Human Behavior Based Predictive Brake Assistance

Joel C. McCall and Mohan M. Trivedi
Computer Vision and Robotics Research Laboratory
University of California, San Diego
{jmccall,mtrivedi}@ucsd.edu

Abstract—Driver assistance systems have both the potential to alert the driver to critical situations and distract or annoy the driver if the driver is already aware of the situation. As systems attempt to preemptively warn drivers more and more in advance, this problem becomes exacerbated. We present a predictive braking assistance system that identifies not only the need for braking action, but also whether or not a braking action is being planned by the driver. Our system uses a Bayesian framework to determine the criticality of the situation by assessing (1) the probability that braking should be performed given observations of the vehicle and surround and (2) the probability that the driver intends to perform a braking action. We train and evaluate our system using over 22 hours of data collected from real driving scenarios with 28 different drivers.

I. INTRODUCTION

Rear-end collisions account for a large portion of traffic accidents [1]. To help mitigate this problem, predictive braking systems and adaptive cruise control systems have been developed [2]. However, these types of systems usually rely solely on the vehicle and vehicle surround sensors, either ignoring the human component of driving or learning the driver's control behavior using only these sensors. As with all human-computer interfaces, this has the potential to work against the driver, distract the driver further, or even annoy the driver so that the driver ignores or disables the system [3]. It is therefore important to directly take the driver's actions into account when designing a driver assistance system.

To build an effective brake assistance system, we must first assess the criticality of the situation and the intended actions of the driver. This allows us to not only tailor our system based on the learned behaviors of human subjects, but also predict future behavior based on the driver’s intended actions. Put into a Bayesian framework, we can construct a probability of the need for system intervention. In this way, the system can sense critical situations in which braking is required. If the system also determines that the driver is already planning a braking action or evasive maneuver, a warning or preventative action might not be taken by the system unless the situation becomes more severe. Likewise, if a slightly less critical situation occurs, but the driver is distracted or otherwise inattentive to the need for corrective action, an early warning or subtle corrective action can be taken by the system. By using a probabilistic model for the system, we can construct warnings and preventative measures based on varying levels of situational severity and driver attentiveness.

A. Research in Driver Behavior Analysis and Braking Assistance Systems

Longitudinal vehicle control and braking assistance systems have been studied extensively in recent years. Vahidi et al. [2] provide an extensive summary of such efforts. Many of these systems are designed for either autonomous vehicle control or Adaptive Cruise Control (ACC) and based on metrics such as the distance to the lead vehicle. Sun et al. [4] proposed a fuzzy decision making algorithm and vision perception to ascertain the “degree of exceeding safe distance.” Others have based their systems on learned driver behavior. Hillenbrand et. al [5] demonstrate a system that takes into account the driver’s braking action by classifying braking into either normal braking or emergency braking. No predictive or direct information beyond that obtained from the vehicle is used. We attempt to go beyond what has been previously researched by including information on the driver’s intended actions to predict situations in which the active safety system’s intervention is not necessary. To do this we need to analyze the driver more directly using video sensors to determine behavior and intent.

Driver behavior has also been explored extensively. Various techniques such as cognitive models [7], Dynamic Bayesian Networks [8] and other variants such as Hidden Markov Models (HMMs) [9], [10] and Coupled-HMMs [11] have been proposed. Previously, we have used sparse Bayesian learning to infer lane change intent [12]. While these present frameworks for assessing the behavior, intent, and state of the driver, what is truly of interest is the driver’s role in handling critical situations and assessing the need for system intervention. It is this problem that we will explore in the following sections.

In this paper we introduce a probabilistic model for determining the criticality of the current situation with respect to lead vehicle collisions. We train and evaluate key components of this model using data captured from real-world driving situations to help show the system’s potential. In Section II we will present the probabilistic framework and design of our system. In Section III we will present results from various components of our system as well as demonstrate its functionality. Finally, we will highlight our research and explain possible future directions for this research in Section IV.
II. HUMAN-BEHAVIORAL BASED PREDICTIVE BRAKING ASSISTANCE

