Learning Driver's Behavior to Improve the Acceptance of Adaptive Cruise Control

Avi Rosenfeld[1], Zevi Bareket[2], Claudia V. Goldman[3], Sarit Kraus[4], David J. LeBlanc [2] and Omer Tsimoni[3]
[1]Department of Industrial Engineering, Jerusalem College of Technology, Israel
[2]University of Michigan, Transportation Research Institute, USA
[3]General Motors Advanced Technical Center, Israel
[4]Department of Computer Science, Bar-Ilan University, Israel
rosenfa@jct.ac.il, bareket@umich.edu, claudia.goldman@gm.com, sarit@cs.biu.ac.il, leblanc@umich.edu, omer.tsimhoni@gm.com

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 save on the 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. We also learn when users tend to engage and disengage the automated system. 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.

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 (van Arem, van Driel, and Visser 2006), and can be effective in reducing driver fatigue and fuel consumption (Bishop 2000). 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 (Naranjo et al. 2003; 2006). Basically, 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 (Ervin et al. 2005). 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.

Related Work

The concept of using a group of characteristics to learn people's behavior has long been accepted by the user model-

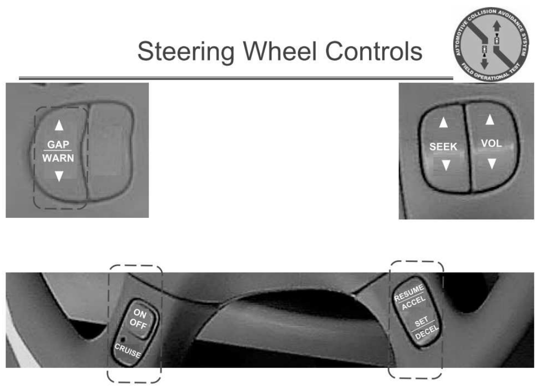

Figure 1: A steering wheel fitted with ACC technology.

ing 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 (Rich 1979). Even more similar to our work, Paliouras et. al (Paliouras et al. 1999) 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 (Fancher and Bareket 1996), 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 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 (Naranjo et al. 2003; 2006). 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 (Rosenfeld and Kraus 2012) and the Focal Points (Zuckerman, Kraus, and Rosenschein 2011) 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.

Learning Method

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 the default (in our case this value was 6) and the user may change it during his driving 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. In general regression models operate by statistically predicting the value of a continuous dependant variable from a number of independent variables. In this problem, the goal was to predict the gap setting value a given driver would select based on the independent variables of the current driving conditions. The second type of model was a decision tree model (C4.5). In general, decision trees predict the value of a discrete dependant variable from a number of independent variables. Specifically, here we learn which of the discrete gap values a driver will likely choose given all possible values given current driving conditions. Note that while discrete regression functions and continuous decision algorithms also exist, we focused on these two types of models to differentiate between these categories of models.

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.

Additionally, we focus on two secondary goals, when the ACC is first engaged, and when the ACC is disengaged. Here, the goal was not to create an agent to autonomously engage or disengage the ACC. However, by analyzing when people are most comfortable with the ACC, we hope to understand the user acceptance of such systems.

In both of these learning tasks, we are confronted by the known dataset imbalance problem (Chawla et al. 2002). In many real-world problems, as is the case here, each class is not equally represented. In fact, in the specific case of the ACC engagement task, over 90% of manual driving cases continue their manual driving, and in only a small percentage of cases do people engage the ACC. From a statistical perspective, a classifier could then naively classify all cases as being in the majority case and still have extremely high accuracy. However, because only the "minority" cases are relevant, novel methods are needed to find them. While several algorithms exist, we specifically focused on the MetaCost algorithm. Metacost is a general algorithm for making any type of classification learning algorithm cost sensitive, allowing us to stress certain categories more than others. Metacost has the advantage of treating of working well with any classification algorithm, as it operates by wrapping a cost-minimization procedure around any classifier (Domingos 1999). We opted to use this algorithm because of its flexibility and the ease within this algorithm in controlling the bias size given to the minority case. Empirical results for the learning gap settings and classifying engagement and disengagements of and from the ACC are explained in the next section.

