USING ARTIFICIAL POTENTIAL FIELDS TO MODEL DRIVER SITUATIONAL AWARENESS

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Abstract: Recently, the use of artificial potential fields, known as risk fields, has been proposed for modeling human driver decision making. Such potential fields map from vehicle states and control inputs to a numerical risk measure such that the probability of choosing a control decreases as the risk associated increases. In this paper, we show that such a model can be used in a natural manner to also capture aspects of the driver's situational awareness, assuming that the risk fields govern their underlying behavior. We demonstrate our ideas on a specific obstacle avoidance scenario wherein obstacles to be avoided are placed in front of a driver at predicable intervals. Using data collected on a pilot experiment involving six different drivers using a high-fidelity driving simulator, we demonstrate the ability of our approach to capture the likelihood that the driver has perceived/reacted to the obstacle. Our approach works for scenarios when the driver collides with the obstacle as well as scenarios involving successful collision avoidance.

Keywords: Situational Awareness, Driver Modeling, Potential Functions, Risk Fields, Convex Optimization.

1. INTRODUCTION

Situational awareness, as the name implies, refers to the perception by an agent of different aspects of their operating environment as well as knowledge of how these would affect their goals and overall performance (Cf. Endsley (1995)) [1]. For instance, an agent driving a car may possess situational awareness of other cars that are in close proximity, so that they are aware of the positions, headings and velocities of these cars as well as whether a future collision with any of these cars may be imminent. Inferring the (lack of) situational awareness of an agent during task performance is a challenging problem.

In this paper, we use an existing probabilistic model of decision making introduced in our previous work (Cf. Jensen et al. (2022)). This model predicts the probability $P(\mathbf{u}|\mathbf{x})$ that a given control input $\mathbf{u}$ is chosen by the agent for a given state $\mathbf{x}$. We extend our previous work to infer key aspects of the driver's situational awareness on the fly. Our approach relies on passive observations of the vehicle state and control inputs. For instance, our framework can predict the likelihood that the driver is aware of an obstacle in front of them by matching the driver's actions against two different hypotheses: one where the driver is *unaware* of the obstacle and the other where the driver is aware. We use the underlying probabilistic model to predict the likelihood of the driver's currently observed control inputs under each hypothesis. Therefore, using Bayes rule, we can then predict the probability that the driver is unaware of the obstacle in front of them, or more precisely, the driver's actions are consistent with someone who is unaware under the assumed probabilistic model. We show that our approach can extend to other aspects such as ascribing a spatial position to the vehicle that is most compatible with the driver's current choice of control inputs under the assumed probabilistic model. Such a position could inform us about the driver's likely mental model of the vehicle state given their actions.

We ground our approach to a specific data-set collected by asking 6 human drivers to operate a vehicle around a simulated course inside the NADS high fidelity simulation environment. The simulated course places obstacles at regular intervals. The goal of the driver is to avoid these obstacles, stay in their lanes as much as possible and keep their speeds as close to a target value as possible. The environment records the vehicle state and control inputs applied by the driver. Our previous work showed that it is possible to define a simple probabilistic model based on carefully defining a potential function called a risk field (Jensen et al. (2022)). Furthermore, we showed that convex optimization approaches can be used to find the potential function with maximum likelihood and the resulting driver model is quite accurate in predicting the paths taken by various drivers around the obstacle although some key limitations are also noted. The key

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[1] The terms "situational awareness" and "situation awareness" are used interchangably. We will exclusively use the former in this paper.

contribution in this paper is to use this model to predict aspects of the driver's mental state.

Our approach can be quite useful in many practical applications in Human Cyber-Physical Systems. Originating in the aviation domain (Krems and Baumann, 2009), there has long been a focus on understanding operator behavior in uncertain or dynamic environments. In particular, pilots as well as other vehicle drivers need to be able to detect potentially dangerous situations so that they may react in a timely manner. For vehicle drivers, unsafe situations may arise due to a variety of factors such as fatigue during a long drive, a pedestrian suddenly entering the road, or when the autonomous vehicle fails to identify a stopped emergency vehicle (Boudette and Chokshi, 2021).

The motivation for this work is to model driver situational awareness with the ultimate goal of providing interventions through shared controllers or user interfaces. In this paper, we predict whether or not a driver has detected an imminent obstacle in a night-time simulation. We use a risk field modeling approach to infer the driver's mental state and their estimate of the distance to an upcoming obstacle. We show that this approach can distinguish between trials where drivers successfully avoid an obstacle and trials where drivers collide with the obstacle.

