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Smart Driving: A New Approach to Meeting Driver Needs

A B M Shawkat Ali

School of Computing Sciences, CQUniversity, Australia

M Ameer Ali

**Department of Electronics and Communication Engineering
East West University, Bangladesh**

G M Shafiullah

College of Engineering & Built Environment, CQUniversity, Australia

Colin Cole

**Centre for Railway Engineering, Faculty of Sciences, Engineering & Health
CQUniversity, Australia**

Abstract

The use of machine learning algorithms in different automated applications is increasing rapidly. The effectiveness of algorithms performances helps the user to operate their machine accurately and on time. Road sign classification is a very common type of problem for an automated driving support system. In this research, road speeding measure and sign identification is conducted using four popular machine learning algorithms to develop a smart driving system. This system informs forward-looking decision making and the initiation of suitable actions to prevent any future disastrous events. The robustness of the classification algorithms is examined for classification accuracy through 10-fold cross validation and confusion matrix. Experimental results prove that the accuracy of Support Vector Machine (SVM) and Neural Network (NN) is almost 100% and it is very promising compared to the earlier research performance. However, in terms of computational complexity NN is a slower classifier. Therefore, the experimental results suggest that SVM can make an effective interpretation and point out the ability of design of a new intelligent speed control system.

Keywords: Road Sign Classification, Support Vector Machine, Accuracy, Computational Complexity.

1.0 Introduction

There is an unexpected increase in the number of road deaths every year all over the world. One of the important attribute causes over the world of death is speeding. It is reported in [1] that 68% of casualty crashes involved cars which were exceeding 60 km/h compared to 42% of those not involved in a crash. The difference was even greater at higher speeds: 14% of casualty crashes involved cars which were travelling faster than 80 km/h in a 60 km/h speed zone compared to less than 1% of those not involved in a crash. Moreover, research argued that not one of the travelling speeds below 60 km/h was shown to be associated with a risk of involvement in a casualty crash that was statistically significantly different from the risk at 60 km/h [1]. Therefore, ensure safety and security of road system is a key concern issue. Recent developments in Information Communication Technology (ICT) have adopted machine learning as one of today's promising technologies. Machine learning techniques have improved during the last decade with development of more effective pattern recognition techniques. As a result, the use of machine learning techniques, especially classifier systems in smart driving, is increasing gradually. Evaluation of data taken from the street and development of an intelligent decision system are the most important factors in smart driving. Classification techniques play a key role in developing an intelligent smart driving system. Many algorithms for the road sign detection and classification have been introduced based on image data analysis. Road signs are often used as convenient real-world objects suitable for algorithm testing purposes.

Paclik [2] reports the first work on the automated road sign recognition was reported in 1984. Fuzzy ARTMAP networks [3] is used to classify Swedish road and traffic signs. In this research the Swedish Speed-Limit signs are selected as a case study; but the system can be applied to other signs. Basically colour image thresholding

segmentation is done to classify pixels of an image into road sign pixels or background (non-roadsign) pixels [4,5]. Principle components analysis, the popular statistical approach [6] that transforms the original road sign data to a new coordinate system, better captures the essential information of the road-sign data for recognition. Kellmeyer and Zwahlen suggest NN can be trained to recognise patterns containing certain colours. NN is found to be an efficient tool to reduce the colour resolution of image [7]. Some other areas of NNs are well known for their powerful classification capability including Multilayer Perceptron (MLP) network, Radial Basis Network (RBF), etc. After generating the gray-level features on histogram, projections and simple spatial moment invariants, another useful algorithm decision can be made to recognise particular road sign [8]. The decision tree allows faster rejection of non-sign regions. The extensive real life road sign classification has been conducted by Nguwi and Kouzani [9]. This research suggested that the NN algorithm is an efficient tool for colour road sign classification. There may be some other researchers focusing on the presentation of successful recognition of particular road sign by some special algorithm in literature. However, our research is a valuable source of information about different recognition approaches including tree based algorithm C4.5, probability based algorithm Naïve Bayes, Neural based algorithm Backpropagation and statistical based learning algorithm SVM. First we consider five types of road signs on Australian street. All the signs are in colour but we used gray scale images in our experiment. We tried to put all the image information together as an algorithms input without any feature selection.

