Integration of Vehicle Dynamic Model and System Identified Model for Navigation in Autonomous Mobile Robots

Conference Paper · February 2023

DOI: 10.33012/2023.18637

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BIOGRAPHY

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ABSTRACT

Vehicle dynamic models are the basis of various navigation algorithms in autonomous mobile robots (AMRs), describing the vehicle motion purely by physical law. However, its simplifications on the system complexity and assumptions on the environments prevent it from providing accurate positioning results. Instead of introducing sensors to correct its pose estimation error, this study aims to utilize the endogenous information of AMRs to improve positioning performance. A system identification process is conducted to identify the system dynamics of the plants in AMRs, where the identified system dynamics is integrated into the development of vehicle dynamic models. Experiments on two scenarios show that the proposed method achieves better positioning results and navigation performance than conventional vehicle dynamic models, demonstrating the potential of endogenous information in AMRs to enhance their ability on navigation tasks. In addition, this study contributes to the literature that builds the bridge between system identification and navigation in AMRs.

1. INTRODUCTION

Vehicle dynamic models (VDM) are the application of the physical laws to a vehicle in motion (Sae International, 2021), playing an important role in designing navigation algorithms in autonomous mobile robots (AMRs) (Siegwart et al., 2011). Typical applications can be seen in the sensors/VDM integrated navigation systems, such as IMU/VDM integrated systems in unmanned aerial vehicles (Bryson & Sukkarieh, 2004; Khaghani & Skaloud, 2016) and LiDAR/VDM fusion in autonomous vehicles (Xiao et al., 2022). In these applications, VDMs usually provide a coarse estimation of robotics' pose while corrections on it are made by sensors' measurements, eventually generating a better state estimation. However, the navigation performance is largely attributed to the accuracy and reliability of sensors. To pursue lower positioning error, the common way is to introduce high-precision sensors or integrate multiple sensors (Huang et al., 2022). However, instead of purely being enabled by sensors, it is also worthwhile to investigate the possibility of utilizing endogenous information from other sources to improve navigation performance.

One possible approach, different from leveraging sensors, is to re-examine the use of vehicle dynamic models in navigation. VDMs usually make some assumptions about the vehicle operating environment and simplification on the system complexity *which may overlook the latency (the time required to reach a steady response) caused by control systems* (Dorf & Bishop, 2016). It is impractical to consider all these factors in VDM modeling with specialized knowledge, such as the cornering stiffness of tires and the bank angle of roads in autonomous vehicles (Rajamani, 2012). As mentioned above, the pose estimation error brought by these factors is usually corrected by sensor measurements. Nevertheless, a system identification (SI) of the control systems brings the opportunity to provide a new kind of correction to VDM. System identification is a term in the control field, which refers to the technology of "building mathematical models of dynamic systems from observed input-output data"(Ljung, 2010). To apply system identification to the control system of AMRs, the system responses affected by these factors can be estimated in a data-driven approach(Ljung, 1999), consequently correcting VDM estimation by providing a better control input signal.

Bearing this finding in mind, this paper integrates system identification into the design of VDM to improve its navigation performance. The development of the algorithm and its evaluation are based on AVs. First, a system identification process is executed during the operation of AVs. Control commands obtained from planning and control modules of AVs are regarded as the input data, while the controller's responses, such as the linear velocity and angular velocity measured by sensors from the perception module, are taken as the output data. Then, the bicycle kinematic model (Wang & Qi, 2001) which describes the vehicle dynamics is applied to estimate the ego-pose of vehicles. The responses of control commands are calculated with identified system dynamics, which are finally fed into the bicycle kinematic model as the control input. To concentrate on the navigation performance of VDMs, no sensors are used to correct the pose estimation result of VDMs. In other words, this paper aims to exploit the potential of the VDM standalone with the help of the SI proposed in this paper. The performance of the proposed method is evaluated and compared with the conventional VDMs based on an AV in a simulated environment created by the 3D simulator, Gazebo (Koenig & Howard, 2004). Two scenarios including a 90-degree bend and an S-Curve are designed to examine the performance of the proposed methods. The contribution of this study is twofold: 1) proposed a method to improve the navigation performance of VDM in the perspective of system identification; 2) built the bridge between system identification and navigation in AMRs, demonstrating the potential of endogenous information in AMRs to enhance their ability on navigation tasks and is verified using two datasets.

