A LEARNING FRAMEWORK FOR ENABLING ROBOTS TO AUTONOMOUSLY DISPENSE GRANULAR MATERIAL ON-DEMAND

Jeon Ho Kang, Rishabh Shukla, Moksh Mehta, and Satyandra K. Gupta *
Center for Advanced Manufacturing, University of Southern California, Los Angeles, California 90007
Email: jeonhoka@usc.edu, shuklar@usc.edu,mdmehta@usc.edu guptask@usc.edu

ABSTRACT

This paper presents a learning framework for enabling robots to autonomously dispense granular materials on demand. This framework enables robots to scoop and transfer the requested material amount with milligram scale accuracy. Our approach is capable of handling challenging cases where the amount left in the source container is significantly less than the container volume. In such cases, robots must build piles before scooping the material to capture enough material within the scooper. We use Gaussian Process Regression (GPR) to predict granular material behavior during scooping and pouring tasks. GPR is effective in learning the behavior of granular material with task parameters, such as robot joint angles, joint accelerations, and end-effector geometry. During task execution, we use GPR to solve the inverse problem and determine the task parameters based on the desired scooping and pouring amounts. The system performance is evaluated by showing GPR's ability to predict scooped and poured amounts with reasonable uncertainty. We benchmark our method against the traditional approach of fine-tuning the amount via closed-loop control from the scale sensor feedback. Our method shows 55.2% improvement in time taken to dispense the granular material over the benchmark approach. The proposed framework shows promising results in terms of reducing dispensing times.

1 INTRODUCTION

Many applications, such as food preparation, pharmaceutical manufacturing, medical testing, and handling of energetic materials, require precise manipulation of granular materials. The dynamics of granular material are highly complex, characterized by chaotic behavior and inter-particle interactions, making it challenging to develop predictive models for accurately controlling the amount dispensed [1]. The physics community has been striving to characterize granular dynamics.

FIGURE 1: Example container amount for the edge case and regular case.

There is significant interest in using robots to dispense controlled amounts of granular materials on-demand [2, 3]. However, accurately weighing granular materials at the milligram scale remains notoriously laborious and time-consuming, posing ergonomic challenges even for skilled human operators.

In this paper, we introduce a learning framework that enables robots to autonomously dispense the requested amount of granular material on-demand. Using our approach, robots are able to scoop granular materials autonomously from the source container, accurately adjust the material in the scooper (a tool used by the robot to scoop and dispense material) to the specified target weight, and transfer this amount to a source container with milligram accuracy. The task of dispensing granular materials can be divided into two scenarios, depending on the quantity

*Address all correAspondence to this author.

of material available in the source container. In scenarios where the source container is amply filled, the task is straightforward and is termed as a *regular case*. Conversely, the task becomes more challenging in *edge cases*, where the amount of material in the source container is small relative to its capacity. This necessitates an additional step of building a small pile. Our system is adept at managing both regular and edge cases, ensuring precise material dispensing regardless of the initial material volume in the source container.

A critical aspect of our system is its focus on optimizing the time efficiency of the transfer process, especially in instances requiring multiple stages, to enhance the overall throughput of the operation. This paper adopts a human-like skill acquisition framework, leveraging active learning based on Gaussian Process Regression (GPR). This methodology enables the robot to learn and model the relationships between actions and outcomes. It mimics how humans acquire new skills by observing experts and refining them through practice, thereby fine-tuning their motor and perceptual abilities.

The key contributions of this paper include:

1. A complete system for robotic transfer of granular materials with milligram accuracy, emphasizing time efficiency and the ability to handle edge cases.
2. The use of GPR for predicting motor parameters needed to manipulate granular materials, which is challenging due to its complex inter-particle interactions.
3. A hierarchical decision-making framework that allows the robot to adapt its plan based on the amount of material in the source container and the requested target weight, optimizing for both regular and edge cases.

2 RELATED WORK

The topic covered in the paper closely relates to robotic handling of fluids and granular materials. Significant efforts have been directed towards developing methods for handling both liquids [4–9] and granular materials, given their widespread application in industrial and household environments [1, 10].

In fluid manipulation, goal-conditioned reinforcement learning has been explored to improve the adaptability and accuracy of robotic scooping, with frameworks like GOATS demonstrating enhanced performance in both simulated and real-world scenarios [11]. Deep learning models have been used to refine the precision of robotic pouring, leveraging gated recurrent units and self-supervised learning to better understand pouring dynamics [12]. These advancements underscore the shift towards learning-based approaches for improved control over complex manipulation tasks. Efforts to incorporate force-based control and perception have also been noteworthy. Rozo et al. utilized parametric hidden Markov models for force-based learning in robotic pouring, capturing the intricacies of force-torque dynamics with respect to liquid volume [5].

Granular material manipulation poses unique challenges due to the unpredictable nature of granular flow. Research in this area has introduced manipulation strategies based on Gaussian mixture models and hybrid force-velocity systems, facilitating real-time, adaptive handling of granular materials [13, 14]. Moreover, bimanual scooping methods have been developed to improve the efficiency of such operation [15].