2. RELATED WORK

Developers and researchers of cyber-physical human systems have consistently pointed out the need for systematic models of human behavior (Munir et al., 2013). Such models can help design shared control systems and behavioral interventions. When dealing with driver safety and situational awareness, recent work has focused on takeover requests when an autonomous vehicle detects a possible collision or dangerous situation (Ko et al., 2021; Tabrez et al., 2020; Pakdamanian et al., 2021, for example).

A few recent papers have developed models to predict situational awareness. In a review focused on situational awareness for connected cars, Golestan et al. (2016) discuss previous modeling approaches applied to the core stages of situational awareness: perception, comprehension, projection, and management. More recently, researchers have used advances in artificial intelligence to improve real-time prediction of situational awareness using eye tracking data (Zhou et al., 2022; Hofbauer et al., 2020). In each case, the operational definition of situational awareness varies, ranging from a composite of avoidance behaviors in a takeover situation (Zhou et al., 2022) to a function of eye fixations in key areas such as vehicle instruments (Hofbauer et al., 2020).

In contrast to machine learning methods, other approaches to modeling driver decision making behavior are based on an interaction field approach (Gibson and Crooks, 1938; Kadar and Shaw, 2000). A pair of recent studies is similar to the proposed work in that the authors aimed to quantify human perception of risk in the environment when navigating in a driving task. In a simulator study, Kolekar et al. (2020b) systematically measured human perception and reactions to obstacles that were placed at different positions relative to the vehicle. Using this data, they then fit a model of perceived risk that decreases as objects appear farther away from the vehicle. Kolekar et al. (2020a) extended the study by combining this egocentric risk measure with the perceived consequence of colliding with an item in the environment. They then developed a model to navigate in the environment based on this value. The Kolekar model is able to generate naturalistic behavior in a variety of driving configurations, although it was only evaluated on a single driver.

The approach in this paper derives from the risk fields framework proposed in Jensen et al. (2022). In this framework, personalized human operating behaviors are modeled based on risks inherent in the environment and as a result of control actions they might take. In particular, humans are modeled to choose control actions that lead to lower overall risk with exponentially higher probability than actions that lead to higher overall risk. This approach is also summarized in Section 3.2. While this approach showed promise in recreating human driver trajectories, more work is needed to understand how it may predict other aspects of human behavior.

The main contribution of this paper is that we show the risk field framework can naturally be used in order to estimate a driver's situational awareness; specifically, we can show that a driver's behavior can be used to indicate whether or not they have perceived an oncoming obstacle. This property of the risk field framework can be used in controls or user interface design to react to instances where the driver has not perceived a dangerous situation.

3. DRIVER MODELING USING RISK FIELDS

We first describe the driving scenario, a mathematical description of risk fields and how they can be used to capture driver decision making.

3.1 Driving Scenario

We first begin by describing the driving task and the corresponding obstacle avoidance scenario, as depicted in Figure 1. The driving task consists of participants driving a simulated vehicle around a set course with obstacles inside the NADS-miniSim environment. The simulation is set for night time driving on a two lane city highway with four fixed, static obstacles placed along a 4.8km (3 mile) route. To increase the difficulty of the task, participants were asked to drive one handed with their non dominant hand. Furthermore, the road lighting is designed to limit the visibility of the road ahead of the driver. There were no oncoming, leading, or trailing vehicles. The obstacles were placed so that they were about 2 seconds before the driver would collide with them. The objectives for the human driver are as follows:

(1) Keep the vehicle within their lane and minimize deviations. They must never exit the paved road.
(2) Avoid Obstacles (a tire) placed in the operator's lane.
(3) Maintain speed as close as possible to 45 mph (≈ 20 m/s) at all times.

