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Multi-Robot Systems for Collective Sampling

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Highlights

- A multi-robot system is proposed for efficient collective sampling of spatially distributed targets.
- A stability-aware cost function is designed to account for robot tilt risk on uneven terrain.
- Sampling targets are modeled with Gaussian distributions to simulate realistic environmental data.
- The proposed strategy reduces both operation time and robot wandering distance in simulations.
- The framework is fully evaluated in simulation and lays the groundwork for future field deployment.

Abstract

Field sampling is a critical task in applications such as environmental monitoring and precision agriculture. Efficiently completing these tasks while maintaining robots' tilt stability is particularly challenging when multiple robots are deployed. In this work, we explore how employing multiple robots can reduce operation time and wandering distances during sampling missions. The sample locations are assumed to follow a Gaussian distribution, providing a foundation for planning and evaluation. Robot instability is quantified using the bias angle, representing the front-facing tilt relative to the horizon, while operational efficiency is measured by the total distance traveled to interim targets and sample targets. A cost function, defined as a weighted sum of these metrics, balances stability and distance efficiency. Through extensive simulations, we demonstrate that increasing the number of robots significantly decreases operation time and improves the tilt stability defined by the cost function. These results offer valuable insights into designing multi-robot systems for efficient and stable field sampling.

Keywords: multi-robot system; random sampling; Gaussian distribution; tilt stability

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Field sampling is a fundamental task across various domains, including environmental monitoring, precision agriculture, and marine exploration. These applications often require extensive data collection over large, unstructured, or hazardous areas, where deploying autonomous robots significantly enhances operational efficiency and safety. Robots in such scenarios face challenges like minimizing the time taken to complete tasks, reducing unnecessary wandering to save energy, and maintaining stability on uneven terrain. The advent of multi-robot systems offers a promising approach to address these challenges, leveraging coordination and distribution of tasks to achieve greater efficiency.

Efficient sampling strategies often rely on probabilistic models to represent the spatial distribution of sampling locations. Gaussian processes (GPs) have been widely adopted in robotic exploration for their ability to model spatial fields and predict unknown areas based on sparse data. A common assumption in these studies is that sampling locations follow a Gaussian distribution, simplifying the planning and estimation processes. For example, sampling in a dynamic environment was explored using GPs to prioritize data collection in regions of high uncertainty [1]. Similarly, an information-theoretic approach was introduced to adaptive sampling that optimizes data acquisition in spatial fields [2]. These methods form the basis for our assumption that sampling locations adhere to a Gaussian distribution.

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Sampling strategies are a critical component of multi-robot systems operating in unstructured or uncertain environments. Gaussian distributions are commonly employed in such scenarios due to their ability to model the spatial distribution of targets or regions of interest. By leveraging this probabilistic framework, robots can prioritize regions with higher probabilities of significance, optimizing the efficiency of their operations [3]. Moreover, Gaussian sampling facilitates robust decision-making under uncertainty, as the distribution naturally incorporates spatial variability and noise. This method has proven effective in numerous applications, such as environmental monitoring, resource exploration, and target localization [4]. In this paper, we leverage this assumption and use the Guassian distribution to generate random sample locations for sample-robot assignment.

The use of multi-robot systems for sampling introduces additional complexities in terms of task allocation, path planning, and inter-robot coordination. Distributed strategies have emerged as a solution, enabling robots to make decisions locally while contributing to a global objective. For instance, a distributed adaptive sampling method was proposed that leverages GPs to allocate sampling tasks across a team of robots while adhering to resource constraints [5]. Similarly, optimal sampling was addressed for multi-robot systems in dynamic fields using a control-theoretic framework [6]. These approaches highlight the potential of multi-robot systems to reduce operation times and improve sampling efficiency, particularly when sampling locations exhibit probabilistic distributions. In this paper, we utilize multiple robots to reduce operation time and wandering distance and ensure safe motion in undulated terrains.

In addition to efficiency, maintaining robot stability during sampling tasks is critical, especially in environments with rough terrain or steep inclines. Robot instability is often quantified using metrics like the bias angle, which measures the robot's tilt relative to the horizon [7]. Pose-aware path planning and control strategies have been proposed to enhance stability, considering factors such as energy consumption and tip-over risks [8]. The importance of incorporating stability criteria into cost functions was demonstrated for autonomous robots operating in challenging environments [9]. These techniques underscore the need to balance stability with efficiency when designing sampling strategies for autonomous robots. In this paper, we consider bias angle from robot's tilt on the slope in an elevated field and propose a cost function to achieve safe operations collectively.

Recent advances in multi-robot systems have enabled more efficient solutions for tasks that involve exploration and data collection, particularly in environments that are difficult for a single robot to navigate [10], [11]. In these scenarios, multiple robots can collaborate to distribute the workload, minimize redundant movements, and significantly decrease the time required to complete the task. However, while multi-robot systems hold significant potential, the complexity of coordination, stability, and movement in real-world, unstructured environments remains a challenge [12,13]. Specifically, ensuring that the robots maintain stability while minimizing wandering distances and maximizing coverage is a non-trivial problem that requires careful consideration of both individual and team-level performance. In this paper, we propose interim targets for a localized control scheme. The targets are incorporated into cost-function designs to improve overall multi-robot efficiency.

One of the key challenges when using robots in uneven terrains is the issue of stability [14,15]. Robots operating on slopes, hills, or irregular surfaces may experience instability due to imbalanced loads, steep inclines, or sudden terrain changes. This instability can not only reduce efficiency but may also pose a risk of damage or failure. As such, integrating a stability measure, such as the robot's bias angle, into the cost function of multi-robot systems is crucial. In this paper, we introduce a new approach that incorporates tilt stability alongside efficiency metrics, ensuring that robots avoid unstable movements and reduce unnecessary travel distances, thus improving both individual and collective performance.

