Swarm Control with Particle Filter for Search and Rescue Operations Using Mobile Robots

Ryo Murakami, Hiroyuki Yomo, and Yasuhisa Takizawa
Graduate School of Science and Engineering, Kansai University, Japan

Abstract—**During search and rescue operations carried out for emergency response or disaster relief, there are many targets requiring rescue operations in a given environment, whose number and locations are unknown. In this paper, we investigate how to control the mobility of swarm of autonomous robots to efficiently search for and approach to targets to execute given tasks. We propose a swarm control algorithm, which includes the search and approach operations based on swarm intelligence, called mobile sensing cluster (MSC), combined with target localization employing particle filter (PF). We design mobility control that takes full advantage of the integrated operations of MSC and localization using PF. With computer simulations, we show that the proposed swarm control reduces the time required for searching targets and for completing their required tasks in comparison to reference schemes.**

I. Introduction

Search and rescue (SAR) operations employing a group of autonomous robots or drones are envisioned to play an important role to realize a variety of civil applications such as emergency response and disaster relief [1]. In these applications, mobile robots, which are equipped with sensing and communication capabilities, are required to autonomously identify locations of targets and approach to them in order to conduct rescue and/or surveillance tasks.

In this work, we focus on a SAR scenario where unknown number of targets emit radio signals, e.g., beacons emitted by emergency devices or signals generated by mobile phones owned by victims at a disaster area, which need to be quickly searched and rescued/surveyed by multiple mobile robots. In this case, two operations are required: (1) estimation of target locations and (2) movement to the vicinity of each target. For the first operation of location estimation, there have been several studies exploiting received signal strength indicator (RSSI) detected by a group of mobile robots. Among these, an algorithm based on particle filter (PF) with appropriate selection of observation points (i.e., positions of mobile robots) has been shown to achieve high accuracy of estimation [2][3]. However, these studies mainly focus on the location estimation, and do not consider the movement to each target, i.e., their algorithms do not consider the approach of mobile robots to targets. On the other hand, in order to realize the second operation of the movement to targets, our previous study introduced an algorithm based on swarm intelligence, called mobile sensing cluster (MSC) [4]. MSC applies the concept of particle swarm optimization (PSO) [5] to the mobility control of swarm robots, where robots evaluate their positions based on their detected RSSIs and exchange these results with the surrounding robots through wireless communications. The movement vector of each robot is controlled in such a way that they move to the position with higher evaluation value or follow robots located in better positions. However, due to the noise and/or fluctuation added to RSSIs, each robot is not able to evaluate its position appropriately, which leads to redundant movement when heading to targets.

In order to solve the above problems of existing work, in this paper, we propose a swarm control algorithm combining the concept of PF and MSC, i.e., encompassing both operations of target localization and movement to targets. In the proposed algorithm, robots execute the operations of location estimations of multiple targets while approaching to a selected target. The robots employ a mobility control, which forms a swarm in such a way that the accuracy of estimation is improved while approaching to the target. Once the accuracy of location estimation for the selected target exceeds a certain threshold, robots directly move to the estimated location as straightly as possible. Once the selected target is captured (i.e., its rescue/surveillance task is completed), robots exploit the available results of location estimations of the other targets to decide the next movement. With computer simulations, we evaluate the gain brought by introducing the operation of location estimation based on PF and mobility control into MSC.

II. System Model

The system model considered in this paper is shown in Fig. 1, where unknown number of targets, which emit signals with identity information facilitating their discoveries, exist within a sensing field. The examples of signals are beacons generated by emergency devices or signals generated by mobile phones owned by victims. Mobile robots, which are equipped with sensors detecting the emitted signals, search for these targets, and execute tasks such as rescue or surveillance operations after approaching to them. We assume that the task can be executed by a robot if it is sufficiently close to a

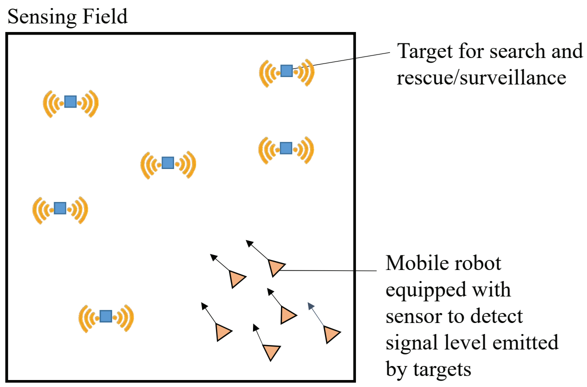

Fig. 1. System model.

