Tracked Vehicle Velocity Estimation by Disturbance Observer and Machine Learning, and its Application to Driving Force Control for Slippage Suppression

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Tracked vehicles generally involve slippage owing to the interaction between the road and track surfaces, which renders accurate motion control difficult. This paper proposes a velocity estimation method for a tracked vehicle with slippage, and its application to driving force control. In this method, the disturbance estimated by a disturbance observer was used as information related to slippage, and a neural network was constructed for velocity estimation. In addition, a driving force observer was designed using the estimated velocity. The driving control of the tracked vehicle to suppress slippage was achieved by using the feedback of the estimated driving force. The proposed method was evaluated experimentally through the velocity estimation performance and slippage suppression performance tests.

Keywords: tracked vehicle, velocity estimation, slippage, disturbance observer, machine learning, driving force control

1. Introduction

Tracked vehicles have various applications, ranging from rescue tasks in rough terrains in disaster sites to exploration of extraterrestrial surfaces. Since a tracked vehicle can secure the contact between the track and road surfaces, high driving performance is expected. However, during its movement, there is slippage due to changes in the distribution of the shear stress generated between the road and track surfaces. In general, as slippage is not considered in the control of a mobile robot with wheels, it is difficult to apply this control method to tracked vehicles. Therefore, it is important to develop methods for estimating states with slippage and study their applications in tracked vehicles.

Research in the field of terramechanics has led to developments in soil models to elucidate the mechanism of slippage. Owing to the constant changes in the soil model parameters depending on the road surface conditions, they should be continuously estimated. However, the computational cost of real-time control of tracked vehicles is of concern. Wills demonstrated an easy track-road handling method for the estimation of slip conditions using a pre-identified track-road contact friction model. An experimental model was reported in demonstrating the relationship between the driving current and slip velocity of the tracked vehicle. In addition, solely for turning motion, geometrical methods for obtaining the slip velocity from the momentary center of the tracked vehicles have been proposed. Two methods of describing the slip velocity can be derived from existing literature: (1) Slip velocity as a parameter that correlates with the frictional force between the track and road surfaces from the perspective of dynamics. This is based on the fact that the driving force of mobile mechanisms, including that of tracked vehicles, is related to the friction of the road surfaces. (2) Slip velocity as a parameter expressing the relationship between the track and vehicle translation velocities from the perspective of kinematics. In addition, we have considered controlling the tracked vehicle with slippage by estimating and controlling the driving force. For this, an observer technique can be applied to estimate the driving force from the vehicle velocity. However, to improve the reliability of the driving force control under slippage, it is also necessary to estimate the velocity from slippage. Therefore, we propose a method to estimate the vehicle velocity, including slippage.

This paper proposes a velocity estimation method that includes tracked vehicle slippage, based on which driving force control is developed. We have considered that the disturbance applied to the drive motor of the tracked vehicle contains slip information. This is estimated using a disturbance observer. In addition, we construct a neural network to estimate the vehicle translation velocity based on the information collected from the tracked vehicle. The neural network learning is achieved through an image processing system. An observer that estimates the driving force of a track using the estimated vehicle translation velocity is designed. Based on the driving force feedback, a driving control system that suppresses slippage is achieved. The velocity estimation performance of the tracked vehicle and the slip suppression performance by driving force control are experimentally demonstrated. The contributions of this paper are as follows: (1) The proposed method uses motor disturbance information...
and neural networks to estimate the velocity of a tracked vehicle, which, unlike a normal automobile, is almost always slippery and difficult to model owing to the complex surface conditions of the road and tracks. (2) The application of the estimated correct velocity, including slippage for estimating and controlling the driving force, is demonstrated; conventional driving force control uses velocity without slippage, based on the motor encoder.

The remainder of this paper is further organized as follows: Section 2 describes the tracked vehicle model and its operating principle. Section 3 describes the proposed method for estimating the vehicle translation velocity by a disturbance observer, applying machine learning. In Section 4, the driving force observer based on the estimated vehicle translation velocity is explained. In addition, we describe the driving force control architecture of the constructed tracked vehicle. Section 5 presents the experimental results of the velocity estimation and driving control. The conclusions and implications are provided in Section 6.

