Autonomous Search for Grinding Conditions using Robots and Bayesian Optimization

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1. Introduction

Particle size distribution (PSD) critically determines material performance in applications such as ceramics, batteries, and pharmaceuticals[1, 2, 3]. Conventional grinding relies on empirical trial-and-error to achieve desired PSD. This approach is time-consuming and lacks reproducibility. Data-driven approaches, including machine learning-based analysis and Bayesian optimization (BO), have been proposed to efficiently explore these complex process parameters. Recent studies have demonstrated the effectiveness of such approaches in analyzing industrial-scale grinding circuits [4]. However, the majority of such studies are tailored to large-scale industrial systems, leaving a gap in frameworks for precision laboratory-scale experimentation.

In this study, we developed an autonomous grinding system that integrates collaborative robots with force-feedback control and BO. The force-feedback control enables precise and reproducible handling at the laboratory scale. The system performs systematic exploration of grinding parameters to achieve target PSD efficiently. We demonstrate that target distributions can be reached with significantly fewer experiments than exhaustive search. This work provides a practical framework for laboratory-scale process optimization.

2. Methods

2.1 Automated Grinding System Configuration

The automated system integrates the following components (Figure 1).

Force-controlled grinding robot: A robotic arm (UR5e, Universal Robots) equipped with a pestle applies constant loads ranging from 5 to 20 N using force-feedback control[5, 6].

Rotating mortar: An agate mortar is driven by a motor (GO-M8010-6, Unitrue Robotics) in velocity control mode. This rotating mortar system was previously developed by our group[7].

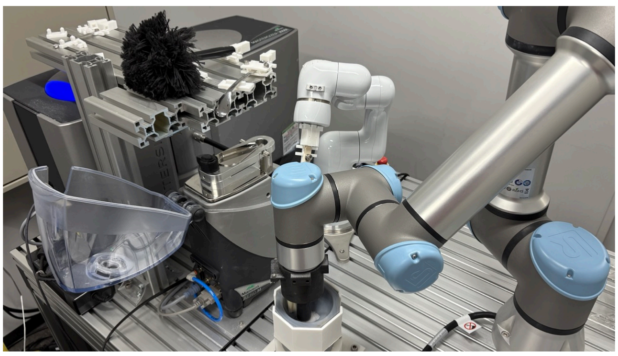

Fig. 1: Overview of the autonomous grinding system

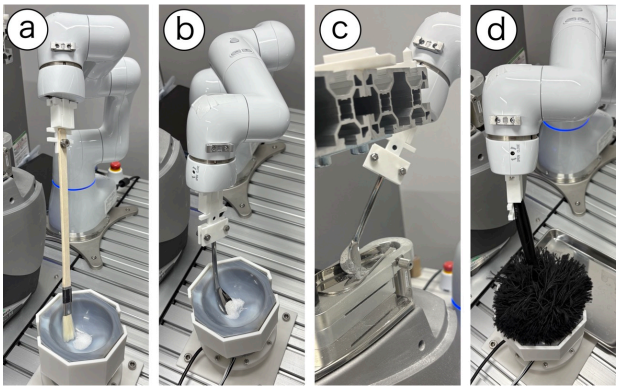

Fig. 2: Robot operations: (a) powder stirring with brush, (b) sample collection with spatula, (c) sample loading into analyzer, and (d) mortar cleaning with cleaning brush

Sample handling robot: A robotic arm (COBOTTA, DENSO WAVE) automates the entire sample handling sequence (Figure 2). The robot stirs the powder in the mortar using a brush, collects the sample with a spatula, loads it into the measurement device, and cleans the mortar using a cleaning brush.

PSD measurement device: A laser diffraction particle size analyzer (Mastersizer 3000E, Malvern Panalytical) measures volume-based PSD. The measured data are fitted to the Rosin-Rammler distribution:

$$R(x) = 1 - \exp\left[-\left(\frac{x}{x'}\right)^n\right] \tag{1}$$

where $R(x)$ is the cumulative distribution, x is particle diameter, x' is the scale parameter, and n is the shape parameter. Both parameters are determined by least-squares fitting.

2.2 Sample Preparation

Reagent-grade sodium chloride with 99.5 % purity was used as the model material. The powder was sieved to obtain particles in the size range of 250 µm to 500 µm. For each trial, 1000 mg of the sample was weighed. The weighing error was controlled within 5 mg.

2.3 Autonomous Search Strategy

The search for target PSD parameters (x', n) was performed in a discrete experimental space using NIMO[8]. Three factors were defined at four levels each (Table 1), yielding 64 candidate conditions.

