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Effect of Communication Modes to Swarm Robotic Search

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Abstract. Interactions in swarm robotic search are explored for intelligence emergence based on Extended Particle Swarm Optimization (EPSO) model. For this end, the best combination of proper properties in typical versions of PSO is transferred to swarm robotic search. Synchronous / asynchronous communication modes and respective control strategies under conditions of parallel distributed control are comparatively studied by simulations. The results showed that the asynchronous communication mode predominates over its synchronous opponent in efficiency.

Keywords: Communication, particle swarm optimization, swarm robots, target search.

INTRODUCTION

We can cope with swarm robotic search by learning from swarm optimizers. The Extended Particle Swarm Optimization (EPSO) method provides an example [1]. In fact, PSO work is parallel in nature. As for parallel algorithms, they can be classified with granularity metrics [2]. Wang [3] presents a parallel PSO based on model with controller. Huang [4] proposes parallel version by island population modelling. Zhao [5] introduces migration into PSO, presents a parallel version based on multi-groups evolving simultaneously. These are all attributed to coarse-grained parallelism. To the contrary, the fine-grained parallel algorithms are characteristic with majority advantages [6]. To overcome communication bottle-neck due to massive increase in size of fine-grained PSO, Chang [7] designs three types of communication strategies. These parallel versions are all synchronous paradigms. However, asynchronous algorithm can increase efficiency in heterogeneous environment [8]. For example, an asynchronous version proposed by Luo [9] makes each particle act as an independent individual and search asynchronously. In a word, the asynchronous pattern is introduced into PSO for speed enhancement [10].

Also, swarm robots involve parallel operation [11]. First, robots spatially distribution makes cooperation algorithms parallel in nature. Besides, differences in sampling frequency of sensors carried by robots make it more realistic to control robots in an asynchronous way. In the field of swarm robotics, one area capturing more attention is target search, where a group of robots work together to localize one or more targets. Simply, a single stable target is considered here. Then, the problem of parallel asynchronous swarm robotic search with different communication modes is proposed. In this paper, the remainder is organized as follows. Section 2 maps swarm robotic search to PSO. Then it models the swarm robots and describes the control principles. In Section 3, communication modes in swarm robotic search are introduced. To describe the corresponding strategies in swarm search taken place in obstacle-free environment, we begin with analyzing the properties of different PSO versions for transferring the expected properties to swarm search. Then the synchronous and asynchronous communication modes are discussed. In addition, the corresponding algorithms with specific communication modes are described. Based on this, the experiment settings are explained and metrics are given. In Section 4, the results from simulations and their implications are shown. Finally, it concludes in Section 5.

MODEL

By extending PSO, Pugh [1] investigates the problem of target search in an ideal environment. In PSO, particles are guided by the best positions having optimal fitness. Here, each particle has perfect knowledge about environment and its neighbours. While swarm robots work depending on individuals' experience and social experience, for robots move according to their own behavioural decision making. The former comes from signals measurement by robot itself, the latter from local communications within its neighbourhood. Consider the two cases, we can map swarm robotic search to PSO [12]. Based on this mapping relation between swarm robotic search and PSO, EPSO method can be taken to model the swarm robotic system [1,12], as is shown below:

$$v^i_{k+1} = w_k v^i_k + c_1 r_1 (p^i_k - x^i_k) + c_2 r_2 (p^g_k - x^i_k) \quad (1)$$

$$v^i_{k+\Delta k} = v^i_k + (v^i_{k+1} - v^i_k)\Delta k \quad (2)$$

$$x^i_{k+\Delta k} = x^i_k + \Delta k v^i_{k+\Delta k} \quad (3)$$

Where, x^i_k is the position vector of robot R_i at time kt, and v^i_k velocity vector, subscript k the abbreviation of time increment kt. While p^i_k and p^g_k are the best-found positions of R_i and its swarm at time k respectively. The coefficient matrix ω_k is diagonal matrix whose elements are inertia coefficients with range [0,1]. Similarly, r_1, r_2 are diagonal matrices whose elements are sampling of uniformly-distributed random variable in [0,1]. And c_1, c_2 diagonal matrices whose

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elements are cognition and social acceleration constants, respectively. x^{i}_{k+1} is the expected velocity vector of R_i at $k+1$. $\text{¢}k$ a factor to decrease the step taken by robots. It is used to make robots move "smoothly" so as that a more refined search is obtained [12].

The cooperative control over swarm robots can be carried out following swarm intelligence principles [13]. Mainly, the limitations on hardware and power supply make it impossible that robots interact beyond the maximum communication range. Clearly, the swarm that each robot dwells in differs from others, since every robot selects some robots as its evolving swarm.

