

Physics and gaze-based drift trajectory prediction with an online learning framework

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Abstract

This work is the first to address vehicle trajectory prediction under extreme handling conditions relevant to drift-assist ADAS, extending the operational envelope of current trajectory prediction approaches beyond normal/near-linear driving regimes. The proposed framework is based on physics and driver gaze to predict the driver's desired course during drifting. We introduce kinematics-based models for trajectory prediction to consider the unique vehicle dynamics in drifting including high sideslip and counter steering. Dynamics-based models are also utilized to account for the driver's desired yaw rate and sideslip angle. Moreover, the driver's gaze behavior during drifting is analyzed and two gaze-based travel-point and waypoint models are further adopted for trajectory prediction. In order to fuse the predictions from the above models, a *t*-distribution-based regression is applied to accommodate more outliers in the extreme drifting maneuver. Furthermore, a Gaussian process-based online learning model is deployed using the prediction error of previous timesteps to correct the current prediction according to vehicle and driver states. Driver-in-loop drifting data collected from the driving simulator of Cranfield University is utilized for validation of the effectiveness of the proposed framework.

Keywords

drift trajectory prediction, vehicle dynamics model, driver gaze behavior, *t*-distribution, Gaussian process-based learning

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Introduction

Drifting is a distinctive cornering method defined by high sideslip and counter steering, where the yaw rate direction opposes the steering input.¹ The vehicle operates at its handling limit with the rear tyres fully saturated in adhesion,^{2–7} which requires a cooperation of throttle and steering in order to maintain the vehicle dynamics at an unstable equilibrium.^{8,9} This technique requires advanced driving skills or the intervention of a sophisticated control system.

Significant research has been reported in the area of autonomous drifting to demonstrate the capability of vehicle dynamics controllers in extreme operating conditions. The desired vehicle trajectory in such cases is determined by the path planning layer^{10–19} of the autonomous driving controller where various control methods^{11,13,20–32} are applied. Different from autonomous drifting, for drift assist control in the field of Advanced Driver Assist System (ADAS) where the driver is expected to be responsible for path tracking, trajectory prediction is essential in our proposed drift

assist control framework.³³ After driver drift intention recognition,³⁴ trajectory prediction interprets the desired trajectory and serve as the reference for the subsequent drift assist control concepts proposed in our work.^{35,36} With trajectory prediction, the assist system can better intervene with the vehicle motion during drifting to override unreasonable driver inputs³⁷ or simply help the driver maintain the desired course.³⁶ This study concentrates exclusively on trajectory prediction as the interface between driver intention and our proposed drift-assist control concepts.^{35,36} Novel low-level drift tracking controllers utilizing this prediction will be presented in future work.

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Previous studies have extensively studied the topic of trajectory prediction in normal driving,^{38,39} the approaches are generally classified into three types: physics-based, which depends on vehicle dynamics^{40,41} or kinematics^{42–47} model and its state equations in an iterative process; maneuver-based, which considers vehicle future motions and the driver's intentions (i.e., lane changing); interaction-aware prediction, where the vehicle interacts with other participants on the road, for instance multi-vehicle interactions and lane-change decision-making using social and game-theoretic frameworks.^{48–50} Categorizations based on different algorithms^{51–53} could also be found where learning-based approaches are discussed in detail to better consider road and interaction-related input information.

In contrast to normal driving, drifting is a more challenging scenario for trajectory prediction since the prediction error increases significantly when extreme maneuvers are involved.⁵⁴ In this article, given that drifting is a racetrack maneuver not suggested on public roads, we do not take into account surrounding vehicles or any prior map information. Instead, our focus is solely on internal vehicle signals, with novel kinematics and dynamics models proposed to consider the unique vehicle motions during drifting.

Moreover, this article further considers the driver's gaze behavior for drift trajectory prediction. A previous study⁵⁵ has suggested that gaze information is vital to understand the trajectory demand of a human driver. In normal cornering, both the longitudinal^{56,57} and lateral^{55,58} vehicle behaviors have a strong correlation with gaze movements. Recent studies have discussed the possibility of using gaze angle to guide steering control design.⁵⁹ Unlike the above gaze studies in normal driving/racing cornering, this article firstly discusses the gaze behaviors observed in drift cornering, followed by implementing two gaze-based trajectory prediction models^{60–62} for drift trajectory prediction.

In order to fuse the data from different prediction models and to improve the trajectory prediction accuracy, earlier studies^{42,47,63} have introduced the Kalman filter (KF), which assumes that the prediction model's errors follow a normal distribution (white noise). More recently, the Interacting Multiple Model (IMM)^{64–69} has been further applied to account for various vehicle motion behaviors (such as velocity tracking or distance keeping⁶⁵) and switch between different prediction models (i.e., CV or CA model⁶⁷) accordingly, with each model has its own KF.

Unlike the aforementioned studies that presume the error from a certain prediction model adheres to a normal distribution, this article adopts a *t*-distribution regression that accommodates less samples and more outliers,^{70,71} making it more suitable for extreme maneuvers with heavy-tailed noise.^{72–74} Furthermore, rather than distinguishing vehicle motions between limited behavior modes through IMM, we also propose an online learning-based approach to correct the model

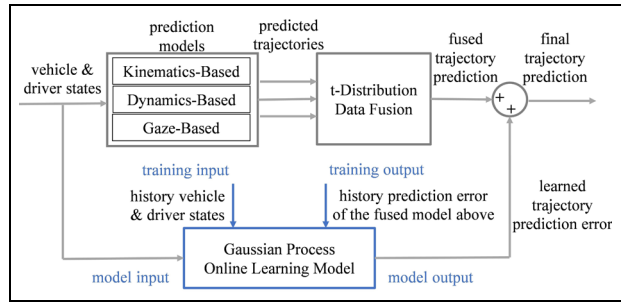


Figure 1. Framework of this article.

outputs utilizing historical data (detailed in section “The Gaussian process-based learning model”).

The trajectory prediction framework

To serve in our proposed drift assist control framework,³³ interpreting the desired trajectory after driver drift intention recognition³⁴ and providing reference for the subsequent drift assist control concepts,^{35,36} this article proposes the following framework as shown in Figure 1 for trajectory prediction during drifting. The novelties and contributions are as follows:

- (1) The introduction of physics-based drift trajectory prediction models, namely kinematics-based drift trajectory prediction models (Model A) that capture the unique vehicle dynamics behaviors in drifting, including high sideslip angle (A1) and counter steering (A2); and dynamics-based drift trajectory prediction models (Model B) to account for the desired yaw rate (B1) and sideslip angle (B2) from the driver's inputs.
- (2) The adaptation of gaze-based trajectory prediction models (Model C) for drifting. After analyzing the gaze behaviors observed during drifting, two prediction models (travel-point and waypoint, C1 and C2) are adopted and fused for output.
- (3) A *t*-distribution based data fusion of the predictions from the above models, which accommodates less samples and more outliers, therefore is more suitable than normal distribution for extreme maneuvers like drifting.
- (4) A Gaussian process-based online learning model based on vehicle and driver states, in order to learn the trajectory prediction error of the fused output above, and improve the accuracy of the final trajectory prediction.

The driving simulator to provide data for validation

Driver-in-loop data is collected using the driving simulator of Cranfield University, in order to support the evaluation of the trajectory prediction model proposed

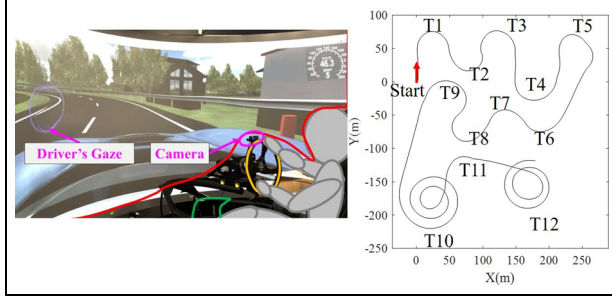


Figure 2. The driving simulator and the drift track.

in this article. Detailed specifications about the simulator are elaborated in our previous study.^{33,35} In this work we added a camera to capture the driver's gaze behavior with the software Beam Eye Tracker.⁷⁵ The drift track is shown in Figure 2 which includes both turning directions, different radii (20–50 m), and curvature-varying corner segments (i.e., T10, T12). The experimental dataset includes three drivers (students from Cranfield University, no professional drift driver), for the multi-driver evaluation (Table 1), four laps from each driver are used (12 laps in total).

The physics and gaze-based trajectory prediction model for drifting

Given that drifting is a racetrack maneuver where no other vehicles or obstacles are present, this article presents a trajectory prediction framework only relies on vehicle physics (Model A: kinematics-based and Model B: dynamics-based models) and the driver's gaze behaviors (Model C: gaze-based models).

