Efficient and Safe Vehicle Navigation Based on Driver Behavior Classification

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Abstract

We present an autonomous driving planning algorithm that takes into account neighboring drivers' behaviors and achieves safer and more efficient navigation. Our approach leverages the advantages of a data-driven mapping that is used to characterize the behavior of other drivers on the road. Our formulation also takes into account pedestrians and cyclists and uses psychology-based models to perform safe navigation. We demonstrate our benefits over previous methods: safer behavior in avoiding dangerous neighboring drivers, pedestrians and cyclists, and efficient navigation around careful drivers.

1. Introduction

There are different kinds of drivers in urban environments, and an expert human driver will identify dangerous drivers and avoid them accordingly. However, existing autonomous driving systems often treat all neighboring vehicles the same and do not take actions to avoid the dangerous drivers. This problem has been studied in transportation and urban planning works [30]. This line of works map drivers' behaviors with background information like age, gender, driving history, etc., but this information is not available to autonomous vehicles. Therefore, to allow autonomous driving algorithms to account for driving behaviors, a mapping between sensor data and driving behaviors must be available.

Previous studies in transportation and urban studies [15, 30] usually study the difference between aggressive drivers, careful drivers and typical drivers. In particular, Guy et al. [19] and Bera et al. [4, 5, 3] applied psychological theory to capture human behaviors. Autonomous driving systems that are on the roads right now uses a range of different algorithms to interpret the sensor data: trajectory data computation using semantic understanding or object detection methods [17]. Some uses an end-to-end approach to compute driving actions directly from sensor data[8].

Main Results: Our approach takes into account behaviors of neighboring entities and plans accordingly to perform safer navigation. We leverage the results of an extensive user study that learned the relationship between vehicular trajectories and the underlying driving behaviors: Trajectory to Driver Behavior Mapping [11]. This work allows our navigation algorithms to classify the driving behaviors of neighboring drivers, and we demonstrated simulated scenarios with vehicles, pedestrians, and cyclist where navigation with our approach is safer.

Compared to prior algorithms, our algorithm offers the following benefits:

1. Driving Behavior Computation: Trajectory to Driver Behavior Mapping established a mapping between five features and six different driving behaviors, and conducted factor analysis on the six behaviors, which are derived from two commonly studied behaviors: aggressiveness and carefulness. The results show that there exists a latent variable that can summarize these driving behaviors and that can be used to measure the level of awareness that one should have when driving next to another vehicle. The same study examined how much attention a human pays to such a vehicle when it is driving in different relative locations. We leverage the results of this study and develop a proximity cost that reacts to aggressive drivers more appropriately.

2. Improved Realtime Navigation: We enhance an existing Autonomous Driving Algorithm [7] to navigate according to the neighboring drivers' behaviors. Our navigation algorithm identifies potentially dangerous drivers in real-time and chooses a path that avoids potentially dangerous drivers. In particular, our approach accounts for pedestrians and cyclists, and avoids them by considering their velocity relative to the ego-vehicle. Our method can offer saver navigation and plan more appropriately to avoid dangerous drivers than prior works.

An overview of our approach is shown in Figure 1. The rest of the paper is organized as follows. We present a detailed overview of previous work in Section 2. We describe the mapping from trajectories to driving behaviors in Section 3 and our autonomous driving algorithm in Section 4.

2. Related Works

2.1. Driving Behaviors Studies

Psychology, transportation, and urban planning researchers have been studying human driving behaviors. Aljaafreh et al. [1] classified drivers into four different levels of aggressiveness with accelerometer data. Feng et al. [15] categorized drivers into three different level of aggressiveness according to drivers' background information (age, gender, experience, etc.), and environmental factors (weather, traffic, etc.). Apart from that, social psychologist have also studied the correlation between driver background information and driving behaviors [28, 2], and previous driving behaviors [9]. Besides, Meiring et al. [30] pointed out that careless drivers, including drunk and distracted drivers, are also dangerous. Despite the fact that these works have found mappings between driving behaviors and a lot of other different factors, most of these factors are unknown to autonomous vehicles during navigation. We use neighboring vehicles' trajectories, which can be computed from sensor data, to map driving behaviors.

