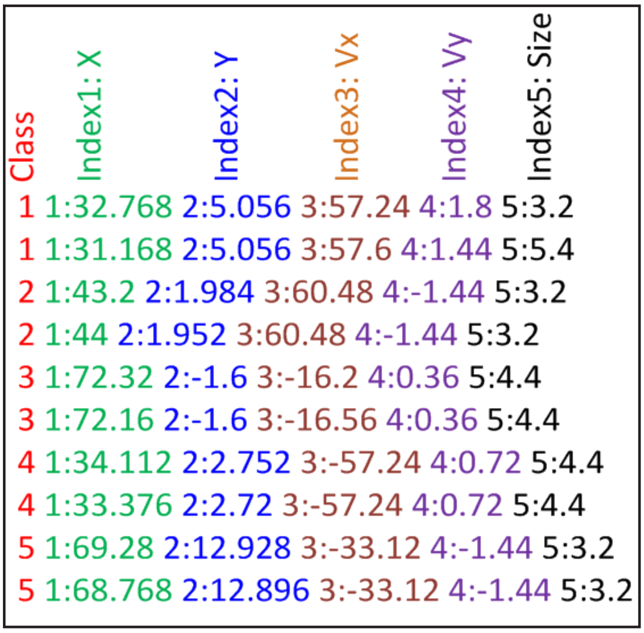

Figure 7. *Display examples of data used for training of SVC*

In the SVC training, we obtained data totally 19,298 samples from UMRR. In each sample, wecategorized data intoclass (the label of data), horizontal position (x), vertical position (y), horizontal velocity (v_x) vertical velocity (v_y), and the vehicle size as shown in Figure 7.

To manually classify the obtained data from the sensor into five classed mentioned above for SVC model training which requires human vision, we create a computer program for visual comparing vehicle data obtained from the sensor and vehicle images from the closed-circuit television (CCTV) camera. The program allows users to set virtual traffic lanes, boundary lines and areas as a criterion to divide the data into each class as shown in Figure 8.

Each sample is then identified into one of the five incident classes as proposed in this work.

Class 1 means the sample is the vehicle moves along the traffic lane and in the direction away from the sensor. It is represented by the symbol as shown in Figure 9.

Class 2 means the sample is the vehicle moves out of the traffic lane and in the direction away from the sensor. It is represented by the symbol as shown in Figure 10.

Class 3 means the sample is the vehicle moves along the traffic lane and in the direction toward the sensor. It is represented by the symbol as shown in Figure 11.

Class 4 means the sample is the vehicle movesout of their traffic lane and in the direction toward the sensor. It is represented by the symbol as shown in Figure 12.

Class 5 means the sample is the sensor's reading error of traffic sign. It is represented by the symbol as shown in Figure 13.

