Automatic Trigger Speed for Vehicle Activated Signs using Adaptive Neuro fuzzy system and ClassificationRegression Trees

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Abstract—Vehicle activated signs (VAS) are speed warning signs activated by radar when driver speed exceeds a pre-set threshold, i.e., the trigger speed. In order to be able to operate the sign more efficiently, it is proposed that the sign be appropriately triggered by taking into account the prevalent road and traffic conditions. This study presents the use of adaptive neuro-fuzzy inference systems (ANFIS) and classification and regression trees (CART) to predict the trigger speed of the VAS by using a historical speed data. The speed data is first explored and clustered by using a self-organizing map (SOM). Input vectors for simulation composed of time of day, traffic flow and standard deviation of mean vehicle speeds whereas the output vector consists only of vehicle speeds in the 85th percentile. The two models examined in this study were tested with historical speed data collected in Sweden during a period of one week and their performance was compared with Multi-layer perceptron (MLP). The results show that CART is reliable for predicting trigger speed for vehicle activated signs. However, compared to MLP and ANFIS, CART has superior performance than the other algorithms in terms of accuracy and complexity.

Keywords- ***vehicle activated signs; adaptive neuro-fuzzy inference systems; classification and regression tree; self-organizing maps; trigger speed.***

I. INTRODUCTION

Vehicle activated signs (VAS) are road warning signs that measure the speed of passing vehicles and when a driver exceeds a particular threshold, display a warning message, e.g., 'Slow down' in combination with the current speed limit [1]. The threshold, which triggers the message to the driver, is commonly based on a vehicle's speed, and accordingly, is called a trigger speed. At present, the trigger speed activating the VAS sign is usually set to a constant value that is relative to the static speed limit for the particular road segment. At the same time, static signs fail to provide the appropriate speed during dynamic traffic conditions [2]. To cope with the real time traffic management and time lags, a self-learning algorithm based on historical traffic speed data is proposed in this study. The proposed algorithm will be able to control the appropriate threshold, i.e., trigger speed for the VAS according to traffic situations. However, a large number of input factors, which impact the current traffic situations, need to be considered. These input factors include time/day, traffic flow, speeds, and type of vehicle. Several statistical approaches and artificial intelligence algorithms have been developed and implemented among road traffic management and control applications. Examples of statistical methods are the auto-regressive integrated moving average (ARIMA) [3] and several non-parametric regression models. Several artificial intelligence approaches have been properly explored and developed. Among these neural networks (ANN) [4, 5], fuzzy logic [6], and further hybrid neuro-fuzzy intelligent systems [7] have been properly explored and developed. Given this background, the first objective of this study is to analyse the traffic speed data using a Self-organising map (SOM). SOM will further partition the data into separate clusters that have similar traffic patterns without the need of prior determination of the output. The second objective is the comparison of adaptive neuro-fuzzy inference system (ANFIS) with classification and regression trees (CART) for predicting the trigger speed for a VAS within each cluster obtained by the SOM.

The paper is organised as follows. Section II describes the automatic algorithm for triggering VAS. Section III presents the data collection and the experimental results obtained in this study and the paper is concluded in Section IV.

II. AUTOMATIC ALGORITHM FOR TRIGERRING VAS

A. Traffic pattern clustering

In the first step, SOM is initially used to visualize and explore the speed characteristics of the traffic data that has been collected. A SOM is further used to group traffic patterns into clusters that have similar speed characteristics. Based on the SOM algorithm described in the previous section, the SOM network is trained with 4 input factors based on the historical data: speed, time of the day, day of the week and type of vehicle. In this study, the type of the vehicles is mainly based on the length of vehicle detected by the radar. Speed characteristics for cars may be different than speed characteristics for trucks/trailers. Moreover, they may change or may repeat over time of the day and day of the week such as morning and evening hours or rush hours and non-rush hours during the weekday and weekend.