The remainder of this paper is structured as follows. The overview of the proposed method is introduced in Section 2. The VDM-based localization and its limitations are described in Section 3. In Section 4, the system identification procedure is briefly introduced. In addition, the integration of the vehicle dynamic model and system identified model is also presented in this section. Experiments including identifying two plants in the AV and the navigation performance of the proposed method are presented in Section 5. Finally, the conclusion is drawn with suggested future work in Section 6.

2. OVERVIEW OF THE PROPOSED INTEGRATION SYSTEM

In this study, the autonomous vehicle is taken as the experimental platform to develop the research method. The autonomous vehicle usually consists of four modules, including perception, localization, planning and control. We only focus on the localization, planning and control modules in this study, and their relationships are given in Fig. 1. The localization module receives the measured pose information from sensors to synthesize the localization result. The planning and control module utilize the localization result to produce control commands which will be executed by plants. During this process, the system identification is executed to identify the system dynamics of the plants, where the control command is taken as the input and the measured system responses such as velocity are taken as the output. Then a vehicle dynamic model is deployed to estimate the vehicle's ego-pose, whose control input is the estimated response of control commands obtained from the previously identified system dynamics. The pose estimation made by the modifed VDM approach can be utilized to develop an advanced positioning algorithm with the aid of sensors. However, in this study, the proposed method is only used to compare with the conventional VDMs to highlight the strength of the proposed method. Therefore, sensors will not be used to correct the pose estimation by VDM, and their integrations would be explored in our future work.

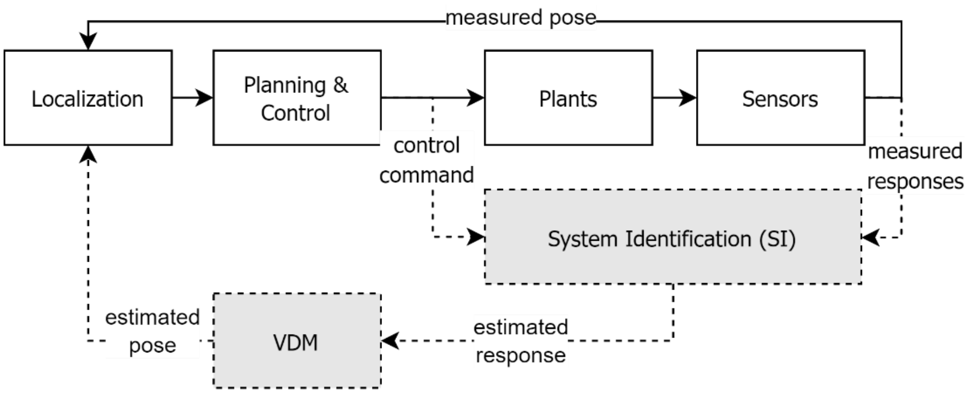

Figure 1. *Architecture of the Proposed Method.*

3. VDM BASED LOCALIZATION

In this study, the bicycle kinematic model is employed to describe the vehicle's movement, which is able to estimate the vehicle's state without the sensors' support. Fig. 2 shows the two-wheel kinematic bicycle model used in this study. In this model, the front wheels and the rear wheels of a four-wheel vehicle are represented by one front wheel at point A and one rear wheel at point B, respectively. The differential equation of this kinematic bicycle model is given below (Kong et al., 2015):

$$\begin{gathered}\dot{x} = vcos(\psi + \beta) \\ \dot{y} = vsin(\psi + \beta) \\ \dot{\psi} = \frac{v}{l_r}\sin(\beta) \\ \dot{v} = a \\ \beta = \tan^{-1}\left(\frac{l_r}{l_f + l_r}\tan(\delta_f)\right)\end{gathered} \tag{1}$$

where x, y are the coordinates of the centre of gravity at point C, ψ indicates the vehicle's orientation. β is the slip anlge of the vehicle, which is the anlge between the direction of vehicle velocity v and the longitudinal axis of the vehicle. l_r and l_f are two parts of the wheelbase which is divided by Point C. δ_f is the steering angle of the front wheel, and δ_r is the steering angle of the rear wheel. As the rear wheel in most vehicles cannon be steered, δ_r is set to zero. a is the acceleration along the velocity orientation. The motion of the vehicle can be described by three coordinates (x, y, ψ), and δ_f and a are taken as the control inputs.

