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Development of a real-time prediction model of driver behavior at intersections using kinematic time series data

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ABSTRACT

As connected autonomous vehicles (CAVs) enter the fleet, there will be a long period when these vehicles will have to interact with human drivers. One of the challenges for CAVs is that human drivers do not communicate their decisions well. Fortunately, the kinematic behavior of a human-driven vehicle may be a good predictor of driver intent within a short time frame. We analyzed the kinematic time series data (e.g., speed) for a set of drivers making left turns at intersections to predict whether the driver would stop before executing the turn. We used principal components analysis (PCA) to generate independent dimensions that explain the variation in vehicle speed before a turn. These dimensions remained relatively consistent throughout the maneuver, allowing us to compute independent scores on these dimensions for different time windows throughout the approach to the intersection. We then linked these PCA scores to whether a driver would stop before executing a left turn using the random intercept Bayesian additive regression trees. Five more road and observable vehicle characteristics were included to enhance prediction. Our model achieved an area under the receiver operating characteristic curve (AUC) of 0.84 at 94 m away from the center of an intersection and steadily increased to 0.90 by 46 m away from the center of an intersection.

1. Introduction

An autonomous vehicle can be loosely defined as a vehicle where no human supervision or human controlled driving is needed. The National Highway Traffic Safety Administration (NHTSA) provides a more detailed definition with five levels of classification (National Highway and Traffic Safety Administration, 2013), ranging from Level 0 – the driver completely controls the vehicle at all times (typical of a 20th century vehicle before the introduction of electronic stability control or antilock braking) – to Level 4, where vehicle performs all functions for the entire trip, with the driver not expected to control the vehicle at any time. An example of a Level 4 autonomous vehicle is a vehicle from the Google Self-Driving Car Project.

In 2009, Google started testing these self-driven vehicles on the streets of Mountain View, California and Austin, Texas. As of August 2015, Google reported that they had self-driven these vehicles for more than 1 million miles (Google, 2015), and they had been involved in a total of 14 accidents since 2009 (CNNMoney, 2015). In all these accidents, Google asserted that human error and inattention was the main cause. Google's claim is not surprising since these vehicle will have to interact with human drivers. Unfortunately, human drivers do not always communicate their decisions clearly, leading to near crashes and crashes. As such, autonomous vehicles can benefit from predicting human driver decisions using information conveyed by the human driver's vehicle.

In this paper, we hypothesized that the kinematic behavior of a human driven vehicle provides enough information to make a good prediction of driver intent within a short time frame. We envision a system whereby a driver-intent model is evaluated on the human driver's vehicle and transmitted via vehicle-to-vehicle (V2V) communication. Although current autonomous vehicles under development generally use onboard sensors to gather information, V2V communication will increasingly be available as an additional source of information, resulting in connected and automated vehicles (CAVs). Hence, using the kinematic behavior of a human driven vehicle to predict driver intent makes sense if a driver's unique tendencies are an important predictor. Thus, a human-driven vehicle can learn its driver's intent patterns and communicate these to CAVs nearby.

In particular, we studied the speed of a human driven vehicle. We focused on predicting whether a driver will stop at an intersection before executing a left turn. This is important for two reasons. First, left turns at intersections can result in injury-causing side impacts.

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According to the National Motor Vehicle Crash Causation Survey (NMVCCS), 22% of the tow-away crashes in the US in 2008 were due to left turn maneuvers at intersections (Choi, 2010). Second, knowing if a human driven vehicle would stop before executing the left turn maneuver would allow the driverless vehicle to make a critical decision of whether to execute its own planned maneuver or wait.

To build the prediction model, we used naturalistic driving data from about 100 licensed drivers in Michigan. We converted the time series data to a distance series and defined a new distance-varying outcome. Because we believed that recent speeds contain more information about the human driver's intention to stop compared to past speeds, we employed a moving window on the distance-varying speeds. Next, we used principal components analysis (PCA) to reduce the number of variables employed in our prediction algorithm. To link our distance-varying outcomes to our principal component (PC) variables and five other road and observable vehicle characteristics predictors, we used a model we recently developed, the random intercept Bayesian additive regression trees (riBART). riBART (Tan et al., 2016) is an extension of Bayesian additive regression trees (BART; Chipman et al., 2010) which is able to account for the repeated left turns made by the same driver. We evaluated riBART's prediction performance at every meter away from the center of an intersection by using the area under the receiver operating characteristic curve (AUC) and compared these results with standard BART and linear logistic regression. Finally, we plotted the sensitivity and false positive rate (FPR; Davis and Goadrich, 2006) profiles of riBART where sensitivity $= \frac{\text{True positives}}{\text{All left turn stops}}$ and FPR $= \frac{\text{False positives}}{\text{All left turn } \textbf{non} - \text{stops}}$ to investigate how the predicted probability cut-off level affects unnecessary stops by the CAVs and crashes.