The paper is organized as follows. Section 2 describes the whole real life data extraction process. An overview of SVM is provided in Section 3. Section 4 presents the proposed road-sign recognition system including the performance evolutions. Finally, section 5 discusses the performance of the developed system. Concluding remarks are given in section 6.

2.0 Data Description

The name of the dataset is Australian Road Sign. Basically we consider five types of road sign in our experiment: type one, about vehicle turning, type two no entry/stopping/parking, type three speed from 40-100, type four stop/give way/round about/no turn and finally type five one way directions. All the basic signs are placed in Figure 1. A simple digital camera is used to collect these images. The data set contains 253 samples.



Figure 1. Symbols of Australian Road Signs

Our aim was to consider equal class distribution of the different types of road signs. However type four holds the maximum number of instances 60 and speed signs hold the minimum instances 42 in our database. A comparison of number of instances about different types of sign is shown in Figure 2. Finally we generated the numeric data from the images using Matlab image processing toolbox. The numeric values of the generated data were in different ranges. A basic statistics about a sample is shown in Table 1.

3.0 Algorithm Descriptions

Until today many machine learning algorithms have been proposed to deal with the identification of road sign. The most common include NN, Bayesian classifiers, decision trees, and Support Vector Machine (SVM) [8,9]. In this research, backpropagation from NN, Naïve Bayes from Bayesian, C4.5 from decision tree and SMO from SVM are

evaluated for road sign classification. All these algorithms are implemented in WEKA [10]. The WEKA platform, which is open source software, was used for the road sign experiments described below. For further information on the algorithms, the reader may refer to [11]. However, among this list we found SVM is an efficient algorithm. Therefore, the below section will provide a brief overview on support vector classification.

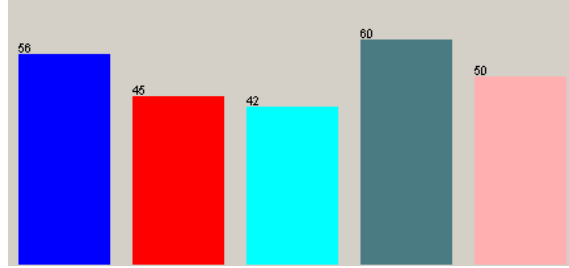


Figure 2. Road sign class distribution. The numbers are corresponding sign with Figure 1.

Table 1. Road sign sample statistics

Statistic	Value
Minimum	0
Maximum	232.93
Mean	34.494
StdDev	82.215

Support Vector Classification

Let us consider a set of training data $\{(x_1, y_1), \dots, (x_l, y_l)\}$, where each $x_i \in \mathcal{R}^n$ denotes the input space of the instance and has a corresponding target values $y_i \in \mathcal{R}$ for $i=1, \dots, l$ where l corresponds to the size of the training instances. The dual formulation of SVM classification [12-15] is as follows:

$$\begin{aligned} \min_{\alpha_i} \quad & \sum_{i=1}^l \alpha_i - \frac{1}{2} \sum_{i=1}^l \sum_{j=1}^l \alpha_i \alpha_j y_i y_j K(\mathbf{x}_i, \mathbf{x}_j) \\ \text{subject to:} \quad & 0 \leq \alpha_i \leq C, \text{ for all } i \\ & \sum_{i=1}^l \alpha_i y_i = 0 \end{aligned} \quad (1)$$

where α_i is called Lagrange multipliers, which represents the solution to the above quadratic problem that act as forces pushing predictions towards target value y_i . Only the non-zero values of the Lagrange multipliers in equation (1) are useful to predict the possible road sign and are known as support vectors. And C is a so called "regularization parameter" that controls the trade off between empirical error and complexity of the hypothesis space used.

