Computing and Informatics, Vol. 32, 2013, 89–112

A SOCIAL FORCE MODEL FOR ADJUSTING SENSING RANGES IN MULTIPLE SENSING AGENT SYSTEMS

Jiuchuan Jiang

State Key Laboratory of Robotics and System (HIT)
Harbin 150080, China
&
School of Computer Science and Engineering, Southeast University
Nanjing 211189, China(The corresponding address)
&
Department of Computer Science, Aalborg University
Aalborg 9220, Denmark
&
Key Laboratory of System Control and Information Processing
Ministry of Education, Shanghai, 200240, China
e-mail: jiangjiuchuan@163.com

Yungui Zhang

School of Electrical Engineering and Automation
Harbin Institute of Technology, Harbin 150080, China
e-mail: yunguizhang@263.net

Communicated by Ivana Budinská

Abstract. In previous work of multiple sensing agent systems (MSASs), they mainly adjust the sensing ranges of agents by centralized heuristics; and the whole adjustment process is controlled in centralized manner. However, such method may not fit for the characteristics of MSASs where the agents are distributed and decide their activities autonomously. To solve such problem, this paper introduces the social force model for adjusting the sensing ranges of multiple sensing agents, which can make the agents adjust their sensing ranges autonomously according to their social forces to other agents and the sensing objects. Based on the social force model, the coverage and optimization models are presented for both point-type and area-type objects. The presented model can produce appropriate social forces among the sensing agents and objects in MSASs; thereby the system observability and lifetime can be improved.

Keywords: Multiple sensing agent systems (MSASs), coverage, lifetime, communication ranges, social force model

1 INTRODUCTION

Sensing agents are the ones that have sensing abilities, which are often spatially distributed in an uncertain surveillance environment to sense surrounding information in order to achieve a global goal [1]. One of the typical examples are the sensor network which may be naturally modeled as a multiagent system (MAS) by regarding each sensor as an agent [2]; another typical example is the mobile multi-robot systems, where each robot can sense its surrounding environment [3]. Obviously, the concept of sensing agent is more general than sensor or sensing robot, which can also be used to model any other distributed sensing systems [4].

In the collective multiple agent systems, the formation control has received a lot of attention in many areas [5, 6, 7, 8]. Formation of multiple agents includes many aspects, such as positions of agents [5], path of mobile agents [9], orientation of agents [3], etc. In this paper, we think that the formation of sensing agents within two-dimensional zone mainly includes the sensing ranges of agents. Such formation is very typical in some multiple sensing agent systems; for example, in the wireless sensor networks, the appropriate sensing ranges of sensors can ensure the coverage and life time of networks [10, 11].

Coverage is a very important issue in multiple sensing agent systems (MSASs), which determines how well an interested object is monitored by agents [11]; lifetime is another important issue in MSASs which defines how long a MSAS has an effective operating time [10, 11]. Due to the constraint of associated capacities of agents, the coverage and lifetime of a MSAS may be contrary. In MSASs, the agent may be capacity controlled such that different capacity levels could be used to achieve different sensing ranges [11]. To improve the coverage of MSAS, we may increase the sensing ranges of agents, which, however, may consume more capacities of agents; thus the lifetime of MSAS may be reduced. Therefore, we should find the balance between coverage and lifetime of a MSAS.

To make coordination between the two issues of coverage and lifetime, there are many related works on adjusting the sensing ranges of agents. As to coverage of MSASs, there are broadly three types of related works classified based on what is to be covered, namely discrete points coverage, area coverage and barrier coverage [11, 12]. To optimize the lifetime of MSASs, the related work is implemented by the adjustment of the sensing ranges [13]. In summary, the related work mainly adjusts the sensing ranges of agents by centralized heuristics, and the whole adjusting process is controlled in centralized manner. Obviously, such method may not fit for the distributed characteristics of MSASs. In the MSASs, the agents are distributed in an unknown environment and autonomously decide their activities, thus we should let the agents determine their sensing ranges autonomously.

To solve the above problem, this paper introduces the social force model for determining the sensing ranges of agents, which can make the agents adjust their sensing ranges autonomously according to their social forces with the sensing objects and other agents. The main contribution of this paper is that we can exert the advantage of autonomy of agents by using social force model, thereby our model can fit for the distribution characteristics of MSASs.

The rest of this paper is organized as follows. In Section 2, we introduce the related work; in Section 3, we model the sensing multiagents and sensing environments; in Section 4, we present the model for social forces among sensing agents; in Section 5, we present the model for adjusting the sensing ranges of agents; in Section 6, we provide the experimental simulation results to validate our proposed model; finally, we discuss and conclude our paper in Section 7.

2 RELATED WORK

Our research is related to the formation control of MASs and MSASs, and the coverage and lifetime optimization of MSASs.

The formation control of multiagent systems (MASs) attracts much attention in the multi-robot area. The formation includes many aspects, such as the coalition formation [14], the shape and orientation of the robot formation [9], the positions and orientations of agents in a group [3]. Egerstedt and Hu propose a model independent coordination strategy for multiagent formation control, which is platform-independent and general enough to support a number of different actual controllers [9]. Aveek K. Das et al. describe a framework for cooperative control of a group of nonholonomic mobile robots, which can enable both decentralized and centralized cooperative control [3]. Tabuada, Pappas, and Lima develop a systematic framework for studying formation motion feasibility of multi-agent systems [15]. Zhang and Hu present a framework for studying the centralized optimal multi-agent coordination problem under tree formation constraints [16]. In summary, most research works investigating the formation control of MASs can be categorized into centralized or decentralized manners [5]. In the centralized manner, there is a single controller that controls the formation of agents, which requires high computational power and is not robust to the dynamic environments; in the distributed manner, the agents can control their formation based on local adjustments, which requires less computational efforts and is more robust to the dynamic environments.

MSAS is a special form of MAS, where the sensing capabilities of agents are required to observe the surrounding environments [4]. In the formation of MSAS, the sensing ranges are very important which can define the sensing abilities of agents; the sensing ranges of agents can be set from near places to the whole area [17, 18, 19].

The main aim of sensing range control of MSAS is to optimize the coverage and lifetime of MSAS; thus now we introduce the related work on the coverage and lifetime optimization of MSASs. The coverage and lifetime optimization of MSASs is always seen in the wireless sensor networks due to constraint of associated battery power [10]. The coverage is to ensure that the whole area (or all targets) can be well monitored by the sensors [20]; the lifetime is denoted by how long the system can monitor the targets effectively [10]. The critical factor that determines the quality of coverage is the deployment of sensing agents, i.e., the formation of localities and sensing ranges of agents. The lifetime can be increased by adjusting the sensing ranges of agents only which are necessary to meet the requirements of coverage.

