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Modeling, Learning and Prediction of Longitudinal Behaviors of Human-Driven Vehicles by Incorporating Internal Human Decision-Making Process using Inverse Model Predictive Control

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***Abstract*— Understanding the behaviors of human-driven vehicles such as acceleration and braking are critical for the safety of the near-future mixed transportation systems which involve both automated and human-driven vehicles. Existing approaches in modeling human driving behaviors including driver-model-based approaches and heuristic approaches have issues in either model accuracy or scalability limitation to new situations. To address these issues, this paper proposes a new inverse model predictive control (IMPC) based approach to model longitudinal human driving behaviors. The approach incorporates the internal decision making process of humans, and achieves better predicting accuracy and improved scalability to different situations. The modeling, learning, and prediction of longitudinal human driving behaviors using the proposed IMPC approach are presented. Experimental results validate the effectiveness and advantages of the approach.**

***Index Terms*— longitudinal human driving behaviors, inverse model predictive control, modeling, learning and prediction**

I. INTRODUCTION

Autonomous driving technology is becoming increasingly prevalent in the automobile industry. It is widely believed that autonomous vehicles can significantly reduce traffic accidents, save fuel, avoid traffic congestion and increase productivity [1]. However, autonomous vehicles need to share roads with human-driven vehicles to form a mixed-traffic in the foreseen future, which introduces safety challenges due to uncertainties in human driving behaviors. If the states of human-driven vehicles can be predicted, those autonomous vehicles can then plan-ahead to better handle the safety challenges.

The states of human-driven vehicles are the results of human actions and vehicle dynamics. Human actions are underlined by the internal mechanisms of human perception, information processing and decision making. Many general human driver models that mimic such process have been developed. Car following models such as the Tampère (TMP) model [2], Optimal Velocity Model (OVM) [3], and Intelligent Driver Model (IDM) [4] were proposed. These models can be iterated over the prediction horizon with the vehicle dynamics model to predict vehicle states after their parameters have been identified from human driving demonstrations. However, their accuracy is merely moderate when being applied to individual drivers although they can be applied to interpret general human driving behaviors.

Some data-driven heuristic approaches have also been proposed to model the behaviors of human-driven vehicles. Artificial Neural Networks (ANN) based approaches are the most popular among them. Radial basis function network (RBFN) [6], recurrent neural network (RNN) [7] and Dynamic Bayesian Networks [8] are all used to model and predict vehicle motion states. Other heuristic approaches such as Gaussian Mixture Models (GMM) [9], Hidden Markov Models (HMM) [10] and Particle Filter (PF) based approaches [11] have also been used for the same purpose. However, these approaches usually require a large amount of data to train the models properly. More importantly, instead of incorporating the internal decision-making process of a human driver, these approaches mainly aim to replicate the same driving behaviors or trajectories of human-driven vehicles as demonstrations. Thus, the scalability of such approaches is limited by the scenarios covered by the training data, and they consequently have difficulties to handle never-seen situations.

To address the issues of existing approaches, this paper proposes an inverse model predictive control (IMPC) based approach to model and predict the longitudinal behaviors of human-driven vehicles. Model Predictive Control (MPC) [12] is an optimal control method that utilizes cost function optimization to determine the decision-making process during controls. IMPC is based on Inverse Optimal Control (IOC) [13] which tries to derive the optimal cost functions. Some latest research works have tried to extend IOC to IMPC to derive the cost functions from control behaviors [14]. The major contribution of this paper is to leverage these attempts and further extend them to the modeling and prediction of longitudinal behaviors of human-driven vehicles. Furthermore, we evaluate different forms of cost functions in IMPC and propose a cost function selection process to determine the appropriate cost function in IMPC in order to achieve the best prediction performance of longitudinal behaviors in human-driven vehicles. With the proposed approach, we can more accurately model and predict the longitudinal behaviors of human-driven vehicles, and more importantly, the proposed approach has much better scalability in terms of handling unseen situations when compared to the state-of-the-art existing approaches.