Experimental Setup

Data for our analysis were taken from the Automotive Collision Avoidance System Field Operational Test (ACAS FOT) (Ervin et al. 2005). 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 (Fancher and Bareket 1996).

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.

Results

For the training experiments, we used the three previously defined datasets. Figure 2 presents the accuracy of the decision tree model to learn a driver's preferred gap setting based on these datasets. 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 at-

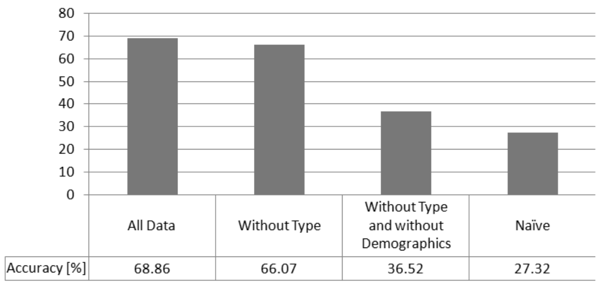

Figure 2: The importance of driver type and demographics in predicting the gap setting within the ACC for a discrete decision tree model.

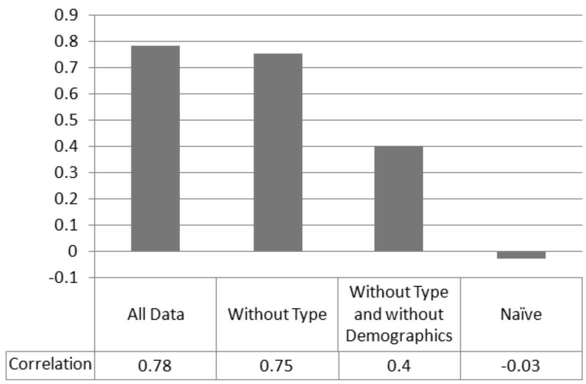

Figure 3: The importance of driver type and demographics in predicting the gap setting within the ACC for a regression model.

tribute. 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 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.

While the focus of the ACC is on the gap setting that differentiates the adaptive cruise control, from the "standard" cruise control, we also considered two additional problems: when people activate the ACC and when they deactivate it. The goal behind the gap value task was to allow an autonomous agent to set, at least initially, this value within the ACC. However, by understanding when people are more likely to use this product we can hopefully increase its acceptability and use. Similarly, by understanding when people disengage the ACC we can hopefully create new generations of this technology where people will use it longer and not feel compelled to disengage it.

In both of these learning tasks, we are confronted by the known dataset imbalance problem (Chawla et al. 2002). In this paper, we constructed two models for these two problems based on the same three types of datasets. The first model is a basic C4.5 without any modification. As was the case in gap setting task, we considered attributes based on the behavior type model, driver demographics and the vehicle's characteristics. In the second model, we again used the same three datasets, but created a learning bias to find the important minority cases. We specifically focused on the MetaCost algorithm (Domingos 1999).

Table 1 displays the complete results demonstrating the tradeoff between a model's accuracy and the success in finding the minority cases in the task of predicting when a driver engages or disengages the ACC. The first four rows represent different models created to predict when a person would activate the ACC. The first model is the standard decision tree algorithm C4.5. In addition, we considered three weight biases within the MetaCost algorithm: 0.5, 0.7 and 0.9. Note that raising these weights allows us to give greater weight to the minority case, thus increasing the recall of cases found, but at a cost to the overall accuracy of the model. For each of these models we trained four different models: one created with all information, one without the type information but with the demographic information, one without the type and without the demographic information, and a naive model that assumes the majority case– that a person continues driving in manual mode. The accuracy of each of these models are found within the first four columns in Table 1, and the corresponding recall levels for these models are found in the last four columns of the table. Similarly, we also considered the task of predicting when a person turns off the ACC, and trained models based on the same four algorithms with the same four datasets. The results for the accuracy and the recall of these models are found in the last four rows of Table 1.