Learning from demonstration (LfD) has gained popularity for teaching robots granular material manipulation skills, enabling the acquisition of complex motion primitives from human demonstrations [16, 17]. By observing human experts, robots can acquire motion primitives that are difficult to design through traditional programming methods. Early work by Yamaguchi et al. [18] explored acquiring pouring skills through demonstration, emphasizing the optimization of continuous parameters for actions such as pouring, shaking, and tapping. Their follow-up work [19], delved into planning and learning modeled from human demonstrations to adapt pouring behaviors across a variety of scenarios. To achieve this, robots must be equipped with a library of skills and learn to select appropriate behaviors and behavioral parameters for each specific task. Integrating these techniques has resulted in robots that can effectively plan and learn to handle various strategies for scooping, pouring, and even complex tasks like pile-building [20]. In addition to LfD, active learning strategies have been employed to refine the robot's performance over time. For example, Langsfeld et al. [16] address the challenges of dynamic pouring tasks by introducing an approach that iteratively refines local metamodels based on exploitation-driven updates, significantly reducing the need for physical trials in learning trajectory parameters.

Simulation techniques play a crucial role in the development and testing of manipulation policies. High-performance simulation platforms like Isaac Gym allow for the rapid prototyping of tasks, facilitating a smoother transition from simulated environments to real-world applications [21, 22]. Similarly, sim-to-real reinforcement learning has been employed to manipulate deformable objects, demonstrating the efficacy of domain randomization in bridging the simulation-to-reality gap [23, 24].

Advancements in robotic perception, such as stereo vision, tactile sensing, and audio-visual networks, have improved precise material handling and manipulation tasks [2, 25, 26]. Research has shown tactile sensing's effectiveness in granular media manipulation [26] and explored tactile-based motions for challenges like pouring from deformable containers [27, 28]. Multi-modal approaches that combine audio-visual networks have been used for improved material handling [2, 3, 29–31]. These efforts highlight the significance of multimodal sensing in enhancing robotic efficiency and accuracy in complex tasks [32, 33].

Recent works in this domain have focused on the physical properties of granular materials and the challenges they pose for robotic manipulation. For example, Matl et al. [34] focused on inferring material properties of granular media to simulate these substances more accurately. Also, Tuomainen et al. [1] proposed learning particle interactions through a graph-based representation, offering a novel approach to planning manipulation trajectories. Schenck et al. [35] tackled the challenge of robotic manipulation of granular media by evaluating predictive models that accurately simulate scooping and dumping actions.

Gaussian Process Regression (GPR) is a useful tool for modeling the complex dynamics of granular materials. Its ability to incorporate prior knowledge and provide predictions with uncertainty estimates makes it well-suited for applications in robotic manipulation where direct modeling of the physics is challenging [36]. Furthermore, GPR also improves the model's explainability compared to neural-network (NN) based methods. Our research builds upon these foundations by proposing an end-to-end learning framework that employs GPR informed by real-world, physics-based data. Unlike the reinforcement learning and simulation-based approach utilized by Kadokawa et al. [37], our method leverages GPR to model the unpredictable behavior of granular materials under various conditions. The use of such data-driven insights into granular media dynamics lays the groundwork for more adaptive and precise robotic systems capable of autonomously dispensing granular materials on-demand.

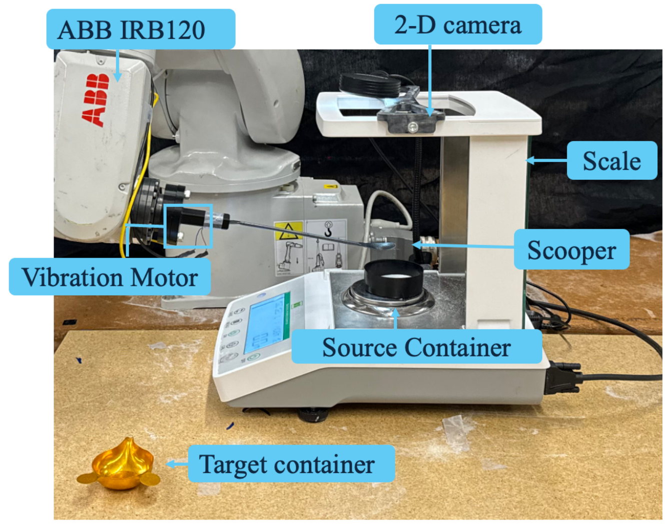


FIGURE 2: Our hardware setup of the system. We incorporate a vibration motor attached to the end-effector, mimicking the human finger-tapping action. This vibration motor introduces perturbation like human finger-tapping, helping a more uniform distribution before the pouring phase. This motor is also used for bulk-pouring discussed in Section 7

3 PROBLEM FORMULATION

Background. In this paper, we aim to minimize the expected dispensing time. Our experimental setup uses an ABB IRB120 industrial robot, which produces smooth motions and does not cause vibrations in the scooper. We utilize a 0.1mg precision scale to monitor the weight of the source container, enabling us to accurately estimate the amount of material the scooper has collected. The source container, with a diameter of 6.5cm, was placed on the weighing scale, while the target container was placed outside the scale. We also have a 2-D RGB camera to capture the granular material's profile on the weighing scale. The hardware setup is illustrated in Fig. 2.