II. IMPC-BASED MODELING FRAMEWORK

In this paper, we propose the IMPC-based approach and its application in modeling and predicting the longitudinal states of human-driven vehicles. The general structure of MPC-based driving model is very similar to the mindset of a human

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driver. The vehicle/driver combined dynamic model resembles the human's perception of the vehicle-road system, and the cost function resembles the human's preferences and tendencies. It is intuitive that the preferences and tendencies will vary a lot between different human drivers while the perceived vehicle-road system would roughly be the same. Thus, it would be effective to mimic and eventually predict a human driver's behavior by adjusting the cost function of the MPC to fit the 'preferences' in a human's head.

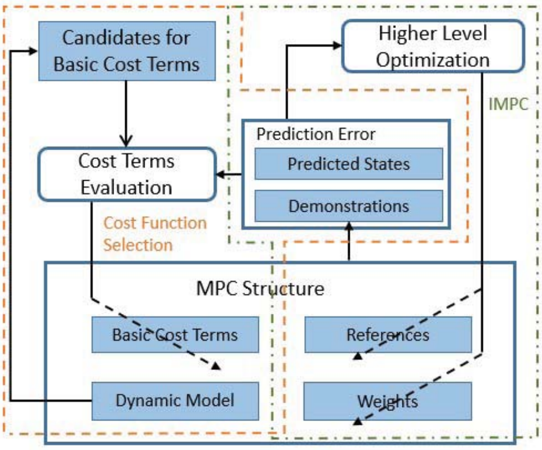

Figure 1 Structure of proposed IMPC-based model

In existing IMPC or IOC controllers, the references of each basic cost terms (or features) are given as priori since the tasks are known and the targets are fixed. By adjusting the weights of the cost terms, the IOC or IMPC can find a best weighted cost function for that given task. However, such preset references may not be ideal for predictors since different human drivers may have different goals during their driving. In this paper, we propose to train the references of the cost function together with the weights using a high-level optimization to make IMPC suitable for vehicle longitudinal state prediction. Another challenge is that the basic terms to be included in the cost function need to be selected through a trial-and-error process, which is troublesome and inefficient. In this paper we propose a cost function selection and evaluation method that can be applied before running IMPC and find the best combination of basic terms from a set of candidates obtained from the system model. The structure of the proposed evaluation method and IMPC are shown in Figure 1.

In the rest of the paper, the details of the MPC model we used to describe the human driven vehicles will be introduced in section III. The learning of the MPC model will be described in detail in Section IV. Section V will show a comparison between the proposed method and other existing methods.

III. Modeling of Longitudinal States of Human-Driven Vehicles

A. *Vehicle Models in Longitudinal Driving*

The goal of longitudinal driving is this paper is to make an ego vehicle safely follow a lead vehicle. The model used for ego vehicle is given in (1):

$$\begin{bmatrix} \dot{s_e} \\ \dot{v_e} \\ \dot{a_e} \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} s_e \\ v_e \\ a_e \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} u_e \tag{1}$$

where s_e, v_e and a_e represent the predicted displacement, speed and acceleration of the ego vehicle, u_e is the input to the system and its physical meaning is the longitudinal jerk of the vehicle. A similar model is used for the lead vehicle. Constant speed assumption is used:

$$\dot{s_l} = v_l \tag{2}$$

where s_l and v_l represent the predicted displacement and speed of the lead vehicle. The speed v_l is measured at the start of the prediction and is assumed to remain constant during that prediction. The outputs of this two-car system are:

$$\begin{aligned} v_r &= v_e - v_l \\ THWi &= \frac{v_e}{s_l - s_e} \\ TTCi &= \frac{v_r}{s_l - s_e} \end{aligned} \tag{3}$$

where v_r is the relative speed between the lead and the ego vehicles, $THWi$ is the inverse time headway, and $TTCi$ is the inverse time to collision.

B. *Constraints in Longitudinal Driving*

In order to formulate the longitudinal control in an MPC form, constraints need to be designed to ensure feasibility, reasonability and safety of the solution. In this paper the following constraints are employed:

$$\begin{gathered} a_{min} \le a_e \le a_{max} \\ v_e \le v_{max} \\ s_l - s_e \ge L \\ TTCi \le TTCi_{max} \end{gathered} \tag{4}$$

where a_{min} and a_{max} define the physical limitation that is put on the acceleration of the ego vehicle, v_{max} is the speed limit of the ego vehicle in a highway driving scenario and L is the minimum allowed headway distance between the two vehicles. Inverse time to collision is a good indicator of driving safety based on our previous work [5]. $TTCi_{max}$ poses the limit on inverse time to collision. When an MPC is working as a controller, the constraints should be set conservatively in order to guarantee safety during driving. However, the MPC is working as a predictor in this paper, which requires it to mimic the human driver's actions as close as possible, even including some undesirable behaviors. To meet this requirement, safety constraints should be relaxed.