- *Time-Varying Character Swarm*. Each robot selects its near neighbors as its temporary swarm members because those within its maximum communication range are capable of interacting with it. Accordingly, a concept of time-varying character swarm (TVCS) for computational evolution is presented [12]. Take the position of robot R_i at time t as the center, the maximum communication range R of R_i as radius for a circular neighborhood construction. The set of those robots covered by this neighborhood is named as TVCS of R_i at time t.
- *Signals Detection*. In PSO-type algorithms, motion control of robot depends on cognitive position and the best-found social position. While the two best-found experiential positions come from position evaluatation. Each robot is assumed to be equipped with one sensor to detect the intensity of signal emitted from target [1, 14]. This intensity $\mathrm{I}(d_i)$ is determined with model below:

$$I(d_i) = \begin{matrix} 0; & d_i > r \\ \frac{P}{d_i^2} + \text{´}(); & \text{otherwise} \end{matrix} \tag{4}$$

Where, P is target signal power, d_i distance from robot R_i to target, r radius of sensor detection and $\text{´}()$ a sampling of additive Gaussian noise.

- *Position Evaluate and Cognitive Decision*. For robot R_i, its cognitive position at time t is determined following the rule:

$$p_i^{\text{€}}(t) = \begin{matrix} x_i(t); & \text{if } I(x_i(t) \text{ ¸ } I(p_i^{\text{€}}(t \text{¡ } 1)) \\ p_i^{\text{€}}(t \text{¡ } 1); & \text{otherwise} \end{matrix} \tag{5}$$

Where $p_i^{\text{€}}(t)$ is the cognitive position of robot R_i at time t, $x_i(t)$ the current position.

- *Social Experience of TVCS*. Based on the definitions of TVCS and signals evaluate, the best-found social position $p^{\text{€}}_{(i)}(t)$ within the TVCS of robot R_i at time t can be decided:

$$p^{\text{€}}_{(i)}(t) = p_k^{\text{€}}(t); \arg_k \max f I(p_k^{\text{€}}(t)) g \tag{6}$$

COMMUNICATION MODES

In PSO-type control, each robot independently detects signals emitted from target in a fine-grained parallel way and compares intensity of signals with the best in its TVCS. Then the velocities and positions of robots are updated immediately. But the shared information within TVCS is updated asynchronously. As comparison, a synchronous pattern is also given in this section. We begin by analysis thr characteristics of PSO.

(a) Synchronous *vs.* Asynchronous

To explore characteristics of different PSO versions, we consider two issues, i.e., serial or parallel fitness evaluate, synchronous or asynchronous communication mode. Thus, we divide the different versions into four types.

- *Serial Evaluate and Synchronous Update.* PSO is traditionally considered to be implemented in serial and synchronous on single-processor computing environment.8 The fitness evaluate of all particles is carried out one by one in optimization process through cost function computation. And the best positions, both of particle itself and of swarm are determined by fitness comparison in the same way. Then the update of all velocities and positions occurs simultaneously at each iteration.
- *Serial Evaluate and Asynchronous Update.* Immediately updates on velocity, position of particle as well as its history cognition and the best of swarm are carried out as soon as completing evaluate on its cost function.8 The evaluate and update process on different particles are not completed at the same time.
- *Parallel Evaluate and Synchronous Update.* The most obvious PSO parallel implementation is to simplify fitness evaluate for particles at iteration in parallel [6,8,10]. And the property of synchronous refers to all particles being sent to parallel computing environment and moving from the current iteration to the next if the fitness of all particles has been obtained.
- *Parallel Evaluate and Asynchronous Update.* Parallel implementations being asynchronous in PSO can enhance the algorithmic computation efficiency.10 The asynchronous approach does not need a synchronous point to determine new velocities and positions.

As stated above, different versions of PSO have different running properties. But the most desirable that we would like to transfer to swarm robotic system may be parallel and asynchronous properties [15].