The following works have conducted analysis on aggressiveness and carefulness in accordance to trajectory related data. Qi et al. [33] presented the relationship between driving style, speed, and acceleration. Shi et al. [38] concluded that measuring throttle opening is better than merely measuring acceleration, as measuring deceleration (negative acceleration) is not helpful in understanding the aggressiveness of a driver. Murphey et al. [32] presented results to show that measuring longitudinal jerk (changing lanes) is more helpful than progressive jerk (along the traffic direction) in terms of correlation to aggressiveness of drivers. Mohamad et al. [31] performed abnormal detection using speed, acceleration, and steering wheel movement. Sadigh et al. [34] proposed a Convex Markov Chains model to predict the attention drivers spend on driving. There are also works that are deployed in cars to sound an alert when they find the user is not paying attention to the road [18, 42, 6]. Besides, there is considerable number of simulated driving models[39, 25, 12] that have proposed different factors that imply driving behaviors that can be mapped to navigation plans. Our work leverages the results from a detailed user study described in Section 3 to use the most relevant trajectory features to driving behaviors.

2.2. Adaptation to Human Drivers' Behaviors

One line of work went further to study how humans would react to an autonomous vehicle's actions. Sadigh et al. [35] discovered that human drivers' behaviors can be affected when they observe an autonomous vehicle and that they will react in certain ways when they observe different actions of the autonomous vehicle [36]. Huang et al. [23] proposed a technique to make autonomous car actions more easily understand by humans, so that their reactions are more predictable. Besides, an active learning approach [13] using examples of expert human driver's preferences has been to model human driving behaviors. These works show the importance of having autonomous vehicles navigating according to human behaviors.

2.3. Autonomous Car Navigation

There is a significant number of works on navigating autonomous vehicles [24, 37, 43, 27, 22, 41]. During the DAPRA Urban Grand Challenge and the Grand Cooperative Driving Challenge, the participating research teams proposed different navigation approaches [10, 16, 26, 14]. Recently, Best et al. [7] proposed a novel navigation algorithm, AutonoVi, which also considers steering and acceleration planning, dynamic lane changes, and several other scenarios. We proposed a new approach that takes into account driving behavior, which is complimentary to these previous work and can be combined with them.

3. Trajectory to Driver Behavior Mapping

In this section, we describe the trajectory features that are used to identify driver behaviors, the driving behavior metrics, and the attention metrics used in a detailed user study, Trajectory to Driving Behavior Mapping [11].

3.1. Features

The goal of Trajectory to Driving Behavior Mapping is to leverage a set of trajectory features that map to driving behaviors, assuming that the trajectories have already been extracted from the raw sensor data. As described in the previous section, a lot of features (e.g., drivers' backgrounds, throttle opening, environmental factors, etc.) that have been mapped to driving behavior are not available for autonomous vehicles. Therefore, the user study has derived a set of variants and performed feature selection to select the most relevant ones to use in the mapping.

Notation	Description
v_{nei}	Relative speed to neighbors
v_{avg}	Average velocity
s_{front}	Distance with front car
j_l	Longitudinal jerk
s_{center}	Lane following metric