Problem Statement and System Objective. During each request, the robot's task is to dispense a target quantity of granular material, m_t, with an accuracy of $\pm 1mg$. At the initiation of the task, the system acquires data regarding the mass of granular material in the source container, symbolized by m_s. The primary goal of our system is to minimize the cumulative duration required for the material's transfer, symbolized by t_T. This aggregate metric encompasses the duration associated with various phases of the process. Specifically, t_p represents the time spent pile building, while t_s indicates the time spent for scooping activities. The variable t_d denotes the time spent on removing the excess material from the scooper to achieve the target weight, m_t. Furthermore, t_t denotes the duration involved in the complete transfer and dispensing all to the target container. The overall time component of the time taken can be represented as the following:

$$t_T = t_p + t_s + t_d + t_t \tag{1}$$

Within this framework, we assume that t_t is almost constant. Hence we can disregard it during optimization. Additionally, we introduce t_o as the time duration used in the objective function.

$$t_o = t_p + t_s + t_d \tag{2}$$

and our objective function can be defined as the following:

$$minimize(E(t_o)) \tag{3}$$

where $E(t_o)$ is the expected value of t_o.

We use different methods for managing different cases based on the material mass present in the source container. The primary focus of our study is to discuss in detail the method for addressing edge cases, which represent challenging scenarios in granular material manipulation. These cases require the robot to build a pile to form a granular material profile to facilitate effective scooping.

Within the context of the scooper and container configuration depicted in Figure 1, we categorize edge cases as situations where the amount of material in the source container, m_s, ranges from $1000mg$ to $3000mg$. This range can be empirically identified as requiring a pile-building method to ensure the robot can accurately scoop a target amount within the same range, $20mg \leq m_t \leq 200mg$.

Inverse Problem using Physics-Informed GPR. Our method uses GPR as a predictive mechanism to improve skills in manipulating granular materials through active learning. During the training phase, GPR forecasts task outcomes, such as scooped and poured amounts, based on task parameters (e.g., joint angle, acceleration, and granular material shape). After establishing the model, we solve the inverse problem to retrieve task parameters that will most likely result in the desired material amount. During execution, we solve the optimization problem to find the performance parameters suited to achieving the desired outcome, such as poured and scooped amount. We aim to find such parameters with minimum standard deviation since GPR predictions have both physical and model uncertainties. In our framework, we recognize the presence of noise in physical experimental data. To account for this variability in our model, we conduct multiple repetitions of experiments with the same input parameter. Details of the approach are shown in Fig. 3.

We use the Limited-memory BFGS with Bounds (L-BFGS-B) algorithm, a variant within the quasi-Newton optimization methods, to solve the uncertainty minimization problem [38]. This technique is particularly effective for solving smooth, non-convex optimization problems that involve multiple variables. An initial estimate, x_0, is necessary for the algorithm to search for a minima. We perform iterations using various initial guesses to enhance the likelihood of finding a minimum that aligns with our requirements. However, due to the inherent non-linearity of GPR's approximated functions, it is worth noting that the minima may not necessarily represent the global minimum.

Let σ be the standard deviation associated with the GPR-predicted value for granular material behavior, $m_{desired}$ be the desired mass of the grains, and P_{target} be the target performance. The objective function of the optimization problem is given as:

$$minimize(\sigma) \tag{4}$$

Subject to the constraint:

$$P_{\text{target}} = m_{\text{desired}} \tag{5}$$

$$30 \leq \theta_{\text{joint}} \leq 80 \tag{6}$$

We apply a constraint that the joint angle, given as θ_{joint} must fall within the range of $(30, 80)$ degrees. This is based on our experimental findings, which indicate that a joint angle lower than 30 degrees fails to pour any material from the scooper, and an angle beyond 80 degrees results in pouring all the material, thereby not affecting the end result.

At this stage, we are given P_{target} (e.g., amount to be poured or scooped) and determine the task parameters. We progressively narrow the uncertainty margin by continuously augmenting our dataset with real-time feedback. The active learning scheme is shown in Fig. 3.

Typically, GPR models rely on the proximity of data points for accurate fitting and predictions, with their effectiveness depending on the quantity and quality of the data available. However, it is often impractical to collect large amounts of physical data. To address this, we integrate mean functions and physical constraints derived from real-world observations of granular materials. For example, we introduce constraints to prevent the model from suggesting negative values for certain variables, as such results are not physically feasible. Additionally, we incorporate knowledge indicating that parameters such as pile size, joint acceleration, and joint angle directly impact the average quantity of material scooped and poured. This mean function, represented as $m(x)$, is defined as follows:

$$m(x) = \frac{K}{1 + e^{-B(x_i - x_0)}} \tag{7}$$

Where:

x_i is the i-th feature in the prediction.
x_o is the mid point of the curve.
K is the gain component to the sigmoid function.
B is the rate of increase of the function.

Subject to the constraint:

$$m_s, m_p \geq 0 \tag{8}$$

where:

m_s refers to the amount scooped
m_p refers to the amount poured.