Model A: Kinematics-based trajectory prediction model

Previous studies have extensively discussed the possible kinematics and dynamics-based models for trajectory prediction. Both of the two types of models rely on a particular vehicle dynamics model for iterative processes. In contrast to dynamics-based models (normally bicycle model^{40,41}), kinematics models ignore detailed dynamics like tyre forces, and mainly depend on the current vehicle states and driver's input. Therefore kinematics models are more commonly used for trajectory prediction with low computation complexity.⁵² For example, the 'Constant Acceleration (CA)' model⁴² is applied and compared with the "Constant Turn Rate Constant Tangential Acceleration (CTRA)" model.⁴³ The CTRA model⁴⁴ is considered together with the "Constant Turn Rate and Velocity (CTRV)" model and the "Constant Curvature and Acceleration (CCA)" model. Results based on the above models are also discussed in studies.^{45–47}

Together with the aforementioned CTRV, CTRA, and CCA models which are originally proposed for

Table 1. Driver-wise cumulative prediction error over the whole track (sum of 4 laps per driver).

Driver	Best single model	t-Distribution	Diff. (%)
1	242.83	230.23	−5.19
2	217.34	198.44	−8.69
3	271.43	252.27	−7.06

normal cornering, this article further develops the following kinematics models to consider the unique vehicle behaviors in drifting (i.e., high sideslip angle and counter steering^{1,2,35,36}) for trajectory prediction.

(1) Model A1: Sideslip-based kinematics model

As previously mentioned, drifting is a distinctive cornering technique characterized by high sideslip angle,^{1,2,35,36} which must be considered in the kinematics model. Given the sideslip angle β and employing a single-track model, the kinematics radius based on sideslip angle $R_{A1\beta}$ for a drifting vehicle could be expressed as (1) and illustrated in Figure 3(a), where v_x, v_y denote the vehicle speeds, r is the yaw rate, and a is the distance from the front axle to the center of gravity (CoG).

$$R_{A1\beta} = a \left[\sin\beta + \cos\beta / \tan \left(\beta - \text{atan} \left(\frac{v_y + ra}{v_x} \right) \right) \right] \quad (1)$$

(2) Model A2: Steering angle-based kinematics model

In addition to the sideslip angle, we further consider the other crucial aspect of drifting: counter steering (the steering direction opposes the yaw rate) which is not explicitly included in (1). Notably, for steady-state drifting, while the rear wheels may be fully saturated with a high sideslip angle, the front wheels are typically unsaturated with a limited sideslip angle (i.e., $< 7^\circ$ according to study,² similar findings in literature^{8,21}). This configuration allows the front to adjust lateral force, enabling the driver to change the vehicle's direction in drifting through steering. Therefore, by assuming the sideslip angle of the front axle to be zero, the kinematics radius based on steering angle δ could be written as (2) and illustrated in Figure 3(b) to provides additional information about trajectory evolution.

$$R_{A2\delta} = a [\sin\beta + \cos\beta / \tan(\beta - \delta)] \quad (2)$$

(3) Data fusion of Model A1 and A2

Next, we propose a weighted function to integrate the kinematics-based radii ($R_{A1\beta}, R_{A2\delta}$) outputs from the above two models, because they estimate the same

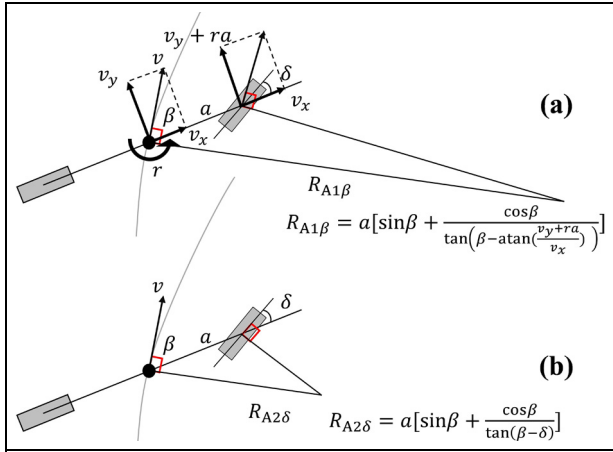


Figure 3. Sideslip-based: (a) and steering angle-based and (b) trajectory prediction for drifting.

physical quantity and exhibit a consistent estimation pattern.

Specifically, for drifting on a track with constant radius, our previous studies^{33,35} indicate the driver must coordinate the steering with CoG sideslip angle to maintain the intended trajectory. For instance, when the driver demands more CoG sideslip by applying throttle, additional counter-steer is required to balance the yaw moment and to stay on track, while simultaneously keeping the front-axle sideslip low, as discussed in the previous section. In this sense, throughout drifting the front axle typically operates in an unsaturated region with low sideslip, enabling counter steering to serve as a stabilizing input rather than a direct determinant of drift radius.

But what if the driver applies a “wrong” amount of counter steering and a greater sideslip for the front axle? Two scenarios are considered and illustrated in Figure 4. Firstly, when the counter steering is excessive, it is presumed that the driver is requesting a higher radius (Figure 4(a)). Conversely, when the counter steering is insufficient, it is presumed that the driver demands a lower radius (Figure 4(b)). In both scenarios, the steering-based radius $R_{A2\delta}$ better reflects driver’s demand than the sideslip based $R_{A1\beta}$. An example was also given below for the second scenario based on our driver-in-loop data,^{33,35} where the driver temporarily desires to reduce the drifting radius to negotiate a corner.

Based on the above observations, the following weight function (3) is designed to calculate a fused kinematics-based radius R_A . Specifically, when the sideslip of the front axle β_f is high, more priority is given to the steering-based radius $R_{A2\delta}$ (4).

$$R_A = (1 - k)R_{A1\beta} + kR_{A2\delta} \quad (3)$$

$$k = \begin{cases} 0.25 |\beta_f| \leq 5 \\ |\beta_f|/20 \quad 5 < |\beta_f| < 15 \\ 0.75 |\beta_f| \geq 15 \end{cases} \quad (4)$$

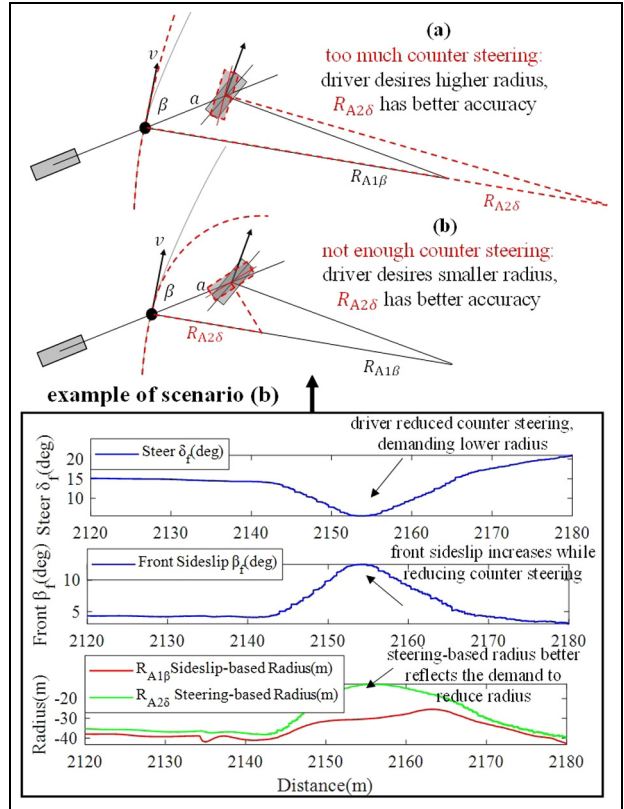


Figure 4. When the driver produces (a) too much and (b) too little counter steering (driver-in-loop data from driving simulator^{33,35}).

It should be noted that counter-steering does not monotonically determine the drifting radius. Instead, the steering input is used as an indicator of the driver’s intended direction of radius modification, which becomes meaningful only when the front-axle sideslip deviates from its typical unsaturated level during drifting.