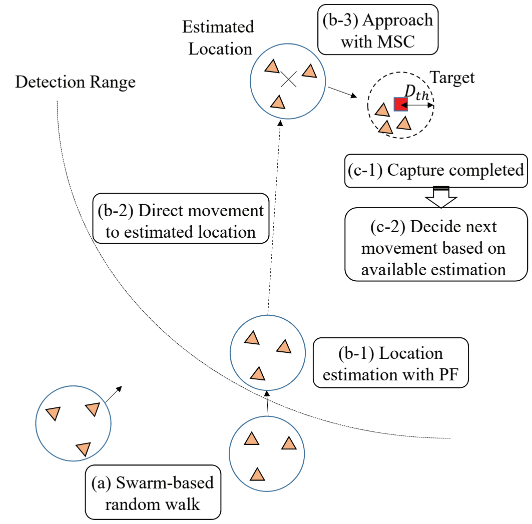

Fig. 2. The overview of the proposed swarm control.

target, i.e., within D_{th} [m] from a target. We assume that a fixed amount of load of W is required to complete a task while the work efficiency of each robot is R_w [load/s] [6]. Once the task is completed, i.e., the remaining work load reaches 0, the target is considered to be *captured*. The identity information on the captured target is continuously broadcast by each robot, and after this information is received by the other robots, they ignore the signal transmitted by the corresponding target.

Each mobile robot detects a target signal with its identity if its received signal strength indication (RSSI) is larger than γ_{th}^{D}. We assume that RSSI is affected by path-loss and additive white Gaussian noise (AWGN) at the receiver. We assume that GPS is not available at target devices due to lack or disabled setting of GPS receiver or it is not reliable because the targets can be located indoor or under debris. On the other hand, it is reasonable to assume that GPS is available at each mobile robot, and robots can exchange information to facilitate their swarm control, such as their locations obtained by GPS and RSSIs detected for different targets, with the other robots within their wireless communication range.

III. Proposed Swarm Control with Particle Filter

The proposed swarm control combines the operations of target search/approach with target localization while adding the additional mechanism of mobility control to improve the efficiency to capture multiple targets. The operations differ depending on whether each robot has already detected signals emitted by targets, and if so, its distance to a searching target. The overview of the proposed swarm control is shown in Fig. 2, which is explained in detail below.

a) Operations before detecting signals of any targets: In this case (shown in (a) in Fig. 2), each robot has no information to exploit to control their movement. Therefore, the basic operation is *random walk*, where each robot decides its movement vector (direction) randomly. However, the simple application of random walk causes each robot to move back and forth to the positions that have been already covered for its search operation. There is also a risk of collision among mobile robots. Therefore, in this work, we employ a history-based search, where a movement vector of robot i is set as follows:

$$v_i(t+1) = v_i^r + \alpha \overrightarrow{S_i} + k_s v_i^s(t) + k_o v_i^o(t), \tag{1}$$

where $v_i(t)$ is the movement vector of robot i at time t, v_i^r is the random vector choosing a direction uniformly, $\overrightarrow{S_i}$ is the vector to avoid collisions with the other robots [7], $v_i^s(t)$ is a vector heading to different direction from the history of positions already searched by robot i, and $v_i^o(t)$ is a vector heading to different directions from the history of positions already searched by the other robots located within the communication range of robot i. The parameters of α, k_s, and k_o are the weights to control the contribution of each vector.