C. *Full Cost Function in Longitudinal Control*

A quadratic full cost function considering all states, inputs, and outputs of the two-car system is designed in the MPC formulation as:

$$\begin{aligned} J = \sum_{k=1}^{K} [& \left(x_e(k) - x_e^{ref}\right) w_x \left(x_e(k) - x_e^{ref}\right)^T + \\ & (y(k) - y^{ref}) w_y (y(k) - y^{ref})^T + (u_e(k) - u_e^{ref})^2] \end{aligned} \tag{5}$$

where x_e is the states in (1), y is the outputs in (3), and u_e is the input to the system. x_e^{ref}, y^{ref} and u_e^{ref} are the references respectively. In this paper, references are assumed to be constants. w_x, w_y, and w_u are diagonal matrices, K is the total number of prediction steps. Notice that in some traditional

MPC setups the reference of control input u_{ref} is set to 0 to reduce the control cost of the controller. In this paper, a non-zero reference for control input may reflect the preference of a human driver better when prediction is the task. In addition, the full cost function may not be necessary for the prediction and some partial items can be sufficient, which will be introduced in the cost function selection section.

D. Longitudinal Driving MPC Formulation

Based on the vehicle models, constraints and cost function, the longitudinal driving can be modelled as an MPC process. The states update equation (1) - (4) can be organized into a combined generalized state space form. Then the MPC problem is to find out the optimal input u_e that can minimize the cost function J subjecting to the vehicle models and constraints, which can be expressed by (6), where A and B are the matrices in (1), $G(X)$ is the outputs in (3), and $H(X,Y)$ is the constraints in (4).

$$\begin{aligned} &\min_{u_e} \quad J \\ &s.t. \ \dot{X} = AX + Bu_e \\ &\qquad Y = G(X) \\ &\qquad H(X,Y) \leq 0 \end{aligned} \tag{6}$$

IV. Learning and Prediction of Longitudinal States of Human-Driven Vehicles based on IMPC

A. IMPC Learning from Human Demonstrations

We propose to learn the cost function of the longitudinal driving MPC formulation from human driving demonstration data once the form of the cost function is given. $x_R(\tau)$ is used to represent the states of the vehicle system recorded during an actual human driving demonstration. The data can be augmented into many short trajectories X_R^i:

$$X_R^i = [x_R(t_i), \dots, x_R(t_i + n_R \Delta t_R)] \tag{7}$$

where t_i is the starting time of the trajectory, Δt_R is the sampling time during data recording, n_R is the length of a recorded short trajectory. By initializing the MPC's initial condition x_t with the first element in the trajectory, $x_R(t_i)$, the MPC can predict another trajectory by iterating the OCP problem defined in (6):

$$X_C^i = [x_C(t_i), \dots, x_C(t_i + n_C \Delta t_C)] \tag{8}$$

where n_P is the length of the predicted short trajectory. Δt_C is the control interval and is not necessarily the same as Δt_R, the length of the predicted trajectory n_C may also be different from n_R.

The error between the predicted trajectory and the reference trajectory is:

$$X_E^i = [x_E(t_i), \dots, x_E(t_i + n_E \Delta t_E)] \tag{9}$$

where $x_E(\tau) = |x_C(\tau) - x_R(\tau)|$ is the error between the predicted trajectory and reference trajectory at time τ. The total error between all predicted trajectories and reference trajectories is given by (10). ω is a weight vector, M is the total number of trajectories augmented from the whole human driving demonstration.

$$E = \frac{1}{M} \sum_{i=1}^{M} \frac{\omega}{n_E} \cdot \sum_{n=1}^{n_E} x_E(t_i + n\Delta t_E) \tag{10}$$

