Probabilistic Modeling of Human Perception for Semi-Autonomous Robotics

Dorsa Sadigh, Roy Dong, S. Shankar Sastry, Sanjit A. Seshia
Department of Electrical Engineering and Computer Sciences, UC Berkeley
{dsadigh, roydong, sastry, sseshia}@eecs.berkeley.edu

***Abstract*—We develop a data-driven probabilistic model of human perception and actions in the context of semi-autonomous driving. We define a metric for perception and complexity of driving environment. Using this measure, we synthesize a warning system that informs the driver to look at specific frames to gain visual awareness whenever there is a high risk of accidents.**

I. Introduction

The problem of human modeling has long been studied by psychologists. Recently, there is growing interest in deploying semi-autonomous systems in safety-critical applications with substantial autonomy. Formal verification and synthesis of such systems require formal models of all system components, including the human operators. Thus human modeling is an important aspect of the design of semi-autonomous systems.

Salvucci[1] uses the ACT-R architecture to model human driving. This architecture consists of perception, decision and action modules. The driver *perceives* a scenario and monitors the environment, then based on her perceptions, she *decides* on the future actions, finally she performs the intended *action*. In this poster, we propose a data-driven driver modeling scheme for quantifying perception, and integrating it with her actions in a Markov Decision Process. We then synthesize a warning system using perception and complexity of environment to assess the risk of danger and provide appropriate warnings.

II. Formalism

A. Modeling Perception

Perception represents situational awareness of the environment. We let $P(t, \alpha, f) \in [0, 1]$ quantify perception, where $P = 1$ represents full awareness of the environment, t is the time step, $\alpha \in \mathbb{R}$ is a factor for unmodeled variables e.g. age, experience, etc. The term f is an indicator for the direction or frame human is looking at at time t representing her visual awareness. In our driving experiments, we provide three different frames (front, right, left view) to the driver. Thus, $f(t) = \begin{bmatrix} f_1(t) & f_2(t) & f_3(t) & f_4(t) \end{bmatrix}$, where $f_1(t)$ corresponds to looking at an external frame (steering wheel, the stereo system, cell phone, etc.), $f_2(t), f_3(t)$, $f_4(t)$ correspond to looking at left, front and right frames respectively. These indicators take value 1 if their frame is selected by the eyes[2].

[1]Dario D Salvucci. Modeling driver behavior in a cognitive architecture. Human Factors: The Journal of the Human Factors and Ergonomics Society, 48(2):362380, 2006.

[2]http://www.eyetracking-glasses.com/

Let $\mathbf{P}(t) = \begin{bmatrix} P_1(t) & P_2(t) & P_3(t) \end{bmatrix}$. Here, $P_i(t) \in [0, 1]$ is the perception of each frame. We model the evolution of perception using Γ. β and ϵ model the dependence between neighboring frames and the exponential decay of perception based on memory models respectively. We update the perception when a new frame is selected $\mathbf{P}^{t+1} = \begin{bmatrix} f_1 & f_2 & f_3 & f_4 \end{bmatrix} \Gamma(\mathbf{P}^t)$ where:

$$\Gamma(\mathbf{P}^t) = \alpha \begin{bmatrix} \beta P_1^t & \beta P_2^t & \beta P_3^t \\ 1 & \beta P_2^t + \epsilon(1 + P_1^t) & \beta P_3^t + \epsilon P_2^t \\ \beta P_1^t + \epsilon P_2^t & 1 & \beta P_3^t + \epsilon P_2^t \\ \beta P_1^t + \epsilon P_2^t & \beta P_2^t + \epsilon(1 + P_3^t) & 1 \end{bmatrix}$$

B. Complexity of Environment

We quantify the complexity of the environment for each frame as a weighted sum of variables that represent the state of the vehicle in the environment. Our model of vehicle in simulation[3] has front, left and right radars with full observability of the sensors. The complexity for each frame is defined by $\mathbf{C}(t) = \begin{bmatrix} C_1(t) & C_2(t) & C_3(t) \end{bmatrix}$, where $C_i(t) = \sum_j a_j s_j(t)$. $s_j(t)$ are the sensor values from the radars, and $C_i(t)$ is a weighted sum of these sensor values, normalized appropriately.

C. Warning System

We define risk of danger in frame i as $Risk_i(\mathbf{P}(t), \mathbf{C}(t)) = C_i(t) - P_i(t)$. We would like to raise a warning for frame i when $Risk_i(\mathbf{P}(t), \mathbf{C}(t)) > \rho_i$, where ρ_i is a threshold for frame i. The goal of the warning is to find an advisory policy that minimizes the risk of the worst frame $Risk(\mathbf{P}(t), \mathbf{C}(t)) = \max_i Risk_i(\mathbf{P}(t), \mathbf{C}(t))$, i.e. provides maximum situational awareness, while not overwhelming the human with data.

III. Integration and Conclusion

We represent the perception, action model proposed in this poster as a Markov Decision Process. The states of the MDP at time t are perception complexity pairs at time t. The transition probabilities are learned from empirical traces of human driving behavior. For a reward function, we use the amount that the worst-frame risk decreases, i.e. the reward for the action at time t is $Risk(\mathbf{P}(t+1), \mathbf{C}(t+1)) - Risk(\mathbf{P}(t), \mathbf{C}(t))$.

In conclusion, we proposed a new technique for quantifying perception based on visual awareness, and defined a metric for complexity of environment. We represented this model as a MDP, defined a measure for the risk of danger, and proposed a monitor to warn the human whenever necessary.

[3]http://www.force-dynamics.com/