We further extend the above operation of history-based search to a swarm-based search, where at most L_{th} robots form a group to search for the signals emitted by targets. A *leader* is elected as a robot that has the minimum identification number, e.g., MAC address, and the other robots within a swarm are considered as *follower* robots. The follower robots obtain the movement vector of leader robot through wireless communications, and set their movement vectors in such a way that they move to the same direction as its leader. The size and number of swarms can be controlled by the parameter of L_{th}. This swarm-based control enables robots to cooperatively execute the operations of target approach and localization once they detect the signals emitted by targets.

b) Operations of target localization after detecting signals of any targets: After detecting signals emitted by targets, robots can exploit the information on their RSSIs for estimating target locations and/or approaching to them. In the proposed swarm control, robots attempt to estimate the locations of targets by employing PF (shown in (b-1) in Fig. 2) [2]. The basic idea of PF is for each robot to deploy virtual particles over a sensing area, and update their positions and weights according to the observed RSSIs. Denoting the number of particles as N_p, the weight of jth particle of a robot calculated for the ith observed RSSI over time is given as

$$w_j^{(i)} = \frac{\tilde{w}_j^{(i)}}{\sum_{j=1}^{N_p} \tilde{w}_j^{(i)}}, \tag{2}$$

$$\tilde{w}_j^{(i)} = \exp\left(-\frac{(P^{(i)} - R_j^{(i)})^2}{\sigma^2}\right), \tag{3}$$

$$R_j^{(i)} = P_0 - 10K \log_{10} d_j^{(i)}, \tag{4}$$

where $d_j^{(i)}$ is the distance between the robot and jth particle when it observes the ith RSSI, P_0 is RSSI at unit distance [8], K is the path-loss coefficient, σ^2 is the variance of observation noise, and $P^{(i)}$ is the ith observed RSSI. Basically, $R_j^{(i)}$ calculated in eq. (4) represents RSSI that the robot should observe when the target is located at the position of particle j. The likelihood of the jth particle is given in eq. (3), calculated based on the difference between the observed RSSI and $R_j^{(i)}$. This gives larger (smaller) weight to a particle closer (farther) to the target emitting the signal observed by the robot. Eq. (2) is introduced just for normalization. After calculating the weights given in eq. (2), resampling operations are conducted in such a way that more number of particles are deployed around the particles with larger wights [9].

The above processes are repeated for every target whose signal is detected by a robot until the updated positions of particles are considered to be converged. At time step k, the location of a target is estimated as

$$P_k = \sum_{j=1}^{N_p} w_j^{(k)} L_j^{(k)}, \tag{5}$$

where $L_j^{(k)}$ is the position of particle j at time k. The convergence is considered to be achieved when the following two conditions are satisfied [10]:

$$\sigma_k \leq R_{conv}, \tag{6}$$

$$|\mathbf{P}_n - \bar{\mathbf{P}}| \leq R_{err}, \tag{7}$$

where $\sigma_k^2 = \sum_{j=1}^{N_p}[|L_j^{(k)} - P_k|^2 \cdot w_j^{(k)}]$, R_{conv} is the radius of the convergence circle, $\mathbf{P}_n$ is a sequence composed of the most recent n estimated locations, $\bar{\mathbf{P}}$ is the mean of all elements in $\mathbf{P}_n$, and R_{err} is the radius of the permissible error circle.

The existing study in [2] showed that the estimation accuracy of PF can be improved by appropriately selecting observation points of different robots. However, their objective is the location estimation, and does not consider the approach to the searching target. For SAR considered in this paper, we need to control the mobility of robot in such a way that it improves the estimation accuracy and also quickly approaches to the searching target. To this end, in this paper, we introduce an additional mobility control for a group of robots. We set a threshold of RSSI, γ_{th}^{l}, used for each robot to decide that it is likely to be located far enough from a target. In this case, the accuracy of estimation can be low, therefore, it is better to increase the diversity in terms of RSSI observed by each robot. Therefore, we control the movement of follower robots to be in parallel with the leader robots. This helps robots within a swarm to keep a fixed distance with each other. Furthermore, the movement vector of a leader robot is set to head to the direction of a particle with the largest weight so that a swarm can move toward a searching target. This mobility control allows a group of robots to move to the direction of a target while enhancing the diversity in terms of the observed RSSIs of multiple robots conducting location estimation employing PF.