About the coverage of MSASs, there are broadly three types of related works classified based on what is to be covered, namely discrete points coverage, area coverage and barrier coverage [11, 12]. For example, Zhao and Gurusamy investigate the discrete points coverage and present a method for lifetime maximization for connected point target coverage [11]; Ma et al. present a model for managing the mobility of a mobile sensor network using network dynamics, which can get a better coverage [21]; Carle and Simplot address the energy-efficient area monitoring for MSASs, and present that optimizing energy consumption in area coverage can significantly extend network life [22]. Chen et al. present the concept of local barrier coverage which can develop localized algorithms and is more useful in practice [23].

To optimize the lifetime of MSASs, the related works are mainly classified into three types: adjustment of the sensing ranges, scheduling the activities of sensing agents, and deployment structure optimization of sensing agents. Cardei et al. present the method for maximizing the network lifetime by adjusting sensing ranges in MSASs [13]. Li et al. provide efficient distributed algorithms to optimally solve the best-coverage problem with the least energy consumption so as to improve the lifetime of MSASs [20]. Moreover, the lifetime of MSASs can be increased by scheduling only a subset of sensors necessary to be active for meeting the application requirements [11]. One general approach for the deployment structure optimization is deploying more sensors close to the base station so as to combat against excessive load near the base station [10]; another approach is implementing clustered MSASs [24].

In summary, the related works mainly adjust the sensing ranges of agents by centralized heuristics. Obviously, such method may not fit for the distributed and dynamic environments of MSASs. Therefore, being inspired from the distributed manner of MASs, this paper investigates the autonomous adjustment method for the sensing ranges of agents in MSASs, which is based on social force model.

3 MODELING THE MSASS

3.1 Modeling the Sensing Multiagents

Sensing agents have sensing abilities to sense surrounding information in order to achieve a global goal [1]. To maintain certain sensing abilities, the agents should have certain capacities. In this paper, we associate the capacity to each agent, which is similar to the power of sensors and can be waned by consumption. The higher the sensing range of an agent is, the more capacities will be consumed by such agent.

Definition 1 (Capacity of agent)**.** The capacity of agent a_i is a nonnegative real number: $c_i \longrightarrow \mathbb{R}$. The higher c_i is, the more probably a_i can sense the surrounding environment effectively.

Definition 2 (Sensing range of agent)**.** The sensing range of an agent is related to certain capacity consumption, i.e, a higher sensing range will consume more capacity. Let the sensing range of agent a_i be s_i and the consumed quantity for the capacity of agent a_i be cu_i; the sensing range is in direct proportion to the consumed quantity, i.e., $s_i = g(cu_i)$, where g is a monotonically increasing function.

Example 1. Let the initial capacity of agent a_i be 100; the agent will consume cu_i capacities for maintaining the sensing range $2cu_i$ for 1 minute. Now we can demonstrate the relations among the sensing ranges, consumed capacities, and maximum lifetime, shown as Figure 1.

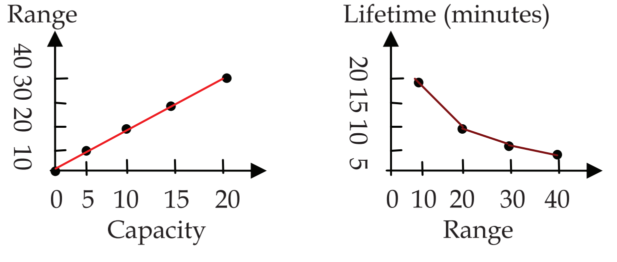

Fig. 1. Illustrating the relations among sensing ranges, capacities and lifetime of agents

By referring to the model of situated MAS in [25], now we present the model of a MSAS.

Definition 3. From the example shown in Figure 2, a multiple sensing agent system is a tuple $MSAS =< Z, A, D, C, S, O >$, where:

1. Z denotes a two-dimensional geographical zone where the multiple sensing agents are situated. $Z = \{(x, y)|\delta_1 \leq x \leq \delta_2, \gamma_1 \leq y \leq \gamma_2\}$, where $\delta_1, \delta_2, \gamma_1, \gamma_2$ prescribe the scopes of agent locations.
2. $A = \{a_1, a_2, \ldots a_n\}$ denotes the set of sensing agents, where n is the number of agents.
3. $D : Z \times A \rightarrow \{true, false\}$ is a mapping from the geographical localities to the sensing agents, which denotes the geographical distribution of sensing agents, e.g., if the mapping value from (x_i, y_i) to a_i is true, then it shows that there is an agent a_i which locates at the place of (x_i, y_i).

4. $A \to \mathbb{R}$ is the set of agent capacities, $C = c_1, c_2, \ldots, c_n$, where c_i denotes the capacity of agent a_i in the field.
5. $S : A \times Z \to \{s_i | s_i = g(cu_i)\}$ is the agent sensing range function, which denotes the sensing range of each agent at different places of the field, s_i, whose radius is denoted as r_i. The sensing area of agent a_i is $\pi {r_i}^2$.
6. $O = \{o_1, o_2, \ldots, o_m\}$ denotes the set of sensing objects, where m is the number of objects.

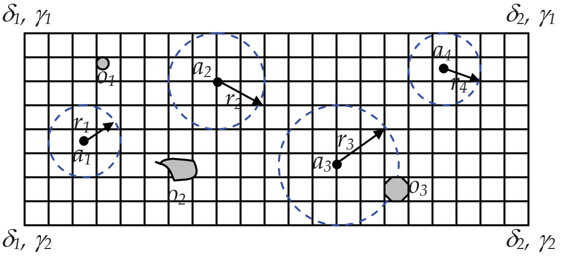

Fig. 2. An example of MSAS

3.2 Modeling the Sensing Environments

As to the sensing objects of MSASs, discrete points-type sensing objects and area-type sensing objects are typical. Thus, now we model the sensing environments by mainly considering such two sensing objects.

3.2.1 Discrete Points-Type Sensing Objects

Let the location of sensing agent a_i be (x_{a_i}, y_{a_i}), and the location of point p_j be denoted as (x_{p_j}, y_{p_j}). As to the discrete points-type sensing objects, we should try to find weak points in the sensing field and suggest future adjustment of sensing ranges of agents [26].

Definition 4. A point $p_j(x_{p_j}, y_{p_j})$ can be sensed by a MSAS if the following situation can be satisfied: $(\exists a_i \in A) \Rightarrow (d(a_i, p_j) \le r_i)$, where r_i denotes the radius of sensing range of a_i, A denotes the set of all sensing agents in the MSAS, $d(a_i, p_j)$ denotes the distance between a_i and p_j in the two-dimensional zone, $d(a_i, p_j) = \sqrt{{(x_{a_i} - x_{p_j})}^2 + {(y_{a_i} - y_{p_j})}^2}$.