3.2 Risk Fields

We will now describe a mathematical model of the human driver using artificial risk fields. First, we will fix a

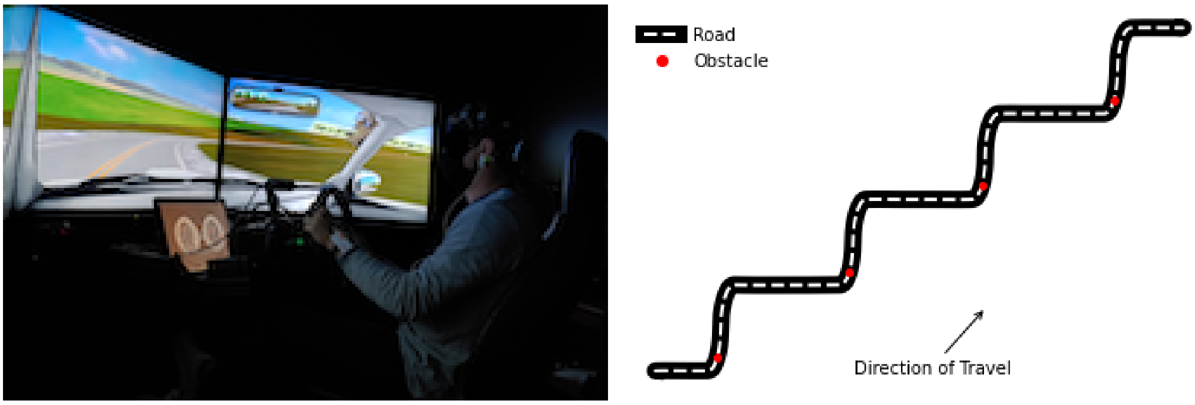


Fig. 1. (Left) Picture of the NADS miniSim setup showing a participant driving along a course (daytime simulation), (Right) plot of the center line of the simulated course showing obstacle placement as red circles.

mathematical model of the vehicle and describe the vehicle state in terms of this model. Let $\mathbf{x} : (x, y, v, \psi)$ denote the vehicle state wherein (x, y) denote the vehicle's position in a global coordinate frame, v denotes its velocity along the current direction of travel and ψ denotes the heading (yaw) angle of the vehicle. The control inputs include $\mathbf{u} : (u_1, u_2)$ wherein u_1 denotes the acceleration/braking input and u_2 denotes the steering input. The overall vehicle model is described by an ODE:

$$\dot{x} = v\cos(\psi),\ \ \dot{y} = v\sin(\psi),\ \ \dot{v} = u_1, \dot{\psi} = u_2\,. \tag{1}$$

For a given state $\mathbf{x}$, and time increment $\delta > 0$, let $\mathsf{next}(\mathbf{x}, \mathbf{u}, \delta)$ denote the new state $\mathbf{x}(\delta)$ obtained at time δ when starting from initial state $\mathbf{x}(0) = \mathbf{x}$, applying the controls $\mathbf{u}$ (held constant).

We model the risk of the potential state $\mathsf{next}(\mathbf{x}, \mathbf{u}, \delta)$ in terms of the three objectives stated in Section 3.1. We operationalize keeping within the lane by defining a quadratic increase as the vehicle location (x, y) moves away from the center line C. Similarly, risk increases quadratically as the vehicle's speed deviates from the target speed $v_{tgt} =$ 45 mph. Finally, the driver encounters high risk then the vehicle is close to the obstacle O with diameter d_o; this risk decays exponentially with increasing distance from the obstacle. In addition to risk associated with states, we define quadratic *costs* for acceleration/braking and steering rate control inputs.

To summarize, the overall risk for a given state $\mathbf{x}$: (x, y, v, ψ) and control $\mathbf{u}$ is given by $\mathsf{risk}(\mathbf{x})$:

$$\mathsf{risk}(\mathbf{x}) : \begin{cases} \mathbf{A} \cdot \mathsf{dist}((x, y), C)^2 + \\ \mathbf{B} \cdot \exp\left(-\dfrac{\mathsf{dist}((x, y), O)^2}{d_o^2}\right) + \\ \mathbf{C} \cdot (v - v_{tgt})^2 \end{cases}. \tag{2}$$

and the cost of the control input is given by $\mathsf{cost}(\mathbf{u})$:

$$\mathsf{cost}(\mathbf{u}) :\ \mathbf{D} \cdot u_1^2 + \mathbf{E} \cdot u_2^2\,. \tag{3}$$

The coefficients $\mathbf{A}, \ldots, \mathbf{E} \geq 0$ are unknown, participant-specific parameters that determine the relative weights each driver places on the individual risk components.

