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End-to-End Current Consumption Estimation for a Driving System of a Mobile Robot Considering Geology

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***Abstract*—Mobile robots are often tasked with environmental surveys and disaster response operations. Accurately estimating the energy consumption of these robots during such tasks is essential. Among the various components, the drive system consumes the most energy and exhibits the greatest fluctuations. Since these energy fluctuations stem from variations in current consumption, it is crucial to estimate the drive system's current consumption with high accuracy. However, existing research faces challenges in accurately estimating current consumption, particularly when the ground geology changes or when internal states cannot be measured. Moreover, there is no clearly defined methodology for estimating the current consumption of a mobile robot's drive system under unknown geological conditions or internal states. To address this gap, the present study aims to develop an end-to-end method for estimating the current consumption of a mobile robot's drive system, taking ground geology into consideration. To achieve this, we propose a novel approach for collecting interaction data and generating a current consumption model. For data collection, we introduce a method that effectively captures the internal and external factors influencing the drive system's current consumption, as well as their interactions. This is accomplished by treating the physical phenomena resulting from the interaction between the driving mechanism and the ground as vibrations. Additionally, we propose a method for generating a current consumption model using a neural network, accounting for measurement errors, outliers, noise, and global current fluctuations. The effectiveness of the proposed method is demonstrated through experiments conducted on three different ground types using a skid-steering mobile robot.**

***Keywords*—Current consumption estimation; mobile robot; neural network; snow environment**

I. INTRODUCTION

Mobile robots are increasingly being deployed to perform diverse missions, including social infrastructure maintenance, i-Construction, agriculture, forestry, fisheries, nursing care and welfare, disaster response, and investigations in extreme environments [1]–[4]. Among these missions, environmental surveys and disaster responses require wheeled or crawler-type mobile robots to perform tasks in terms of robustness, maneuverability, and drivability [5]–[8]. Long-term, long-distance, and continuous operation of mobile robots is essential for task execution in environmental surveys and disaster responses. Therefore, estimating the energy consumption is necessary to determine the amount of energy that the mobile robot will consume for efficient task execution. Based on the social background described above, various studies have been conducted on estimating the energy consumption of mobile robots [9], [10]. In particular, optimizations based on energy consumption have been conducted in research fields such as path planning, motion planning, and task management for mobile robots. Because the accuracy of energy consumption estimation significantly affects the results in these research fields, methodologies for energy consumption estimation have been discussed, and methods such as mathematical model approaches and data-driven approaches have been proposed.

This section reviews previous studies on energy consumption estimation. First, we discuss studies that employed mathematical modeling approaches, assuming a solid, non-deformable ground and considering its geometric shape. Ganganath et al. proposed a path planning method that considers the energy consumption of mobile robots in uneven terrain environments where flat and sloped terrains coexist [11], [12]. In Ganganath et al.'s method, the terrain (ground elevation and slope) traversed by a mobile robot is used to plan a path that optimizes the energy consumption and distance between two points. The path is determined by integrating the energy and distance costs, thereby calculating an optimal solution that satisfies both the energy and distance constraints. In this process, a mathematical model that considers the terrain was employed to estimate the energy consumption of the mobile robot. However, the method of Ganganath et al. is limited because it does not consider the characteristics of a mobile robot. Mobile robots such as differential two-wheeled, steering-type, skid-steer-type, and crawler-type mobile robots have different energy consumption levels and variability characteristics depending on their mobility type; therefore, it is necessary to consider the mobility type.

In response to the work of Ganganath et al., Mei et al. proposed a motion planning method that considers energy efficiency for omnidirectional mobile robots operating on flat terrain [13]. Mei et al.'s method plans energy-efficient paths and speeds for task execution using a three-wheeled omnidirectional mobile robot. In this approach, a mathematical model that considers the kinematic characteristics of omnidirectional mobile robots, such as their geometric shapes, is used to estimate the energy consumption. Additionally, Zhang et al. proposed a path planning method that takes energy efficiency into account for steering-type mobile robots operating on flat terrain [14]. Zhang et al.'s method plans energy-efficient paths for task execution using a four-wheeled steering-type mobile robot. In this case, a mathematical modeling approach considering the geometric shape of the steering-type mobile robot and other kinematic characteristics was used to estimate the energy consumption. Furthermore, Jaramillo-Morales et al. proposed an energy consumption estimation model for a differential two-wheeled mobile robot, taking into account payload and acceleration on flat terrain [15]. Their method estimates the energy consumption by identifying dynamically changing motor parameters from real data based on a mathematical model. The studies by Mei et al., Zhang et al., and Jaramillo-Morales et al. considered terrain and mobile robot characteristics, but did not consider ground geology. The energy consumption of mobile robots traveling on the ground is affected by terrain features, such as elevation and slope, as well as by the geology of the ground in contact with the mobile robot. Therefore, it is necessary to consider the geology. Geology affects energy consumption through a combination of materials such as soil, concrete, grass, and snow, as well as dryness and moisture. For example, in mobile robot navigation, energy consumption and its variability can differ significantly between dry concrete surfaces and muddy, moisture-laden ground. In the next section, we discuss previous studies that estimated energy consumption by considering geology using a mathematical modeling approach.

