Automatic Maneuver Recognition in the Automobile: the Fusion of Uncertain Sensor Values using Bayesian Models

Arati Gerdes
Institute of Transportation Systems
German Aerospace Center, Lilienthalplatz 7, 38108 Braunschweig, Germany
arati.gerdes@dlr.de

***Abstract*--A probabilistic system for automatic maneuver recognition is in development at the German Aerospace Center (DLR). Automatic maneuver recognition in the automobile would enable assistance systems to offer relevant, maneuver-specific assistance to the driver. Major obstacles to maneuver recognition in the automobile today are the wide variety of styles in which driving maneuvers are performed and the presence of uncertain and sometimes invalid sensor values, which traditional rule-based systems are ill-equipped to handle. Bayesian models, which offer a solid, theoretical framework for the derivation of inferences from uncertain evidence, are used for the inference of the driving maneuver being performed. Driver behavior analysis and tests of a prototype maneuver-recognition system are performed in real traffic using the DLR ViewCar, a research vehicle equipped with cameras and sensors to measure and record CAN-Bus, environment and driver data. Experiments with the prototype system yield a driving maneuver recognition rate of approximately 92%.**

***Index terms*-- Bayesian Networks, probabilistic methods, driving maneuver recognition**

I. INTRODUCTION

The automobile of today has evolved since its conception into a complex system, equipped with numerous sensors that supply a variety of information about the driving environment, and actuators that can be used for automatic control. Advances in vehicle technology have made it possible for systems in the automobile to analyze information about the driving environment, calculate optimal driving strategies and make and execute their own decisions.

The challenge today is in the development of systems that can analyze the driver's intentions, so that assistance can be tuned to the driver's needs.

Acceptability issues, possible liability issues in the case of technical failure, and the Vienna Convention on Road Traffic of 1968, which specifies that the driver of a vehicle must remain in control of the vehicle at all times, all play their role in ensuring that the driver, at least for the time being, retains control of the vehicle at all times during a drive on public roads. As long as the driver remains in final control of the vehicle, Advanced Driver Assistance Systems (ADAS) need to adapt the assistance offered to the intentions of the driver. Assistance systems need to ensure that they aid the driver in performing his intended task and do not override his intentions.

In order to be able to offer relevant assistance to the driver, assistance systems need to know the driver's intentions. Information about the driver's current and upcoming driving maneuvers, combined with information about the environment, would enable systems to offer targeted, maneuver-specific assistance in the automobile. This paper describes the development of a system for the inference of the current driving maneuver being performed by the driver.

II. OBSTACLES TO MANEUVER RECOGNITION

Although the sensors present in the automobile today provide us with valuable information about the driver, the automobile and the driving environment, the problem of driving maneuver recognition is no trivial one.

A major obstacle to automatic driving maneuver recognition is presented by the wide variety of styles in which driving maneuvers are performed. Indicators, for instance, are sometimes, but not always, used to signal lane changes and turns. An overtake maneuver could involve a burst of speed, but could also be performed with no acceleration whatever.

It is relatively easy for a human observer to make an educated guess about the driver's intended maneuver, based on his observations and his experience with the field of driving. It remains, however, relatively difficult to define a set of rules that would perform this identification task.

A second major obstacle to maneuver recognition is presented by the uncertain and sometimes invalid values returned by today's automobile sensors. The values delivered by the sensors cannot be relied upon for their accuracy.

Traditional rule-based methods of computation are insufficient for dealing with these problems. Instead, we use a statistical analysis of the driving patterns found in different driving maneuvers combined with probabilistic reasoning in order to infer the driving maneuver being performed. Bayesian models, which offer a solid theoretical framework for the derivation of inferences from partial beliefs, are used for the inference of the driving maneuver being performed from the uncertain sensor values available.

Several researchers have been studying the problem of driving maneuver recognition. Kuge et al. [1], Salvucci et al. [2,3] and Torkkola et al. [4] have studied methods for maneuver recognition using accurate input data from driving simulators.

Oliver and Pentland [5] have implemented a maneuver-recognition system using data from real drives supplemented by accurate information about vehicle positions and driver gaze direction manually extracted from saved video.

We focus on the problem of maneuver recognition using only the uncertain data available from the automobile data bus and sensors. We present a system for the automatic recognition of the current driving maneuver using Bayesian networks for the analysis of the ambiguous information available in the automobile today.

