A SELF-LEARNING DRIVING BEHAVIOR MODEL FOR MICROSCOPIC ONLINE SIMULATION BASED ON REMOTE SENSING AND EQUIPPED VEHICLE DATA

Marc MISKA[1], Theo H.J. MULLER[2], Henk VAN ZUYLEN[3]

Abstract. Mostly, microscopic simulation models are calibrated with macroscopic measurement data, like flow and speed, which says nothing about the accuracy of the individual driving behavior of the vehicle – driver combinations. The microscopic online simulator MiOS is extended with a driving behavior model based on equipped vehicle and floating car data. It is designed as a self-learning behavior model.

1. Introduction

The problem of microscopic simulation models is the level of detail they are intended to present. Mostly, the calibration of these models is based on macroscopic measurement data, like flow and speed, which says nothing about the accuracy of the individual driving behavior of the vehicle – driver combinations. The goal of this research is to define a framework for a self-learning driving behavior model for microscopic simulations, based on remote sensing and floating car data. These data allow more insight to the individual behavior. Currently, projects in the Netherlands and in Japan provide this information for motorway networks, as well as for urban streets and intersections.

The main part of the model is an autonomous agent, which can be used later on for simulation programs. This agent (virtual driver) is assigned to a vehicle and is familiar with all possible actions. The problem is to teach the agent, to decide which action is appropriate in which situation. Therefore we introduce a component of the agent known as learning area, to which we feed the available microscopic measurement data. Additionally, theoretical values for safety will be taught. After the learning process, the agent should be possible to manage different given traffic situations, based on what he learned.

[1] Delft University of Technology, P.O. Box 5048, 2600GA Delft, The Netherlands, M.Miska@citg.tudelft.nl
[2] Delft University of Technology, P.O. Box 5048, 2600GA Delft, The Netherlands, Theo.Muller@citg.tudelft.nl
[3] Delft University of Technology, P.O. Box 5048, 2600GA Delft, The Netherlands, H.J.vanZuylen@citg.tudelft.nl

2. Methods

2.1. Structure of the Behavior Model

Drivers can be described as reactive agents because of their individual capability to perceive their environment, make decisions based on what they 'see' and take appropriate actions. This autonomous and unpredictable driver behavior leads to the emergence of traffic flow due to interactions between individual agents.

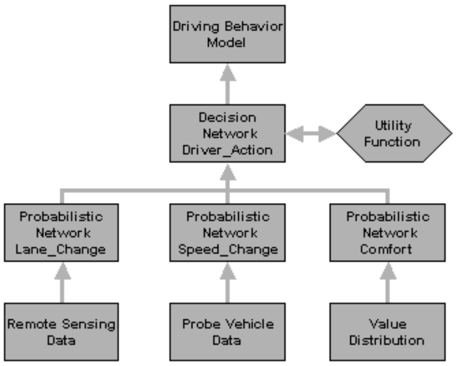

Figure 1. Structure of components for the behavior model

Each agent perceives the actual situation with sensors, which represent the view of the driver. These sensors are used in a Bayesian network (BN) to calculate the actual belief state of the driver according to car following, lane changing and driving comfort. The probability functions of the BN are findings from remote sensing and probe vehicle data and will change online if new measurement data is added. Due to this approach the model is able to adapt to different kinds of driving behavior, as long as there is measurement data available.

Based on the belief states the driver will make a decision. Therefore, an action node is added to the BN to create a decision network (DN). The decision is influenced by the belief states as well as by a utility function that defines the goal for each driver separately.

The probabilistic network for the speed decision is generated from the existing data. So instead of building up the network and defining the probability function later on, the data is given and the UnBBayes learning tool [*1*] generates the nodes and afterward gives the definition of the relations between the nodes, thus the probability functions are calculated. Based on the given data the probabilistic network for the speed decision looks like in Figure 2.

For the decision making process, the DPN is extended by an action node to a dynamic decision network DDN. Additionally the DDN gets a reward node for each time slice. Thatman and Shachter [2] provide an algorithm for computing the policy for a DNN. According to Russell [3] this method is not feasible for real-time application, but in this research the policy is computed offline and so this approach has been chosen.

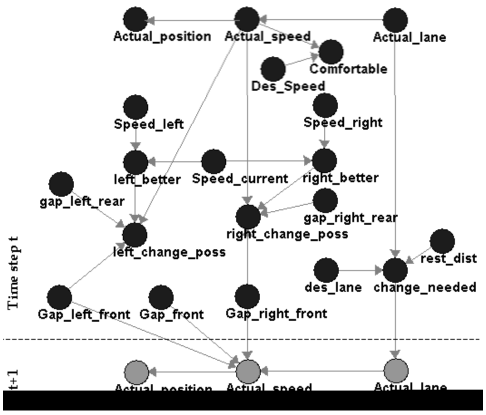

Figure 2. Structure of the BN for the Speed Decision of a driver

The DDN is trained with a set of examples of belief-state/action pairs, which are taken from remote sensing data on Dutch motorways and Japanese intersection. After the training process the DNN should be able to reproduce driving behavior, observed on the video data of the remote sensing process.