This mean function lets the model follow the general trend of a sigmoid function, resulting in a smooth increase in the pre-

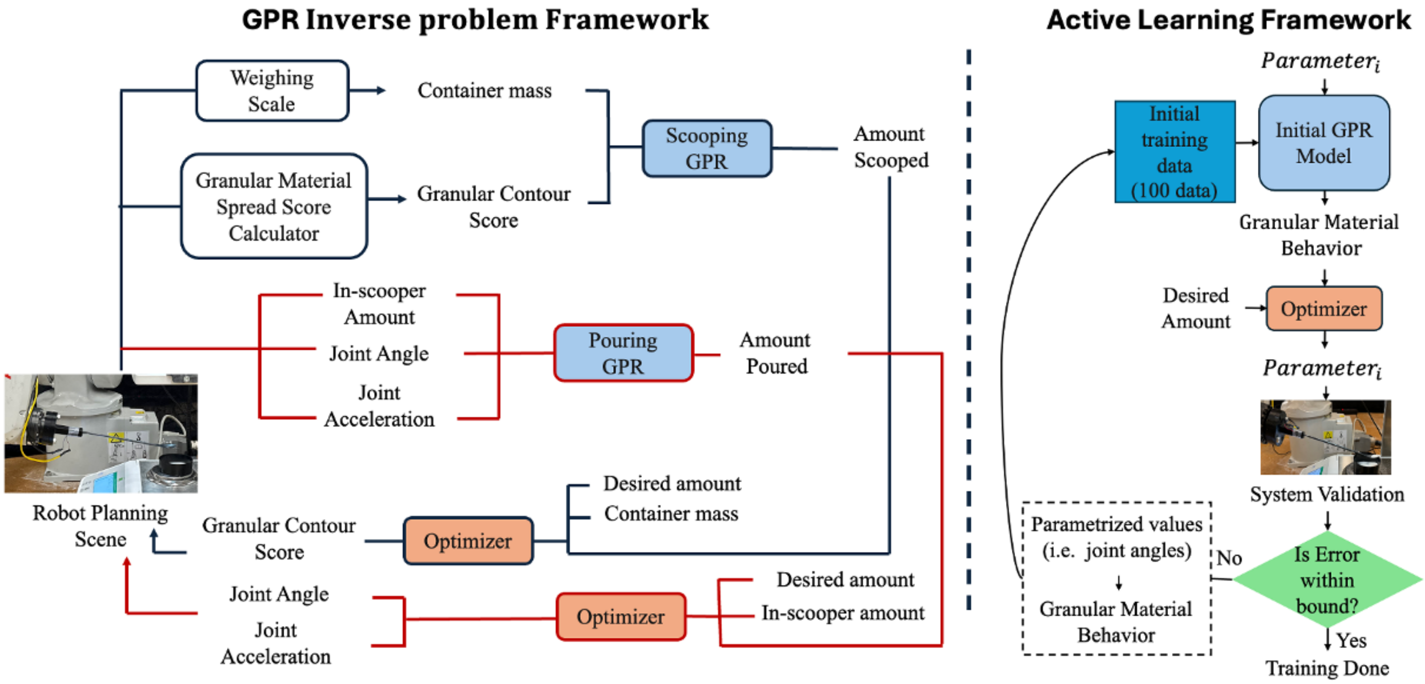


FIGURE 3: **GPR inverse Problem Framework**: We use GPR to predict performance metrics such as scooped and poured amounts with task parameters like joint angle or granular contour score. Upon prediction, we solve the inverse problem with fixed uncontrollable parameters such as amount in the container and in-scoop amount (we assume that pouring is an independent problem from scooping), to make decisions on task parameters that will most likely achieve the desired material amount. **Active Learning System Architecture**: We use this inverse problem framework for scooping and pouring phases to actively learn appropriate values for the desired material amount. Initially, the robot begins with a training dataset. This dataset is updated through iterative task execution, enabling continuous improvement of the robot's performance based on real-time feedback and outcomes.

dicted outcome, with adjustable parameters to regulate the rate of increase in performance outcome.

Overview of Approach. We separate the granular material dispensing tasks into stages that align with the case, depending upon the remaining volume of material in the source container, as explained in Section 4. The robot uses the motion primitives acquired from human expert demonstrations through a motion capture system.

Specifically, within the adjusting phase, we define two distinct motion primitives to optimize the adjustment of the in-scoop material quantity. The first method, termed *bulk-pouring*, uses GPR to calculate the most effective joint angle and acceleration parameters for releasing a substantial volume of material in a single motion. This technique is designed to reduce the initial discrepancy between the current and desired material quantities, thereby reducing the time used in the subsequent fine-tuning phase. The second technique focuses on fine-tuning (shaking motion), which is critical for achieving the precise target amount, m_t, with an accuracy of $\pm 1mg$. Traditional methods for attaining this level of accuracy typically involve incremental adjustments of approximately one milligram. However, this approach is hampered by the inherent sensor delays associated with measuring such minute quantities, a standard limitation of milligram scale problems.

Addressing the challenges of edge cases necessitates an initial focus on constructing an effective pile-building method. Effective pile-building is accomplished by using RGB images of the source container and utilizing binary segmentation to delineate the granular material profile. Subsequent application of k-means clustering identifies clusters within the material profile and determines the centroid of each contour to determine the most effective pile-building paths. This methodology is detailed in Section 5.

Upon completing the pile building, the robot proceeds to scoop along a pre-planned trajectory, aiming to approximate the target mass, m_t, as closely as possible. Given the unpredictable behavior of granular materials and the sensitivity of milligram-scale measurements, exact scooping quantity cannot be guaranteed. Therefore, we approximate the scooping outcome based on the granular contour score calculated based on the distribution of the material in the container. Depending on the initial scooping outcome, a decision is made regarding the necessity for preliminary bulk-pouring before fine-tuning to the precise target mass. Further details of using GPR for both the scooping and adjusting are explained in Section 6 and 7.

