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THEORETICAL FOUNDATIONS OF INTELLIGENT CONTROL OF MOBILE ROBOTIC PLATFORMS

Sumarry. *The paper considers the theoretical foundations of intelligent control of mobile robotic platforms as an integrated problem of generating control actions that ensure achievement of a required state under constraints, uncertainties, and changing operating conditions. The current state of wheeled-platform control is analyzed. It is shown that further autonomy requires not only improved controllers but also mathematical models, computational methods, and controllability assessment procedures. State, control, and controlled-parameter vectors are introduced. Controllability is represented through three interrelated components: control capability, sensitivity, and optimality. A generalized mathematical representation of platform dynamics, terminal-state reachability conditions, and optimal-control criteria is presented. The role of feedback, sensor data, and computer simulation in an intelligent control system is defined. Discretization of the admissible control set is shown to provide a practical basis for numerical engineering analysis and autonomous-platform*

design.

Key words: *Mobile Robotic Platform, Intelligent Control, Controllability, State Vector, Control Vector, Control Capability, Sensitivity, Optimal Control*.

Introduction. Mobile robotic platforms are used as autonomous vehicles and carriers of technological, measuring, or specialized equipment. Advances in the mechanical design of wheeled platforms have led to the development of a broad class of technical devices suitable for use in industry, agriculture, transportation, the military, and emergency response. Under these conditions, the primary focus of improvement is on control and automation systems, which must ensure autonomous operation modes and reduce human involvement in hazardous and monotonous operations.

The structure of the control system is determined by the platform's design, its intended use, and the characteristics of the environment. Changes in wheel-surface traction, load uncertainty, external disturbances, sensor errors, and limitations of actuators complicate the use of standard controllers. Therefore, fully autonomous platforms require specialized solutions that combine mathematical modeling, numerical analysis, sensor-based state estimation, and decision-making algorithms.

The aim of this article is to formulate generalized theoretical principles for the intelligent control of mobile robotic platforms based on the concepts of state, control, and controllability. To achieve this goal, it is necessary to define a mathematical representation of the platform's dynamics, formalize the control capacity and sensitivity, and establish principles for selecting the optimal control action.

Analysis of Recent Studies and Publications. Current research covers both the design aspects of mobile platforms and the challenges of autonomous navigation, trajectory control, and interaction with the environment. The works [1-4] examine mechanical configurations, active suspensions, and the fundamental principles of wheeled mobile robotics. A separate area of research is dedicated to autonomous vehicles for indoor use, as well as for industrial and agricultural operations [5; 8; 9].

To improve motion accuracy, PID controllers with specified quality metrics, predictive control, artificial intelligence methods, and trajectory reconfiguration algorithms are employed [6-8]. However, most known approaches are focused on a specific design, a particular operating mode, or a single controlled parameter – such as speed, position, direction, or trajectory. This limits the ability to transfer the resulting solutions to other platforms and operating conditions.

The problem of controllability is fundamental, as it characterizes a platform's ability to change its state using available control elements [10]. In practical problems, it is complemented by requirements for transition time, energy consumption, motion smoothness, and positioning accuracy [11-13]. Therefore, a generalized approach is needed, in which controllability is considered not merely as the fact that a state is attainable, but as a combination of control capability, sensitivity, and optimality.

Formalization of the State and Control of a Mobile Robotic Platform. A mobile robotic platform is an electromechanical system in which mechanical, electrical, electronic, and information components interact. Its state at any given moment is determined by a set of parameters: coordinates, orientation, velocity and acceleration components, angular velocities of the wheels, drive currents, power source charge, and other quantities. For a generalized description, these parameters are combined into a state vector.

Let $t \geq t_0$ be the operating time of the system, and $x(t)$ be an n-dimensional state vector. Then, the change in the platform's state is considered a continuous process over time. Control actions – such as actuator voltages, motor torques, or specified wheel speeds – are combined into a vector $u(t)$ of dimension m.

$$x = x(t), u = u(t)\,. \tag{1}$$

A mathematical model of the platform's dynamics can be formulated as an initial value problem for a system of differential equations:

$$\dot{x} = X(t, x; u), x(t_0) = x_0\,. \tag{2}$$

where $X(t,x;u)$ – given state-change function;

x_0 – initial state.

Model (2) allows us to determine the state trajectory for a given control. The specific form of the function X depends on the platform design, the kinematic scheme, the drive model, wheel-surface contact, and external disturbances.

In a practical system, there is no need to directly control all components of the state vector. Therefore, a vector of controlled parameters y is introduced, which contains only quantities related to the system's operational objectives: coordinates, velocity, direction, distance traveled, energy consumed, or other metrics.

$$y = Y(x)\,, \tag{3}$$

where y – control vector representing the controlled parameters;

$Y(x)$ – function that defines the controlled parameters of the mobile robotic platform.

