Using Driver Type to Better Predict Drivers' Adaptive Cruise Control Settings

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Abstract. Adaptive Cruise Control (ACC) is a technology that allows a vehicle to automatically adjust its speed to maintain a preset distance from the vehicle in front of it based on the driver's preferences. Individual drivers have different driving styles and preferences. Current systems do not distinguish among the users. We introduce a method to combine machine learning algorithms with demographic information and expert advice into existing automated assistive systems. This method can reduce the number of interactions between drivers and automated systems by adjusting parameters relevant to the operation of these systems based on their specific drivers and context of drive. This method sheds light on the kinds of dynamics that users develop while interacting with automation and can teach us how to improve these systems for the benefit of their users. While accepted packages such as Weka were successful in learning drivers' behavior, we found that improved learning models could be developed by adding information on drivers' demographics and a previously developed model about different driver types. We present the general methodology of our learning procedure and suggest applications of our approach to other domains as well.

1 Introduction

Cruise control is a known technology that aids drivers by reducing the burden of controlling the car manually. This technology controls the vehicle speed once the user sets a desired speed. Cruise control is not only convenient, but it has the potential to improve the flow of traffic [11], and can be effective in reducing driver fatigue and fuel consumption [1]. In this paper, we focus on a second generation of cruise controls–adaptive cruise control (ACC). ACC is designed as a comfort-enhancing system, which is an extension of conventional cruise control (CC). The ACC system relieves the driver from some of the longitudinal-control tasks by actually controlling speed and headway keeping, but the driver can choose to engage or disengage the ACC at any time. The major difference between ACC and CC is the use of radar technology to maintain a preset distance between the vehicle with the ACC and other vehicles on the road. This distance is controlled by a "gap" parameter which sets the minimum gap (headway distance) to the vehicle in front of it. Figure 1 shows a picture of a steering wheel with the ACC technology. Note the existence of a "gap" switch on the left side of the figure.

While ACC adds more automation to the driving experience, it typically also requires the driver to set and adjust one more parameter, the gap setting. The current approach is to preset the gap setting to a default value which can be adjusted by the driver manually based on his driving preferences. Another approach taken in previous published attempts was to learn this setting focusing on mechanisms such as fuzzy logic [6, 7]. In these previous approaches, rules were learned manually after having interviewed human drivers. Based on these rules the gap setting value was adjusted automatically to the conditions of the drive without considering the particular driver in the vehicle. Individual drivers, however, differ in their driving styles and preferences. Therefore, a personalized learning approach may be valuable.

In this paper, we primarily focus on a method that learns how to quickly and accurately adjust the gap setting based on the specific driver and context of a drive. To accomplish this task, we created general driver profiles based on an extensive database of driving information that had been collected from 96 drivers [4]. We used post-processing of data from that study. Our general method is that once a new driver is identified we classify this driver as being similar to previously known drivers and set the initial gap setting accordingly.

The challenge of this study was to process real world data so as to obtain the most accurate and practical rules from the learning algorithms. We found that the information gleaned from demographics and the driver's type was crucial for creating more accurate learning models. This work focuses on which attributes will help, and a general methodology for adding them. By following this methodology, we found that a better application could be created in this domain, and are confident that better applications can be created in other domains as well.

2 Related Work

The concept of using a group of characteristics to learn people's behavior has long been accepted by the user modeling community. Many recommender systems have been built on the premise that a group of similar characteristics, or a stereotype, exists about a certain set of users [9]. Even more similar to our work, Paliouras et. al [8] suggested creating questionnaires, distributing them, and then creating decision trees to automatically define different groups of users. Similarly, our application assumes that some connection exists between users, which can be learned using machine learning techniques. We propose that this approach be applied to customize settings within an application, here ACC, and not within recommender systems.

Previously, Fancher et. al [5], analyzed a group of 36 drivers and their acceptance of adaptive cruise control (ACC). While all drivers enjoyed and accepted the ACC, they found that drivers could be divided into three types with each group demonstrating specific driving tendencies which impact their headway and closing speeds, relative to vehicles ahead. In very general terms, these groups were assumed to be: one that is most aggressive, another that is least aggressive, and a third that is in between. Although it is