Definition 5. The sensing degree of point $p_j(x_{p_j}, y_{p_j})$ is k, where $k = |\{a_i | \forall a_i \in A \wedge d(a_i, p_j) \le r_i\}|$. Obviously, it denotes that there are k sensing agents that can sense point p_j.

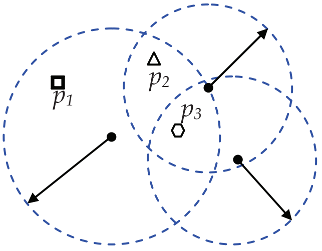

Fig. 3. K-sensing point objects in MSAS

For example, in Figure 3, the sensing degree of p_1 is 1, the sensing degree of p_2 is 2, and the sensing degree of p_3 is 3.

In the MSASs, each agent has certain capacities and will utilize them to sense the surrounding environments. The agents should consume some capacities to maintain a sensing range until the capacities are used up. Given an agent a_i, it will cost $\delta_{st} = g(s)$ capacities to maintain the sensing range s for duration time of t. Now, we have the following lemma.

Lemma 1. Given an agent a_i whose locality is (x_{a_i}, y_{a_i}) and initial capacity is c_i; now there is a point-type object p_j whose locality is (x_{p_j}, y_{p_j}). Then, the maximum lifetime of ai to sense p_j is $(c_i/g(\sqrt{(x_{a_i} - x_{p_i})^2 + (y_{a_i} - y_{p_i})^2})) \times t$.

Definition 6. Let the sensing degree of point p_i be k_i, and the set of agents that can sense p_i be A_i; then we can say that the lifetime of A_i to sense p_i is:

$$T_{A_i} = \min_{T_{A_i}}((c_j/g(\sqrt{(x_j - x_i)^2 + (y_j - y_i)^2})) \times t). \tag{1}$$

Example 2. Now we take the MSAS in Figure 4 as an example to compute the lifetime. Let the capacity consumption function be $g(x) = x^2$, and given a point-type sensing object p whose locality is (4,2); there are three sensing agents that can sense p, a_1, a_2 and a_3, whose localities are $a_1(1,1)$, $a_2(2,3)$, $a_3(6,2)$; the initial capacities of the three agents are $c_1 = 100$, $c_2 = 150$, and $c_3 = 200$. Now we can compute the sensing distance from the three agents to p, which are $s_1 = 3.162$, $s_2 = 2.236$, and $s_3 = 2$. Then, we can compute the maximum lifetimes of those three agents to sense p, which are $l_1 = 10t$, $l_2 = 30t$, $l_3 = 50t$. Therefore, according to Equation (1), the lifetime of such MSAS is $10t$.

3.2.2 Area-Type Sensing Objects

Area-type sensing object is another typical object. The main objective of the MSAS is to cover (monitor) an area (also sometimes referred to as region). Now we have the definition of area-sensed.

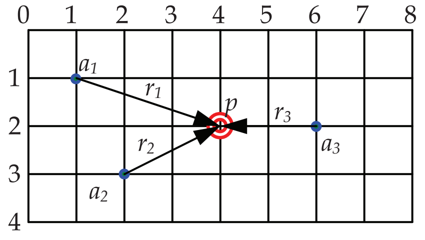

Fig. 4. An example to compute the lifetime of MSAS with point-type object

Definition 7. Given an area, Z, which is sensed by a MSAS, if: $Z \subseteq \cup_i s_i$, where s_i is the sensing range of a_i in the MSAS.

Factually, an area consists many points which have different distances to the agents.

Definition 8. Now given an area, Z, and a sensing agent, a_i. The far pole of Z regarding a_i is:

$$fp(Z \to a_i) = \arg \max_{\forall p_j \in Z} (d(a_i, p_j)). \tag{2}$$

The near pole of Z regarding a_i is:

$$np(Z \to a_i) = \arg \min_{\forall p_j \in Z} (d(a_i, p_j)). \tag{3}$$

Therefore, we can say that Z is *completely sensed* by a_i if $fp(Z \to a_i)$ can be sensed by a_i, i.e., $r_i \geq d(a_i, fp(Z \to a_i))$; we can say that Z is only just encountered by a_i if only $np(Z \to a_i)$ in Z can be sensed by a_i, i.e., $r_i = d(a_i, np(Z \to a_i))$; we can say that Z is not sensed by a_i if $np(Z \to a_i)$ can not be sensed by a_i, i.e., $r_i < (a_i, np(Z \to a_i))$.

Example 3. Figure 5 is an example to denote the far and near poles.

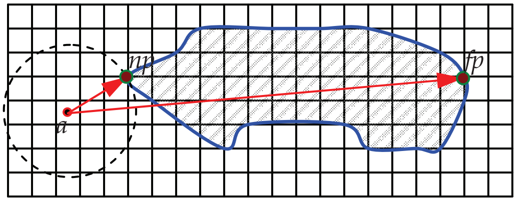

Fig. 5. An area-type object and the poles

Let there be an agent a_i; it will cost $\delta_{st} = g(s)$ capacities to maintain the sensing range s for duration time of t. Then, we have the following lemma.

Lemma 2. Given an agent a_i whose locality is (x_{ai}, y_{ai}) and initial capacity is c_i; now there is an area-type object Z whose far pole regarding a_i is $fp(Z \to a_i)$, and near pole regarding a_i is $np(Z \to a_i)$. Then, the maximum lifetime of a_i to completely sense Z is $\left(c_i/g\left(\sqrt{(x_{ai}-x_{fpi})^2+(y_{ai}-y_{fpi})^2}\right)\right)\times t$, the maximum lifetime of a_i to encounter Z is $\left(c_i/g\left(\sqrt{(x_{ai}-x_{npi})^2+(y_{ai}-y_{npi})^2}\right)\right)\times t$.

Therefore, we can say that the maximum lifetime of a_i during which a_i can take any sensing effects on A is:

$$\left(c_i/g\left(\sqrt{(x_{ai}-x_{npi})^2+(y_{ai}-y_{npi})^2}\right)-c_i/g\left(\sqrt{(x_{ai}-x_{fpi})^2+(y_{ai}-y_{fpi})^2}\right)\right)\times t. \tag{4}$$

Example 4. Now we take the MSAS in Figure 6 as an example to compute the lifetime. Let the capacity consumption function of sensing agent be $g(x) = x^2$, and the locality of agent be (1,1); there is an area-type object, whose far pole regarding the agent is $fp(8, 3)$, and the near pole regarding the agent is $np(2, 2)$; the initial capacity of the agent is $c_1 = 100$. Now we can compute the sensing distance from the agent to fp and np, which is $d(a_1, np(Z \to a_1)) = 1.414$, $d(a_1, fp(Z \to a_1)) = 7.071$. Then, the maximum lifetime of a_1 to completely sense Z is $1.89t$, the maximum lifetime of a_1 to encounter Z is $50t$; thus the maximum lifetime of a_1 during which a_1 can take any sensing effects on Z is $48.11t$.