In a study considering the geology of the ground on which mobile robots operate, Saad et al. first proposed a path planning method that takes into account both terrain and ground surface to reduce the energy consumption of mobile robots on uneven terrains [16], [17]. Saad et al. used a mathematical model approach based on terramechanics (the mutual mechanical relationship between mobile robots and soil) to estimate wheel sinking effects, terrain slopes, and soil deformation characteristics to estimate energy consumption. Terrain-related parameters in the mathematical model were obtained from digital elevation models (DEMs), while surface-related parameters were derived from the Unified Soil Classification System (USCS). The method was evaluated through simulation. Second, Mohamadi et al. proposed a method for estimating the energy consumption of a differential two-wheeled mobile robot with an unknown payload on flat terrain [18]. In their approach, model parameters were identified through both offline and online estimation using actual motion data, enabling accurate estimation of the robot's energy consumption. Third, Morales et al. proposed a method for estimating the energy consumption of a crawler-type mobile robot operating on flat terrain [19]. Their method analyzed the effects of slippage and friction between a crawler-type mobile robot and the ground. They proposed a mathematical model that considered kinematics and kinetic friction. A crawler-type mobile robot changes direction depending on the speed difference between the left and right crawlers; therefore, slippage occurs while moving, which affects the energy consumption. Morales et al.'s method estimated the energy consumption based on parameters such as the robot's velocity, acceleration, turning radius, and kinetic friction coefficient, and its effectiveness was verified through experiments with an actual machine. Parameters such as the kinetic friction coefficient included in the mathematical model were derived from experimental tests. Fourth, Ínal et al. proposed a path-planning algorithm that considered dynamics to reduce the energy consumption of a crawler-type mobile robot on rough terrain [20]. Many conventional path planning algorithms focus on optimizing distance and time, Ínal et al. proposed an energy-efficient path-planning method that improves the A* algorithm. They evaluated their proposed method using an actual off-road terrain model. The dynamics include parameters such as rolling resistance and acceleration force, and consider the terrain and ground surface. In this study, the dynamic parameters were obtained from two experiments. The parameters included in the mathematical model were derived from experiments conducted using an actual vehicle.

Fifth, Dogru et al. proposed a mathematical model-based energy-consumption estimation method that considers friction using a skid-steering mobile robot [21]. In their method, Dogru et al. proposed a mathematical model that considers rolling friction when the wheels rotate and skid friction when the robot skids while turning. Experiments were conducted using an actual skid-steering mobile robot. Energy consumption was measured under varying speeds, turning conditions, and centers of mass, and the results were compared with the predicted values from the mathematical model. The model matched the actual measured values with high accuracy, demonstrating its usefulness in estimating energy consumption. Mathematical model-based studies before Dogru et al. had issues such as being limited to linear movements, ignoring changes in friction due to speed and curvature radius, and not considering slopes. Dogru et al. proposed a general-purpose energy consumption model that covered the entire operating range of skid-steering mobile robots and quantified the effect of friction. Sixth, Otsu et al. proposed a method for estimating the energy consumption of an Ackerman-type mobile robot on uneven terrain [22]. Otsu et al. used the actual driving data of a mobile robot. The energy consumption of the Ackermann-type mobile robot was estimated using a mathematical model based on geological classifications and topographical information. In this case, features were extracted using the mobile robot's acceleration data as training data, and the geological conditions were classified into three types: dense sand, fine gravel, and coarse gravel, from the camera images using a Support Vector Machine (SVM). Saad et al., Mohamadi et al., Morales et al., Ínal et al., Dogru et al., and Otsu et al. were based on mathematical models. The parameters included in the mathematical model were identified from actual driving data using numerical analysis, optimization, and machine learning, and the power consumption was estimated. However, the geology combines soil, concrete, grass, and snowy conditions, such as dryness and moisture. There are infinite combinations of materials, conditions, and them, so estimating energy consumption based on a mathematical model for various geologies has a limit.

In contrast to the studies described above that estimate energy consumption using mathematical models, Sakayori et al. proposed a path planning method that considers energy efficiency for Ackermann-type mobile robots operating in rough terrain environments [23]. Sakayori et al.'s method evaluated the energy consumption and power generation and planned a path considering the mobile robot's dynamics and terrain mechanics. In this case, an energy consumption model was constructed using a neural network. The inputs were speed, slope angle, and azimuth angle, and the outputs were energy consumption and longitudinal slip. Góra et al. proposed a method to estimate the energy consumption of a differential two-wheel mobile robot and a skid-steering mobile robot on indoor rigid ground [24]. Góra et al. used a mobile robot's actual driving data and estimated its energy consumption using a neural network. In this case, parameters such as the actual velocity of the mobile robot, actual angular velocity, weight, and friction were inputted into the neural network, and the consumed energy was the output. Friction parameters were identified using a mathematical model based on the travel data of a mobile robot. However, although Sakayori et al.'s method takes into account dynamics and terramechanics in path planning, geology is not taken into account in the energy consumption model, and the accuracy of the estimation of energy consumption decreases when the geology is unknown or changes. Additionally, Góra et al.'s method targets rigid indoor ground, and the geology is expressed as friction, which is calculated using a mathematical model based on actual travel data. Therefore, the accuracy of energy consumption estimation is problematic when the geology causes the wheels to sink, when the terrain is difficult to model mathematically, or when the parameters included in the mathematical model are unknown.

In response to the previous research described thus far, the author proposed a method for derive the current consumption using vibration data [25]. However, this method uses instantaneous vibration data. Therefore, although it is possible to calculate current consumption in real time, this method is not suitable for estimating current consumption. To summarize the previous studies described thus far, there is no transparent methodology for estimating the energy consumption of a mobile robot using an end-to-end data-driven approach, considering the mobile robot's characteristics, the geology of the ground on which it runs, and changes in the geology. Additionally, the energy consumption of a mobile robot's drive system is the most significant and variable component of its overall energy consumption. Generally, a rated voltage is applied to the drive system, and energy fluctuations occur owing to changes in current consumption. Therefore, it is important to estimate the current consumption of the drive system accurately when estimating the energy consumption of a mobile robot. The purpose of this study was to develop an end-to-end estimation method for the current consumption of a mobile robot drive system that considers geology.

The remainder of this paper is organized as follows: Section II describes the interaction data collection and current consumption model generation methods proposed in this study for estimating the current consumption of a mobile robot's drive system. Section III describes the effectiveness of the proposed method in changing environments through experiments using a real machine in a real environment. Experimental results and a discussion are also presented. Finally, Section IV presents conclusions and future work.