(4) Trajectory calculation using Model A

The predicted vehicle trajectory at timestep $k + 1$ based on the vehicle states from step k $[\hat{X}_{Ak+1|k}, \hat{Y}_{Ak+1|k}]^T$ is updated according to (5), where $[X_{CAk}, Y_{CAk}]^T$ (6) is the turning center based on the kinematics radius R_{Ak} , v_k is the vehicle speed, Ψ_k is the vehicle heading angle, β_k is the sideslip angle and t_s is the timestep size (Figure 5).

$$\hat{x}_{Ak+1|k} = [\hat{X}_{Ak+1|k}, \hat{Y}_{Ak+1|k}]^T = [X_{CAk}, Y_{CAk}]^T + \begin{bmatrix} \cos\left(\frac{v_k t_s}{R_{Ak}}\right) & -\sin\left(\frac{v_k t_s}{R_{Ak}}\right) \\ \sin\left(\frac{v_k t_s}{R_{Ak}}\right) & \cos\left(\frac{v_k t_s}{R_{Ak}}\right) \end{bmatrix} \begin{bmatrix} X_k - X_{CAk} \\ Y_k - Y_{CAk} \end{bmatrix} \quad (5)$$

$$\begin{bmatrix} X_{CAk} \\ Y_{CAk} \end{bmatrix} = \begin{bmatrix} X_k \\ Y_k \end{bmatrix} + R_{Ak} \begin{bmatrix} \cos(\Psi_k + \beta_k + \pi/2) \\ \sin(\Psi_k + \beta_k + \pi/2) \end{bmatrix} \quad (6)$$

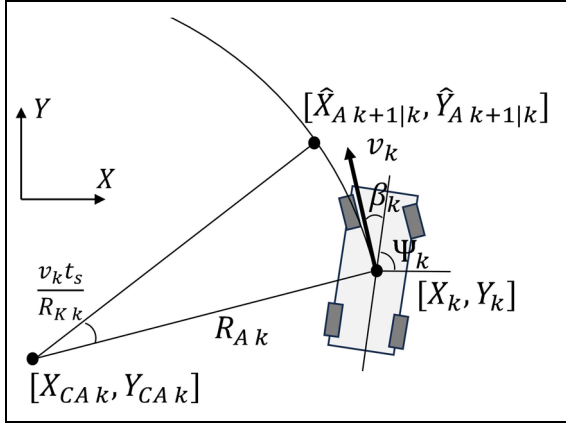


Figure 5. Trajectory calculation using Model A.

Model B: Dynamics-based trajectory prediction model

Dynamics models are capable of considering more intricate details in vehicle modelling, such as vehicle mass and tyre adhesion.^{40,41} Nevertheless, this doesn't ensure improved accuracy in trajectory prediction,⁵² as it depends on precise vehicle modelling (otherwise risks introducing greater error). Furthermore, these models primarily depend on the current state of the vehicle without considering the driver's inputs in future time-steps. Despite the limitations of dynamics-based models, this article considers them for their capability to handle detailed vehicle behaviors such as the variation of sideslip angle, which is essential for the subject of drifting.

This article will present two dynamics-based models in the subsequent sections, both of which are derived from a single-track vehicle model, with modifications to account for drifting behaviors.

(1) Model B1: Desired yaw rate-based dynamics model

We first consider the linear single-track vehicle model⁷⁶ and its steady-state yaw rate r_d determined by steering input δ , written as (7), where v_x is the longitudinal speed, m is the vehicle mass, k_f, k_r are the tyre cornering stiffnesses, a, b are the distances from front/rear axle to CoG and L is the wheelbase.

$$r_d = \frac{v_x/(a+b)}{1 + Kv_x^2} \delta \quad (7)$$

$$K = \frac{m}{L^2} \left(\frac{a}{k_r} - \frac{b}{k_f} \right) \quad (8)$$

But in the context of drifting (which operates outside the validity of the linear approximation), the above equation for desired yaw rate cannot be applied directly, as drifting is a cornering technique that

involves counter steering.^{1,2,35,36} However, as discussed in the previous section of Model A2, despite counter steering, the front wheels always have unsaturated sideslip angle,^{2,8,21} to provide lateral force that allows the driver to alter the vehicle's direction (yaw) in drifting through steering and track the desired path.^{35,77,78} Therefore, assuming small sideslip angle for the front tyres, we replace the steering angle δ in (7) with the front axle sideslip β_f as (9), where β_f is approximated as the average sideslip angle of the two front wheels. It is important to note that the linearized rear axle cornering stiffness k_r , as indicated in (8), is not appropriate for drifting maneuvers where the rear tyres are fully saturated with high sideslip. However, we utilize this parameter not for its physical features, but rather to represent a tunable yaw response and consistent behavior from the vehicle as seen in normal cornering.

$$r_d = \frac{v_x/(a+b)}{1 + Kv_x^2} \beta_f \quad (9)$$

(2) Trajectory calculation using Model B1

Assuming the actual yaw rate follows the above desired yaw rate r_{dk} (9) at timestep k , in a global coordinates system as shown in Figure 5, the trajectory prediction for timestep $k+1$ based the states from step k : $\hat{\mathbf{x}}_{B1 k+1|k}$, could be written as (10–12), where X, Y are the coordinates, Ψ is the vehicle heading, v_x, v_y are the speeds, a_x, a_y are the accelerations, and t_s is the time-step size.

$$\mathbf{x}_{B1 k} = [X_k, Y_k, \Psi_k, v_{xk}, v_{yk}, r_{dk}, a_{xk}, a_{yk}, \beta_{fk}]^T \quad (10)$$

$$\dot{\mathbf{x}}_{B1 k} = \begin{bmatrix} \dot{X}_k \\ \dot{Y}_k \\ \dot{\Psi}_k \\ \dot{v}_{xk} \\ \dot{v}_{yk} \\ \dot{r}_{dk} \\ \dot{a}_{xk} \\ \dot{a}_{yk} \\ \dot{\beta}_{fk} \end{bmatrix} = \begin{bmatrix} v_{xk} \cos \Psi_k - v_{yk} \sin \Psi_k \\ v_{xk} \sin \Psi_k + v_{yk} \cos \Psi_k \\ \frac{v_{xk}/(a+b)}{1 + Kv_{xk}^2} \beta_{fk} \\ a_{xk} + v_{yk} r_{dk} \\ a_{yk} - v_{xk} r_{dk} \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} \quad (11)$$

$$\hat{\mathbf{x}}_{B1 k+1|k} = \mathbf{x}_{B1 k} + \dot{\mathbf{x}}_{B1 k} t_s \quad (12)$$

(3) Model B2: Desired yaw rate and desired sideslip-based dynamics model

In order to better reflect the vehicle motions during drifting, we expand upon the previous yaw rate-based dynamics model by further incorporating the “desired” sideslip dynamics according to driver's throttle input. Previous researches^{10,21} have indicated that during steady-state drifting the sideslip angle is strongly related to the drive force/slip ratio of the rear wheels. In our

previous studies^{33,35} we have also proposed an intuitive drift control concept that interprets the desired sideslip angle based on the driver's throttle input, which was subsequently validated through a human trial. Based on the above discussion, the desired sideslip β_d is written as (13), where γ is the throttle input and k_γ is the gain. For the sideslip dynamics we further consider a first-order system just as previous studies^{24,33,35} have applied for drift control, written as (14), where β is the actual sideslip and $\frac{1}{\tau_\beta}$ is the gain.

$$\beta_d = k_\gamma \gamma \quad (13)$$

$$\dot{\beta}_d = \frac{1}{\tau_\beta} (\beta_d - \beta) \quad (14)$$

Besides the sideslip dynamics, we also take into account the path angle rate $\dot{\varphi}$ ^{13,15,24} which is the sum of vehicle yaw rate r and sideslip rate $\dot{\beta}$, and determines the actual vehicle trajectory, written as (15). Subsequently, we replace the desired yaw rate r_d from the previous model in (9) with $\dot{\varphi}_d$ as (16), since the driver is modifying the front axle sideslip through steering to attain the intended trajectory ultimately.

$$\dot{\varphi} = r + \dot{\beta} \quad (15)$$

$$\dot{\varphi}_d = \frac{v_x/(a+b)}{1 + Kv_x^2} \beta_f \quad (16)$$

With the above desired path angle rate $\dot{\varphi}_d$ and the desired sideslip rate $\dot{\beta}_d$, the desired yaw rate could be written as (17) according to (15). And another first-order section is considered for the yaw rate dynamics, similar to previous researches,^{24,33,35} as (18).

$$r_d = \dot{\varphi}_d - \dot{\beta}_d \quad (17)$$

$$\dot{r} = \frac{1}{\tau_r} (r_d - r) \quad (18)$$

Then, take (13–17) into (18), we have:

$$\begin{aligned} \dot{r} &= \frac{1}{\tau_r} (r_d - r) = \frac{1}{\tau_r} (\dot{\varphi}_d - \dot{\beta}_d - r) \\ &= \frac{1}{\tau_r} \left[\frac{v_x/(a+b)}{1 + Kv_x^2} \beta_f - \frac{1}{\tau_\beta} (k_\gamma \gamma - \beta) - r \right] \\ &= \frac{1}{\tau_r} \left[\frac{v_x/(a+b)}{1 + Kv_x^2} \beta_f - \frac{1}{\tau_\beta} \left(k_\gamma \gamma - \text{atan} \left(\frac{v_y}{v_x} \right) \right) - r \right] \end{aligned} \quad (19)$$

(4) Trajectory calculation using Model B2

Similar to the previous Model B1 (10–12) but with desired sideslip dynamics involved, the prediction of

this desired yaw rate and sideslip-based model for time-step $k+1$ based the states from step k : $\hat{\mathbf{x}}_{B2k+1|k}$ could be written as (20–22).