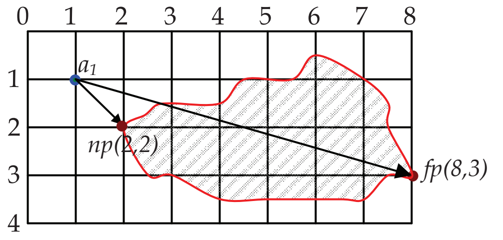

Fig. 6. An example to compute the lifetime of MSASs with area-type object

4 SOCIAL FORCES IN MSASS

The collective motion of multiagents can be described as if they were subject to social forces [27, 28]. Social force is a measure for the internal motivations of agents to perform certain actions, which are always related to the comparison between agents. Therefore, in this paper we introduce the social forces into the collective adjustment of sensing ranges of agents.

The prominence of an agent is always defined by its comparison with other agents [25, 29]. In this paper, the comparisons between any two agents are mainly on their capacity and sensing range comparisons.

Definition 9. Given two sensing agents, a_i and a_j, whose capacities are c_i and c_j respectively, the capacity prominence of a_i by comparing to a_j is $\lambda(i \to j) = (c_i - c_j)/c_i$, the capacity prominence of a_j by comparing to $\lambda(j \to i) = (c_f - c_i)/c_j$.

Definition 10. Given two sensing agents, a_i and a_j, their localities are (x_{a_i}, y_{a_i}) and (x_{a_j}, y_{a_j}) respectively, their radiuses of sensing ranges are r_i and r_j. Then, the sensing overlapping degree between a_i and a_j is:

$$\omega_{ij} = \frac{d_{ij} - (r_i + r_j)}{d_{ij}}. \tag{5}$$

If $\omega_{ij} > 0$, it denotes that the sensing ranges of a_i and a_j do not intersect; if $\omega_{ij} \leq 0$, it denotes that the sensing ranges of a_i and a_j intersect. For example, in Figure 7, $\omega_{12} < 0$, $\omega_{13} > 0$, $\omega_{23} < 0$; it denotes that the sensing ranges of a_1 and a_2 intersect, the sensing ranges of a_1 and a_3 do not intersect, and the sensing ranges of a_2 and a_3 intersect.

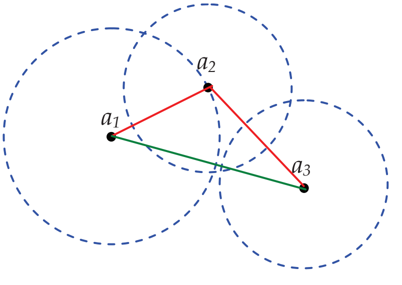

Fig. 7. Comparison among sensing ranges of three agents

4.1 Attractive and Repulsive Forces between Sensing Agents

Two agents should adjust their sensing ranges by regarding the situation of the other side; therefore, their adjustment of sensing ranges can be implemented according to their social force. The social force between two sensing agents is attractive if their sensing ranges do not intersect with each other, and is repulsive if their sensing ranges intersect with each other. Therefore, we have the following definition about social forces between agents.

Definition 11 (Social forces between agents.)**.** Let there be two agents, a_i and a_j; now we have:

- If $\omega_{ij} > 0$, the force that a_i attracts a_j is $Af(a_i \rightarrow a_j) = (c_j/c_i)\omega_{ij}$, the force that a_j attracts a_i is $Af(a_j \rightarrow a_i) = (c_i/c_j)\omega_{ij}$.
- If $\omega_{23} < 0$, the force that a_i repulses a_j is $Rf(a_i \rightarrow a_j) = (c_j/c_i)\omega_{ij}$, the force that a_j repulses a_i is $Rf(a_j \rightarrow a_i) = (c_i/c_j)\omega_{ij}$.

c_i is the current capacity of agent a_i.

For example, in Figure 7, the social force between a_1 and a_2 is repulsive, thus they should shrink their sensing ranges to save capacity; the social force between a_1 and a_3 is attractive, thus they should extend their sensing ranges to cover the object between them; the social force between a_2 and a_3 is repulsive, thus they should shrink their sensing ranges to save capacity.

4.2 Attractive Forces from Objects to Sensing Agents

In the MSAS, the agents will try their best to sense the objects. Thus, we can describe them as the attractive forces from objects to sensing agents.

Definition 12 (Social forces from objects to sensing agents)**.** Now we can define the social forces from objects to agents in two situations.

1. Given a sensing agent, a_i, and a point-type object, p_j. The attractive force from p_j to a_i is $Af(p_j \rightarrow a_i) = c_i/d(a_i, p_j)$.
2. Given a sensing agent, a_i, and an area-type object, Z. The far and near poles of Z regarding a_i are $fp(Z \rightarrow a_i)$ and $np(Z \rightarrow a_i)$. If the agent wants to completely sense Z, then the minimum attractive force from Z to a_i is $Min - Af(Z \rightarrow a_i) = c_i/d(a_i, fp(Z \rightarrow a_i))$; if the agent wants to only encounter Z, then the maximum attractive force from Z to a_i is $Max - Af(Z \rightarrow a_i) = c_i/d(a_i, np(Z \rightarrow a_i))$.

For example, in Figure 4, the attractive force from object p to agent a_1 is $Af(p \rightarrow a_1) = 100/3.162 = 31.6$. In Figure 6, the maximum attractive force from Z to agent a_1 is $Max - Af(Z \rightarrow a1) = 100/1.414 \approx 70.7$, the minimum attractive force from Z to agent a_1 is $Min - Af(Z \rightarrow a1) = 100/7.071 \approx 14.1$.

5 ADJUSTMENT FOR SENSING RANGES OF AGENTS

5.1 Performance Metrics of Sensing

The aim of sensing agents is to sense and monitor the surrounding environments. Therefore, we present the definition of observability of MSAS, which can measure how effectively the agents sense the surrounding environments.