2. Tracked Vehicle Model and Its Operating Principle

2.1 Tracked Vehicle Model Fig. 1 shows the model of the tracked vehicle. Table 1 presents the model parameters, where the subscript \( i \) denotes the motor ID (r: right, l: left). The world and robot coordinates are defined as shown in Fig. 1. The center point and the traveling directions of the tracked vehicle are the origin and axes, respectively, of the robot coordinates. The position vector representing the position and posture of the tracked vehicle in the world coordinates is defined as follows:

\[
x = [x, y, \phi].
\]

2.2 Kinematics From Fig. 1(a), the relationship between the velocities in the world coordinates and robot coordinates is expressed by the following equations:

\[
\dot{x} \cos \phi + \dot{y} \sin \phi = v_x,
\]

\[
\dot{x} \sin \phi - \dot{y} \cos \phi = v_y.
\]

From (3), the nonholonomic constraint of the tracked vehicle is not satisfied owing to the slip. The slip angle of the tracked vehicle is obtained from the following equation:

\[
\phi' = \tan^{-1} \frac{\dot{y}}{\dot{x}}.
\]

The relationship between the velocities of the tracked vehicle (\( v_x, \phi \)) and track (\( v_i \)) is given by the following equations:

\[
v_x + \frac{W}{2} \dot{\phi} = v_i = (1 - \lambda_i)R \dot{\theta}_i,
\]

\[
v_x - \frac{W}{2} \dot{\phi} = v_i = (1 - \lambda_i)R \dot{\theta}_i.
\]

where \( \lambda_i \) represents the slip ratio defined as follows:

\[
\lambda_i = \begin{cases} 
R \theta_i - v_x & (R \theta_i \geq v_x) \\
R \theta_i - v_x & (R \theta_i < v_x).
\end{cases}
\]

2.3 Dynamics From the equation of motion, the relationship between the velocity of the tracked vehicle and frictional force (driving force) between the track and road surfaces is expressed as follows:

\[
m \ddot{v}_x = F_{x,i}^{dr} + F_{x,i}^{dr},
\]

\[
m \ddot{v}_y = F_{y,i}^{dr}.
\]

\[
J \ddot{\phi} = \frac{W}{2} (F_{x,i}^{dr} - F_{x,i}^{dr}),
\]

\[
F_{x,i}^{dr} = N \mu(\dot{\lambda}_i),
\]

where \( m \) is the mass of the tracked vehicle, \( J \) is the moment of inertia of the tracked vehicle, and \( \mu(\lambda_i) \) is the coefficient of dynamic friction between the track and road surfaces. From (11), the driving force depends on the slip ratio.

From Fig. 1(b), the dynamics between the track and the road surfaces are expressed as follows:

\[
J_m \ddot{\theta}_i = R (F_{x,i}^{dr} - F_{x,i}^{dr}),
\]

where \( J_m \) denotes the motor shaft conversion moment of inertia. From (12), the movement of the tracked vehicle from the driving force, and its application to the motor as a disturbance, are observed to be simultaneous.

3. Tracked Vehicle Velocity Estimation Method

3.1 Disturbance Observer The disturbance observer
Tracked Vehicle Velocity Estimation and Driving Force Control (Hiroyuki Kuwahara et al.)

(DOB)\(^{13}\) used in this study is shown in Fig. 2. Here, \(K_r\), \(I\), \(\tau\), and \(g_{DOB}\) represent the torque constant of the motor, current, torque, and cutoff frequency of the disturbance observer, respectively. The hat symbol (‘\(\hat{\cdot}\)’) indicates an estimated value. The superscript characters \(ref\), \(dis\), and \(res\) denote the reference value, disturbance, and response value, respectively. The subscript \(i\) indicates the nominal value. When the estimated disturbance \(\hat{\tau}_{dis}\) by the disturbance observer is fed to the control system, the dynamics of the motor is given as follows:

\[
\hat{\theta}_{i}^{res} = \frac{1}{J_{ms}} \left( K_m \theta_i^{ref} - \frac{s}{s + g_{DOB}} \hat{\tau}_{dis} \right) \quad \ldots (13)
\]

From (13), for compensation through the disturbance observer, the disturbance applied to the motor is considered as equivalent to passing through the high-pass filter. Therefore, the disturbance below the cutoff frequency \(g_{DOB}\) can be removed to make the control system robust.