II. Proposed Method

A. Outline

This study targets the operation of a mobile robot in the flow shown in Fig. 1. It is assumed that the ground topography is known and the ground geology is unknown. First, the robot was given a task, such as conducting an environmental survey or moving to a destination. Next, the mobile robot autonomously adjusts its velocity and angular velocity on the task-performing ground, and interaction data, such as vibrations and current consumption, are collected. Next, the interaction data are trained to generate the current consumption model. Next, the path planning and time-series behaviors of the commanded velocity and angular velocity of the mobile robot were planned. Next, the required energy was estimated using the current consumption model. Next, the mobile robot begins the task and moves. When a task is assumed to be performed over a long period and distance, the internal and external factors are expected to change. Therefore, if the error exceeds a threshold value, the consumption current model is updated by comparing the actual current consumption with the estimated value. To update the model, the mobile robot adjusts its velocity and angular velocity in the ground area where the error surpasses the threshold, and interaction data, such as vibration and current consumption, are collected again. The current consumption model was updated by retraining using the collected real data. Subsequently, the errors are compared, and if they exceed a threshold, the data are re-collected and re-trained repeatedly to complete the task.

Previous studies have discussed task, path, and action planning (Fig. 1). In addition, previous studies have discussed energy consumption estimations that consider topography, such as slopes. In this study, we focus on geological changes on flat terrain as a fundamental step toward estimating the current consumption of end-to-end mobile robot drive systems, considering geological features. We propose a novel method for collecting interaction data and generating a current consumption model, as highlighted in the red-boxed section of the flow in Fig. 1. Prior to the task, we explain the validity of setting up a problem in which the topography is known and the geology is unknown. The topography (geometry) of the ground on which the mobile robot moves can be measured with high precision in advance using noncontact sensors, such as satellites and UAVs. Although real-time measurements may be difficult with topography data measured by satellites and UAVs, the topography is unlikely to change shape over time. In contrast, satellite and UAVs' non-contact sensors can only measure the surface of the ground on which the mobile robot is moving. Therefore, the measurement accuracy is low when the geological conditions differ between the surface and the interior of the ground. Additionally, because the conditions of geological materials change with rain and snow, it is highly probable that the conditions of geological materials change over time. For these reasons, this study sets up a problem in which the topography on which the mobile robot moves is known in advance, and the geology is unknown but will become known through actual driving.

B. Collecting Methods of the Interaction Data

When controlling a mobile robot, velocity and angular velocity are generally input as command values. Based on these

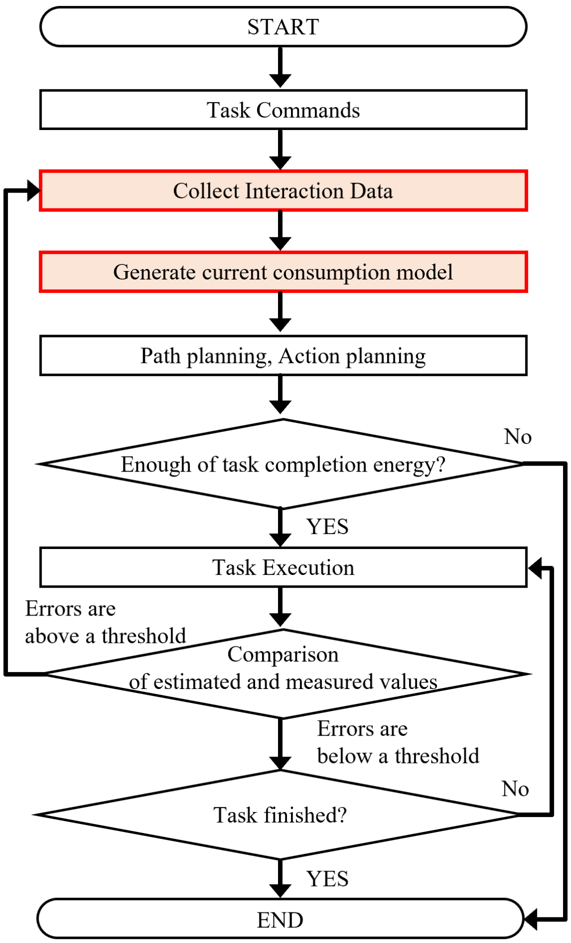


Fig. 1. Task execution of mobile robots and the position of this study.

command values, the target angular velocity of each actuator is calculated using kinematics. Based on the target angular velocity of the actuator, the wheels and crawlers (hereinafter collectively referred to as the driving mechanism) are operated by controlling the actuators to move the mobile robot. As explained in Section I, most previous studies represented the interaction in a mathematical model and estimated the energy consumption by identifying limited parameters such as geology and friction in the mathematical model. However, using a mathematical model-based approach to estimate energy consumption considering various geological conditions, geological changes, and surface and interior conditions is challenging. In addition, noncontact sensors that can be mounted on mobile robots, such as RGB cameras and LiDAR, are unsuitable for geological estimation because they can only measure the ground surface and not the internal conditions. To estimate the geology, considering both the surface and internal conditions of the ground, specialized sensors such as spectrum cameras and electromagnetic radar, not typically installed on mobile robots, are required. However, this is unrealistic in terms of sensor cost (sensor price, measurement time, data volume, and data processing time). In addition, the accurate identification of geological features and their parameters is not essential for energy consumption estimation.

For the reasons explained above, this study proposes a novel method to estimate the end-to-end current consumption of the drive system from the physical phenomena caused by interaction. The interaction between the ground and driving mechanism caused by the movement of a mobile robot depends on the geology of the ground. For example, the interaction differs between a flat surface, like a gymnasium floor, where the surface remains undisturbed by movement, and a sandy beach, where the surface is slightly uneven and ruts are formed as the robot travels. In addition, the interactions differed depending on the grain size and water content of the soil, even if the soil had the same geology. The physical phenomena caused by the interaction between the ground and the driving mechanism, owing to differences in the geology of the ground, are expressed in the mobile robot's vibration. Therefore, we propose a method for estimating end-to-end current consumption from the vibration caused by the interaction.