III. Driving Maneuvers

The driving task can be classified into individual driving maneuvers in several different ways. Nagel suggests a classification into seventeen different driving maneuvers [6]. For the purposes of our research, ten driving maneuvers were selected for identification, loosely based upon Nagel's classification. The selected maneuvers were defined in the context of the experiment. They were defined as being mutually exclusive. The selected maneuvers are:

1. Stopped
2. Follow road
3. Follow car
4. Turn left
5. Turn right
6. Merge left
7. Merge right
8. Overtake
9. Enter freeway
10. Exit freeway

IV. Analysis and Test Tool: the ViewCar

Figure 1: The ViewCar

Data patterns in the different driving maneuvers in real traffic conditions were analyzed using the DLR ViewCar, a research vehicle equipped with cameras and sensors to measure and record information about the driver, the automobile and the driving environment during the drive.

Figure 2: ViewCar sensors

The position of the automobile is measured using a high-precision positioning system. The positions and speeds of objects ahead of the ViewCar are measured using a laser scanner. FaceLab software records the driver's gaze direction. Lane information is measured using a camera-based lane-detection system. Data from the automobile data bus and physiological data of the driver (e.g. his heartbeat and skin resistivity) are also recorded.

The values returned by the various sensors vary in their accuracy. The lane-detection system and the gaze-detection system supply estimates of the momentary accuracy of their outputs.

Front, rear and side cameras record video information about the driving environment. A camera focussed on the driver records video information about the driver during the drive. The video information is analyzed manually after the drives in order to identify the maneuvers driven.

Table 1: ViewCar Sensors

Sensor	Description	Manufacturer
Laser scanner	Detection of the position and speed of objects in front of the ViewCar	IBEO Automobile Sensor GmbH, Hamburg
Positioning system	Determine the position of the automobile in absolute coordinates	iMar GmbH, St. Ingbert
Lane detector	Video-based lane detection system	ADCS GmbH, Lindau
FaceLab system	Detection of the driver's gaze direction	Seeing Machines, Canberra
Physiolog	Measurement of the physiological data of the driver	GEFATECH GmbH, Tiefenbach
Optical Cameras	Video recording of the driver and the environment around the automobile	Aglaia GmbH, Berlin

Test drives were conducted in real traffic on highways, country roads and town roads in the Braunschweig area, and the resulting data was analyzed to identify evidence patterns in different driving maneuvers.

V. Dealing with Uncertainty

Researchers in the field of Artificial Intelligence have developed several methodologies for dealing with uncertainty. Some schools have invented entirely new calculi for the task, such as the Dempster-Schafer calculus, fuzzy logic and uncertainty factors. Followers of the Bayesian school, in contrast, use the conventional theoretical framework of probability theory with the support of computational facilities needed to perform AI tasks.

The basis of Bayesian modeling lies in Thomas Bayes' inversion formula:

Given a hypothesis *H* and evidence *e*, the conditional probability of *H* being true given *e* can be calculated as:

$$P(H \mid e) = \frac{P(e \mid H) \times P(H)}{P(e)}$$

This rule, easily derivable from the definition of conditional probabilities,

$$P(H \mid e) = \frac{P(H,e)}{P(e)}$$

and

$$P(e \mid H) = \frac{P(H,e)}{P(H)}$$

is used to update our belief in a hypothesis in response to incoming evidence. The importance of this formula is that it expresses the probability $P(H \mid e)$, usually difficult to compute, in terms of quantities which can be directly determined from experiments [7].

A Bayesian Network is a directed, acyclic graph. Nodes represent variables of interest and the edges represent causal dependencies between the nodes. The strengths of these dependencies are described by local conditional probability tables [8].

A key feature of Bayesian Networks is their support of bidirectional inference. Inferences can be derived by propagating information in any direction. When the network is given evidence about any subset of its variables, it supports the computation of probabilities of any other subset.

Bayesian Networks also offer an efficient framework for the combination of prior knowledge with information learned from experiments. They can continuously update the conditional probability distributions based on observational data when new evidence is propagated through the network [9].

VI. Maneuver Recognition System

A Bayesian system for automatic driving maneuver recognition in the automobile has been implemented at the Institute of Transportation Systems of the German Aerospace Center. The inputs to the system are CAN-Bus data, lane position, laser scanner data about the position of vehicles ahead of the automobile and the automobile position.

A reference stretch of road was defined for test drives. Static environmental information about the stretch was recorded. Information from the vehicle's positioning system is mapped to information about the speed limit, the number of lanes and the presence of a ramp at the given position.

A Bayesian Network model of the domain of driving maneuvers is used to fuse the input data from the data bus and the various sensors and to map the input data to the most likely driving maneuver. The output of the system is the recognized maneuver and the confidence level that the system has in the recognition.

The system has been designed for real-time operation in the ViewCar. At present, however, data from the laser scanner and the lane-detection system are fused offline, in order to filter out objects which are outside the boundaries of the road. The maneuver-recognition system was validated by replaying the saved data from the drives.