The problem now is to minimize the total error E by adjusting the parameters in the cost function. In this paper, the adjustable parameters include weights w_x , w_y , w_u and references $x_e^{ref}, y^{ref}, u_e^{ref}$. Since only the relative values of weights are important, it is practical to set one weight to 1 and optimize the others[15]. This problem can be formed into a higher-level constrained optimization problem:

$$\begin{aligned} &\min_{w_x, w_y, w_u, x_e^{ref}, y^{ref}, u_e^{ref}} \quad E \\ &s.t. \ w_x, w_y, w_u \geq 0 \\ &{x_e^{ref}}_{min} < x_e^{ref} < {x_e^{ref}}_{max} \\ &{y^{ref}}_{min} < y^{ref} < {y^{ref}}_{max} \\ &{u_e^{ref}}_{min} < u_e^{ref} < {u_e^{ref}}_{max} \end{aligned} \tag{11}$$

However, the Jacobian of E is not obtainable. Thus, a gradient-free optimization method needs to be adopted. In this paper, the Nelder-Mead Simplex (NMS) method [17] is adopted. The optimization process will terminate when the standard deviation σ in (12) is no larger than a threshold value σ_{ter} . E_i is the total error of vertex j evaluated over the training data, $\bar{E}$ is the average error of all points.

$$\sigma = \sqrt{\frac{\sum_{j=1}^{N+1} (E_j - \bar{E})^2}{N+1}} \tag{12}$$

B. Prediction of Longitudinal States with Optimal Cost Function Selection in IMPC

In the longitudinal driving problem presented in this paper, there are two states, three outputs and one input that can be included in the full cost function, resulting in up to eleven parameters to be optimized in (11). However, the higher-level optimization is very likely to end with different local optima. Due to the non-convexity of the MPC. Leaving all possible basic terms to the full cost function and letting higher level optimization handle too many parameters will result in a highly inefficient learning process and may even result in undesirable solutions. It's necessary to evaluate the basic cost terms and select the best ones to be included in the cost function before performing the high-level optimization.

When a human is performing a driving task, he/she may try to maintain some of the system states/outputs/inputs at desired target values while leaving the rest unattended. In this paper we propose to evaluate the basic terms by using them independently as stand-alone cost functions, which can be written as a simplified form of (5) as

$$J = \sum_{k=1}^{K} (z(k) - z^{ref})^2 \tag{13}$$

and then learning the z^{ref} with a simplified form of the higher-level optimization (11) as:

$$\min_{z^{ref}} \quad E$$
$$s.t.\ {z^{ref}}_{min} < z^{ref} < {z^{ref}}_{max} \tag{14}$$

where z is a candidate for the basic terms in the cost function. When the higher-level optimization finishes, a minimum E_z will be obtained for candidate z_e. If the human driver is trying to maintain z_e at a specific target value during driving, then the resultant E_z should be small, which means z_e can be a 'good' term in the cost function and vice versa. All candidates can be ranked based on their E_z values.

After each candidate term has been evaluated, the cost function can be formed by trying different combinations of 'good' candidates. Since humans normally consider more than one target during driving, it is reasonable to start with a combination of the top two or three best candidates, then try adding the next best candidate to the cost function in the following attempts. This process will be repeated until the evaluated performance of the predictor starts to decrease, then the previous candidate combination can be determined to be the final cost function.

Once the cost function has been selected and parameters learnt from human demonstrations, the prediction of longitudinal behaviors/states of the human-driven vehicle can be realized by running the MPC with the determined cost function. The performance of the prediction will also be evaluated. At each time t, the MPC will be run till time $t + n_C \Delta t_C$ and generate a series of predicted states like (8). By comparing the difference between the predicted states with the actual states from demonstration data, the performance of the predictor can be evaluated. The evaluation results will be presented in the experimental section.

V. Experimental Results and Analysis

A. Experiment setup

A 3D simulation environment that includes two vehicles was constructed. The lead car is autonomous and the one behind is controlled by the human subject in real-time. Both vehicles were built with full longitudinal dynamics that is more complete than (1) and (2). The simulator used in this paper is shown in Figure 2.