In order to assess the criticality of the situation, we condition the probability of a critical situation on the need for braking action to be performed and the intended action of the driver. This is shown in (1),

\[ P(C|B_s, B_d, O) = \frac{P(B_s, B_d|C, O) P(C)}{\sum_{c \in C} P(B_s, B_d|C = c, O) P(C = c, O)} \] (1)

where C represents the criticality of the system, O represents our input observations, \( B_s \) represents the need for braking based on the vehicle and surround sensors, and \( B_d \) represents the probability that the driver does not intend to begin braking or evasive action. Furthermore, assuming conditional independence, the relationship between \( B_s \) and \( B_d \) can be described by (2). While this “naive” Bayes assumption does not necessarily hold, in practice, this assumption can greatly simplify the system and provide good results [13].

\[ P(B_s, B_d|C, O) = P(B_s|C, O) P(B_d|C, O) \] (2)

As we will describe in Section III-A, these density functions are learned from the sensory inputs described in Section II-B. This model is depicted graphically in fig. 1.

Furthermore, its underlying Bayesian framework allows for probabilistic outputs, fitting well into our Bayesian network.

\[ P(B|O = x) \approx \sigma(y(x)) = \sigma\left(\sum_{i=1}^{M} w_i K_i(x)\right) \] (3)

where

\[ \sigma(y) = \frac{1}{(1 - e^{-y})} \] (4)

and \( B \) represents the random variable for which we are estimating the density function (i.e. either \( B_s \) or \( B_d \)). In our implementation we choose to use a radial basis function for \( K_i \).

B. Sensory Inputs

The framework we have just described presents us with natural classes of sensory inputs: sensors that convey information about the vehicle state and surround and sensors that convey information about the driver’s intended actions. Note that certain sensors such as steering wheel positions and pedal actions can provide information about both the vehicle and the driver and therefore belong to both classes of sensory inputs. All data was collected from real-world driving using an intelligent vehicle test bed outfitted with a variety on onboard sensors, color cameras, near-infrared (NIR) cameras, and LASER RADAR.

1) Vehicle and Surround Sensors: Onboard vehicle sensors obtained from the vehicles Controller Area Network (CAN) data bus include:

- steering angle
- wheel speed
- longitudinal acceleration
- lateral acceleration
- yaw rate
- brake pedal pressure
- accelerator pedal position

In addition to these sensors, a LASER RADAR range finder is also installed in the vehicle, providing information on the distance and relative velocity of the lead vehicle. LASER RADAR “cut-in” sensors provide information about the relative distance to vehicles on the periphery of the current lane. For illustration, a time series of selected signals is shown in fig. 2.

2) Driver Behavioral Sensors: In order to capture information about the driver’s actions, we have installed a color camera observing the driver’s head and a NIR camera observing the driver’s feet. Example images from these sensors can be seen in fig. 3.

Driver head and facial movement are then estimated using optical flow around the area of the driver’s head. Also, a face detector provides information on whether or not the driver is looking forward. In this way we can capture information about the driver’s head movements, lip and facial feature movements, and whether their attention is on the road ahead of them. Driver foot movements are captured using a combination of the pedal positions and pressures as well as tracking the
is uniform, thereby simplifying (1) to

\[ P(C|B_s, B_d, O) = k P(B_s, B_d|C, O) \]  \hspace{1cm} (5)

where \( k \) is a scale factor derived from the denominator in (1) and \( P(C) \). Combining this with (2), we can see that we need to learn the probabilities \( P(B_s|C, O) \) and \( P(B_d|C, O) \). However, our system further simplifies if we assume that \( P(B_d|C, O) \), or the driver’s inattentiveness, is situationally independent, yielding

\[ P(B_d|C, O) = P(B_d|O) = (1 - P(B_{ca}|O)) \]  \hspace{1cm} (6)

where \( P(B_{ca}|O) \) represents the probability that the driver is planning corrective action, given the current observations. This assumption is necessary in order to ensure that the prediction of the driver’s intended actions is based solely on the driver’s attentiveness and not biased by the surrounding situation.

To learn the density function \( P(B_s|C, O) \), we look at the braking profiles for situations that are deemed critical. For our system, we labeled all situations encountered in driving requiring heavy braking and having a time-to-collision (TTC) metric smaller than threshold \( T_{TTC} \) as critical. We then separated our vehicle and vehicle surround training data into two classes (critical and non-critical) and used them to train the expected braking profiles (thereby representing the need for braking given the situation). In the density function \( P(B_s|C, O), O = O_{es} \) where \( O_{es} \) represents the observations taken from the vehicle and surround. Driving behavior can also vary greatly between drivers, making predicting comfortable safety margins between drivers difficult. To help relieve this problem, it is also possible to specify the density functions based on the safety margins computed from the TTC and vehicle dynamics. This would allow a more rigid definition of a critical event, but would remove the learned driving behavior from the estimation. Combining these two types of classifier yields a classifier in which a learned behavior classifier with a low false positive rate is used until a specific safety margin limit is reached.

