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Extending Navigation Service under Sensor Failures: An Approach by Integrating System Identification and Vehicle Dynamic Model

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Abstract*—Localization plays a vital role in various autonomous systems, providing essential information for perception and planning tasks. However, mainstream localization methods are based on the sensors approach, which is vulnerable in some extreme conditions where sensors probably fail in a short period, such as the camera-based visual positioning. This study proposes a sensor-free localization method by integrating vehicle dynamic models and an online system identification module. First, a system identification process is conducted online to identify the system dynamics of the powertrain system and the steering system of the autonomous vehicle. Then, the identified system responses are taken as the control input of the vehicle dynamic model to produce the positioning results. The simulated experiments show that the proposed method achieves better positioning performance than the conventional vehicle dynamic models. In addition, the extendibility of the proposed method is explored by fusing it with extra sensors based on the extended Kalman filter (EKF). Furthermore, the navigation ability of the proposed method without sensors is also examined along a trajectory of 140 meters. The proposed method successfully accomplishes the navigation task without any collisions, demonstrating the effectiveness in enhancing the security of autonomous systems with navigation needs when sensors fail in extreme conditions.

***Keywords*—localization, vehicle dynamic model, online system identification formatting, autonomous systems, sensor failures**

I. Introduction

Localization plays a vital role in various autonomous systems, providing essential information for perception and planning tasks. Especially in autonomous vehicles (AV), localization performance directly affects the generation of collision-free trajectories, which ensures the safe navigation [1]. Mainstream localization methods in these autonomous systems highly rely on accurate information from sensors [2], such as light detection and ranging (LiDAR), cameras, inertial measurement unit (IMU), and global navigation satellite system (GNSS) receivers.

However, some inevitable limitations of these sensors prevent the development of those autonomous systems. For example, LiDAR and camera are vulnerable to adverse weather conditions such as rain, snowing, and fogging [3], and IMU may fail in highly vibrating conditions [4]. Consequently, serious accidents might be caused by the failure of sensors, such as the crashes of Adam Air 574 mainly due to the malfunction of IMU [5]. In short, these sensors are sensitive to environmental conditions. Therefore, to release the reliance on sensors, it is worthwhile to employ information from other environment-independent sources to enhance localization performance and fight against sensor failures.

One possibility is to re-examine the use of vehicle dynamic models (VDMs). According to the definition of The Society of Automotive Engineers (SAE), VDM is the application of physical laws to a vehicle in motion [6]. One distinctive strength of VDM is that it is not affected by sensors' conditions. Many researchers have integrated vehicle dynamics into the development of localization methods. In general, VDMs usually provide a coarse estimation which would be corrected by sensors' measurements [7-8]. For example, measurements of vehicle position from exogenous sensors will correct the estimation made by VDMs in the extended Kalman filter (EKF) [9] based localization process [10]. However, such kind of corrections might be impossible when sensors fail. In addition, VDMs could not account for highly dynamic environments and complicated systems, which are common in the real world, making the positioning even worse when corrections are unavailable.

Our previous work reveals that the endogenous feature of the system is able to provide corrections to VDM even when sensors fail [11], which could be achieved by introducing system identification (SI). System identification is a technology in the control community, which tackles the problem of "building mathematical models of dynamic systems based on observed data from the system" [12]. As the estimation errors of VDM mainly come from unknown system characteristics and changing environments, it is impractical to consider all these factors in modeling VDM with specialized knowledge, such as the cornering stiffness of tires and the bank angle of roads [13]. Nevertheless, the knowledge of system identification can be applied to estimate the system responses affected by these factors in a data-driven approach [12]. Based on the estimated system responses, a better control input signal than the raw control command can be provided to VDM as a correction.

In this study, we integrated vehicle dynamic models and system identification to extend the navigation service of AVs when sensors fail in a short period of time. Firstly, an online system identification process is implemented to identify the characteristics of the drivetrain system and the steering system of the AV. For each identification, control commands from planning and control modules are taken as the input signal, while the system responses measured by sensors are regarded as the measured response. Note that all identification processes in this paper are conducted online with well-

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functioning sensors, which differ from the previous work that implements an offline system identification [11]. Then, during the period of sensor failures, the ego-pose of the vehicle is estimated by VDM, whose control inputs are computed by the identified system dynamics. For convenience, this method is named VDM-OnSI. To demonstrate the extendibility of VDM-OnSI in mainstream positioning and navigation systems, an extended Kalman filter (EKF) [9] is designed by integrating the VDM-OnSI and extra sensors noted as EKF-VDM-OnSI.

