Control over Swarm Robots Search with Swarm Intelligence Principles

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Abstract: Swarm robots possess the potential to save lives by providing the rescuers location of victim during the most critical early hours in coal mine disaster areas. *Robot and its controller as an inertial element and modeled such distributed system at an abstract level were viewed according to the swarm intelligence principles*, which used a virtual multi-agents search to locate the target in a closed 2-D space. The control over robots was attributed to two kinds: *moving spirally to search for cues and extending particle swarm optimization to search for target*. The former is to offer evidence for the latter working. Then *the definitions of sensing function, neighborhood structure and initiating area of robots were given*. Taking the limited sense ability and local interaction mechanism into account, the properties of the system were obtained by changing different parameters such as number of robots, communication range and sense scope in simulating experiment. The simulation results indicate validity of the control strategy.

Key words: swarm intelligence; swarm robots; extended particle swarm optimization; target search

用群体智能原则控制群机器人搜索

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摘　要：用群机器人搜索定位矿难幸存者，可为人工施救提供决策参考。群机器人系统的建模基于个体有限感知和局部交互等群体智能原则，将机器人抽象为封闭 2 维空间的运动粒子，**机器人与控制器综合抽象为一阶惯性环节。给出了机器人的感知函数、邻域结构及初始化区域的定义**，以此为基础进行虚拟多 agent 搜索。针对机器人的最大运动速度和质量惯性等约束，**交替施加螺旋控制以发现信号线索；施加扩展微粒群控制进行目标搜索**。通过改变通信距离和感知范围进行了仿真实验，结果表明了控制策略的有效性。

关键词：群体智能；群机器人；扩展微粒群算法；目标搜索

中图分类号：TP391.9　　**文献标识码：**A　　**文章编号：**1004-731X (2008) 13-3449-06

Introduction

Autonomous robot can be viewed as embodied agent, then swarm robots may therefore be used to carry out the dangerous, dirty and dull missions instead of human being for search and locate in disaster scenarios, e.g., urban search and rescue [8], tracing chemical plumes [6,15]. Similarly, when a working coal miner is confronted with natural forces or man-made disasters in closed laneway, he would be likely to lose touch with the outside and be trapped underground. Unfortunately, search operations here tend to be very difficult. Common elements of these types of operations are large-scale devastation, communication problems, confusion, and limited numbers of rescue workers during the early phases of the disaster. One approach for reducing the confusion and utilizing the available personnel most effectively would be to use swarm of low-cost, mobile search robots to provide the person in charge on site with location of the potential victims as quickly as possible. To locate target within dynamic and unstructured environment is such task well fitted to swarm robots, since many robots can massively work in parallel and efficiently explore the areas for searching their goals. In particular, robots can be equipped with different types of sensors to detect target signals and be guided by appropriate algorithms to move [2]. Such inspiration taken from biology is called swarm intelligence principles [20]. That is, swarm systems are based on the emergent collective intelligence of groups of simple agents. Utilizing swarm robots to search for interested target can offer some key advantages over using a single elaborate robot to carry out the same task [13].

For insight into swarm emergency mechanism,

Received: 2007-09-10　　**Revised:** 2008-01-16

Foundation: National Natural Science Foundation of China（No.60674104）

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strict theoretical analysis or experimental statistics support seems indispensable in the study on swarm robotics. Martinoli [19] and Lerman et al. [17] offered an analysis tool, which integrated macroscopic stochastic process and microscopic finite state machine at different abstract levels. Michel [18] showed a realistic modeling tool, which can be used to collect experimental data with multiple agents by senor and actuator-based simulation. The two methods were rather complex and time-consuming in use. Such constraints motivated the development of more abstract models, since which can make easier in tackling not only model algorithms but also control policies [2]. Di Chio et al. [3,4] extended particle swarm optimization to model and simulate animal foraging behavior. In general, PSO was often viewed as an optimization algorithm for nonlinear functions. But animals looking for food sources were modeled as particles in a swarm moving over an abstract food landscape. The particles were guided to the food by a smell, which surrounded it and whose intensity was proportional to the amount of food available. In [2], robot was assumed to have a sensor to detect the intensity of the target signal. Robots were directed to the target by such best signal sensed by themselves and others. The above works were demonstrated in different communication and environment ways, but the limited sense capability of robot has not been involved. Marques et al. [1] addressed search across very large searching spaces. The relationship between exploitation and exploration was emphasized and the global search for cues and local search for target was discussed. However, this work did not mention the explicit concept of limited sense, and did not also use local interaction mechanism in search process, i.e., new velocities and locations of robots were iterated depending on the global best among all members rather than local best among those members within same neighborhood structure. Therefore, control strategy for swarm robots search under conditions of limited sense and local interactions based on an abstract model was presented in our work.

