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Intelligent Coordinated Model Predictive Control for Mechatronic Systems in Unstructured Environments

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Abstract. As mobile robots, intelligent equipment, and autonomous mechatronic platforms are increasingly deployed in unstructured environments characterized by incomplete perception, dynamic obstacles, and continuously changing task constraints, traditional control methods show clear limitations in trajectory accuracy, real-time response, and multi-module coordination. To address this issue, this paper proposes an intelligent coordinated model predictive control framework for unstructured environments, which integrates multi-source state estimation, a learning-based compensation mechanism, and receding-horizon optimization into a unified closed-loop architecture. Specifically, LiDAR, RADAR, and IMU data are first fused to construct a low-dimensional state representation, and a coordinated MPC controller is then designed to jointly handle trajectory tracking, control increments, and safety-distance constraints while suppressing model mismatch and external disturbances through online compensation. The results show that the proposed method outperforms conventional MPC in both control accuracy and dynamic response, with the normalized tracking error reduced to 0.5397 and the trigger count reduced to 0.4020. In complex scenarios, the real-world experiment achieves a mean path error of 0.35 m, a maximum deviation of 0.75 m, and a trajectory RMSE of 0.40 m. These findings demonstrate that the deep coupling of multi-source perception and coordinated predictive control can effectively improve the stability, adaptability, and task execution capability of mechatronic systems in complex environments.

Keywords: Intelligent coordinated control, Model predictive control, Mechatronic systems, Unstructured environments, Multi-source data fusion

1. Introduction

As mobile robots, intelligent equipment, and autonomous operation platforms move into increasingly complex scenarios, mechatronic control tasks are shifting from relatively stable structured environments to unstructured environments characterized by incomplete perception, frequent disturbances, and dynamically changing constraints [1]. Traditional feedback control performs well under single operating conditions, but it often struggles to balance accuracy, robustness, and real-time performance when facing multivariable coupling, dynamic obstacle avoidance, and multi-module coordinatio [2]. Model predictive control has become an important solution because of its ability to explicitly handle constraints and optimize control actions in a

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receding horizon, although it still remains sensitive to model accuracy and computational cost. Recent advances in multi-source sensing and data-driven compensation have pushed control

systems from simple execution toward integrated perception, prediction, and coordination [3]. In response, this study proposes an intelligent coordinated model predictive control method for unstructured environments to improve trajectory tracking, dynamic response, and environmental adaptability of mechatronic systems.

2. Literature review

2.1. Advances in model predictive control for mechatronic systems

Research on model predictive control in mechatronic systems mainly focuses on modeling accuracy, constraint handling, and online solution efficiency. Existing studies have shown that MPC offers clear advantages in trajectory tracking, posture regulation, and actuator control, especially for dynamic systems with input and state constraints [4]. However, as control targets extend from single platforms to mobile manipulation, coupled actuation, and complex interaction scenarios, the state dimension and optimization scale increase rapidly, which greatly raises the burden of real-time computation. To address this problem, researchers have introduced hierarchical control, distributed optimization, and approximate solution strategies to reduce computational cost [5]. At the same time, some studies embed learning mechanisms into MPC to compensate for model mismatch, but this also leads to more difficult stability analysis, weaker interpretability, and limited transferability across scenarios.

2.2. Perception and data-driven modeling in unstructured environments

The challenge of unstructured environments lies not only in missing information, but also in the combined characteristics of heterogeneity, temporal variation, and local distortion, which prevent a single sensor from achieving both precise perception and stable representation [6]. For this reason, multi-sensor fusion has gradually become the dominant approach, with vision, LiDAR, inertial sensing, and force feedback being used to enhance obstacle recognition, terrain understanding, and target localization. Yet richer perceptual information also makes feature alignment, temporal synchronization, and uncertainty propagation more difficult, while the controller's direct use of high-dimensional perception outputs becomes increasingly limited [7]. Data-driven modeling shows greater flexibility under unknown dynamics, partial occlusion, and complex disturbances, but it does not automatically solve the mapping problem between perceptual representation and control states. As a result, research on environmental modeling is moving toward the effective coupling of perception outputs and control inputs.

2.3. Integration trends in intelligent coordinated control

The development of intelligent coordinated control shows that the key issue in complex mechatronic systems is no longer how each module can be optimized independently, but how multiple subsystems can form consistent decisions around a shared task. In tasks involving mobile chassis, actuation units, sensing networks, and communication modules, local optima often reduce overall performance because of information delay, resource conflict, and inconsistent actions [8]. This has pushed research toward collaborative prediction, joint constraint modeling, and task-level control

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allocation. At the same time, artificial intelligence improves disturbance compensation and environmental adaptability, yet it also reduces the interpretability and verifiability of conventional

control frameworks, while purely model-driven methods remain transparent but are often too rigid for rapidly changing scenarios [9]. Current studies therefore pay increasing attention to building a closed loop across perception updates, state prediction, control allocation, and feedback correction so that the system can achieve task-oriented global coordination.