The positioning performance and the navigation ability of the proposed method are evaluated in a simulated environment created by Gazebo [14], where an AV with full autonomy is developed based on autoware [15] for algorithm realization. The contribution is as follows:

1) This paper proposes a localization method based on vehicle dynamic models and online system identification to extend the navigation service during sensor failures, enhancing the security of autonomous systems with navigation needs in extreme conditions;

2) This paper experimentally shows that the proposed method can be easily extended with the availability of extra sensors to provide improved positioning performance; This paper also demonstrates the potential of endogenous information in autonomous systems (such as system characteristics) to enhance its ability on localization tasks, encouraging researchers to explore this direction.

II. Overview of the Proposed Integration System

The overall architecture of the proposed VDM-OnSI method is described in Fig. 1, where the autonomous vehicle is taken as the experimental platform. In the autonomous vehicle, the localization module receives sensor measurements to produce positioning results which are employed in the planning and control module to generate control commands. The plants execute these commands to drive the vehicle to move, and the sensors measure the vehicle pose after the control, which in turn adjusts the control commands. The difference between the vehicle pose and the desired pose is eventually minimized in such feedback control when sensors are available. During this process, an online system identification is conducted to identify the time-varying dynamics of the plants. The control command (such as velocity command) and the measured responses (such as velocity responses) are processed recursively to update the parameters of the identified model which produces the estimated response of control commands. Then a vehicle dynamic model (VDM) is deployed to estimate the vehicle pose with the control input as the previously estimated system responses. Such pose estimation could be used to develop an advanced positioning system based on sensor fusion methods, such as Kalman filters. When sensors fail, the process depicted with the dash line in Fig.1 becomes unavailable. The system identification module will use the latest identified parameters to estimate the response of control commands. The pose estimation given by the VDM-OnSI will be the only source adopted in the localization module for vehicle positioning and navigation.

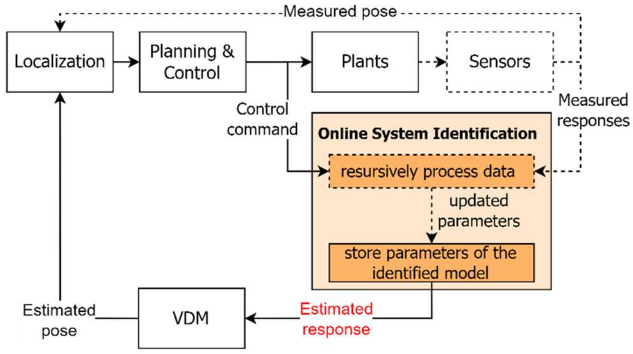

Fig. 1. The architecture of the proposed VDM-OnSI method.

III. Vehicle Dynamic Models Based Localization

We adopt the notation from the previous work and use the two-wheel bicycle kinematic model to describe the planar motion of the vehicle [11]. Fig. 2 shows the basic idea of the bicycle kinematic model, and the differential equations describing the vehicle motion in an inertial frame are listed below [13]:

$$\dot{x} = v cos(\psi + \beta) \qquad (1a)$$

$$\dot{y} = v sin(\psi + \beta) \qquad (1b)$$

$$\dot{\psi} = \frac{v}{l_r} \sin(\beta) \qquad (1c)$$

$$\dot{v} = a \qquad (1d)$$

$$\beta = \tan^{-1}\left(\frac{l_r}{l_f + l_r} \tan(\delta_f)\right) \qquad (1e)$$

where x, y are the coordinates of the center of mass at point C, and ψ is the vehicle orientation. Point A and point B represent the center of the front wheel and the rear wheel, respectively. The line segment AB is the wheelbase of the vehicle which is divided into two parts lr and l_f by point C. δ_r is the steering angle of the rear wheel which is assumed to be zero, and δ_f is the steering angle of the front wheel. According to Ackerman turning geometry [13], the line perpendicular to the axis of the rear wheel intersects with the line perpendicular to the axis of the front wheel at point O, which is the instantaneous rolling center. The direction perpendicular to line OC is the direction of the vehicle velocity v, and the angle made by the velocity direction and the wheelbase is the vehicle slip angle β. In this setting, the acceleration along the velocity direction a and the front wheel steering angle δ_f are taken as the control input.

As can be seen, the bicycle kinematic model can provide an estimation of the vehicle state even when sensors are not available. However, such an estimation result is not precise since certain assumptions made by the bicycle kinematic model will not always be satisfied in the real world. In general, two main assumptions are made by the bicycle kinematic model. Firstly, the vehicle is assumed to be operated at a low speed; Secondly, the wheel slip angle, which is the angle made by the tire orientation and the wheel velocity direction, is assumed to be zero [13]. Although advanced vehicle dynamic models can be developed to consider more complicated operation conditions, assumptions about the environments and simplification of the system's complexity still exist.