The current consumption of a mobile robot drive system varies depending on the internal (robot velocity, angular velocity, weight, driving mechanism, etc.) and external (terrain, geology, temperature, etc.) factors, making it necessary to consider these factors and their interactions. However, it is difficult to represent all these factors in a mathematical model. Therefore, this study attempts to estimate the current consumption by clarifying the relationship (current consumption model) between the vibration and output (current consumption of the drive system) when the inputs (velocity and angular velocity) are provided. By capturing the physical phenomena caused by the interaction between the ground and driving mechanism as vibrations, a model was constructed to consider the internal and external factors that affect the current consumption of the drive system and their interaction. Specifically, a current consumption model is generated from the commanded velocity, commanded angular velocity, vibration (acceleration in the robot's vertical direction), and current consumption of the drive system, which can be measured during the actual movement of the mobile robot.

In the data collection for the current consumption model generation, the mobile robot collects interaction data autonomously in a real environment where it performs its task. Four types of interaction data were measured in the time series: the commanded velocity, commanded angular velocity, vertical acceleration of the robot, and currents in the drive system, which were the inputs to the robot. The actions that a mobile robot can perform are velocity, angular velocity, or a combination of both. Therefore, the robot collects interaction data by moving through a portion of the real environment where it will perform a task, using the velocity, angular velocity, or a combination of both that it can achieve. Once a certain amount of interaction data has been collected, a current consumption model for the environment is generated based on the interaction data, the current consumption is estimated, and the task is performed.

C. Generation Method of the Current Consumption Model

This section describes the current consumption estimation. The current consumption of a mobile robot's drive system varies depending on internal and external factors and their interactions. Therefore, it is difficult to mathematically model all these factors and their interactions. In addition, the drive

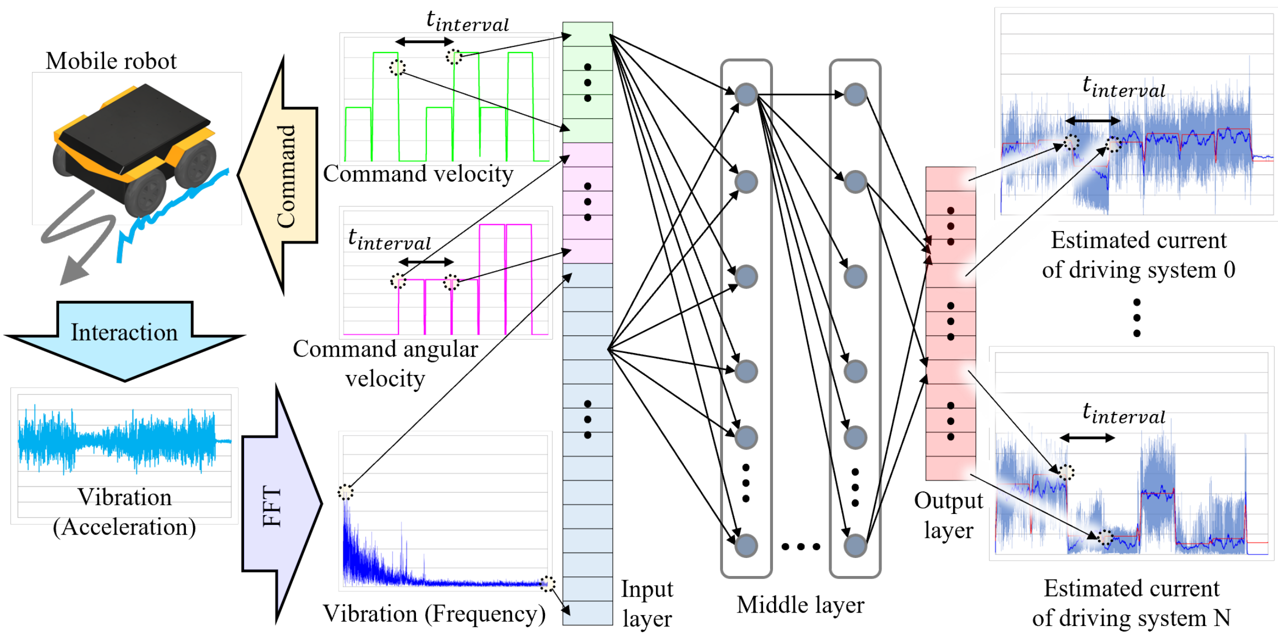


Fig. 2. Dataset and network structure of the proposed method.

system's current consumption varies with the mobile robot's velocity, angular velocity, acceleration, and driving load mechanisms, resulting in nonlinear data with noise. For the reasons explained above, this paper proposes a data-driven end-to-end current consumption estimation method for the drive system using neural networks, a type of machine learning, as a fundamental study.