VII. Experimental Results

Validation of the system was performed on data from 40 minutes of driving by two test subjects in real traffic. The test drives were performed on the defined test route, which included highways, country roads and town roads in the Braunschweig area.

The recorded video information from the drives was analyzed manually in post-processing together with the databus and sensor information in order to classify the driving maneuvers performed during the drive. The manually classified maneuvers were compared with the maneuvers identified by the recognition system in order to test the system accuracy.

Tests with the prototype system returned the following results with the minimum recognition confidence threshold set to 60%.

1. 140 out of 152 driven maneuvers (92.1%) were correctly recognized by the system.
2. The correct maneuver was recognized during 77.0% of the total drive duration.
3. The system returned an "unrecognized maneuver" during 9.2% of the total drive duration.
4. The system returned a false maneuver during 13.7% of the total drive duration.

Table 1: Driving maneuvers

Maneuver	**Number driven**	**Number recognized**
Stopped	2	2
Follow Road	48	48
Follow Car	41	40
Turn left	5	4
Turn right	3	3
Merge left	11	10
Merge right	23	19
Overtake	13	8
Enter freeway	2	2
Exit freeway	4	4

Recognition of the overtake maneuver was observed to be strongly dependent upon the output of the laser scanner. Due to the limited range of the laser scanner, vehicles far ahead of the ViewCar were not detected. Maneuvers which involved the overtaking of vehicles far ahead of the ViewCar were poorly recognized.

Due to the position of the laser scanner at the left edge of the ViewCar's front bumper, the scanner ceased to detect vehicles being overtaken soon after the beginning of the overtake maneuver. Once the ViewCar began to pass the vehicle being overtaken, recognition confidence in the maneuver was observed to drop steeply, as the vehicle being overtaken was no longer detected.

The prototype maneuver-recognition system delivered promising results. Further optimization is, however, required in order to increase the recognition accuracy of the system and decrease the rate of false recognition.

VIII. Future Work

Extensive validation with more driving data is underway. More complex models of the driving maneuvers are being constructed in order to improve recognition accuracy.

Work is in progress on the online fusion of the data from the laser scanner and the lane detection system, in order to enable the real-time use of the maneuver-recognition system in the ViewCar.

A long-range radar sensor is being built onto the front of the ViewCar. As the range of the radar is longer than that of the laser scanner, the detection of vehicles far ahead of the ViewCar is expected to improve.

Researchers [3,4] have described the usefulness of driver gaze behavior in predicting driver intent. The correlation of gaze behavior with current and upcoming driving maneuvers is being studied. If strong correlations are found, the integration of this information could provide the maneuver-recognition system with useful predictive power.

IX. REFERENCES

[1] N. Kuge, T. Yamamura, O. Shimoyama and A. Liu., "A Driver Behavior Recognition Method Based on a Driver Model Framework", Society of Automotive Engineers Publication, 1998.

[2] D.D. Salvucci, E.R. Boer and A. Liu, "Toward an Integrated Model of Driver Behavior in a Cognitive Architecture". Transportation Research Record, No. 1779, 2001.

[3] D.D. Salvucci, "Inferring Driver Intent: A Case Study in Lane-Change Detection," in Proceedings of the Human Factors and Ergonomics Society 48th Annual Meeting, Santa Monica, CA, USA, 2004.

[4] K. Torkkola, S. Venkatesan and H. Liu, "Sensor Sequence Modeling for Driving," in Proceedings of the 18th International FLAIRS Conference, Clearwater Beach, Florida, USA, May 2005.

[5] N. Oliver and A. Pentland, "Graphical Models for Driver Behavior Recognition in a SmartCar," in Proceedings of the IEEE Conference on Intelligent Vehicles 2000, Detroit, Michigan, USA, October 2000.

[6] H.H. Nagel, "A Vision of "Vision and Language" Comprises Action: An Example from Road Traffic," Artificial Intelligence Review, Volume 8. The Netherlands, Kluwer Academic Publishers, 1994.

[7] J. Pearl, Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference. San Mateo: Morgan Kaufmann, 1988.

[8] J. Pearl, "Bayesian Networks," UCLA Cognitive Systems Laboratory, Technical Report (R-216), Revision 1. In M.Arbib (Ed.) Handbook of Brain Theory and Neural Networks, MIT Press, 149-153, 1995.

[9] J. Pearl, "Bayesian Networks, Causal Inference and Knowledge Discovery", UCLA Cognitive Systems Laboratory, Technical Report (R-281), March 2001. In Second Moment, March, 2001.