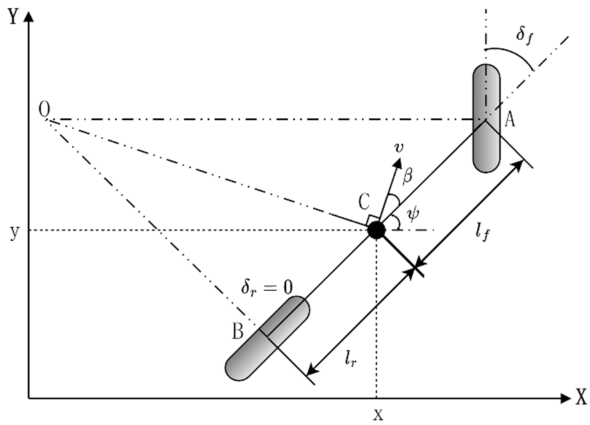

Fig. 2. Two-wheel bicycle kinematic model (The figure is taken from [11]).

IV. Integration of Vehicle Dynamic Model and Online System Identification

To provide a correction to the state estimation made by VDM, our previous work explores the possibility of introducing system identification [11]. System identification is the science of "*building mathematical models of dynamic systems from observed input–output data*"[16]. Our previous work identifies the system dynamics of the AV in an offline way and applies it in estimating the system responses during the operation of the vehicle. The estimated responses are adopted to synthesize a new kind of control input, which is taken as the input of the vehicle dynamic model in (1). Fig. 3 shows the basic idea of this process. Although the experiment in the previous work shows that the positioning performance of VDM is improved by adopting the estimated responses from system identification, the positioning error still significantly increases with time and eventually becomes too large to be used in a navigation task. One dominant reason is that the vehicle system is highly dynamic and consistently affected by the changing environment, which is hard to be captured by the offline system identification. Considering this, this work introduces online system identification to model the system dynamics in real time.

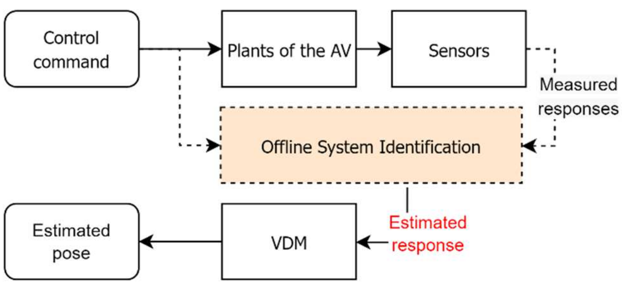

Fig. 3. Integration of offline system identification and VDM.

A. Online System Identification

In the real world, there is a need to "have a model of the system available on-line while the system is in operation" [12], especially when the physical properties of the system change rapidly. Methods coping with such problem usually refer to online system identification, where the model parameters are usually updated at regular time intervals by recursively processing the measured input-output data. [12]. In general, the exact form of online system identification methods depends on the types of model structures and parameter estimation algorithms. Autoregressive with exogenous inputs (ARX) model, Autoregressive moving average model with exogenous inputs (ARMAX) model, and autoregressive autoregressive with exogenous input (ARARX) model are the most common model structures in the online system identification. As for the parameter estimation algorithms, recursive algorithms including recursive least squares (RLS), recursive prediction error methods (RPEM), and recursive pseudo-linear regression (RPLR) are widely adopted, which can "compute the new parameters at time k in dependency on the parameters at the previous sampling instant k-1 and the new incoming information" [17].

In this study, we simply adopt the ARX model to represent the system dynamics, which is given below:

$$A(q)h(k) = B(q)u(k) + n(k) \tag{2a}$$
$$A(q) = 1 + a_1 q^{-1} + a_2 q^{-2} + \cdots + a_n q^{-n} \tag{2b}$$
$$B(q) = b_1 q^{-1} + b_2 q^{-2} + \cdots + b_m q^{-m} \tag{2c}$$

where $u(k), n(k), h(k)$ are the input signal, gaussian white noise, and model output at time instant k, respectively, q is the forward shift operator, i.e., $q^{-1}h(k) = h(k-1)$, and $a_1, a_2, \ldots, a_n, b_1, b_2, \ldots, b_m$ are time-varying parameters, n and m are the degree of $A(q)$ and $B(q)$, respectively. Our previous work shows that a system model with 2 poles and 2 zeros could precisely describe the dynamics of the powertrain system and the steering system in an offline way while maintaining relatively low complexity for a practical purpose [11]. Therefore, instead of conducting a trial-and-error process to select the best order of the ARX model, we directly set $m = n = 2$ to put focus on the impacts of online system identification on the positioning performance of VDM.

