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APPLICATION OF MACHINE LEARNING METHODS TO A WHEELED MOBILE ROBOT TRAJECTORY TRACKING CONTROL

МАШИНАЛЫҚ ОҚЫТУ ӘДІСТЕРІН ҚОЛДАНА ОТЫРЫП ДӨҢГЕЛЕКТІ МОБИЛЬДІ РОБОТТЫ ТРАЕКТОРИЯСЫ БОЙЫНША БАСҚАРУ

ПРИМЕНЕНИЕ МЕТОДОВ МАШИННОГО ОБУЧЕНИЯ ДЛЯ ТРАЕКТОРНОГО УПРАВЛЕНИЯ КОЛЕСНЫМ МОБИЛЬНЫМ РОБОТОМ

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Wheeled mobile robot (WMR), skid-steered wheeled mobile robot (SSMR), recurrent neural network (RNN), microelectromechanical systems (MEMS)

ABSTRACT

This paper presents new results of an experimental study of the application of machine learning methods to trajectory tracking control of a wheeled mobile robot (WMR). The experiments were conducted using a custom-assembled wheeled mobile platform and software developed for its programmable components, enabling the implementation of WMR trajectory tracking control using machine learning. A model of a skid-steered wheeled mobile robot control was developed based on a recurrent neural network. The neural network was trained using experimental data obtained during testing of the robot control system, and it was demonstrated that the control and data collection system of the experimental robot ensures high accuracy in following a given trajectory. Specifically, the model constructed using machine learning methods allows predicting the robot's movement with high accuracy over a time horizon of approximately 3-4 seconds at an average robot speed of 1.2 meters per second. The results obtained during the trajectory tracking control of the experimental onboard control system are promising for skid-steered wheeled mobile robot of any carrying capacity and provide progress in the current field of machine learning applications in robotics, automatic control, and inertial navigation.

Түйінді сөздер:

Дөңгелекті мобильді робот (ДМР), боргтық бұрылуы бар дөңгелекті мобильді робот (SSMR), рекурренттік нейрондық

ТҮЙІНДЕМЕ

Бұл мақалада дөңгелекті мобильді роботтың (ДМР) траекториялық басқаруында машиналық оқыту әдістерін қолдануға арналған эксперименттік зерттеудің жаңа нәтижелері ұсынылған. Эксперименттер арнайы құрастырылған дөңгелекті мобильді платформа және оның бағдарлама жасалатын компоненттеріне арнайы өңдел-



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желі (RNN),
микроэлектро-
механикалық жүйелер
(MEMS), машиналық
оқыту әдістері

ген бағдарламалық қамтамасыз ету негізінде жүргізілді, нәтижесінде машиналық оқыту көмегімен ДМР-дың траекториялық басқаруын жүзеге асыруға мүмкіндік берді. Борттық басқаруы бар ДМР-дың басқару моделі рекурренттік нейрондық желі негізінде өңделді. Нейрондық желі роботты басқару жүйесін сынақтан өткізу барысында алынған эксперименттік деректер негізінде оқытылды және эксперименттік роботтың басқару мен деректерді жинау жүйесі берілген траекторияны жоғары дәлдікпен жүріп өтетіндігін қамтамасыз ететіні көрсетілді. Атап айтқанда, машиналық оқыту әдістерін қолдану арқылы құрылған модель роботтың қозғалысын орташа жылдамдығы секундына 1,2 метр болған жағдайда 3-4 секундтық уақыт көкжиегінде жоғары дәлдікпен болжауға мүмкіндік береді. Эксперименттік ДМР-дың траекториялық басқару нәтижелері кез келген жүк көтергіштікке ие борттық басқаруы бар дөңгелекті мобильді роботтар үшін перспективалы болып табылады және робототехника, автоматтандырылған басқару және инерциялық навигация салаларында машиналық оқытуды қолданудың өзекті бағытының дамуына ықпал етеді.

Ключевые слова:

Колесный мобильный робот (КМР), колесный мобильный робот с бортовым поворотом (SSMR), рекуррентная нейронная сеть (RNN), микроэлектронномеханические системы (MEMS)