Figure 2 A human driver sitting in our driving simulator

The lead vehicle is following three different driving cycles. The first one is the EPA Highway Fuel Economy Test Cycle (HWFET), which is a 12-minute-long mild highway cycle. The second is the Artemis Motorway 130 cycle which is an 18-minute-long aggressive motorway cycle with heavier braking and wider open throttle. The last one is the New York City Cycle (NYCC) with shortened stop time, which is an eight-minute-long urban driving cycle. Human subject was required to drive the ego vehicle in his/her preferred way and follow the lead vehicle. Two sets of data were collected from HWFET cycle, one set of data was collected from the Artemis cycle and the NYCC cycle respectively. The learning process for all approaches in the following sections is only using the first set of HWFET cycle data. The other set of HWFET data is used to test the prediction performance in the seen situation. The data from Artemis and NYCC cycles are used to test the performance in unseen situations. In this paper, the MPC problem is solved using ACADO toolkit [16].

B. Learning of Driving Model

$v_e, a_e, v_r, THWi, TTCi$ and u_e are the six candidates being evaluated using the HWFET cycle training data. The results are shown in TABLE 1.

TABLE 1 Evaluation results of different cost candidates

Candidates	v_e	a_e	v_r	$THWi$	$TTCi$	u_e
z^{ref}	22.9 m/s	0.019 m/s^2	−0.977 m/s	0.5831 s^{-1}	−0.002 s^{-1}	0.0005 m/s^3
E_z	1.3472	0.3291	0.8580	2.2191	0.8567	0.2017

One can see that a^e and u are the two 'good' candidates since their minimum total prediction error E_z can be very low. The $THWi$ and $TTCi$ are two 'bad' candidates since their minimum E_z is still quite large. We tried three different combinations of these candidates:

- Combination 1: u, a^e
- Combination 2: $u, a^e, TTCi, v^r$
- Combination 3: $u, a^e, TTCi, v^r, v^e$

In combination 2 we added both $TTCi$ and v^r at the same time since their minimum E_z values are very close. These 3 different combinations are formulated into cost functions in the form of (5), and are trained with the method described in IV.A. The initial guesses of the references are using the values obtained in TABLE 1. The initial weights are all chosen to be 1 and the weight of the last term in the cost function is fixed during the training. The termination condition is selected to be $\sigma_{ter} = 3 \times 10^{-4}$. Other parameters are listed in TABLE 2. Δt_s is the sampling time-step. $\Delta t_s = 0.2s$ means that a predicted state trajectory is made every 0.2s in the test driving cycles.

TABLE 2 Parameters for the model

Variable	Value	Variable	Value	Variable	Value
Δt_C	0.4s	Δt_s	0.2s	v_{min}	0m/s
a_{min}	$-8\ m/s^2$	a_{max}	$4.5 m/s^2$	v_{max}	40m/s

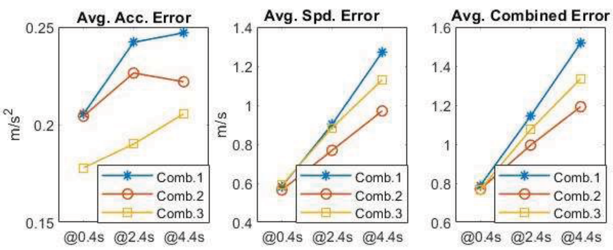

Figure 3 Cost function evaluation results

The performance of these three cost functions are evaluated using the HWFET cycle test data set. The terminal speed, acceleration and combined (speed + acceleration) prediction errors at 0.4s (1 prediction step), 2.4s (6 prediction steps) and 4.4s (11 prediction steps) are compared. The evaluation results are shown in Figure 3. One can see that the 2nd terms combination is outperforming the other two combinations in speed prediction at all 3 predict horizons byD significant margins. In terms of acceleration prediction, the performance of combination 2 sits between that of combination 1 and 3. However, the performance difference in predicting acceleration is less obvious than in predicting speed. Moreover, predicting speed is more important than predicting acceleration when such prediction information is shared between vehicles for improved control since speed is directly related to system outputs according to (3). The combined prediction error, which is the sum of speed prediction error and accelerating prediction error, show that combination 2 is the best among the 3. We can organize combination 2 according to (5) and use it as the best cost function for the predictor. Adding the 'bad' basic term v^e to the cost function will weak the predictor's performance. In fact, during our exploration, we found that adding either $THWi$ or v^e to any existing combination will make the predictor perform worse.