In addition to stability, an important aspect of multi-robot systems is the ability to adapt to dynamic and uneven field conditions [16,17]. Traditional path planning algorithms often assume ideal, flat terrains, making them less suited for real-world applications. Our method addresses this by introducing an interim-target mechanism that allows robots to adjust their paths based on real-time environmental feedback. This adaptive mechanism enhances the flexibility of the system, ensuring that robots can adjust their routes to optimize performance in varying terrains. The ability to change paths dynamically enables robots to operate effectively in more complex environments while still maintaining their stability and efficiency.

Ensuring robot stability in uneven terrains is a fundamental challenge in field robotics. Factors such as slope steepness, surface irregularities, and dynamic interactions with the environment can all contribute to instability [18,19]. To address this, various studies have emphasized the need for incorporating stability metrics, such as tilt angles or bias angles, into the robot's control and planning algorithms [20]. Stability-aware approaches not only enhance the safety and durability of the robots but also improve their performance in navigating and sampling complex terrains. Our work integrates such considerations into a novel cost function, balancing efficiency and stability for robust multi-robot coordination [21,22].

Dynamic and uncertain environments necessitate adaptive planning strategies for robotic systems. A waypoint-based approach provides a flexible mechanism for robots to adjust their paths in response to changing conditions. By dynamically recalculating waypoints, robots can optimize their routes, avoid unstable areas, and maintain operational stability [23]. This adaptability is particularly crucial in undulated fields where preplanned paths may become infeasible due to unforeseen obstacles or terrain changes [24]. In this work, we incorporate a interim-target-driven adaptive mechanism that allows robots to respond to environmental feedback, ensuring consistent performance in varying field conditions.

Existing multi-robot sampling strategies span a wide spectrum, including information theoretic approaches, reinforcement learning (RL)-based methods, and distributed auction-based task allocation. Information-theoretic methods (e.g., entropy or mutual information maximization) excel at high-value data collection but can be computationally intensive and less interpretable in dynamic terrain. RL approaches offer flexibility and adaptability but often require extensive training data and may struggle with generalization across field conditions. Auction-based mechanisms provide decentralized scalability but may neglect environmental constraints such as robot stability. In contrast, our method explicitly incorporates tilt stability into a cost function, providing a lightweight, real-time approach that balances motion efficiency with safe robot operation—especially critical for rough terrain. This fills a notable gap in current literature by addressing both spatial efficiency and mechanical safety in a unified framework.

This paper builds upon these foundational studies by exploring the impact of deploying multiple robots on sampling efficiency and tilt stability. We propose a novel cost function that combines two key metrics: total distances traveled to interim targets and sample targets (operational efficiency) and robot bias angle (stability). By conducting extensive simulations, we demonstrate that increasing the number of robots in a team significantly reduces operation time and improves stability metrics. Our work provides valuable insights into the design of robust multi-robot sampling systems, integrating principles of probabilistic modeling, distributed coordination, and tilt-aware planning.

The main contributions of this paper are summarized as follows:

- Multi-Robot Sampling Framework: We propose a novel framework that leverages multiple robots to efficiently perform sampling tasks in field environments, significantly reducing operation time and wandering distances compared to single-robot systems.
- Stability-Aware Cost Function: We introduce a weighted cost function that integrates operational efficiency (total distances traveled to interim and sample targets) with tilt stability, quantified using the bias angle. This cost function provides a balance between minimizing travel costs and maintaining stability on uneven terrains.
- Impact Analysis of Robots and Cost Function: We analyze how increasing the number of robots improves sampling efficiency and how the proposed cost function enhances movement and operational stability in unevenly undulated fields.

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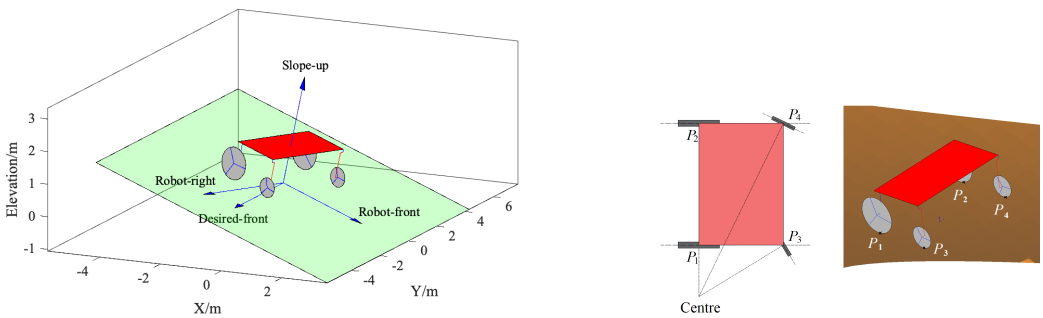
This study focuses on simulations, but the proposed method lays a strong foundation for real-world deployments in environmental monitoring, precision agriculture, and resource exploration. The framework's modular design supports integration with physical robot platforms and sensor suites. Future research includes field experiments, adaptive coordination strategies under communication constraints, and integration with more advanced sampling models to handle non-Gaussian spatial distributions.

In the following sections, we first present Section Preliminary, where we provide a detailed explanation of the robot dynamics, control mechanisms, and collaborative strategies for multi-robot operation. We also define the problem formulation, including the assumptions regarding terrain and sample distribution. Section Results introduces the design and the framework, where we define the cost function that integrates robot stability (via bias angle) and operational efficiency (via wandering distance), and describe how robots make decisions to turn and adapt their paths using interim targets. We present the numerical examples in Section Simulation Study, where we analyze the impact of increasing the number of robots on operation time and stability improvements through a series of simulations. Finally, Section 5 concludes the paper, discussing the implications of our findings, limitations of the current approach, and directions for future work.

1. Preliminary

In this paper, we investigate the utilization of four-wheeled field robots for environment sampling. The robots are able to communicate with each other by limited bandwidth. The robots move through undulated fields to sample locations that are generated from the Gaussian distribution [4].