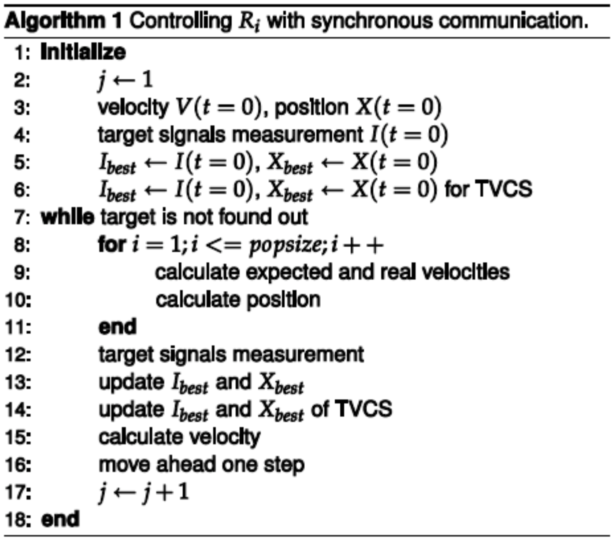
(b) Strategies

Now, we can examine swarm robotic search in a closed obstacle-free environment. According to the analysis, controlling robots should be in a fine-grained way, as each robot detects target signals independently at the same time to determine the best-found position of TVCS [12]. Here, asynchronous communication mode refers to that each robot compares at once with the optimal value of the swarm after iterating, if their detective signals are discovered stronger, updates immediately the optimal value of the swarm, thereby, other robots can share the experience timely.

The key to asynchronous implementation of control algorithm is to partition the individual from the group update behaviors, which include updating individual robot and the shared information [6, 8]. For swarm robotic search, signals detection depends on their respective on-board processors. Each robot updates its velocity, position as soon as target signals measurement is made and decision on the best-found position in its TVCS is made too. But the update on the shared information should start with specific asynchronous control strategy. This is, in fact, the decision on communication triggers. Differing from the ideal case in PSO, robot possesses mass in real world that causes it to have inertia when moving about in the search environment. Therefore, in a similar evolution position of a certain particle, it is not limited to reach at any speed in PSO, while robot may arrive at the same position in several sampling times due to constraint of kinematics and dynamics because the evolution position is only expected [1,12]. These factors should be considered when we design asynchronous interaction strategies. Based on this, some update strategies have been developed. One is communication cycle-based control principle. Here, communication cycle is named as evolution iterations. Similar to the coarse-grained parallel PSO, we can make robot R$_i$ communicate every n iterations to decide the best-found position within R$_i$'s TVCS [12]. To improve efficiency, a communication cycle can be assigned to several fixed times of sampling periods. Besides, different robots can be allowed to have different sampling frequencies. On the other hand, the best-found fitness value and position of TVCS should be remembered before the next iteration starts. Another update strategy is evolution position-based control principle. According to this principle, update of the shared information does not been carried out in the current iteration before the previous evolution position has not been reached. It means that the robots communicate when they arrive at the decisive expected or desired evolution positions regardless of the iteration history and the next iteration required. No communication between two consecutive ideal evolution positions makes motion continuous, saving power and decreasing communication time consumption. As for the synchronous mode, update time points depend on the last particle completed fitness evaluate at each step. Thus the communication triggers do not need to consider in synchronous mode.

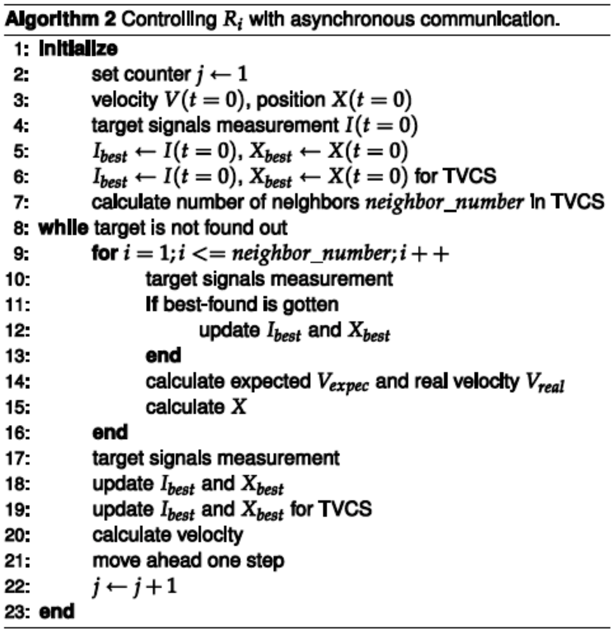
(c) Algorithm Description

The synchronous version is taken according to the characteristics of signals detection, search completion judging as well as velocity and position updating, see Algorithm 1. Differently, the moment that robot updates shared information of TVCS is more flexible in asynchronous mode, see Algorithm 2 for details.