4 HIGH-LEVEL DECISION MAKING PROCESS FOR DISPENSING GRANULAR MATERIAL

The complexity of the task depends on the amount of material present in the source container. Therefore, the framework begins with task difficulty assessment, utilizing inputs such as the RGB image of the source container and material mass estimate obtained from the scale. We assume that the density of the material is known in advance. Based on this assessment, tasks are categorized into edge or regular cases. Our system defines edge cases as scenarios involving less than 3000mg of material. These cases often necessitate a pile-building method for scooping tasks, especially when aiming to scoop a target amount of up to 200mg, the maximum our system is designed to handle.

In regular cases, where the container's material volume is sufficient, the robot can easily scoop amounts exceeding the target. Following scooping, we solve the inverse problem using GPR for pouring to optimize joint angle and acceleration based on the in-scoop material amount and the target amount. After initial adjustment by removing excess material, the robot fine-tunes the amount until achieving the material within $\pm 1mg$. The system diagram is shown in Fig. 4. While our paper covers the process for handling regular cases, it primarily details the method developed for managing edge cases.

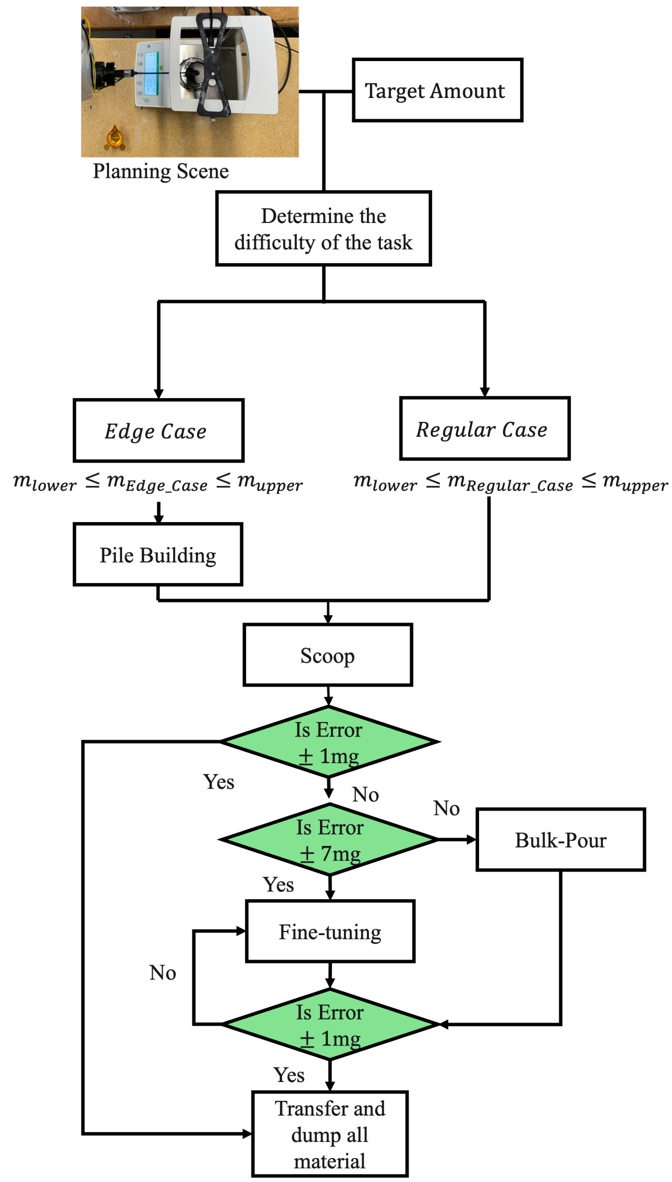


FIGURE 4: Overall plan for granular material dispensing. This diagram shows approaches for handling the regular and edge case.

5 APPROACH FOR AUTOMATED PILE BUILDING

When there is a relatively low amount of material in the source container, humans either tilt the container or use pile-building strategies to scoop enough amount. In our system, we use pile-building method, because we aim to build a system that mimics the human's approach as much as possible. Currently, we use one robot arm, and therefore container tilting is not possible. Using a second arm will increase the cost of the system considerably.

To minimize the overall expected execution time for transferring granular material, we develop a pile-building perception pipeline. This pipeline is designed to maximize the amount of material gathered while minimizing the number of tool movements. We use RGB images without depth information because depth data at this scale is often too noisy to be useful. To address the lack of depth information, we assume a uniform height and calculate the height using the material's density and volume. This allows us to approximate the mass distribution in the container by using scale feedback.