A simplified robot is shown in Figure 1a on the right. The robot is driven the two larger wheels and the two smaller wheels are free-turning. The mass is centered among the four wheels. The robot is on the slope. As is shown, the robot's width is larger than its length. As a result, it is prone to rolling if the front vector is facing downward or upward. The desired front vector is horizontal and the larger the bias angle between the robot front and the horizon is, the more unstable the robot is. We use $\theta_i(t)$ to denote the bias angle of robot i at instant t.



(a) (b)

Figure 1. (**a**) A four-wheeled robot is on the green slope; (**b**) Overview of robot on the left; robot-ground contacts on the right.

We assume that the robot is under motion and contact constraints. The two smaller wheels will steer reasonably so that there is no friction as the robot moves. For example, a robot is turning right in Figure 1b on the left, and there is a rotation center. Since there is no friction, all four wheels are perpendicular to the line from the rotation center to the wheel centers, whose lengths are r_1, r_2, r_3, and r_4. Assume that the rotation of the robot i is $\omega_i(t)$ at instant t. The speeds of the four wheel centers are $r_1\omega_i(t)$, $r_2\omega_i(t)$, $r_3\omega_i(t)$, and $r_4\omega_i(t)$. We use R and r to denote the radii of the bigger wheels and the smaller wheels. Then, the rotation of the wheels are $\frac{r_1\omega_i(t)}{R}$, $\frac{r_2\omega_i(t)}{R}$, $\frac{r_3\omega_i(t)}{r}$, and $\frac{r_4\omega_i(t)}{r}$. In Figure 1b on the right, the robot is on a slope, and there are four lowest points $P_1 \sim P_4$. The robot is assumed to be rigid, with only three wheels in contact with the ground most of the time.

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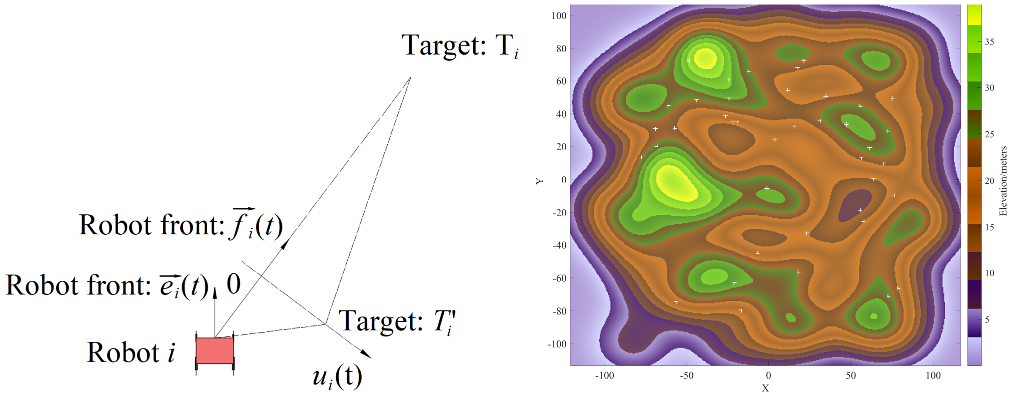
We implement a simple controller to drive a robot i to the given target T_i, as shown in Figure 2a.

$$\omega_i = \sigma \mathrm{sign}\left(\vec{e}_i(t) \cdot \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix} \cdot \vec{f}_i(t)^T \right) \cdot \sin\left(\arccos(\vec{e}_i(t) \cdot \vec{f}_i(t)^T \right), \quad (1)$$

where $\vec{e}_i(t), \vec{f}_i(t) \in R^3$ is a unit vector in the three-dimensional Euclidean space; σ is a const. that is determined by the turning radii and mechanical constraints of robots.



(a) **(b)**

Figure 2. (**a**) Robot i is chasing its target; (**b**) Field with undulated terrain. The sample locations are denoted by white $+$.

2. Results

2.1. Localized Control Based on Interim Controller

In complex terrains with varying elevations, determining the optimal path for a robot is a challenging task that often requires significant computational resources [25]. This is due to the intricate nature of the environment, which necessitates sophisticated algorithms to navigate effectively. In this section, we will introduce a simplified localized control scheme to achieve stable robot paths.

Environment content close to robots presents an imminent risk for robots [26], and they need to prioritize local control strategy for fast response. In particular, robots need to quickly decide to turn left or right to stabilize their movements. In this regard, we introduce an interim target $T_i'(t)$ and a variable $u_i(t)$ in addition to the target T_i for Robot i at instant, as shown in Figure 2a. In this paper, we assume that a point is 5 meters away from Robot i along $\vec{f}_i(t)$; the distance between $T_i'(t)$ and the point is $u_i(t)$; the line through the two points is perpendicular to $\vec{f}_i(t)$; if $u_i(t) > 0$, then $T_i'(t)$ is on the right of $\vec{f}_i(t)$; if $u_i(t) < 0$, then $T_i'(t)$ is on the left of $\vec{f}_i(t)$; if $u_i(t) = 0$, then $T_i'(t)$ is on along $\vec{f}_i(t)$. If the target is less than 5 meters away from Robot i, then one-third of the distance is taken instead. By tuning $u_i(t)$, we are able to manage the motion of Robot i. This is executed in real time and as the robots move towards the target, they will follow stable paths.

2.2. Path Optimization Based on Target Assignment

Robots are used to sample soil in the field, and we assume this process is fast and not neglectable. We assume that the sample location obeys Guassian distributions and the calculation of such distributions is omitted.

