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RESEARCH OF CONTROL METHODS FOR A MOBILE MANIPULATION ROBOTIC PLATFORM WITHIN THE FRAMEWORK OF INDUSTRY 5.0 CONCEPTS

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The paper considers current methods of controlling a mobile robotic manipulation platform in the context of implementing Industry 5.0 concepts, which envisage the integration of humans and robots into a single collaborative production environment. The research focuses on analyzing the possibilities of applying predictive control models, impedance strategies, and machine learning methods to achieve adaptability, flexibility, and safe interaction with the operator in dynamic conditions. The feasibility of using hybrid control architectures that combine the reliability of classical approaches and the intelligence of modern algorithms is substantiated. The results emphasize that effective control of mobile manipulation platforms is the key to creating innovative, human-centered production systems that comply with Industry 5.0 principles.

The current stage of robotics development is characterized by the integration of mobile manipulation platforms into production processes, which opens up new opportunities for the implementation of Industry 5.0 concepts [1-3]. Unlike previous generations of industrial automation, the modern paradigm is aimed at creating human-centered, flexible, and highly efficient production systems in which robots not only perform auxiliary functions but also act as active elements of a collaborative environment [4-7]. Mobile manipulation platforms, capable of combining the functions of movement and precise execution of manipulation actions in dynamic production conditions, play a special role in this context. Research into methods of controlling such systems requires the development of adaptive algorithms that ensure a balance between the robot's autonomy, its ability to collaborate, and a high level of safety in interaction with humans. Within the framework of Industry 5.0, issues of integrating artificial intelligence, computer vision systems, fuzzy logic, and optimization methods into the control structure of mobile platforms are becoming relevant. This allows for an increase in the level of self-learning, adaptability, and resilience of robotic systems to environmental uncertainties. Thus, research into methods of controlling mobile manipulation platforms creates the basis for the development of intelligent production, in which humans and robots interact as equal participants in joint activities. We will conduct research on modern methods and present the results below[8-10].

Model Predictive Control (MPC) is a classic optimal approach that predicts the future behavior of a mobile manipulation platform over a finite horizon and solves the motion and manipulation problem as an integrated optimization problem, allowing for dynamic, contact, and safety constraints to be taken into account. This method is well suited for real-time trajectory planning and obstacle avoidance tasks, but requires accurate models or fast learning surrogates for real-world applications.

Integrated Whole-Body MPC approaches distribute priorities between the mobile base and the manipulator, allowing simultaneous optimization of robot kinematics and dynamics during transitions between spatial tasks and manipulation, significantly improving manipulability and stability in complex scenarios.

Neural network and model-oriented variations of MPC (e.g., NN-MPC or quasi-model schemes) extend the applicability of the approach to nonlinear, poorly modeled mobile manipulator systems, but require careful validation to ensure safety when interacting with humans.

Impedance and admittance control are fundamental methods for ensuring safe physical interaction between the manipulator and its environment and humans. They formalize the desired contact dynamics as a force-displacement relationship, making them a natural choice for collaborative mobile platforms in Industry 5.0. The use of variable impedance control allows the stiffness and damping to be adapted to specific phases of the task (movement, approach, contact), which increases resistance to surface uncertainties and minimizes the risk of injury to humans during collaboration. Adaptive impedance controllers based on MRAC and similar schemes provide automatic adjustment of controller parameters when the load mass changes, model distortions occur, or contact conditions change, which is important for platforms that perform diverse operations in production. ([Frontiers][5])

Classic PID/LQR control and its extensions remain useful as verified low-level components for stabilizing the drives and actuators of a mobile platform, but they are limited when operating in uncertain environments or when multitasking without external schedulers.

Adaptive control and online learning (adaptive control) make it possible to compensate for unknown dynamic parameters and slowly changing environmental influences, making them useful for mobile manipulators with variable loads and mechanical wear.

Sliding-mode control and H-infinity strategies provide high resistance to uncertainties and external disturbances, but can introduce high frequencies in the command and require filtering, which is critical when interacting with humans; these methods are often used in hybrid architectures for robust low-level control.

Behavior-based and reactive architectures use simple rule modules to respond quickly to unpredictable events, which is useful for safe movement in crowded areas, but they typically do not guarantee global optimality or smoothness of manipulation trajectories.

Hybrid approaches combine high-level trajectory planners with low-level reflexive modules and provide a compromise between efficiency and safety; in the context of Industry 5.0, such architectures allow human involvement in control to be maintained while delegating routine operations to robots.

Reinforcement learning (RL), and especially its deep variants (Deep RL), show strong potential for learning complex manipulation skills and autonomously mastering contact-rich tasks, but they often require large amounts of data and carefully designed simulations for safe transfer to the real world.

Multi-agent RL and decentralized learning schemes are useful for coordinating groups of mobile manipulators, allowing each agent to learn locally with minimal communication, which increases the scalability of systems and their resistance to communication failures.

Combinations of MPC and RL (e.g., RL for learning models or policy variations that integrate into MPC) have a synergistic effect: MPC ensures safety and dynamic constraints, while RL reduces the need for an accurate model and increases adaptability to unknown scenarios.

Sim-to-real and knowledge transfer methods are critical for applying DRL in mobile manipulation; they include domain adaptation, model randomness, and experiments on real equipment to minimize discrepancies between the simulator and real conditions.

Bayesian and meta-learning approaches allow policies to be adapted more quickly to new tasks or new payload configurations, which is useful for production lines with frequent changes in product and operating rules.

Optical vision methods and visual servo control remain key for accurate manipulator positioning when grasping objects and for situations where GPS or global localization tools are not available; integration with MPC or RL improves response to dynamic scene changes.

Real-time fusion of sensor data (vision, lidar, force/torque, IMU) improves the reliability of platform and object state estimation in the environment, which directly affects motion planning accuracy and safety when working with humans.

POMDP/Belief-space approaches and planning under uncertainty are useful in tasks where observations are incomplete or noisy; they allow decisions to be made taking into account uncertainty and risks, which is important in crowded industrial environments.

Safety services and behavior verification (safety verification, runtime monitoring) are becoming mandatory for Industry 5.0 applications, as humans work alongside autonomous platforms and certification and behavior audit requirements are becoming more stringent.

Decentralized control architectures with local controllers and minimal centralized coordination increase the resilience of the production line to communication failures and allow robot groups to be scaled without exponential growth in communication costs.

In short, an effective control architecture for a mobile manipulation platform in Industry 5.0 is a hybrid multi-level system that combines the predictability and guarantees of MPC, the adaptability of impedance circuits, the learning capabilities of RL, and the reliability of decentralized and reactive modules focused on safety and the human factor.

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