Supplementary Material for *IDCode: An End-to-end Decision and Control Library for High-level Autonomous Driving System*

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I. Evaluation Metrics

To evaluate the performance of the proposed methods, we employ several metrics, including safety, comfort, and traffic efficiency. These indexes are defined as follows.

The safety index evaluates the potential risks between the ego vehicle and obstacles, which is computed by the position and speed of ego vehicle and obstacles, i.e.,

$$\begin{aligned}
V_t &= \alpha \cdot \frac{(\boldsymbol{v}_t^i - \boldsymbol{v}_t)\cdot(\boldsymbol{p}_t - \boldsymbol{p}_t^i)}{|\boldsymbol{p}_t - \boldsymbol{p}_t^i|} + (1-\alpha)(|\boldsymbol{v}_t^i| + |\boldsymbol{v}_t|) \\
G_t &= (M + M^i)\cdot \log(V_t + 1.8) \\
\omega_T &= \exp\left(-0.1 t \beta_a\right) \\
\omega_d &= \exp\left(-d_{\min \beta_{\mathrm{b}}}\right) \\
I_{\text{Safety}}^{i,t} &= \omega_T \cdot \omega_d \cdot G_t \\
I_{\text{Safety}} &= \max_{i,t} I_{\text{Safety}}^{i,t},
\end{aligned}$$

where $\alpha = 0.7, \beta_a = 1.04, \beta_b = 1.94, M = M^i = 1$, $\boldsymbol{v}_t^i$ and $\boldsymbol{v}_t$ are the velocity vectors of i-th obstacle and ego vehicle, $\boldsymbol{p}_t^i$ and $\boldsymbol{p}_t$ are the position vectors of i-th obstacle and ego vehicle.

The traffic efficiency index is the ratio between the speed of ego vehicle and the average speed of obstacle vehicles, which is defined as

$$I_{\text{efficiency}} = \frac{v}{\bar{v}}, \tag{1}$$

where v is the speed of the ego vehicle, and $\bar{v}$ is the average speed of the obstacle vehicles. If there is no obstacle, $\bar{v}$ is set to the speed limit of the road.

The comfort index is calculated using lateral and longitudinal acceleration:

$$I_{\text{comfort}} = \sqrt{(I_{\text{lat}}^2 + I_{\text{lon}}^2)/2},$$

where I_{lat} and I_{lon} are computed through interpolation of the data in Table I. Higher accelerations lead to more pronounced changes in vehicle motion, resulting in a diminished level of occupant comfort and subsequently yielding a lower corresponding comfort index.

TABLE I
I_{lat} AND I_{lon}

Longitudinal Acc.	I_{lon}	Lateral Acc.	I_{lat}
7.6,	0.6	7.6	0.6
3.07,	0.4	5.6	0.4
1.47,	0.2	4.0	0.2
0,	0,	0	0
-2,	0.2	-4.0	0.2
-5.08,	0.4	-5.6	0.4
-7.6,	0.6	-7.6	0.6

TABLE II
KEY PARAMETERS

Parameters of vehicle dynamics	Value
Mass, m	1200 [kg]
Polar moment of inertia at CG, I_z	1600 [kg·m^2]
Distance from CG to front axle, L_f	1.1 [m]
Distance from CG to rear axle, L_r	1.2 [m]
Front-wheel cornering stiffness, C_f	-90000 [N/rad]
Rear-wheel cornering stiffness, C_r	-90000 [N/rad]
Time interval, ΔT	0.1 [s]

II. Vehicle Model used in the experiments

The vehicle model used in the experiments is defined as

$$F_{\text{ego}} = \begin{bmatrix} p_x + \Delta T(v_x \cos\phi - v_y \sin\phi) \\ p_y + \Delta T(v_x \sin\phi + v_y \cos\phi) \\ \phi_t + \Delta T \omega_t \\ v_x + \Delta T(a_x + v_y \omega) \\ \frac{m v_x v_y + \Delta T[(L_f C_f - L_r C_r)\omega - C_f \delta v_x - m v_x^2 \omega]}{m v_x - \Delta T(C_f + C_r)} \\ \frac{-I_z \omega v_x - \Delta T[(L_f C_f - L_r C_r) v_y - L_f C_f \delta v_x]}{\Delta T(L_f^2 C_f + L_r^2 C_r) - I_z v_x} \end{bmatrix}. \tag{2}$$

The calibration results of the vehicle dynamics are shown in Table II.

III. IDC and HDC

Taking the planning module and tracking module as an example. These two modules have an upstream-downstream relationship in the entire system and can be seen as two optimization problems. For the planning model, its optimization objectives are safety, comfort, and whether it meets dynamic constraints and other indicators, i.e.,

$$\tau^* = \arg\max \mathcal{J}_1(\tau). \tag{3}$$

For the control module, it solves a set of actions to track the target trajectory with the highest possible accuracy, i.e.,

$$u^* = \arg\max \mathcal{J}_2(u|\tau^*). \tag{4}$$

Here, the target trajectory is an intermediate variable introduced by manual modularization, and the ultimate goal of the system is to obtain the optimal control variable. Therefore, the real problem we want to solve is

$$u^\star = \arg\max \mathcal{J}_3(u|\tau), \tag{5}$$

where $\mathcal{J}_3$ is the final evaluation index of autonomous driving, such as comfort, safety, etc.

Usually, due to the high complexity of accurately solving planning problems, additional approximation operations need to be introduced, resulting in suboptimal planning trajectories. And the errors of suboptimal planning trajectories will also affect the solution of optimal actions.

In IDC, due to the usage of a unified optimization index, there is no problem of optimal index conflicts and error accumulation caused by modular solving.

IV. Discussion

Currently, the practical deployment of high-level autonomous driving represents a significant challenge, with current issues primarily centered on safety concerns and the ability to handle complex scenarios. We argue that the key to enabling autonomous driving systems to meet the requirements of stakeholders lies in the system's capacity for self-evolution. Once self-evolution capabilities are established, autonomous driving services can be provided within limited areas, such as the Robottaxi services offered by companies like Google, Tesla, and Baidu. This process not only enables the collection of data to enhance system performance but also fosters users' trust in the system.