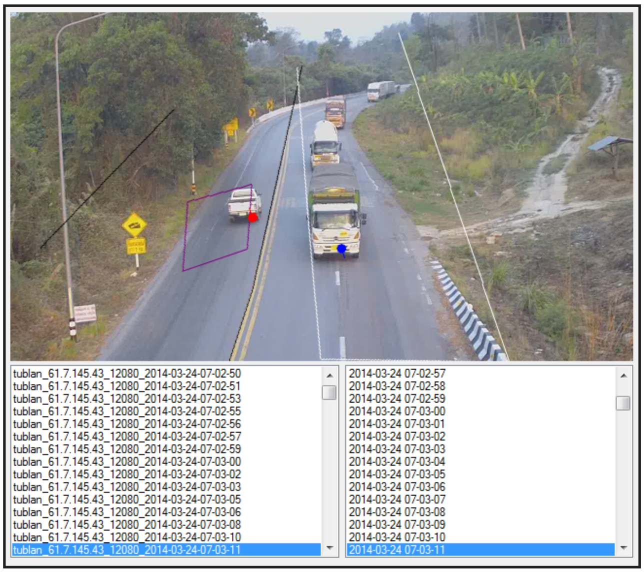

Figure 8. *The program for SVC model training*

Figure 9. *Example of Class 1*

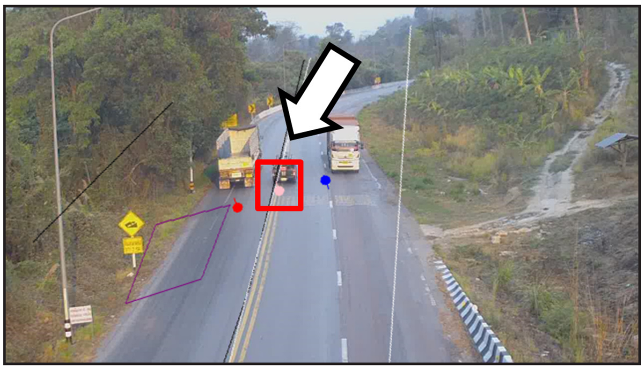

Figure 10. *Example of Class 2*

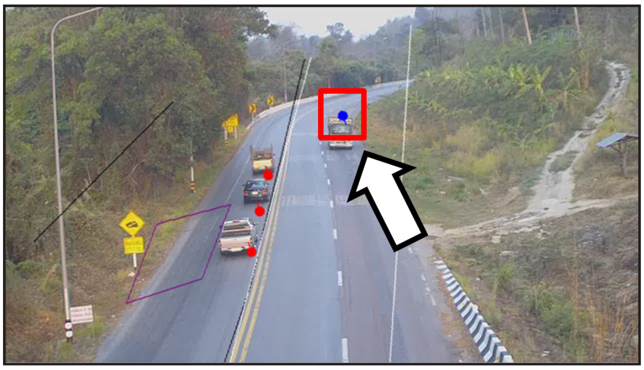

Figure 11. *Example of Class 3*

Figure 12. *Example of Class 4*

Figure 13. *Example of Class 5*

When the training set data have been classified, the next step is to create the SVC model which has different Kernel functions that are appropriate for different types of data. We select the Kernel function by scaling training data andbrute force testing value of Kernel parameter between $log_2(-i)$ *and* $log_2(i)$, $-20 \leq i \leq 20$ to find the most accurate results verify by Cross Validation with 5 fold as appeared in Table 3.

As noted by previous research [16-17], scaling is important for the success of Artificial Intelligent (AI) paradigms such as Artificial Neural Network (ANN) and SVC. Before training, all the data were linearly scaled to a range of [0-1]. To maximize the usefulness of the training data and search for optimal parameters.

Table 3. *Different Kernel functions are tested and the results*

Kernel functions	$\log_2(d)$	$\log_2(\gamma)$	$\log_2(coef0)$	$\log_2(C)$	Accuracy (%)
Linear	-	-	-	8	95.04
Poly nomial	1	-5	-4	3	98.30
RBF	-	-1	-	15	99.93
Sigmoid	-	-20	-12	2	95

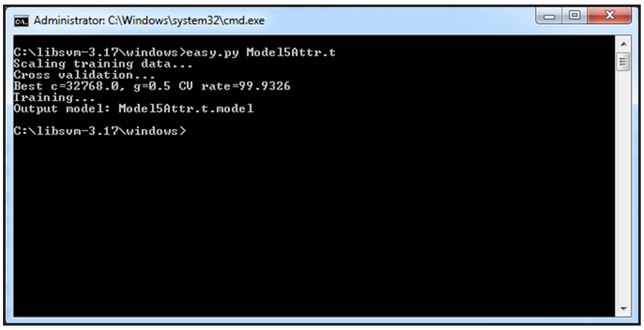

Figure 14. *Example of using the Cross Validation to identify the optimum γ and C for training the SVC model*