Definition 13. The *observability* of MSAS. Let the set of points be P, and r_i be the radius of sensing range of agent a_i; then the observability denotes the percentage of points that can be sensed by any agents, which is denoted as:

$$\Omega_1(P) = \frac{|\{p_j|(p_j \in P) \wedge ((\exists a_i \in A) \Rightarrow (d(a_i, p_j) \leq r_i))\}|}{|P|}. \tag{6}$$

If the system wants to achieve the sensing degree k, then the observability with sensing degree k is:

$$\Omega_k(P) = \frac{|\{p_j|(p_j \in P) \wedge (|\{a_i|(\forall a_i \in A) \wedge (d(a_i, p_j) \leq r_i)| \geq k)\}|}{|P|}. \tag{7}$$

Let the set of area-type objects be $Z = \{Z_i\}$, and each area-type object can only be sensed by one agent; the observability that the area-point objects are completely sensed is:

$$\Omega_1(Z) = \frac{|\{Z_j|(Z_j \in Z) \wedge ((\exists a_i \in A) \Rightarrow (d(a_i, fp(Z_j \to a_i)) \leq r_i))\}|}{|P|}. \tag{8}$$

Lifetime is another important issue in MSASs which defines how long a MSAS has an effective operating time. Therefore, now we give the definition of lifetime of MSAS, shown as follows.

Definition 14. The *lifetime* of MSAS. Let there be some sensing objects in the MSAS, which include point-type and area-type objects, $P = p_i$, $Z = z_i$. Now the lifetime of MSAS can be defined as the time when:

$$\begin{aligned}&(\exists p_i \in P \Rightarrow \neg(\exists a_i \in A \Rightarrow d(a_i, p_i) < r_i))\\ &\vee (\exists z_i \in Z \Rightarrow \neg(\exists a_i \in A \Rightarrow d(a_i, np(z_i \to a_i)) < r_i))\,.\end{aligned} \tag{9}$$

Therefore, if any points or areas cannot be sensed, we can say that the MSAS is invalid. Now we express the relation between lifetime and sensing ranges of agents, shown as follows.

From Lemma 1 and 2, we can see that the lifetime of MSAS varies inversely as the real sensing ranges of agents and varies directly as the capacities of agents. Since the sensing range of an agent varies directly as the amount of consumed capacity of such agent, the lifetime of an agent can be improved by reducing such agent's real sensing range. From Definition 14, the lifetime of MSAS is determined by the minimum lifetime of agents when all objects can be sensed; therefore, to achieve longer lifetime, agents should try their best to minimize real sensing ranges in the condition that all objects can be sensed.

5.2 Adjustment Model

There are two situations where agents will adjust their sensing ranges; one is for point-type objects, and the other is for area-type objects. For each type of objects, the adjustment model includes two aspects; one is coverage model which tries to sense the unsensed objects, and the other is optimization model which tries to reduce the redundant sensing coverage of agents.

5.2.1 Point-Type Objects

For a point, agents will negotiate with each other to vote some ones to cover such point if the point is not covered by any agents, which is called coverage model. However, if a point is covered by more redundant agents, some agents will reduce their sensing ranges to save capacities so that the lifetime of systems can be improved, which is called optimization model.

1) Coverage model

For any point p_j, at first the agents will negotiate with each other to vote the one with the maximum attraction force from p_j, then such voted agent will adjust its sensing range to cover p_j. Then the final set of agents that sense p_j is $A_j = \{a*\}$.

$$a_* = \arg\min_{\forall a_i \in A} (Af(p_j \to a_i)) \tag{10}$$

If the system wants to implement k-sensing degree, then the agents will negotiate with each other to vote k agents that have the maximum attracting forces from p_j.

Algorithm 1. K-sensing agents voting.

1) Agents autonomously collect the location and capacity information of other agents by broadcasting/listening mechanism;
2) Agents autonomously sense their communication distances to the objects;
3) Agents autonomously compute their social forces between other agents and objects;
4) ${A_j}^k = \{\}$;
5) **For**$(n = 1; n <= k; n++)$:
   5.1) Agents negotiate with each and vote the agent with the maximum attracting force from object p_j:
   $a_* = \arg\min_{\forall a_i \in A} (Af(p_j \to a_i))$;
   5.2) a_*tags itself as the sensing agent for object p_j:
   $A_{j_k} = A_{j_k} \cup \{a_*\}$;
   5.3) $A = A - \{a_*\}$;
   /* the tagged agent will be excluded in the next negotiation round */
6) **Return** $({A_j}^k)$;
7) **End**.

Example 5. Figure 8 is an example to demonstrate the coverage model for point-type object. The initial capacities of a_1, a_2 and a_3 are $c_1 = 100$, $c_2 = 120$, $c_3 = 110$. Then, the three agents will compute the attracting forces from p to them: $Af(p_1 \to a_1) = 100/1.414 \approx 70.72$, $Af(p_1 \to a_2) = 120/1.414 \approx 84.87$, $Af(p_1 \to a_3) = 110/2 = 55$. Therefore, according to Algorithm 1, we have: ${A_1}^1 = \{a_2\}$, ${A_1}^2 = \{a_1, a_2\}$, ${A_1}^3 = \{a_1, a_2, a_3\}$.

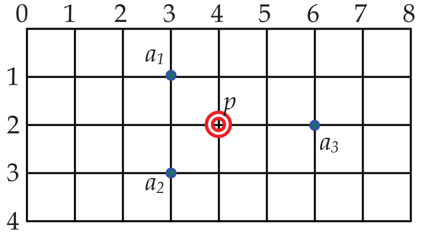

Fig. 8. An example of the coverage model for point-type objects

2) Optimization model

After Algorithm 1 is implemented, now agents will autonomously optimize their sensing ranges to save capacities, shown as Algorithm 2.

Algorithm 2. Optimization algorithm for point-type objects.

1) **For** $\forall a_i \in A$:

1.1) a_i initially sets a temporary value: $r_i(temp) = 0$;

1.2) **For** $\forall p_j \in P$:

1.2.1) **If** a_i tagged itself as the sensing agent of object p_j in Algorithm 1, i.e., $a_i \in {A_j}^k$, **then**:

1.2.1.1) a_i broadcasts query information to other agents whether they have already covered p_j;

1.2.1.2) **If** a_i finds that p_j has not been covered by k agents, **then**:

1.2.1.2.1) a_i senses its distance to p_j, $d(a_i, p_j)$;

1.2.1.2.2) **If** a_i finds $d(a_i, p_j) > r_i(temp)$, **then**: a_i sets a temporary value: $r_i(temp) = d(a_i, p_j)$.

1.3) a_i adjusts its sensing range as: $r_i = r_i(temp)$;
/* r_i is the radius of final sensing range of a_i */

2) **End**.

From Algorithm 2, each agent can autonomously minimize their capacity consumptions to satisfy the sensing requirements for point-type objects. Therefore, the lifetime of system can be improved according to the relation between lifetime and sensing ranges of agents described in Section 5.1. For example, in Figure 8, if the system wants to implement k-sensing of p, then the final sensing ranges of the three agents are $s_1 = 1.414$, $s_2 = 1.414$, $s_3 = 2$.