We can apply a similar technique for learning \( P(B_{ca}|O_{db}) \) using the input observations from the driver behavioral sensors, represented by \( O_{db} \). Again we split the data into classes of “planning a braking action” and “normal driving without braking”. Observational data is taken from a time window preceding the actual braking action. Some false alarms and overlap may occur because, using this method, we are grouping aborted braking actions into the “driving without braking” category. Labeling these types of events would require more meticulous hand labeling of the data.

B. Results for Predicting the Need for Braking in Real Driving Scenarios

As discussed above, estimating and accurately classifying driver behavior from the vehicle dynamics and surround is difficult because of the large variations in driver behavior. Certain drivers are more comfortable with shorter time-to-collision before initiating a braking maneuver. By predicting
situations in which driver’s would normally start braking, we can issue earlier warnings in cases where the driver is distracted or inattentive.

![ROC curve for predicting driver braking behavior from vehicle and LASER RADAR data.](image)

Fig. 4. ROC curve for predicting driver braking behavior from vehicle and LASER RADAR data.

C. Results for Advanced Prediction of Driver Intent

One of the most important parts of our system is the estimation of the \( P(B_{oa}|O_{db}) \) density function. An accurate prediction of braking behavior before any braking action has occurred can inform the system that the driver is aware and in control of the situation. We tested the accuracy of this part of our system using the data set as described in Section III-A by looking at the driver’s behavior before any braking action has occurred. This allows our system not only to determine when the driver is braking by examining the pedal positions, but also predict in advance the intention of the driver to initiate a braking maneuver.

![ROC curve for predicting braking behavior from driver behavioral data at various times before the braking event.](image)

Fig. 5. ROC curve for predicting driver braking behavior from driver behavioral data at various times before the braking event.

D. Results of a Case Study

To help demonstrate the system, we will show the results generated during a specific braking maneuver and analyze the system performance. For this study we have trained the classifier to detect driver intent to brake one second before braking and combined this with a median filter with a one second window to provide hysteresis. The probabilities of the driver’s intent to brake and the need for braking based on the vehicle data are shown in fig. 7 and fig. 8, respectively. The combined probability of a critical event requiring system intervention is shown in fig. 9. The system first identifies the need for a braking action about 5 seconds before the braking takes place. When the driver’s intentions to brake are observed by the system, at about 3.3 seconds before the braking action, the criticality of the situation is reduced. Cut-scenes from this sequence are shown in fig. 6.

![Video images from the foot camera and the forward viewing camera from the sequence detailed in Section III-D. The images are taken 4 seconds before the braking occurs.](image)

Fig. 6. Video images from the foot camera and the forward viewing camera from the sequence detailed in Section III-D. The images are taken 4 seconds (a), 2 seconds (b), and 0 seconds (c) before the braking occurs.

IV. CONCLUSION AND FUTURE DIRECTIONS

In this paper we have introduced a novel method for fusing predicted driver behavioral information with vehicle and surround information for braking assistance. The framework allows for the assessment of the criticality of the current situation and the need for intervention by an intelligent vehicle safety system. Data for training and testing of the system was compiled from real-world driving scenarios, thereby tuning the system to common braking behaviors. By using sensors that capture the driver’s intended actions as well as the vehicle and surround information, we can create systems that behave in a complementary manner to the driver’s actions and are less prone to annoy the driver. Individual components of the system were evaluated and a demonstration of the system as a whole was shown.

While we used the example of a braking assistance system, this framework could be used for a broad range of applications.
Other important driver behaviors or critical events could be detected in advance. The system can be expanded further by combining it with systems for lane change prediction or other behavioral analysis. Another key aspect of any driver assistance system is its interface with the driver itself. While we have shown the observational portion of the system, the types of warnings purveyed to the driver are no less important. However, determining the optimal warning levels, the method for warning the driver (aural, visual, haptic), and the proper times in which to warn the driver require much more controlled studies. While data collection and behavioral observations can be made using a real vehicle in real driving scenarios, simulator studies would allow the system to be evaluated in more critical situations.

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