ICRA2026 Late Breaking Results Poster presented at
2026 IEEE International Conference on Robotics and Automation (ICRA 2026)
June 1-5, 2026. Vienna, Austria

Inverse Reachability Map Guided Motion Planning of Mobile Manipulator

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Abstract - Mobile manipulators must coordinate end-effector (EE) tracking and mobile base motion to perform manipulation tasks robustly. However, even when the same EE trajectory is feasible, different base poses can lead to substantially different manipulator configurations, manipulability levels, and proximity to singularities. Thus, accurate EE tracking does not guarantee kinematically suitable whole-body behavior. To address this issue, a hierarchical framework is proposed that combines 1) an manipulator controller for EE tracking considering base motion, 2) an inverse reachability map (IRM) that encodes kinematically feasible base regions for the current and predicted EE states, and 3) a model predictive controller (MPC) that optimizes base velocity using the IRM as a soft cost. In the proposed architecture, the manipulator executes the task, the IRM evaluates which base regions are more reachable for the task, and the MPC generates base motion accordingly. Simulation results demonstrate that the proposed method improves manipulability while maintaining accurate EE tracking, highlighting the importance of reachability-aware base behavior in mobile manipulation.

I. INTRODUCTION

Mobile manipulators combine the mobility of a wheeled base with the dexterity of a robotic manipulator, but successful task execution depends not only on the manipulator behavior but also on the base motion from which the task is performed. A key observation is that, due to kinematic redundancy, the same EE target can often be realized by multiple base-manipulator configurations, yet these solutions can differ significantly in manipulability and proximity to singularity. Some base poses allow the manipulator to operate with high manipulability and sufficient margin from singular configurations, whereas others lead to less desirable manipulator configurations even though the EE trajectory is still tracked successfully.

Most existing whole-body or tracking-based approaches mainly optimize tracking accuracy, control effort, and constraint satisfaction. While effective for following EE references, they do not explicitly encode whether the selected base pose is suitable from the manipulator's kinematic perspective. As a result, the base may remain in a configuration that leads to low-manipulability manipulator postures throughout the task.

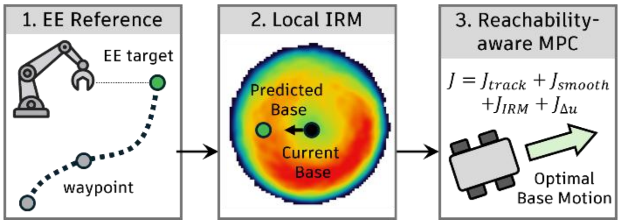

Figure 1. Schematic diagram of IRM-guided MPC

In this work, the mobile base was treated as an active task-level optimization variable rather than a passive support component. Accordingly, a motion planning framework is proposed that combines manipulator EE tracking, IRM-based geometric preference, and MPC-based base optimization. In Fig.1, the manipulation controller tracks the desired EE motion, the IRM evaluates suitable base regions for the task, and the MPC uses this information as a soft reachability-aware cost to generate base velocity commands.

II. INVERSE REACHABILITY MAP GUIDED MOTION PLANNING OF MOBILE MANIPULATOR

The proposed framework consists of three modules: Manipulation, IRM, and MPC. In this paper, the end-effector trajectory is generated by a trajectory planner, such as a B-spline, Catmull-Rom spline, or linear segment with parabolic blends (LSPB). The manipulation module tracks the desired EE trajectory using a pseudo-inverse $J^{\dagger}$ based computed torque structure. Let the desired task-space states be $x_d, \dot{x}_d, \ddot{x}_d$, and the current states be $x, \dot{x}$. The reference task-space acceleration $\ddot{x}_{ref}$ is derived as (1) and the corresponding joint-space reference acceleration $\ddot{q}_{ref}$ is obtained as (2). The torque command τ_{cmd} is then generated using inverse dynamics as (3). To exploit the redundancy of the 7-DoF manipulator, a null-space term($N = I - J^{\dagger}J$) based on the Yoshikawa manipulability[1] gradient $H(q)$ is added on (4) so that the manipulator maintains suitable configurations while preserving the primary EE tracking task. The current base state is fed-forward to the manipulation module, allowing the manipulator to compensate for platform motion while tracking the desired EE trajectory.

$$\ddot{x}_{ref} = \ddot{x}_d + K_d(\dot{x}_d - \dot{x}) + K_p(x_d - x) \tag{1}$$

$$\ddot{q}_{ref} = J^{\dagger}\left(\ddot{x}_{ref} - \dot{J}\dot{q}\right) \tag{2}$$

$$\tau_{cmd} = M(q)\ddot{q}_{ref} + C(q, \dot{q}) \tag{3}$$

$$\ddot{q}_{ref} \leftarrow \ddot{q}_{ref} + N(\alpha\nabla H(q) - \beta\dot{q}), \tag{4}$$

The IRM module provides a geometric prior over suitable base locations for a given EE target. Rather than being imposed as a hard constraint, the IRM is incorporated into the MPC objective as a soft preference map. In this work, normalized IRM scores and Gaussian neighborhood weights computed from predicted base positions are combined to form a preference distribution, represented by the weighted centroid of suitable base positions $\hat{x}_k^{ref}$. This formulation avoids abrupt switching and improves numerical smoothness.