АННОТАЦИЯ

В статье представлены новые результаты экспериментального исследования применения методов машинного обучения для траекторного управления колесным мобильным роботом (КМР). Эксперименты проводились с использованием специально смонтированной колесной мобильной платформы и программного обеспечения, разработанного для ее программируемых компонентов, что позволило реализовать траекторное управление КМР с помощью машинного обучения. Модель управления КМР с бортовым управлением была разработана на основе рекуррентной нейронной сети. Нейронная сеть была обучена с использованием экспериментальных данных, полученных в ходе тестирования системы управления роботом, и было продемонстрировано, что система управления и сбора данных экспериментального робота обеспечивает высокую точность следования заданной траектории. В частности, модель, построенная с использованием методов машинного обучения, позволяет прогнозировать движение робота с высокой точностью на временном горизонте длительностью 3-4 секунды при средней скорости робота 1,2 метра в секунду. Результаты, полученные при траекторном управлении экспериментальным КМР, являются многообещающими для колесных мобильных роботов с бортовым управлением любой грузоподъемности и обеспечивают прогресс в актуальной области применения машинного обучения в робототехнике, автоматизированном управлении и инерциальной навигации.

INTRODUCTION

Autonomous mobile robots are currently the core platform for agricultural, industrial, and other robots. Mobile robots can be equipped with manipulators and actuators of various types. Rapidly developing machine learning methods offer a promising solution for solving local navigation and control problems in autonomous mobile robots. According to an analysis of contemporary literature (Juman et al. (2019), Westenbroek et al. (2020), Wu et al. (2022), Rybczak et al. (2024), two main approaches to the application of machine learning methods to the development of mobile robot controllers can be identified. The first approach involves using a machine-learning-generated model of the controlled object within a traditional control scheme.

In other words, with this approach, a learning-based model (LBM) is incorporated into a "conventional" controller, typically implementing a variation of model-predictive control methods. Machine learning methods are used in this approach to create a model that most accurately describes the controlled object. Learning data can be collected from experiments with a system operating under a controller that doesn't employ neither machine learning methods, nor a human-controlled radio-controlled mobile robot, or even a computer simulation system.

The learning process in this approach is qualitatively no different from training a neural network used to simulate a sensor, or more precisely, to simulate a measurement process, such as the operation of a microelectromechanical (MEMS) inertial sensor mounted on a moving platform.

Another approach involves using machine learning methods to develop a controller that is optimal for a given control object, based on criteria specified by the developer. The most straightforward implementation of this general approach is to directly use a neural network trained to perform controller functions as the controller. Using this radical approach, the neural network acts as a converter of feedback signals into a control signal, i.e., it functions as a controller. A striking example of this approach is the trajectory tracking controller for a four-wheeled mobile robot, developed by Juman et al. (2019). The controller was developed using a neural network architecture named by its authors an "Advanced Self-Organizing Incremental Neural Network." Neither the kinematic nor the dynamic models of the robot were used in the development of the controller, and the controller did not directly or indirectly utilize any robot models specified by the developers. In essence, the controller developed its own robot model during the learning phase.

However, the general idea of developing a learning system that, when modified during the learning process, would begin to perform its functions in an optimal way in the sense of the term "optimal" defined by the system developers, can be used not for the direct development of the controller, but for the development of its key block. Thus, Westenbroek et al. (2020) proposed to use machine learning methods to develop a linearizing controller for use in a control system for a nonlinear object with unknown dynamics. The only restriction on the control objects to which this method can be applied is that the control object must be described by a model of a nonlinear affine control system. To train the linearizing controller, Westenbroek et al. (2020) formulated an optimization problem, for the solution of which reinforcement learning methods were used. Another possible approach to using machine learning to develop a linearizing controller in a control system built using a feedback linearization scheme was presented by Wu et al. (2022). In general, the second approach to applying machine learning to controller development is characterized by the use of reinforcement learning. Information on its application to trajectory planning, obstacle detection and avoidance, and other mobile robot navigation and control tasks can be found in the review by Rybczak et al. (2024).

Since the research described in this paper focuses exclusively on the implementation of the first approach, it is appropriate to explore it in more detail. As noted above, this approach to designing mobile robot controllers is based on the LBM general concept. From a developer's perspective, in any system that employs machine learning methods, neural network functions or support vector machines are, strictly speaking, reduced to solving one of the two main problems of machine learning methods: classification or regression.

The term "regression problem" in the context of machine learning methods is associated with the problem of prediction. The term "regression" in the title of this fundamental machine learning task refers to the search for optimal parameters for approximating a given sample sequence. However, when solving a regression problem, the computing system itself selects an approximation method based on the learning results, rather than using an approximation method predefined by the programmer. For applications of machine learning methods to control

problems in general and to the mobile robot control in particular, it is important that when solving a regression problem, the computing system essentially constructs a mathematical model of the empirically defined relationship of one quantity to another (or to a set of other quantities).