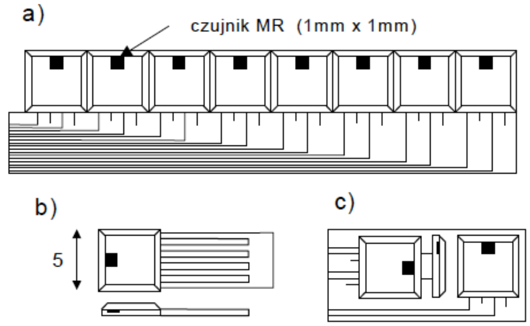
Algorithm 1 Controlling R_i with synchronous communication.

```
Initialize
    $j \leftarrow 1$
    velocity $V(t=0)$, position $X(t=0)$
    target signals measurement $I(t=0)$
    $I_{best} \leftarrow I(t=0)$, $X_{best} \leftarrow X(t=0)$
    $I_{best} \leftarrow I(t=0)$, $X_{best} \leftarrow X(t=0)$ for TVCS
while target is not found out
    for $i = 1; i <= popsize; i++$
        calculate expected and real velocities
        calculate position
    end
    target signals measurement
    update $I_{best}$ and $X_{best}$
    update $I_{best}$ and $X_{best}$ of TVCS
    calculate velocity
    move ahead one step
    $j \leftarrow j + 1$
end
```



Algorithm 2 Controlling R_i with asynchronous communication.

```
Initialize
    set counter $j \leftarrow 1$
    velocity $V(t=0)$, position $X(t=0)$
    target signals measurement $I(t=0)$
    $I_{best} \leftarrow I(t=0)$, $X_{best} \leftarrow X(t=0)$
    $I_{best} \leftarrow I(t=0)$, $X_{best} \leftarrow X(t=0)$ for TVCS
    calculate number of neighbors $neighbor\_number$ in TVCS
while target is not found out
    for $i = 1; i <= neighbor\_number; i++$
        target signals measurement
        if best-found is gotten
            update $I_{best}$ and $X_{best}$
        end
        calculate expected $V_{expec}$ and real velocity $V_{real}$
        calculate $X$
    end
    target signals measurement
    update $I_{best}$ and $X_{best}$
    update $I_{best}$ and $X_{best}$ for TVCS
    calculate velocity
    move ahead one step
    $j \leftarrow j + 1$
end
```



SIMULATIONS

Two algorithms are performed and repeated for 10 runs respectively to get the statistics from simulation results.

(a) Parameter Settings

The parameters of working space, robot and swarm influence system running directly. Thus some important parameters and their configurations are given in Table **1**. The symbol meanings can be found in the third column of this table.

(b) Performance Metrics

To comparatively evaluate the running performance of algorithms, some metrics need to be presented in advance.

- *Efficiency*. Search efficiency is defined as reciprocal of mean steps required for one successful search. In fact, it concerns search speed, indicating the elapsed time in a run. Because the sampling cycle in simulations has been determined, a relation between steps and spent time can be established. Clearly, the more the average time steps, the lower the efficiency, and vice versa.
- *Energy Consumption*. The metric is distance principle-based, being expressed in form of the sum of passed distance of all the robots when search task is completed. Since the energy consumption of robot is fixed per distance unit, the average energy consumption of robots can measure performance for economical efficiency.

Table 1. Parameters used in simulations. Note that expressed in certain dimensions should be assigned proper one respectively.

Symbol	Value	Meaning
Space	500£ 500	size of searching space
StartArea	160£ 160	range for robots at the beginning of simulations
popsize	3; 5; 8; 10	number of robots
R_{detec}	250; 125	sensor detection radius
R_{comm}	250	max comm. radius
V_{max}	5	max velocity of robot
P	1600	signals power
T	70	inertia element constant
¢t	0:8	step contracted factor

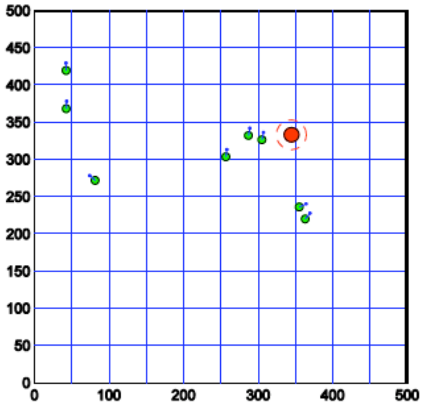


Fig. (1). Typical screenshot of robotic search in case of 8-swarm.

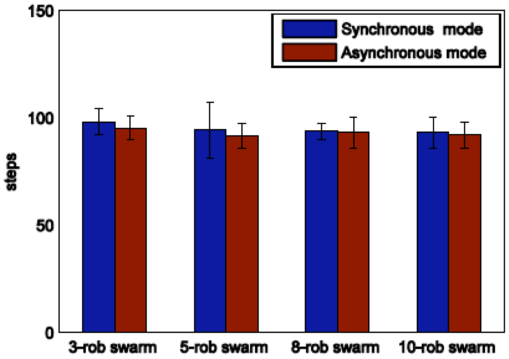


Fig. (2). Average time steps required to complete search task for 10 repeated runs under conditions of $R_{detec} = 250; R_{comm} = 250$.