We first use binary segmentation to separate granular material from the container. Based on this binary segmentation, we calculate the distribution score from the image. Then, using the k-means clustering, we determine the centroid and the clusters. When considering the scooping method, we know that the most efficient method would be to scoop from the container edge to prevent granular material from slipping from the scooper. Therefore, we compute the tool path from the centroid, which is the likely point with the most material, to the edge point of the container. We then draw the potential pile-building paths from the contour edges to the edge point to enable effective pile-building. Example paths and implementation are shown in Fig. 5. For each pile-building motion, the robot queries the system for the cur-

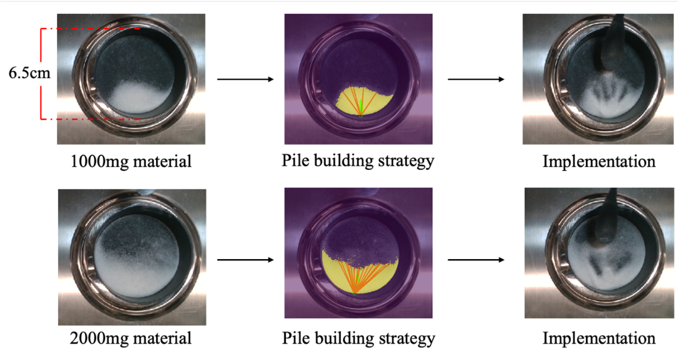


FIGURE 5: Path-planning framework for pile-building. The green line shows the path for scooping, and the red shows the pile building. Initially, we have RGB image of the container. Then, we use binary segmentation to get the spread of the material. Then, using clustering, we know the contour and the centroid of the material inside the container. Using the centroid lets the robot plan the scooping tool path as well as the pile-building method to gather granular material along the tool path.

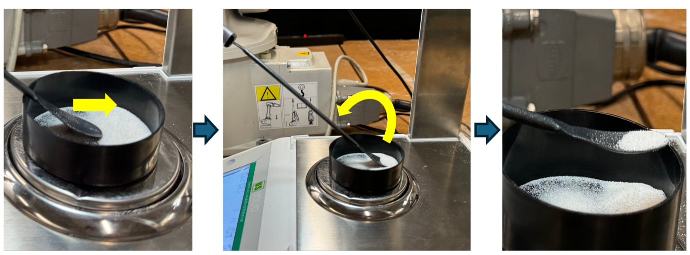


FIGURE 6: The figure illustrates the robot executing a predefined scooping motion primitive, guided by a tool path derived from an RGB image, as detailed in Fig. 5. The sequence begins with the robot strategically approaching the container, subsequently engaging in a scraping action along the container's bottom at a specific pitch angle to accumulate material. The process ends with the robot elevating the scoop and completing the scooping task.

rent score, and pile-building will terminate once it has reached the spread score, enabling the robot to scoop as close to the target amount as possible. This score is also used in training GPR model for scooping discussed in Section 6.

6 GPR FOR ENABLING EFFICIENT SCOOPING

The ability to scoop a target amount of material with the least amount of uncertainty is essential to minimizing the time required to adjust the in-scoop amount to the desired level. To address this challenge, we use a motion primitive for scooping derived from observations of human demonstrations. Motion primitive for scooping is shown in Fig. 6.

Initially, we provide GPR with the granular contour score and amount in the container to estimate amount of material

TABLE 1: Six representative data for scooping from 100 trials used during training.

# Exp.	Material Distribution Score	Amount in container (mg)	Amount Scooped (mg)
1	1.99	1024	8.2
2	4.80	1011	8.3
3	5.15	1006	11.2
4	5.16	3009	121.5
5	5.25	3007	139.3
6	5.50	3011	133.5

scooped. Example trial data is shown in Tab. 1. In the execution phase, we solve the inverse problem by inputting the desired amount scooped to the optimizer while fixing mass of the granular material in the container to estimate the granular contour score suitable for achieving the nearest scooped amount to the target. These steps are shown in Fig. 3. The methodology for deriving the granular contour score is detailed in Section 5. This approach enables the robot to construct an appropriately sized pile. Illustrations of the amounts scooped following this pile-building method are depicted in Fig. 5, with subsequent examples of the scooped amounts provided in Fig. 7. Upon completing a scooping action, the robot waits for feedback from the scale to determine if the in-scoop amount meets the target requirement. Should the scooped quantity fall short of the target, the robot engages in additional scooping from the pile to augment the in-scoop amount. This iterative process continues until the material scooped surpasses the target amount. To conclude this phase, the robot initiates a vibration motion akin to a human's finger-tapping motion, consolidating the material at the center of the scooping surface. This technique prevents material loss during movement and facilitates a more consistent pour in subsequent steps.

7 GPR FOR ADJUSTING IN-SCOOPER MATERIAL CONTENT BY DISCARDING EXCESS MATERIAL

After the robot has scooped material from the container, it ends up with a quantity exceeding the desired target amount. For minor discrepancies within a $\pm 7mg$ range, employing fine-tuning primitives is a practical approach. These primitives incrementally adjust the quantity, enabling the robot to achieve the target amount accurately. Fig. 8 illustrates the adjusting motion primitives.