5.2.2 Area-Type Objects

For an area, first the agents will negotiate with each other to vote some ones to adjust their sensing ranges to cover such area if the area is not fully covered by any agents, which is called coverage model. However, if an area is covered by more redundant agents, some agents will reduce their sensing ranges to save capacities so that the lifetime of systems can be improved, which is called optimization model.

1) Coverage model

In this paper, the system tries to sense an area by making the agents number be as small as possible. Thus, first agents will negotiate and vote the one with the maximum attractive force from the area, and then such voted agent will try its best to sense the area. If such agent cannot fully cover the area, the agents will negotiate and vote the one with the second highest attractive force to sense. Such process will repeat until the area is completely sensed.

Algorithm 3. Completely sensing area Z.

1) Agents autonomously collect the location and capacity information of other agents by broadcasting/listening mechanism;
2) Agents autonomously sense their communication distances to the objects;
3) Agents autonomously compute their social forces between other agents and objects;
4) Agents memorize the initial covered parts of the area $Z : Z' = \{\}$;
5) While $Z' \neq Z$:
   - 5.1) Agents negotiate with each and vote the one with the maximum attracting force from object: $a_* = \arg\min_{\forall a_i \in A} (Af(\mathrm{Z} \to a_i))$;
   - 5.2) a^* will try its best to sense the area, now the already-sensed part of Z is Z';
   - 5.3) $A = A - \{a^*\}$.

   /* the voted agent will be excluded in the next negotiation round */
6) **Return** (A_k);
7) **End**.

Example 6. Figure 9 is a MSAS to demonstrate the coverage of an area-type object, where there are three agents – a_1, a_2 and a_3. The radiuses of maximum sensing ranges of those three agents are: $r_{1\max} = 3$, $r_{2\max} = 4$, $r_{3\max} = 2.5$. The capacities of agents are $c_1 = 100$, $c_2 = 130$, $c_3 = 70$. According to Algorithm 3, a_1 will be voted to sense the area since a_1 has the maximum attracting force from the area. Now a_1 cannot fully cover the area, so a_3 will be voted to sense the area since a_3 has the maximum attracting force from the area except for a_1. Finally, a_1 and a_3 can fully cover the area. However, there exists redundancy between the sensing ranges of the two agents, thus the optimization should be implemented by the agents autonomously, shown as the next section.

2) Optimization model

Now agents will optimize their sensing ranges to save capacities. Given an area Z, the set of agents that can sense Z is A_z. For every two agents in A_z, if their

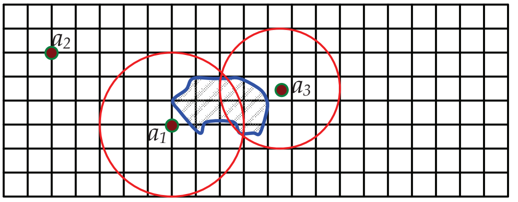

Fig. 9. An example of the coverage model for area-type object

sensing ranges intersect, they will reduce their sensing ranges in the condition that Z can be fully sensed. Therefore, the lifetime of system can be improved according to the relation between lifetime and sensing ranges of agents described in Section 5.1.

Algorithm 4. Optimization algorithm for area-type objects.

1) **For** $\forall a_i \in A_Z$:
   For $\forall a_j \in A_Z$:
   1.1) a_i (and a_j) collects the locality information of a_i(and a_j) and object through broadcasting/listening mechanism;
   1.2) a_i and a_j compute ω_{ij};
   1.3) **If** $\omega_{ij<0}$:
   Repeat:
   a_i and a_j negotiate to reduce their sensing ranges according to their capacity comparison and ω_{ij},
   Until the reduction of a_i and a_j influence the coverage for Z.
2) **End**.

6 COMPUTER SIMULATIONS AND ANALYSES

To validate our presented model, we made a series of simulation experiments. In the experiments, we use a grid to simulate the sensed zone where some agents with different capacities and initial sensing ranges are distributed. In the simulated zone, we put some point-type and area-type objects with different shapes. To demonstrate the effects of our model in different environments, now we set some parameters for several simulation cases:

1. Density of agents, which denotes the proportion of the number of agents to the whole sensing zone.
2. Density of objects, which denotes the proportion of the number of objects to the whole sensing zone.

Then, we can simulate varying simulation cases by changing the above parameters.

In the simulation experiments, we mainly compare the social force model with some typical heuristics methods: 1) the closest agent first, i.e., each object is sensed by the closest agent; 2) the agent with the largest sensing range first, i.e., the agent with the largest sensing range will exert its maximum sensing range to cover objects, and the remaining uncovered objects will be sensed by selecting the agent with the second largest sensing range; such process will repeat until all objects are covered. Moreover, we also compare our model with the random method where some agents are selected randomly for each object.

In this paper, the observability is defined as percentage of objects that can be sensed by any agents, but the lifetime is defined as the time when all objects can be sensed by any agents. Therefore, the lifetime is the duration when the observability is 100 %, i.e., the experiment of lifetime is only for a special case where observability is 100 %. Thus, we made two series of simulation experiments, one is to test what observability that our model can achieve, shown as Section 6.1; the other is to test how long our model can maintain the observability of 100 % (i.e., lifetime), shown as Section 6.2.

Moreover, to test the effects of social forces to observability and lifetime, we make another series of simulation experiments, shown as Section 6.3.

6.1 Effects of Social Force Model on System Observability

Now we test the effects of the social force model on system observability by comparing such model with other adjustment methods. The experimental results are seen in Figures 10 and 11, where the x-axis denotes the cases with varying agents densities and objects densities, and the y-axis denotes the system observability. From the experiments, we can see:

1. the "largest sensing range agent first" method can always perform well in varying cases, the potential reason is that the sensing capacities of agents can be fully utilized well with such method;
2. the social force model performs close to the "largest sensing range agent first" method, which denotes that the social force model can also utilize the sensing capacities of agents well;
3. the "closest agent first" method and random method perform worse than the other two methods for observability of objects, which denotes that they cannot utilize the sensing capacities of agents well. Therefore, the simulation results can prove that the social force model is effective for improving the observability of system.