We assume that the operator is driving according to a fixed risk and cost model so that for a given state, the choice of control inputs is given by :

$$\mathbb{P}(\mathbf{u}|\mathbf{x}) \propto \exp\left(-\mathsf{risk}(\mathsf{next}(\mathbf{x}, \mathbf{u}, \delta)) - \mathsf{cost}(\mathbf{u})\right)\,, \tag{4}$$

wherein δ is a fixed preview time that is inferred from an analysis of the human driving data. Eq. (4) thus models the distribution of possible control inputs $\mathbf{u}$ chosen by a driver for a given state $\mathbf{x}$. The chosen control depends on the risk evaluated at the state $\mathsf{next}(\mathbf{x}, \mathbf{u}, \delta)$ for a preview time δ and the cost of the control $\mathbf{u}$. The expression for probability is obtained by normalizing. Suppose the set of possible actions U is a finite set $\{\mathbf{u}_1, \ldots, \mathbf{u}_N\}$. The denominator normalizes the probability over all actions. For continuous set of control actions, we can replace the summation by an integral over the set U. Doing so, we obtain the following expression for $\mathbb{P}(\mathbf{u}|\mathbf{x})$:

$$\mathbb{P}(\mathbf{u}|\mathbf{x}) = \frac{\exp(-\mathsf{risk}(\mathsf{next}(\mathbf{u}, \delta)) - \mathsf{cost}(\mathbf{u}))}{\sum_{j=1}^{N} \exp(-\mathsf{risk}(\mathsf{next}(\mathbf{u}_j, \delta)) - \mathsf{cost}(\mathbf{u}_j))}\,. \tag{5}$$

4. DATA

Participants. Six participants (3 male, 3 female), all undergraduates at Purdue University, completed the study [2]. The mean age was 21.33 years (SD = 0.82). Before the experiment, participants practiced driving the vehicle in the simulator using a daytime scene on an open highway.

Data Collection. Each participant drove the night-time course with obstacles on at least three times, yielding nineteen separate trials for the six participants, in total (one participant recorded four trials). We recorded data at 60 Hz, including vehicle states such as position, velocity, heading angle, steering wheel position, and accelerator/brake pedal positions.

Model Fitting. For each of the 19 trials, we fit a risk model by finding the coefficients $\mathbf{A}, \ldots, \mathbf{E}$ in Equations 2 and 3 that maximizes the likelihood $\mathbb{P}(\mathbf{u}|\mathbf{x})$ of the driver's data. This can be framed as a convex optimization problem; see Jensen et al. (2022) for more details.

We evaluated the approach by comparing trajectories generated by the risk model with the actual human trajectory for the trial using a cross-validation approach wherein the model was trained on one half of each particpant's data and evaluated over the other half. To do this, we discarded two trials where the driver collided with the obstacle. We found that while the models were able to track the position very well up to 20 seconds in the future (trajectories match

[2] This study was approved by Purdue IRB number 1905022220

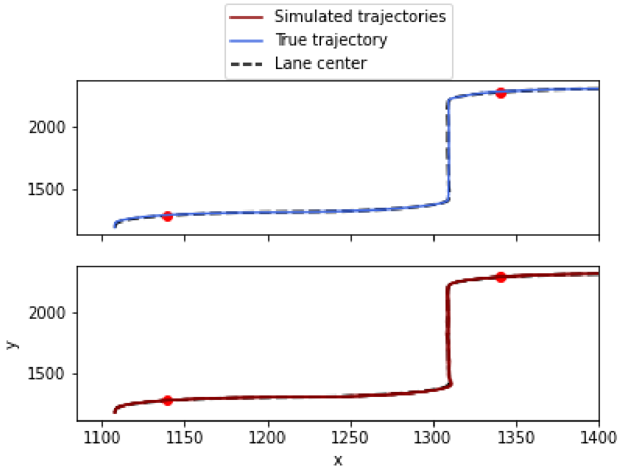


Fig. 2. Plot of actual user trajectory (blue) with 20 trajectories (red) using the stochastic risk field model. Note that the conditions are plotted separately for clarity since they are virtually indistinguishable when superimposed.

within 1.5 meters, see Figure 2), the model is less accurate when it comes to tracking the driver's velocity. Some of the reasons for this discrepancy in the predicted vs actual velocities are discussed in Jensen et al. (2022).

The fitted coefficients show that the model is able to capture a range of driving behaviors by assigning different weights to the different risk or cost terms (see Table 1). The meaning and significance of these parameters are discussed in Jensen et al. (2022).