The problem of developing a learning-based model of a sensor or control object is often formulated as the problem of modeling a signal converter with memory, i.e., a signal converter characterized by state. For example, if we consider the feedback signals generated by sensors measuring the current state of an object as a single output signal, then the control object can be viewed as a converter of the control signal into an output signal. In digital control systems, control signals and the output of the control object represent discrete time sample sequence. Functionally, the model of the control object is nothing more than a discrete signal converter. This approach to modeling the control object was applied by Jiang et al. (2022) to simulate the dynamics of a quadcopter. A different approach to modeling control objects and sensors is possible, where the relationship between the signal at the converter input and the output signal is described by a random process model. The application of this approach to the development of a control system for a four-wheeled mobile robot, which adjusts a given trajectory in real time to avoid obstacles, was described by Trivedi et al. (2023) and by Wang et al. (2023), where a Gaussian random process model was chosen to describe the control object.

Most practical tasks of the wheeled mobile robot (WMR) control in general are associated with the task of following a trajectory, which can be formulated as follows: control the robot so that at any moment of its movement, the position of the robot deviates as little as possible from a given spatial trajectory, and the speed of the robot deviates as little as possible from a constant given speed. Most of the research in the field of the skid-steered wheeled mobile robot control is related to this problem, and not to the more general problem of trajectory tracking control, in which the trajectory is determined over a time interval by specifying the position, orientation in space and velocity of the robot for all moments of time of movement. A method for controlling skid-steered four- wheeled mobile robots was presented by Khan et al. (2020) and successfully applied to the popular Pioneer 3-AT research robotic platform with various tire and soil types. Khan et al. (2020) proposed an approximate parameterized kinematic model of a skid-steered four- wheeled vehicle and a method for experimentally determining the parameters of this model. In fact, Khan et al. (2020) replaced the extremely complex problem of identifying the parameters of a wheeled robot's dynamic model with the relatively simple task of experimentally determining just two parameters of its approximate kinematic model.

Almost any trajectory control method, like any path following algorithm, is developed for the kinematic model of the specific type of wheeled robots for which it will be used. For a skid-steered wheeled mobile robot (SSWR), developing an adequate kinematic model proves extremely difficult. It should be noted that modeling the motion of this type of WMRs presents a serious challenge for a simple but fundamental reason: when turning and moving along any curved path, lateral slippage of the wheels inevitably occurs. Moreover, with independent wheel control, longitudinal slip is sometimes observed, which occurs when the wheels on one side rotate at different speeds, as described by Trojnacki, (2025). For SSWRs, it is impossible to separate the robot's kinematic model from its dynamic model, assuming no longitudinal or lateral wheel slip. Approximate kinematic models of SSWRs, such as the unicycle model, are not directly applicable to solving path-following problems, and in general, when solving practical control problems, models operating with the so-called instantaneous center of rotation of the robot are used (Trojnacki, (2025).

The results presented by Khan et al. (2020) and by Trojnacki, (2025) can be seen as confirmation of the validity of the opinion expressed by Salzmann et al. (2022) that for SSWRs the kinematic model must be combined with the dynamic one. For example, Dorbetkhany et al. (2023) presented a predictive path following model for controlling SSWRs in the presence of

obstacles. To develop a model of a robot moving along a given trajectory while avoiding any random stationary obstacles, a spatial kinematic model was used. At the same time, extensive computational experiments were carried out in the environment of a physical robot simulator, showing that the proposed control approach effectively ensures the robot converges to a given trajectory with minimal deviations.

Thus, the approach to choosing control methods based on machine learning depends directly on the WMR type. It should be noted that SSWRs are characterized by extreme simplicity of design, in which there are no special mechanisms for turning steering wheels, like the Ackermann trapezoid used in the steering system of cars. Robots of this type make turns while moving due to the difference in the speed of rotation of the wheels installed along the left and right sides of the robot. The most common type of SSWR design is a mobile cart with four wheels, the axles of which are rigidly connected to the shafts of independently controlled electric motors. In addition to the obvious advantages over other types of WMRs associated with simplicity of design, SSWRs are characterized by high maneuverability and good load capacity, therefore this type of WMRs is most often used in various applications: in agriculture, industry, military affairs, etc. On the other hand, designing a control system for robots of this type presents specific difficulties and great interest from the theoretical side. The development of control algorithms for SSWRs requires experimental research using local positioning systems with high accuracy and allows the direct transfer of the solutions found to a SSWR of any carrying capacity.

The objective of this study was to apply machine learning methods to the trajectory control of a skid-steer wheeled mobile robot of an experimental design.