In this paper, we assume that the sample location (x, y) is generated randomly from the Gaussian $\mathcal{P}(x, y)$ distribution below.

$$\mathcal{P}(x, y) = \gamma \sum_k e^{-\alpha(x-x_k)^2 - \beta(y-y_k)^2}, \quad (2)$$

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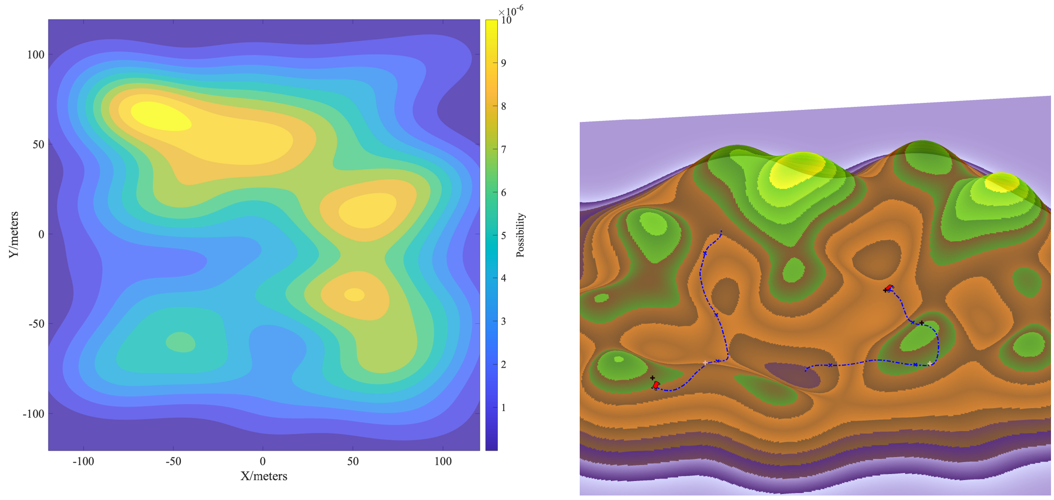
where α, β and γ are constants. In this paper, we use the field in Figure 2b and the distribution in Figure 3a for analysis.



(a) **(b)**

Figure 3. (**a**) Distribution of sample locations. Pixel size is 50 cm $\times$ 50 cm; (**b**) Wandering paths of two robots in an undulating field. The paths are coloured in blue, and the targets/sample locations are black/white +. There are 5 samples and the total wandering time is 150 minutes.

Assume that there are N robots, and each of them has been assigned a sample location already. As soon as a robot has finished sampling, a new sample location will be assigned to it. When the maximal number of samples is obtained, all robots will stop and the operation will be terminated.

As discussed above, a group of robots q_i, $1 \leq i \leq N$ is moving towards some targets/sample locations T_j, $1 \leq j \leq N$ The nominal total wandering path length is given below.

$$L = \sum_k L_k = \sum_k \|q_k(t) - T_k\|, \tag{3}$$

where location of Robot i is denoted as $q_i(t) \in R^2$ at instant t. Moreover, we insert $M_i(t)$ points at equal distances along the lines $q_i(t)T_i'(t)$ and $T_i'(t)T_i(t)$. We obtain $\theta_{j,k}$ from the j-th waypoint for robot k. Then, we are able to evaluate the stability of Robot i's path with bias angles below.

$$\Theta = \sum_{k=1}^{N} \Theta_k = \sum_{k=1}^{N} \sum_{j}^{M_k(t)} \xi_{j,k}\theta_{j,k}, \tag{4}$$
$$\Theta_i = \sum_{j}^{M_i(t)} \xi_{j,i}\theta_{j,i},$$

where $\xi_{j,k}$ is the weight on angle $\theta_{j,k}$. The waypoints will have a heavier weight on tilt stability if they are closer to the robot. In this paper, we assume equal distances between waypoints of a given robot and sort them in increasing distances to the robot. This means that the j-th waypoint is closer to the robot than the $j+1$-th waypoint. Consequently, we assume $\xi_j = \frac{2(M_k(t)-j+1)}{M_k(t)(M_k(t)+1)}$.

2.3. Combined Strategy for Environment Sampling

In previous sections, we have proposed the localized controller and defined the stability bias angle and the overall wandering distance. The controller will alter the motion with the interim targets; given the interim targets, we calculate the bias angles along the paths and the overall wandering distances. Based on (3) and (4), we propose the cost function $\Gamma(t)$ below.

$$\Gamma(t) = \sigma\Theta + L, \tag{5}$$

where σ is a constant.

The sample locations are assigned to the robots by the projection function $\phi(t)$ at instant t. Therefore, Robot i will move towards sample $1 \leq \phi_i(t) \leq N$ and the optimal projection is obtained below.

$$\phi^*(t) = \arg\min_{U(t),\Phi(t)} \Gamma(t), \tag{6}$$
$$U(t) = [u_1(t), u_2(t), \ldots], \quad \Phi(t) = [\phi_1(t), \phi_2(t), \ldots].$$