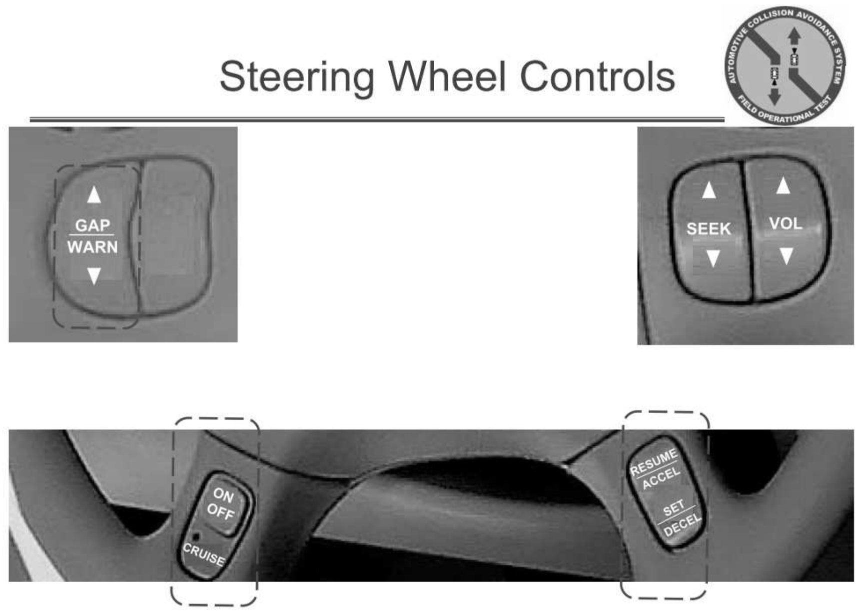

Fig. 1. A steering wheel fitted with ACC technology.

clear that more detailed grouping may exist, and that a different profiling of the drivers' population can be made, for the purpose of this study the characterization analysis was aimed at identifying the above three grouping types. The three driving styles are: 1. Hunters (aggressive drivers who drive faster than most other traffic and use short headways); 2. Gliders (the least aggressive drivers who drive slower than most traffic or commonly have long headways); and 3. Followers (whose headways are near the median headway and usually match the speed of surrounding traffic). In this scheme of things, Hunters are drivers who tend to drive faster than the surrounding flow and they tend to travel at shorter headway times than those adopted by other drivers. In contrast, at the other end of driver characteristics, Gliders tend to travel slower than the surrounding flow and they tend to travel at longer headway times than those adopted by other drivers. Between the Hunters and Gliders lie the Followers who tend to go with the flow of traffic. They tend to adapt their driving behavior to the situation they are in.

The idea of assisting the driver in the task of longitudinal control has been the focus of research in the last decade [6, 7]. Operation tests have given insight into this task. However, the goal of this project was to attempt to create an intelligent ACC agent that could potentially set this longitudinal value autonomously through adjusting its gap setting per each driver.

In this paper, we use driver characterization into types (hunter, glider or follower) in addition to other demographic information to attempt to build an application that predicts how the ACC should set its gap (headway) given this information and road situation. In general, other research has previously found that we can better predict people's behavior by combining relevant behavior theory, here about people's driving type and demographics, in conjunction with machine learning methods. These studies have included how other behavior theories: Aspiration Adaptation [10] and the Focal Points [12] could be used in conjunction with machine learning algorithms to create an improved classifier. These results also showed some positive correlation between the complexity of the problem domain and the improvement in performance when augmenting the behavior model. Thus, the more complex the learning task, the added gain in the learning model by adding behavior information. This paper explores how the behavior model of a driver's type impacts their gap setting.

3 Experimental Setup and Results

Current ACC systems allow the user to choose a value for the gap setting between six possible values (1–6). These values control the distance the ACC autonomously maintains with the vehicle in front of it. Currently, one value is set as default (in our case this value was 6) and the user may change it during his drive as he wishes. In order to study the problem of predicting what gap setting a person would select, we constructed two different types of models. The first type of model was a regression model which attempted to predict the number a given driver would select given the current driving conditions. The second type of model was a decision tree model (C4.5) which treats each number within the system as discrete values representing different categories a driver can choose. Our goal was to use the output of either model to automatically set the gap setting. Towards this goal, the second model is seemingly the better choice as its output directly correlates to a value within the system. In contrast, the regression model outputs a decimal value (e.g. 3.5) that must be first rounded to the closest value within the system to be used. However, the advantage of this model is that a mistake between two close values (e.g. 3.5 being close to 3 and 4) is not as mathematically significant as mistakes between two extreme values (e.g. between 2 to 6). In contrast, the discrete decision tree model weighs all types of errors equally. In practice, the regression model will likely be more useful if the user is willing to accept errors between two similar values.