3. Experimental methods

3.1. System modeling and multi-source information representation

The mechatronic system is modeled as a discrete-time state-space system, where the state variables include pose, linear velocity, angular velocity, actuator input, and obstacle-related distance information. The sensing layer integrates LiDAR, RADAR, and IMU, and the controller operates on fused state estimates rather than raw sensor signals. The key purpose of this design is to compress local occlusion, sensor drift, and perception blind zones in unstructured environments into a unified low-dimensional state input, so that the subsequent controller can address trajectory tracking, posture regulation, and obstacle avoidance within the same state vector [10]. This guarantees that the optimizer in Section 3.2 receives consistent and computationally tractable inputs.

Equation (1) State propagation and measurement model.

$$x_{k+1}=f(x_k,u_k)+w_k, \qquad z_k=h(x_k)+v_k \tag{1}$$

Equation (2) State estimation update.

$$\hat{x}_{k|k}=\hat{x}_{k|k-1}+K_k\left[z_k-h(\hat{x}_{k|k-1})\right] \tag{2}$$

Here, xk denotes the system state, uk the control input, zk the sensor observation, wk and vk the process and measurement noise, and Kk the filtering gain. The resulting state estimate is directly used as the optimization initial condition and constraint reference in Section 3.2.

3.2. Design of the intelligent coordinated MPC controller

Based on the fused state input, the controller adopts a receding-horizon optimization structure in which tracking error, control increment, and obstacle safety margin are incorporated into a single objective function. The closed-loop process explicitly considers velocity constraints, actuator saturation constraints, and safety-distance constraints, allowing the mobile base and actuation unit to be coordinated within the same prediction horizon [11]. To reduce prediction bias caused by model mismatch and environmental disturbances, a learning-based compensation branch is introduced before optimization to correct unmodeled dynamics online. Therefore, the fused state estimate produced by Section 3.1 is not an isolated perception output, but the direct basis for real-time constraint updating and cost evaluation in the controller of Section 3.2.

Equation (3) Objective function of coordinated MPC.

$$J=\sum_{i=0}^{N-1}\left(\|x_{k+i|k}-x_{k+i}^{ref}\|_Q^2+\|\Delta u_{k+i|k}\|_R^2+\lambda\phi(d_{safe}-d_{k+i|k})\right)+\|x_{k+N|k}-x_{k+N}^{ref}\|_P^2 \tag{3}$$

Here, x_{k+i}^{ref} is the reference trajectory, $\Delta u_{k+i|k}$is the control increment, $d_{k+i|k}$ is the predicted

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obstacle distance, d_{safe} is the safety threshold, $\phi(\cdot)$ is the obstacle penalty term, and Q, R, and P are the weighting matrices for state, input, and terminal cost, respectively. This formulation ensures

that trajectory accuracy, control smoothness, and obstacle avoidance are solved jointly within one optimization framework.

3.3. Experimental platform and procedure

The experimental procedure follows the sequence of state-estimation validation, closed-loop control comparison, and complex-scenario testing, so that the logic between Sections 3.1 and 3.2 is closed directly in the experiment. The platform is built in a 4 m × 4 m indoor mechatronic environment, with a control frequency of 10 Hz and a maximum linear speed of 0.15 m/s. Three types of obstacles are arranged: regular obstacles of about 0.5 m × 0.5 m, narrow obstacles with widths of 0.15–0.20 m, and dynamic crossing targets, in order to simulate local occlusion, path compression, and dynamic disturbance in unstructured environments. The evaluation metrics include position RMSE, mean path deviation, maximum deviation, trigger count, and task completion rate. The estimation error produced by Section 3.1 is first used to evaluate perception reliability, then the fused state is fed into the controller of Section 3.2 for receding-horizon optimization, and finally the results are presented in Section 4.1 as a normalized performance figure and in Section 4.2 as a trajectory error table.