Table 1. Five Features selected in Trajectory to Driving Behavior Mapping

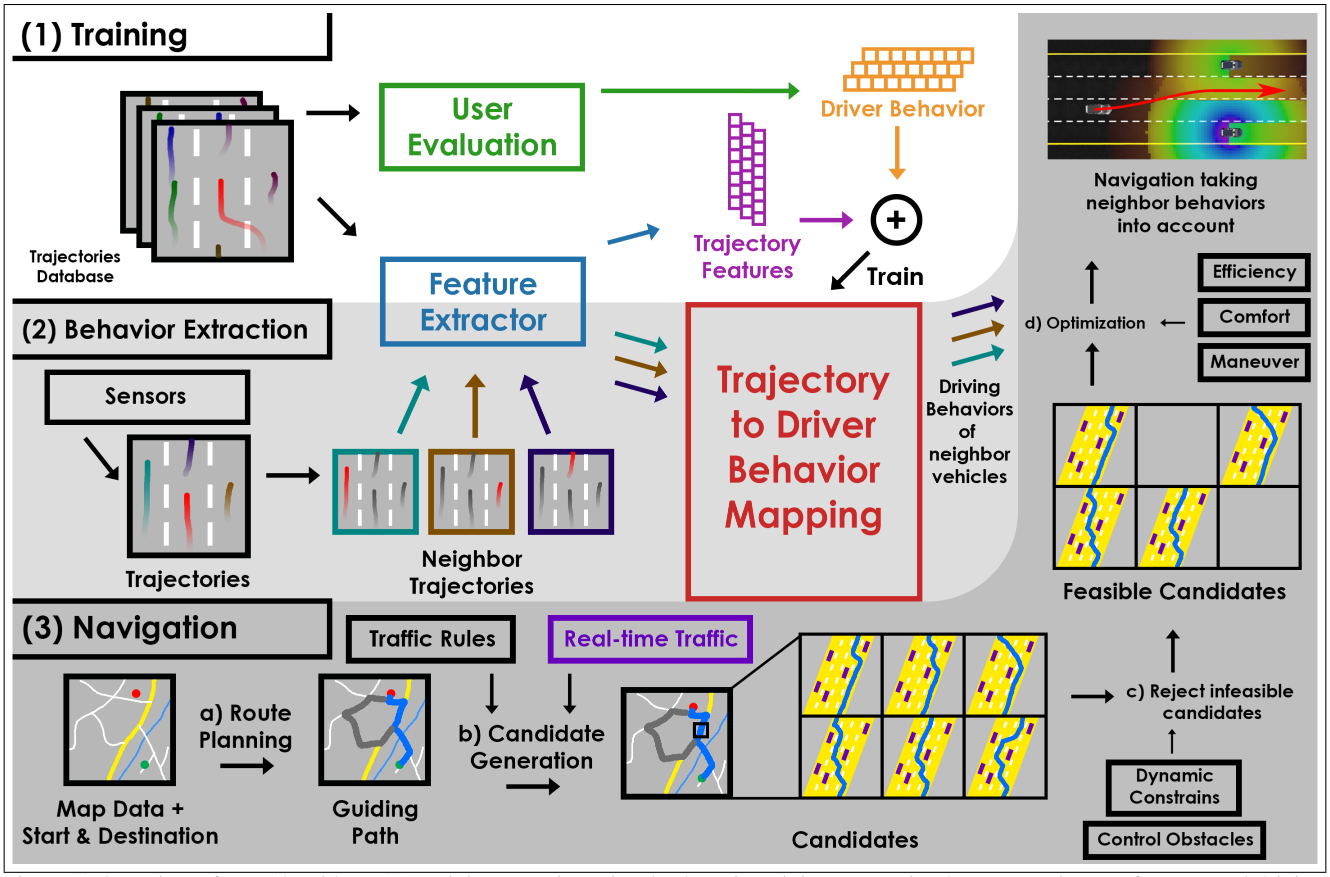

Figure 1. Overview of our Algorithm: (1) Training: a trajectories database is training a mapping between trajectory features and driving behaviors. (2) Behavior Extraction: During navigation, the same set of features is extracted from neighboring vehicles' trajectories and mapped to driving behaviors. (3) Navigation: a) the navigation algorithm first plans a global route in accordance with map data, starting point, and destination, and b) generates a set of candidate local routes that obey traffic rules while considering real-time traffics; c) the algorithm then removes infeasible candidates using dynamic constrains and control obstacles; d) after that, it performs an optimization to obtain the best navigation plan based on the driving behavior we extracted in (2), along with several other factors: Efficiency, Passenger Comfort, etc.