To estimate parameters of the ARX model in real time, the RLS algorithm with exponential forgetting factors is employed:

$$\hat{\theta}(k) = \hat{\theta}(k-1) + \gamma(k)e(k) \tag{3a}$$
$$\gamma(k) = \frac{P(k-1)\psi(k)}{\psi^T(k)P(k-1)\psi(k) + \lambda} \tag{3b}$$
$$e(k) = h(k) - \psi^T(k)\hat{\theta}(k-1) \tag{3c}$$
$$P(k) = \frac{1}{\lambda}\left(I - \gamma(k)\psi^T(k)\right)P(k-1) \tag{3d}$$
$$\psi(k) = [u(k-1) \ldots u(k-m) \quad -h(k-1) \ldots -h(k-n)]^T \tag{3e}$$
$$\hat{\theta}(k) = \left[\hat{b}_1(k) \ \ldots \ \hat{b}_m(k) \ \hat{a}_1(k) \ \ldots \ \hat{a}_n(k)\right]^T \tag{3f}$$

where $\psi(k)$ is the regressor, $\hat{\theta}(k)$ is the time-varying parameter, $e(k)$ is the prediction error, $\gamma(k)$ is the gain which determines how much the current prediction error affects the update of the parameter, and $0 < \lambda < 1$ is the forgetting factor. Then, the optimal ARX predictor is given by,

$$\hat{h}(k|k-1) = b_1 u(k-1) + \cdots + b_m u(k-m) - a_1 h(k-1) - \cdots - a_n h(k-n) \tag{4}$$

where $\hat{h}(k|k-1)$ is the optimal prediction at time instant k, which can also be interpreted as the identified system response.

B. Integration of Vehicle Dynamic Model and Online System Identification

Assuming the identified acceleration response is $\hat{a}$ and the identified steering angle response of the steering system is $\hat{\delta}_f$, the integration of VDM and the online system identification is achieved by taking $\hat{a}$ and $\hat{\delta}_f$ as the control input of the VDM model in (1), as shown below:

$$\dot{x} = vcos(\psi + \beta) \quad (5a)$$

$$\dot{y} = vsin(\psi + \beta) \quad (5b)$$

$$\dot{\psi} = \frac{v}{l_r}\sin(\beta) \quad (5c)$$

$$\dot{v} = \hat{a} \quad (5d)$$

$$\beta = \tan^{-1}\left(\frac{l_r}{l_f + l_r}\tan(\hat{\delta}_f)\right) \quad (5e)$$

The above modified vehicle dynamic model is denoted as VDM-OnSI. Note that VDM-OnSI has the same formulation as the VDM-SI in our previous work [11]. The main difference is that VDM-OnSI uses online system identification to obtain the control input, while VDM-SI adopts offline system identification. Section VI will discuss their difference in detail.

V. Fusion with Extra Sensors Based on Extended Kalman Filters

To demonstrate the extendibility of the proposed method in mainstream positioning and navigation systems, we integrate the VDM-OnSI with LiDAR based on extended Kalman filters (EKF). A loosely-coupled structure is adopted where the NDT-matching algorithm[18] is employed to estimate the ego-pose of the vehicle based on raw LiDAR measurements and the VDM-OnSI is employed to propagate the state.

A. Discretization and Linearization

The discrete form of VDM-OnSI in (5) is given below:

$$x_{k+1} = x_k + v_k cos(\psi_k + \beta_{k+1}) * \Delta t \quad (6a)$$

$$y_{k+1} = y_k + v_k sin(\psi_k + \beta_{k+1}) * \Delta t \quad (6b)$$

$$\psi_{k+1} = \psi_k + \frac{v_k}{l_r} sin(\beta_{k+1}) * \Delta t \quad (6c)$$

$$v_{k+1} = v_k + \hat{a}_{k+1} * \Delta t \quad (6d)$$

$$\beta_{k+1} = tan^{-1}\left(\frac{l_r}{l_f + l_r}\tan(\hat{\delta}_{f,k+1})\right) \quad (6e)$$

By taking the first-order Taylor expansion at point $(\hat{x}_k, \hat{y}_k, \hat{\psi}_k, \hat{v}_k)$, (6a-b) can be linearized as below:

$$\begin{aligned} x_{k+1} = x_k &- \Delta t * \hat{v}_k \sin(\hat{\psi}_k + \beta_{k+1})\,\psi_k \\ &+ \Delta t * \hat{v}_k cos(\hat{\psi}_k + \beta_{k+1}) v_k \\ &+ \Delta t * \hat{v}_k\,\hat{\psi}_k \sin(\hat{\psi}_k + \beta_{k+1}) \end{aligned} \quad (7a)$$

$$\begin{aligned} y_{k+1} = y_k &+ \Delta t * \hat{v}_k \cos(\hat{\psi}_k + \beta_{k+1})\,\psi_k \\ &+ \Delta t * \hat{v}_k sin(\hat{\psi}_k + \beta_{k+1}) v_k \\ &- \Delta t * \hat{v}_k\,\hat{\psi}_k \cos(\hat{\psi}_k + \beta_{k+1}) \end{aligned} \quad (7b)$$