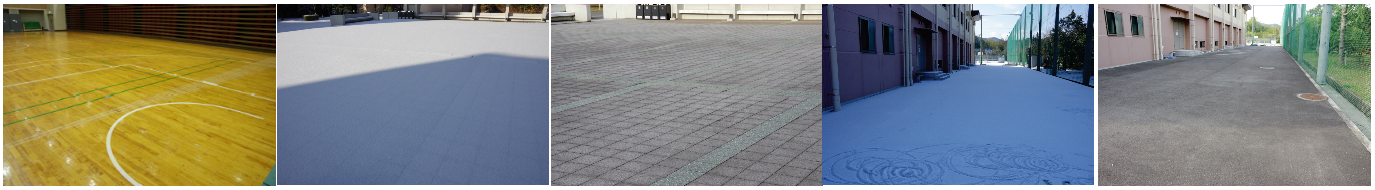
This section describes the method for estimating the current consumption of a drive system using a neural network. A typical mobile robot inputs command velocity and angular velocity. It causes the actuators of the driving mechanism to move, causing the current consumption of the driving system to fluctuate. Internal and external factors and their interactions must be considered to clarify the relationships among command velocity, command angular velocity, and current consumption in task-performing environments. In this method, vibration (acceleration in the vertical direction of the robot) is utilized, and the neural network is configured to take the robot's commanded velocity, commanded angular velocity, and vibration as inputs, with the output being the drive system's current consumption. The current consumption of the drive system fluctuates globally due to changes in velocity, angular velocity, and acceleration. Additionally, even with filtering, noise processing, and sensor calibration, measurement errors and outliers are expected to occur momentarily during the current measurement. Local fluctuations due to noise can also be expected to occur in relation to global current volatility. Due to the reasons mentioned above, the consumption current estimation for a single step at a given moment is expected to have significant measurement errors, outliers, noise, and other inconsistencies. Therefore, the input-output in this method is based on time-series data, separated by an arbitrary interval $t_{interval}$. Even if the geology is the same, the vibration data may differ, depending on the velocity and angular velocity of the mobile robot. Therefore, we move in the actual environment at velocities, angular velocities, or combinations of both that the mobile robot can achieve. The vibrations obtained from this movement are converted into frequency components and input into the neural network. In other words, the frequency component input to the neural network represents the interaction between all the possible actions of a particular mobile robot in a specific environment.

Fig. 2 shows the neural network structure and the dataset used in this method. A neural network consists of input, intermediate, and output layers. The inputs were the velocity, angular velocity, and vibration frequency data, and the outputs were the current consumption of the drive system. The dataset was created by shaping four types of data (velocity, angular velocity, vibration frequency in the vertical direction of the robot, and current consumption) in the line and column directions using the interaction data described in the previous section. The velocity, angular velocity, and current consumption of the dataset are time-series data separated by an arbitrary interval $t_{interval}$, as shown in Fig. 2. Vibrations are frequency data obtained by Fast Fourier Transform (FFT) processing of all the acceleration data during data acquisition. The reason for using all acceleration data was to account for the interaction of all possible actions of a unique mobile robot in a unique environment. At this time, since the velocity, angular velocity, current consumption, and frequency data have different units and scales, each physical quantity is normalized to the range of 0 to 1.

III. Experiment

A. Experiment Outline

The following is an overview of the experiment. The purpose of this experiment is to evaluate the effectiveness of the proposed method in changing environments. To achieve this, we conducted evaluations in various environments, collecting



(a) Coated wood Ground A (b) Snow-covered Ground B (c) Internal condition of snow-covered Ground B (d) Snow-covered Ground C (e) Internal condition of snow-covered Ground C

Fig. 3. Experimental environment.

Fig. 4. Skid-steer type mobile robot used in the experiment.

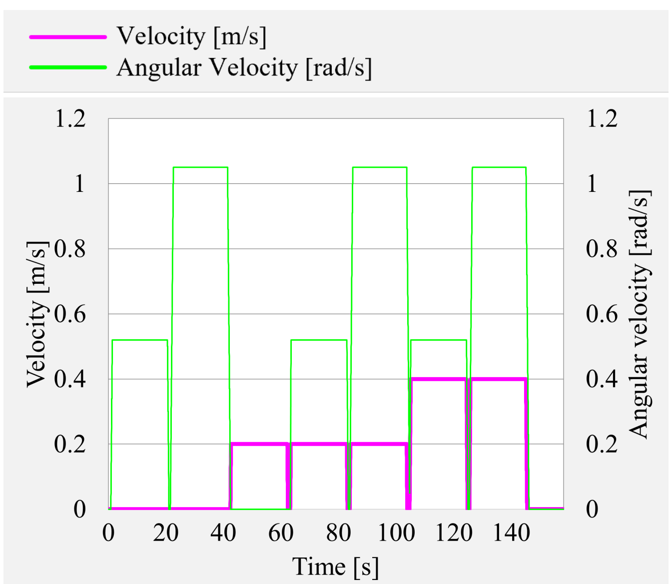
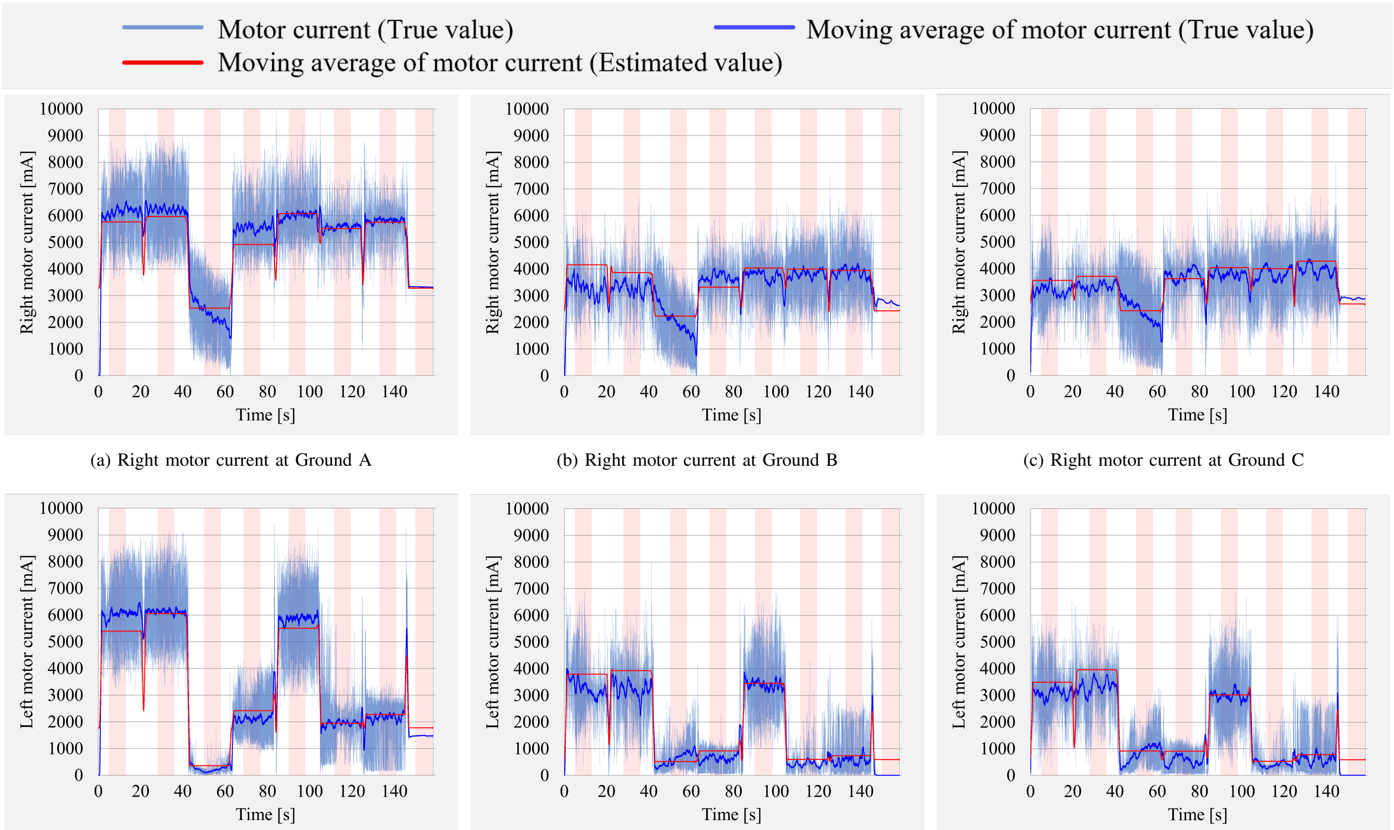