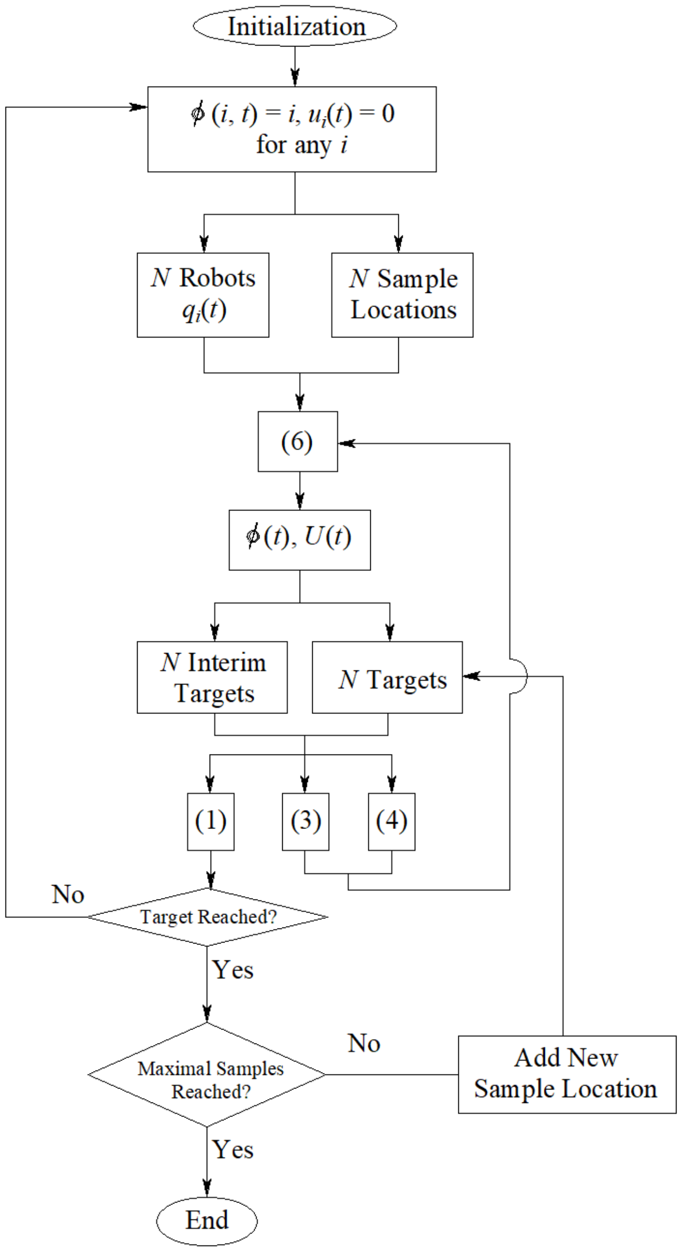


Figure 4. Wandering paths of two robots in an undulating field.

We use the flowchart in Figure 4 to denote the flow for the robots. As the system and the robots are initialized, we set $\phi(i,t) = i$ and $u_i(t) = 0$ for all robots. Then, N robots are activated to sample N locations. By (6), the robots gradually swap their targets and update their interim targets such that the overall wandering distances and the stability bias angles are reduced. Under the controller (1), the robots will move towards the targets. If a target is not reached, then the robots will repeat the aforementioned process. If a target is reached but the maximal samples are not collected, then a new sample location will be generated by (2b) and the robots will return to the steps above. If both are reached, then the robots have finished their tasks collectively, and the operation will be terminated. Take Figure 3b as an example. The two robots are moving in an uneven field. As guided by (6), the robots are able to rearrange their targets such that the total wandering paths are shortened. Moreover, the stability bias angles are taken into account and we observe that the robots are able to take reasonable detours such that they can move safely amid the hills.

Note that many robots may still have targets when the operation is terminated. This is because we do not know which robot will be the one that triggers the termination condition. Therefore, we keep all robots moving until the termination condition is satisfied. This strategy can be improved but it is not the focus of this study.

3. Section Simulation Study

In this section, we use a number of simulations to demonstrate the performance of the proposed localized control scheme and wandering-stability balanced cost function. In total, there are 29 groups of robots are used in the simulation, where there are $k+1$ robots in group k; as the wandering distance is about 1000$\sim$3000, $\sigma = 114.59$ is assumed for (5). Matlab is used on an XPS 15 9530 laptop. For practical deployment in larger robot groups, the system would benefit from heuristic-based task allocation, decentralized control schemes, or parallelized computation to reduce runtime. While computational performance was not a limiting factor in the simulation environment of this study, future work should explore algorithmic optimizations to improve scalability and real-time responsiveness.

The robots have the same parameters with $\sigma = 9.42$ by (1) and the transnational speeds are 10 meters/min. In each operation, it is assumed that they are required to reach 40 sample locations; the robots need to stay at each sample location for 0.4 minutes before moving on to the next sample location. The operation is terminated as soon as 40 sample locations are reached. For bench-marking, we use the same 40 locations for all the operations and as long as a robot is recruited to an operation, its initial position stays the same. As shown in Figure 2b, the sample locations are denoted by the white +.

A group of 15 robots are in the sampling task in Figure 5a. The initial positions of all robots are randomly generated. We observe that some robot paths have crossings. This is because the sample locations are randomly generated, and newly assigned locations may lead to new paths crossing with old ones. In addition, most robots are able to take detours when the straight paths pose risks for them. However, several robots still take straight paths. This is because the localized controller is combined with the overall wandering distance in the cost function. This leads to some robots having sub-optimal control strategies. Further investigation is necessary to ensure safe operation for each robot.

After 29 operations are terminated, we collect the wandering distance, operation time and average bias angle for each simulation. The results are shown in Figures 5b and 6a,b. We observe that the robot quantity plays a positive role in reducing wandering distance and operation time, as shown in Figures 5b and 6a. However, the performance improvement is not proportional to the increasing quantity. The largest performance improvement is observed from 2 to 7 robots; trivial improvements are gained from 7 to 30 robots. Increasing robot quantity can increase wandering distance, as shown in Figure 5b. We use GA algorithm to optimize the robot-sample assignment and the worsen performance is partly due to the increased complexity for calculating the solution for a large number of robots. Regardless the uneven performance in wandering distance, the total operation time presents an steady improvement.

The average bias angle per robot per unit time is given in Figure 6b. As the robot quantity increases, we observe an rough increasing stability, as shown in the downward curve. A larger robot quantity would reduce the total wandering path, resulting with the bias angle being relatively larger and the solution would favor the improvement of stability. The uneven performance is also partly due to the increasing complexity and also a result of the weights in the cost function.