6.2 Effects of Social Force Model on System Lifetime

Now we test the effects of the social force model on system lifetime by comparing such model with other adjustment methods. The experimental results are seen in

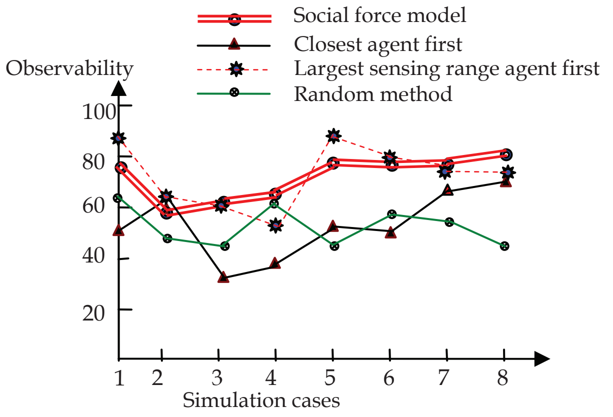

Fig. 10. Effects of varying methods on system observability (for point-type objects)

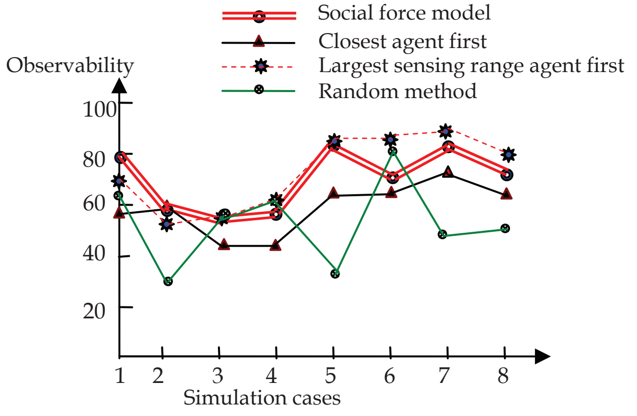

Fig. 11. Effects of varying methods on system observability (for area-type objects)

Figures 12 and 13, where the x-axis denotes the cases with varying agents densities and objects densities, and the y-axis denotes the system lifetime. From the experiments, we can see:

1. for both point-type objects and area-type objects, the social force model can achieve the best lifetime performance, the reason is that the optimization mechanism in Algorithm 2 and 4 can minimize the sensing ranges in the condition that all objects can be sensed so that the sensing capacities of agents can be saved;
2. the "largest sensing range agent first" method results in bad performance on lifetime, the potential reason is that the agents with largest sensing ranges may sense too many objects so that those agents' capacities will be used up soon;

3. the "closest agent first" method and random method can take medium performances on lifetime, which denotes that those two methods cannot optimize sensing ranges as the social force model but do not assign many objects to few agents as the "largest sensing range agent first" method.

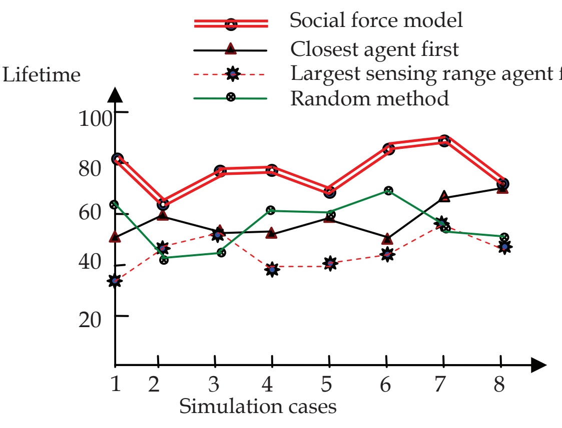

Fig. 12. Effects of varying methods on system lifetime (for point-type objects)

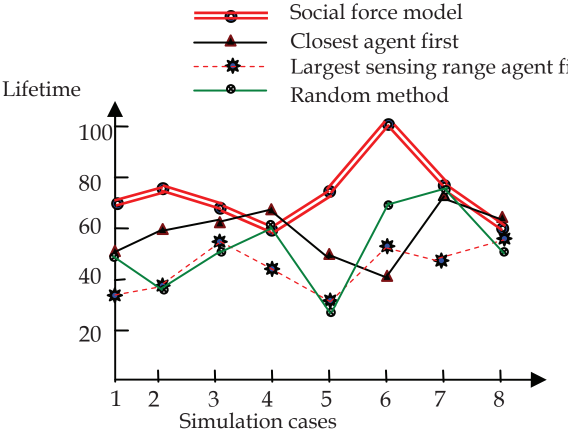

Fig. 13. Effects of varying methods on system lifetime (for area-type objects)

6.3 Relations Between Social Forces and System Performances

Now we will make simulation experiments to test the relations between social forces and system performances.

6.3.1 Relation Between Social Forces and System Observability

Now we change the comparison between attracting forces and repulsive forces, and observe the changes of system observability. The experimental results are seen in Figure 14, where x-axis denotes the ratio of attractive forces to repulsive forces in increase step by step, y-axis denotes the systems observability. From the experimental results, we can see that the system observability will descend as the attractive forces increase (repulsive forces decrease); the reason is that the sensing ranges of agents become smaller as the attractive forces increase so that more and more objects cannot be sensed.

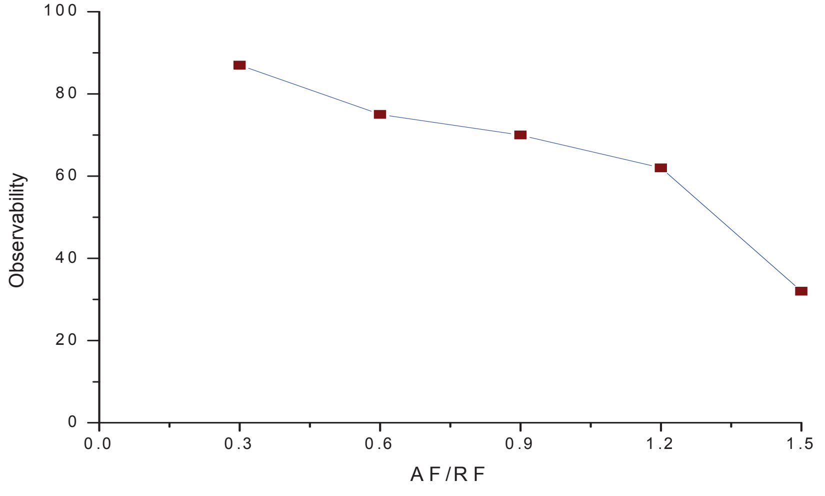

Fig. 14. Relation between social forces and systems observability

6.3.2 Relation Between Social Forces and System Lifetime

Now we change the comparison between attracting forces and repulsive forces, and observe the changes of system lifetime. The experimental results are seen in Figure 15, where x-axis denotes the ratio of attractive forces to repulsive forces in increase step by step, y-axis denotes the systems lifetime. From the experimental results, we can see that the system lifetime will ascend as the attractive forces increase (repulsive forces decrease), the reason is that now the sensing ranges of agents can be optimized as the attractive forces decrease, so that the capacities can be saved.