$$\mathbf{x}_{B2k} = [X_k, Y_k, \Psi_k, v_{xk}, v_{yk}, r_k, a_{xk}, a_{yk}, \beta_{fk}, \gamma_k]^T \quad (20)$$

$$\dot{\mathbf{x}}_{B2k} = \begin{bmatrix} \dot{X}_k, \dot{Y}_k, \dot{\Psi}_k, \dot{v}_{xk}, \dot{v}_{yk}, \dot{r}_k, \dot{a}_{xk}, \dot{a}_{yk}, \dot{\beta}_{fk}, \dot{\gamma}_k \end{bmatrix}^T = \begin{bmatrix} v_{xk} \cos \Psi_k - v_{yk} \sin \Psi_k \\ v_{xk} \sin \Psi_k + v_{yk} \cos \Psi_k \\ r_k \\ a_{xk} + v_{yk} r_k \\ a_{yk} - v_{xk} r_k \\ \frac{1}{\tau_r} \left[\frac{\frac{v_{xk}}{a+b}}{1 + Kv_{xk}^2} \beta_{fk} - \frac{1}{\tau_\beta} \left(k_\gamma \gamma_k - \text{atan} \left(\frac{v_{yk}}{v_{xk}} \right) \right) - r_k \right] \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} \quad (21)$$

$$\hat{\mathbf{x}}_{B2k+1|k} = \mathbf{x}_{B2k} + \dot{\mathbf{x}}_{B2k} t_s \quad (22)$$

Model C: Gaze-based trajectory prediction model

An earlier study⁵⁵ has already demonstrated the importance of gaze information in understanding the driver's desired trajectory. In detail, for longitudinal vehicle motion (straight line acceleration/deceleration), the gaze preview distance (the longitudinal distance in front of the vehicle where the driver is looking at) is normally around 1–3 s ahead of the vehicle.^{56,57} During cornering correlation is observed between gaze angle and vehicle yaw rate, while an increase of the gaze angle is reported approximately 1 s before the vehicle begins to rotate (in yaw).^{55,58}

In this section we first discuss the gaze behaviors observed in drifting as opposed to normal driving or even racing conditions considered in the previous studies. Two gaze-based trajectory prediction models are introduced respectively: travel-point model (C1) and waypoints model (C2).^{60–62} A fusion method is further proposed in this article to post-process the outputs from both models.

(1) Gaze behaviors in drifting

Before introducing the detailed trajectory prediction models, we examine whether the above gaze patterns discovered in normal driving are valid in drifting.

For both drifting/normal driving vehicle, the data collected from our driver-in-loop test (one driver doing a drifting lap and normal cornering lap respectively, Figure 2) generally agrees with the findings in studies.^{55–58} Longitudinally, the preview time (calculated by longitudinal preview distance/vehicle speed, the preview distance is determined by the gaze pitch angle and the

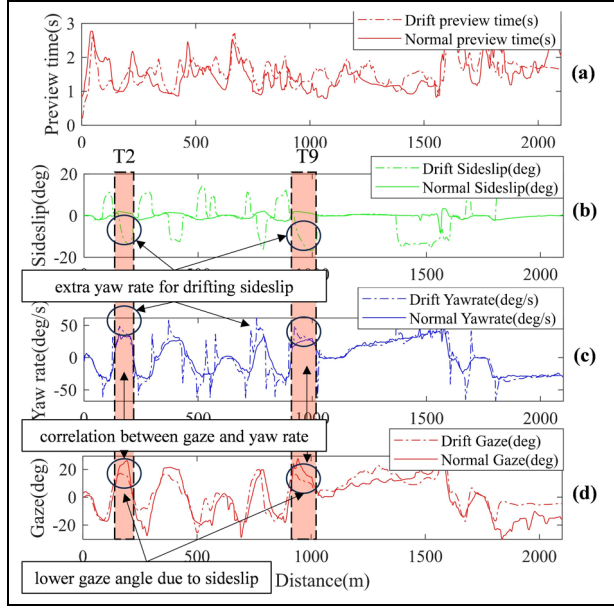


Figure 6. Gaze behaviors: ((a) preview time, (d) gaze angle) and vehicle motions ((b) sideslip, (c) yaw rate) comparison between drifting and normal driving.

vertical position of the eyes above ground) for both drifting/normal driving is around 1–3 s (Figure 6(a)). Laterally, we take the time intervals T2 and T9 as examples, as shown in Figure 6(c) and (d). An overall correlation is observed between yaw rate and gaze angle, both in drifting and normal driving. Also, for drifting there is higher yaw rate (Figure 6(c)) to generate high sideslip (Figure 6(b)) so that the vehicle body rotates deeper towards the corner. Consequently, less gaze angle (Figure 6(d)) is required to track the same point on the path (i.e., apex of a corner) compared to normal driving.

(2) Model C1: travel-point gaze model for trajectory prediction

As shown in Figure 7(a), given a corner with fixed radius, the travel-point model relies on the assumption that the gaze angle (θ) is constant (23). The gaze angle is assumed to be fixed towards a ‘tangent point’ on the inner edge of a circular track,^{61,79} or on the zero horizontal flow circle^{60,62} after considering retinal flow.^{80,81} Given θ and the gaze distance D (calculated according to gaze pitch angle and the vertical position of eyes above ground), the travel-point trajectory radius could be written as (24).

$$\frac{d\theta}{dt} = 0 \quad (23)$$

$$R_{C1} = \frac{D}{2\sin\theta} \quad (24)$$

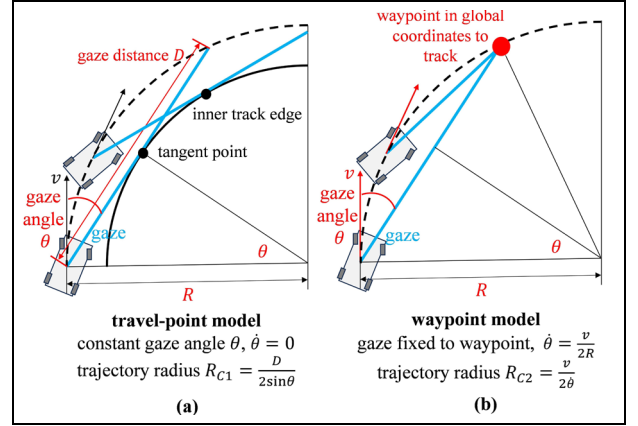


Figure 7. Gaze-based trajectory prediction: (a) travel-point and (b) waypoint model.^{60,61}

(3) Model C2: Waypoint gaze model for trajectory prediction

In contrast to travel-point model, recent studies^{57,60,82} have suggested that the waypoint model is predominantly used by human drivers. The gaze is tracking a certain point in the global coordinates,⁶⁰ and the retinal image is stabilized by compensatory eye movements (CEM)⁸³ therefore $\frac{d\theta}{dt} \neq 0$. In detail, the gaze behavior is described as ‘optokinetic pursuit’ and ‘gaze-pursuit-switch’^{57,82}: the driver firstly looks to a waypoint which is normally 2 s ahead; visually tracks it for around 0.5 s; then switches to another waypoint. Besides normal driving,^{84–86} such behavior is also observed in race driving: in a corner the gaze starts from a ‘saccade’ towards tangent point (apex fixations) followed by another ‘saccade’ during the exit (exit fixations).^{55,58}

As shown in Figure 7(b), the waypoint model assumes a waypoint to be tracked by gaze in the global coordinates, so the relationship between gaze angle rate $\frac{d\theta}{dt}$ and the waypoint trajectory radius R_{C2} can be written as (25),^{60,61} where v is the vehicle speed.

$$R_{C2} = \frac{v}{2\frac{d\theta}{dt}} \quad (25)$$

(4) Data fusion of Model C1 and C2

As will be demonstrated in this section, there are occasions where each of the two gaze-based models outperforms the other. Therefore, we propose a method to integrate the two models in such a manner that we attain an improved prediction of the path throughout the vehicle’s operational range. To mix the results from the above two gaze models, we further consider the path angle rate $\frac{d\phi}{dt}$ ^{13,15,24} which is the sum of vehicle

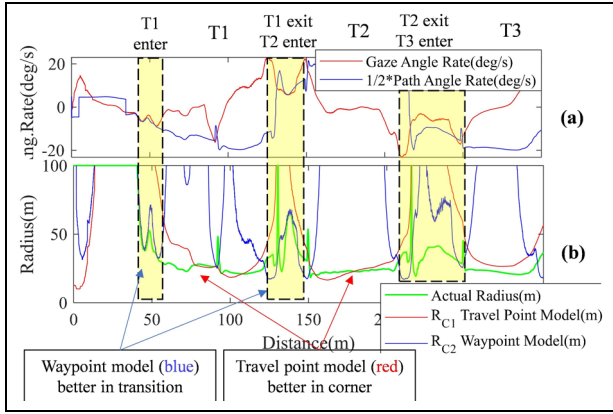


Figure 8. Gaze angle rate: (a) and predicted radius (b) comparison between the travel-point and waypoint model.