Table 1. Description of risk field fitted coefficients. Distribution is reported as mean ± SD

Coefficient	Weight given to ...	Distribution
A	Keeping to lane center	0.561 ± 0.220
B	Staying far from obstacle	29.982 ± 50.738
C	Keeping to target speed	0.011 ± 0.056
D	Using low acceleration	3.114 ± 4.652
E	Using low steering rate	48.748 ± 28.104

5. MODELING SITUATIONAL AWARENESS

In this section, we will use the driver model from the previous section in order to reason about the possible situational awareness of the driver. Situational awareness refers to perception of key aspects of the environment that will be critical for decision making on the part of the driver. Specifically, we will capture the probability that the driver's action indicate that they are aware of the obstacle in front of them. Similarly, we will use the driver's action to ascribe a "mental estimate" of the distance to the obstacle.

Consider a vehicle state $\mathbf{x} : (x, y, v, \psi)$ with an obstacle O at some distance $\mathsf{dist}((x, y), O)$ from the vehicle. Let us consider two alternative mental states: AWARE: the driver is *aware* of the obstacle in front of them, versus UNAWARE: the driver is *unaware* of the obstacle in front of them. The key difference lies in the *perceived* risk in these states. If the driver is unaware of an obstacle the risk model will not include the term associated with the obstacle, or in other words $\text{dist}((x, y), O)$ is taken to be ∞ in Eq. (2). Let $\mathsf{risk}_{\text{un}}(\mathbf{x})$ denote the risk associated with state $\mathbf{x}$ assuming that the driver is unaware of the obstacle. This is equivalent to setting the distance $\mathsf{dist}((x, y), O) = \infty$ (or alternatively, $B = 0$) in Eq. (2). Note that when the driver is aware of the obstacle, $\mathsf{risk}(\mathbf{x})$ according to Eq. (2) will continue to model the risk associated with a state $\mathbf{x}$.

Thus, we define the probability:

$$\mathbb{P}(\mathbf{u}|\mathbf{x}, \text{UNAWARE}) \propto \exp\left(-\mathsf{risk}_{\text{un}}(\mathsf{next}(\mathbf{x}, \mathbf{u}, \delta)) - \mathsf{cost}(\mathbf{u})\right) \tag{6}$$

whereas the probability of control choice when the driver is aware is given by Eq. (4), recalled below:

$$\mathbb{P}(\mathbf{u}|\mathbf{x}, \text{AWARE}) \propto \exp\left(-\mathsf{risk}(\mathsf{next}(\mathbf{x}, \mathbf{u}, \delta)) - \mathsf{cost}(\mathbf{u})\right) \tag{7}$$

The difference lies in the use of risk function as opposed to the risk_{un} function. Suppose we have a *prior belief* that the driver is *unaware* of the obstacle with probability p_U, then by Bayes rule, we obtain the following expression for $\mathbb{P}(\text{UNAWARE}|\mathbf{u}, \mathbf{x})$:

$$\frac{\mathbb{P}(\mathbf{u}|\mathbf{x}, \text{UNAWARE}) \times p_U}{\mathbb{P}(\mathbf{u}|\mathbf{x}, \text{UNAWARE}) \times p_U + \mathbb{P}(\mathbf{u}|\mathbf{x}, \text{AWARE}) \times (1 - p_U)} . \tag{8}$$

This allows us to provide a *recursive* estimate of the probability that the driver remains unaware of the obstacle in front of them. We initialize the probability of being unaware to some suitable starting value eg., $p_U = 0.5$. At each step, we obtain a state $\mathbf{x}$ and a control input $\mathbf{u}$ from the data. We use this to update the posterior probability according to Eq. (8). This provides us the prior distribution for the next time step. Often however, when p_U is close to 0 or 1, the recursive process stops evolving when new data is available. To avoid this, we use an "ϵ-transition" wherein the posterior value of p_U is updated as $p'_U = (1 - \epsilon)p_U + \frac{\epsilon}{2}$ to yield a prior value for the next time step. We set $\epsilon = 0.05$ for our experiments.