C. Prediction Performance Comparison with Existing Approaches

In this section, the state-of-the-art IDM and Artificial Neural Network (ANN) models used for performance comparison are introduced briefly. We chose these two models since they achieved best speed prediction accuracy among existing driver model based and heuristic approaches according to [18].

Intelligent Driver Model is a widely used adaptive cruise control (ACC) model that can describe accelerations and decelerations in a satisfactory way. The acceleration function is given by:

$$a_{IDM} = a\left[1 - \left(\frac{v_e}{v_0}\right)^4 - \left(\frac{s^*}{s_l - s_e}\right)^2\right] \qquad (15)$$
$$s^* = s_0 + v_e T + \frac{v \cdot v_r}{2\sqrt{ab}}$$

where v_0 is the desired velocity, s_0 is minimum desired spacing, T is the desired time headway, a is maximum acceleration and b is comfort braking deceleration. These 5 parameters are tunable/trainable parameters of this model.

The ANN model proposed in this paper is based on a feed-forward structure with the hidden layer having 16 sigmoidal neurons and the output layer having linear neurons. The inputs to the network are the most basic system states v_e, v_l and system output $s_l - s_e$. The training is done by fitting the output of the network to the human demonstrated accelerations $a_R(t)$. The training data set is the same one that is used by all other 3 predictors. The training algorithm we used is Levenberg-Marquardt method.

The trained IDM and NN are making predictions in the same way as the IMPC based predictor. The prediction time step and reference evaluation time step are sharing the same settings as Table 2. The performance of all predictions is shown in Table 3 to Table 5.

Table 3 shows that under HWFET cycle, the acceleration prediction accuracy of IMPC, IDM and NN is very close. That's because this test cycle is the same as the training data. Although IDM and NN do not catch the internal preference of the human driver, they can still obtain a good prediction accuracy since they are trained to reproduce state trajectories

TABLE 5 PREDICTION ERROR FOR HWFET CYCLE

Model Type		IMPC			Intelligent Driver Model			Artificial Neural Network		
Error Type		Avg. Error	Std. Error	Max./Min. Error	Avg. Error	Std. Error	Max./Min. Error	Avg. Error	Std. Error	Max./Min. Error
Predicted Speed Error	@0.4s	0.565	0.869	5.35/-2.83	0.604	0.903	3.96/-3.25	0.616	0.931	4.95/-3.40
	@2.4s	0.768	1.177	7.18/-5.11	0.912	1.350	5.42/-5.72	0.948	1.397	6.59/-6.29
	@4.4s	0.970	1.418	6.66/-6.36	1.146	1.762	7.47/-8.15	1.184	1.703	8.47/-6.27
Predicted Acceleration Error	@0.4s	0.204	0.352	1.90/-2.66	0.214	0.336	1.14/-2.99	0.269	0.446	1.87/-3.61
	@2.4s	0.226	0.359	1.88/-2.32	0.2000	0.319	1.68/-1.74	0.260	0.393	1.73/-2.72
	@4.4s	0.222	0.319	2.00/-1.70	0.211	0.336	2.02/-1.48	0.244	0.359	2.07/-1.69

TABLE 5 PREDICTION ERROR FOR ARTEMIS CYCLE (NEW)

Model Type		IMPC			Intelligent Driver Model			Artificial Neural Network		
Error Type		Avg. Error	Std. Error	Max./Min. Error	Avg. Error	Std. Error	Max./Min. Error	Avg. Error	Std. Error	Max./Min. Error
Predicted Speed Error	@0.4s	1.585	2.280	12.56/5.74	1.775	2.439	11.17/-20	1.854	2.559	13.61/-7.97
	@2.4s	2.168	3.076	20.30/-9.16	2.938	3.419	12.77/-20	3.279	4.156	18.80/-13.98
	@4.4s	2.657	3.737	24.10/-12.34	3.958	4.257	19.06/-20	4.342	5.251	18.97/-14.17
Predicted Acceleration Error	@0.4s	0.619	1.033	4.33/-5.22	1.034	1.095	2.34/-10	1.009	1.300	5.52/-8.65
	@2.4s	0.666	1.031	4.76/-4.62	0.823	0.927	5.21/-10	1.015	1.294	5.72/-8.91
	@4.4s	1.585	2.280	12.56/5.74	1.775	2.439	11.17/-20	1.854	2.559	13.61/-7.97