MATERIALS AND METHODS

The SSWR was assembled in the "Machine Vision, Automatic Control, and Inertial Navigation of Mobile Robots" laboratory at the Center for Competence and Technology Transfer at D. Serikbayev EKTU as part of the implementation of the research project AP19679327 with funding from the Ministry of Science and Higher Education of the Republic of Kazakhstan.

The SSWR is mounted on a 4WD1 Rover A4WD1-KT v2 chassis manufactured by Lynxmotion. This chassis includes body components, mounting hardware for electronic boards (processor control board and expansion boards), four brushed DC motors, and the robot's wheels. The SSWR also includes an STM32F3Discovery development board, RB-Dim-42 Sabertooth brushed motor driver modules, and an NRF24L01 radio module. One development board is installed on the robot, while the other board serves as a jumper between the Wi-Fi module and the computer. A general view of the mobile platform under test (with components indicated) is shown in Figure 1.

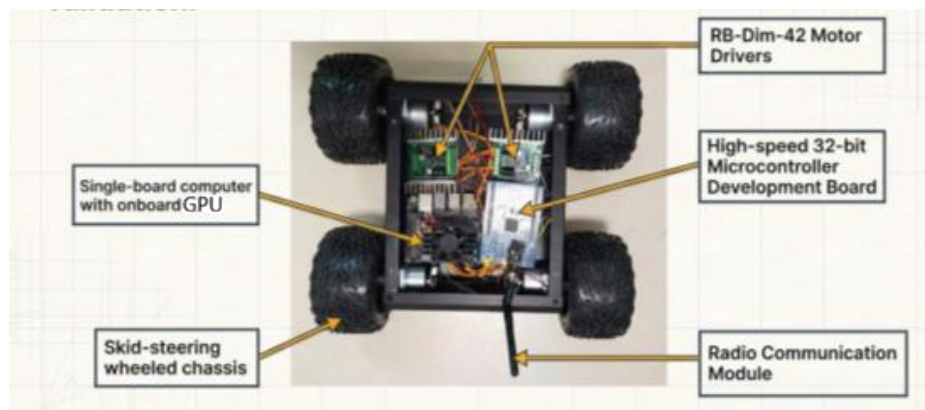


Figure 1. Mobile controlled platform for research of WMR control and navigation algorithms

Embedded software components were developed and debugged for the STM32F303VC microcontroller installed on the STM32F3Discovery board. These components implement low-level control of the robot's motors, support for the radio communication protocol with the master personal computer (PC), and collect data from the inertial sensors and magnetometer installed on the Discovery3 development board, as well as the Intel RealSense T265 tracking camera, which is part of the local positioning system. PC software was developed that supports a bidirectional (full-duplex) radio communication interface with the WMR. This software is designed to perform two primary functions: high-level WMR control and data collection from the sensors installed on the WMR as described in previous articles by Krasavin et al (2024), (2025).

An optical local positioning system based on the Zed 2 stereo camera was developed. This experiment included installing the manufacturer's software (Zed 2 SDK), which provides a programming interface to library functions that enable capturing video streams from the camera, synchronized with data from the camera's built-in sensors, as well as performing both standard stereo image processing operations and high-level image capture and recognition operations.

Camera functionality was tested using the Visual Studio Community Edition C/C++ compiler, installed on a Dell XPS-15-9570 laptop with a GPU capable of supporting the Zed 2 camera software.

The experiment also included installing an operating system (Linux xxx) on an NVIDIA JETSON NANO single-board computer (SBC) and testing software for the SBC interfaces, which is necessary for using the SBC as a control board for a mobile wheeled robot. Software was developed for programmable devices included in the mobile robot, implementing the developed algorithms using machine learning methods. Embedded software was developed for the Wi-Fi module with an on-board microprocessor for full-duplex communication with the WMR.

Embedded software for the STM32F303VC microcontroller installed on the STM32F3Discovery development board has been developed. It supports bidirectional (full-duplex) radio communication with the WMR. It is designed to perform two primary functions: high-level control of the WMR and data collection from sensors installed on the robot. The corresponding PC software features a modular architecture to support bidirectional communication with the robot's Wi-Fi module.

A separate module has been developed that uses a socket mechanism and an original communication protocol with one master (PC) and one slave (mobile robot control board), which can potentially support multiple slaves if there is a need to collect data from individual devices.