By solving equation (1), the generic equation can be rewritten as:

$$\begin{aligned} f(x) &= \sum_{i=1}^l (\alpha_i - \alpha_i^*) (\Phi(x_i) \cdot \Phi(x)) + b \\ &= \sum_{i=1}^l (\alpha_i - \alpha_i^*) k(x_i, x) + b \end{aligned} \quad (2)$$

In equation (2) the dot product can be replaced with function $k(x_i, x)$, the popular name is kernel function. Kernel

functions enable the dot product to be performed in high-dimensional feature space using low dimensional space data input without knowing the transformation Φ . The basic rule is all kernel functions must satisfy Mercer's condition that corresponds to the inner product of some feature space. Some common kernels are shown in Table 2. In our studies we have experimented with these two non-linear kernels.

Table 1. Common kernel functions

Kernels	Functions
Polynomial	$[(x * x_i) + 1]^d$
RBF	$\exp\left\{-\gamma x - x_i ^2\right\}$

4.0 Algorithms Performance Measure

In this section, we present the performance evaluation methods used to evaluate the proposed method. Finally, we give the experimental results and discuss our observations from the obtained results.

A. Performance evaluation methods

We have used four methods for performance evaluation of road sign classification. These methods are classification accuracy, precision and recall, F-measure and Receiver Operating Curve (ROC) area. These calculations have been done using the confusion matrix. Since the number of instances is less than 100, we consider 10-fold cross validation (10FCV). We explain these methods in the following sections.

B. 10FCV

Cross validation is a well known method for estimating the true error of a model and it is also used to evaluate a model in deciding which algorithm to deploy for learning, when choosing from among a number of learning algorithms. It can also provide a guide as to the effect of parameter tuning in building a model from a specific algorithm. Test sample cross-validation is often a preferred method when there is plenty of data available. The basic idea is to use, say, 90% of the dataset to build a model. The data that were removed (10%) are then used to test the performance of the model on "new" data (usually by calculating the error). This simplest of cross validation approaches is referred to as the holdout method [16]. This approach is referred to as k-fold cross validation. We define the value of k is 10 in our experiment.

C. Confusion Matrix

A confusion matrix [17] contains the classifier performance about actual and predicted classifications. Performance of such a system is commonly evaluated using the data in the matrix. The basic attributes of a confusion matrix are true positives, true negatives, false positives, and false negatives, respectively. The matrix is represented in Figure 4.

True positive (TP): An input speed 60 is detected as a speed 60 by the expert system.

True negative (TN): An input a no right turn is detected as a no right turn by the expert system.

False positive (FP): An input speed 90 is detected as a speed 60 the expert system.

False negative (FN): An input a no right turn is detected as a no left turn by the expert system.

D. Classification Accuracy

In this study, the classification accuracies for the datasets are measured using the equation:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100 \quad (3)$$

Sensitivity and Specificity

For sensitivity and specificity we use the below expression

$$Sensitivity = \frac{TP}{TP + FN} \times 100 \quad (4)$$

$$Specificity = \frac{TN}{FN + TN} \times 100 \quad (5)$$

F-measure

The F-measure is the harmonic mean of precision and recall.

$$F\text{-measure} = \frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}}$$

$$\text{Where, } \text{precision} = \frac{TP}{TP + FP} \quad (6)$$

$$\text{recall} = \frac{TP}{TP + FN} \quad (7)$$

ROC Area

The ROC curve is a graphical technique to measure the classifier performances and is a procedure derived from the early days of radar and sonar detection used in the Second World War, hence the name receiver-operating characteristic. A graph of sensitivity against 1 – specificity is called a receiver operating characteristic (ROC) curve. It shows its performance as a tradeoff between selectivity and sensitivity. The performance of a classifier can be quantified by calculating the area under the ROC curve (AUROC). The ideal test would have an AUROC of 1, whereas a random guess would have an AUROC of 0.5. The solid line in Figure 3 is indicated the AUROC is 0.5. When the line will move towards the x-axis that means the performance will improve.