Fig. 5. Control input for current estimation.

data using a mobile robot, training a neural network, and comparing the estimated and measured current consumption values. Three types of geologies were used: Ground A, coated wood surface; Ground B, with a snow-covered surface and stone tiles inside; and Ground C, with a snow-covered surface and concrete inside, as shown in Fig. 3. A mobile robot was used in the experiments, as shown in Fig. 4. JACKAL is a 17 kg skid-steer mobile robot measuring 508 mm in length, 430 mm in width, and 250 mm in height. The driving mechanism was a four-wheeled skid-steer type, with one motor driving two wheels on each side using a belt, for a total of two motors driving the four wheels. Two runs were conducted in each environment to obtain experimental data. Data from the first run were used for learning, model generation, and estimating the driving current consumption in the second run. The control inputs are shown in Fig. 5. The control input shown in Fig. 5 was provided to the mobile robot, and the second-run data were acquired. Evaluation was performed by comparing the estimated current consumption after the first run with the actual current consumption in the second run. The control input comprised a commanded velocity between 0 and 0.4 m/s and a commanded angular velocity between 0 and 1.05 rad/s. The running data were acquired using the combinations shown in Fig. 5.

The measurement method is as follows: The drive system's current consumption was measured by connecting an INA226 current sensor from Texas Instruments, with a measurement range of $\pm$ 20 A, to the motor cable. Vibrations were measured using an IMU sensor module from RT, which incorporates an MPU9250 with an acceleration range of $\pm$ 16 G and an angular velocity range of $\pm$ 2,000 deg/s. The control and measurement system of the mobile robot used Robot Operating System 1 (ROS 1) to acquire the control input synchronously, drive current consumption, and collect vibration data at a sampling rate of 100 Hz.

The structure of the dataset is as follows: The arbitrary interval $t_{interval}$ was set to 0.1 s, and the dataset consisted of 10 samples each for velocity and angular velocity. The vibration (frequency) data comprised 8,000 samples from 0 to 50 Hz per set. The current consumption of the left and right drive systems consisted of ten samples for each dataset. Therefore, the neural network consists of 8,020 inputs in the input layer and 20 outputs in the output layer. The neural network consisted of one input layer, three intermediate layers, and one output layer, with 100 neurons in each intermediate layer. ReLU (Rectified Linear Unit) was used as the activation function for the intermediate and output layers. The data were normalized to a range of 0 to 1, with command velocity ranging from 0.0 to 1.0 m/s, command angular velocity from 0.0 to 1.0 rad/s, and current values from 0 to 10,000 mA to estimate the neural network's learning and the drive system's current consumption. The absolute values were used for the velocity, angular velocity, and current consumption of the left and right drive systems. For the training data, we used



(a) Right motor current at Ground A

(b) Right motor current at Ground B

(c) Right motor current at Ground C

(d) Left motor current at Ground A

(e) Left motor current at Ground B

(f) Left motor current at Ground C

Fig. 6. Actual and estimated current consumption of the left and right motors.

data obtained by changing the velocity and angular velocity and running for approximately 160 s. The test data were acquired at different times from the training data and run for approximately 160 s, changing the velocity and angular velocity in the same manner as the training data.