Phase 1 randomly selected 15 conditions to build an initial dataset. In Phase 2, a Gaussian process model was constructed to map input parameters to PSD results. The model iteratively minimized the

Table 1: Experimental parameters and discrete levels

Parameter	Unit	Levels
Grinding load	N	5, 10, 15, 20
Rotation speed	rad/sec	5, 10, 15, 20
Grinding time	sec	300, 600, 900, 1200

objective function:

$$f(x', n) = \sqrt{\left(\frac{x'_{\text{target}} - x'}{\sigma_{x'}}\right)^2 + \left(\frac{n_{\text{target}} - n}{\sigma_n}\right)^2} \quad (2)$$

where $\sigma_{x'}$ and σ_n are standard deviations from Phase 1. This function represents the standardized Euclidean distance from the target distribution. The search continued until both relative errors fell below 3 %.

3. Results

We set the target PSD parameters as $(x'_{\text{target}}, n_{\text{target}}) = (113.8, 1.067)$ and conducted an autonomous search. After 15 random exploration trials in Phase 1, the target distribution was successfully reached through 9 additional experiments in Phase 2.

Figure 3 shows the obtained PSD parameters in the (x', n) space. The 15 points from Phase 1 are broadly distributed, demonstrating exploration of diverse grinding conditions. In Phase 2, the parameters obtained from conditions proposed by Bayesian optimization systematically approached the target.

The final parameters achieved relative errors of 2.9 % for x' and 0.93 % for n, satisfying the convergence criterion of 3 %.

The proposed method required only 24 trials to reach the target, compared to 64 experiments for exhaustive grid search. This represents a 62.5 % reduction in experimental workload.

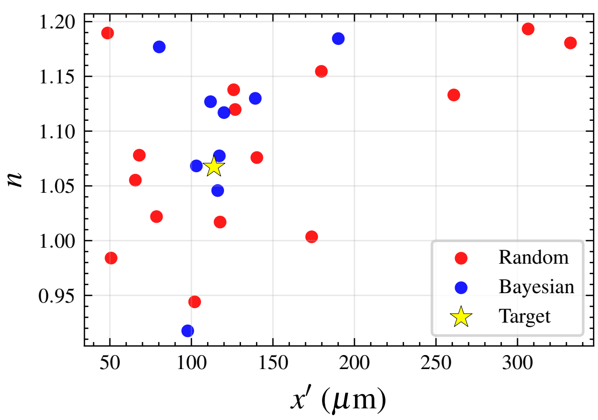

Fig. 3: Obtained PSD parameters in (x', n) space: red circles denote Phase 1 random exploration, blue circles denote Phase 2 Bayesian optimization, and yellow star denotes target

4. Discussion

4.1 System Advantages

The integrated system achieved complete automation through coordinated collaborative robots. The most significant advantage is force-feedback control, which enables the grinding load to be treated as a precise quantitative parameter rather than an empirical setting. This eliminates operator-dependent variability in powder handling and provides a foundation for reproducible experiments.

4.2 Search Efficiency

The target PSD was reached within 24 experiments, compared to 64 trials required for exhaustive grid search. This represents a reduction of more than 60 % in experimental workload. Bayesian optimization successfully captured the non-linear relationship between grinding parameters and PSD from the initial 15 random samples. This enables efficient search even when the relationship is complex. The reduction in experimental workload provides practical benefits for laboratory settings where sample quantities and researcher time are limited.

4.3 Limitations and Future Work

Several limitations remain in this study. First, sodium chloride was used as a model material. Applicability to materials with different mechanical properties, such as highly cohesive or elastic powders, requires further investigation. Second, the current approach assumes that PSD follows the Rosin-Rammler distribution. For grinding processes where PSD deviates significantly from this distribution, alternative parameter representations would be required. Third, this study focused solely on achieving target PSD. In practical material development, additional objectives such as energy efficiency or processing time are often important. Future work will expand the system to handle diverse materials and incorporate multi-objective optimization.

5. Conclusion

We developed an automated grinding system using collaborative robots with force-feedback control and Bayesian optimization. The target particle size distribution was achieved efficiently with significantly fewer experiments than exhaustive search. The integrated robotic system eliminates human-dependent factors and provides a practical framework for laboratory-scale process optimization. Future research will focus on expanding applicability to diverse materials and incorporating additional optimization objectives such as energy efficiency or processing time.

Acknowledgments

This work was partly supported by the JST-Mirai Program (Grant Number JPMJMI21G2).

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