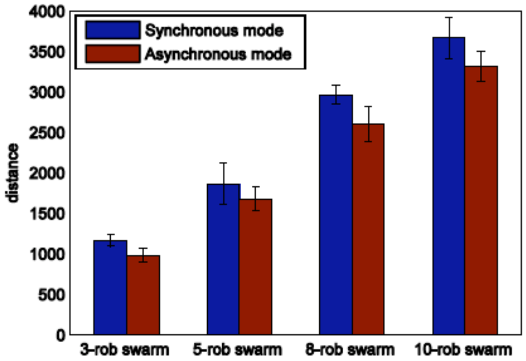


Fig. (3). Average total distance passed by swarm for 10 repeated runs when $R_{detec} = 250; R_{comm} = 250$.

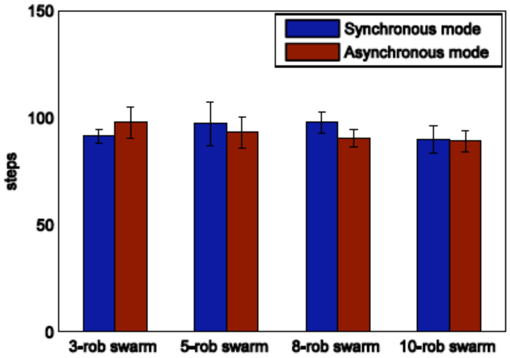


Fig. (4). Average time steps required for 10 repeated runs when $R_{detec} = 125; R_{comm} = 250$.

(c) Results

Simulations with the same settings are conducted and repeated for 10 runs, then make the settings vary and repeat the process for reducing the effect caused by the inherent randomness from the swarm intelligence - based algorithms. The results are shown in Figs. (**1-5**).

(d) Discussions

We can analyze the indications of results, trying to reveal effects of communication modes to swarm robotic search.

- As for the same parameter settings, time steps decrease as swarm size increases regardless of which communication mode taken in control process. It indicates that efficiency enhances as swarm size expands.
- As for the same parameter settings, average total distance required for a success search varies in the same direction as system size increases regardless of which communication mode taken. It indicates that energy consuming increases as swarm size scales expand.

- Swarm search with asynchronous communication mode runs more efficiently than with synchronous mode, which seems to indicate that information and experience of certain dominant individual can be shared timely among its TVCS.
- As to different parameter settings, such as detection radius $R_{detec} = 250; 125$ respectively but the communication radius remains the same, efficiencies and energy consumption do not vary obviously. The reason for this may be that at the beginning of simulations, robots are far from the target so they may not to detect target signals either for case of $R_{detec} = 250$ or for $R_{detec} = 125$. Therefore, robots only move randomly without guiding.

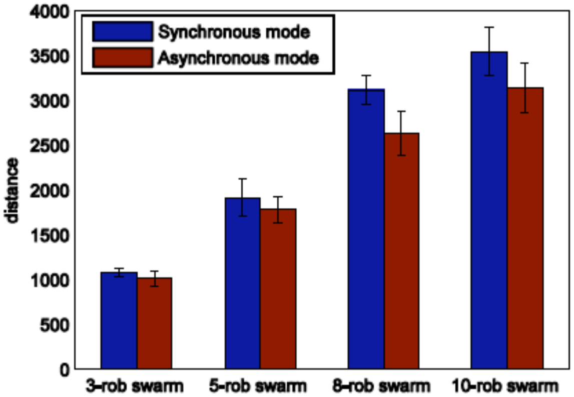


Fig. (5). Average total distance passed by all robots in certain size swarms for 10 repeated runs search success under conditions of $R_{detec} = 125; R_{comm} = 250$.

CONCLUSION

With EPSO method, we model swarm robotic system and control it for carrying out search task. Because of the relation between swarm robotic search and PSO, some ideal characteristics of PSO can be transferred to swarm robotic search. Inspired from asynchronous PSO versions, we develop algorithm with asynchronous communication mode for efficiency enhancement. To reveal the effect, we compare the algorithm with synchronous communication mode. From the statistics of results, a conclusion can be drawn that asynchronous communication mode is more efficient than synchronous under conditions of the same parameter settings for efficiency.

CONFLICT OF INTEREST

The authors confirm that this article content has no conflict of interest.

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