B. Results and Discussion

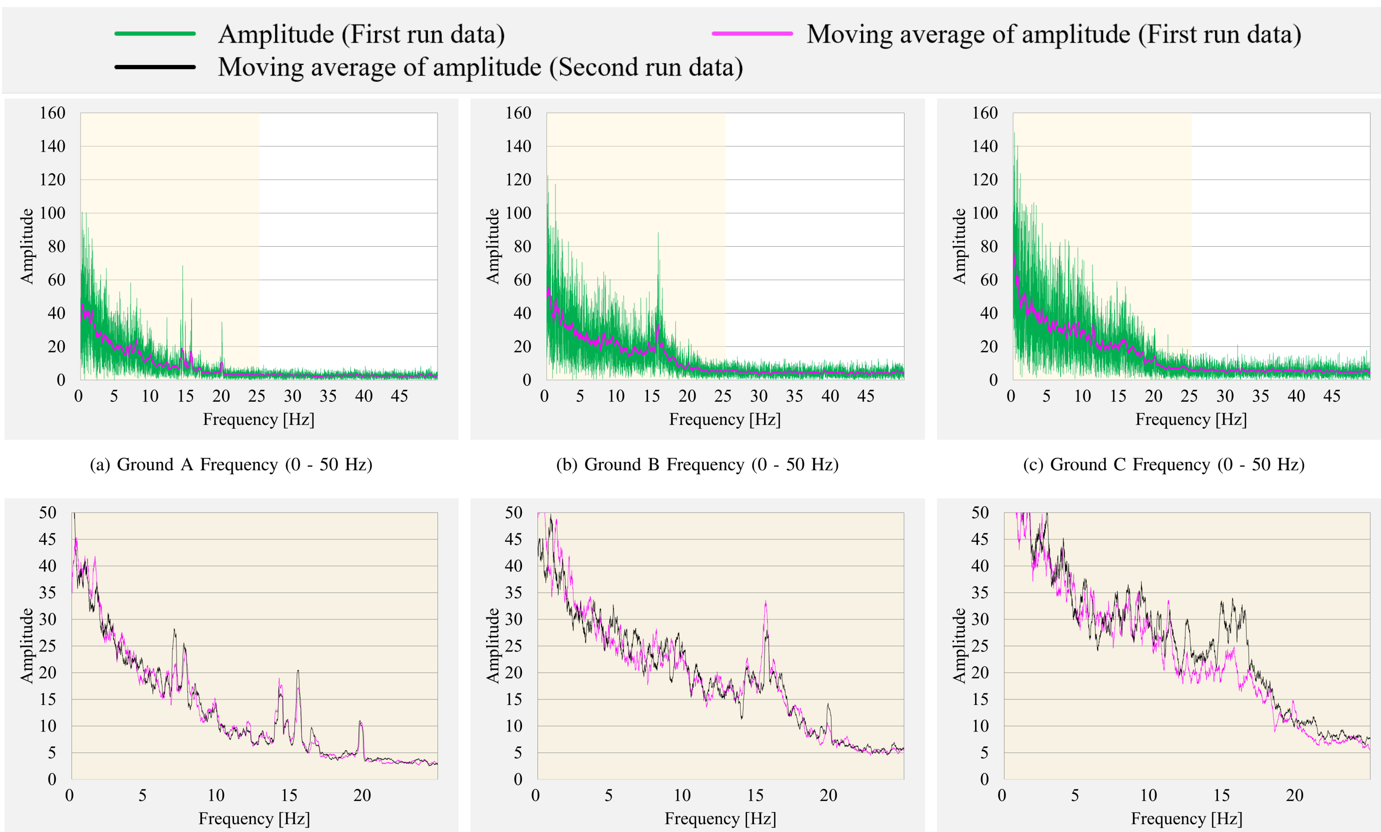
The experimental results are shown in Fig. 6. Fig. 6 (a) and (d) show the current consumption of the mobile robot's right and left drive systems on Ground A, respectively. The horizontal axis represents the time (s), and the vertical axis represents the current (mA). The light-blue line represents the measured current consumption of the drive system (actual value). The dark blue line represents the moving average of the measured value, and the red line represents the moving average of the estimated current consumption of the drive system. The moving averages for the dark blue and red lines were calculated using a median moving average of 100 samples. The remaining figures follow a similar approach, as shown in Fig. 6 (b) and (e), which display the current consumption of the drive system at Ground B, and Fig. 6 (c) and (f), which show the current consumption at Ground C.

The evaluation method is as follows: The experiment was evaluated in the global and local sections of each graph (Fig. 6). The quantitative evaluation involved calculating and comparing the current amount (mAh) in the global and local sections. Specifically, for the global interval, the total amount of current (mAh) was calculated from the beginning (0 s) to the end (158 s) of the graph, and the error rate (%) was determined by comparing the measured value (true value) with the estimated value. To evaluate the local intervals, the amount of current (mAh) was calculated for the interval highlighted in light red (8 s) on the graph, and the error rate (%) for the total amount of current was calculated from the error between the measured (true) and estimated values. Local sections were evaluated for eight sections from Sections 1 to 8, which are highlighted in light red in the graphs. Table I lists the measured (true) and estimated values and error rates for each graph's global and local sections.

First, the results in Fig. 6 show that the estimated current consumption fluctuates in response to changes in the mobile robot's velocity and angular velocity, mirroring the fluctuations in the drive system's current consumption in both environments. Next, the evaluation of the global interval in Table I confirmed that current consumption could be estimated with an error of 3.15 % for the right drive system and 2.18 % for the left drive system in Ground A. We also confirmed that in a snowy environment, the amount of current could be estimated with an error of 15 % or less, even for Grounds B and C. We estimated the current with an error of 15 % or less for all grounds because, using vibrations, we generated a current consumption model that corresponded to the geology,