3.1.1 Acceleration

Previous works [32, 31, 38, 40] have shown that acceleration can be used to identify driver aggressiveness. This study [32] found out that longitudinal jerk can reflect aggressiveness better than progressive jerk, and this has been further verified during the feature selection in the user study.

3.1.2 Lane following

The metric proposed in this work [6] measures the extent of lane following using the mean and standard deviation of lane drifting and lane weaving. Trajectory to Driving behavior proposes a feature that also depends on lane drifting, but further differentiates drivers who keep deviating from the center of the lane to the left and right, and those drivers who are driving stably off the center of the lane. Furthermore, when a vehicle is performing lane changing, the effect on this metric of these trajectory segments is nullified and will not impact this metric.

Let y_l and $y(t)$ be the center longitudinal position of the lane in which the targeted car is in and the longitudinal position of the car at time t, respectively. Also suppose a set of lane changing events happened at time t_i, $C = \{t_1, t_2, ..., t_n\}$, the lane drift metric $s_C(t)$ is given by:

$$s_C(t) = \begin{cases} 0, & \text{if } \exists t \in C \text{ s.t. } t \in [t-k, t+k], \\ y(t) - y_l, & \text{otherwise.} \end{cases} \tag{1}$$

where k is the amount of time that we nullify the impact of lane changing to this metric.

Trajectory to Driving Behavior Mapping measures the rate of change in drifting in τ seconds, so that this metric can highlight those drivers who are drifting more frequently from the center of the lane. The overall lane following metric is therefore defined as below. It is also illustrated in

Figure 2.

$$s_{center} = \int |s_C(t)| \left[\mu + \int_{t-\tau}^{t} |s'_{\emptyset}(t)| dt \right] dt, \quad (2)$$

where μ is a parameter that differentiates drivers who are driving stably off the center of the lane, and those who are driving along the center of the lane.

3.1.3 Relative Speed

Trajectory to Driving Behavior Mapping designed the following metric to capture the relationship between a given driving behavior and the relative speed of the car with respect to neighboring cars:

$$v_{nei} = \int \sum_{n \in N} \max(0, \frac{v(t) - v_n(t)}{dist(x(t), x_n(t))}) dt, \quad (3)$$

where N is the set containing all neighboring cars within a reasonably huge range. $v(t)$, $x(t)$, $v_n(t)$, $x_n(t)$ are the speed and the position of the targeting car, and the position and the speed of the neighbor n, respectively.

This metric relies merely on the speed and position of the neighbors, and it can represent the actual driving speed of the targeted vehicle with respect to it's neighbor better than simply using relative speed.

3.2. Driving Behavior Metrics and Attention Metrics

Aggressiveness [15, 1, 21] and Carefulness [30, 34, 29] are two metrics that are commonly used to identify dangerous drivers. In typical social psychology studies, related items are introduced into user evaluation to ensure the robustness of the results. Therefore, Trajectory to Driving Behavior mapping evaluated four more driving behaviors apart from Aggressiveness and Carefulness, and those are listed in Table 2.

When an aggressive or careless driver is observed, depending on the position of that driver with respect to the targeted vehicle, the amount of attention that the driver of the targeted vehicle pays would still vary. Therefore, when evaluating the users' responses when driving as the targeted vehicle, the users are also asked to rate the four attention metrics listed in Table2.

3.3. Data-Driven Mapping

Trajectory to Driving Behavior Mapping conducts a user study that, has 100 participants identifying driver behaviors from videos. The trajectories of the videos are extracted from the Interstate 80 Freeway Dataset [20]. The users were asked to rate the metrics we listed in Table 2 on a 7-point scale and a 5-point scale for driving behavior and attention metrics, respectively.