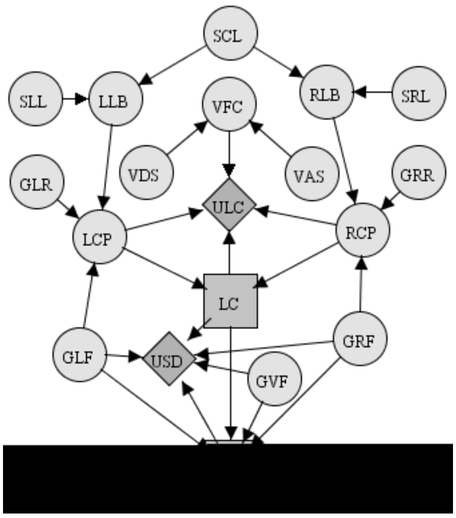

Figure 3. Structure of the BN for the Speed Decision of a driver

2.2. Calibration and Training of the model

In present practice, typically microscopic simulation models are calibrated with macroscopic measurement data, like flow and speed, but this data says nothing about the accuracy of the individual driving behavior of the vehicle – driver combinations. Therefore for this research, microscopic measurement data was chosen. There are two types of microscopic measurement data: First the equipped vehicle data and second the remote sensing data.

Equipped vehicle data generates speed, position, gyro, front and rear headway distance. The data is collected in 30 frames per second and stored in a database. From this collection the relation between different parameters of neighbored cars are extracted. The remote sensing is done with sequences of high-resolution pictures from a helicopter or with video detection from a high spot. The picture below shows an example image from the remote sensing from a helicopter in the Netherlands [4] [5]. In Japan the high spots are used or kite balloons, which are located over the research area. The collected data is translated to vehicle trajectories for further use. Even if the observed distance is small, the number of vehicles, which can be observed, delivers still a good data basis.

To train the model with the microscopic data, the Bayesian network, coupled with the decision network are fed with different data sets, which has been extracted from the measurement data. The data set includes the position and speed of the base car, the distances of the leading and following car, the occupancy of the neighbored and the changes in the driving state of the base car for the time step t+1.

The given training method of the UnBBayes package is used to input the data sets to the model. The outcome is a deterministic behavior model, which cannot directly be used for traffic simulation, since human behavior cannot be seen as deterministic at all. Drivers react differently on comparable situations, because of their perception of the situation. To compensate this, a noise function is added to the perception of the driver. Therewith, the resulting behavior becomes a stochastic one and can be used for traffic simulation.

3. Results

To test the behavior model it has been connected to the microscopic online simulator MiOS [6], which was developed to forecast traffic situations and travel times with a rolling horizon of 60 minutes. The speed of the simulator could be increased and a simulation has been performed on an arterial road where travel time measurements it available by video detection with number plate recognition.

The results show that the MiOS with the new behavior model is performing well and can reproduce travel times for the arterial road. Figure 4 shows the results.

4. Conclusions and further Research

First result of the research show that the behavior model is performing well in the simulation model. To evaluate these results, it has to be shown that the parameter sets are unique and a definition has to be found to determine the significance of the parameter value differences.

In further research the model has to be calibrated with more data and a validation of the data regarding to real world video observations of various scenarios is needed. This will take place with data from video observations on motorways and urban roads from the Netherlands and Japan. Additionally, it will be investigated, if the noise function can be determined from the measurement data as well.

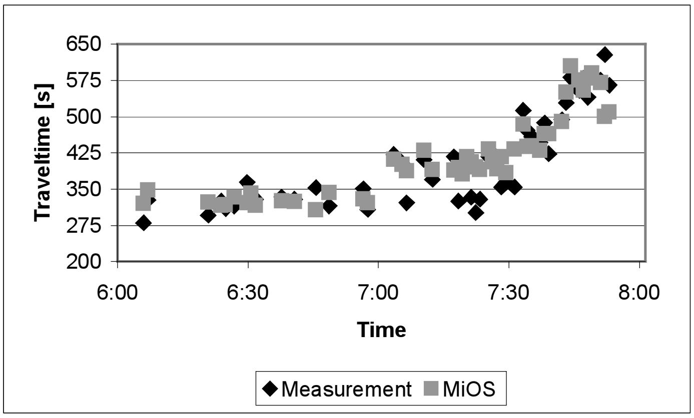

Figure 4. Simulation result compared with travel time measurements

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