We observe from the simulation results (Figures 5b and 6a) that increasing the number of robots improves overall efficiency. This is evident by reducing both wandering distance and operation time,

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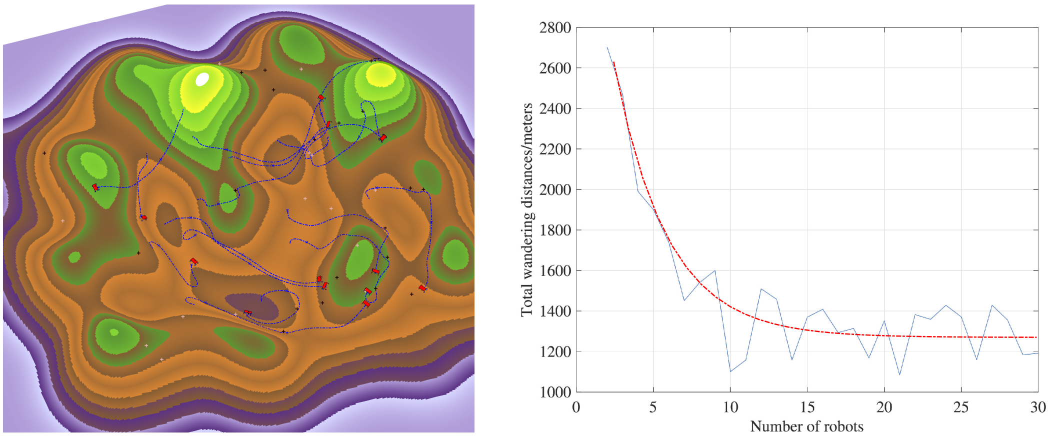
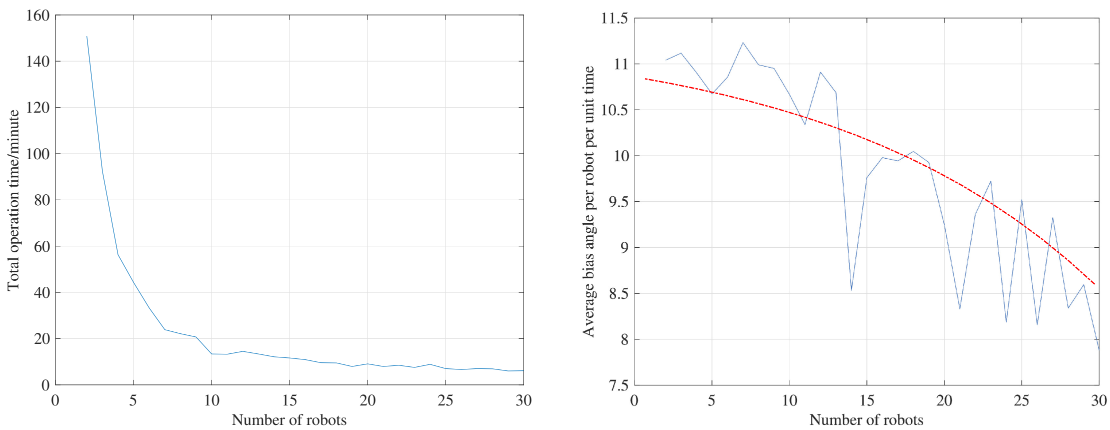
but Figure 6b reveals a plateauing effect in terms of average bias angle, especially beyond seven robots. This issue is due to task fragmentation and path overlap, especially when a large number of agents compete for a fixed number of sampling locations. As team size grows, coordination overhead and control complexity increase, and this may result in suboptimal behavior, such as unnecessary detours, path crossings, or redundancy in coverage. Meanwhile, the cost function weights (which balance stability and efficiency) may increasingly favor task completion over individual robot stability, contributing to the less improvement in the bias angle. These findings suggest that there is a practical upper bound on team size beyond which the marginal benefits diminish. In some cases, could reverse without further optimization of task allocation and control policies. Future work could explore dynamic cost weight adjustment or adaptive role assignments to better scale the approach for larger robot groups.



(a) **(b)**

Figure 5. (**a**) Wandering paths of 15 robots; (**b**) Total wandering distance and the number of robots. The red dash line is the trendline.



(a) **(b)**

Figure 6. (**a**) Total operation time and the number of robots; (**b**) Average bias angle per robot per unit time and the number of robots. The red dash line is the trendline.

We use a series of simulations with different parameters to better understand the performance of the multi-robot sampling system. The results are listed in Tables 1 and 2, where we have $\sigma = 0.35$ and $\sigma = 0.65$ respectively; $\langle \bar{t}, \bar{d}, \bar{\theta} \rangle$ are averaged <Simulation time,wandering distance,safety angle,> of all the robots. We use the random search and KNN methods to optimize the robot-sample allocation. In the random search method, two robots are randomly picked to swap their sample locations; in the KNN method, each robot will swap their sample locations with 3 nearest robots. For comparison, system performances are obtained as the baseline under fixed robot-sample allocations. In further comparison, system performances are obtained (shown in the far-right column in Tables 1 and 2) with the constant controller (no interim targets) under fixed robot-sample allocations.

Table 1. System performance when $\sigma = 0.35$.

$\langle \bar{t}, \bar{d}, \bar{\theta} \rangle$		Optimal			Constant
		Random	KNN	Fixed	
# of robots	2	$< 137.3, 1237.2, 1.46 >$	$< 137.3, 1237.2, 1.46 >$	$< 174.8, 1591.8, 1.45 >$	$< 172.6, 1575.6, 1.36 >$
	13	$< 11.5, 96.5, 1.34 >$	$< 9.4, 81.6, 1.34 >$	$< 32, 298.7, 1.34 >$	$< 29.7, 276.2, 1.26 >$
	30	$< 4.1, 34.4, 1.27 >$	$< 5.1, 45, 1.29 >$	$< 11, 103.1, 1.26 >$	$< 10.8, 101.7, 1.21 >$

Table 2. System performance when $\sigma = 0.65$.