Equations (2) and (3) form the basis for the controllability analysis. They distinguish the platform's overall physical state from the parameters that must be ensured by the control system.

The Concept of Intelligent Control and the System Architecture.

Intelligent control can be defined as the process of automatically generating control actions based on the current state, a specified objective, constraints, and an assessment of possible consequences. Unlike local control of a single parameter, an intelligent system must select an operating mode, adapt to changing conditions, predict behavior, and ensure a balance among multiple criteria.

The architecture of such a system is shown in Figure 1. Tasks and target states are fed into the intelligent algorithm, which generates control signals for the actuators. Sensors measure motion and technical condition parameters, after which the information is fed back to the algorithm via a feedback channel.

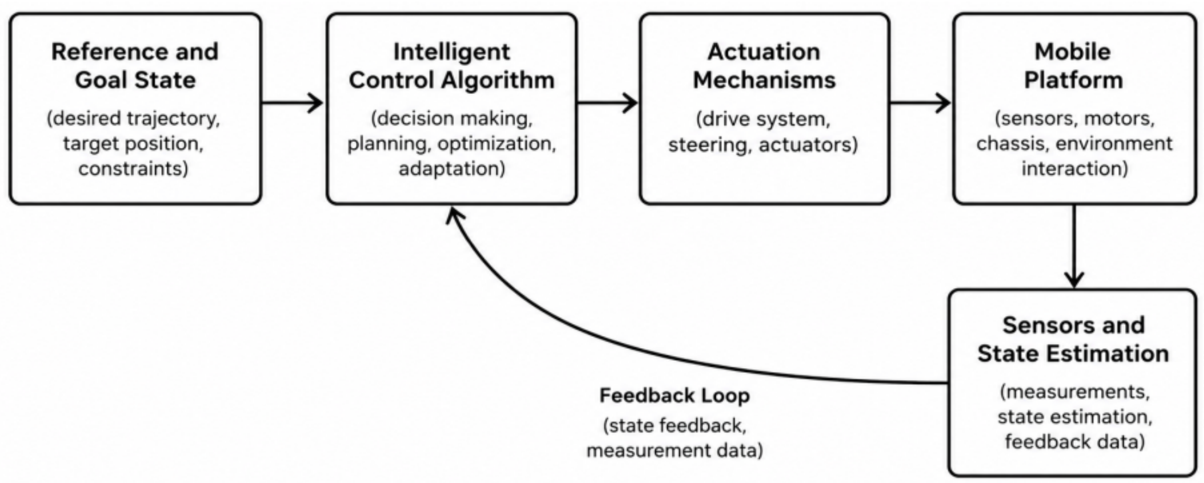

Fig. 1. Architecture of the Intelligent Control System for a Mobile Robotic Platform

The intelligent level may include a state estimation unit, a rule base or environmental model, a prediction module, an optimizer, and diagnostic tools. However, regardless of the specific implementation, its functional core remains the task of determining a value of $u(t)$ that transitions the platform from its initial state to the desired final state while satisfying the specified constraints.

Feedback is of fundamental importance, since the calculated control is implemented under conditions of uncertainty. The measured state differs from the calculated state due to sensor errors, delays, wheel slip, and changes in mass and drive parameters. An intelligent algorithm must not only correct the current error but also assess the likelihood of eventually achieving the goal.

Management Capacity. Controllability is characterized by the existence of at least one admissible control that brings the controlled vector from its initial value y_0 to a specified final value y_1 within a given time. Let U be the set of admissible controls that satisfies the constraints on voltage, current, torque, speed, and safety. Then the controllability condition can be expressed as:

$$\exists u(t) \in U : y(t_1, u) = y_1 . \quad (4)$$

Condition (4) reflects the attainability of a given state but does not specify a particular method for achieving it. For a real-world platform, the set U is functional and continuous, so its direct analysis is complex. A practical approach involves parameterizing the control and discretizing the ranges of its parameters.

For example, the control can be represented as a sequence of constant or linearly varying segments. Each combination of amplitudes and durations corresponds to a distinct state trajectory, which is determined by the numerical solution of Model (2). The set of obtained final values forms an approximate reachability region. If the specified state lies within this region, taking into account the permissible error, the control is feasible.

This approach makes it possible to evaluate the platform's operational limitations as early as the design stage. It allows for determining the maximum speed, minimum turning radius, permissible acceleration time, and other characteristics that cannot always be obtained analytically for a nonlinear model.

Control Sensitivity. Sensitivity characterizes the change in the final controlled state resulting from small changes in control parameters, initial conditions, or model parameters. High sensitivity means that a small error in signal generation or measurement can cause a significant deviation in the final state. For an autonomous platform, this directly affects positioning accuracy and mission stability.