yaw rate r and sideslip rate $\frac{d\beta}{dt}$, and decides the actual vehicle trajectory radius R_{real} written as (27).

$$\frac{d\varphi}{dt} = r + \frac{d\beta}{dt} \quad (26)$$

$$R_{real} = \frac{v}{\frac{d\varphi}{dt}} \quad (27)$$

Assuming that the gaze behavior is following the waypoint model ($R_{real} = R_{C2}$) and taking (25) into (27), the relationship between gaze angular rate $\frac{d\theta}{dt}$ and path angle rate $\frac{d\varphi}{dt}$ in the waypoint model can be written as (28).

$$\frac{d\theta}{dt} = \frac{1}{2} \frac{d\varphi}{dt} \quad (28)$$

To justify this, the gaze angular rate $\frac{d\theta}{dt}$ and half of the path angle rate $\frac{1}{2} \frac{d\varphi}{dt}$ are plotted as shown in Figure 8(a). During the transition stage between corners (i.e., T1 exit, T2 enter), a correlation is observed between gaze angular rate and the path angle rate, and the radius from the waypoint model (blue) shows higher accuracy compared to the travel-point model (red) in Figure 8(b). However, for mid-corners (i.e., T1, T2) and steady-state cornering, the radius from travel point model performs better when the gaze angular rate doesn't follow the path angle rate as (28) but gets closer to zero which satisfies the assumption in travel point model (23).

Based on the above observations, the following weight function (Figure 9 and equation (29)) is designed to predict the desired radius based on gaze (the gains are selected by manual tuning). Specifically, when the gaze angular rate shows more dependency on the path angle rate ($\frac{\frac{d\theta}{dt}}{\frac{1}{2} \frac{d\varphi}{dt}} \rightarrow 1$), more weight is given to the waypoint model output R_{C2} . And when the gaze angular rate is closer to zero (which satisfies the assumption of

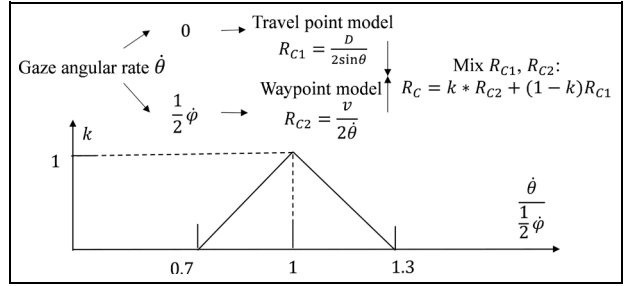


Figure 9. Data fusion of the travel-point and waypoint model.

travel point model (23)), or deviates too far from half of the path angle rate, the output from the travel point model R_{C1} is utilized more.

$$R_C = kR_{C2} + (1 - k)R_{C1} \quad (29)$$

It should be noted that the adopted gaze models are not intended to describe a universal driver gaze policy, but rather serve as practical abstractions for trajectory prediction in drifting scenarios, where systematic gaze studies are still limited and to be developed in future work.

(5) Trajectory calculation using Model C

Given the gaze-based predicted trajectory radius R_C , similar to the trajectory calculation based on the kinematics model as shown in Figure 5, the gaze-based trajectory prediction can be written as (30–31), where $[X_{CCk}, Y_{CCk}]^T$ is turning center according to the gaze-based radius R_{Ck} , v_k is the vehicle speed, Ψ_k is the vehicle heading angle, β_k is the sideslip angle and t_s is the timestep size.

$$\begin{aligned} \hat{x}_{Ck+1|k} &= [\hat{X}_{Ck+1|k}, \hat{Y}_{Ck+1|k}]^T \\ &= [X_{CCk}, Y_{CCk}]^T + \begin{bmatrix} \cos\left(\frac{v_k t_s}{R_{Ck}}\right) & -\sin\left(\frac{v_k t_s}{R_{Ck}}\right) \\ \sin\left(\frac{v_k t_s}{R_{Ck}}\right) & \cos\left(\frac{v_k t_s}{R_{Ck}}\right) \end{bmatrix} \\ &\quad \begin{bmatrix} X_k - X_{CCk} \\ Y_k - Y_{CCk} \end{bmatrix} \end{aligned} \quad (30)$$

$$\begin{aligned} &[X_{CCk}, Y_{CCk}]^T \\ &= [X_k, Y_k]^T + R_{Ck} \begin{bmatrix} \cos(\Psi_k + \beta_k + \pi/2) \\ \sin(\Psi_k + \beta_k + \pi/2) \end{bmatrix} \end{aligned} \quad (31)$$

The t-distribution-based data fusion for all prediction models above

To reduce the trajectory prediction error in drifting we consider combinations of three types of models:

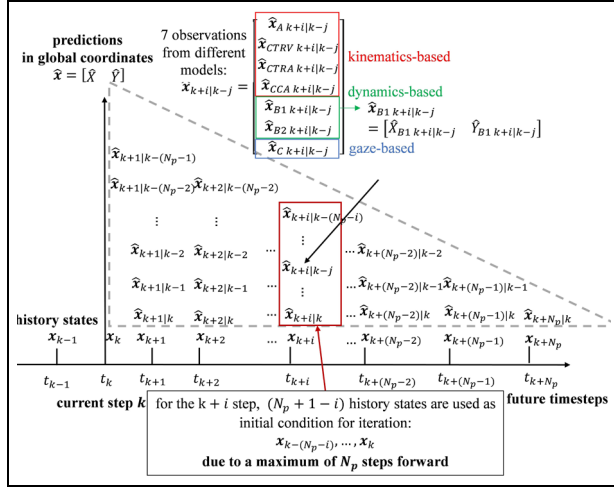


Figure 10. Inputs for the t -distribution regression.

- (1) *Kinematics-based models:* The sideslip and steering angle-based kinematics model (Model A), and the CTRV, CTRA, and CCA model⁴⁴;
- (2) *Dynamics-based models:* The desired yaw rate-based dynamics model, and the desired yaw rate and sideslip-based dynamics model (Model B1 and B2);
- (3) *Gaze-based model:* The fusion of the travel-point and waypoint model (Model C).

In order to fuse the data from different models and to improve the trajectory prediction accuracy, earlier studies^{42,47,63} have introduced a Kalman filter (KF), which assumes that the prediction model's errors follow a normal distribution (white noise). More recently, the Interacting Multiple Model (IMM)^{64–69} was applied to account for various vehicle motion behaviors (such as velocity tracking or distance keeping⁶⁵) and switch between different prediction models (i.e., CV or CA model in Kim et al.⁶⁷) accordingly.

Unlike the aforementioned studies presuming that the error from a certain prediction model adheres to a normal distribution, this paper adopts a t -distribution regression that accommodates less samples and more outliers,^{70,71} making it more suitable for extreme maneuvers with heavy-tailed noise.^{72–74} Furthermore, rather than distinguishing vehicle motions between limited behavior modes through IMM, we also propose an online learning-based approach to correct the model outputs utilizing historical data.

Inputs for data fusion

As shown in Figure 10, a prediction horizon of N_p steps ($t_s = 0.1$ s) is considered, and 7 models from 3 different types (kinematics, dynamics and gaze-based as mentioned) are utilized to predict the future trajectory based on various history states. The history states are used as initial

conditions for the prediction models to iterate, with a maximum of N_p steps forward. For instance, to predict the vehicle coordinates $\hat{x}_{k+i}$ that is i steps ahead of the current position x_k , history states from $x_{k-(N_p-i)}$ to x_k could be utilized as the initial conditions for the models to iterate. Consequently, we have a total of $7 \times (N_p + 1 - i)$ predictions available for the i th future step.