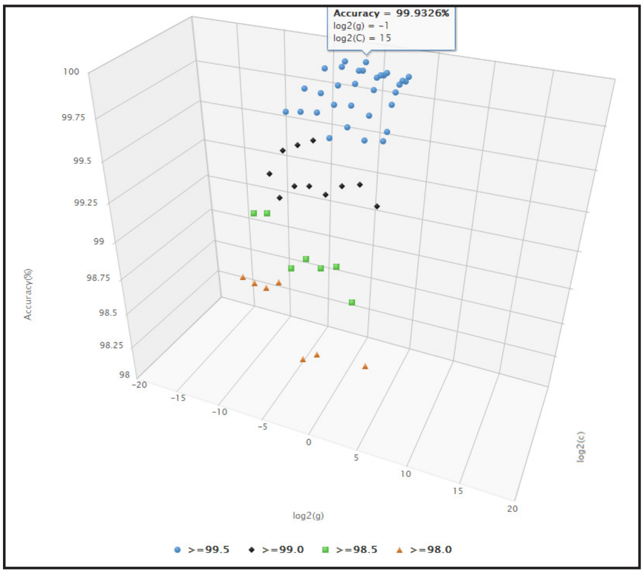

Figure 15. *Example of result from using the Cross Validation to identify the optimum Kernel parameter γ and C between $\log_2(-20)$ and $\log_2(20)$ that make the SVC model has the highest accuracy*

From the results of Kernel testing, shown in Table 3, we have selected the Radial Basis Function (RBF) as the Kernel function [18-19], which provides 99.93 percent of accuracy verify by Cross Validation with 5 fold as shown in Figure 14 and 15. To obtain the optimal result of accuracy of using RBF as the SVC Kernel function, we have performed sensitivity tests on variables γ, C using value between *$\log_2(-20)$* and *log2(20)* and number of index of sample. Sensitivity tests are divided into 6 tests. Form observation, the researcher found that if v_x is greater than 0, the direction of vehicle is moving away from the sensor. In the opposite way, if v_x is less than 0, the direction of vehicle is moving toward the sensor. In case $v_x = 0$, the researcher cannot identify the direction of vehicle. So, we will not use the data content, $v_x = 0$, in the test 1 to 6. In the test 4 to 6, we present the v_x as shown in Table 4

Table 4. *Condition and replace value of v_x*

Condition	Replace value
$v_x>0$	1
$v_x<0$	0

Indexes of data for test 1 to 6 as shown in Table 5 and result of test 1 to 6 as shown in Table 6.

Table 5. *Indexes of data for test 1 to 6*

Test no.	x	y	v_x	v_y	size
1	✓	✓	✓	X	X
2	✓	✓	✓	✓	X
3	✓	✓	✓	✓	✓
4	✓	✓	0,1	X	X
5	✓	✓	0,1	✓	X
6	✓	✓	0,1	✓	✓

Table 6. *Result of test 1 to 6*

Test no.	C	γ	Accuracy (%)	Times (ms/sample)
1	1	13	99.94	0.0193
2	-1	15	99.92	0.0225
3	-1	15	99.93	0.0259
4	1	15	99.95	0.0173
5	3	13	99.95	0.0246
6	-1	13	99.94	0.0273

From the result Table 6 shows that the result of test 4 is the highest accuracy and lowest time. So, we select the indexes and Kernel Parameters of the test 4 for training model.

4. EXPERIMENT RESULTS

For our experiments, we use data in the testing set which includes six sets of data as shown in Table 7. Each set has two different characteristics, the time of day and the average speed. For example, the set No. 1 is collected at the daytime, but has the lowest average speed compared to the set No. 3 and No. 5 which are collected at the daytime as well. In addition, the set No. 4 is collected at the night time, but has the lowest average speed compared to the set No. 2 and No. 6.

