Action Conditioned Response Prediction with Uncertainty for Automated Vehicles

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Abstract—Interaction-aware prediction is a critical component for realistic path planning that prevents automated vehicles from overly cautious driving. It requires to consider internal states of other driver such as driving style and intention, which the automated vehicle cannot directly measure. This paper proposes a probabilistic driver model for response prediction given the planned future actions of automated vehicle. The drivers internal states are considered in an unsupervised manner. The proposed model utilizes mixture density network to estimate future acceleration and yaw-rate profile of interacting vehicles. The proposed method is evaluated by using real-world trajectory data.

Index Terms—action conditioned prediction, mixture density network, response prediction, autonomous vehicle

I. INTRODUCTION

In most motion planning studies [1]–[3] for autonomous vehicles, the robot first makes predictions of surrounding vehicles and then plans the trajectory based on the predictions. These approaches tend to make the vehicle overly cautious because they consider surrounding vehicles not as interacting objects but as obstacles to avoid.

For naturalistic driving, an automated vehicle is required to have the ability to interact with surrounding vehicles while driving. When the automated vehicle tries to merge into dense traffic, the success of the attempt depends on the concession of the traffic participant. In other words, the other human driver’s action can influence to the autonanated vehicle’s action, and vice versa as shown in Fig. 1.

In this context, it is important to predict responses of human taking into account uncertainty arising from the interaction or driver’s internal states (e.g. intentions, preference and driving style). From this point of view, the main contributions of this paper are:

- Developing a model to predict the response of the human driver given the planned action of the automated vehicle.
- Considering internal states of the human driver in an unsupervised manner.
- Predicting both the response and its uncertainty.

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Fig. 1: Various situations that require inter-vehicle interaction

II. PROBABILISTIC HUMAN DRIVER MODEL

A. Problem Formulation

The goal of response prediction problem is learning a posterior distribution of human responses, $u_H$, under planned action of robot, $u_R$, initial states, $x^0$, and internal states of human, $z$. This distribution can be written as $P(u_H^0:N_p|u_R^0,N_p,x^0,z)$

where $u_H^k = [a_H^k, \psi_H^k]^T$, $u_R^k = [a_R^k, \psi_R^k]^T$ and $x^0 = [x_{env}^0,x_R^0, x_H^0]^T$. $a$ is acceleration and $\psi$ is yawrate. In this representation, superscript means time horizon and subscript means the agent. Since the trajectory appears through the internal states of driver, it is assumed that the internal states can be estimated from past history of action $u_H^{0:N_h}$ and $u_R^{0:N_h}$ where $N_h$ is length of history. In short, inputs and expected outputs of the response prediction problem are as follows:

- Inputs: $u_H^{0:N_h}$, $u_R^{0:N_h}$, $x_R^0$, $x_H^0$, $x_{env}^0$, $u_R^{0:N_p}$.
- Output: $P(u_H^0:N_p|u_R^0,N_p,x^0,z)$.

B. Model

In order to consider the sequence, we adopt a Sequence-to-Sequence Variational Auto-encoder [4] in our framework. While this model generally consists of encoder and decoder, proposed model has additional state embedding part considering initial states for robot and human. The encoder takes past histories of robot and human as inputs, and generates latent vector of size $N_z$. History sequence and reversed history sequence are fed into encoder. As a result, the encoder compresses the historical information into latent vector, $z$, which follows $N \sim \mu, \sigma$. To summarize this part, latent vector, $z$, is defined as random vector conditioned on action history.

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The decoder predicts $u_H^k$ corresponding to $u_R^k$ for every horizon step $k$. The distribution of $u_H^k$ is modeled by the Gaussian Mixture Model (GMM) with $M$ gaussian distributions $p(u_H^k|x^0, x^0, z) = \sum_{i=1}^{M} \pi_i^k \mathcal{N}(\mu_i^k, \Sigma_i^k)$, where $\pi_i$ represents the mixture weights of the GMM. Fig. 2 shows an example of predicted response distribution in two seconds.

### C. Loss function

The objective of training for this model is to minimize the three kind of loss functions: the Prediction loss, $L_P$, the Kullback-Leibler Divergence Loss, $L_{KL}$, and the Weight regularization loss for $W_y$:

$$L_p = -\frac{1}{N_p} \sum_{k=0}^{N_p} \log(\sum_{i=1}^{M} \pi_i^k \mathcal{N}(u_H^k|x^0, x^0, z))$$  \hspace{1cm} (1)

$$L_{KL} = -\frac{1}{2N_z} (1 + \sigma - \mu^2 - \exp(\sigma))$$  \hspace{1cm} (2)

$$L_{l2} = \sum_{i,j} (w_{y})_{ij}^2$$  \hspace{1cm} (3)

where $(w_y)_{ij}$ is the $(i, j)$ element of matrix $W_y$.

The total loss function is a weighted sum of losses mentioned above:

$$L_{total} = L_p + w_{KL}L_{KL} + w_{l2}L_{l2}$$  \hspace{1cm} (4)

### III. EXPERIMENTAL RESULTS

#### A. Dataset

We use the public Next-Generation Simulation (NGSIM) datasets collected from US Highway 101 [5]. In order to make interacting robot-human pairs from the dataset, we manually extract the vehicles that attempt to change the lane. The vehicle trying to change lane is assumed as robot and the most interacting vehicle in the situation is assumed as human driver.

#### B. Evaluation Metric and Baselines

In order to evaluate the future response prediction problem, predicted control inputs are compared. We evaluate mean and maximum absolute error for acceleration, $\dot{a}$, and yawrate, $\dot{\psi}$, at a future point in two seconds.

The following models are selected for comparison:

- Proposed: Proposed model with $M = 10$ Gaussian mixtures and size of latent vector $N_z = 80$.
- LSTM-ED: A LSTM encoder-decoder model directly predicting human inputs using initial states and planned robot inputs.
- CTRA: A constant turn rate and acceleration model.

#### C. Results

Table I shows the prediction errors of proposed method and baseline models. For acceleration error, CTRA model has best performance in terms of mean absolute error. This is because the number of data with large acceleration change within 2 seconds is relatively small considering the natural characteristic of vehicles driving on highway. However, CTRA model has poor performance in terms of maximum acceleration error. It seems that CTRA model cause large acceleration errors in the situation where deceleration is required through interaction. For yawrate error, the proposed methods perform better than others in terms of both mean and maximum error. Compared with LSTM-ED, the performance of the proposed method, which uses latent vector, performed better in all aspects.

### IV. CONCLUSION

In this paper, the probabilistic human driver model is proposed to predict the control input response of human driver to the planned control inputs of automated vehicle (robot). The proposed model estimates the latent vector representing drivers internal states first and then predicts the future control input response of human driver with uncertainty by using the latent vector. The uncertainty is modeled as a Gaussian mixture model with mixture density network. The simulation results demonstrate that the proposed method predicts the future response of human driver accurately in terms of acceleration and yawrate errors.

### REFERENCES


### TABLE I: Quantitative prediction results

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<tr>
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<th>$\dot{a}$ error [m/s²]</th>
<th>$\dot{\psi}$ error [rad/s]</th>
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