This paper is structured as follows. In section 1 we give a brief introduction to the background of research and the abstraction to swarm robots search. Section 2 describes our integrated control policy: the spiral move and extended PSO-inspired swarm robots search depending on limited sense capability and local interaction mechanism. In section 3, we summarize the settings for the experiments and discuss the results of our simulations. We conclude in section 4.

1 Background and Abstraction

In search tasks, the key factors under consideration include: consumption of energy and time elapsed [15]. For swarm simulations, there are two main aspects that should be modeled to simulate the search for victim by mobile robots. The first is the related environment, e.g., signal-for-help (shout, active radio-frequency wave etc.) transmitting and gas transportation in the closed workspace, and the second is modeling to the mobile robots [1]. Thus, we investigate the two facets of this simulation in the experiment.

1.1 Environment

Analyzing the working environment, there are three kinds of detectable signals as follows. What we do in the first step is how to simulate the measurement of these signals.

1.1.1 Shout

The phenomena that one may make irregular sound for help now and then are often observed while he has to be confronted with disastrous situations. This intermittent shout can be detected by sensor built in robot. But the “signal” intensity may be rather low and it usually lasted for a short time, which can only be captured within a limited range.

1.1.2 RFID Wave

Underground mine personnel tracking systems have been taken effect in many coal mine enterprises today, which work on the basis of UHF radio frequency identification (RFID) systems with active tags and interrogator. The remote transponder is a message receiver and reader on-board, read-only type of device, It can read data periodically transmitted by RFID chip embedded inside card within the reading range. Such a tag is usually fixed onto miner’s helmet with his lamp [10,11,21]. When robots are plunged into workspace, they can surely be expected to locate the victim depending on the use of the signals-for- help-like RFID. Note that we are only concerned with electromagnetic wave itself, not message carried by electromagnetic wave in search process.

1.1.3 Gas

Consider the hazardous gas in coal mine. Gasmolecules released in the sap of coal mine are carried by the wind forming an odor plume. As the plume travels away from the source, it becomes more diluted due to diffusion. Two processes cause the diffusion of odors: molecular diffusion and turbulence. The former is a very slow process whose effect can be neglected for a plume characterization. While the latter is manifested in the boundary layer by different

size eddies. The action of eddies on the plume can be separated in three zones. Near the odor source eddies with size much larger than the plume width cause plume meandering. In the second zone it is possible to observe high concentration intermittency periods caused by eddies with diameter identical to the plume diameter. Those eddies shred the plume by introducing puffs of clean air inside the odor patches, producing high peak-to-mean concentration ratios. Far away from the odor source, the turbulence act like mixers that homogenize the plume. In this zone the instantaneous concentration is mainly small and uniform [1].

1.2 Robot

The robots were assumed to be able to locate both themselves inside the workspace and obstacles in the neighborhood, via either GPS or another global positioning mechanism even or relative localization system [12]. They were therefore able to take advantage of swarm intelligence principles to determine their successive desired velocities. However, there were some key differences between PSO and swarm robots search. It was necessary to make modifications to our algorithm [2].

1.2.1 Evaluating Signals

Robot movement depends on both its best sense and best experience among its neighbors. That is, there is no fitness function in our algorithm. In the first step of our ongoing project, we simply assume each robot has a sensor to detect the intensity of target signal, which has computational significance only but has nothing to do with the third party fitness function in the search process.

1.2.2 Discreting Move

PSO works by having particles update their positions within the search space when iteration of algorithm occurs. Robot search operates in continuous time. We can approximate this jump by having the robot move for a fixed amount of time at the proper velocity towards its desired location.