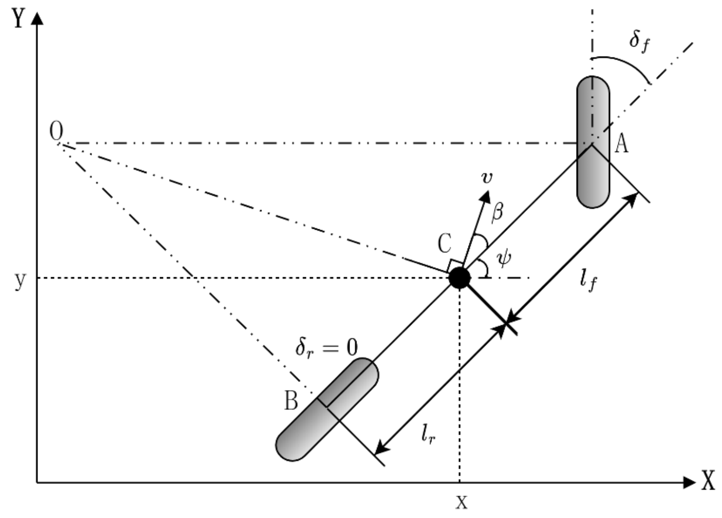

Figure 2. *The Two-Wheel Kinematic Bicycle Model*.

The two-wheel kinematic bicycle model is based on two assumptions that 1) the vehicle operates under low-speed conditions; and 2) the angle between the orientation of the tire and the orientation of the velocity vector of the wheel is zero (Rajamani, 2012). However, these assumptions are not always satisfied in the real world, resulting in considerable positioning errors. Other vehicle dynamic models also have this kind of problem since they usually make assumptions about the environments and simplification on the system's complexity.

4. INTEGRATION OF SYSTEM IDENTIFICATION AND VDM

4.1 System Identification

To model the system response of a physical system, system identification is applied in this study. In particular, system identification is the science of "*building mathematical models of dynamic systems from observed input–output data*"(Ljung, 2010). System identification mainly consists of three procedures, including input-output data collection, candidate model selection, and parameter estimation (Ljung, 1999).

To collect the input-output data, a sequence of step signals is deployed to excite the system. The candidate models are based on transfer functions with different poles and zeros, which is commonly used to algebraically relate a system's output to its input in s-domain (Nise, 2015). A typical transfer function model with n-poles and m-zeros is given below:

$$G = \frac{b_m s^m + b_{m-1} s^{m-1} + \cdots + b_0}{a_n s^n + a_{n-1} s^{n-1} + \cdots + a_0} \tag{2}$$

where s is a complex variable, $a_n, a_{n-1}, \ldots, a_0$ are coefficients of the denominator and $b_m, b_{m-1}, \ldots, b_0$ are coefficients of the nominator, which are the unknown parameters and will be estimated based on least square optimization (Ljung, 1999).

In order to select the best model in the candidate set, two criteria including fit ratio (FIT) and mean-square error (MSE) are used to evaluate the performance of candidate models. Their definitions are given below:

$$FIT = \left(1 - \frac{\sqrt{\sum_{t=1}^{N} e^T(t)e(t)}}{\sqrt{\sum_{t=1}^{N} y_c^T(t)y_c(t)}}\right) * 100\% \tag{3}$$

$$MSE = \frac{1}{N}\sum_{t=1}^{N} e^T(t)e(t) \tag{4}$$

where $y_c(t) = y(t) - \frac{1}{N}\sum_{t=1}^{N} y(t)$, $e(t) = y(t) - \hat{r}(t)$, $y(t)$ is the measured output, $\hat{r}(t)$ is the estimated output, and N is the number of samples in the estimation dataset. It's clear that FIT measures the closeness of the estimated model to the true model (Ljung, 1999), while MSE represents the prediction error of the estimated model.