Symbol	Description	Symbol	Level of Attention when
b_0	Aggressive	b_6	following the target
b_1	Reckless	b_7	preceding the target
b_2	Threatening	b_8	driving next to the target
b_3	Careful	b_9	far from the target
b_4	Cautious		
b_5	Timid		

Table 2. Six Driving Behavior metrics (b_0, b_1, ...,b_5) and Four Attention metrics (b_6, b_7, b_8, b_9) used in user evaluation in obtaining the mapping

After that, feature selection was applied to the results using least absolute shrinkage and selection operator (Lasso) analysis. In addition, the five features that are most appropriate for mapping to driving behaviors are extracted from ten potential ones. It concluded that using $\{s_{center}, v_{nei}, s_{front}, v_{avg}, j_l\}$ in mapping between features and driving behavior, and $\{s_{center}, v_{nei}, v_{avg}\}$ in the mapping between features and attention metrics can produce best regression models.

Using $\{s_{center}, v_{nei}, s_{front}, v_{avg}, j_l\}$ and $\{s_{center}, v_{nei}, v_{avg}\}$ as the features, linear regression is applied to obtain the mapping between these selected features and the drivers' behaviors. The results we obtained are below. For $B_{behavior} = [b_0, b_1, ..., b_5]^T$,

$$B_{behavior} = \begin{pmatrix} 1.63 & 4.04 & -0.46 & -0.82 & 0.88 & -2.58 \\ 1.58 & 3.08 & -0.45 & 0.02 & -0.10 & -1.67 \\ 1.35 & 4.08 & -0.58 & -0.43 & -0.28 & -1.99 \\ -1.51 & -3.17 & 1.06 & 0.51 & -0.51 & 1.39 \\ -2.47 & -2.60 & 1.43 & 0.98 & -0.82 & 1.27 \\ -3.59 & -2.19 & 1.75 & 1.73 & -0.30 & 0.61 \end{pmatrix} \begin{pmatrix} s_{center} \\ v_{nei} \\ s_{front} \\ v_{avg} \\ j_l \\ 1 \end{pmatrix} \quad (4)$$

Moreover, for $B_{attention} = [b_6, b_7, b_8, b_9]^T$,

$$B_{attention} = \begin{pmatrix} B_{back} \\ B_{front} \\ B_{adj} \\ B_{far} \end{pmatrix} = \begin{pmatrix} 0.54 & 1.60 & 0.11 & -0.8 \\ -0.73 & 1.66 & 0.63 & -0.07 \\ -0.14 & 1.73 & 0.25 & 0.15 \\ 0.25 & 1.47 & 0.17 & -1.43 \end{pmatrix} \begin{pmatrix} s_{center} \\ v_{nei} \\ v_{avg} \\ 1 \end{pmatrix} \quad (5)$$

The study further applied leave-one-out cross-validation to the set of samples S by enumerating all samples $s_i \in S$ and leaving s_i as a validation sample, and using $S - s_i$ to produce regression models $M_{i,j}$ for each behavior $b_{i,j}$. Using $M_{i,j}$, the behaviors $b_{i,j}$ of s_i were predicted. The mean prediction error in the cross-validation is less than one (in a 7-point scale) for all behaviors and attention metrics predicted. Thus, the mapping is not overfitted.

Besides, the study applied Principal Component Analysis (PCA) to the survey response. The percentages of variance of the principal components are 73.42%, 11.97%, 7.78%, 2.96%, 2.30% and 1.58%. The results indicate that the Principal Component 1, which has variance of 73.43%,

