TI-P: Tactile-based Interactive Motion Planner in Unknow Cluttered Environemnts

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***Abstract*—Robotic motion in unknown cluttered environments often failures from catastrophic collisions and obstructions due to constrained free-motion space and light-suffer challenges. Multimodal tactile perception with force and proximity sensing offers inherent advantages in overcoming these limitations. This paper proposes a tactile-based interactive motion planning method (TI-P) using multimodal tactile sensing, which utilizes real-time tactile feedback to perceive the environment and infer the force-displacement characteristics of interacting objects. These interaction features are integrated into a sampling-based motion planner to predict the maximum connectivity probability of candidate trajectories. Subsequently, the planner interpolates sampled points and extrapolates the motion of objects along the trajectory to compute the optimal interaction forces for driving the robot. Simulation results demonstrate that the proposed planner effectively guides the robot to compliantly manipulate obstacles in its path, significantly improving motion adaptability in unknown cluttered environments.**

Keywords—interactive motion planning, tactile perception, unknown cluttered environments, perception-motion closed loop

I. Introduction

The recent surge in research interest surrounding the autonomous motion of robotic agents in cluttered environments stems from their potential applicability in community-level scenarios [1-4]. These applications span unstructured domains such as households[5] and elderly care facilities[6], where environmental unpredictability necessitates superior motion adaptability compared to structured industrial environments.

The primary objective of deploying robots in community environments is replace human labor, mitigate workforce shortages, and enhance daily convenience[5, 7]. However, such environments often feature highly cluttered spaces due to efficient space utilization and human living habits. This results in light-suffer and constrained free-motion space, posing significant challenges to robotic perception and movements. While visual perception remains prone to high uncertainty, catastrophic collisions may lead to motion failure. In contrast, humans rely on tactile perception to perceive their surroundings and reconfigure the spatial state of manipulable objects to facilitate movement—a capability that remains challenging for robots to replicate.

Prior studies have incorporated tactile feedback at the control level to achieve compliant environmental interaction through contact force regulation [2, 8]. However, the success of such methods heavily depends on predefined motion trajectories. Recent advances explore tactile-aware motion planning to enhance robotic adaptability in cluttered scenes [9-11]. For instance, [9] introduced a movement primitive-based planning method, where tactile signals are mapped to predefined motion primitives for tactile-guided navigation. In environments with movable objects, a physics simulation-aided planner is proposed[11]. The pre-optimizes actions in simulation can prevent catastrophic collisions. Nevertheless, these methods rely on prior knowledge of object interaction properties, limiting their deployment in unknown environments. Ideally, robots should autonomously infer interaction characteristics and integrate such knowledge into planners to generate adaptive interaction strategies.

Inspired by human tactile-guided interaction behaviors, we propose a Tactile-based Interactive Motion Planner (TI-P)—a closed-loop framework constrained by multi-dimensional object interaction features. The TI-P architecture comprises:

1) An environment understanding module that infers object interaction features from multimodal tactile data

generated during bodily interactions, enabling behavior-guided perception;

2) A planner module that generates interpretable interaction actions using these features, achieving perception-guided behavior.

By integrating real-time tactile inference with spatial state reconfiguration of operational objects, TI-P actively expands the free motion space, significantly enhancing robotic adaptability in unknown cluttered environments (Fig.1).

Specifically, the TI-P framework integrates proximity sensing, force feedback, and from electronic skins and proprioceptive data to achieve real-time object localization. The perceived surface position of an object O_i can be represented as ${}^{W}P_{O_i} = {}^{W}T_{E_i}{}^{E_i}P_{O_i} \in \mathbb{R}^3$, ${}^{W}T_{E_i} \in SE(3)$ denotes the homogeneous transformation matrix of the e-skin relative to the world frame, obtained through the robot's forward kinematics. Meanwhile, ${}^{E_i}P_{O_i} \in \mathbb{R}^3$ represents the position of object O_i relative to e-skin cell E_i, derived from proximity sensing.

The object's interaction characteristics are modeled as a spring-mass-damper system $\boldsymbol{\theta} = [K, M, D]$. To enable real-time estimation and updating of these parameters, the perception module first constructs interaction data pairs $\boldsymbol{\psi}(t) = [\triangle \mathbf{x}_{O_i}, \dot{\mathbf{x}}_{O_i}, \mathbf{F}_{O_i}]^T$ from proprioceptive and contact force measurements, $\triangle \mathbf{x}_{O_i} = {}^{W}P_{O_i,t} - {}^{W}P_{O_i,t-1}$ is the displacement during robot-object interaction, $\dot{\mathbf{x}}_{O_i} = J(\mathbf{q}_t)\dot{\mathbf{q}}_t$ is the interaction velocity, and $\mathbf{F}_{O_i}$ is the measured contact force. The module then employs recursive least squares (RLS) to dynamically estimate the interaction parameters $\boldsymbol{\theta}$ with minimal computational latency.