Ideally, one would wish for a perfect model: e.g. one with 100% accuracy and recall of all cases. Unfortunately, this is unrealistic, especially in tasks involving people which are prone to variations due to noise. Nonetheless, the overall conclusion is that by adding more information, and specifically about a person's demographics, we were able to achieve higher overall accuracies with better recall.

We would like to present the driver for a recommendation as to when to engage the ACC. Towards this goal, we wish to build a model that is as accurate as possible, but with a minimum threshold. Thus, we wished to set the desired confidence level of the model, as found based on the recall of the minority class, before presenting a recommendation to the user. Figure 4 displays the interplay between the overall model's accuracy and the recall within the minority cases in the task of predicting when a driver engages the ACC. Again, the most desirable result is one in the upper right corner– high accuracy **and** recall. However, as one would

ACC On	All Info	Without Type	Without Demo	Naive	All Info	Without Type	Without Demo	Naive
C4.5	92.67	92.32	91.22	91.27	0.35	0.32	0.07	0
MetaCost 0.5	92.42	91.97	90.97	91.27	0.40	0.36	0.13	0
MetaCost 0.7	91.93	91.38	90.37	91.27	0.45	0.42	0.18	0
MetCost 0.9	87.99	86.60	77.12	91.27	0.63	0.61	0.51	0
ACC Off	All Info	Without Type	Without Demo	Naive	All Info	Without Type	Without Demo	Naive
C4.5	88.71	88.64	88.42	86.37	0.37	0.37	0.35	0
MetaCost 0.5	88.59	88.55	88.14	86.37	0.43	0.42	0.41	0
MetaCost 0.7	87.68	87.49	87.31	86.37	0.49	0.49	0.49	0
MetCost 0.9	82.03	82.23	81.15	86.37	0.66	0.67	0.66	0

Table 1: Analyzing the tradeoff between overall model accuracy (left side of table) and recall of the minority cases (right side) in both the task of when people turn the ACC on (top) and off (bottom).

expect, and as evident from Table 1, the naive case of continuing without engaging the ACC constitutes over 91% of the cases, but this model will have recall of 0 for the minority case. By modifying the weights within the MetaCost algorithm we are able to get progressively higher recall rates over the basic decision tree algorithm. Also note that the model trained with all information achieves significantly better results than one without the type and demographic information.

Similarly, Figure 5 displays the same interplay between the overall model's accuracy and the success in finding the minority cases in the task of predicting when a driver disengages the ACC. In this task, the naive case assumes that the driver will continue with the ACC constitutes over 86% of the cases, but this model will have recall of 0 for the minority case (see the left side of Figure 5). Note that we were again able to raise the recall within the minority case by creating weight biases of (0.5, 0.7 and 0.9), but again at the expense of a lower overall accuracy. However, as opposed to the engage ACC task, we noticed that the gain from the demographic and type information was not very significant. In fact, upon inspection of the output trees, we noticed to our surprise that people's decision to disengage the ACC was more dependent on how quickly the ACC slowed the vehicle down, and not on the overall behavior of the driver.

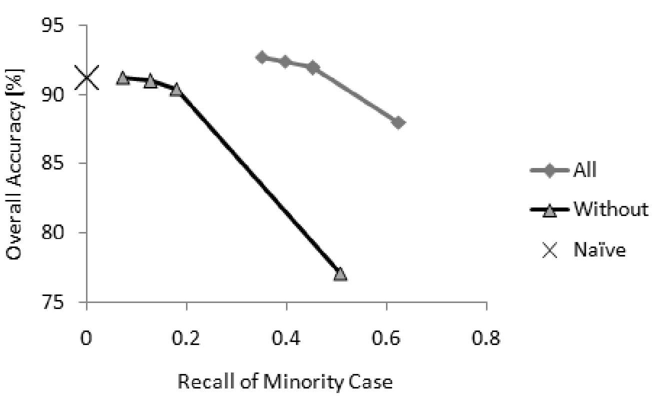

Figure 4: Comparing the overall model accuracy and recall for cases for engaging the ACC

Thus, it should be noticed that simply adding attributes is not a panacea for higher accuracy– it only improves accuracy when relevant to the learning task at hand.