On the other hand, when the observed RSSI is larger than γ_{th}^{l}, each robot is closer to a searching target, and the estimation accuracy becomes higher. In this case, it is better to control the mobility of each robot so that it can accurately move to the searching target. Therefore, we control the mobility of robots based on MSC while each robot continues to estimate the location of target by using PF. The basic idea of MSC is for a swarm of robots to cooperatively move to the positions where they observe larger evaluation value. The evaluation value is calculated based on the observed RSSI and number of robots heading to the same target. With MSC, each robot within a swarm is categorized as leader or follower. The movement vector of leader robot is set so that it heads to the direction where it is likely to detect larger RSSI. On the other hand, the movement vector of follower robot is set so that it heads to the position of robot that has the best evaluation value among its neighbors. MSC also includes a mechanism for multiple swarms to join and split depending on their relative positioning to multiple targets. For the detailed operations of MSC, readers are referred to [4] and [7].

Once a group of robot reaches the convergence of estimation given in eqs. (6) and (7), their movement is controlled in such a way that they move to the estimation location as straightly as possible (shown in (b-2) in Fig. 2). The movement vector of the leader robot is set as

$$v_i(t+1) = \alpha \overrightarrow{S_i} + (x_e - x_i(t)), \tag{8}$$

where x_e is the estimated location of the searching target, and $x_i(t)$ is the location of robot i at time t. This movement vector is shared with the follower robots, which are used to control their mobility.

After moving close enough to a target (i.e., after robots detect larger RSSI than r_{th}^2), robots are controlled to approach to the target solely based on MSC (shown in (b-3) in Fig. 2).

c) Operations of target capture: When a robot detects RSSI larger than r_{th}^3, which corresponds to the distance shorter than D_{th} from the searching target, it decides that it has reached an area where it can execute the task against the target and stays there until the given task is completed (shown in (c-1) in Fig. 2). Note that the task can be executed by multiple robots if they stay within D_{th} from the target.

After completing a task given to the target, i.e., after a target is captured, each robot needs to continue its search operation for the other targets. Here, we also introduce mobility control exploiting location estimation. While approaching to a searching target, each robot is able to detect RSSIs of the other targets if they are within their detection range. Therefore, each robot can continuously estimate the locations of multiple targets by employing PF explained above. In the proposed swarm control, these information are recorded by each robot and exploited for controlling its mobility after it captures a searching target (shown in (c-2) in Fig. 2). Specifically, if a robot has information on the target with its location estimation converged as given in eqs. (6) and (7), its movement vector is set as in (8) with x_e set to the estimated location. Then a robot can directly head to the estimated location. When a robot has information on multiple targets with the converged estimation, a target to approach is selected by evaluating them based on the values corresponding to the detected RSSI (when it can detect the target signal) or distance to the estimated location (when it cannot detect the target signal). Each robot first counts the number of robots located closer to a candidate target than itself among its neighbor based on the information exchanged through wireless communications, denoted as N_r. If a robot can detect the target signal and N_r is larger than a threshold of N_{th}, it multiplies a degradation factor of $R(< 0)$ with N_r, and adds it to the evaluation value to degrade it. Otherwise if a robot cannot detect the target signal and $N_r \geq 1$, it multiplies $R(< 0)$ with N_r, and adds it to the evaluation value. Then, each robot selects a target with the largest evaluation value, and sets its location to x_e in eq. (8). This mechanism allows us to evenly distribute robots into multiple targets with their location estimation converged. We show an example in Fig. 3, where robot 1 has information on 2 targets, target A and target B, with their location estimation converged after capturing the other target. For targets A and B, robot 1 counts N_r as 4 and 3, respectively. Therefore, the evaluation value for target A is degraded more than target B, which makes robot 1 select target B as its searching target.

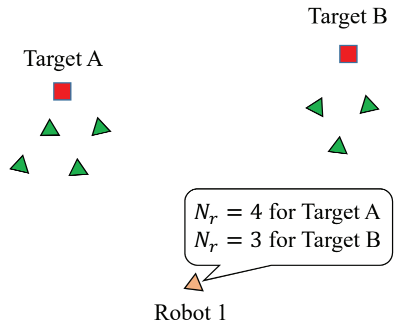

Fig. 3. An example of operation of target selection after capturing a target.