1.2.3 Velocity Limitation

In PSO, particles have infinite acceleration and no intrinsic limitations on velocity. In real world, robots have limits to how quickly they can move. In most swarm robot search scenarios, it would take a substantial amount of time for a robot to cross the search environment at maximum velocity.

1.2.4 Neighborhood Structure

The neighborhood structures in PSO require particles to share information with others anywhere in search space. Robots always have strict limitations on maximum communication range. In this context, it makes more sense to define a neighborhood structure based on position in the search space, where nearby robots belong to the same neighborhood. We define neighborhood structure of a robot as all robots within some fixed geometrical distance (could be the maximum communication range *R*). Because robots are constantly in motion, this means that the neighborhood structure is dynamic.

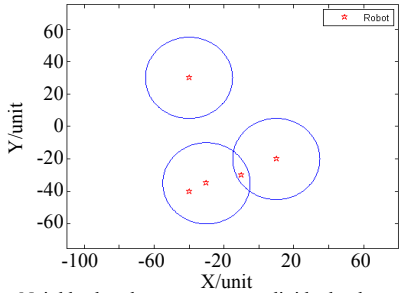

Fig. 1 Neighborhood structures of individual robots, which depends on the distance from involved robot to others. Those robots belong to the same structure can interact (communicate) one another and then determine the best local location by intensity comparison when iteration occurs

1.3 Search Parameters

The main parameters considered here are ones responding to environment, robots and simualtion in Table 1. Note that we simplify the experimental environment by neglecting the real conditions mentioned above, especially gas plume. And the simulation of real conditions will be taken into account in the future study.

Table 1 Search Parameters

Symbol	Implication	Value
Squ	size of the workspace	150 unit ×150 unit
Ori	origin of the coordinates	(20,20)
R	maximum communication range	50 unit
r	detection radius of sensor	50 unit
Loc	target position	(150,150),fixed
N	number of robots	10
vmax	maximum velocity	2 unit/s
Area	robot starting search area	(20,20)-(70,70)
P	power of target signal	1000 unit
Δt	inertia coefficient of robot (sampling period)	0.4 s
T	simulation step size	0.6 s

2 Algorithm Description

Before starting to describe our work, we should point out that the simulation of searching victim in an unstructured environment is extremely complex. Therefore, in order to make progress, we focus here on simulating an abstraction of the problem. We do not consider the majority characteristics described in the previous section. However, swarm intelligence principles emphasize limited sense capability and local interaction

mechanism in particular. Then our model and control policy have to be the embodiment of these principles.

2.1 Assumptions

In the beginning of our work, we envision that a single victim is in a large-scale area. The extent of this 2-D surface enclosed within a boundary is 150 unit ×150 unit. A swarm of homogeneous robots are assigned to search the target, moving about in space according to the rules of spiral or extended particle swarm algorithm in different cases. Each robot is equipped with an appropriate electronic sensor. We assume that the sensor cannot always read the correct intensity value of signals everywhere and sensor errors are considered as a kind of random noise. Compared with the scale of the search area, the communication range of robots is related small. We also assume that no robot in the course of search has global communication capability. Based on the assumptions, simulations are developed to evaluate effects. To compare the results, we initialize a target at a fixed position in the environment. In addition, the environment is "static", there is no obstacle in the environment, and the intensity of the signal at each point depends on the distance from the target. The farther is away from the target, the lower the intensity of the signal is [5]. To simplify the simulation, we use following mathematical model to generate the intensity of each point in the environment.

2.2 Signal Sensing

As mentioned above, the robots being used in the study should only have limited sensing ability. This constraint ensures that the coordination between the robots is distributed. Therefore, the size of the experimental arena should be much bigger than the perceptual range of the robots [14]. As was described in Section 1, each robot has a sensor to measure the intensity of the target signal within its reaction distance. This intensity $I(d)$ is determined by

$$I(d)=\begin{cases}0, & d>r\\ P/d^2+\eta(), & d\le r\end{cases} \tag{1}$$

where P is the target signal power, d is the distance from robot to target, r is the radius of detection of sensor and $\eta()$ is a sampling of additive Gaussian noise [2], which satisfying distance inverse square law within the reaction range of the sensor. Therefore, if the distance from target to robot is greater than the sensor reaction range then $I(d)$=0. Note that most swarm robots based on search and optimization algorithms found in the literature start the population randomly across the search space. This kind of initialization provides a good sampling of the workspace from the beginning because the initial positions of some robots maybe have them sensed target signal very well, it is not very realistic to implement in robot search, since usually those robots start searching from the same area, usually a corner of the search space [1]. This detail is specially considered in our algorithm. We make sure a small area around the origin of coordinates to be the starting initialize population zone.