The t -distribution regression

The univariate t -distribution is defined by a probability density function as (32) where μ is the mean value (also known as location parameter), σ^2 is the variance (scale parameter), ν is the number of degrees of freedom (shape parameter that determines the tail heaviness), and $\Gamma(\cdot)$ is the gamma function.⁸⁷

$$f(x) = \frac{\Gamma(\frac{\nu+1}{2})}{\sqrt{\nu\pi\sigma}\Gamma(\frac{\nu}{2})} \left[1 + \frac{1}{\nu} \left(\frac{x-\mu}{\sigma} \right)^2 \right]^{-\frac{\nu+1}{2}} \quad (32)$$

To fit a t -distribution to data predicted by the seven different models at a given future timestep (i.e., with a prediction horizon of $N_p = 10$, the predicted coordinates $\hat{X}_{k+i}$ from all previous models at timestep $k+i$ are shown in (33)), log-likelihood (34) is applied with the command “fminsearch” in Matlab for the estimation of μ, σ^2 , while keeping ν as constant ($\nu = 6$). This design was made to avoid potential instability or oscillations that could arise from online estimation of ν , and to ensure smooth fusion behavior during rapid drifting maneuvers. The mean value $\mu_{X_{k+i}}$ of the fitted t -distribution is utilized as the output of the regression model for timestep $k+i$, denoted as (35), for Y coordinates we also have (36).

$$\begin{aligned} \hat{X}_{k+i} = & [\hat{X}_{A k+i|k-(10-i)}, \dots, \hat{X}_{A k+i|k}, \\ & \hat{X}_{CTRV k+i|k-(10-i)}, \dots, \hat{X}_{CTRV k+i|k}, \\ & \hat{X}_{CTRA k+i|k-(10-i)}, \dots, \hat{X}_{CTRA k+i|k}, \\ & \hat{X}_{CCA k+i|k-(10-i)}, \dots, \hat{X}_{CCA k+i|k}, \\ & \hat{X}_{B1 k+i|k-(10-i)}, \dots, \hat{X}_{B1 k+i|k}, \\ & \hat{X}_{B2 k+i|k-(10-i)}, \dots, \hat{X}_{B2 k+i|k}, \\ & \hat{X}_{C k+i|k-(10-i)}, \dots, \hat{X}_{C k+i|k}]^T \end{aligned} \quad (33)$$

$$\begin{aligned} \mathcal{L}(\mu_{X_{k+i}}, \sigma_{X_{k+i}}^2, \nu) \\ = \sum_{n=1}^{7 \times (11-i)} \log f(\hat{X}_{k+in} | \mu_{X_{k+i}}, \sigma_{X_{k+i}}^2, \nu = 6) \end{aligned} \quad (34)$$

$$\hat{X}_{tdk+i} = \mu_{X_{k+i}} \quad (35)$$

$$\hat{Y}_{tdk+i} = \mu_{Y_{k+i}} \quad (36)$$

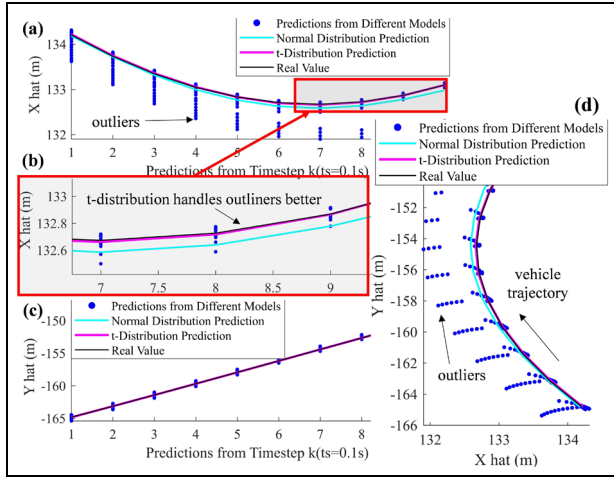


Figure 11. Trajectory prediction comparison (d) between t -distribution and normal distribution (predicted X in (a) (b) and Y in (c)).

The t -distribution regression results

- (1) t -Distribution versus normal distribution at a given timestep

The results of t -distribution fitting at a given timestep are demonstrated in Figure 11 below. As depicted in Figure 11(a) and (c), significant noise could be observed from the prediction of $\hat{X}$, whereas for $\hat{Y}$ the noise is negligible, since the vehicle is driving into a right turn as indicated in Figure 11(d). In contrast to normal distribution, t -distribution shows a clear advantage by being less affected by outliers, resulting in predictions with lower error compared to the actual trajectory.

- (2) The prediction error comparison on the whole track

The prediction errors of different models for the entire track at a given lap are illustrated in Figure 12. It is important to note that only the errors during drift cornering are considered with a predict horizon of 1 s (10 steps forward), denoted as (37). A 1 s prediction horizon is used throughout this study to match the prediction horizon of the downstream MPC-based drift assist controller which will be addressed in future work and fit in our framework.³³ With 1 s prediction horizon and a discretization step of 0.1 s, the proposed trajectory prediction framework requires an average of 74 ms per cycle with a standard deviation of 4.8 ms, in MATLAB on a desktop platform with Intel i7-10750H CPU, demonstrating feasibility for real-time drift assist applications.

For the aforementioned kinematics (Model A, CTRV, etc.), dynamics (B) and gaze-based (C) models, from Figure 12(a) we observe that no single model can maintain a consistent advantage/disadvantage in all corners. For instance, in T2 the gaze-based trajectory

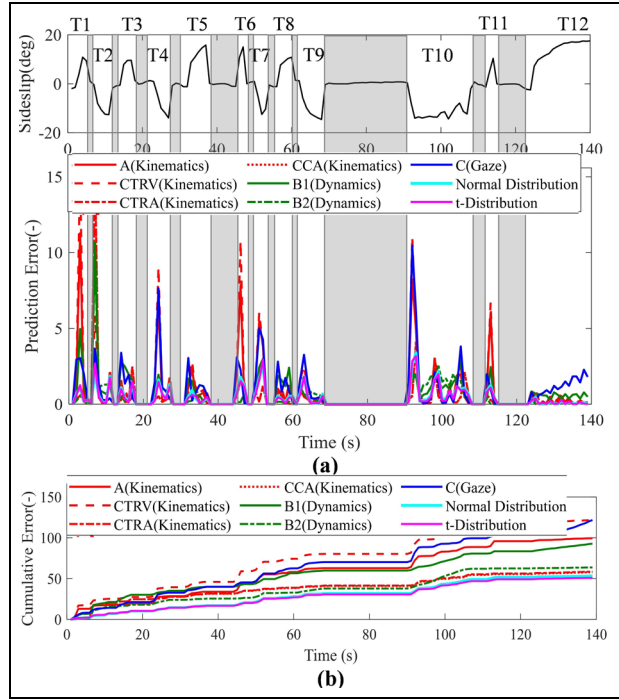


Figure 12. Prediction error at each timestep (a) and cumulative error (b) on the whole track.

produces the lowest error, whereas in T12 it performs poor; In T12, the kinematics-based models demonstrate the highest accuracy, however in T2, T6 they significantly diverge from the actual trajectory. This absence of a distinct pattern underscores the necessity of data fusion utilizing distribution-based approaches. As shown in Figure 12(b), the fused outputs from normal/ t -distribution produce less cumulative error compared to the other models, and the t -distribution-based regression performs better than normal distribution, since it is less affected by outliers as previously discussed in Figure 11. This fusion approach inherently performs adaptive suppression of model outputs producing heavy-tailed errors, while retaining all models to ensure robust performance across diverse drifting phases.

$$J_k = \sum_{i=1}^{10} [(\hat{X}_{k+i} - X_{k+i})^2 + (\hat{Y}_{k+i} - Y_{k+i})^2] \quad (37)$$

To further evaluate multi-driver consistency, as shown in Table 1, over the whole track, the proposed t -distribution fusion consistently achieves the lowest cumulative prediction error across all three drivers (four laps per driver), indicating the robustness of this proposed framework. In addition to driver-wise aggregate results, we further analyze lap-wise cumulative prediction error across all 12 laps (3 drivers $\times$ 4 laps). Table 2 reports mean $\pm$ standard deviation as well as median and interquartile range (IQR). A paired statistical test is conducted between the proposed method and the best single model baseline. The statistical analysis indicates a

Table 2. Lap-wise cumulative prediction error statistics across 12 laps (3 drivers $\times$ 4 laps). The reported p -value corresponds to the paired comparison between the proposed method and the best single model baseline.

Method	Mean	Std	Median	IQR	Paired t-test
Best single model	60.97	14.91	57.55	16.22	$p < 1e-3$
t-Distribution	56.74	14.80	52.96	14.71	

consistent and statistically significant reduction in prediction error achieved by the proposed method.

The Gaussian process-based learning model

Previous research⁵⁴ has indicated that the trajectory prediction error increases significantly in the scenarios when risky driving behaviors are involved, and the physics-based approaches have concerning performance as they are based on simplified vehicle dynamics.^{52,88,89} Thus learning-based trajectory prediction has been extensively studied in recent years,^{52,53,88} and numerous algorithms have been utilized. Earlier studies^{90,91} started from artificial neural networks (ANN), and recently the recurrent neural networks (RNN) such as long-short term memory (LSTM)^{92–94} are more preferable as they can consider a sequence of historical states while predicting the vehicle trajectory during lane changes⁹³ or on winding roads.⁹⁵ Furthermore, the performance has been further improved through the use of transformer network,^{96,97} which are more effective in dealing with long-term dependencies. Additionally, convolutional neural networks (CNN) has also been applied to for image-based trajectory prediction.⁹⁸

In contrast to all the neural network-based methods above that require extensive of data for offline model training, this paper employs a Gaussian process-based⁹⁹ online learning approach, which has been successfully implemented in controller design to predict the system dynamics error in extreme maneuver, applicable to vehicles,^{100–102} robots¹⁰³ and quadrotors.¹⁰⁴ For example,¹⁰⁰ utilizes Gaussian process regression to predict the vehicle dynamics uncertainty in autonomous racing, and therefore reduce the lap time by 10% in an extreme environment where the vehicle behaviors are highly nonlinear and complicated to identify.