IV. Numerical Results and Discussions

In this work, we evaluate the efficiency of target capture achieved by the proposed swarm control by computer simulations. This section presents the evaluations of our proposed swarm control based on computer simulations.

A. Simulation Model and Parameters

We assume that targets for SAR operations are deployed uniformly within a field with its size of $2000m \times 2000m$. The initial position of mobile robots are uniformly decided within a circle with its radius of 30m located in the center of the field. The other simulation parameters are summarized in Table I.

As a performance measure, we consider capture completion time (CCT), which is the time required for robots to capture all the targets in the given field. For performance comparison, we consider the following 2 schemes:

- MSC: In this scheme, robots search for the signals emitted by targets based on eq. (1). After detecting the signals, robots search for and approach to targets solely by employing MSC without any operation of target localization.
- MSC+PF: This scheme also applies eq. (1) before robots detect any signal emitted by targets. After detecting signals, it exploits the location estimation using PF like the proposed swarm control, but only employs MSC for mobility control. Furthermore, it does not include the mobility control exploiting the recorded information on the location estimation after capturing each target.

Note that we do not include the sole application of target localization employing PF into our reference schemes since it is not applicable to our SAR scenario due to the lack of mechanism to approach to each target.

B. Simulation Results and Discussions

Fig. 4 shows CCT of MSC, MSC+PF, and the proposed swarm control (Proposed SC) for the number of targets of 10, 15, and 20. From this figure, we can first see that

TABLE I
Simulation Parameters.

Simulator		ns-3.35 [11]
Robot Velocity		1 m/s
Communication Range		150 m
Target Tx Power		13 dBm
Detection Threshold γ_{th}^{D}		-101 dBm
Task Area D_{th}		5 m
Work Efficiency R_w		5 load/s
Work Load W		100
Path-Loss Coefficient K		3
P_0		40.046
Noise Variance σ^2		1
SC	α outside D_{th}	20
	α inside D_{th}	5
	k_s	1.2
	k_o	0.5
	L_{th}	3
	N_{th}	3
	R	-100
	γ_{th}^{1}	-78 dBm
	γ_{th}^{2}	-58 dBm
	γ_{th}^{3}	-48 dBm
PF	N_p	5041
	R_{conv}	20
	R_{err}	10
MSC [4][7]	Cognitive Weight	1
	Social Weight	1
	Inertial Weight	0.5
	Avoidance Degree	2
	Dispersion Degree	-100

CCT is increased with more number of targets for all the schemes.

Next, we can see that MSC has the largest CCT among 3 schemes. With MSC, swarms of robots approach to targets based on the observed RSSIs, however, RSSIs can fluctuate due to the observation noise. Each swarm can move back and forth due to this fluctuation and cannot approach to each target straightly. The introduction of location estimation with PF can alleviate this problem, and MSC+PF shows better performance than MSC since each swarm can directly approach to the searching target once its location estimation is converged. However, the direct application of PF to MSC does not show significant gain. This is because each swarm is still slow in approaching to the searching target before the location estimation using PF is converged. Furthermore, locations of robots within a swarm tend to be close to each other with MSC, which reduces the diversity in terms of RSSIs observed by robots. This makes the convergence of location estimation using PF slow, which causes each swarm to spend longer time in operating with MSC.

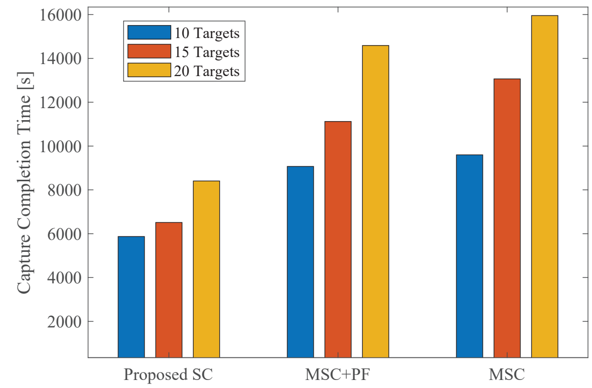

Fig. 4. Target capture completion time (CCT) of different schemes for different number of targets.