Figure 5: Comparing the overall model accuracy and recall for cases for disengaging the ACC

Overall, these results suggest that finding attributes beyond the observed data can be critical for accurately modeling a person's behavior. Similar to previous studies that found that other behaviorial theories can better predict people's actions (Rosenfeld and Kraus 2012; Zuckerman, Kraus, and Rosenschein 2011), this work found that a driver's preferred gap setting could be better predicted by using a model of driving behavior (Fancher and Bareket 1996). Even if this measure was not readily available, an accurate estimate of this value could be learned based on a driver's demographic data.

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 (Rosenfeld and Kraus 2012; Zuckerman, Kraus, and Rosenschein 2011), exclusively using behavior models alone, such as the driver type possible in this domain (Fancher and Bareket 1996), 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. 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 (Fancher and Bareket 1996). 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.

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 (Ervin et al. 2005).

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 (Fancher and Bareket 1996) 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 (Naranjo et al. 2003; 2006) are less effective. Therefore, driver characterization is essential for adapting automated systems in the vehicle. These differences among humans are made more salient when trying to learn when users engage or disengage from an automated system such as the ACC. Reactions could be very different teaching us also about the tendencies of users towards automation. Moreover, another challenge here was learning in cases where a strong majority category existed but the important events were in the minority category. We therefore, turned to the implementation of the MetaCost algorithm to learn from unbalanced data sets.

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.

References

Bishop, R. 2000. Intelligent vehicle applications worldwide. *IEEE Intelligent Systems* 15(1):78–81.

Chawla, N. V.; Bowyer, K. W.; Hall, L. O.; and Kegelmeyer, W. P. 2002. Smote: Synthetic minority over-sampling technique. *J. Artif. Intell. Res. (JAIR)* 16:321–357.

Domingos, P. 1999. Metacost: a general method for making classifiers cost-sensitive. In *KDD '99: Proceedings of the fifth ACM SIGKDD international conference on Knowledge discovery and data mining*, 155–164. New York, NY, USA: ACM Press.

Ervin, R.; Sayer, J.; LeBlanc, D.; Bogard, S.; Mefford, M.; Hagan, M.; Bareket, Z.; and Winkler, C. 2005. Automotive collision avoidance system (acas) field operational test methodology and results, (us dot hs 809 901). washington, dc: Department of transportation.

Fancher, P., and Bareket, Z. 1996. A comparison of manual versus automatic control of headway as a function of driver characteristics. *3rd Annual World Congress on Intelligent Transport Systems*.

Naranjo, J. E.; Gonzalez, C.; Reviejo, J.; Garcia, R.; and de Pedro, T. 2003. Adaptive fuzzy control for inter-vehicle gap keeping. *Intelligent Transportation Systems, IEEE Transactions on* 4(3):132–142.

Naranjo, J. E.; Gonzalez, C.; Garcia, R.; and de Pedro, T. 2006. ACC+Stop&go maneuvers with throttle and brake fuzzy control. *Intelligent Transportation Systems, IEEE Transactions on* 7(2):213–225.

Paliouras, G.; Karkaletsis, V.; Papatheodorou, C.; and Spyropoulos, C. D. 1999. Exploiting learning techniques for the acquisition of user stereotypes and communities. In *UM99 User Modeling: Proceedings of the Seventh International Conference*, 169–178.

Rich, E. 1979. User modeling via stereotypes. *Cognitive Science* 3:329–354.

Rosenfeld, A., and Kraus, S. 2012. Modeling agents based on aspiration adaptation theory. *Autonomous Agents and Multi-Agent Systems* 24(2):221–254.

van Arem, B.; van Driel, C. J. G.; and Visser, R. 2006. The impact of cooperative adaptive cruise control on traffic-flow characteristics. *IEEE Transactions on Intelligent Transportation Systems* 7(4):429–436.

Zuckerman, I.; Kraus, S.; and Rosenschein, J. S. 2011. Using focal point learning to improve human-machine tacit coordination. *Autonomous Agents and Multi-Agent Systems* 22(2):289–316.