

# A Dynamic Bayesian Network Based Merge Mechanism for Autonomous Vehicles

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## Abstract

This work explores the design of a central collaborative driving strategy between connected cars with the objective of improving road safety in case of highway on-ramp merging scenario. Based on a suitable method for predicting vehicle motion and behavior for a central collaborative strategy, a dynamic Bayesian network method that predicts the intention of drivers in highway on-ramp is proposed. The method was validated using real data of detailed vehicle trajectories on a segment of interstate 80 in Emeryville, California.

## Introduction

Interest in intelligent vehicles research has been growing in the last two decades, which significantly improves transportation security and comfort (Ozbilgin et al. 2016). In full collaborative autonomy, on-board sensors from individual cars and data sharing between connected vehicles are used in conjunction to increase the overall “intelligence” of traffic (Ozbilgin et al. 2016)(Bengler et al. 2014). In order to exploit the advantages of the combination of communication technology and autonomous driving that use artificial intelligence techniques, we designed a centralized decision-making strategy for autonomous vehicles.

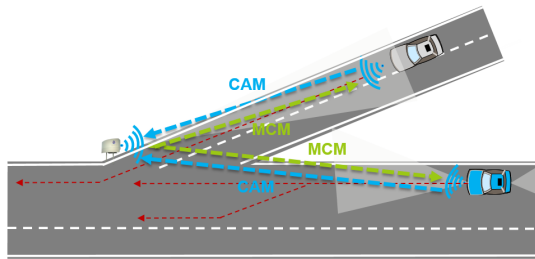


Figure 1: Highway on-ramp merge in situation of connected and autonomous vehicles: vehicles send a Cooperative Awareness Message (CAM) to the off-board unit that processes vehicles data and sends a Maneuver Coordination Message (MCM).

This configuration may have various advantages such as increased perception that exceeds the limits of embedded sen-

sors and significant computing capacity compared to the on-board calculators of the vehicles. Nevertheless, the exploitation of vehicles data using communication to improve driving automation requires taking into account several essential locks such as the communication latency, the loss of the communicated data and the random behavior of drivers.

The present work is part of an industrial research project for a car manufacturer. The objective is to design a centralized collaborative driving strategy that uses embedded data sharing to perform highway on-ramp merging (fig. 1). We propose a Hidden Markov Model to estimate driver behaviors and decisions in the highway on-ramp merge situation. The proposed model uses contextual states which greatly reduce calculation while keeping a good output precision. The results show that the model has good performance.

## Dynamic Bayesian Network Model

The proposed Dynamic Bayesian 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:  $\delta_{map\_function}(X_{merge\_lane}, X_{main\_lane})$ . This vector contains for the vehicle in the merge lane (resp. main lane):  $C_1$  (resp.  $C'_1$ ): Distance from the merging point,  $C_2$  (resp.  $C'_2$ ): Speed,  $C_3$  (resp.  $C'_3$ ): Acceleration,  $C_4$  (resp.  $C'_4$ ): Relative distance from the vehicle ahead in the main lane (resp. from the vehicle in the merge lane),  $C_5$  (resp.  $C'_5$ ): Relative speed from the vehicle ahead in the main lane (resp. from the vehicle in the merge lane),  $C_6$  (resp.  $C'_6$ ): Relative acceleration from the vehicle ahead in the main lane (resp. from the vehicle in the merge lane),  $C_7$  (resp.  $C'_7$ ): Relative distance from the vehicle behind in the main lane (resp. from the vehicle ahead in the main lane),  $C_8$  (resp.  $C'_8$ ): Relative speed from the vehicle behind in the main lane (resp. from the vehicle ahead in the main lane),  $C_9$  (resp.  $C'_9$ ): Relative acceleration from the vehicle behind in the main lane (resp. from the vehicle ahead in the main lane).