B. Fusion based on Extended Kalman Filter

Let $\boldsymbol{x}_k = [x_k, y_k, \psi_k, v_k]^T$ be the state of the vehicle, the propagation function based on (6) could be written as:

$$\boldsymbol{x}_{k+1} = f(\boldsymbol{x}_k, \hat{a}_{k+1}, \hat{\delta}_{f,k+1}) + v_k \quad (8)$$

where v_k is the process noise which is assumed to be the zero-mean Gaussian noise with covariance P_k, and $f(\cdot)$ is a non-linear function whose Jacobian matrix is given by:

$$F_k = \left.\frac{\partial f(\boldsymbol{x}_k, \hat{a}_{k+1}, \hat{\delta}_{f,k+1})}{\partial \boldsymbol{x}_k}\right|_{x_k = [\hat{x}_k, \hat{y}_k, \hat{\psi}_k, \hat{v}_k]^T}$$

$$= \begin{bmatrix} 1 & 0 & -\Delta t * \hat{v}_k \sin(\hat{\psi}_k + \beta_{k+1}) & \Delta t * \hat{v}_k cos(\hat{\psi}_k + \beta_{k+1}) \\ 0 & 1 & \Delta t * \hat{v}_k cos(\hat{\psi}_k + \beta_{k+1}) & \Delta t * \hat{v}_k \sin(\hat{\psi}_k + \beta_{k+1}) \\ 0 & 0 & 1 & \Delta t * \dfrac{\sin(\beta_{k+1})}{l_r} \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

Let $\boldsymbol{z}_k$ be the estimated pose by the NDT-matching algorithm, the measurement function could be written as:

$$\boldsymbol{z}_k = C_k \boldsymbol{x}_k + \eta_k \quad (9)$$

$$C_k = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$

where η_k is the measurement noise and is assumed to be the zero-mean Gaussian noise with covariance Q_k.

The fusion of VDM-OnSI and LiDAR measurement based on the extended Kalman filters is given below and noted as EKF-VDM-OnSI:

$$\hat{\boldsymbol{x}}_k^- = F_{k-1}\hat{\boldsymbol{x}}_{k-1} \quad (10a)$$

$$P_k^- = F_{k-1}P_{k-1}F_{k-1}^T + Q_{k-1} \quad (10b)$$

$$K_k = P_k^- C_k^T (C_k P_k^- C^T + R_k)^{-1} \quad (10c)$$

$$\hat{x}_k = \hat{x}_k^- + K_k(\boldsymbol{z}_k - C_k\hat{\boldsymbol{x}}_k^-) \quad (10d)$$

$$P_k = (I - K_k C_k)P_k^- \quad (10e)$$

where $\hat{\boldsymbol{x}}_k^-$ is the prior estimation, $\hat{x}_k$ is the posterior estimation, and K_k is the Kalman gain at time instant k.

VI. Numerical Experiments

The performance of the proposed method is evaluated in a simulated environment created by Gazebo [14], where an AV with full autonomy is developed based on autoware [15] for algorithm realization. Similar to the previous work [11], the perception and localization module of AV are developed based on the LiDAR measurements, while the planning and control module are realized by pure pursuit algorithm [19] and the Ackerman turning geometry [13].

A. Implementation of Online System Identification

The 3D simulator Gazebo [14] provides the prototype of the autonomous vehicle where two plants, including the powertrain system and the steering system, are identified. The powertrain system converts the power of the engine into the movement of the vehicle [20], while the steering system can turn the vehicle around the vertical axis while driving [21].

In the powertrain system identification, the velocity command is taken as the input signal, and the velocity measured by LiDAR is regarded as the output data. The identification process is conducted during the vehicle's operation, and the parameters are updated in real time. Fig. 4 shows the track on which the AV is driving in the simulated environment, and Fig. 5a shows the velocity command and the angular velocity command produced by the control module of AV along the track. The prediction error of the ARX model for the powertrain system identification is plotted in Fig. 5b. At the beginning of the identification, the prediction error is the largest since the vehicle suddenly changes the mode from rest to motion and the estimated parameters have not converged. With time increasing, the prediction error gradually reduces and maintains at a relatively low level. Nevertheless, a surge of the prediction error at the endpoint of the track is observed, which is also the result of an abrupt change of the operation mode from motion to rest. The mean prediction error during the whole process is less than 5.97e-04 m/s, and the standard deviation is around 0.035 m/s. Note that the identified velocity response of the powertrain system will be converted to the acceleration response by taking the time derivative to accommodate the VDM model described in (1).

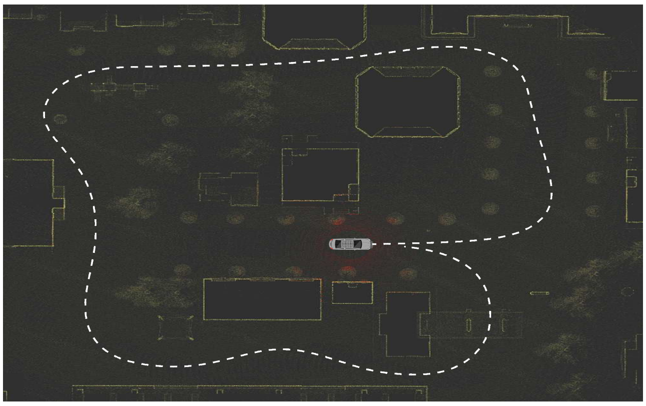

Fig. 4. The simulated environment in Gazebo. The white dash line is the designed track where the AV is driving counterclockwise.