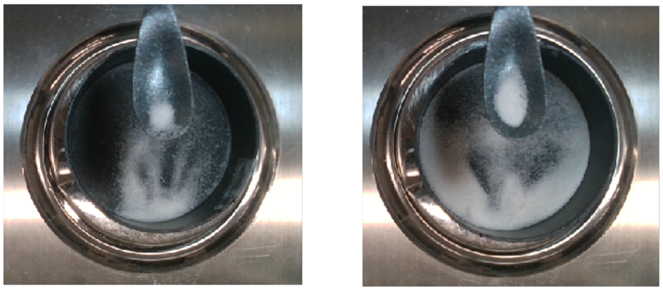
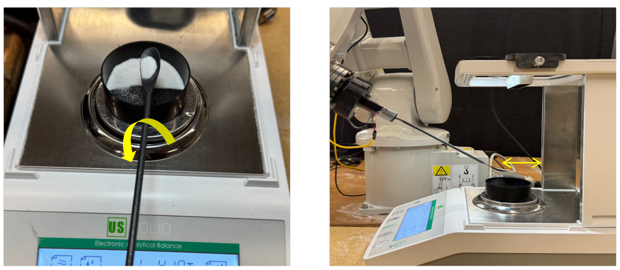


FIGURE 7: Robot scoops from the pile-building and scooping methods presented in Fig. 5.



a) Bulk-pouring motion primitive b) fine-tuning motion primitive

FIGURE 8: Motion primitive for pouring. a) shows the motion primitive for pouring bulk amount at once, and b) shows the shaking small amount to fine-tune in-scoop amount by under 1mg.

However, challenges emerge when the discrepancy between the scooped and target amounts is substantial. When the deviation from the target amount is significantly beyond the $\pm 5mg$ range, relying solely on fine-tuning primitives for adjustment becomes time-inefficient. To address this issue and minimize the time spent in fine-tuning, our approach shifts towards removing the excess amount in bulk. This approach involves pouring out a portion of the scooped material before fine-tuning the remaining quantity to reach the target. By initially reducing the excess amount through bulk-pouring, the time required to adjust the in-scoop amount to the desired level is significantly reduced, and this result is shown in Section 8. We empirically determine the deviation values, $\pm 5mg$ and $\pm 7mg$, based on observed data.

Our approach draws parallel with the scooping method to efficiently manage the challenge of adjusting the material quantity within the scoop to the target amount, particularly after scooping more than necessary amount. We parameterize the pouring motion based on variations in joint angle, acceleration and in-scooper amount. We create a model that maps these task parameters and the initial scooped quantity to the amount poured. Then, we use the same approach used in scooping to solve the inverse problem described in Fig. 3.

An example of trial data for GPR is shown in Tab. 2. While recognizing the inherent physical and model uncertainties that may prevent the precise pouring of an exact amount, our method enables the robot to search for the parameters with minimum standard deviation in predictions. This process optimizes the bulk-pouring action to bring the in-scoop quantity close to the desired target amount. Following the adjustment through bulk-pouring, the robot employs a fine-tuning primitive characterized by gentle shaking motions as shown in [37]. This step precisely adjusts the remaining amount in the scooper, ensuring that the final quantity matches with the target amount with the required accuracy.

TABLE 2: 6 representative training data for scooping from 100 data.

# Exp.	Joint Angle (degrees)	Amount Scooped (%)	Acceleration Factor (mg)	Amount Poured (mg)
1	25	584.0	0.4	100.2
2	26	656.3	0.4	118.3
3	27	430.9	0.4	45.3
4	28	555.0	0.4	84.9
5	29	521.4	0.4	93.4
6	30	423.0	0.4	78.5

8 RESULTS

We test our system with granular material, 70 mesh silica sand shown in Fig. 9 and system setup shown in Fig. 2.

8.1 GPR Efficacy

We demonstrate the predictive capabilities of our model in handling granular materials during scooping and bulk-pouring in Figure 10. We illustrate the deviation between actual and predicted values and the uncertainty bounds based on training dataset of 100 initial trials. The findings indicate a higher level of uncertainty in predictions for scooping compared to pouring, which aligns with our expectations. Specifically, the uncertainty bounds for scooping are observed with an upper limit of 40mg and a lower limit of 25mg. In contrast, the uncertainty bounds are lower for bulk-pouring, with an upper limit of 6mg and a lower limit of 3mg.

a) 50mg of 70 Mesh Silica Sand

b) 10mg of 70 Mesh Silica Sand

FIGURE 9: The figure shows the comparative size of 10mg and 50mg of 70 mesh silica sand used in our case study.

8.2 Total Execution Time of Granular Material Transfer

In this section, we show the total execution time taken for real-world execution of the granular material transfer. We report each parameter that we aim to optimize involved in t_o, composed of t_p, t_s, and t_d. It is important to highlight that the parameter t_p is influenced by the current material distribution within the container. The observed behaviors in different scenarios evidence this relationship. For instance, it was noted that the robot decided to accumulate more material into a pile despite having a considerable amount of material, 2000mg, in the container in case 1. Conversely, the robot often bypassed the pile-building step in situations with a denser material presence, as did in case 3. However, upon receiving feedback from the scale indicating an insufficient amount of material had been scooped, the robot proceeded to scoop additional material. This extra material was subsequently adjusted within the scooper to correct the under-scooping. Tab. 3 depicts each parameters for number of trials.