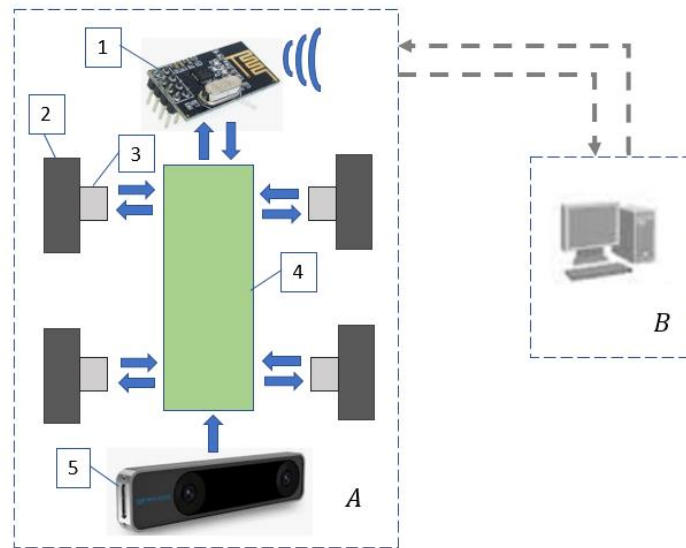
An odometry system was developed and experiments were conducted for robot navigation control: the primary data for the odometry system are the data from quadrature rotation encoders installed on the robot's motors; hardware capture units of the STM32F303VC microcontroller are used for the primary processing of encoder data.

To develop the neural network model used for machine learning of the DVR, the PyTorch library of the Python language, included in the freely distributed Anaconda distribution, was used.

RESULTS AND DISCUSSION

Let's take a closer look at the data collection system and debugging the control algorithms for a four-wheeled SSMR. To collect the data necessary for identifying the model of the SSMR and developing its model based on learning, as well as for testing high-level control algorithms, a system was created, as noted above, consisting of two main components - a wheeled mobile robot with skid steering, and a PC connected to the SSMR via a radio channel, on which a program is executed that carries out high-level control of the robot and collects data coming from the robot.

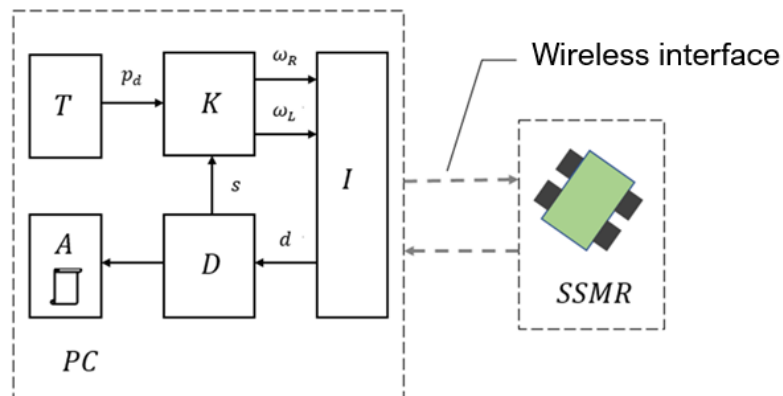
The main components of the SSMR used in the experiments, as well as the interaction diagram of the SSMR with the PC, are shown in Figure 2.



- 1 – Radio module
- 2 – Wheels
- 3 – Geared electric motors with encoders
- 4 – Control board
- 5 – Intel Realsense T265 tracking camera

Figure 2. The SSMR main components (A) and the PC controlling the robot via radio (B)

The program running on the PC and the robot control system form a two-level system for trajectory control of the robot. The robot control system receives commands via radio - the angular velocities of the wheels on the right ω_R and left ω_L sides of the robot - and transmits data on the robot's current position and orientation in space, as well as its linear and angular velocity, to the high-level controller (the computer that controls the robot) (see Figure 3).



- T – trajectory generation module,
- K – trajectory tracking controller module, which generates control signals for the low-level robot control system based on a given trajectory p_d and data on the robot's current state s .
- I – software module supporting the bidirectional communication interface with the SSMR control system,
- D – data processing unit for data received from the SSMR,
- A – data archiving unit

Figure 3. Functional diagram of the SSMR high-level control system (running on a PC)

Low-level control functions for the electric motors on whose shafts the robot's wheels are mounted are performed by a microcontroller on the robot's control board, regulating the wheel speeds to minimize deviations from those set by the high-level controller. The SSMR, mounted on a 3WD ROVER chassis manufactured by Lynxmotion, was equipped with four independently controlled DC geared motors with encoders. A standard position-speed control scheme with feedback from signals generated by the encoders was used to control the motors. Thus, the microcontroller on the control board implements the functions of four digitally controlled DC motor drives.

In addition to the robot's motors control, the SSMR low-level control system performs two other functions: collecting data from sensors and maintaining a communication interface with the master computer. The STM32F3Discovery development board was used as the mobile robot's control board, and the motors were controlled using software-implemented PID controllers.