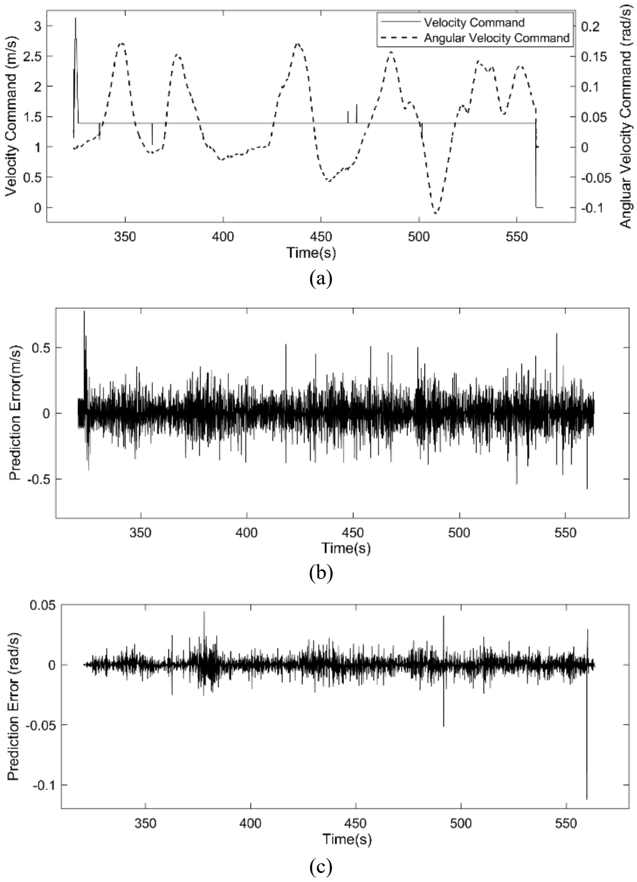

Fig. 5. (a) The velocity command and angular velocity command published by the control module of AV along the track; Prediction error of the ARX model in identifying (b) the powertrain system; (c) the steering system.

Similar processes are taken for identifying the steering system where the input and output are the angular velocity command and the measured angular velocity, respectively. Fig. 5c shows the prediction error during the identification process which has a similar pattern to that of identifying the powertrain system. One difference is that the initial surge of the prediction error in identifying the steering system is not at the start point of the track but near the first turn, where the angular velocity increases rapidly. The mean and standard deviation of the prediction error in identifying the steering system are 4.35e-05 rad/s and 0.0018 rad/s, respectively. To accommodate the VDM model, we convert the estimated angular velocity response to the steering angle response according to the Ackermann steering geometry [13].

B. *Positioning Performance with Well-Functioning Sensors*

In this section, we investigate the positioning performance of the proposed method along the track, as shown in Fig. 4. The vehicle is required to move at a constant speed of 5km/h, although the real speed will fluctuate around this value due to the impacts of the turning movement. To keep the AV running along the track, the LiDAR measurement (standard deviation is 0.1m) is adopted in the localization module of the AV to produce precise positioning results, which are the basis of successfully executing the planning and control modules. The proposed VDM-OnSI is implemented in depend of the AV system, estimating the ego-pose of the AV. The VDM integrated with offline system identification (VDM-SI) proposed in the previous work [11] and the pure VDM are also constructed for comparison. For clarity, the difference between the three methods is listed in Table I.

TABLE I. DIFFERENCE BETWEEN THREE POSITIONING METHODS

Positioning Method	**Bicycle Kinematic Model**	**Offline System Identification**	**Online System Identification**
pure VDM	√[a]	-[a]	-
VDM-SI	√	√	-
VDM-OnSI	√	-	√

a. "√" means "adopted", "-" means "not adopted".

Fig. 6 plots the planar trajectory of the estimated pose for each method. The black dash line is the trajectory that the vehicle actually traced, which is taken as the ground truth. It's clear that the trajectory of the estimated pose by VDM-OnSI has the smallest deviation from the ground truth, indicating that VDM-OnSI has the best positioning performance among the three VDM-based methods. VDM-SI performs overall better than pure VDM, but they both suffer large deviations in the long-term view, indicating that offline system identification is vulnerable in capturing time-varying system dynamics. The absolute translation error (ATE) of the three methods is listed in Table II. As can be seen, the mean ATE of VDM-OnSI decreases by more than 77% compared to that of pure VDM, while VDM-SI only achieves around a 13% reduction in mean ATE.