The disturbance to the motor is represented as follows:

\[
\tau_{i}^{dis} = \tau_{i}^{ext} + \tau_{i}^{fr} + \tau_{i}^{if} + \tau_{i}^{tr}, \quad \ldots (14)
\]

where \(\tau_{i}^{ext}\), \(\tau_{i}^{fr}\), \(\tau_{i}^{if}\), and \(\tau_{i}^{tr}\) represent the external force on the motor, the inertial fluctuation torque, the torque ripple, and the friction force, respectively. The external force \(\tau_{i}^{ext}\) to the motor in (14) includes the external force obtained by converting the driving force \(F_{d}^{dr}\) into torque. From (12), the driving force depends on the slip ratio. Thus, the estimated disturbance \(\hat{\tau}_{i}^{dis}\) can be considered to contain the slip information. Therefore, in addition to applying the disturbance observer to the robust control of the motor, we have also used it in the velocity estimation method described later.

### 3.2 Velocity Estimation by Machine Learning

As described in Section 2.2, the tracked vehicle slips in the translational and turning directions. However, when measuring the turning velocity with the gyro sensor attached to the tracked vehicle, the velocity owing to the slippage in the turning direction is included in the measured velocity. Therefore, in this paper, we consider methods for estimating the translational velocity of the tracked vehicle, including the slippage.

Conventional velocity estimation methods for mobile robots can be classified into the following four types\(^{12}\):

- Estimation based on kinematics, such as velocity conversion from motor angular velocity to translational velocity.
- Estimation based on dynamics, such as the Kalman filter\(^{13}\).
- Estimation using a designed observer, such as the velocity estimation observer\(^{14}\).


All of these methods, except that based on learning from artificial neural network, require a model that additionally includes slippage. However, in the estimation method by learning, nonlinear information can be expressed by the neural network, even in the absence of complex models. Therefore, we examine the structure of the neural network for the velocity estimation of the tracked vehicle, including nonlinear slip.

Considering (5) and (6), the translational velocity \(v_t\) of the tracked vehicle can be expressed by the function \(f_1\) of the angular velocity of the motor, given by:

\[
v_t = \frac{R}{2} \left( (1 - \lambda_r) \dot{\theta}_r + (1 - \lambda_l) \dot{\theta}_l \right) \equiv f_1(\dot{\theta}_r, \dot{\theta}_l), \ldots \quad (15)
\]

From (8), the translational acceleration \(\ddot{v}_t\) can be expressed by the function \(f_2\) of the estimated disturbance to the motor, given by:

\[
\ddot{v}_t = \frac{F_{s,r} + F_{s,l}}{m} \equiv f_2(\hat{\tau}_{dis}, \hat{\tau}_{dis}^{r}), \ldots \quad (16)
\]

In general, the translational acceleration \(\ddot{v}_t\) is measured by an accelerometer, from which the translational velocity is obtained by integration over time. However, in this approach, the effects of drift and noise appear in the calculated velocity. To improve this issue, in the proposed approach, we built a neural network with the estimated translational velocity \(\hat{v}_t\) as the output, according to the measured motor velocity \((\hat{\theta}_{i}^{res}, \hat{\theta}_{i}^{res})\), estimated motor disturbance \((\hat{\tau}_{dis}, \hat{\tau}_{dis}^{r})\), and translational acceleration \((\ddot{v}_{i}^{res})\) as the inputs, as shown in Fig. 3. This neural network is defined as a translational velocity estimation neural network (TVNN). The TVNN generates a regression function through machine learning to determine the translation velocity from the information of the tracked vehicle.

### 4. Driving Force Control based on the Estimated Vehicle Translation Velocity

#### 4.1 Driving Force Control based on the Estimated Vehicle Translation Velocity

Based on the estimated translational velocity \(\hat{\theta}_t\), a driving force observer (DFOB) is designed to observe the driving force.

By substituting the estimated translational velocity and the turning velocity \(\hat{\theta}_{i}^{res}\) measured by a gyro sensor into the inverse kinematics shown in (5) and (6), the estimated track velocity \(\hat{\theta}_t\) is obtained as follows:

\[
\hat{\theta}_t = \begin{cases} 
\dot{\theta}_r + \frac{W}{2} \hat{\theta}_{i}^{res} (i = r) \quad \ldots \quad (17) \\
\dot{\theta}_l - \frac{W}{2} \hat{\theta}_{i}^{res} (i = l).
\end{cases}
\]

