Physics-Informed Force Prediction with Reactive Surface Following for Granular Material Manipulation on Complex Hidden Surfaces

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***Abstract*— Granular material manipulation in containers with complex geometries is challenging due to hidden rigid surfaces and uncertain interaction forces. This paper proposes a framework that combines physics-informed force prediction with reactive control. A Gaussian Process model predicts the expected interaction force between the tool and the granular material, which is used as a baseline for an adaptive controller. Experiments show that the proposed method captures the forces trend and enables stable surface following, providing a basis for contact identification and probabilistic surface mapping.**

I. INTRODUCTION

In granular material manipulation tasks, robots often interact with unstructured environments where both granular materials and rigid surface coexist. During scooping, the resistive force experienced by the robot originates from two different sources: the interaction with the granular material and the contact with a hidden rigid surface (e.g., the container's floor). Reliable motion control under such complex interaction events is important for tasks where the robot must actively interact with the environment to infer hidden surface geometry under granular materials.

This paper proposes a framework that predicts the expected resistive force from granular material interaction and interprets deviations between the prediction and measurement as potential contact events. Meanwhile, an attractor-based impedance controller enables the robot to follow the unknown surface inside the granular material.

The main contributions of this work are: i) a physics-informed Gaussian Process model for predicting material-tool interaction forces, ii) a reactive attractor-based impedance controller for surface following without prior knowledge of the surface geometry, and iii) a unified framework that integrates force prediction and control to facilitate probabilistic hidden surface mapping.

II. RELATED WORK

A. Soil-tool interaction model

Research in terramechanics has extensively studied soil–tool interaction, and these models can serve as a starting point. One of the most widely used models is the FEE [1], which describes the resistive force during soil cutting. For example, Singh et al. [2] implemented the FEE model for online soil parameter identification and force prediction on a real excavator. However, classical terramechanics models assume steady-state interaction, which limits their ability to capture disturbances arising from varying soil states or dynamic motion. To address this limitation, recent works have introduced machine learning techniques to model soil-tool interaction forces under non-static conditions [3], [4]. These approaches learn additional features related to soil states or tool dynamics. However, most existing works focus on simulation-based training and evaluation, which may not generalize well to real-world manipulation scenarios. In contrast, this work focuses on learning from real-world manipulation trajectories and integrates a physics-based prior with a probabilistic learning model.

B. Adaptive impedance control

Impedance control is widely used for compliant robot interaction, allowing the robot to behave as a virtual spring-damper system. It has been successfully applied in tasks such as surface exploration [5] and robotic excavation [6]. Many existing approaches focus on adaptive tuning of impedance parameters, such as stiffness or damping, to improve task performance. However, such parameter adaptation can introduce instability or oscillations, especially in highly uncertain environments. Instead of tuning impedance parameters, this work adopts a reactive attractor-based impedance controller. The controller modifies the motion attractor based on force and motion feedback, enabling the robot to follow unknown surfaces without requiring environment knowledge.

III. METHODOLOGIES

This work integrates force prediction with reactive surface following for hidden surface estimation in granular materials. The system consists of two main components: a force prediction module and an adaptive controller, as illustrated in Fig. 1 (a).

Granular material–tool interaction force prediction. A Gaussian Process (GP) regression model with a physics-informed prior is employed. The GP predicts the resistive force at the next time step based on the current tool state, including tool velocity, penetration depth, and displacement from the beginning of the dragging phase. The mean function is derived from the FEE, whose parameters are obtained through a data-driven fitting process under simplified assumptions. Since the tool orientation remains constant during dragging, the material parameters are assumed to remain approximately constant, and the interaction force mainly

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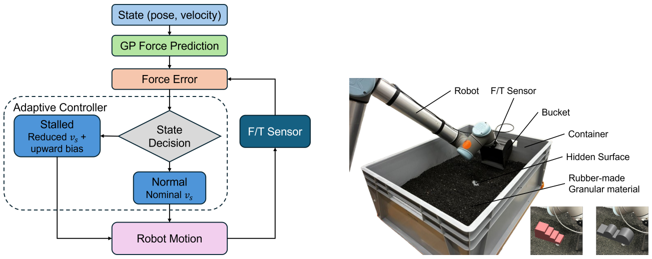


Fig. 1: Left (a) system overview and right (b) experiment setup with granular material and hidden surfaces.

depends on tool depth and surcharge pressure. The covariance function is defined as a combination of a Matérn 5/2 kernel and a periodic kernel. The model is trained using data from 45 Penetrate–Drag–Scoop (PDS) trajectories collected at depths of 4 cm, 5 cm, and 6 cm. Variational inference is adopted for training due to the large number of data points.