TABLE II. THE POSITIONING PERFORMANCE

ATE (m)	**Max**	**Mean**	**RMSE**
pure VDM	48.69	26.02	30.38
VDM-SI	38.86	22.66	25.49
VDM-OnSI	11.16	5.94	6.97
EKF-VDM-OnSI	3.38	0.57	0.63
Improved by VDM-SI[b]	20.19%	12.91%	16.10%
Improved by VDM-OnSI[b]	**77.08%**	**77.17%**	**77.06%**
Improved by EKF-VDM-OnSI[b]	93.06%	97.81%	97.93%

b. The improvement compared to pure VDM.

In addition, the positioning performance of the EKF-VDM-OnSI is also examined. The proposed VDM-OnSI model is fused with LiDAR in a loosely-coupled structure where the NDT-matching algorithm gives the pose estimation based on raw LiDAR measurements. Note that LiDAR used in the fusion system has different precision from that used in the vehicle navigation. In the EKF-VDM-OnSI system, the LiDAR measurement has a standard deviation equal to 2m. The trajectory of the estimated pose of EKF-VDM-OnSI is plotted in Fig. 6a. Compared to VDM-based methods, EKF-VDM-OnSI largely boosted the positioning performance. The trajectory of the estimated pose by EKF-VDM-OnSI tightly fits with the ground truth. The positioning error of EKF-VDM-OnSI in Table II also suggests the same finding where the mean ATE of EKF-VDM-OnSI is around 97% less than that of pure VDM.

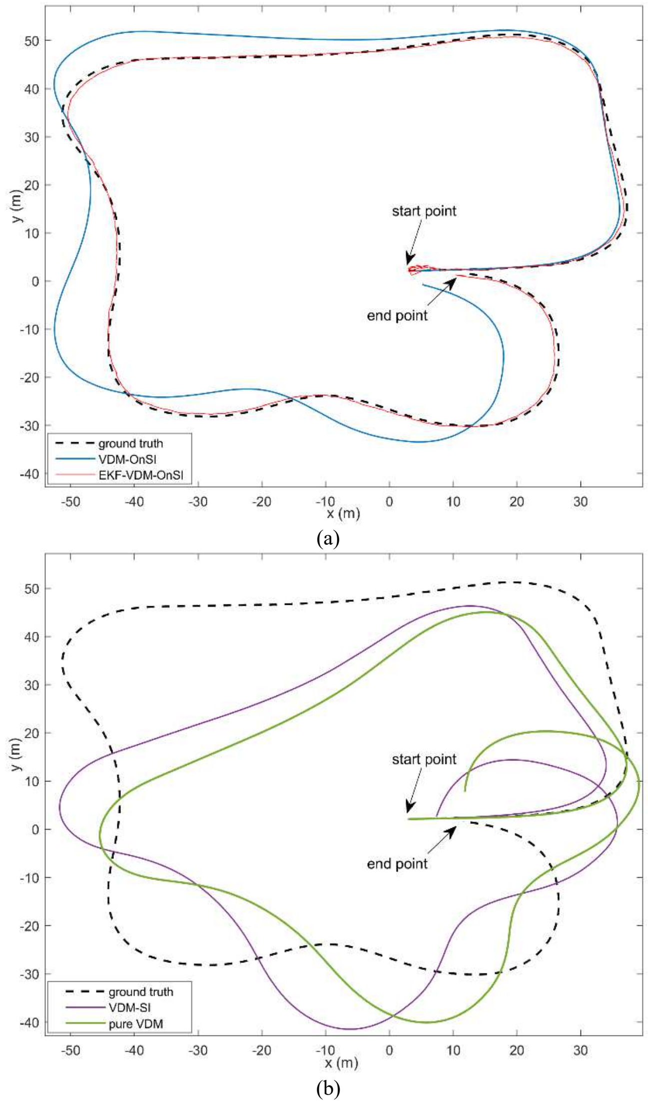

Fig. 6. Trajectory of the estimated pose when sensors function well by (a) VDM-OnSI, EKF-VDM-OnSI, (b) pure VDM, and VDM-SI.

C. Navigation Performance when Sensors Fail

In this section, we examine the navigation ability of VDM-OnSI when sensors fail. The AV is deigned to start at a constant speed of 5km/h to move along a pre-designed track, denoted as the black dash line in Fig. 7. Before the AV arrives at a specific location, the AV has well-functioning sensors to provide essential information to the localization module, ensuring that the vehicle could precisely trace the track. During this period, the identification process of VDM-OnSI is executed, and the ARX parameters are continuously updated and stored. When the AV arrives at the specific location which is marked as the red rectangular in Fig. 7, the AV is programmed to be isolated to all sensors, simulating the condition that all sensors fail. However, LiDAR sensors can be used in a separate program to monitor the real pose of the AV. Without sensors' information, the AV can only utilize the pose estimation by VDM-based methods to continue the navigation task. Note that VDM-OnSI will stop updating the ARX parameters but instead use the latest stored parameters for the system response and pose estimation.