**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.

## Simulation

The proposed Dynamic Bayesian network was simulated using Next Generation Simulation (NGSIM) Vehicle Trajectories and supporting Data, which is a database of detailed vehicle trajectory data 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 Maximum Likelihood Estimation (MLE) method, and using the full situation contextual vector  $C$ .

The resulting LRM parameters are summarized in the following table (table 1):

Vehicle in the merge lane		Vehicle in the main lane	
Parameter	LRM value	Parameter	LRM value
$C_0$ (constant)	0.2677	$C'_0$ (constant)	1.0394
$C_1$	-0.5494	$C'_1$	-0.2550
$C_2$	0.0197	$C'_2$	-0.0189
$C_3$	0.1222	$C'_3$	-0.1603
$C_4$	0.5178	$C'_4$	-0.1606
$C_5$	-0.2764	$C'_5$	-0.6503
$C_6$	0.0871	$C'_6$	-0.1668
$C_7$	-0.0035	$C'_7$	0.1287
$C_8$	0.0322	$C'_8$	0.1198
$C_9$	0.0242	$C'_9$	-0.0723

Table 1: LRM parameters.

The comparison between the real situation output and the output of the proposed model is shown in the figure below:

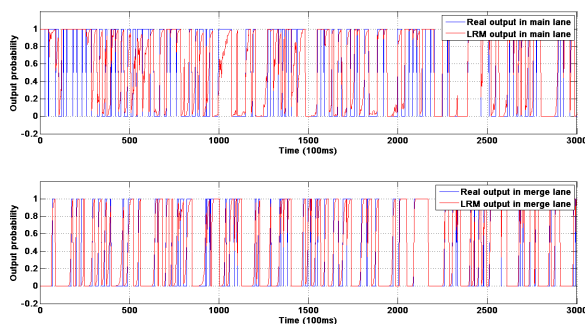


Figure 2: Comparison between the real output and the LRM output.

We notice in the figure 2 that the output of the proposed DBN is very similar to the real output in both main lane

and merge lane. In order to evaluate the prediction quality of the proposed model, we calculate the root-mean-square error (RMSE). The mathematical expression of RMSE is given by:  $\sqrt{\frac{1}{n} \sum_i^n (Real_{output_i} - LRM_{output_i})^2}$ .

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 of 0.2168 and 0.1674 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. The comparison of LRM parameters values in table 1 shows that the variables  $C_1, C_3, C_4, C_5$  and  $C_6$  are the most significant parameters for highway on-ramp merge decision for the vehicle in the merge lane. For example, we notice that the speed of the vehicle does not reflect the intention of the drivers in the merge lane to take priority of insertion in the highway. For the vehicle in the main lane highway, we remark that the value of the parameters  $C'_1, C'_3, C'_4, C'_5$  and  $C'_6$  are the most pertinent variables that determine if the driver has the intention to take priority and merge in the highway on-ramp. We also notice that the speed is a neglected parameter for merge decision. In order to optimize our Dynamic Bayesian Network, we neglect all irrelevant parameters, and we consider only the most pertinent contextual situation variables. The new obtained LRM parameters values take the same relevance. The evaluation of the RRMSE gives the same precision as for the previous model, despite the reduction of pertinent parameters and the optimization of the DBN situation contextual vector.

The model was trained and tested for different ratios of the training dataset, and has shown an average accuracy greater than 95% with a good robustness. Besides, the learning stage of the proposed method makes it adaptable for other highway on-ramp topology. Hence, the same semantic model can be retrained for different highway on-ramp merge situations.

## Conclusion

This paper studied the designing of a central collaborative strategy decision for highway on-ramp merging situation using Dynamic Bayesian Network. The model was trained using nominal logistic regression. The analysis of the resulting model parameters shows that the decision of highway on-ramp merging is determined mainly by relevant parameters. The proposed model was validated using real-world data, and the results show a prediction with an accuracy greater than 95%. Also, the proposed method can be used in other collaborative situations such as intersection, by changing the situation contextual vector: distance, speed and acceleration from the intersection point, etc.

## References

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