The driving force is estimated based on the estimated track
velocity \( \hat{v}_i \) and the dynamics of the track, as shown in (12). In (12), \( F_{\text{act}}^{\text{ref}} \) is the force generated by the motor torque response. However, in (13), when the cutoff frequency of the disturbance observer is set sufficiently high, the torque response approaches the torque reference \( \tau_i^{\text{ref}} \). Therefore, we use the torque reference to calculate \( F_{\text{act}}^{\text{ref}} \). Fig. 4 shows the driving force observer using the estimated track velocity. The track acceleration is obtained by differentiating the estimated track velocity. However, high-frequency noise is generated when the velocity signal is differentiated. Therefore, a low-pass filter is used to reduce high-frequency noise. The driving force estimated thus, is derived as follows:

\[
\hat{F}_{ds,i} = \frac{g_{\text{DFOB}}}{s + g_{\text{DFOB}}} \left( F_{\text{act}}^{\text{ref}} - sJ_{\text{mn}} \frac{\hat{v}_i}{R^2} \right), \quad \cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdot (18)
\]

where \( g_{\text{DFOB}} \) represents the cutoff frequency of the driving force observer. The driving force can be controlled through the feedback of the estimated driving force.

4.2 Control Design  Fig. 5 shows the control system that suppresses the slippage of the tracked vehicle by controlling the estimated driving force. The proposed control system consists of two different closed-loop controls: an outer velocity loop and an inner driving force control. These controllers are set in a cascade, where the output of the velocity controller manipulates the set-point of the driving force controller. In the velocity control loop, the driving force reference \( F_{\text{act}}^{\text{ref}} \) for each track is determined by the velocity reference \( v_i^{\text{ref}} \) and the estimated track velocity \( \hat{v}_i \) as follows:

\[
F_{\text{act}}^{\text{ref}} = C_v(s)(v_i^{\text{ref}} - \hat{v}_i), \quad \cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdot (19)
\]

where \( C_v(s) \) represents a velocity controller that is physically equivalent to impedance.

In the driving force control loop, the estimated driving force is controlled to follow its reference, \( F_{\text{act}}^{\text{ref}} \). The motor torque reference is calculated as:

\[
\tau_i^{\text{ref}} = C_f(s)(F_{\text{act}}^{\text{ref}} - \hat{F}_{ds,i}), \quad \cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdot (20)
\]

where \( C_f(s) \) represents the force controller. In the proposed control system, the driving force required for the track movement is controlled to ensure that the intended track velocity is achieved regardless of the slip conditions.

5. Experiments

5.1 Experimental Conditions  Fig. 6 shows the experimental setup, and Table 2 shows the specifications of the experimental device. The tracked vehicle used in the experiment was driven by two direct-current (DC) motors with encoders. In addition, it was equipped with an inertial measurement unit (IMU) to measure the acceleration and angular velocity. The Kalman filter was applied to the measured acceleration and angular velocity to estimate the attitude angle. An augmented reality (AR) marker \(^{(15)}\) was installed on the surface of the tracked vehicle, and the positional information from the tracked vehicle was detected by processing the images captured by a camera.

5.2 Evaluation of Velocity Estimation Performance  The angular velocity of the motor was controlled for the TVNN learning. The angular velocity command provided for the TVNN learning is shown in Fig. 7. The parameters of the proportional-integral (PI) controller and disturbance observer, shown in Table 3, were used to control the motor angular velocity.

The information from the tracked vehicle was used as the input, while the translation velocity in the robot coordinates, calculated from the position detected by image processing, was used as the teacher data. The TVNN consisted of a two-layer feedforward neural network. The hyperbolic tangent sigmoid and linearized transfer functions were used as the
Tracked Vehicle Velocity Estimation and Driving Force Control (Hiroaki Kuwahara et al.)

### Table 2. Specifications of experimental devices

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Values</th>
</tr>
</thead>
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<tr>
<td>Mass of tracked vehicle $m$</td>
<td>5.3 kg</td>
</tr>
<tr>
<td>Thread of tracked vehicle $W$</td>
<td>0.24 m</td>
</tr>
<tr>
<td>Motor shaft conversion moment of inertia $J_m$</td>
<td>3.1 E-06 kgm$^2$</td>
</tr>
<tr>
<td>Radius of sprocket $R$</td>
<td>0.05 m</td>
</tr>
<tr>
<td>Torque constant of motor $K_t$</td>
<td>0.0134 Nm/A</td>
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<tr>
<td>Motor encoder resolution (quadruple)</td>
<td>3072 PPR</td>
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<tr>
<td>Sampling time</td>
<td>3 ms</td>
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<tr>
<td>Camera frame rate</td>
<td>30 fps</td>
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</table>