TABLE 5 PREDICTION ERROR FOR NYCC CYCLE (NEW)

Model Type		IMPC			Intelligent Driver Model			Artificial Neural Network		
Error Type		Avg. Error	Std. Error	Max./Min. Error	Avg. Error	Std. Error	Max./Min. Error	Avg. Error	Std. Error	Max./Min. Error
Predicted Speed Error	@0.4s	1.271	1.804	7.35/-5.01	1.482	1.946	7.55/-5.76	1.596	2.024	8.65/-5.88
	@2.4s	1.814	2.509	9.79/-7.60	2.542	2.951	9.12/-9.45	3.061	3.394	13.51/-9.84
	@4.4s	2.355	3.201	11.96/-9.18	3.348	3.766	10.12/-12.29	2.677	3.372	14.37/-12.29
Predicted Acceleration Error	@0.4s	0.686	0.963	3.72/-3.69	0.906	0.923	2.54/-2.77	1.763	1.673	4.45/-4.16
	@2.4s	0.700	0.951	3.82/-2.52	0.816	0.924	2.96/-2.89	1.070	1.244	3.64/-4.04
	@4.4s	0.670	0.905	3.74/-2.25	0.649	0.849	3.23/-2.43	1.217	1.253	4.00/-5.90

under HWFET cycle. However, the IMPC-based predictor is showing noticeable advantages in speed prediction compared to all other predictors at all 3 horizons thanks to our proposed cost function evaluation method.

Table 4 shows that under Artemis cycle, the IDM and NN models' lack in scalability starts to appear. They fall behind IMPC by quite a lot in speed prediction, and the difference increases as the prediction horizon extends. This indicates that IMPC based approaches can catch the internal stimulus of human actions and perform better in unseen situations. Moreover, the IMPC's prediction accuracy difference between 2.4s and 4.4s is much smaller than that of IDM and NN, which also indicates the advantage of the proposed approach. One interesting finding is that the IDM performs better in maximum prediction error. That's possibly caused by the constant speed assumption we used in (2) for the lead vehicle. Since IDM is inherently a conservative collision-free model, it may not try as hard as the IMPC models to keep up with the lead vehicle within the predicting horizon. This situation happens when the lead vehicle is having sudden and big acceleration changes and appropriate information is not passed to the ego vehicle. However, when the vehicles are connected and information about the environment is shared between them, the IMPC model holds a lot of potential for improvement.

Table 5 shows the results obtained from NYCC cycle. The general observations are similar with those from Artemis cycle. The IDM and NN are performing much worse than the IMPC approach. It needs to be noticed that the acceleration prediction of NN is significantly worse than other 2 predictors. That is because the training data set is not able to provide enough information to get the NN trained properly since these two driving cycles are almost entirely different from each other. The NN has basically lost predicting capability under NYCC cycle. Compared to the NN based approach, the IMPC based approach is showing advantage by being able to be trained properly using a small training data set.

Overall, the IMPC based approach outperforms the other two by providing a much higher prediction accuracy and a much better scalability. It can adapt to never-seen situations better than other approaches. The proposed cost function selection process can help our proposed IMPC capture the human driver's driving intentions better and further improve the prediction accuracy.

VI. CONCLUSION

In this paper a new IMPC based approach is proposed to model and predict the longitudinal behaviors of human-driven vehicles. A new cost function selection process is also proposed to determine the appropriate cost function in IMPC. The proposed approach can capture the internal decision-making process of humans and thus result in better accuracy and scalability which is validated by the experimental results. The capability of predicting a human-driven vehicle's longitudinal states is tested under different driving scenarios, and the performance is compared with existing approaches. The results illustrate the effectiveness and advantages of the proposed approaches in predicting the forthcoming behaviors/states and handling unseen situations compared with other existing approaches.

As for future work, we will plan to extend the proposed framework to the prediction of other behaviors/states of human-driving vehicles such as lane tracking and lane switching in addition to the studied longitudinal driving.

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