The IRM[2] used in this work is constructed from a pre-computed 3-D inverse reachability representation. Following an offline voxelization of the workspace, base poses are sampled relative to the end-effector, and each voxel is assigned a score based on inverse-kinematics feasibility and manipulability. At runtime, for a given EE pose, a 2-D IRM is obtained by slicing the 3-D IRM with the task-specific ground plane and transforming the resulting map into the world frame. This enables efficient computation of base regions that are more likely to satisfy inverse kinematics for the current task. In the proposed framework, the resulting 2-D IRM is interpreted as a IRM guided map and incorporated into the MPC objective as a soft cost.

The MPC module generates base velocity commands by jointly considering tracking error, control effort, smoothness, and IRM-based reachability cost in (5). As a result, base motion emerges from a unified receding-horizon optimization that balances task tracking and kinematic feasibility.

$$J = \sum_{k=0}^{N-1} \big(\| x_k - \hat{x}_k^{ref} \|_Q^2 + \| u_k \|_R^2 + \| \Delta u_k \|_S^2 + w_{IRM} \phi_{IRM}(x_k) \big) \tag{5}$$

III. SIMULATION

To validate the proposed framework, simulations were conducted in Gazebo using a 7-DoF Franka Emika Panda manipulator mounted on an Agile-X Scout 2.0 mobile base. In simulation 1, the proposed method was compared against a whole-body MPC controller[3] implemented with the OCS2 library[4]. Both methods were evaluated under the same linear trajectory. In simulation 2, different mobile manipulation tasks were conducted with a predefined trajectory.

Fig. 2 shows the EE tracking accuracy and manipulability of the two methods in simulation 1. The proposed method maintained a smaller EE position error than the OCS2-based baseline. More importantly, while the OCS2 controller exhibited a drop in manipulability, the proposed method preserved relatively high manipulability. As shown in Fig. 3, the resulting manipulator configurations are notably different. The baseline tends to drive the manipulator toward a configuration with lower manipulability, whereas the proposed method maintains a configuration with higher manipulability.

In simulation 2, task success was demonstrated for two mobile manipulation tasks as shown in Fig. 4. Specifically, a spray-painting task was validated with a predefined trajectory on the wall, and an inspection task was validated for object examination. The feasible mobile base region was determined by the IRM and the obstacle map, and the results confirmed that the task was executed from base positions that provide high manipulability.

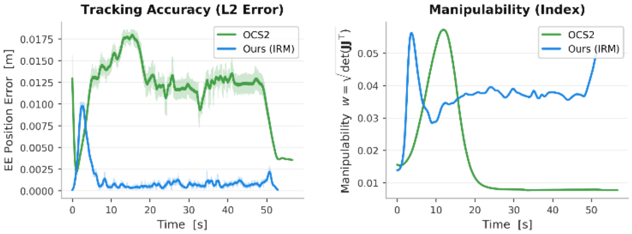

Figure 2. EE error and manipulability index (Tracking linear path)

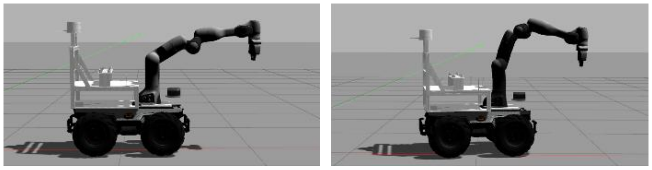

Figure 3. Whole-body configuration (left : OCS2- baseline, right : Ours)

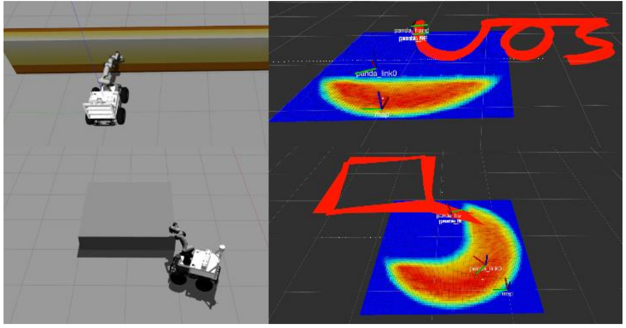

Figure 4. Mobile manipulation task (left: spray-painting task, right : inspection task)

IV. CONCLUSION

This paper presented an IRM-guided MPC framework for mobile manipulation. By using inverse reachability map as a soft cost, the proposed method generates base motion that better preserves high-manipulability arm configurations during task execution. Simulation results showed accurate EE tracking, higher manipulability, and more balanced manipulator configurations than the baseline. Future work will consider learning-based methods in generating an inverse reachability map and incorporating whole-body dynamics

ACKNOWLEDGMENT

This work was supported by ITECH R&D program of MOTIE/KEIT. (Project No. 20026194), and by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIT) (RS-2026-25492007).

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