4.2 Integration of Identified System Dynamics and VDM

In AVs, the control command is given in the time domain. For example, a typical control command is given by "setting the steering angle to 0.2 rad in the following 3 seconds". However, the transfer function model is built in the s-domain, which cannot be directly employed to estimate the time response of a given control command signal. Considering this, the transfer function model is converted to state-space equations using the method described in (Nise, 2015):

$$\begin{aligned} \dot{x} &= Ax + Bu \\ y &= Cx + Du \end{aligned} \tag{5}$$

where A, B, C, D are state-space parameters, x is the state vector, $\dot{x}$ is the derivative of x with respect to time, y is the output vector, and u is the input vector. The state vector x is taken as the estimated response, which can be applied to VDM model.

In this study, the powertrain system and the steering system in AVs are identified. The powertrain consists of the engine and all of the components that convert the engine's power into vehicle movement, such as the transmission, driveshafts, differential, and axles (Mashadi & Crolla, 2012). The steering system consists of the steering wheel, the steering column, the steering gear and other necessary components that turn the vehicle around the vertical axis while driving (Harrer & Pfeffer, 2017). Assuming the estimated system response of the powertrain system is $\hat{a}$, and the estimated system response of the steering system is $\hat{\delta}_f$, VDM will adopt $\hat{a}$ and $\hat{\delta}_f$ as the control inputs. The modified vehicle dynamic model is denoted as VDM-SI which can be represented below:

$$\begin{aligned} \dot{x} &= v\cos(\psi + \beta) \\ \dot{y} &= v\sin(\psi + \beta) \\ \dot{\psi} &= \frac{v}{l_r}\sin(\beta) \\ \dot{v} &= \hat{a} \\ \beta &= \tan^{-1}\left(\frac{l_r}{l_f + l_r}\tan(\hat{\delta}_f)\right) \end{aligned} \tag{6}$$

5. EXPERIMENTS AND RESULTS

The performance of the proposed method is evaluated and compared with the conventional VDMs based on an AV in a simulated environment created by the 3D simulator, Gazebo (Koenig & Howard, 2004). For the development of the autonomous driving system in AV, a Velodyne HDL-32 LiDAR is used to provide essential measurements to develop perception and localization algorithms, while the pure pursuit algorithm (Conlter, 1992) and the Ackerman turning geometry (Rajamani, 2012) are adopted to construct planning and control algorithms. All of these are developed based on autoware (Kato et al., 2015), an open-source autonomous driving software, providing the essential ability for the vehicle to run on a pre-recorded path. Key parameters used in the simulation are listed in Table 1.

TABLE 1. *Key Parameters in the Simulation.*

parameters	l_f	l_r	Maximum steering angle	Maximum acceleration
value	$1.75m$	$1.2m$	$1.7\ rad$	$4.5m/s^2$