Surface following control. A reactive attractor-based impedance controller is designed to enable surface following without prior knowledge of the environment. Inspired by Franceschini et al. [7], and different from conventional impedance control approaches such as force–position control in that it does not rely on predefined force or position references. Instead, it adapts the motion based on the difference between the predicted and measured forces. The controller includes two motion states: normal state motion and stalled state motion. When the difference between measured and predicted forces exceeds a threshold and the robot motion stalls for a short duration, the controller switches from the normal state to the stalled state. The commanded motion is decomposed into tangential v_t and vertical v_z. Tangential speed is reduced during adaptation, while vertical motion is adjusted using a force-informed factor with an additional upward bias term in the stalled state.

$$v_t = v_{t,\text{nom}}\,\gamma(\alpha, m) \tag{1}$$

$$v_z = v_{z,\max}\,\text{sat}\left(\frac{f_{drive} - f_z}{d_f}\right) + \delta_{\text{stall}}\, v_{z,\text{bias}}^{\max}\,\alpha \tag{2}$$

Where $f_{\text{drive}} = -f_{\text{des}} + f_{\text{gp}}$ is a motion-driving force, not a strict force tracking target and $\gamma(\alpha, m)$ scales tangential motion according to the adaptation level α and controller mode.

IV. EXPERIMENTS AND RESULTS

To evaluate the proposed prediction method and adaptive control law, real-world manipulation experiments are conducted. Two types of complex hidden surfaces, a stair-shaped and an arc-shaped structure, are fixed inside a container and buried under rubber material, as shown in Fig. 1 (b). The robot is equipped with a 6-axis force–torque sensor, and a bucket is mounted at the end-effector. Each excavation experiment involves two interaction scenarios: rubber–bucket interaction and rubber–bucket–surface interaction. Fig. 2 illustrates the comparison between the predicted and measured forces in these two scenarios. In the first scenario, the predicted interaction force is compared with the measured force during the dragging phase, before contacting the surface. The results show that the proposed model captures the overall trend of the rubber–tool interaction forces. In the second scenario, the proposed controller is evaluated in surface-following tasks under rubber–tool–surface interaction. By comparing the predicted force with the measured force, the controller switches between different motion states to maintain stable motion while adapting to changes in interaction conditions. Deviations between prediction and measurement are observed when interacting with rigid surfaces, indicating the potential of the framework for contact identification.

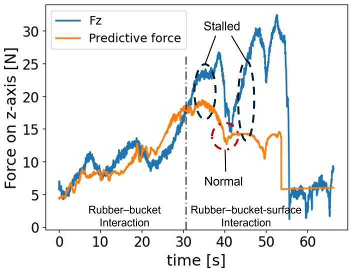
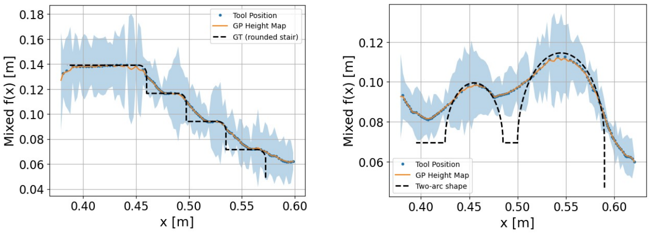


Fig. 2: Comparison between GP predicted force and measurement in different scenarios



(a) Stair-shaped surface

(b) Arc-shaped surface

Fig. 3: Primary results of the height maps and ground truth

To estimate the hidden geometry, Fig. 3 shows the probabilistic height maps constructed from contact-rich trajectories that are fused over multiple passes during surface following. Compared with the ground truth, the robot is able to follow the surface smoothly. However, gaps can be observed in the reconstructed map, particularly for the stair-shaped surface. These gaps occur because the bucket compresses the granular material, forming a compacted layer that prevents direct contact between the tool and the underlying rigid surface. Consequently, reliable measurements cannot be obtained in these regions. This limitation highlights the need for improved contact identification, which will be addressed in future work.

V. CONCLUSIONS

This work presents a framework that integrates force prediction and adaptive control for robotic excavation. The proposed method enables stable surface following by adapting motion based on prediction errors. Experimental results demonstrate its effectiveness, while limitations arise when material compaction prevents reliable contact. Future work will focus on improving contact identification.

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