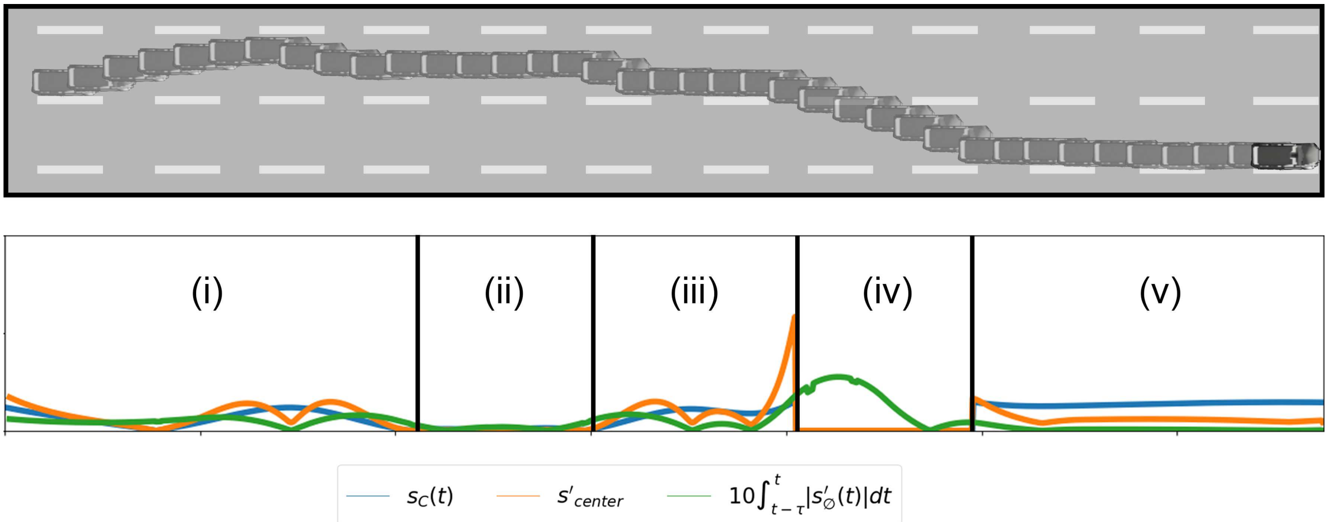

Figure 2. Lane following metric illustration. The lane following metric, s_{center}, is given by the sum of the area under the plot s'_{center}. The example shows that the lane following metric can differentiate drivers from drifting left and right (i iii), driving along the center of the lane (ii), changing lanes (iv), and consistently driving off the center of the lane (v).

can model most of the driving behaviors. It discovered that there is a latent variable that is negatively correlated with aggressiveness and positively correlated with carefulness. Therefore, the study considers the Principal Component 1 as a safety score reflecting the amount of attention awareness that a driver or an autonomous navigation system should take into account. Trajectory to Driving Behavior Mapping is therefore computed as below:

$$S_{TDBM} = \begin{pmatrix} -4.78 & -7.89 & 2.24 & 1.69 & -0.83 & 4.69 \end{pmatrix} \begin{pmatrix} s_{center} \\ v_{nei} \\ s_{front} \\ v_{avg} \\ j_l \\ 1 \end{pmatrix} \tag{6}$$

4. Navigation

In this section, we describe how we leverage the benefits of identifying driver behaviors and ensure safe navigation. TDBM [11] extends an autonomous car navigation algorithm, AutonoVi [7], and shows improvements in its performance by using our driver behavior identification algorithm and TDBM. AutonoVi is based on a data-driven vehicle dynamics model and optimization-based maneuver planning, which generates a set of favorable trajectories from among a set of possible candidates, and performs selection among this set of trajectories using optimization. It can handle dynamic lane-changes and different traffic conditions.

The approach used in AutonoVi is summarized below: The algorithm establishes a graph of roads from a GIS database and computes the shortest global route plan using A* algorithm. Taking into account traffic rules and real-time traffic, the plan is translated to a static guiding path, which consists of a set of C^1 continuous way-points. AutonoVi then samples the speed and steering angle in a favourable range of values to obtain a set of candidate trajectories. Using the Control Obstacles approach, AutonoVi eliminates the trajectories that would lead to a possible collision. With the set of collision-free trajectories, AutonoVi selects the best trajectory using an optimization approach. It selects trajectories that avoid: i) deviating from the global route; ii) unnecessary lane changes; ii) sharp turns, breaking, and acceleration, which lead to discomforting experiences for passengers; and iv) getting to close to other road entities (including vehicles, pedestrians, and cyclists).