The microcontroller's duty cycle duration, $T_w = 25$ ms, was set by the activation of one of its built-in timers, each sequentially occurring at a frequency of 40 Hz. At the beginning of each cycle, the microcontroller read data from the sensors and performed actions related to motor speed control. Data read from the sensors was buffered in RAM and transmitted to the upper-level control system via requests received via the serial communication interface.

To navigate the robot (that is, to determine the current position and spatial orientation of the robot body), only data from sensors mounted on the SSMR was used; external stationary beacons, cameras, and similar devices were not used.

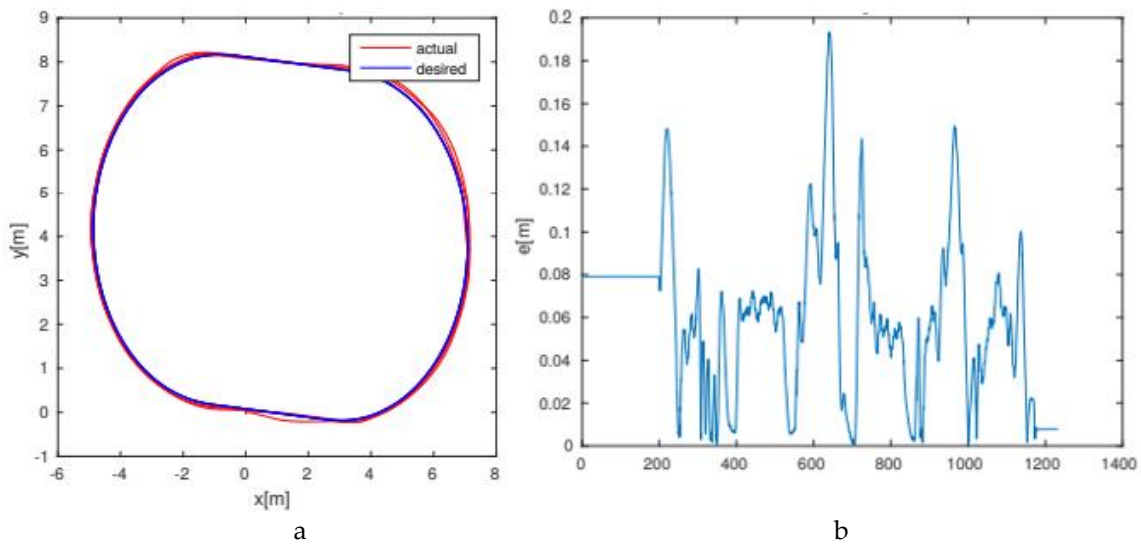
The high-level control system (a program running on a PC) received data on the robot's current state (its position and spatial orientation, angular velocity, acceleration, and wheel speeds) via a serial data interface from the mobile robot's low-level control system.

To organize data exchange between the master computer and the SSMR control board via a radio channel, a logical-level master-slave communication protocol was used, particularly a simplified modification of the widely used ModBus protocol. The PC acted as a master, sending several types of commands to the robot's low-level control system (data transfer requests, a command to update task values (rotational speeds of the robot's wheels), and a command to stop the system). The slave responded with a response, the form of which depended on the received command. Data transfer was initiated by the upper-level system, and a timestamp mechanism was used to synchronize the upper- and lower-level control systems.

The robot's low-level control system generated data frames corresponding to a work cycle time of $T_w = 25$ ms. Upon receiving a data transfer request, the low-level control system either transmitted all data frames accumulated in the buffer, each marked with the work cycle number during which it was generated, or informed the master that new data was not ready. The received raw data frames from the sensors installed on the mobile robot were processed by a specific software module, generating a data stream that served as feedback signals for the high-level software controller. Analysis of the robot's trajectory following accuracy is presented in Figure 4.

The high-level control system also performed data collection functions. For each test session, a report was generated as a specially formatted text file containing a complete timeline of the mobile robot's control system operation during the session. The data collection system archived both raw sensor data received from the mobile robot and the results of its processing used by the high-level controller, as well as the control signals generated by this controller. The control and data collection system enables a fairly high accuracy in following a given trajectory (see Figure 4), at least at the low speeds at which the initial experiments were conducted.

Data archives collected during experiments with the SSMR were used for computer simulation of trajectory control algorithms and for a learning-based model of a wheeled mobile robot with onboard controls. The model is intended for use in further research to develop a learning-based controller for trajectory control of the mobile robot.



a – given spatial trajectory (blue line) and actual robot trajectory (red line);
b – distribution of path following error along the path traveled

Figure 4. The SSMR trajectory following accuracy (the average robot speed is $1.2 \text{ m}\cdot\text{s}^{-1}$)

The open-source STM32CubeIDE development environment was used to develop the embedded software (programs for the 32-bit STM32F303VCT6 microcontroller installed on the STM32F3Discovery development board, which served as the control board for the wheeled mobile robot).