TABLE I. COMPARISON OF MEASURED AND ESTIMATED CURRENT AMOUNT FOR THE LEFT AND RIGHT DRIVE

		Sec. 1	Sec. 2	Sec. 3	Sec. 4	Sec. 5	Sec. 6	Sec. 7	Sec. 8	Sec. all
Ground A (Coated wood)	Measured current amount of the right drive [mAh]	13.67	13.86	4.95	12.29	13.46	12.44	13	7.4	227.2
	Estimated current amount of the right drive [mAh]	12.82	13.27	5.63	10.94	13.52	12.27	12.79	7.3	220.04
	Error rate of the right drive [%]	0.37	0.26	0.3	0.59	0.03	0.08	0.09	0.04	3.15
	Measured current amount of the left drive [mAh]	13.51	13.64	0.38	4.74	13.12	4.36	4.93	3.30	146.36
	Estimated current amount of the left drive [mAh]	12.01	13.48	0.80	5.38	12.24	4.33	5.06	3.96	143.16
	Error rate of the left drive [%]	1.02	0.11	0.29	0.44	0.6	0.02	0.09	0.45	2.18
Ground B (Snow / Stone tile)	Measured current amount of the right drive [mAh]	7.41	7.36	4.35	8.40	8.30	8.49	8.72	6.09	145.30
	Estimated current amount of the right drive [mAh]	9.24	8.60	4.98	7.38	8.99	8.89	8.77	5.41	154.34
	Error rate of the right drive [%]	1.26	0.86	0.44	0.7	0.48	0.27	0.04	0.46	6.22
	Measured current amount of the left drive [mAh]	7.35	7.09	1.49	1.48	7.57	1.02	1.29	0.00	70.51
	Estimated current amount of the left drive [mAh]	8.44	8.74	1.16	2.05	7.68	1.33	1.64	1.32	81.36
	Error rate of the left drive [%]	1.54	2.34	0.47	0.81	0.16	0.45	0.49	1.87	15.4
Ground (Snow / Concrete)	Measured current amount of the right drive [mAh]	7.31	7.45	5.11	8.29	8.41	8.33	8.74	6.42	148.61
	Estimated current amount of the right drive [mAh]	7.93	8.26	5.40	8.07	9.00	8.90	9.53	5.96	155.80
	Error rate of the right drive [%]	0.42	0.55	0.2	0.15	0.4	0.38	0.53	0.31	4.84
	Measured current amount of the left drive [mAh]	6.86	7.51	2.15	1.50	6.75	0.86	1.30	0.01	68.64
	Estimated current amount of the left drive [mAh]	7.77	8.81	2.03	2.02	6.71	1.17	1.73	1.31	79.26
	Error rate of the left drive [%]	1.33	1.89	0.17	0.76	0.05	0.47	0.64	1.9	15.47



(a) Ground A Frequency (0 - 50 Hz)

(b) Ground B Frequency (0 - 50 Hz)

(c) Ground C Frequency (0 - 50 Hz)

(d) Ground A Frequency (0 - 25 Hz)

(e) Ground B Frequency (0 - 25 Hz)

(f) Ground C Frequency (0 - 25 Hz)

Fig. 7. Frequency analysis for each ground.

making it possible to estimate the current consumption with high accuracy. This discussion is explained as follows: Fig. 7 shows the frequency analysis of the vibration (acceleration) measured on each ground surface. Fig. 7 (a) and (d) show the frequency analysis results on Ground A. The horizontal and vertical axes represent frequency and amplitude, respectively. The graph in Fig. 7 (d) is a zoomed-in view of the yellow-highlighted section in Fig. 7 (a). The green line represents the raw amplitude data, and the magenta line represents the moving average of the amplitude. The magenta line represents vibration data from the first run, and the black line represents vibration data from the second run. The same was true for the other graphs. Fig. 7 (b) and (e) show the results of the frequency analysis for Ground B, and Fig. 7 (c) and (f) show the results of the frequency analysis for Ground C.

The results in Fig. 7 confirmed that the frequency characteristics and amplitude magnitude differed depending on the ground type. Specifically, it was confirmed that Ground A has a relatively small amplitude and fluctuation compared to Ground B and Ground C. In addition, we confirmed that local peaks appeared for Ground A in the frequency bands of 7 Hz, 15 Hz, and 20 Hz. The amplitude of ground B was moderate compared to those of Ground A and C, and local peaks appeared in the frequency bands of 9 Hz and 16 Hz. The amplitude at Ground C was relatively higher than that at Ground A and B, with local peaks appearing in the frequency bands of 9 Hz and 16 Hz. While local peaks were observed in similar frequency bands for Ground B and Ground C, the characteristics of these peaks differed. The 9 Hz local peak was gentle in both rounds B and C. When comparing Grounds B and C, it was concluded that Ground C had a larger amplitude. In addition, it was confirmed that the 16 Hz local peak had a sharp peak for Ground B and a gentle peak for Ground C. In addition to the features described above, a neural network can capture other features necessary for estimating the current consumption of the drive system. We believe that we were able to generate a current-consumption model corresponding to the geological environment using vibrations. As a result, highly accurate consumption current estimation is possible.

IV. Conclusions

This study aims to develop an end-to-end method for estimating the current consumption of a mobile robot drive system that considers geological conditions. We proposed new methods for collecting interaction data and generating current consumption models. In the interaction data collection method, we proposed an approach that effectively considers both internal and external factors affecting the drive system's current consumption and interactions by capturing physical phenomena, such as vibrations, generated by the interaction between the driving mechanism and the ground. In the current consumption model generation method, we introduced a neural network-based approach for generating a current consumption model using interaction data, accounting for measurement errors, outliers, noise, and global current fluctuations. Through experiments in a real environment, we confirmed that the current can be estimated with an error of 15 % or less. Specifically, on Ground A, which was coated with wood, the error rate was 3.15 % for the right drive system and 2.18 % for the left drive system. On Ground B, which had a snow-covered surface and a stone tile interior, the error rates were 6.22 % for the right drive system and 15.40 % for the left drive system. On Ground C, which had a snow-covered surface and a concrete interior, the error rate was 4.84 % for the right drive system and 15.47 % for the left drive system. Additionally, we confirmed that the frequency characteristics and amplitude sizes differ depending on the ground type, and that a neural network can capture the features necessary for estimating the current consumption of the drive system. Furthermore, we confirmed that vibrations can generate a current consumption model adapted to geological conditions. The experimental results demonstrate the effectiveness of the newly proposed interaction data collection and current consumption model generation methods. Therefore, we established an end-to-end method to estimate the current consumption of a mobile robot drive system that considers geological conditions.

We will now explain our future work. This study verified the method using three types of ground and one type of mobile robot. In future work, we plan to confirm the method with different types of ground and mobile robots. Additionally, the operating time in this study was limited to about three minutes; we will conduct verification over a longer period to assess the method's applicability.

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