2. Data and methods

2.1. Naturalistic driving data

We obtained our dataset from a previous study by Sayer et al. (2011). In brief, our naturalistic driving data was collected from 108 licensed drivers in Michigan between April 2009 and April 2010. Sixteen late-model Honda Accords were fitted with cameras, recording devices, and a collision warning system – the Integrated Vehicle Based Safety System (IVBSS) – to collect visual and kinematic data from the drivers for a total of 40 days – 12 days baseline period with IVBSS switched off followed by 28 days with IVBSS activated. To avoid confounding due to the IVBSS system, we used the 12 days baseline unsupervised driving data to develop our prediction model. Because information about road types and intersections outside Michigan was not available, we restricted our analysis to driving within Michigan in order to facilitate the accurate identification of an intersection and its associated road type. Accurate identification of an intersection allows us to determine a reference time to start extracting the information necessary for our prediction model.

In this study, we had data from 108 drivers who made 3795 turns. Of these 3795 turns, 1823 were left turns. We took the time at 100 m away from the center of an intersection (−100 m) as the reference point for the start of data extraction and stopped extraction at the time the vehicle was beyond the center of an intersection i.e. 0 m. We extracted both the speed of the vehicle (in m/s) and the amount of distance traveled (in m) at 10 ms intervals starting from our reference point. We also defined a vehicle as stopped when its speed was ≤1 m/s.

Because our goal is prediction of stopping before turning for future turns, we rescale the original time series predictors to measure distance from the intersection. We do this because, in a turn that is not complete, only the distance from the intersection will be known in advance; we will know the duration that the vehicle takes to reach the center of an intersection only after the vehicle has reached the center of an intersection. Fig. 1 illustrates this conversion using an example with Driver 40 Trip 34 Turn 1. Fig. 1(a) shows the speed profile of this particular turn. In this example, our target is the vehicle speed at 70 m away from the center of an intersection (−70 m). To obtain this speed, we first “draw” a line at −70 m and focus on the speed sample points closest to this −70 m line. Fig. 1(b) shows the blow up of this focal point. To set the speed at −70 m, we then compared which of the two speed sample points was closest to −70 m. In our example, because the point on the left was closest, it was set as the speed at −70 m for this turn. For the speeds of this turn from −100 m to −1 m at every 1 m interval, we employed a similar approach. In the situation where more than one speed sample point was closest to the line, we took their average as the speed at that distance.

Because vehicles can stop and restart before reaching the center of the intersection, we define “stopping” as a distance-varying outcome. Let i be the ith turn and j be the jth meter away from the center of intersection, $j = -100,\ldots,-1$. Let s_{ij} be the distance series of vehicle speed and y_{ij} be the distance-varying outcome (1 = stopped in future, 0 = will not stop in future). We defined y_{ij} as follows:

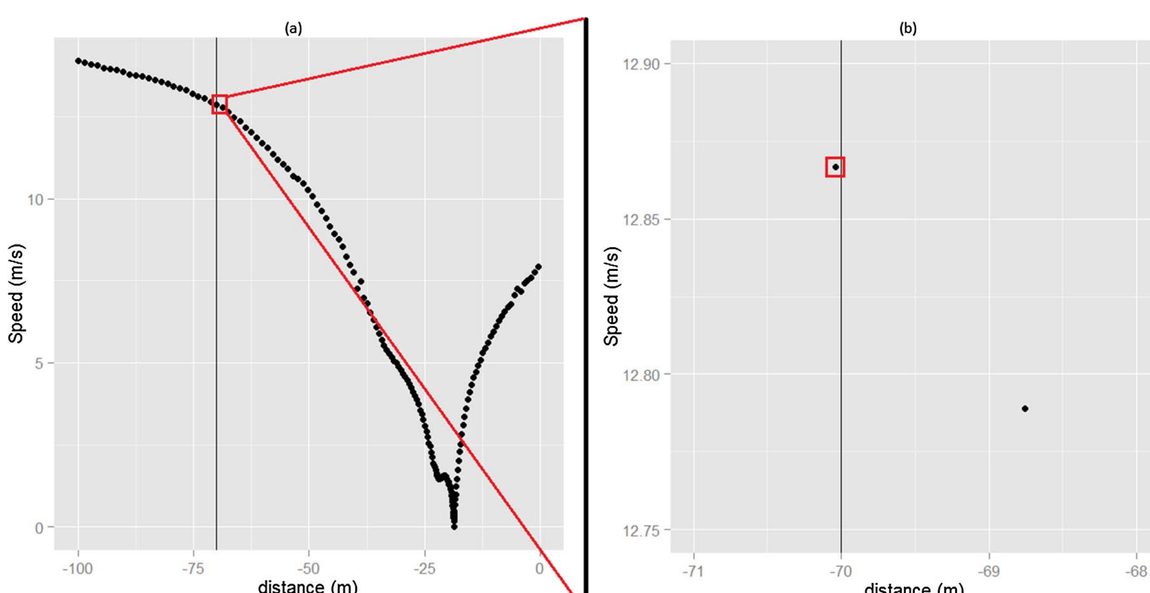

Fig. 1. Original speed profile of Driver 40 Trip 34 Turn 1.