To implement machine learning methods for robot control, experiments were conducted to develop a robot control model based on a recurrent neural network (RNN). A well-known approach was employed, in which a neural network is used to predict the robot's behavior based on its current state and a predetermined control signal that will be fed to the robot's control system in the future. More specifically, a RNN was used to develop a model of the SSMR control object as a discrete signal converter with memory. The neural network then predicts how the vector p , which describes the SSMR position and spatial orientation, will change over time.

We consider the case where a robot moves along a horizontal plane, and its position is determined by the (x, y) coordinates of some point on the robot's body (usually the geometric center of the robot or the position of the system's center of mass is chosen as such a point), while its spatial orientation is determined by the heading angle θ . We can then describe the robot's state by a three-component vector $p = (x, y, \theta)^T$. Strictly speaking, with this choice of description for the state of a mobile robot, $p \in SE(2)$, i.e., the state is an element of the special Euclidean group of rigid body motions $SE(2) = \mathbb{R}^2 \times S^1$ и $\theta \in S^1$, i.e., θ is a cyclic variable. This circumstance must be taken into account when choosing a data representation format when working with software implementations of machine learning methods.

Of course, the current state of a mobile robot s is not fully described by its position and orientation in space p . In the actual process of the SSMR control, which we are going to simulate, the controller operates with the measured position of the robot $\hat{p}$ (in our case, the discrete sequence $\hat{p}_1, \hat{p}_2, \dots$ corresponds to the data stream from the tracking camera) and data from other sensors measuring the angular velocity of the robot's body, its linear acceleration, etc.

A common modeling technique is to consider the result of measuring the robot's state $\hat{s}$ as a composite vector $\hat{s} = (\hat{p}, \hat{z})$, where $\hat{z}$ is the result of measuring other quantities characterizing the state of the mobile robot. The specific choice of $\hat{z}$ components from the available sensor data is determined, of course, by the specific application. We chose as such components the vertical

component ω_z of the angular velocity vector of the robot body $\Omega = (\omega_x, \omega_y, \omega_z)$, measured by the gyroscope, the linear velocity vector $v = (v_x, v_y)$ of the attachment point of the MEMS inertial sensor to the control board, calculated from the accelerometer data and the measurement results, and the angular velocities of rotation of the four wheels of the robot measured by the low-level control system, which we will denote as components of the four-dimensional vector $w = (w_1, w_2, w_3, w_4)$.

Thus, we assume that the measurement results $\hat{z} = (\hat{\Omega}, \hat{v}, \hat{w})$ together with the measurement result of the robot's position and orientation in space $\hat{p}$, yield an estimate of the robot's state $\hat{s} = (\hat{p}, \hat{z})$, which allows us to predict its response to a given control signal u . The inputs of the RNN in this case will be the discrete signal $\hat{z}_i$, corresponding to the data flow from the sensors, and the discrete control signal u_i .

Trying to directly predict the state s_{i+1} at the next $i + 1$ time point would be unwise for technical reasons. It is much more convenient to calculate the state change $\delta s_i = (\delta p_i, \delta z_i)$. Then, the robot's future position and orientation in space p_{i+1} are determined simply as the sum of the increment δp_i predicted by the network and the current value of the vector p_i . Accordingly, the network output will be a discrete signal δp_i . The general architecture of the neural network is shown in Figure 5.