8.3 Comparison between Control-Loop Fine-Tuning and Our Method

We also benchmark our method against the traditional method of scale feedback based closed-loop adjusting of the in-scoop amount with small shaking motions. For the benchmark, we use the same method for scooping tool-path planning shown in Fig. 5. For our approach, we use the same experiment results shown

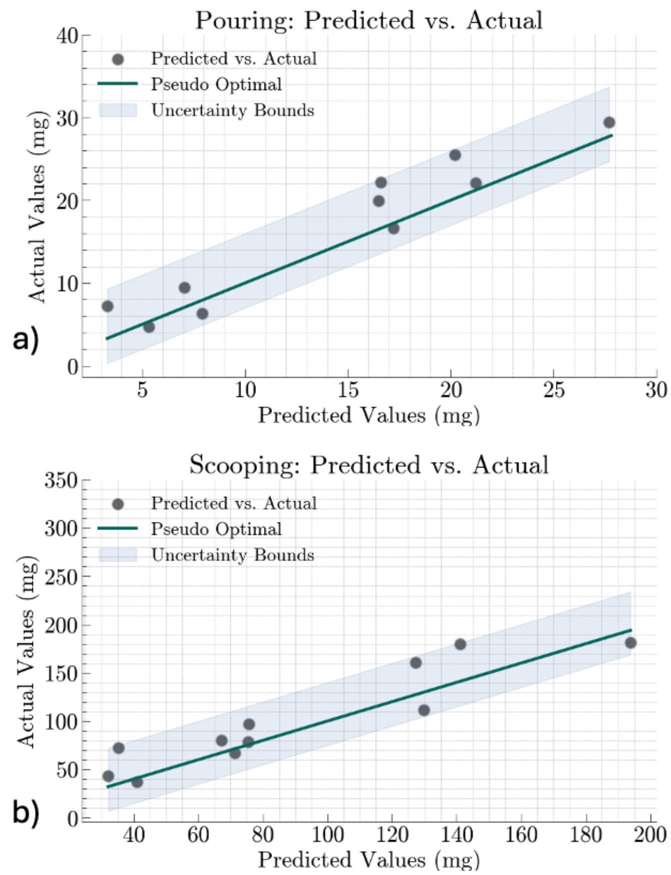


FIGURE 10: The graph compares actual and predicted values, illustrating the accuracy and uncertainty bounds of the pouring and scooping GPR model. The ideal scenario would show the straight line with slope of 1.

in Section 8.2.

Fig. 11 shows that our method can effectively minimize the time taken by decreasing the necessity for closed-loop shaking motion based on scale feedback. Our method performs significantly better in scenarios where there is a significant difference between the amount of material in the container and the target amount, as observed in case 1 and case 3. Consequently, this necessitates a longer phase to adjust the in-scooper amount. In contrast, the performance difference is less pronounced for cases like case 9 and case 10, where the difference between the actual and target amounts is minor because our method also tends to scoop more than the target amount, requiring additional time to fine-tune and adjust the scooped quantity to meet the target.

TABLE 3: Total time taken for granular material weighing, denoted as t_o.

# Exp.	Amount Requested (mg)	Amount in Container (mg)	Amount In-scooper (Result) (mg)	t_o (s)	t_p (s)	t_s (s)	t_d (s)
1	50	2086	50.5	65	17	3	45
2	30	1035	30.9	44	27	8	9
3	95	2028	95.4	24	0	12	12
4	60	1020	59.5	32	15	5	12
5	75	1202	74.4	110	74	3	33
6	40	1776	40.8	107	89	14	4
7	100	1700	99.2	29	10	5	14
8	150	2129	149.7	37	12	4	21
9	170	3017	169.2	89	0	25	64
10	200	3004	200.3	67	21	6	40

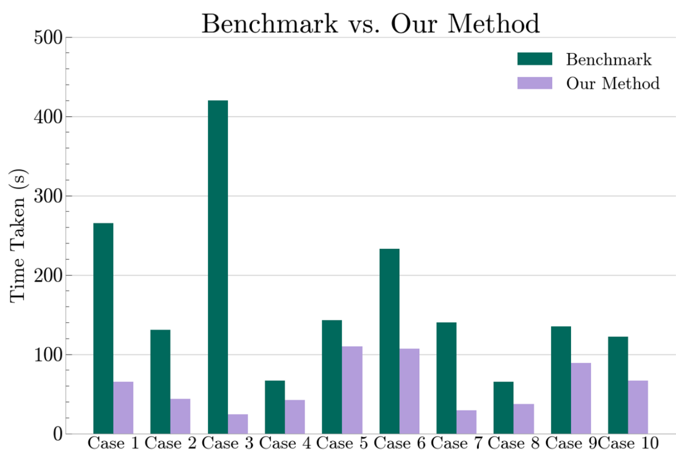


FIGURE 11: Comparison between our method and using scale sensor feedback as a control loop to adjust sub-milligram fine-tuning.

9 CONCLUSIONS

In this paper, we show that the robot can dispense a target amount with $\pm 1mg$ accuracy from the source container to the target container in a time-efficient manner. We use an effective method for pile-building to minimize the number of motions to gather enough material for scooping. Then, we use GPR to learn the parameters for scooping as close to the target as possible to minimize the time needed to adjust the in-scooper amount. We propose another GPR for discarding excess material in the scooper to map the parameters to minimize the control-loop fine-tuning needed. Our result shows that the robot can learn methods to scoop the approximate amounts for the target amount and discard the excess material to bring the material in the scooper close to the target amount while minimizing the time taken.

For future work, we will explore the generalizability of our method by experimenting with a wide variety of materials and scooping tools. Also, we aim to extend our work by extending material amount bounds to a higher threshold to ensure that the robot can handle more diverse cases for dispensing granular material.

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