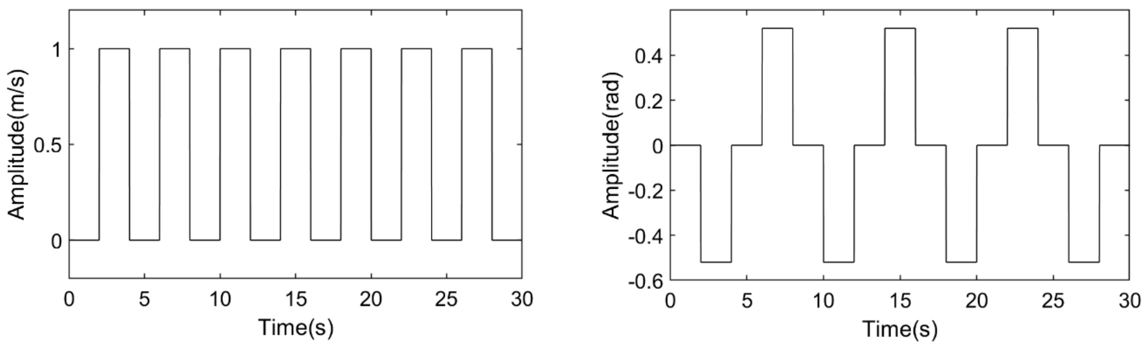

Figure 3. *Test Input: (a) the powertrain; (b) the steering system.*

5.1 Implementation of System Identification

In the autoware-Gazebo simulation, the control module sends the velocity command to the powertrain to drive the vehicle to move, while the real velocity of the vehicle is measured by LiDAR. The input velocity command and the measured velocity will be used as the input-output data in identifying the powertrain. Specifically, a series of step signals last for 30 seconds was taken as the velocity command to stimulate the powertrain, as shown in Fig. 3a. The sampling rate of the signal is 100Hz and the amplitude is 1m/s. During the experiment, the steering command is kept to zero. Then a set of candidate models based on transfer function models as defined in Equation (2) was constructed, and we use PxZy to represent these candidates where 'P' means pole, 'Z' means zero, 'x' is the number of poles which ranges from 1-5, and 'y' is the number of zeros which range from 0-5. By employing least square optimization, the optimal parameters of each model were estimated (Ljung, 1999). Fig. 4 shows the performance of these candidate models where models with FIT less than 60% are not listed. As can be seen, P5Z4 has the highest FIT and the lowest MSE among these candidate models; however, its order (number of poles and zeros) is almost the highest. On the contrary, P2Z2 balances the model order and the performance with FIT equal to 0.889 and MSE equal to 2.87E-3. Comparing to P5Z4, the FIT of P2Z2 is only 0.45% lower while the model order is significantly smaller. In industrial practice, identification for control is usually based on the construction of low-order models (Ljung, 2002). Therefore, P2Z2 is chosen as the best model in the candidate set. Note that the kinematic bicycle model takes acceleration as input, therefore time derivative of the identified velocity response is applied to obtain the acceleration.

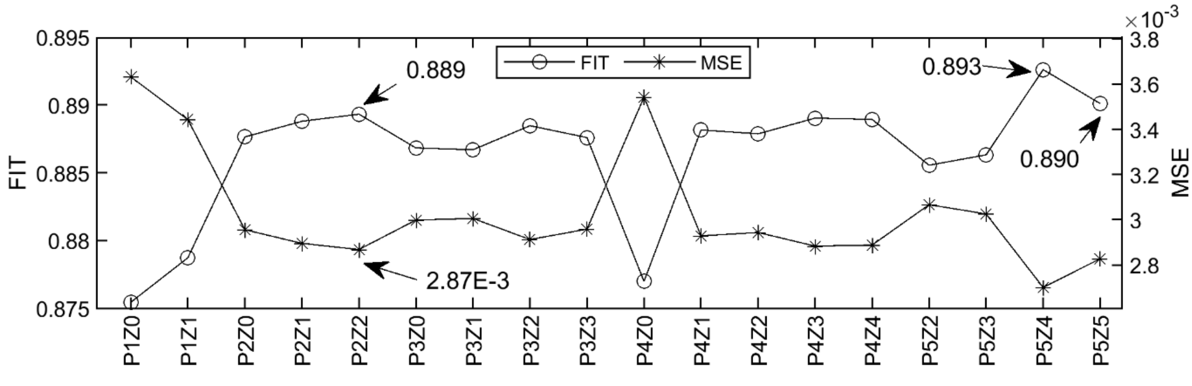

Figure 4. *Performance of Candidate Models in Identifying the Powertrain*.

On the other hand, the steering system receives the steering angle command from the control module to turn the wheel. Similar to the identification of the powertrain, a series of step signals last for 30 seconds was taken as the input data, as shown in Fig. 3b. The sampling rate of the signal is 100Hz and the amplitude is 0.52 rad (around 30 degree). LiDAR measures the angular velocity of the vehicle, which is converted to steering angle by applying the Ackermann steering geometry (Rajamani, 2012). The calculated steering angle is taken as the output data of the system identification. In addition, the velocity is set to 1m/s during the identification of the steering system. As can be seen in Fig. 5, the FIT value of P2Z2, P3Z3, P4Z4 and P5Z5 are almost the same and larger than other models, while a similar pattern is also found in the performance on MSE. However, P2Z2 has the lowest order among these four models, suggesting that P2Z2 is more suitable to describe the steering system. Therefore, P2Z2 is chosen to accomplish the experiments in the following sections. The estimated parameters for the best candidate model in each identification process are listed in table 2.