Data for our analysis were taken from the Automotive Collision Avoidance System Field Operational Test (ACAS FOT) [4]. In that study, to understand how different drivers use an ACC, each of 96 drivers was presented with a vehicle fitted with the ACC which they used for a period of 4 weeks. During the first week the ACC system was not available. That is, if the driver engaged the cruise control, it simply maintained speed just like the conventional system (CC). During the next three weeks, if the driver chose to engage the cruise control, it functioned as ACC. In general, three different datasets were considered. The first, and most basic, dataset were objective characteristics that can be studied based on the location of the vehicle itself, e.g., headway distance to the lead vehicle, vehicle speed, longitudinal acceleration, road type (country, city, or highway), weather (including day or night) and road density (is there traffic). A second dataset added driver characteristics. These properties focus on driver demographics such as age, sex, income level (high, medium, low), and education level (High School, Undergraduate, and Graduate). The ACAS FOT data consists of a good mixture of these demographics with a 51% male to 49% female split, 31% young (aged 20–30), 31% middle aged (aged 40–50), and 38% older drivers (aged 60–70), and people from a variety of education and socioeconomic levels. The last dataset also logged a previously developed measure used to quantify a driver's behavior [5].

The experimental design of the ACAS FOT was a mixed-factors design in which the between-subjects variables were driver age and gender, and the within-subject variable was the experimental treatment (i.e. ACAS-disabled and ACAS-enabled). The disabled period was treated as a baseline measure, since the research vehicle operated like a conventional passenger vehicle. The drivers operated the vehicles in an unsupervised manner, simply pursuing their normal trip-taking behavior using the ACAS test vehicle as a substitute for their personal vehicle. Use of the test vehicles by anyone other than the selected individuals was prohibited. The primary emphasis on user selection for the field operation test was to roughly mirror the population of registered drivers, with simple stratification for age and gender. No attempt was made to control for vehicle ownership or household income levels. Thus, although the ACAS FOT participants may not be fully representative of drivers who might purchase such a system, they were selected randomly and represent a wide range of demographic factors.

Figure 2 presents the accuracy of the decision tree model to learn a driver's preferred gap setting based on this data. Clearly, adding the demographic data here is crucial, as the model's accuracy drops from over 66% accuracy with this data to less than 37% accuracy without this. As a baseline, we also include the naive classifier, which is based on the most common gap setting– here the value of 6, which is also the system's default. Note that the naive model had an accuracy of nearly 27%, far less than other models. The user's type did improve accuracy, as adding this information to the type increased accuracy to near 70%. In line with previous work, we hypothesized that adding this behavior model yields less significant increases if it can be learned from other attributes within the data. Here, we believed that adding information about drivers' type is less important, as their type was already evident from information such as the driver's demographics.

To support this hypothesis, we constructed a decision tree (again C4.5) to learn the driver's type. We found that this value could be learned with over 95% accuracy (95.22%)– which strongly supports our hypothesis. Possibly equally interestingly, we found that the most important attributes in predicting a driver's behavior are his age, education, and income level. Young men with above High School education tended to be "hunters" or those with extremely aggressive driving habits. While men with only a high school education and college educated women were "flow-followers" or those that basically adhered to the flow of traffic. Older women tended to be "gliders" or those who drive slower than most vehicles. Naturally, exceptions existed, which typically focused on the person's income, the third most important attribute. We found that people with higher incomes tended to be more aggressive drivers.

Similarly, the demographic information was equally crucial in creating an accurate regression model, found in Figure 3. Within these models, correlation values can range from 1.0 (fully positive correlated) to -1.0 (fully negatively correlated) with 0 signifying no correlation. We found a model with both demographic and type data yielded a correlation of 0.78, while without this information the accuracy dropped to 0.75. Using

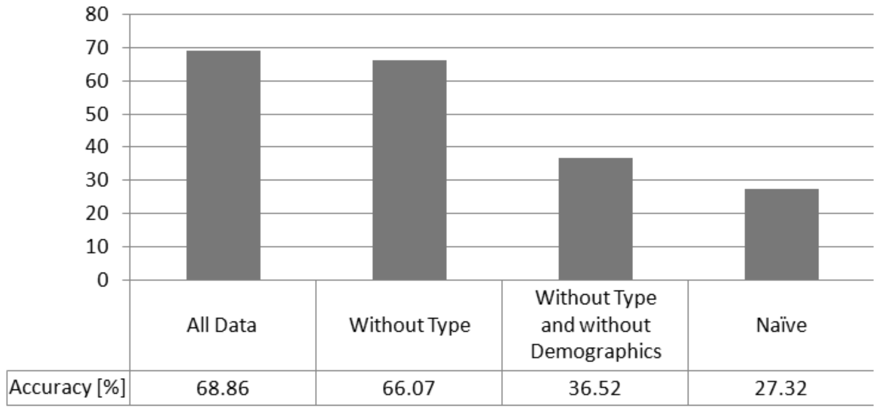

Fig. 2. The importance of driver type and demographics in predicting the gap setting within the ACC for a discrete decision tree model.

only vehicle specific data yielded a model of only 0.4, and the naive model (here using the average gap value of about 3.5) yielded a value of nearly 0. Again, we found that the type only slightly improved the model's accuracy, as much of this information was already subsumed within the drivers' demographics.