The above problems of MSC combined with PF are effectively solved by the proposed SC. During location estimation, each swarm moves toward the direction of particle with the largest weight while robots keep a fixed distance with each other. This increases the diversity of RSSIs observed by a swarm of robots, which helps to reduce the convergence time of location estimation. Furthermore, after capturing a target, each robot can quickly move to the estimated location of new target with the proposed SC by exploiting the recorded information on location estimation of multiple targets. These additional mechanisms allow swarms to quickly approach to multiple targets, which contribute to the significant reduction of CCT as shown in Fig. 4.

V. Conclusions

In this paper, we proposed a swarm control mechanism, in which swarms of robots autonomously search for targets of SAR operations, and approach to them to execute the required tasks. The proposed swarm control combines MSC, which realizes the operations of target search and approach, with target localization employing PF. We designed mobility control exploiting the information obtained by the localization for improving the efficiency to capture multiple targets while achieving higher accuracy of localization. With computer simulations, we showed that the proposed swarm control reduces the time required for capturing targets in comparison to MSC and simple integration of MSC and PF.

Our future work includes the investigation on the impact of deployment pattern of targets on the capture efficiency. The experimental evaluation of the proposed swarm control using our test-bed of robot platform is also an interesting future work.

Acknowledgement

This work was supported by JSPS KAKENHI Grant Number 22K04114.

References

[1] J. P. Queralta, J. Taipalmaa, B. Can Pullinen, V. K. Sarker, T. Nguyen Gia, H. Tenhunen, M. Gabbouj, J. Raitoharju, and T. Westerlund, "Collaborative multi-robot search and rescue: Planning, coordination, perception, and active vision," *IEEE Access*, vol. 8, pp. 191 617–191 643, 2020.

[2] S. Fujita, T. Yairi, K. Hori, and S. Komatsu, "An active beacon-based target localization method for unmanned aerial vehicles with particle filter," in *2017 20th International Conference on Information Fusion (Fusion)*, 2017, pp. 1–6.

[3] G. M. Hoffmann and C. J. Tomlin, "Mobile sensor network control using mutual information methods and particle filters," *IEEE Transactions on Automatic Control*, vol. 55, no. 1, pp. 32–47, 2010.

[4] S. Nishigami, E. Nii, N. Fujiyama, S. Izuhara, H. Yomo, and Y. Takizawa, "Self-cloning mobile sensing cluster based on swarm intelligence with multiple autonomous mobile systems," in *2023 IEEE Wireless Communications and Networking Conference (WCNC)*, 2023, pp. 1–6.

[5] Y. del Valle, G. K. Venayagamoorthy, S. Mohagheghi, J.-C. Hernandez, and R. G. Harley, "Particle swarm optimization: Basic concepts, variants and applications in power systems," *IEEE Transactions on Evolutionary Computation*, vol. 12, no. 2, pp. 171–195, 2008.

[6] X. Su, M. Zhang, and Q. Bai, "An innovative approach for ad hoc network establishment in disaster environments by the deployment of wireless mobile agents," *ACM Trans. Auton. Adapt. Syst.*, vol. 13, no. 4, Jul. 2019. [Online]. Available: https://doi.org/10.1145/3337795

[7] A. Asada, H. Yomo, E. Nii, and Y. Takizawa, "Mobility control exploiting swarm intelligence for mobile sensing searching for indistinguishable multiple targets," in *2019 IEEE International Conference on Systems, Man and Cybernetics (SMC)*, 2019, pp. 4367–4372.

[8] A. Goldsmith, *Wireless Communications*. Cambridge University Press, 2005.

[9] N. J. Gordon, D. J. Salmond, and A. F. M. Smith, "Novel approach to nonlinear/non-gaussian bayesian state estimation," *IEE Proceedings F (Radar and Signal Processing)*, vol. 140, pp. 107–113(6), April 1993.

[10] J.-G. Li, Q.-H. Meng, Y. Wang, and M. Zeng, "Odor source localization using a mobile robot in outdoor airflow environments with a particle filter algorithm," *Springer Autonomous Robots*, vol. 30, pp. 281–292, April 2011.

[11] "n3-3 Project." [Online]. Available: https://www.nsnam.org/