2.3 Local Communication

A swarm system should involve robots that have only local communication ability, as already mentioned above. In fact, system wide interactions, unpractical, global communication costly, given that both suffer of exponential explosion as the number of individuals in the system increases. Robots should therefore rely only on local interactions and simple modes of communication. The latter are often beneficial for the achievement of coordinated behaviors or for an increased efficiency of the group. Here, we introduce a form of explicit communication. The communication forms or modes, that is, the ways of global or local interactions, among the individual robots depend heavily on neighborhood structures. As illustrated in section 1, neighborhood structure of robot is the same as circle whose radius equals to robot's communication distance R. As a matter of fact, if the communication range of robots is big enough compared to the environment, "local" mode would be converted into "global" one. From the relationship, if $R\approx\infty$ then there will be only one structure, and all robots belong to the only structure; while if $R=0$ then there will be as many structures as the number of robots. Note that all the neighbors change dynamically as each robot moves about, though the communication range remains fixed. Therefore, local communication mode gives birth to the passive modification of the social component to the iteration equation, which relies only on the best experience within the neighborhood structure instead of the global best in the swarm [2-4].

2.4 Search for Signal Cues

A typical problem of search algorithms is the balance between the ability of an algorithm to exploit new search cues and to explore the whole search space looking for new cues. Move control is employed before a robot obtains sense cues to exploit, so the best thing to do is to explore the environment trying to find such cues. Because in most of the space no intensity can be sensed due to the limited sense ability of robots, the robots become stopped without exploring unknown areas. Both the exploration of new areas and the

exploitation of signal cues eventually found can be solved by means of a state-based search policy that changes the policy from search for cues (exploration) to search for target (exploitation) whenever a new search cue was found [1]. As for the move control to find cues, we implement spiral moving mode, which was showed the best performance among several modes [15]. Note that the step-interval of spiral should be set to equal to communication range *r*.

2.5 Search for Target

Given N stands for the magnitude of robots involved in this search. $X_i = (x_{i1}, x_{i2})$ and $V_i = (v_{i1}, v_{i2})$ are position and velocity of robot *i* at current moment *t* respectively in 2-D space; $X^*_i = (x^*_{i1}, x^*_{i2})$ and $X^*_{(i)} = (x^*_{(i)1}, x^*_{(i)2})$ are the best historical location of robot *i* itself and all robots within its neighborhood structure, that is, where robot *i* and certain robot which belongs to its neighborhood structure can sense the highest intensity respectively. As is shown in Fig.2, when an iteration in the course of search occurs, the current best position of robot *i* can be determined by the following rule

$$X^*_i(t+\Delta t) = \begin{cases} X^*_i(t), & if\ I(X^*_i(t+\Delta t)) < I(X^*_i(t)) \\ X^*_i(t+\Delta t), & if\ I(X^*_i(t+\Delta t)) \geq I(X^*_i(t)) \end{cases} \quad (2)$$

where Δt is a factor to decrease the step the robots take when they move about. We added the factor in order to have a "smoother" movement, and therefore a more refined search. The parameter is somehow different from the others, as it is not related to the physical nature of the problem. However, we can also understand it in this fashion: real object has inertia due to its mass. We can even think of the factor as the sampling period. In fact, the choice of the best Δt is not purely algorithmic: a too small one causes the robots to move with a step too short to find target; with $\Delta t = 1$ (i.e. the default step of the classical PSO), the particles move with big jumps which may cause them to miss target [4].

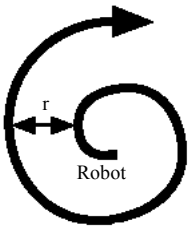

Fig. 2. Control over robot before signal cues have been found.

