Planning and Control of Mobile Manipulators for Inspection of Clustered Environments

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I. INTRODUCTION

MANY industries have confined, clustered environments that require routine inspections. Nuclear facilities, in particular, have extensive pipe networks that pose additional radiological challenges, making human inspection unsuitable. A mobile manipulator can inspect areas unreachable by most mobile robots without the additional risks and hazards associated with using aerial robots.

This work formulates a whole-body controller for a non-holonomic mobile manipulator as a Quadratic Program (QP), utilising Vector Field Inequalities (VFIs) to constrain the system. We introduce a stochastic point-to-plane constraint to handle uncertainty in the walls' localisation and an online path planner that combines coverage path planning and 3D reconstruction.

II. WHOLE-BODY CONTROL OF A NON-HOLONOMIC MOBILE MANIPULATOR

The motion controller, formulated as a constrained QP [1], enforces exponential convergence of the task-space error and is given by

$$\boldsymbol{u} \in \underset{\dot{\boldsymbol{q}}}{\operatorname{argmin}} \quad ||\boldsymbol{J}\dot{\boldsymbol{q}} + \beta\tilde{\boldsymbol{x}}||_2^2 + \zeta \, ||\dot{\boldsymbol{q}}||_2^2$$
$$\text{subject to} \quad \boldsymbol{W}_i\dot{\boldsymbol{q}} \preceq \boldsymbol{w}_i, \boldsymbol{W}_e\dot{\boldsymbol{q}} = \boldsymbol{w}_e, \quad (1)$$
$$\Pr(\boldsymbol{W}_c\dot{\boldsymbol{q}} \succeq \boldsymbol{w}_c) \succeq \boldsymbol{\alpha}_c,$$

where $\boldsymbol{q} = [\boldsymbol{q}_{\text{base}}^T \quad \boldsymbol{q}_{\text{arm}}^T]^T$ is the combined configuration vector, $\boldsymbol{J} \triangleq \boldsymbol{J}(\boldsymbol{q})$ is the task Jacobian matrix, and $\tilde{\boldsymbol{x}}$ is the task-space error with controller gain and damping given by $\beta, \zeta \in (0, \infty)$, respectively. The system is subject to a series of linear joint and task-space constraints given as differential inequalities. The non-holonomic constraint is enforced as an equality constraint using [2]. We propose chance constraints with VFIs [1] to enforce a probabilistic distance constraint to geometries with uncertainties.

III. STOCHASTIC CONSTRAINT

Geometric primitives can be extracted from sensor data using RANSAC to constrain the system, but this introduces uncertainty that could lead to collisions or constraint violations. Methods like [3] use a buffer to prevent discretization-induced violations, but determining its size to account for noisy measurements is non-trivial. Assuming a normal distribution for the plane pose, we use a VFI and a chance constraint to determine the buffer. We transform it into a deterministic form by applying the inverse cumulative distribution function
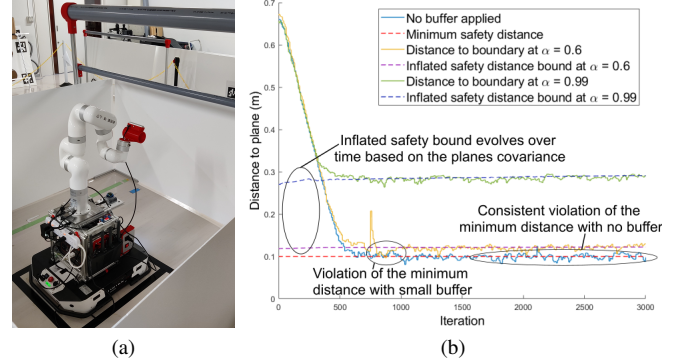
Fig. 1. (*a*) Experimental setup for testing the mobile manipulator enclosed by four walls with an overhead pipe network; (*b*) a graph of the distance between the end effector and an estimated plane with and without the buffered constraint showing violations.

(CDF) to obtain $-\hat{\boldsymbol{J}}_{\boldsymbol{\pi}}\dot{\boldsymbol{q}} \leq \eta(\hat{d}_{\boldsymbol{\pi}} - d_{\min}) - z_{\alpha}\sigma_{\boldsymbol{\pi}}$, where $\hat{\boldsymbol{J}}_{\boldsymbol{\pi}}$ is the expected distance Jacobian, $\hat{d}_{\boldsymbol{\pi}}$ is the expected distance, $d_{\min}$ is the safety distance, z_{α} is the inverse CDF for a given probability, α, and $\sigma_{\boldsymbol{\pi}}$ is the propagated variance.

IV. COVERAGE PATH PLANNING

We initially implemented the algorithm in [4] with a known pipe network; however, when we relaxed the assumption of a known network, the method became unsuitable due to inaccuracies in localising the pipes. A new approach is being developed that combines coverage path planning and 3D reconstruction via Next Best View (NBV) to enable online exploration and inspection of these large pipe networks based on no prior knowledge. The coverage problem is redefined using a coverage information gain, similar to NBV; the weighted combination of reconstruction and coverage information gain selects the best inspection point online.

V. EXPERIMENTAL RESULTS AND DISCUSSIONS

The enclosed mobile manipulator with a pipe network is shown in Fig. 1a. The mobile base pose was estimated using FAST-LIO [5], and the planes and pipes were extracted using RANSAC [6]. Stochastic point-to-plane constraints were used to ensure the manipulator and base did not collide with the environment. Although, at a probability of 0.99, violations of the buffered constraint occurred, the underlying constraint was never violated, unlike when there was no buffer present, as shown in Fig. 1b.

VI. CONCLUSION

Stochastic constraints allow incorporating measurement uncertainty into the distance constraints to provide a probability that the system constraints are maintained. While the deterministic form of the constraint is generalisable to any primitive and has been demonstrated for a plane, propagating uncertainty for other primitives remains to be generalised. The current development of the online planner aims to combine tasks into a single approach, with future work testing this approach and providing formal guarantees of coverage.

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