B. Trigger speed prediction

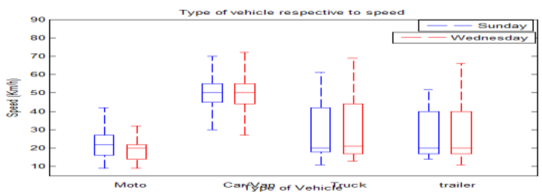
After exploring and grouping the traffic speed data into an appropriate number of clusters, a prediction algorithm is then developed for each cluster, which predicts the 85th percentile speed for each hour on the day. The prediction algorithm will be based on ANFIS and CART methods, which are powerful algorithms for traffic prediction based on a learning process. Time of the day, traffic flow and standard deviation are used as inputs traffic features whereas the 85th percentile is considered as the output of the two algorithms.

 ISBN: 978-1-61208-437-4

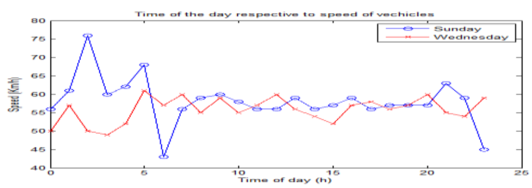
III. DATA COLLECTION AND EXPERIMENTAL RESULTS

All reported analyses were conducted with speed data collected at a roadway in Borlänge Sweden restricted with speed limit 40km/hr. A VAS was installed and was equipped with radar and a data logger to record the speed of passing vehicles 100m before the location of the VAS. The data comprised the vehicle speed, length of vehicle and date and time the vehicle passed the VAS.

In order to analyse and find similar traffic patterns, a SOM was further applied to the original speed data. Figure 1 shows a clear partitioning of the speed data respective to the length of vehicles and to the time of the day (night/day). Based on the clustering results, the speed data was grouped into major clusters, cars/vans (cluster 1) and trucks/trucks with trailers (cluster 2). Motorcycles are excluded from this study. Besides, the analysis showed that the day of the week has no effect on driver behaviour.



(a)



(b)

Figure 1.Analysis of speed of vechiles passing on Wednesday and Sunday respective to (a) type of the vehicles and (b) time of the day

Although, in the case of the trigger speed prediction, traffic flow, standard deviation and time of the day are utilized to alter the trigger speed of the VAS; various trigger speeds of the VAS come into service by assigning a different 85th percentile speed to each hour of the day. Following the practical rule of thumb, for each cluster dataset, ½ is used for training set and ½ used for testing set. Correspondingly, in order to illustrate the accuracy of the predicted trigger speed data set models the real output data set, the root mean squared error (RMSE) and the coefficient of determination (R^2) will be used as a performance index of the ANFIS and the CART. Better performance of the two algorithms requires a low value for RMSE and a high value of R^2. Note that RMSE and R^2 are the average value of the two sets.

Table 1 summarized the results of the trigger speed prediction for each of the two clusters investigated in this study. The results obtained by the CART and the ANFIS are also compared to a multilayer perceptron (MLP). These results clearly demonstrate the superior predictive performance of the CART when compared to ANFIS and to the static MLP. Since, the RMSE for CART are lower to those of ANFIS within the two clusters but similar to the MLP within cluster 2. Furthermore, the learning duration of the CART is much lower than the duration of MLP and ANFIS. This also implies that when using a huge data set, the performance of CART to predict the speed would be more useful to overcome faster the complexity of the problem.

TABLE I. PERFORMANCE FOR ANFIS , CART COMPARED TO THE PERFORMANCE OF MLP WITHIN CLUSTER1 AND CLUSTER2

Cluster 1- cars and vans			
	CART	**MLP**	**ANFIS**
R-squared	0.60	0.55	0.46
RMSE	0.15	0.19	0.18
Time(s)	0.13	22.54	0.27
Cluster 2- Trucks and trucks with trailer			
	CART	**MLP**	**ANFIS**
R-squared	0.59	0.60	0.46
RMSE	0.08	0.08	0.09
Time(s)	0.16	13.81	0.24

IV. CONCLUSION

The results from this study clearly demonstrate that first SOM can group the speed data into two majors clusters, the first one is for all cars/vans and the second one trucks/trucks with trailers. Second, the results show that CART is reliable and could be used for predicting the trigger speed for vehicle activated signs in order to construct adaptive decision support systems. However, compared to MLP and CART are capable of predicting trigger speed with a high degree of performance. The performance is measured by a low value of RMSE and a high value of R^2. In terms of computational complexity, CART is more efficient since regression trees use one pass and offer a fast learning approach when compared to the other learning approaches.

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