To appear in Human Modeling in Assisted Transportation, C. Cacciabue et al, Eds.

Modeling Differences in Behavior Within and Between Drivers

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Abstract

A new generation of driver assistance systems such as advanced collision warning and intelligent brake assist are now available options for the modern automobile. However, the addition of each new system increases the information load on the driver and potentially detracts from their ability to safely operate the vehicle. Over 10 years ago, we [17] suggested that a car that could infer the current intent of the driver would be able to appropriately manage the suite of systems and provide task relevant information to the driver in a timely fashion. This "smart car" would observe the driver's pattern of behaviour in terms of their control of the vehicle then infer their current driving task using a Markov Dynamic Model. The approach could recognize driver actions from their initial behaviour with high accuracy under simulated driving conditions. Since that time new computational approaches and improved in-vehicle technology (e.g., GPS technology, advanced radar and video/computer vision, etc) have moved the realization of this concept further along. Yet, one fundamental question still needs to be carefully addressed: Can these driver models, built on statistical descriptions of driver behaviour, accurately model the differences between drivers or changes within an individual driver's behaviour? In this paper, I describe some examples these differences and discuss their potential impact on a model's ability to consistently recognize behaviour. To ensure the acceptance of the next generation driver assistance systems, these issues will have to be resolved.

Background

Intelligent cruise control and lane departure warning systems have been under development for more than 15 years and have recently reached a level of technical maturity that manufacturers have deemed to be safe and reliable. Most major manufacturers (e.g., Mercedes, Nissan, Ford, BMW, and Toyota) now offer some form of these systems in their luxury automobiles. The driver-system interaction still generally implemented at a “low” level of automation such that ultimate control of the vehicle is still entirely entrusted to the driver, e.g., only visual or audible warnings are presented to the driver to warn of impending collision or lane departure. The intent of the driver, e.g., car following, is established when they activate the system and changes in intent are also initiated by some control activity such as stepping on the brake which disengages the system. The low level of automation prevents the system from interfering with the driver when their intentions change but neglect to deactivate the system. The vehicles are allowed some control authority but only under conditions where the driver may not be able to respond in time to avoid an accident (e.g., activation of brake before collision)

As driver assistance systems are given more control authority under normal driving circumstances, it becomes critical for these partially autonomous driver assistance systems (PADAS) to be aware of the driver’s intentions. The proliferation of PADAS in the vehicles means that more warnings or information alerts may be displayed to the driver, potentially resulting in competition for the driver’s attention. Thus, driver models that quickly and accurately recognize the current actions or anticipate future actions are needed to PADAS to provide appropriate and timely warnings, information, and/or actions.

Driver model development

Our initial work on driver modeling [12, 17] proposed a framework, the Markov dynamic model (MDM), that would be able to recognize human driver’s current action or in the ideal case anticipate the human driver’s intended behavior. Figure 1 illustrates an example of a 4-state MDM that exemplifies how human behavior passes through a constrained series of states within the context of a driving action. The MDM can also be structured as a hierarchy of models covering long-time-scale behavior (e.g., at a tactical level such as deciding to pass another vehicle) down to models that

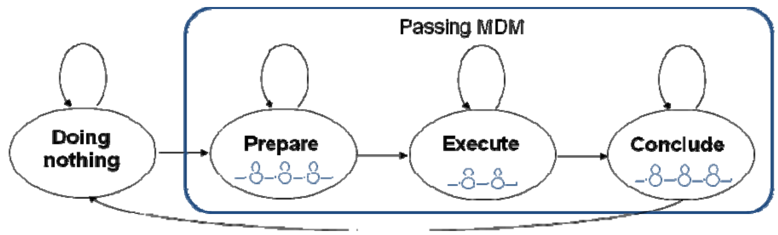

Figure 1 - A Markov dynamic model of driver action (e.g., passing). Finer-grained MDMs could be used to describe driver behavior in the individual sub-states.

describe the finer-grained structure of the behavior in a sub-state (e.g., how the driver prepares to pass another vehicle).

Our initial experiments with MDMs inferred driver behavior based solely on measurements of the driver's vehicle control behaviour which included the heading, velocity, and acceleration control of the vehicle. Experimental tests with our MDMs in a constrained simulated driving scenario showed that we could recognize a driving maneuver in the first 1.5 seconds with 95% accuracy.