Thus, we can obtain an estimate of the probability that the user is unaware of the obstacle at each time step. Next, we can refine our analysis to ask other questions about the situational awareness of the driver. For instance, we can use the risk model to infer the driver's likely estimate of their own position $(\hat{x}, \hat{y})$. To do so, we set up a prior distribution over likely positions $\pi(\hat{x}, \hat{y})$. Typically such a prior is specified as a uniform distribution over positions that are within some distance of their true position. Given the vehicle state $\mathbf{x} : (x, y, v, \psi)$, let $\hat{\mathbf{x}}$ denote the state $(\hat{x}, \hat{y}, v, \psi)$. Furthermore, for simplicity let us consider a finite set of hypothesized mental model positions $\hat{\mathbf{x}}_1, \ldots, \hat{\mathbf{x}}_K$. Our risk model allows us to evaluate $\mathbb{P}(\mathbf{u}|\hat{\mathbf{x}}_j)$ for a given control input $\mathbf{u}$ and position $\hat{\mathbf{x}}_j$. Once again using Bayes rule we obtain:

$$\mathbb{P}(\hat{\mathbf{x}}_j|\mathbf{u}) = \frac{\mathbb{P}(\mathbf{u}|\hat{\mathbf{x}}_j) \times \pi(x_j, y_j)}{\sum_{k=1}^{K} \mathbb{P}(\mathbf{u}|\hat{\mathbf{x}}_k) \times \pi(x_k, y_k)} . \tag{9}$$

6. RESULTS

Figure 3 shows some of the results obtained by our approach on actual encounters of various drivers with different obstacles in the course. First, our risk model parameters $A - E$ are simply fixed to the mean values shown in Table 1. Next, we plot the probability $\mathbb{P}(\text{UNAWARE}|\mathbf{x}, \mathbf{u})$, having initialized it to 0.5 at the very beginning of each obstacle encounter. Figure 3 shows four different scenarios

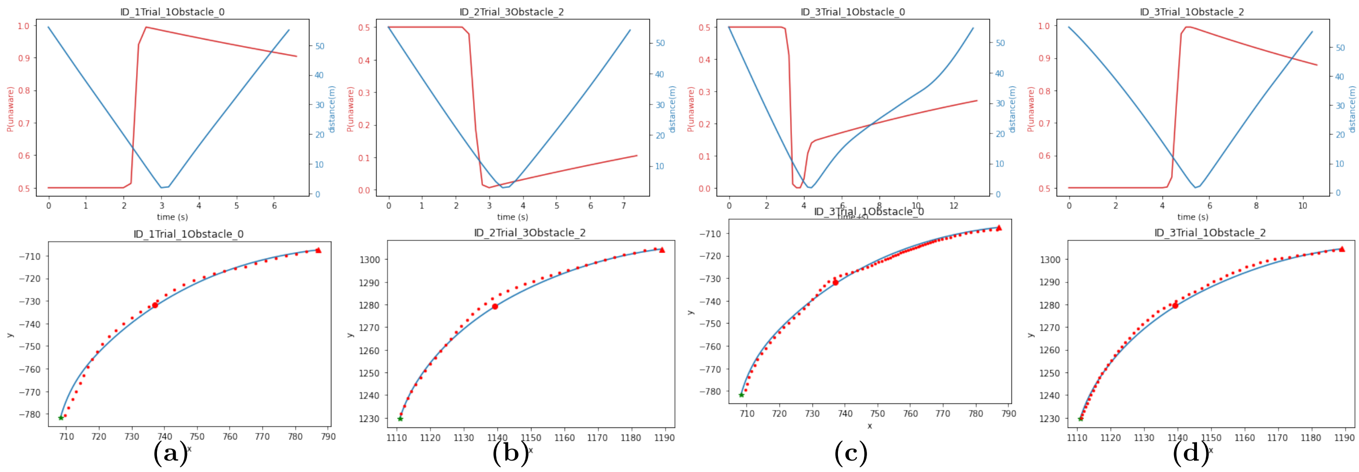


Fig. 3. **Top Row:** Combined plot of probability $\mathbb{P}(\textsc{unaware}|\mathbf{x},\mathbf{u})$ that the driver is unaware of the obstacle in front (red) and distance from obstacle (blue); **Bottom Row:** Plot of vehicle trajectory (shown as dotted red line) against the center line shown in solid blue and obstacle shown as a filled red circle. **(a)-(d)** represent four selected scenarios each involving a different participant, trial and obstacle in the course.

labeled **(a)-(d)**. Scenario **(a)** represents the vehicle colliding with the obstacle. Notice that the probability that the user is unaware of the obstacle rapidly rises from 0.5 to 1.0, about $1 second$ prior to the collision. We contrast that with Fig. 3 **(b)** wherein the obstacle is successfully avoided. As expected, the estimated probability rapidly falls from 0.5 to below 0.1 nearly 1 second prior to the vehicle passing the obstacle. Fig. 3 **(c)** also shows a successful obstacle avoidance that is achieved by deviating from the center line much closer to the obstacle when compared to Fig. 3 **(b)**. As expected, we note that the probability that the user is unaware falls rapidly but also rises back up. Finally, Fig. 3 **(d)** shows a situation where the driver approaches very close to the obstacle without necessarily colliding with it. Our approach estimates that the probability of being unaware of the obstacle rises rapidly.

