Dynamic and Intelligent Control of Autonomous Vehicles for Highway On-ramp Merge

Extended Abstract

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ABSTRACT

This work addresses the problem of predicting the intentions of drivers in a highway on-ramp situation using a dynamic Bayesian network. We present the proposed model and detail its use. Then, we report the simulation results that show good performances for predicting highway on-ramp merging intentions.

KEYWORDS

Connected car; Autonomous car; Collaborative driving; Dynamic Bayesian Network

ACM Reference Format:
Zine el abidine Kherroubi, Samir Aknine, and Rebiha Bacha. 2019. Dynamic and Intelligent Control of Autonomous Vehicles for Highway On-ramp Merge. In *Proc. of the 18th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2019), Montreal, Canada, May 13–17, 2019,* IFAAMAS, 3 pages.

1 INTRODUCTION

Interest in intelligent vehicle research has been growing in the last two decades, which significantly improves transportation security and comfort [5]. Early DAS (Driver-assistance systems) were based on proprioceptive sensors, i.e. sensors measuring the internal status of the vehicle, such as wheel velocity, acceleration, or rotational velocity. Sharing this onboard data would be beneficial to other vehicles on the road. However, the communication requirements for cooperative perception and maneuvering are yet to be understood in detail. Advances in communication technology such as DSRC (Dedicated Short Range Communication), Wi-Fi, and LTE have paved the way for connected vehicles, which will bring the intelligent transportation field towards collaborative autonomy. In full collaborative autonomy, onboard sensors from individual cars and data sharing between connected vehicles are used in conjunction to increase the overall "intelligence" of traffic [5][1].

In order to exploit the advantages of the combination of communication technology and autonomous driving that use artificial intelligence technics, we designed a centralized decision-making strategy for autonomous vehicles. This configuration may have various advantages such as an increased perception that exceeds the limits of embedded sensors and better situation assessment.

The objective of this work is to design a centralized collaborative driving strategy that uses embedded data sharing to perform highway on-ramp merging, which is a use case for level 4 autonomous driving[1]. The highway on-ramp merge is one of the situations requiring large effort from the driver which consists of recognizing surrounding cars and making a decision on the control mode (accelerate, decelerate, stop...). Merging on the highway ramp is one of the tasks which is likely to cause accidents and/or congestion. This task is difficult and needs to be supported particularly for elderly drivers who may benefit the most from such assistance.

2 MODEL AND SIMULATION

Figure 1 shows the Bayesian network structure for the vehicle in the merge lane and the vehicle in the principal highway lane (first lane).

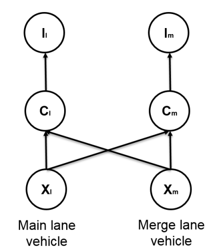

Figure 1: DBN used for highway on-ramp merge situation.

The Network is composed of three layers: Vector X which contains vehicle data (mainly dynamic data), Vector C which contains vehicle situation context, and finally the Output I which is the intention of merging or not merging for the vehicle.

Vector X: contains vehicle states: {*Position, Speed, Acceleration*}.

Vector C: contains the features of local situational context, which are expressed mathematically as a Dirac distribution of a certain mapping function of the vehicle state vector and the main lane vehicle state vector:

$$\delta_{map\_function}(X_{merge\_lane}, X_{main\_lane}) \quad (1)$$

This vector contains for the vehicle in the merge lane: {*Distance from the merging point, Acceleration, Relative distance from the vehicle ahead in the main lane, Relative acceleration from the vehicle ahead in the main lane*}.

This vector contains for the vehicle in the main lane: {*distance from the merging point, acceleration, relative distance from the vehicle in the merge lane, relative speed from the vehicle in the merge lane, relative acceleration from the vehicle in the merge lane*}.

[1]Car is fully autonomous in controlled areas, without driver intervention.

Proc. of the 18th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2019), N. Agmon, M. E. Taylor, E. Elkind, M. Veloso (eds.), May 13–17, 2019, Montreal, Canada.

Vector I: contains the intention of merging or not for the vehicle. The probability of merging is deduced from the situation context vector *P(I/C)*. This conditional probability is learned using nominal logistic regression, which is a discriminative learning classifier. An output probability with a value close to 1 means that the vehicle has the intention to merge before the vehicle in the other lane (either main lane or merge lane) and taking priority in the highway on-ramp merge situation.