Table 7. *The data of the testing set.*

Set No.	Date	Initial Time	Stopping Time	No. of cars	Average Speed (km/h)	Data Quantity (Units)
1	5/4/2557	14:59:59	15:59:58	638	4.153	1,082,372
2	5/4/2557	20:00:00	21:00:00	513	7.966	1,352,412
3	5/4/2557	16:59:58	17:59:59	1474	17.209	1,009,598
4	5/4/2557	21:30:01	22:30:02	849	3.651	2,018,639
5	8/4/2557	13:59:59	14:59:59	1043	37.81	649,611
6	5/4/2557	22:59:58	23:59:58	716	27.647	644,350

In our experiments, we measure the quality of our proposed modelby using Time To Detect (TTD), Detection Rate (DR) andFalse Alarm Rate (FAR). The TTD is time of is duration of incident classification.The DR describes successfulness of certain algorithm.The FAR means that the system reports the incidents; however, there is no actual incident happened [10, 20].

TTD, generally, it should be fast to detect. TTD can be obtained from the equation

$$TTD = \frac{\sum Delay\ of\ True\ alarms}{Total\ number\ of\ alarms} \tag{1}$$

DR, generally, the rate of detected should be close to 100 percent as possible to show how effective of the this research which can find in

$$DR = \frac{Number\ of\ incident\ detected}{Total\ number\ of\ incidents} \tag{2}$$

FAR, generally, should have mistaken values close to 0 percent to reflect the most reliable event. In this research, FAR is the system that reports the event however, no actual incidents happen. FAR could find in

$$FAR = \frac{Number\ of\ Alarms\ not\ Specified\ duration}{Total\ number\ of\ alarms} \tag{3}$$

Bringing testing set of data in Table 7 to classify the test with if-then rule and test with SVC model then calculate the interest variable from the equation 1 to 3 as shown in Table 8 and Table 9.

Table 8 showed that a mean of TTD is 1.616 seconds, DR is 100 percent and FAR is 0.104 percent.

For reducingthe error of reflection between moving truck and traffic sign (Class5), we test the data by using SVC model that the result shown in Table 9.

Table 9 showed that a mean of TTD is 1.616 seconds, DR is 99.85 percent and FAR is 1.74 percent.

FAR of testing set 2 in Table 9 is less than FAR of testing set 2 in Table 8. The errors in testing set 2 that occur in the same pattern as show in Figure 16 are effectively detected by SVC model

Table 8. *Experiment results from if-then rule*

Testing set	TTD (Seconds)	DR (%)	FAR (%)
1	1.61008078	100	0.019
2	1.61001657	100	0.121
3	1.61020843	100	0.047
4	1.61017156	100	0.113
5	1.61030672	100	0.125
6	1.61051165	100	0.197
Mean	1.610215952	100	0.104

Figure 16. *The error of reflection between moving truck and traffic sign*

Table 9. *Experiment results from SVC model*

Testing set	TTD (Seconds)	DR (%)	FAR (%)
1	1.61596032	99.17	1.76
2	1.61601657	100	0.03
3	1.61620843	100	2.96
4	1.61617823	99.91	1.45
5	1.61630668	100	2.54
6	1.61651742	100	1.69
Mean	1.616197942	99.85	1.74

5. CONCLUSION

While most researches focus on detecting road incidents that already occurred, for example, road accidents, traffic obstructing incidents,in this paper, we present the early detection system todetect the incidents of vehicles running in the opposite traffic lane that may cause fatal accidents. Hence, if the driver has been warned when performed unsafe driving behavior, it could possibly reduce the danger on the road in the mountain area.This research proposes the system application using SVC algorithm to classify incidents of vehicles driving in the opposite traffic lane jointly with the radar sensing equipment using microwave techniques to collect the traffic information. The information is prepared for training and verifying the SVC model. The results from our experiments show that the Time To Detect is 1.616 seconds, Detection Rate is 99.85 percent and False Alarm Rate is 1.74 percent which may be acceptable by highway authorities to help them reduce a fatal accident before it happens. In the future, we could improve our research work by increasing the number of sensors along the road used in the coordination of the detection to increase the accuracy.

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