Let the control depend on the parameter vector p. The local sensitivity of the final state can be estimated using the matrix of derivatives:

$$S = \frac{\partial y(t_1, p)}{\partial p}. \tag{5}$$

The elements of the S matrix indicate the extent to which each controlled variable changes when a particular control variable is varied. In the absence of an analytical solution, the derivatives are determined using the finite difference method. For parameter p_i, two or more numerical experiments are performed using closely spaced values, after which the ratio of the change in the final state to the change in the parameter is calculated.

Sensitivity analysis is used to select the discretization step size, estimate the required accuracy of sensors and actuators, and identify the parameters that most significantly affect the result. If the final state is overly sensitive to a particular parameter, it is advisable to use a closed-loop system, adaptation, or a robust algorithm.

Optimal Control. From among the many viable control strategies, it is necessary to select the one that best meets the operational requirements. To this end, a criterion functional $J[u]$ is introduced, which quantitatively evaluates the properties of the process. Depending on the platform's intended use, the criteria may include minimum time, power consumption, path length, deviation from the trajectory, maximum acceleration, or jerk.

The generalized functional can be written as:

$$J[u] = \Phi(y(t_1)) + \int_{t_0}^{t_1} L(t, x, u)\,dt, \tag{6}$$

where Φ – terminal component characterizing the final state;

L – current consumption.

Optimal control is determined by the condition of minimizing the functional over the set of admissible and feasible controls.

For the speed criterion, the functional is related to the transition time. For energy efficiency, power or another quantity proportional to energy consumption is integrated. For motion smoothness, the square of acceleration or jerk is included in the functional. The choice of criterion must correspond to the platform's actual purpose: cargo transport, precise positioning, long-term autonomous operation, or movement in a hazardous environment.

At the same time, optimal control should not be considered in isolation from capability and sensitivity. A solution that is optimal according to a formal criterion may be unsuitable if it is located near the boundary of the operational range or requires excessively high implementation accuracy. Therefore, an intelligent system must use a multi-criteria evaluation, taking into account control margin and robustness.

Computational Implementation of Theoretical Principles. Analytical study of a nonlinear electromechanical platform is possible only for a limited class of models. Therefore, the practical implementation of the proposed approach is based on a combination of computer modeling and numerical methods. The general procedure includes model formulation, control parameterization, generation of a discrete set of control options, numerical integration of the equations of motion, constraint verification, and calculation of evaluation criteria.

The Runge-Kutta methods and other integration methods can be used to solve the initial problem. Capability is assessed by finding control inputs that ensure a given final state. Sensitivity is determined based on the results of repeated calculations with varied parameters. The optimal solution is found by comparing the values of the functional or by applying numerical optimization algorithms.

Discretizing the set of control inputs transforms the abstract problem into a finite computational procedure. The accuracy of the result depends on the discretization step size, but reducing it excessively drastically increases the computational load. Therefore, it is advisable to use an adaptive scheme: first perform a coarse search, and then refine the region around promising options.

The results obtained can be used both during the design phase and in the onboard system. During the design phase, they allow for a comparison of actuator designs, power supply parameters, and sensor characteristics. In real time, pre-calculated control maps or simplified predictive models can enable rapid selection of an action based on the current state.

Discussion of Results. The proposed theoretical framework reconciles the classical concept of controllability with the engineering requirements for mobile robotic platforms. Dividing controllability into capability, sensitivity, and optimality allows for a systematic answer to three practical questions: can the platform perform the task, how reliably will it be performed in the presence of errors, which of the possible control actions is the best according to the selected criterion.

An advantage of this approach is its independence from a specific kinematic configuration. The state vector and model functions can be formulated for differential, automotive, omnidirectional, or multi-wheeled chassis. At the same time, the results directly depend on the adequacy of the model. If slippage, soil deformation, mass changes, or drive dynamics are not taken into account, the calculated reach area may differ from the actual one.

Further development involves combining numerical analysis with adaptive parameter estimation and artificial intelligence methods. Data from onboard sensors can be used to refine the model, and accumulated experience can be used to accelerate the search for control strategies. At the same time, machine learning should complement, rather than replace, a physically grounded model and the verification of safety constraints.

Conclusions. This article establishes the theoretical foundations for the intelligent control of mobile robotic platforms. The platform's state is represented by a vector of variables, and the control is represented by a vector of control inputs that determine the change in state over time. To isolate the target characteristics, a vector of controlled parameters is introduced. Controllability is proposed to be considered as a combination of controllability, sensitivity, and optimality of control. Controllability determines the ability to achieve a given state, sensitivity characterizes the effect of errors and parameter variations, and optimality ensures the selection of the best option according to a specified criterion. It is shown that the computational implementation of this approach can be based on the discretization of the set of admissible controls, the numerical integration of the mathematical model, and the application of optimization methods. The results obtained can be used for engineering analysis, design, and development of onboard algorithms for autonomous mobile robotic platforms.

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