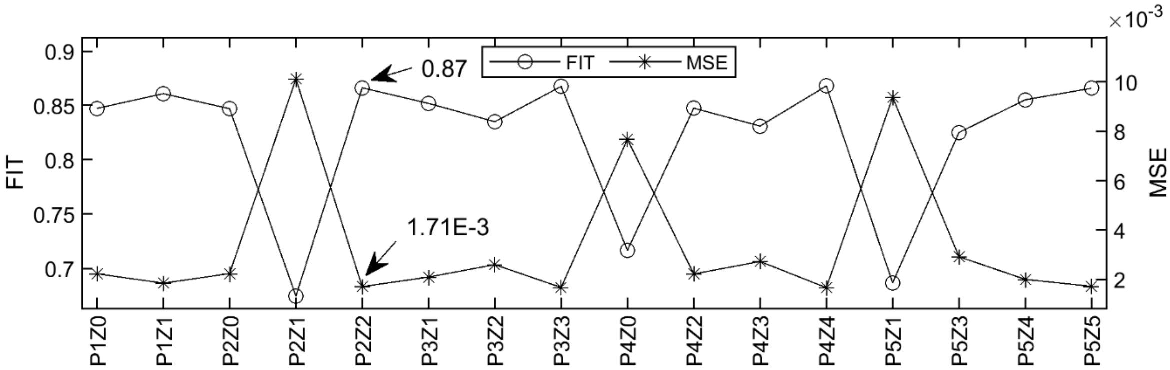

Figure 5. *Performance of Candidate Models in Identifying the Steering System*.

TABLE 2. *Estimated parameters for the best candidate model in identifying the powertrain and the steering system.*

Estimated parameters	a_0	a_1	a_2	b_0	b_1	b_2
P2Z2 for the powertrain	143.20	18.15	1	143.90	2.21	6.31e-02
P2Z2 for the steering system	1.70e-07	25.44	1	-0.49	23.15	0.47

5.2 Numerical Experiments

In this study, the positioning performance of VDM and VDM-SI is compared in two scenarios, as shown in Fig. 6. To concentrate on the difference between the two methods, sensors are only used to provide essential information to keep the AV moving on the designed track. *In addition, the ability of VDM and VDM-SI to accomplish the navigation task without sensors is also evaluated. In this case, VDM or VDM-SI is taken as the only source to provide positioning results to the localization module.*

(a) (b)

Figure 6. *Test Scenarios: (a) a 90-degree bend with radius of curvature equal to 20m; (b) a S-Curve with radius of curvature equal to 15m. The white dash line is the designed track.*

Performance along a 90-Degree Bend. In the first scenario, the autonomous vehicle is required to move along a 90-degree bend with radius of curvature equal to 20m at a constant speed of 15km/h. Sensors such as LiDAR is adopted by the localization module to produce reliable positioning results to keep the AV running along the bend. The VDM and VDM-SI are implemented in depend of the AV system, producing pose estimation only for comparison. In other words, the estimation produced by VDM or VDM-SI will not be fed into the AV. The absolute translation error (ATE) of VDM and VDM-SI along the 90-degree bend are calculated and listed in Table 3. The mean ATE of VDM-SI decreases by more than 70% compared to that of VDM, while a similar result is found in the max ATE and the rmse ATE, indicating that VDM-SI could effectively improve the localization performance.

TABLE 3. *The Positioning Performance of VDM and VDM-SI under Two Scenarios.*

Scenario	ATE(m)	VDM	VDM-SI	Improved by VDM-SI
90-degree bend	MAX	21.65	5.87	72.88%
	MEAN	8.27	2.44	70.44%
	RMSE	10.53	2.94	72.07%
S-Curve	MAX	8.35	1.30	84.37%
	MEAN	3.20	0.70	78.05%
	RMSE	4.03	0.80	80.26%

In order to examine the ability of VDM and VDM-SI in navigation tasks, sensors are designed to be unavailable to the AV while the VDM or VDM-SI serves as the only source to provide positioning results during AV's operation. Specifically, before entering the start point of the bend, the AV had well-functioning sensors to provide essential information to the localization module and the planning module. At the time the AV entered the bend, the AV was isolated from all sensors. However, LiDar can be used in a separate program to estimate the state of the AV, which would be regarded as the ground truth. Fig. 7a shows the translation error of the VDM and VDM-SI based navigation along the bend. As can be seen, the translation error of VDM increases faster than that of VDM-SI.