4.1. Neighboring Vehicles

AutonoVi proposed a proximity cost function to differentiate entities by class to avoid getting too close to other objects. It considers all vehicles as the same and applies the same penalization factor, $F_{vehicle}$, to them. Similarly, it applies higher factors : F_{ped} and F_{cyc} to all pedestrians and all cyclists, respectively. The original proximity cost used in AutonoVi is:

$$c_{prox} = \sum_{n=1}^{N} F_{vehicle}\, e^{-d(n)} \tag{7}$$

This cost function has two issues: i) it cannot distinguish dangerous drivers to avoid driving too close to them, and ii) it diminishes too rapidly due to its use of an exponential function. Therefore, TDBM proposed a novel proximity cost that can solve these problems:

$$c'_{prox} = \sum_{n=1}^{N} c(n) \tag{8}$$

$$c(n) = \begin{cases} 0 & \text{if } d \in [d_{t2}, \inf), \\ S_{TDBM} B_{far} \frac{d_{t2} - d(n)}{d_{t2}} & \text{if } d \in (d_t, d_{t2}], \\ S_{TDBM} \left[\frac{(d_t - d(n))(B_r - B_{far})}{d_t} + B_{far} \right] & \text{if } d \in (0, d_t]. \end{cases} \tag{9}$$

where $d(n)$ is the distance between the car navigating with TDBM and the neighbor n; d_t is a threshold distance beyond which neighbors will be applied with the 'far away' metric B_{far}; and d_{t2} is a threshold distance beyond which neighbors would not have any impact on TDBM's navigation. S_{TDBM} is referring to the metric in Equation 6 and B_{far} and B_r refers to the attention metrics in Equation 5.

This proximity cost used in TDBM discouraged the optimizer from picking any candidate whose path is close to these dangerous drivers. However, this approach has a drawback: when the ego-vehicle and the neighboring vehicle are both slow, some unnecessary lane changing may occur. To avoid this, we add the relative velocity of the neighboring vehicle in relation to the ego-vehicle into the cost function. The new cost function also nullifies the effect of the cost on vehicles that are driving away from the ego-vehicle. The new cost function for vehicles is:

$$c'_{vehicle} = \sum_{n=1}^{N} max(0, v_{ego} - v_n) c(n) \tag{10}$$

where v_{ego} and v_n are the current progression speed along the lane of the ego-vehicle and the neighbor n respectively.

4.2. Pedestrians and Cyclists

The proximity costs for pedestrians and cyclists in AutonoVi and TDBM are still diminishing rapidly and do not take into consideration the velocity of the pedestrian/cyclist. We propose accounting for the current velocity in order to better predict and represent the zones to be avoided by the navigation algorithm:

$$c'_{obs} = \sum_{n=1}^{N} \frac{F(n)\, max(0, v_n \cdot \frac{\vec{s}_{ego} - \vec{s}_n}{||\vec{s}_{ego} - \vec{s}_n||})}{F(n) + ||\vec{s}_{ego} - \vec{s}_n||} \tag{11}$$

where $F(n)$ returns F_{ped} or F_{cyc} depending on the type of obstacle n. v_n represents the current normalized velocity of the pedestrian/cyclist. $\vec{s}_{ego}$ and $\vec{s}_n$ are the position of the ego-vehicle and the obstacle n, respectively.

Using these new cost functions, we can avoid drivers that are potentially riskier, stay away from pedestrians and cyclists more appropriately, and select a better navigation path. Examples of scenarios are illustrated in Figure 3.