### Table 3. Control parameters in learning experiment

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Values</th>
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<tbody>
<tr>
<td>Motor angular velocity control P-gain</td>
<td>500</td>
</tr>
<tr>
<td>Motor angular velocity control I-gain</td>
<td>10</td>
</tr>
<tr>
<td>Cutoff frequency of disturbance observer $f_{DOB}$</td>
<td>188.4 rad/s</td>
</tr>
</tbody>
</table>

### Table 4. Types of sensor configurations and estimation method combinations

<table>
<thead>
<tr>
<th>Velocity</th>
<th>Sensor configurations</th>
<th>Estimation method</th>
</tr>
</thead>
<tbody>
<tr>
<td>$v^{\text{AVE}}$</td>
<td>Axle motor encoders</td>
<td>Average track velocity</td>
</tr>
<tr>
<td>$v^{\text{KF}}$</td>
<td>Axle motor encoders and accelerometer</td>
<td>Discrete Kalman filter</td>
</tr>
<tr>
<td>$v^{\text{TVNN}}$</td>
<td>Axle motor encoders and accelerometer</td>
<td>TVNN</td>
</tr>
</tbody>
</table>

### Table 5. Summary of velocity estimation errors

<table>
<thead>
<tr>
<th>Velocity</th>
<th>Error (rad/s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$v^{\text{AVE}}$</td>
<td>0.12</td>
</tr>
<tr>
<td>$v^{\text{KF}}$</td>
<td>0.08</td>
</tr>
<tr>
<td>$v^{\text{TVNN}}$</td>
<td>0.05</td>
</tr>
</tbody>
</table>

Weighting functions of the hidden and output layers, respectively. The number of neurons in the hidden layer of the TVNN was determined to be 15, according to prior trials. The TVNN was trained by the Bayesian regularization error backpropagation method.

Fig. 8 shows the learning results, according to which the correlation coefficient ($R = 0.96588$) between the actual output and the prediction by the learned TVNN was high, and thus, the velocity was estimated with high accuracy.

To evaluate the performance of the proposed TVNN, a sinusoidal input with an amplitude of 6 rad/s and a period of 4 s was given as a motor angular velocity command. In this experiment, the translational velocity, measured by image processing ($v^{\text{IMAGE}}$), was compared with the estimated velocities ($v^{\text{AVE}}$, $v^{\text{KF}}$, and $v^{\text{TVNN}}$), using the three types of sensor configurations and estimation method combinations, shown in Table 4. In the application of the discrete Kalman filter (16) in Table 4, the required measurement noise variance and process noise variance matrices were determined according to prior experiments.

Figs. 9(a) and (b) show the measured and estimated velocities, along with the errors between each of their values, respectively. Table 5 summarizes the errors of each velocity estimation when the measured velocity was taken as the true
value. Fig. 9 shows that the amplitude of the velocity obtained from the axle motor angular velocity was larger than that of the measured velocity, especially about the occurrence of the maximum and minimum measured velocities. This indicates that the translational velocity was smaller than the track velocity due to slippage. By integrating the axle velocity and acceleration information with the discrete Kalman filter, the velocity estimation performance was improved. However, the errors remained large in the vicinity of the maximum and minimum velocities. In other words, the effect of slippage was still observed as errors. However, the translational velocity estimated by the TVNN almost followed the measured velocity. The results summarized in Table 5 indicate that the TVNN exhibited the highest accuracy in velocity estimation among all the methods in this study. The table further shows that the velocity estimation performance was improved by the TVNN. These results suggest that the TVNN could include the slippage velocity component in its estimate.

### 5.3 Evaluation of Slip Suppression Performance by Driving Force Control
The regression function generated in the learning experiment was incorporated into the tracked vehicle program using C language to evaluate the slip suppression performance by driving force control. The experimental conditions of the performance evaluation are listed in Table 6. In cases 1 and 2, the track velocity, obtained by multiplying the angular velocity from the track axis encoder and the radius of the sprocket used in the tracked vehicle \((R\theta_{\text{track}})\), was used as input to the DFOB \((\delta_i)\). The velocity reference value \(v_{\text{ref}}\) was obtained as a sine wave of amplitude and period 0.3 m/s and 6.0 s, respectively. Table 7 summarizes the control parameters in this experiment.