Generally, one of the goals of this paper is to encourage people who build applications to consider incorporating data from external measures, such as psychological or behaviorial models. As was true in other domains as well [10, 12], exclusively using behavior models alone, such as the driver type possible in this domain [5], is not sufficient. By combining the driver type with other data, we achieved a prediction accuracy of nearly 70% within the discrete decision tree model (Figure 2) and a correlation of 0.78 within the regression model (Figure 3). However, when we used only the driver type information and removed the demographic information these models dropped to an accuracy of 46% and 0.55 respectively. This suggests that exclusively using behavior models is not as effective as the approach we present. Thus, we advocate for synthesizing data gleaned from behaviorial models in conjunction with observed domain data, something we believe can be effective in many other domains as well.

Practically, we are studying how either or both of these attributes can be used in the company's ACC. The advantage to using the demographic data alone is that ostensibly it can be provided before the driver begins using the car (e.g. in the showroom) and thus can be used to accurately model the driver from the onset. However, people may be reluctant to provide this information due to privacy concerns. Using driver profiling information is relatively difficult to calculate and is based on observed behavior over a period of time [5]. Thus, this value cannot be used to initially set values within the ACC. However, this data can be collected without privacy concerns and can be used to further improve the system's accuracy over time.

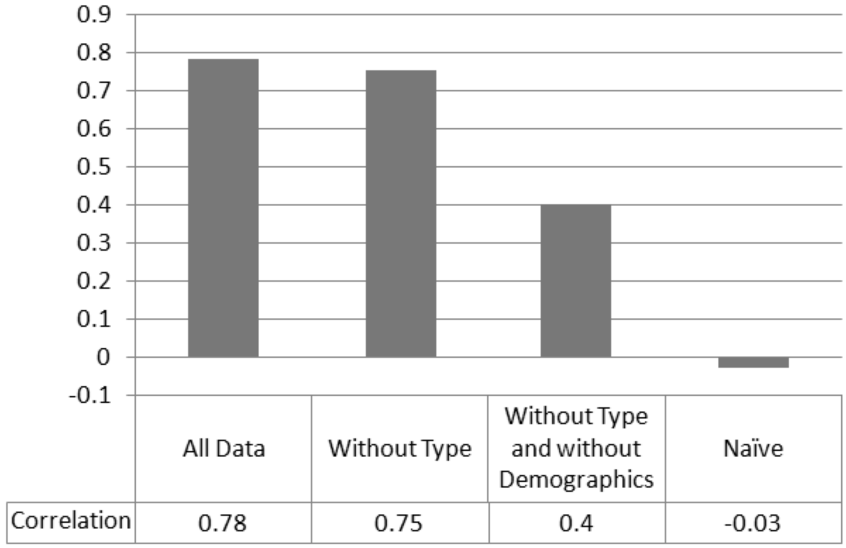

Fig. 3. The importance of driver type and demographics in predicting the gap setting within the ACC for a regression model.

4 Conclusions

Adapting automated processes to better serve humans is a challenging task because humans are characterized by inconsistent behaviors, have difficulties in defining their own preferences, are affected by their emotions, and are affected by the complexity of the problems they face together with the context of these problems. In particular, human drivers also need to react fast enough to road conditions and changes in traffic. Therefore our task was to learn the ACC's gap setting quickly and accurately given data we could use from past experience of many drivers from the ACAS field test data [4].

We empirically studied two learning approaches: regression and decision trees. Both were able to learn accurately the gap setting of an individual given his demographics characterization and driving type (hunter, glider or follower) with nearly 70% for the decision tree model and with a correlation of 0.78 for the regression model. These experiments emphasized the need for driver information including a behavior model about the driver's type [5] in addition to the information collected on the trips themselves. These results stress the fact that drivers may be very different from each other and previous approaches that set the gap setting similarly for all drivers [6, 7] are less effective. Therefore, driver characterization is essential for adapting automated systems in the vehicle. By understanding the current state of acceptance of automated systems and learning about differences among human users, we can improve the next generations of adaptive automated systems adjusted to their particular human users.

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