$\langle \bar{t}, \bar{d}, \bar{\theta} \rangle$		Optimal			Constant
		Random	KNN	Fixed	
# of robots	2	$< 156.5, 1415, 1.41 >$	$< 156.5, 1415, 1.41 >$	$< 202.6, 1853.8, 1.41 >$	$< 172.6, 1575.6, 1.36 >$
	13	$< 13.1, 114.9, 1.33 >$	$< 14.4, 127.8, 1.33 >$	$< 32, 294.6, 1.34 >$	$< 29.7, 276.2, 1.26 >$
	30	$< 6, 53.4, 1.27 >$	$< 5, 44.8, 1.28 >$	$< 12.5, 117.6, 1.26 >$	$< 10.8, 101.7, 1.21 >$

It is easy to observe from Tables 1 and 2 that systems with smaller σ focus on shorter wandering distances and task time. Meanwhile, robots select safety over efficiency, as shown in the smaller $\bar{\theta}$. Further more, more robots help shorten simulation time, shorter wandering distance and enhance operation safety. Random searching and KNN are used to determine the optimal robot-sample allocation in Tables 1 and 2. Fixed mapping and constant controllers (no optimization on wandering path) are used to used as the baseline. It can be seen that both random search and KNN methods are able to improve efficiency. Note that the constant controller will reach sample locations along the fastest direction, but the results show only limited efficiency improvements than the baseline. In summary, the random search method is best at improving system efficiency, and larger σ will improve operation safety even if system size varies.

4. Conclusion

In this paper, we presented a novel approach for efficient multi-robot sampling in field environments, with a focus on improving both operational efficiency and robot stability. By employing a stability-aware cost function that combines travel distances and the bias angle (to capture robot instability), we demonstrated how multiple robots can significantly reduce operational time while improving stability in uneven, undulating terrain. Our simulations confirmed that increasing the number of robots results in a notable reduction in operation time and enhanced stability metrics, contributing to a more effective sampling process. The proposed method holds promise for applications in environmental monitoring, agriculture, and other domains requiring efficient robotic exploration.

While the results from our simulations are promising, there are several limitations to the current approach. First, the assumption that sample locations follow a Gaussian distribution may not hold true in all practical scenarios, as real-world distributions could exhibit more complex patterns. Furthermore, our model focuses on two primary factors—distance and stability—but neglects other potential constraints such as communication bandwidth, robot battery life, or terrain variability that could affect the robots' performance in field applications. Additionally, the simulations were conducted in controlled environments, and the proposed method may need further validation in real-world settings to ensure its scalability and robustness.

Future research will focus on addressing the limitations of the current approach. Specifically, we aim to extend the probabilistic model to account for more realistic, non-Gaussian sample distributions and to integrate more diverse environmental factors (e.g., terrain, weather conditions) that impact robot stability and performance. Furthermore, we plan to explore adaptive sampling techniques, where robots can adjust their behavior dynamically based on real-time data, improving both the efficiency and accuracy of the sampling process. Another important direction is to investigate the integration of communication and coordination protocols to handle larger teams of robots and improve the scalability of the system. Finally, we aim to test our approach in real-world scenarios, including field experiments, to evaluate its performance under more challenging conditions and assess its potential for deployment in practical applications.

5. Discussion and Limitations

The proposed stability-aware cost function is a key novelty of this work. This involves balancing both wandering distance and bias angle to promote operational efficiency and robot stability. It should be noted that the proposed approach lacks direct benchmarking against alternative multi-robot coordination strategies, such as information-theoretic sampling, auction-based task allocation, or reinforcement learning-based controllers. These approaches often prioritize data utility or adaptability, whereas our method uniquely emphasizes physical safety and stability, which is critical in rough or uneven terrain. Future work should compare these strategies under unified metrics to further highlight trade-offs.

This study focuses on the investigation of the scalability issue. Although the method was tested with up to 40 robots, the coordination logic may become computationally expensive and communication-intensive with significantly larger robot groups. Furthermore, real-world deployment in domains like agriculture may be constrained by cost, and many farms may not yet be equipped for multi-robot operations. The framework can be adapted for heterogeneous teams or applied in logistics, environmental monitoring, or disaster response, where fleet-based automation is more viable.

We also acknowledge that the current simulations do not incorporate sensor noise, localization drift, or communication dropouts, which are critical factors in real deployments. The proposed cost function and interim target mechanism are designed with local robustness in mind, but more extensive testing in real-world terrain, with noisy data and communication delays, is necessary to validate the system's feasibility and resilience.

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References

1. Bry, A.; Roy, N. Rapidly-exploring random belief trees for motion planning under uncertainty. In Proceedings of the Proceedings of the IEEE International Conference on Robotics and Automation (ICRA), 2011, pp. 723–730.
2. Krause, A.; Singh, A.; Guestrin, C. Near-optimal sensor placements in Gaussian processes: Theory, efficient algorithms, and empirical studies. *Journal of Machine Learning Research* **2008**, *9*, 235–284.