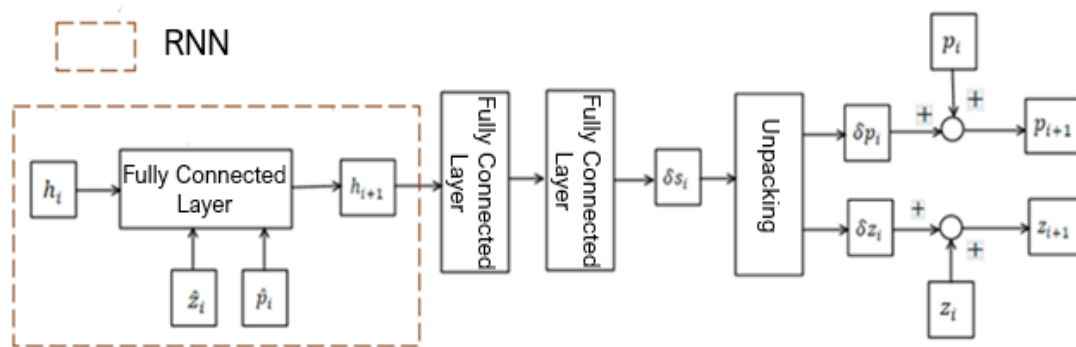


Figure 5. The RNN architecture used to develop the SSMR learning-based model

Given the values of $\hat{z}_i$, u_i , and the hidden state h_i , the RNN (see Figure 5) predicts the hidden state at the next time step h_{i+1} . The hidden state represents information accumulated over time and is equivalent to the system state in a conventional control system mathematical model. When designing a neural network, the dimension of the vector h is specified by the developer. In the experiments described, the dimension $\dim(h)=20$ was chosen, i.e., $\forall i \ h_i \in \mathbb{R}^{20}$.

Data collected during experiments on trajectory control of the SSMR were used to train the network and evaluate the model's accuracy. The data was divided into two groups based on the robot's trajectory structure: one group was used for training, and the other was used solely for evaluating the model's accuracy. The obtained results are preliminary due to the limited amount of data collected, but they allow us to evaluate the model development method as promising.

Figure 6 shows graphs of the root-mean-square error of the position and orientation prediction as a function of the prediction step size.

According to our estimates, at low robot speeds, the machine learning model of the robot as a control system allows predicting robot motion with sufficient accuracy over a time horizon of approximately 3-4 seconds. The adequacy of the model for higher robot speeds requires further research and, possibly, the model's modification.

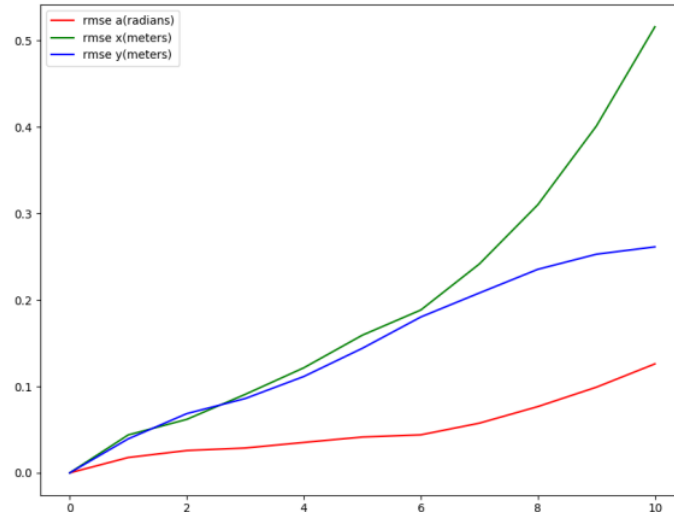


Figure 6. Dependence of the root-mean-square errors of the prediction of the SSMR coordinates and heading angle on the prediction step

Further research is expected to focus on two areas: first, future research will focus on increasing the dataset for model training and expanding the proposed trajectory control method from a kinematic model of the WMR to a full dynamic model; second, an important area of future work is the development of robust machine vision methods for solving local navigation and control problems of autonomous mobile robots, particularly for dynamic trajectory planning of the WMR in a changing environment. We are currently starting to organize a series of full-scale experiments with a local positioning system based on a stereo camera, which allows to determine the position of the robot, and we also plan to use the PlatypOUs mobile robotic platform, as described by RÁCZ et al. (2022) and by Haidegger et al. (2024) to test the developed methods.

CONCLUSIONS

An experimental wheeled mobile robot was designed and assembled to test new navigation and control algorithms. Software was developed for the WMR programmable devices, implementing new algorithms using machine learning techniques.

A model of a skid-steered wheeled mobile robot was developed based on a recurrent neural network, the network was trained, and the accuracy of the model was assessed using data collected during experiments on the SSMR trajectory tracking control.

It has been shown that the control and data acquisition system of the experimental WMR allows for achieving a sufficiently high accuracy in following a given trajectory: at low robot speeds (average robot speed of $1.2 \text{ m}\cdot\text{s}^{-1}$), the model of the robot as a control system developed using machine learning techniques allows for predicting the robot's motion with sufficient accuracy over a time horizon of approximately 3-4 seconds

The results obtained during the experimental WMR control may be applied to control of SSMRs with any load capacity and are very promising from both a practical and theoretical point of view, providing new data and opportunities for the application of machine learning to the WMR control. Thus, these new research results may have a wide range of applications in areas such as robotics, machine learning and machine vision, electronics, automatic control systems, inertial navigation, and may also be of interest to researchers in these areas.

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