Figs. 10–13 show the experimental results of each case. In each figure, panels (a) and (b) show the estimated track velocity and slip ratio, respectively. Fig. 10(a) and Fig. 12(a) show a deteriorating velocity followability approximately about the inflection point of the velocity reference, in the absence of the driving force control. This is because the absolute value of the driving force reference to the track was maximized at the inflection point of the velocity reference; however, it was considered that the followability deteriorated owing to slippage. Conversely, Fig. 11(a) and Fig. 13(a) show that the velocity tracking was improved, especially in case 4, where the velocity followed the inflection point. This indicates that the velocity followability was improved by driving force control. Further, the comparisons of Fig. 10(b) and Fig. 11(b), or Fig. 12(b) and Fig. 13(b), show that the slip ratio changed momentarily in the absence of the driving force control, while the slip ratio was generally low in its presence. This suggests that slippage was suppressed by the driving force control. In addition, the comparison of Fig. 11(b) and Fig. 13(b) shows a sudden change in the slip ratio in case 2, while it remained low across the board under case 4. This demonstrated the slip suppression effect from using the estimated velocity of the vehicle body for driving force control.

The effectiveness of the proposed control system for a tracked vehicle was thus confirmed. In this study, we evaluated in a flat environment for the convenience of image processing; however, it could also be applied to velocity estimation in a known environment by training a neural network that includes environmental information.

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### Table 5. Performance evaluation results of translational velocity estimation methods

<table>
<thead>
<tr>
<th>Case no.</th>
<th>Velocity estimation method</th>
<th>Driving force feedback</th>
</tr>
</thead>
<tbody>
<tr>
<td>case 1</td>
<td>Calculated by motor encoder</td>
<td>Disabled</td>
</tr>
<tr>
<td>case 2</td>
<td>Calculated by motor encoder</td>
<td>Enabled</td>
</tr>
<tr>
<td>case 3</td>
<td>Estimated by the TVNN and inverse kinematics</td>
<td>Disabled</td>
</tr>
<tr>
<td>case 4</td>
<td>Estimated by the TVNN and inverse kinematics</td>
<td>Enabled</td>
</tr>
</tbody>
</table>

### Table 6. Experimental conditions in slip suppression

<table>
<thead>
<tr>
<th>Case no.</th>
<th>Velocity estimation method</th>
<th>Driving force feedback</th>
</tr>
</thead>
<tbody>
<tr>
<td>case 1</td>
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<tr>
<td>case 2</td>
<td>Calculated by motor encoder</td>
<td>Enabled</td>
</tr>
<tr>
<td>case 3</td>
<td>Estimated by the TVNN and inverse kinematics</td>
<td>Disabled</td>
</tr>
<tr>
<td>case 4</td>
<td>Estimated by the TVNN and inverse kinematics</td>
<td>Enabled</td>
</tr>
</tbody>
</table>

### Table 7. Control parameters in slip suppression experiment

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Track velocity control P-gain</td>
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</tr>
<tr>
<td>Driving force control P-gain</td>
<td>0.2</td>
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<tr>
<td>Driving force control I-gain</td>
<td>500</td>
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<tr>
<td>Cutoff frequency of disturbance observer</td>
<td>188.4 rad/s</td>
</tr>
<tr>
<td>Cutoff frequency of driving force observer</td>
<td>188.4 rad/s</td>
</tr>
</tbody>
</table>

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![Fig. 10. Experimental results of case 1](image1)

![Fig. 11. Experimental results of case 2](image2)

![Fig. 12. Experimental results of case 3](image3)

![Fig. 13. Experimental results of case 4](image4)
6. Conclusion

In this paper, we proposed a velocity estimation method for a tracked vehicle using a disturbance observer and machine learning. In addition, a driving force control system based on the estimated velocity was proposed. First, we constructed a neural network that estimated the translational velocity using the estimated disturbance of the motor to include slip information. Thereafter, we designed an observer to estimate the driving force based on the estimated velocity. Finally, we constructed a driving control system to suppress slippage by connecting it to a velocity control system. The validity of the proposed velocity estimation method and driving force control was verified through experimental evaluations of the velocity estimation performance and slippage suppression performance.

The proposed velocity estimation and driving force control method can be applied to mobile robots in general, where the occurrence of slippage cannot be disregarded. The driving force control proposed in this paper suppresses slippage; however, it may saturate based on the provided driving force reference. In such a case, measures such as adjusting the driving force reference become necessary. In the future, we aim to study countermeasures such as anti-windup in the case of extreme slippage.

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References


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