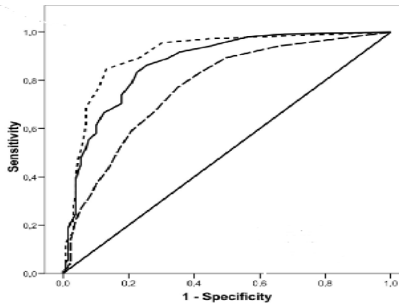


Figure 3. A ROC curve

5.0 Experimental Results

To evaluate the effectiveness of several classification algorithms, we did experiments on the Australian Road Sign data mentioned above. It is observed that our results were better than the previous results reported by earlier methods in [9]. Table 2 gives the classification accuracies using different measuring attributes and computational complexity. The algorithm that performed best is ranked as 1 and the algorithm performs worst is ranked as 4. From experimental results it has seen that this approach is efficient and achieved highest classification accuracy for smart driving system. SVM algorithm outperforms other algorithms and obtains the highest classification accuracy, 100% using 10-fold cross validation.

Table 2. Ranking performance of the classification algorithms.

Performance measure attributes Classifier	C4.5	NB	NN	SVM
Percent correct	3	4	2	1
Percent incorrect	3	4	2	1
Percent unclassified	1	1	1	1
True positive rate	3	2	1	1
False positive rate	2	1	1	1
True negative rate	2	1	1	1
False negative rate	2	3	1	1
Sensitivity	2	1	1	1
Specificity	3	2	1	1
F measure	3	2	1	1
Area under ROC	2	1	1	1
CPU Time training	2	1	3	1
CPU Time testing	1	2	2	1

The obtained classification accuracy, values of sensitivity and specificity, area under roc and other others attributes by SVM classifier for the Australian Road Sign data was shown highest ranking 1 always. A details confusion based matrix SVM performance analysis has been reported in Figure 4.

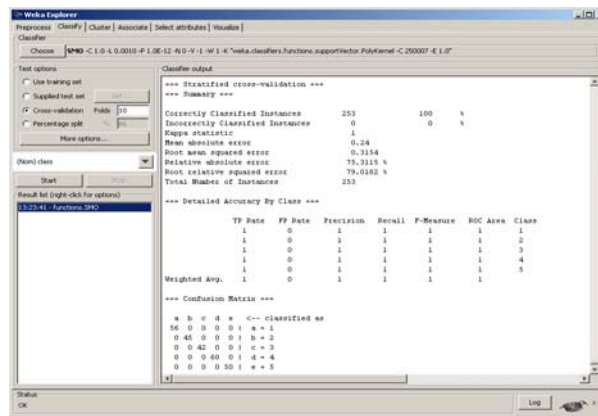


Figure 4. A confusion matrix based SVM performance analysis.

In this study, there were five classes of Australian road sign. Classification results of the different classifier were displayed by using a confusion matrix. In a confusion matrix, each cell contains the raw number of exemplars classified for the corresponding combination of desired and actual classification outputs. From the above results, we conclude that the SVM obtains very promising results in classifying the possible road sign. We believe that the proposed system can be very helpful to the smart driver to make their final decision for driving on board. By using such an efficient tool, they can make very accurate decisions on time to avoid crashes on the street and reduce the number of street deaths every year.

6.0 Discussions

With the improvements in modern machine learning, the effects of these innovations are entering to more application domains day-by-day and transport is one of them. Smart decision making in vehicle driving is an emerging research. A key trend of smart driving is the early detection of road signs and conveying the messages to the driver on board. Proper way road sight identification always plays an important role in highway management by providing drivers and road users guidance, warning and other driving related information. The Road Sign Recognition is a field of applied computer vision research concerned with the automatic detection and classification of traffic signs in traffic scene images acquired from a moving car. Our research investigated the Australian road signs classification in an offline manner.

The SVM classifier had given very promising results in classifying the Australian road sign. The classification performances were investigated using many popular statistical performance measures attributes. From all these measures we found SVM is the number one choice to classify road sign properly. The research reported in this paper is an offline process. Experiments were conducted on the road sign data to classify the signs in a fully automatic manner using SVM. The results strongly suggest that SVM can aid in the classification of road signs. It is hoped that more interesting results will follow on further exploration of data. Although developed method is built as an offline classification system, it can be rebuilt as an online road signs classification system in the future.

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