There are other sources of observable driver behaviors such as driver head movements or eye movements which could be used. The eye movements of drivers have idiosyncratic patterns depending on driving task [8, 9, 11, 15, 23] that could be utilized within the same MDM framework [11] to potentially improve recognition performance [6]. Since drivers tend to preview the road ahead with their eye movements, this information may improve the predictive capability of driver models. The external environment, such as the surrounding traffic, or even path information from a navigation system may further constrain the probable space of driver intentions. Oliver and Pentland [16] used coupled Hidden Markov models (CHMMs) to link the behavior of the surrounding traffic environment with driver control behavior and found that it improved recognition of driver intentions. In the intervening 10 years since our initial work, numerous other techniques have been investigated including stochastic approaches (e.g., Autoregressive HMMs [1], sparse Baysian learning [14], cognitive architectures [5, 22], support vector machines [13], neural networks [26] and Dempster-Shafer evidence theory [28].

Modeling Differences in Driver Behavior

Most driver models have generally been developed from the behavior of a relatively small population of drivers using a limited number of vehicle types, roadways and traffic conditions. The reported results generally show good recognition performance under these constrained conditions, but it remains an open question whether these models perform equally well when tested across a wider set of drivers, vehicles and under different operating conditions. If a suitable model can be used for many types of drivers, then a generic system could be easily implemented across a fleet of vehicles. However, it seems more likely that the population of drivers will need to be subdivided into subgroups with separate models for each group. In either case, it will be critical that the driver models perform well "out of the box" to ensure the acceptance of and trust in the PADAS.

Differences in behavior between individual drivers

Based on the body of research, one obvious dimension to group drivers would be their level of experience. Beginning with a study by Mourant and Rockwell (1972) that showed how novice drivers tended to focus their gaze across a smaller portion of visual space, many other studies have shown that novice drivers tend to drive at higher speeds, keep a smaller time/distance headways to leading vehicles, and brake later in response to the vehicle or roadway ahead [2]. Typically, experiments to collect data for parameter estimation have used experienced drivers in an attempt to get baseline behavior data. But younger less experienced drivers are disproportionately involved in fatal accidents in the US and might derive greater benefit from driving with a PADAS. Amata et al. (2009) compared the performance of multiple regression models estimated from expert, non-expert and mixed population deceleration to recognize deceleration behavior (e.g. releasing the accelerator or using the brake). Model performance was slightly different between the expert and non-expert models, but no conclusions could be drawn since only 2 expert and two non-expert drivers were used.

Even within the population of experienced drivers, there is likely to be significant variability in behavior due to different "styles" of driving. In this instance, driving style reflects the individual's typical choices of speed, time headway and attentiveness for comparable situations. Unfortunately, there seems to be little agreement about the characterization of driving styles and several different measurement tools exploring many possible dimensions of the driver (e.g., risk aversion, gap acceptance, use of turn signals, etc.) been created to describe driving style. One possible approach to reduce the number of classifications might be multidimensional analysis [27]. Using subjective measurements from a questionnaire assessing driving behaviors, self-esteem, and other typical traits, this analysis showed that drivers could be grouped into eight distinct driving styles. While these types of analyses are far from definitive, they could be a useful tool to test whether their actual driving behavior, measured in a real situation, would lead to similar subject groupings.

The variability between individual drivers might also be lessened with the selection of appropriate parameters for the model. Driver inputs such as the accelerator or brake pedal positions are very noisy signals in the sense that the moment-to-moment position of the pedals probably has a very small impact on actual vehicle speed due to vehicle dynamics. Different drivers would probably exhibit a large variance in distribution of pedal positions for similar velocity or acceleration profiles. Furthermore, deterioration in vehicle sensors, engine performance, or traffic and weather (e.g., dry versus icy roads) conditions could significantly change the pattern of movements for the same intended action. Qiao et al. [20] showed that a change of 4% in the accuracy of their speed sensor, a typical estimate of deterioration by the manufacturers, led to a 5% drop in the recognition accuracy of their models. A better approach is to model variables that drivers are likely to perceive and control, such as time-to-contact. This was an important conceptual difference between our MDM approach and earlier work using classical techniques such as neural nets or fuzzy logic [19, 25]. The MDM was intended to model how a set of dynamic processes (e.g., the driver's set of intended actions) was controlled in order to generate the observed behaviour rather than trying to model the pattern of vehicle parameters directly.

Changes in behavior within an individual driver

Assuming that a general driver model or a small set of models with reasonable recognition performance could be realized, the models must still account for changes in an individual driver's behavior over both long (e.g., months) and short (e.g., hours or less) time scales. Certainly driver models could be adapted or tuned to a specific driver over time by re-estimating parameters using new behavioral inputs. Figure 2 illustrates how an initial model would segment the driver's real-time behavior into individual actions such as lane changing or passing. Over time, the model would accumulate a number of new examples of a particular behavior, which could be considered a new training set from which to re-estimate the model parameters. For changes that occur slowly over time such as those associated with aging, the model would most likely be able to track the resulting behavioral changes and maintain its recognition performance.