The proposed Bayesian network was simulated using Next Generation Simulation *(NGSIM)* Vehicle Trajectories and supporting Data, which is a database of detailed vehicle trajectory data on southbound US 101 and Lankershim Boulevard in Los Angeles, CA, eastbound I-80 in Emeryville, CA and Peachtree Street in Atlanta, Georgia. Data was collected through a network of synchronized digital video cameras. NGVIDEO, a customized software application developed for the NGSIM program, transcribed the vehicle trajectory data from the video. This vehicle trajectory data provided the precise location of each vehicle within the study area every one-tenth of a second, resulting in detailed lane positions and locations relative to other vehicles [2]. The data used for the training of our model corresponds to vehicles trajectories on a segment of interstate *80* in *Emeryville (San Francisco), California* collected between *4:00 p.m.* and *4:15 p.m.* on *April 13, 2005.* The data from 4:00 p.m. to 4:11 p.m. was used to learn the parameters of the Logistic Regression Model (LRM), which is estimated by the Maximum Likelihood Estimation (MLE) method [3]. 2 shows that at each instant the merging vehicle ID corresponds to either a vehicle in merge lane or in the main lane.

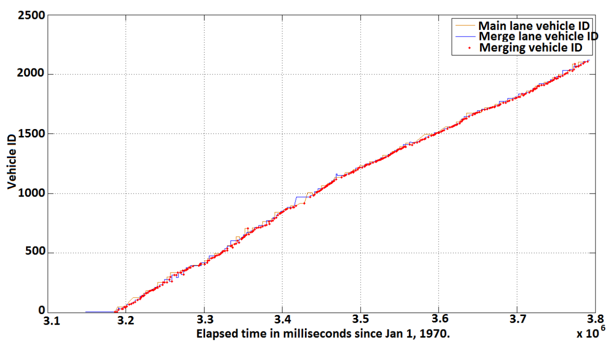

Figure 2: Data preprocessing to identify the merging vehicle ID.

In order to evaluate the prediction quality, we calculate the root-mean-square error (RMSE) between the output of the proposed DBN and the real output. The mathematical expression of RMSE is given by:

$$\sqrt{\frac{1}{n}\Sigma_i^n(Real_{output_i} - LRM_{output_i})^2} \qquad (2)$$

where $Real_{output_i}$ is the real output for the i^{th} data sample, LRM_{output_i} is the output of the resulting LRM for the i^{th} data sample and n is the total number of data samples. It takes the value of *0.2168* for the main lane, and *0.1674* for the merge lane. The model determines the merged vehicle ID regarding the highest probability. An RMSE for the vehicle model in the main lane and the merge lane of values *0.2168* and *0.1674* respectively means that the probability difference between the vehicle in the main lane and the vehicle in the merge lane will be around 0.615, which is a good difference for decision-making. This model is then used to evaluate the probability for both vehicles in the main lane and the merge lane at each instant. The model was trained for different ratios of training datasets. The remaining dataset was used to test the model. The mean accuracy of the proposed model for each training ratio is summarized in table 1.

Training ratio	0.3	0.4	0.5	0.6	0.7
Accuracy mean	95.67%	95.67%	95.73%	95.72%	95.7%
Standard deviation	0.17%	0.22%	0.26%	0.28%	0.32%

Table 1: Model accuracy evaluation.

The model has an accuracy greater than 95%. In fact, [4] has proposed a Bayesian network to analysis highway merging acceptability for a single vehicle in the main lane using a driving simulator and has obtained an accuracy around 85%. Hence, the proposed model in the present work shows a better accuracy for vehicles, while using real-world data and scenario. The standard deviation shows that the model is robust regarding training data. Besides, the learning stage of the proposed method makes it adaptable for other highway on-ramp topologies. Hence, the same semantic model can be retrained for different highway on-ramp merge situations. Figure 3 shows that the proposed model predicts the merged vehicle ID with good precision.

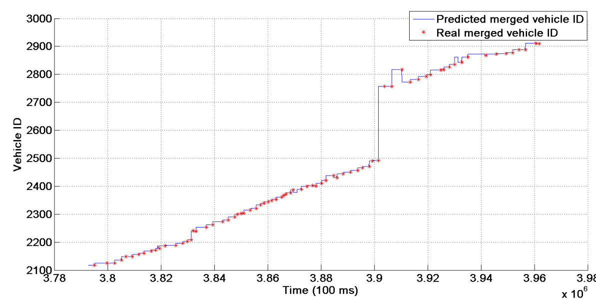

Figure 3: Prediction output of the proposed model: the curve is increasing because the ID of the vehicle crossing the merging point is unique and increases over time.

3 CONCLUSION

This paper studied the enablers for designing a central collaborative strategy decision for a highway on-ramp merging situation. A Bayesian network was proposed to predict in real time the merging vehicle. The model uses a contextual situation vector such as the relative distance from the merging point and the relative acceleration from the vehicle ahead. The model was trained using the nominal logistic regression. The proposed model was validated using real-world data, and the results show a prediction with an accuracy greater than *95%*. Future work will be devoted to the usage of the automaker connected cars to test the proposed method using real data provided from rolling.

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