Fig. 7 plots the trajectory of the vehicle in the navigation task based on pure VDM, VDM-SI, and VDM-OnSI when sensors fail. As can be seen, the vehicle under pure VDM based navigation rapidly deviates from the pre-designed track and eventually collides with an obstacle. Similar patterns are found in the VDM-SI based navigation. However, the VDM-SI based navigation has a smaller deviation than that of the pure VDM based navigation, indicating that even offline system identification could boosted the navigation ability of VDM. Interestingly, VDM-OnSI based navigation is the only one among the three methods that successfully guides the vehicle to arrive at the end point without collisions. When looking into the statistics, the path from the sensor failure location to the end point has a length exceeding 140m, along which the mean deviation of VDM-OnSI based navigation is only 3.18m in terms of ATE.

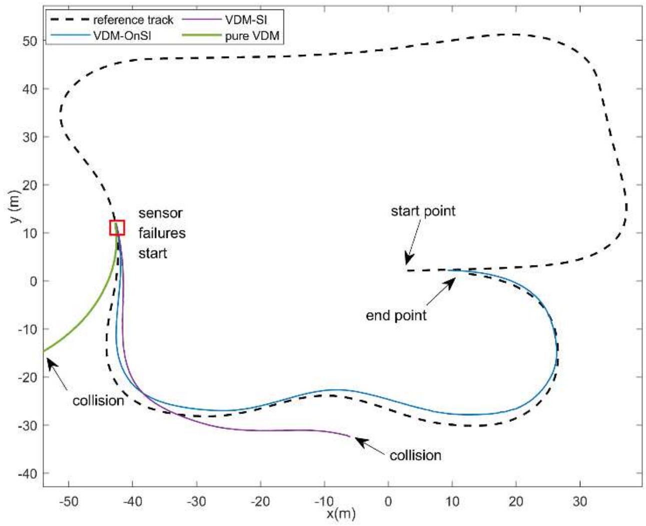

Fig. 7. Trajectory of the vehicle in the navigation task based on pure VDM, VDM-SI, and VDM-OnSI when sensors fail.

VII. Conclusion

This study has integrated the online system identification and the vehicle dynamic models to provide a sensor-free positioning method with considerable positioning accuracy, extending the navigation service of autonomous vehicles under sensor failures. In system identification, two plants including the powertrain and the steering systems of the AV are identified when sensors function well. An ARX model is first constructed for each plant to describe the system dynamics. Its parameters are then updated by recursively processing control commands and measured system responses using the RLS algorithm. The identified system dynamics are then utilized to compensate the VDM to produce positioning results. Along a designed track in the simulated environment created by Gazebo, the positioning results show that the proposed VDM-OnSI method largely improves the positioning performance of VDM with a more than 77% reduction in ATE. In addition, the proposed VDM-OnSI is integrated with extra sensors based on extended Kalman filtering and shows a boosted positioning performance, demonstrating the extendibility of VDM-OnSI in mainstream sensor fusion based positioning systems. Furthermore, the navigation ability of VDM-OnSI when sensors fail is examined. Compared to the pure VDM and VDM-SI approaches, VDM-OnSI based navigation is the only method that accomplishes the navigation task along a 140-meter-long path without collisions. As the VDM-OnSI based navigation does not rely on any sensors, it could be taken as a safety countermeasure to keep the AV normally operated when sensors are out of work in a short period of time.

Nevertheless, there are several limitations to this study. In the online system identification, we simply adopt the ARX model to represent the system dynamics and set the order of $A(q)$ and $B(q)$ as 2 according to experience. Although the identified system dynamics have proven to be useful in the integration with VDM for positioning and navigation tasks, the optimal model structure and order should be selected based on a trial-and-error process. Besides, the model complexity should also be taken into consideration since the identification process has to be carried out at regular time intervals where computation cost matters. On the other hand, in the EKF-based fusion of VDM-OnSI and LiDAR, VDM-OnSI is taken as the process model whose process noise is simply assumed to be the Gaussian noise. However, the process noise consists of at least two parts: one is the noise of the motion model, and another is the control input noise. Since the VDM regards the estimated system response as a constant value at each time instant, the difference between the estimated system response and the real system response is not taken into consideration, which means the control input noise is not explicitly modeled but rather coupled in the final process noise. This simplification makes it hard to determine the reliability of the pose estimation results of VDM-OnSI. Future research should establish a sensor model for VDM-OnSI where the covariance of the estimated system response, as well as the process noise of the motion model, could be modeled explicitly. The comparison between the sensor model of VDM-OnSI and IMU is also worth exploring.

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