Another obvious cause of change in a driver's behavior is the experience they accumulate over many years of driving. Studies of novice and experienced drivers have typically compared one group to another but have not investigated the pattern of the changes from novice to experienced driver. If the changes evolve slowly over time (e.g., over a period of months, the driver slowly increases their time headway as they gain experience), then the process of continuously updating model parameters would most likely be able to follow the changes without a loss of performance.

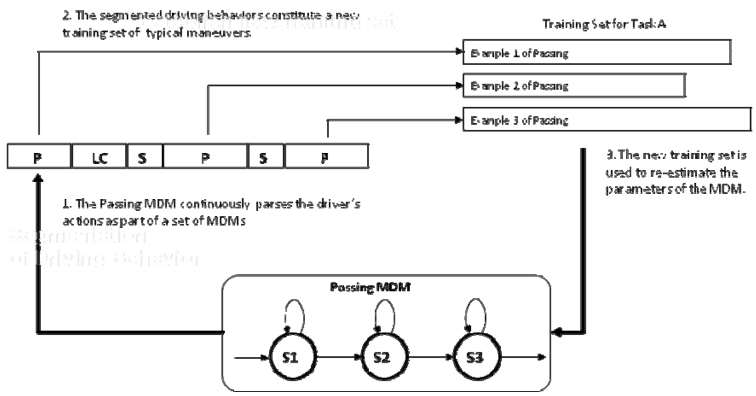

Figure 2 – The parameters of a MDM describing passing could be continuously updated with new examples of the maneuver. The continuous learning could help the model account for changes in vehicle behavior over time.

However, learning a complex skill such as driving may not proceed in a smooth and linear fashion, but instead be punctuated by sudden changes in behavior as the driver decides to adopt a drastically different strategy which is more desirable. For example, a novice driver might begin shifting their lateral lane position close to the lane markings when being passed by large trucks after experiencing a near accident from the side. This could result in the driver model occasionally misinterpreting this shift as an intended lane change and activate an unexpected PADAS action or warning. Over time the model might adapt to the new behavior, but time lag would be depend on the magnitude of the change in behaviour and the frequency at which examples of the new behavior. During the period of adaptation, the driver might perceive the PADAS to be less reliable and reduce their trust in its accuracy.

Fatigue, distraction and emotions are other potential causes of episodic and short-term changes in driving behavior. Fatigue in particular can be problematic since people often underestimate their level of tiredness and often assume that they are able to perform at a level higher than what objective measures would suggest [21, 29]. Presently, most approaches for detecting a driver's state of fatigue use machine vision techniques to observe the driver's eyes and calculate the percentage of time of eye lid closure (i.e., PERCLOS) which correlates with fatigue or drowsiness [30]. Thus, these systems are limited to detecting the state when the driver is likely to lapse into micro-sleep episodes. However, the effects of fatigue can affect behavior even before drivers reach than that level of tiredness. Fatigue from prolonged wakefulness or time-on-driving task has been shown to increase the deviations in speed control, steering behavior, and lateral lane position as well as increase reaction time [4, 18, 24]. Sleep restriction studies in which subjects sleep less than 8 hours per night over a period of days have shown that many cognitive processes such as sustained attention, working memory or executive function can be degraded. [3, 10] Degradations in working memory, as an example, might affect the mental workload they are able to sustain. Thus, drivers may monitor important secondary tasks (i.e., monitoring surrounding traffic) less frequently or even not at all. The problem of sleep restriction is particularly worrisome in today's society since a large proportion of people report getting less sleep than generally required [3]. Gunzelmann and colleagues [7] incorporated mechanisms representing the effects of sleep and circadian rhythms on central cognitive function into a cognitive driver model [22] and generated driver behavior under simulated sleep deprivation conditions. Their generated data showed a pattern of lateral deviation behavior that was very similar to behavior of a human driver under similar conditions [18]. Similar studies using cognitive models will be needed to better understand the relationship of these cognitive functions in the context of performing a complex skill such as driving while fatigued. The knowledge gained from these studies could then be applied to computational driver models for PADAS.

Conclusions

As the next generation of PADAS gain more control authority, they will need to be aware of the driver's current actions or intentions to interact appropriately with the driver. Over the past 10 years, many computational models to recognize driver behavior have been developed with promising results but only for a limited range of drivers. Differences over the larger population of drivers may preclude creating a general driver model. By separating the population into smaller groups along well studied dimensions (e.g., novice versus experienced drivers), the variability in behavior within the group may be reduced, which should improve recognition performance. Driver models must also be able to account for changes in an individual driver's behavior over time. For longer-duration changes, the continuous re-estimation of the model may be sufficient. However, shorterduration changes due to fatigue and other factors may affect recognition performance and impact the reliability of PADAS. The processes that cause these changes will need to be characterized and incorporated into future driver models.

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