Then, we predefine the local best position according to robot *i*'s neighborhood structure as follows

$$X^*_{(i)}(t) = X^*_k(t), \quad \arg\max_k \{I(X^*_k(t)), k \in i\text{'s neighborhood}\} \quad (3)$$

taking robot *i*'s inertia caused by its mass and the limitation of velocity and acceleration into account, we can gain the iteration equations in advance

$$v_{ij\,expect}(t+1) = \omega * v_{ij}(t) + c_1 * rand() * (x^*_{ij} - x_{ij}) + c_2 * rand() * (x^*_{(i)j} - x_{ij}) \quad (4)$$

$$v_{ij}(t+\Delta t) = v_{ij}(t) + 1/T * (v_{ij\,expect}(t+1) - v_{ij}(t)) \quad (5)$$

$$x_{ij}(t+\Delta t) = x_{ij}(t) + \Delta t * v_{ij}(t+\Delta t) \quad (6)$$

where $v_{ij}(t)$ and $x_{ij}(t)$ are *j*-dimensional velocity and position of robot *i* at moment *t* respectively. $v_{ij\,expect}$ is the expected velocity of robot *i* at moment (*t*+1), and ω is an algorithmic inertia coefficient. c_1 and c_2 are the cognizing and social acceleration constant respectively. *rand*() is stochastic variable subject to the distribution of *U*(0,1). $x^*_{(i)j}(t)$ is the highest historical intensity of *j*-dimensional position within robot *i*'s neighborhood.

For the simulation, the maximum velocity is limited to 2 units/s. The initial position and velocity for the robots are randomly generated but the initial area is limited to one corner near the origin of coordinates of the workspace. The successive new velocities and positions are calculated using (5) and (6) respectively. Initially the robot's best position is the same as the initial random position. The initial local best is the intensity value that the robot sense, which is calculated by using (1). Then robot searches through this array for the local maximum value. The coordinates corresponding to this local maximum value is the local best. Within a loop the algorithm calculates the new velocity depending on the parameters passed to it from the previous iteration. The new positions of the robots depend on the current velocity of the robot. After updating the position for every robot, the robot's best position and the local best position need to be recalculated. This loop is executed until some of the robots converge at the target [5].

```
Initialize the swarm
Do
If (robot fails to sense) Then
        move spirally
Else
        evaluate robot's sense value
        If (belongs to the same neighborhood) Then
                compare each robot's intensity
                calculate target positions using (4) - (6)
                move till the target
        End if
End if
Until end criteria
```

3 Results and Discussion

The experiments have been performed in simulation, using an abstract model for the robot swarm. Robots are placed in a square arena, having a side 150 units long,

surrounded by walls. By independently varying the parameters introduced in the previous sections, we performed a large number of runs. The experiment started with different randomly initialized population in the starting area. We observed that search was successfully performed in most replications. Fig.3 plots a significant example of trajectory in the experiment. From the curve, we can see that all robots were controlled to move spirally due to the lack of signal sensing cues in the first course of search, since the distance from the robots starting area to target was beyond the sense range *r*. While, as long as only one robot sensed target signal, the task would be successfully completed early or later in our experiment, even had been spending a substantial number of iterations.

With this simulation, we have begun with a simple abstraction of the victim search problem. In the near future, we will extend the analysis of the search further, by introducing more realistic features for the shout, RF wave transmission and gas transporting in environment, and by defining metrics of time elapsed and energy consumption.

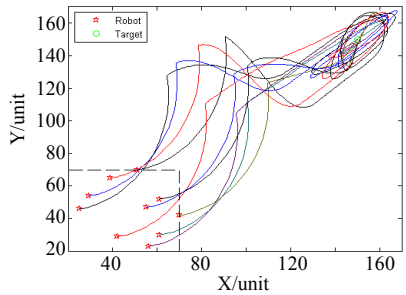

Fig. 3. Typical trajectories of swarm search. Note that the starting area is in the bottom left corner, framed with dashed line

4 Conclusion

The goal of this research is to introduce an innovative way to use the particle swarm algorithm as a simulation tool for biologically inspired search problems. In this paper, we have shown how some simple adaptations to the standard algorithm can make it well suited for search problem. What we want to focus on in this simulation is the emergence of swarm search behavior. We have presented a swarm robots search algorithm based on the swarm intelligence principles and shown it can be successful at finding a target. The implications of results and relevant future work have been discussed.

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