The Gaussian process model

Given a series of training inputs $\mathbf{X} = [X_1, \dots, X_n]^T$ and outputs $\mathbf{Y} = [Y_1, \dots, Y_n]^T$, to predict the output y with a new input x , the joint distribution in a Gaussian process model is expressed as (38), in which m is the mean function, σ^2 is the noise variance, and $\mathbf{K}$ is the covariance function. To be specific, the (i, j) th element in $\mathbf{K}(\mathbf{X}, \mathbf{X})$ is written as $k(X_i, X_j)$, where k is the kernel function. And the predicted $\hat{y}$ is written as (39). A detailed introduction could be found in Carl Edward and Christopher.⁹⁹

$$\begin{bmatrix} \mathbf{Y} \\ y \end{bmatrix} \sim GP \left(\begin{bmatrix} m(\mathbf{X}) \\ m(x) \end{bmatrix}, \begin{bmatrix} \mathbf{K}(\mathbf{X}, \mathbf{X}) + \sigma^2 \mathbf{I} & \mathbf{K}(x_k, \mathbf{X})^T \\ \mathbf{K}(x_k, \mathbf{X}) & \mathbf{K}(x_k, x_k) \end{bmatrix} \right) \quad (38)$$

$$\hat{y} = \mathbf{K}(x, \mathbf{X})^T (\mathbf{K}(\mathbf{X}, \mathbf{X}) + \sigma_n^2 \mathbf{I})^{-1} (\mathbf{Y} - m(\mathbf{X})) + m(x) \quad (39)$$

Inputs and outputs of the Gaussian process-based learning model

The inputs for learning-based trajectory prediction are normally classified into four types⁵³: (1) history trajectory of the target vehicle, for example the trajectory data in a grid map¹⁰⁵ or through intersections¹⁰⁶; (2) history trajectory of the target vehicle and the surrounding vehicles^{107,108}; (3) simplified bird's eye view and (4) raw sensor data. As for the outputs, three main types are discussed⁵³: (1) the intention of a particular maneuver, such as the lane changing intention¹⁰⁹; (2) unimodal trajectory and (3) multimodal trajectory, the difference is the former only represents one specific maneuver, for example the lateral offset during lane change,¹¹⁰ or the vehicle location in intersections.

For this article that considers a specific drifting behavior performed mainly on racetrack with no surrounding vehicles and limited environment information, as shown in Figure 13(a)–(d), the history ego vehicle states s_h and fitted coefficients p_{VXh}, p_{VYh} according to the history prediction errors e_{VXh+i}, e_{VYh+i} are utilized as inputs and outputs respectively to update the dictionary of the Gaussian model. The vehicle current states s_k are used as inputs to predict the trajectory errors $\hat{e}_{Xk+i}, \hat{e}_{Yk+i}$ in the future, then added with the previous t-distribution-based fused results $\hat{X}_{tdk+i}, \hat{Y}_{tdk+i}$ (35, 36) for the final prediction $\hat{X}_{finalk+i}, \hat{Y}_{finalk+i}$ in Figure 13(e).

- (1) Model inputs: Coordinates transform and the fitted coefficients for trajectory prediction error

As shown in Figure 13(a), to simplify and unify the expression of the trajectory prediction error from a history timestep h , the vehicle body coordinates at that timestep $[X_{V0h}, Y_{V0h}, \Psi_{V0h}]$ are utilized as the origin point. The coordinates transform for a given point in global coordinates $[X_h, Y_h]$ into the vehicle body coordinates $[X_{Vh}, Y_{Vh}]$ could be written as (40).

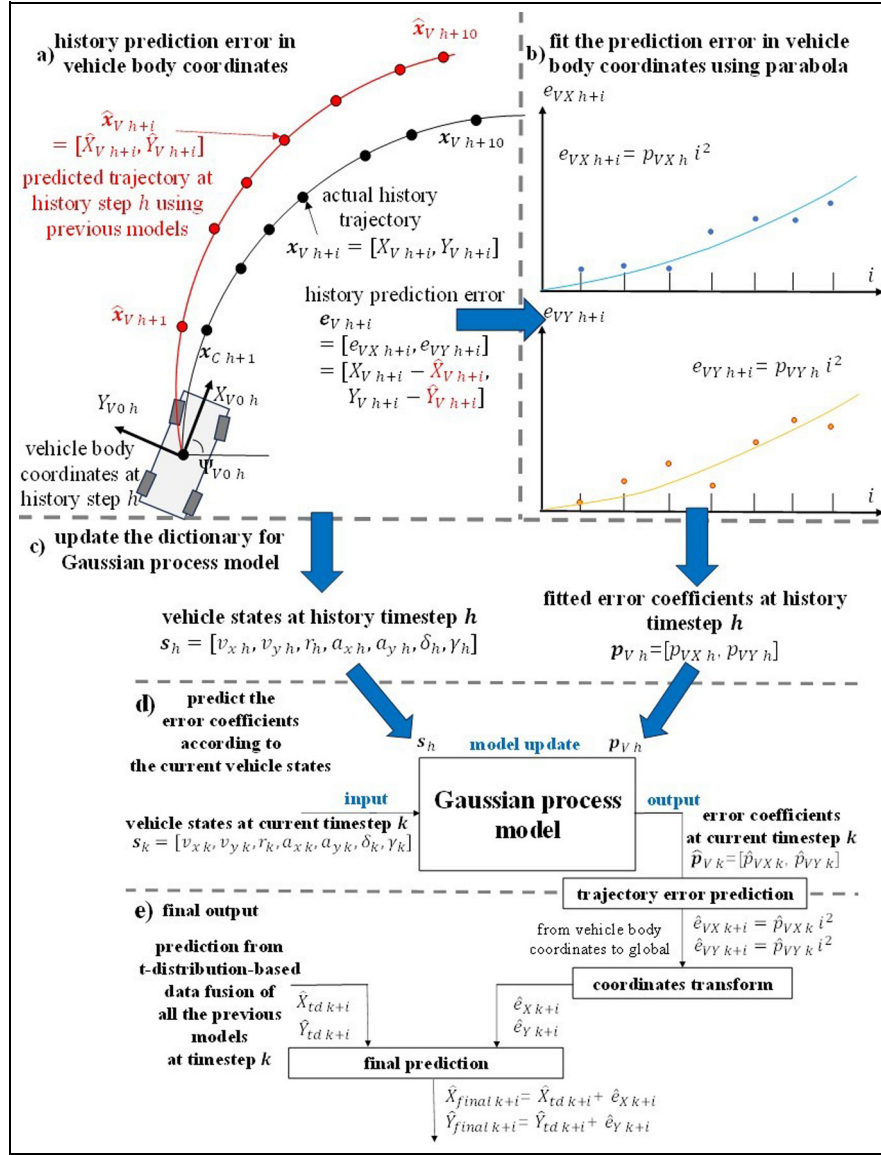


Figure 13. The framework of the Gaussian-process based learning model, to learn the trajectory error of the previous physics and gaze-based models: (a) history prediction error, (b) data fitting, (c) Gaussian model update, (d) error prediction at current timestep, and (e) final output.

$$\begin{bmatrix} X_{Vh} \\ Y_{Vh} \end{bmatrix} = \begin{bmatrix} \cos(\Psi_{V0h}) & \sin(\Psi_{V0h}) \\ -\sin(\Psi_{V0h}) & \cos(\Psi_{V0h}) \end{bmatrix} \begin{bmatrix} X_h - X_{V0h} \\ Y_h - Y_{V0h} \end{bmatrix} \quad (40)$$

Next, in the vehicle body coordinates, the know trajectory prediction errors $[e_{VXh+i}, e_{VYh+i}]$ at the i th ($1 \leq i \leq 10$) steps ahead from h could be expressed as (41), where $[X_{Vh+i}, Y_{Vh+i}]$ are the actual coordinates, $[\hat{X}_{Vh+i}, \hat{Y}_{Vh+i}]$ are the predicted value from step h using the fused t-distribution model as introduced before. Then, a second-degree parabola (Figure 13(b)) is fitted to the prediction errors e_{VXh+i}, e_{VYh+i} by i (42) due to its simplicity. The fitted p_{VXh}, p_{VYh} will be further updated into the Gaussian process model as training outputs (Figure 13(d)), where the training inputs are the history vehicle states s_h (43), which will be elaborated in the next section.

$$e_{Vh+i} = \begin{bmatrix} e_{VXh+i} \\ e_{VYh+i} \end{bmatrix} = \begin{bmatrix} X_{Vh+i} - \hat{X}_{Vh+i} \\ Y_{Vh+i} - \hat{Y}_{Vh+i} \end{bmatrix} \quad (41)$$

$$\begin{bmatrix} e_{VXh+i} \\ e_{VYh+i} \end{bmatrix} = \begin{bmatrix} p_{VXh} \\ p_{VYh} \end{bmatrix} i^2 \quad (42)$$