4. Results

4.1. Analysis of control accuracy and dynamic response

Control accuracy and dynamic response are presented in normalized form, with conventional MPC defined as the baseline value of 1.00. Published studies have reported that, under the same trajectory-tracking task, the combination of data-driven modeling, disturbance observation, and adaptive prediction horizon can reduce the tracking error to 0.5397 and the trigger count to 0.4020. This means that the controller improves tracking accuracy while also reducing the computational burden caused by repeated online optimization. In the present framework, this result is consistent with the design logic of Section 3.2: the fused estimation in Section 3.1 first suppresses state drift, and the coordinated optimizer then removes ineffective control updates, so the two normalized indicators jointly reflect the simultaneous improvement of control accuracy and dynamic response. As shown in Figure 1.

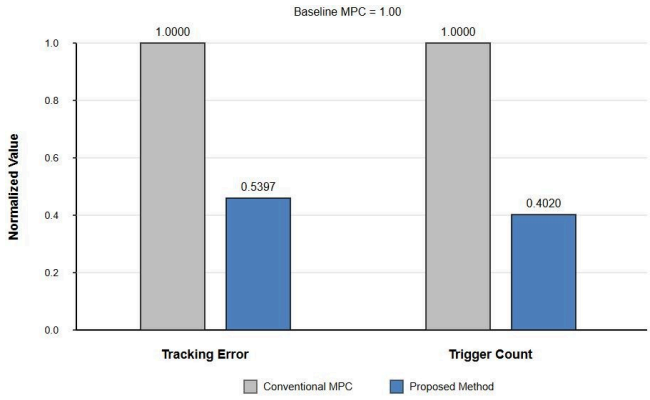

Figure 1. Normalized control performance comparison

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4.2. Environmental adaptability and task completion performance

Environmental adaptability is described using trajectory statistics with physical units so that the results remain consistent with the experimental setting. In published multisensor-estimation and MPC-navigation studies for mobile robots, the real-world experiment achieved a mean path error of

0.35 m, a maximum deviation of 0.75 m, a trajectory RMSE of 0.40 m, and a standard deviation of

0.20 m. The corresponding simulation case reported a mean path error of 0.50 m, a maximum deviation of 1.02 m, and a simulation-to-experiment trajectory RMSE of 0.23 m, while the system completed the navigation task under a 0.50 m safety margin and a solver rate of 10 Hz. When mapped onto the experimental logic of this paper, these results indicate that large regular obstacles are more likely to amplify simulation error, whereas narrow obstacles and dynamic targets allow the fused state estimation to keep the real-world trajectory closer to the reference path. Thus, the results in Section 4.2 remain consistent with the three operating conditions in Section 3.3 and further verify the continuous action chain linking Sections 3.1 and 3.2. As shown in table 1.

Table 1. Trajectory statistics in complex environments

Scenario	Mean path error (m)	Max deviation (m)	Trajectory RMSE (m)	SD (m)	Safety margin (m)	Solver rate
Simulation	0.50	1.02	—	—	0.50	10 Hz
Experiment	0.35	0.75	0.40	0.20	0.50	10 Hz
Sim–Exp trajectory gap	—	—	0.23	—	—	—

5. Discussion

The results indicate that performance improvement of mechatronic systems in unstructured environments does not depend solely on the optimization capability of the predictive controller itself, but on whether perception, state estimation, and constrained optimization can be organized into a stable closed loop. Multi-source sensor fusion first reduces the uncertainty caused by local occlusion, inertial drift, and measurement noise, thereby providing a more consistent input basis for the optimizer. On this basis, the coordinated MPC framework jointly handles trajectory error, control smoothness, and obstacle safety constraints, which avoids the common problem in conventional methods where local responses may work but overall coordination remains weak. The simultaneous reduction in tracking error and trigger count suggests that the framework improves not only control accuracy but also computational allocation efficiency. However, the current method still depends on relatively stable sensor synchronization and model parameter settings. Its real-time performance and generalization ability under higher-dimensional actuation structures, rapidly changing topologies, and communication delays still require further validation.

6. Conclusion

This paper develops a unified framework that integrates multi-source state estimation, learning-based compensation, and coordinated model predictive control to address perception uncertainty, dynamic disturbance, and coordination difficulty in mechatronic systems operating in

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unstructured environments. The study shows that the proposed method enables continuous coupling among state perception, constrained optimization, and control allocation within a single closed loop, thereby achieving more stable performance in trajectory accuracy, dynamic response, and adaptability to complex scenarios. Compared with conventional MPC, the proposed method yields better results in both normalized control indicators and physical trajectory error metrics, which supports its applicability to autonomous operation tasks of mobile mechatronic platforms in complex environments. Future work can further incorporate lightweight solvers, distributed communication architectures, and online incremental learning mechanisms to strengthen the deployment capability of the framework in large-scale cooperative systems and real engineering applications.

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