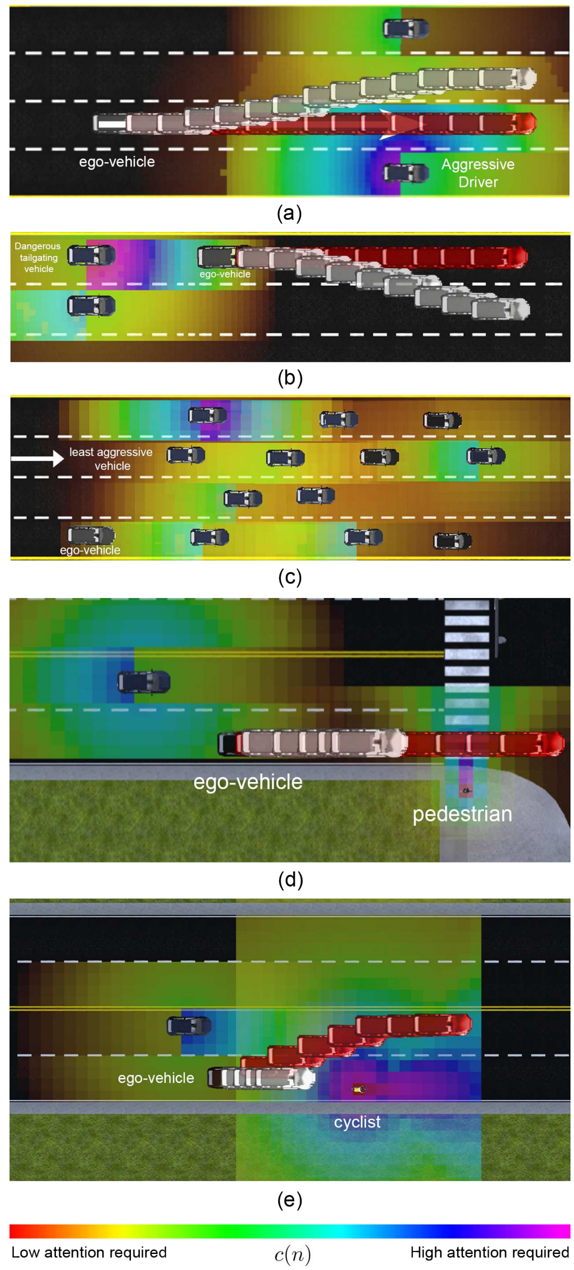

Figure 3. Examples of our navigation approach (white trajectories) taking into consideration other drivers' behaviors, and the approach that does not (red trajectories). The cost map of each neighbor contributing to $c(n)$ is shown for its surrounding area. (a) The aggressive driver with higher cost is avoided; (b) the vehicle tailgating our ego-vehicle and our approach allows the ego-vehicle to switch lanes and avoid it; (c) the ego-vehicle is facing heavy traffic, and it chooses to follow the neighbor with the least amount of attention required; (d) the ego-vehicle stops because a pedestrian is walking towards the road, despite the traffic rule, and suggests the ego-vehicle may proceed and; (e) the ego-vehicle slows down because a cyclist is in front of it, and an aggressive driver is driving next to it.

5. Conclusion and future works

We present a new navigation approach leveraging the estimation of neighboring human drivers' behaviors and react to them accordingly. Using our approach, the navigation algorithm can more accurately estimate the level of awareness the ego-vehicle should have about neighboring vehicles, pedestrians and cyclists, and more effectively avoid those that require a higher level of awareness. Our approach can provide safer navigation among aggressive drivers, pedestrians, and cyclist and more efficient navigation when facing careful drivers.

The trajectory data that is currently available in the autonomous driving research community are limited, as labeling raw images are expensive. Currently, pedestrian and vehicle detection methods are advancing, and soon will be able to extract trajectory data reliably from raw data. The Trajectory to Driving Behavior Mapping applied in this work is based on highways, and the driving behaviors could be different in urban environment as there are pedestrians and cyclists involved. Furthermore, driving and pedestrians behaviors are different across countries and regions. With more data available, we would like to evaluate our approach on urban environments. Besides, there are works conducted to predict pedestrians trajectories (e.g., SocioSense [5]), and we can combine them to navigate even safer around pedestrians and cyclists in the future.

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