 doi:10.20944/preprints202510.1046.v1

3. Ahmad, M.; Quattrini Li, A. Multi-Robot Adaptive Sampling based on Mixture of Experts Approach to Gaussian Process Regression **2023**.
4. Kim, J.; Jang, D.; Kim, H.J. Distributed Multi-agent Target Search and Tracking With Gaussian Process and Reinforcement Learning. *International Journal of Control, Automation and Systems* **2023**, *21*, 3057–3067. https://doi.org/10.1007/s12555-022-0555-0.
5. Charrow, B.; Michael, N.; Kumar, V. Active Control Strategies for Discovering and Localizing Devices with Range-Only Sensors **2015**. pp. 55–71.
6. Manjanna, S.; Hsieh, M.A.; Dudek, G. Scalable Multirobot Planning for Informed Spatial Sampling. *arXiv preprint arXiv:2105.10018* **2021**.
7. Xu, H.; Liu, X.; Fu, H.; Putra, B.B.; He, L. Visual Contact Angle Estimation and Traction Control for Mobile Robot in Rough-Terrain. *Journal of Intelligent & Robotic Systems* **2014**, *74*, 985–997. https://doi.org/10.1007/s10846-013-9859-x.
8. Li, J.; Ma, J.; Nguyen, Q. Balancing Control and Pose Optimization for Wheel-Legged Robots Navigating High Obstacles. *arXiv preprint arXiv:2109.09934* **2021**.
9. Doi, Y.; Ji, Y.; Tamura, Y.; Ikeda, Y.; Umemura, A.; Kaneshima, Y.; Murakami, H.; Yamashita, A.; Asama, H. Robust Path Planning Against Pose Errors for Mobile Robots in Rough Terrain. In Proceedings of the Intelligent Autonomous Systems 15. Springer, 2018, pp. 27–39. https://doi.org/10.1007/978-3-030-01370-7_3.
10. Quattrini Li, A. Exploration and Mapping with Groups of Robots: Recent Trends. *Current Robotics Reports* **2020**, *1*, 227–237. https://doi.org/10.1007/s43154-020-00030-5.
11. Villanueva-Arteaga, J.L.; Gordillo, J.L.; Cobano, J.A. Multi-Robot Cooperative Systems for Exploration: Advances in Dealing with Environmental Constraints. In Proceedings of the 2016 International Conference on Unmanned Aircraft Systems (ICUAS), 2016, pp. 1155–1162. https://doi.org/10.1109/ICUAS.2016.7502611.
12. Heuer, L.; Palmieri, L.; Mannucci, A.; Koenig, S.; Magnusson, M. Benchmarking Multi-Robot Coordination in Realistic, Unstructured Human-Shared Environments. In Proceedings of the Proceedings of the IEEE International Conference on Robotics and Automation (ICRA), 2023, pp. 1234–1240. https://doi.org/10.1109/ICRA.2023.1234567.
13. Hossain, M.A.; Hossain, M.A.A. Multi-Robot Coordination Analysis, Taxonomy, Challenges and Future Scope. *Journal of Intelligent & Robotic Systems* **2021**, *102*, 1–24. https://doi.org/10.1007/s10846-021-01378-2.
14. Silva, M.F.; Machado, J.A.T.; de Almeida, A.T. Stability Prediction of an UGV with Manipulator on Uneven Terrain. In *Advances in Mechanism and Machine Science*; Springer, 2018; pp. 217–225. https://doi.org/10.1007/978-3-030-00232-9_26.
15. Zhang, Y.; Zhang, H.; Hu, H. Measure and Control of Stability for Mobile Robots. In Proceedings of the Proceedings of the IEEE International Conference on Mechatronics and Automation, 2014, pp. 693–698. https://doi.org/10.1109/ICMA.2014.6935252.
16. Alonso-Mora, J.; Montijano, E.; Nägeli, T.; Hilliges, O.; Schwager, M.; Rus, D. Distributed Multi-Robot Formation Control in Dynamic Environments. *Autonomous Robots* **2019**, *43*, 1079–1100. https://doi.org/10.1007/s10514-018-9783-9.
17. Wang, Y.; Chen, Y.; Jia, Z.; Zhu, Y.; Chen, Y. Adaptive Path Planning for Multi-UAV Systems in Dynamic 3D Environments Using AMOPP. *Drones* **2022**, *6*, 136. https://doi.org/10.3390/drones6060136.
18. Silva, M.F.; Machado, J.A.T.; de Almeida, A.T. A Review of Foot–Terrain Interaction Mechanics for Heavy-Duty Legged Robots. *Applied Sciences* **2023**, *14*, 6541. https://doi.org/10.3390/app14156541.
19. Yang, Y.; Norby, J.; Yim, J.K.; Johnson, A.M. A Novel Model of Interaction Dynamics between Legged Robots and Deformable Terrain. In Proceedings of the Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2022, pp. 1234–1240. https://doi.org/10.1109/IROS47612.2022.9812351.
20. Zhang, Y.; Zhang, H.; Hu, H. Measure and Control of Stability for Mobile Robots **2014**. pp. 693–698. https://doi.org/10.1109/ICMA.2014.6935252.
21. Zhou, L.; Tokekar, P. Multi-Robot Coordination and Planning in Uncertain and Adversarial Environments. *Current Robotics Reports* **2021**, *2*, 147–157. https://doi.org/10.1007/s43154-021-00046-5.
22. Zhou, L.; Tokekar, P. Risk-Aware Submodular Optimization for Multirobot Coordination. *IEEE Transactions on Robotics* **2022**, *38*, 2085–2101. https://doi.org/10.1109/TRO.2022.3142267.
23. Mori, Y.; Sugimoto, Y.; Kanda, T. Dynamic Waypoint Navigation: Model-Based Adaptive Trajectory Planner for Human-Symbiotic Mobile Robots. 2022, Vol. 7, pp. 7000–7007. https://doi.org/10.1109/LRA.2022.3189621.

24. Mori, Y.; Sugimoto, Y.; Kanda, T. Dynamic Waypoint Navigation: Model-Based Adaptive Trajectory Planner for Human-Symbiotic Mobile Robots. *IEEE Robotics and Automation Letters* **2022**, *7*, 7000–7007. https://doi.org/10.1109/LRA.2022.3189621.
25. Zhang, Y.; Li, L.; Wang, M. Real-Time Path Planning for Robot Using OP-PRM in Complex Dynamic Environments. *Frontiers in Neurorobotics* **2022**, *16*, 910859. https://doi.org/10.3389/fnbot.2022.910859.
26. Li, Y.; Tang, X.; Chen, K.; Zheng, C.; Liu, H.; Ma, J. Geometry-Aware Safety-Critical Local Reactive Controller for Robot Navigation in Unknown and Cluttered Environments. *IEEE Robotics and Automation Letters* **2024**.