- (2) Model updates and outputs: predict the trajectory prediction error based on the current vehicle states

The fitted coefficients p_{VXh}, p_{VYh} for the history trajectory prediction error are paired with the history vehicle states s_h (43) (which includes the vehicle speed v_{xh}, v_{yh} , yaw rate r_h , accelerations a_{xh}, a_{yh} , steering δ_h and throttle γ_h), then updated into the Gaussian process model as training outputs/inputs respectively in Figure 13(d). In detail, two Gaussian process model are

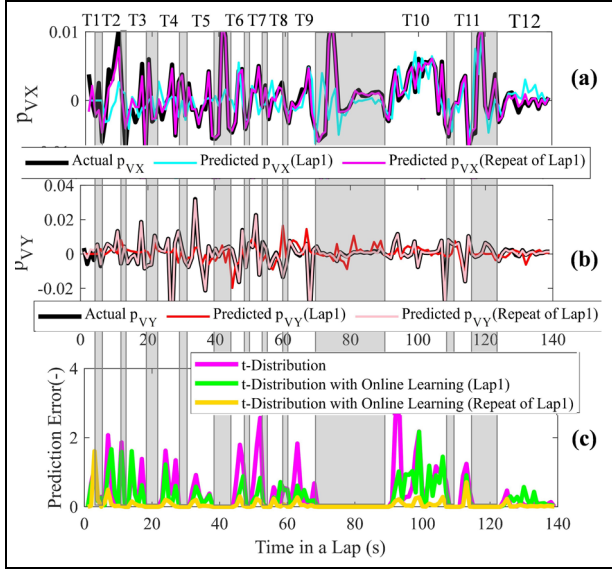


Figure 14. Trajectory prediction error with learning model added (Lap 1 and a repeat of the data from Lap 1 for online training): predicted coefficients in (a) (b), error in (c).

deployed to comprehend the relationships between s_h and p_{VXh} , s_h and p_{VYh} respectively. Given a series of n history states $\mathbf{S}_h$ (44) and their corresponding prediction error coefficients $\mathbf{P}_{VXh}$, $\mathbf{P}_{VYh}$ (45), the current trajectory prediction error coefficient p_{VXk} , p_{VYk} and the vehicle states s_k are assumed to follow a Gaussian process together with the history data as (46). The predicted coefficients $\hat{p}_{VX,Yk}$ is written as (47).^{99,100}

$$\mathbf{s}_h = [v_{xh}, v_{yh}, r_h, a_{xh}, a_{yh}, \delta_h, \gamma_h]^T \quad (43)$$

$$\mathbf{S}_h = [s_{h1}, \dots, s_{hm}]^T \quad (44)$$

$$\mathbf{P}_{VXh} = [p_{VXh1}, \dots, p_{VXhm}]^T \quad (45)$$

$$\mathbf{P}_{VYh} = [p_{VYh1}, \dots, p_{VYhm}]^T$$

$$\begin{bmatrix} \mathbf{P}_{VX,Yh} \\ p_{VX,Yk} \end{bmatrix} \sim GP \left(\begin{bmatrix} m(\mathbf{S}_h) \\ m(s_k) \end{bmatrix}, \begin{bmatrix} \mathbf{K}(\mathbf{S}_h, \mathbf{S}_h) + \sigma^2 \mathbf{I} & \mathbf{K}(s_k, \mathbf{S}_h)^T \\ \mathbf{K}(s_k, \mathbf{S}_h) & k(s_k, s_k) \end{bmatrix} \right) \quad (46)$$

$$\hat{p}_{VX,Yk} = \mathbf{K}(s_k, \mathbf{S}_h) (\mathbf{K}(\mathbf{S}_h, \mathbf{S}_h) + \sigma^2 \mathbf{I})^{-1} (\mathbf{P}_{VX,Yh} - m(\mathbf{S}_h)) + m(s_k) \quad (47)$$

Trajectory prediction error after adding the learning-based model

To evaluate the improvements provided by the learning-based model in trajectory prediction, the results from two specific scenarios will be discussed: (1) the prediction and error in a given lap (Lap 1 in Figure 14)

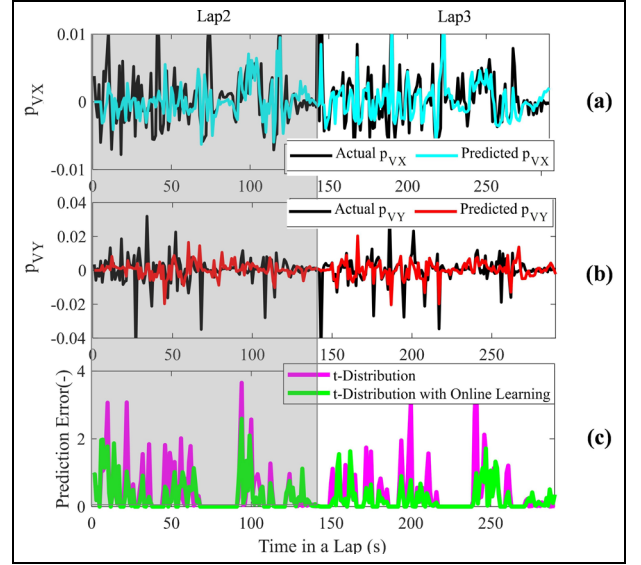


Figure 15. Trajectory prediction error with learning model added (data from Lap 2 and 3 for online training): predicted coefficients in (a)(b), error in (c).

followed by a repeat of the same data from that lap; (2) the prediction and error in two continuous laps (Lap 2 and 3 in Figure 15). Note that the GP learning behavior is illustrated using representative consecutive laps for clarity; this does not limit the overall dataset size used for the previous multi-driver evaluation.

For the first scenario, as shown in Figure 14, the learning model is enabled after 5 s in Lap 1 to produce predictions of $\hat{p}_{VX,Y}$. After T2–T3 when the Gaussian model is fed with enough observations, the learning model is able to reduce the trajectory prediction error (calculated as (37)) significantly in T6–T9 (green curve in Figure 14(c)). However, for T10 and T12, the shape is different from previous corners (reducing/increasing radius respectively, different from previous corners, Figure 2), resulting in less reduced prediction in T10 and even worse in T12, as shown in Figure 14(c). But once the model has acquired enough knowledge of the vehicle dynamics, during the data repeat of Lap 1, the model can predict $\hat{p}_{VX,Y}$ accurately (purple and pink curve in Figure 14(a) and (b)), and the trajectory prediction error is further reduced in Figure 14(c).

For the second scenario where the model is trained and evaluated in two continuous but different laps (Lap 2 and 3 in Figure 15), similarly the learning-based model is enabled after 5 s. The proposed method achieves improved prediction-error coefficient estimation and reduced trajectory prediction error in the subsequent lap (Lap 3 52.75 vs 41.32 without/with learning), demonstrating the effectiveness of online adaptation without offline retraining. It is worth noting that the degree of improvement is not uniform across all corners. For segments such as Lap3 T10/T12, the initial correction performance can be limited or temporarily degraded, since these segments exhibit dynamic characteristics that differ from earlier corners and

require sufficient local observations before accurate error compensation can be learned. As additional data are accumulated through repeated traversal, the correction performance would improve accordingly (similar to Figure 14).

These results highlight the intended behavior of the proposed online correction framework: accurate compensation when similar driving patterns reoccur, and rapid adaptation when encountering new data, within a fixed short prediction horizon. An interesting direction for future work is to further investigate efficient strategies for managing the GP database, including update and forgetting mechanisms, to improve online learning efficiency and robustness.

Conclusion

Based on our proposed drift assist control framework,³³ this study concentrates exclusively on trajectory prediction as the interface between driver intention³⁴ and drift-assist control concepts.^{35,36} In this article we present a physics and gaze-based framework with a Gaussian process-based online learning approach, to predict the vehicle trajectory during the extreme maneuver of drifting.

Kinematics, dynamics and gazed-based models are considered in this article for trajectory prediction without prior environment knowledge. The kinematics-based models are designed to consider the unique features of high sideslip and counter steering during drifting. The dynamics-based models are applied to interpret the driver's desired yaw rate and sideslip angle through steering and throttle. In addition, the driver's gaze behaviors during drifting are also analyzed in this paper, followed by the travel-point and waypoint models to predict the trajectory based on gaze information.

A *t*-distribution-based regression is applied in this article for data fusion of the predictions from the above models, since there are more outliers in the extreme drifting maneuver.

Besides, an online learning model based on Gaussian process is proposed to learn the error of the aforementioned prediction models, providing prediction corrections in real time according to the current vehicle and driver states.

The driver-in-loop drifting data from the simulator of Cranfield University is utilized to prove the effectiveness of the proposed framework.

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Physics and gaze-based drift trajectory prediction with an online learning framework

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