Performance along a S-Curve. In the second scenario, the AV is required to move along a S-Curve with radius of curvature equal to 15m at a constant speed of 15km/h. Similar to the experiment steps in the first scenario, ATE of VDM and VDM-SI based localization along the S-Curve are calculated, as shown in Table 3. VDM-SI has around 78% lower mean ATE than VDM during the S-Curve scenario, which is consistent with the result in the 90-degree bend experiment. In addition, the navigation performance solely based on VDM or VDM-SI is also evaluated, as shown in Fig 7b. The translation error of both approaches shows a steady increase forming a peak at around $Time = 2.7$s followed by a gradual decrease till the end. However, in both stages, the translation error of VDM-SI is smaller than that of VDM.

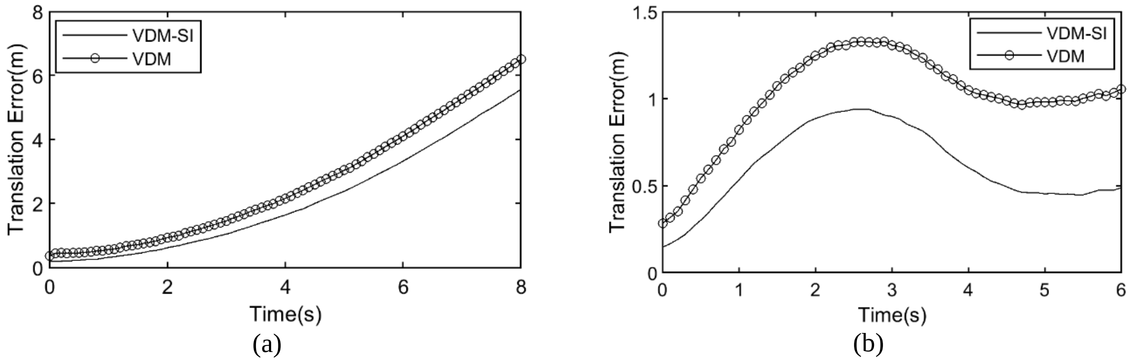

Figure 7. *The Translation Error of VDM and VDM-SI Based Navigation: (a) along the 90-degree bend; (b) along the S-Curve. Note that $Time = 0$s means that the vehicle just entered the start point of the bend of the S-Curve.*

6. CONCLUSION AND FUTURE WORKS

This study has investigated the integration of system identification and vehicle dynamic models for navigation in autonomous mobile robots. Taking the autonomous vehicles as the experimental platform, a system identification process based on transfer function models is executed to identify the system dynamics of plants when sensors function well. The identified system dynamics is then used to compensate the VDM to provide positioning result. The positioning results under two scenarios show that the proposed VDM-SI method significantly outperforms the conventional VDMs. Due to the loosely coupled property of the integration method, the proposed method could be applied in different VDMs to improve their performance in pose estimation. The proposed method can also be integrated into the mainstream sensor-fusion based navigation architecture, providing a more accurate pose estimation from the perspective of vehicle motion than conventional VDMs. This study attempts to build the relationship between system identification in the control field and pose estimation in the navigation field, suggesting a potential research direction to improve the navigation performance in AMRs by investigating the internal connection of the system.

Nevertheless, there are several limitations to this study that restrict the generalisation of its results. The system identification process is undertaken in an offline way, which cannot account for the property of the time-varying system. Further research should seek to establish an online-system identification to capture more accurate system dynamics before its integration with VDMs. Besides, in identifying the powertrain, the identified velocity response is simply transferred to acceleration by time derivative to accommodate the vehicle dynamic model. This is due to the fact that LiDAR is inappropriate for measuring the acceleration of the vehicle. For a real-world application, other sensors such as IMU should be introduced to directly measure the acceleration for identifying the powertrain. Furthermore, this research mianly focuses on improving the positioning performance of VDM by integrating system identification, while future research could consider the integration of VDM-SI and sensors (such as LiDAR and/or camera) to futher improve the positioning performance.

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