Figure 4 plots the average of the driver's own estimate of their position $(\hat{x}, \hat{y})$ as inferred by comparing the chosen control input against the risk model versus the actual ground truth position. Figure 4(b)-(d) show cases where the obstacle is avoided whereas Figure 4(a) shows the case when collision with obstacle occurs. As expected, for the cases when a collision is avoided successfully, the estimated positions seem to coincide with the actual positions. A marked difference is observed in Figure 4(a) where a collision occurs. We interpret this result to mean that the driver's behavior in this case does not match what one would expect from the risk model. As a result, the $(\hat{x}, \hat{y})$ position wherein the driver's control inputs would make "most sense" are farther away from the vehicle's current position. However, for Figures 4(b)-(d), this is less true – in general, the decisions made by the driver seem more or less consistent with what would be expected at that position under the assumed risk model.

7. LIMITATIONS AND CONCLUSION

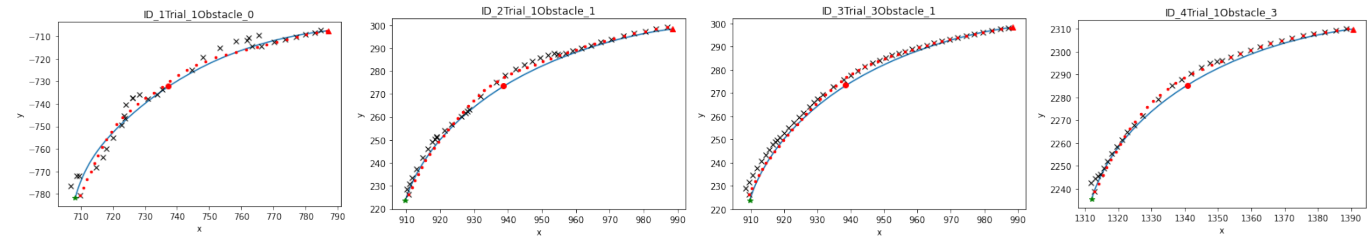
Thus, we present an extension of our previous work that constructs a probabilistic model of human decision making in dynamic environments wherein our extension allows such models to reason about key situational awareness properties of the user. The approach often produces results that are consistent with the ground truth data. We will briefly discuss some of the key limitations of this work that will be addressed in future work.

Key limitations of our data collection methodology include the limited number of participants and the straightforward nature of the driving task in our initial study. Some of these limitations are being addressed by ongoing studies at the time of writing that will explore a larger pool of participants and more dynamic driving scenarios involving traffic patterns, wind, visibility restrictions, moving obstacles on the road and construction.

The data collected did not include *ground truth* data about the actual situational awareness of the drivers. Note that ground truth data about situational awareness is hard to collect, especially since we are interested in detecting the *lack* of situational awareness. In the future, we propose to correlate our approach with indirect measures such as gaze tracking data or more direct user reports of their ongoing situational awareness in the future.

Yet another limitation of our approach lies in its reliance on the driver's steering and throttle actions to infer their situational awareness. For instance, a driver may be aware of an obstacle much longer but choose to react to it at a later time. Our approach here will be unable to detect the driver's awareness of the obstacle until their steering and acceleration inputs actually change to potentially avoid the obstacle. To mitigate this, we will investigate other information sources such as the driver's gaze and fixation.

Another drawback arises from the limitations of our approach so far to model changes in velocities. We plan to explore how the choice to accelerate or apply brakes is made by experienced drivers. One final limitation of our approach is that we have not compared our estimation of situational awareness against some notion of ground truth directly obtained from the driver. We are incorporating gaze tracking data in a systematic manner to check if the



(a) (b) (c) (d)

Fig. 4. Mean over estimated driver positions shown as black x versus actual positions shown using red dots. The center line is shown in blue and obstacle is shown as a bright red circle.

lack of awareness of the obstacle can in fact be concluded from where the driver chooses to look. This data will provide a means to confirm the probability estimates in this paper.

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