To enable robotic interaction data acquisition and task completion, we augment the planner with a motion intent unit. This module evaluates interaction feature parameter errors to assign target positions $\mathbf{x}^* = [\mathbf{g}^*, \mathbf{k}^*]$, $\mathbf{g}^*$ is the goal point for motion planning, and $\mathbf{k}^*$ is the target position for interactive perception. The operational characteristics are encoded in the map as an operational difficulty metric $D = \dfrac{\sum \boldsymbol{\theta}_{O_i}}{\sum \boldsymbol{\theta}_{\max}} \subseteq [0, 1]$, where $\boldsymbol{\theta}_{\max}$ denotes the robot's interaction capability limit (a hyperparameter).

The planner employs a sampling-based method to compute intermediate waypoints with maximal connectivity probability, using operational-weighted grid maps and target positions as constraints [12]. These waypoints are interpolated to generate a reference trajectory. For execution, an impedance controller tracks the trajectory while maintaining compliant interaction [13] (Fig.2).

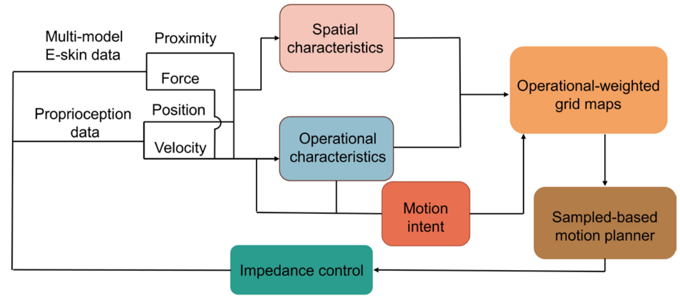

Fig.1: Overview of Tactile-based Interactive Motion Planner (TI-P).

We constructed a cluttered tabletop environment in PyBullet [14] to evaluate TI-P, simulating real-world community settings. The scene contains cylindrical objects with randomized physical properties, fixed at arbitrary locations. During testing, the workflow begins by generating a random target pose within the workspace with number range of [1, 4]. And then loading six objects occupying 57% of the workspace volume. Ten trials were conducted for each test condition.

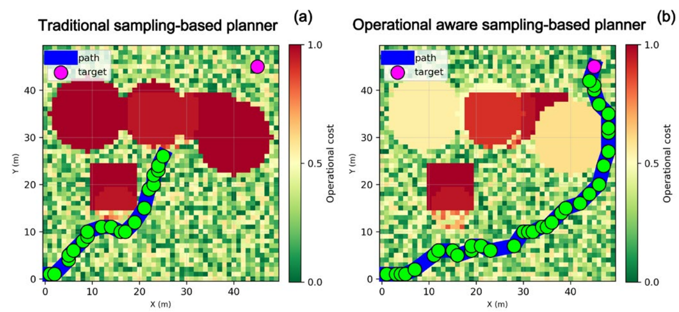

Fig.2: Example comparing the performance of sampling-based planners under constrained free-motion workspace. (a) A boundary-constrained sampling-based planner fails to find a feasible path due to the absence of collision-free solutions. (b) An operational-feature-constrained sampling-based planner successfully completes the task in the same constrained workspace by inferring object interaction characteristics to generate interactive trajectories.

We benchmarked TI-P against a boundary-constrained sampling-based planner (BS-P) with impedance control. Experimental results demonstrate that TI-P achieves a 55% higher success rate, attributed to two key advantages:

1. The baseline fails when intermediate arm links are blocked by fixed objects. TI-P circumvents this by dynamically delineating restricted zones in the configuration space.

2. The baseline's impedance control generates insufficient interaction forces to displace movable objects. TI-P overcomes this by applying force compensation based on real-time interaction characteristics $\boldsymbol{\theta}$ identification.

TABLE I. PERFORMANCE EVALUATION AMOBG TI-P AND BS-P

Planning Methods	Number of target points			
	1	*2*	*3*	*4*
TI-P	100%	100%	80%	60%
BS-P	30%	10%	0%	0%

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