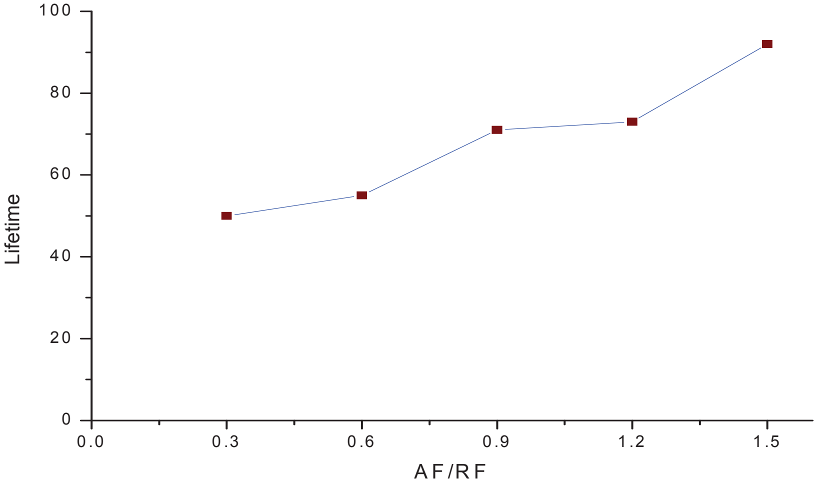

Fig. 15. Relation between social forces and systems lifetime

7 CONCLUSION AND FUTURE WORK

In the related works, the sensing ranges of agents are adjusted mainly by centralized heuristics, and the whole adjustment process is controlled in a centralized manner. Obviously, such method may not fit for the characteristics of MSASs where the agents are dynamically distributed in an environment and decide their activities autonomously.

To solve the above problem, we introduce the social force model for adjusting the sensing ranges of multiple sensing agents, which can make the agents adjust their sensing ranges autonomously. The main contribution of this paper is that the advantage of autonomy of agents can be exerted; thereby our model can fit for the distribution characteristics of MSASs. Based on the social force model, we present the coverage and optimization models both for point-type and area-type objects. With the presented model, the system observability and lifetime can be improved by comparing with other typical heuristics methods and random adjustment methods. Therefore, it shows that our autonomous adjustment model based on social force can exert positive effects for the MSASs.

Regarding the future work, we are currently working on the development and application of the model in real large scale multiple sensing agent systems, and we will try to address the concurrent diffusion mechanism produced by the simultaneous sensing range adjustment processes.

Moreover, in this paper the adjustment algorithms start with an arbitrary point/area but not the critical point/area which is with the smallest number of agents that can sense them completely or partially. The reason is that this paper mainly aims to provide a social force model which can be implemented by agents autonomously;

therefore, for simplification, it assumes that each agent's maximum sensing range can cover all objects, i.e., each object has the same number of agents that can sense it. In the future, we will consider the situation where objects have different numbers of agents that can sense them; in such case, the critical object with the smallest number of agents that can sense them should be considered first.

Acknowledgment

This research was supported by the National Natural Science Foundation of China (61170164), the Specialized Research Fund for the Doctoral Program of Higher Education (20090092110048), FSSP (20110092110053), the State Key Laboratory of Robotics and System (HIT) (SKLRS-2010-MS-06), the Key Laboratory of System Control and Information Processing of Ministry of Education of China (SCIP2011-006), the Funds for Distinguished Young Scholars of Jiangsu Province (BK2012020), and the Program for Distinguished Talents of Six Domains in Jiangsu Province (No. 2011-DZ023).

REFERENCES

[1] Choi, J.—Horowitz, R.: Learning Coverage Control of Mobile Sensing Agents in One-Dimensional Stochastic Environments. IEEE Transactions on Automatic Control, Vol. 55, 2010, No. 3, pp. 804–809.

[2] Vinyals, M.—Rodriguez Aguilar, J. A.—Cerquides, J.: A Survey on Sensor Networks From a Multi-Agent Perspective. The Computer Journal, Vol. 54, 2011, No. 3, pp. 455–470.

[3] Das, A. K.: A Vision-Based Formation Control Framework. IEEE Transactions on Robotics and Automation, Vol. 18, 2002, No. 5, pp.813–825.

[4] Roy, S.—Herlugson, K.—Saberi, A.: A Control-Theoretic Approach to Distributed Discrete-Valued Decision-Making in Networks of Sensing Agents. IEEE Transactions on Mobile Computing, Vol. 5, 2006, No. 8, pp. 945–957.

[5] Do, K. D.: Bounded Controllers for Formation Stabilization of Mobile Agents with Limited Sensing Ranges. IEEE Transactions on Automatic Control, Vol. 52, 2007, No. 3, pp. 569–576.

[6] Jiang, Y.—Hu, J.—Lin, D.: Decision Making of Networked Multiagent Systems for Interaction Structures. IEEE Transactions on Systems, Man, and Cybernetics, Part A: Systems and Humans, Vol. 41, 2011, No. 6, pp. 1107–1121.

[7] Jiang, Y.: Concurrent Collective Strategy Diffusion of Multiagents: The Spatial Model and Case Study. IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews, Vol. 39, 2009, No. 4, pp. 448–458.

[8] Jiang, Y.—Huang, Z.: The Rich Get Richer: Preferential Attachment in the Task Allocation of Cooperative Networked Multiagent Systems with Resource Caching. IEEE Transactions on Systems, Man, and Cybernetics, Part A: Systems and Humans, Vol. 42, 2012, No. 5, pp. 1040–1052.

[9] Egerstedt, M.—Hu, X.: Formation Constrained Multi-Agent Control. IEEE Transactions on Robotics and Automation, Vol. 17, 2011, No. 6, pp. 947–951.

[10] Wang, D.—Xie, B.—Agrawal, D. P.: Coverage and Lifetime Optimization of Wireless Sensor Networks with Gaussian Distribution. IEEE Transactions on Mobile Computing, Vol. 7, 2008, No. 12, pp. 1444–1458.

[11] Zhao, Q.—Gurusamy, M.: Lifetime Maximization for Connected Target Coverage in Wireless Sensor Networks. IEEE/ACM Transactions on Networking, Vol. 16, 2008, No. 6, pp. 1378–1391.

[12] Cardei, M.—Wu, J.: Coverage Problems in Wireless Ad Hoc Sensor Networks. Handbook of Sensor Networks, M. Ilyas and I. Mahgoub (Eds.), Boca Raton, FL: CRC Press 2004.

[13] Cardei, M.—Wu, J.—Lu, M.—Pervaiz, M. O.: Maximum Network Lifetime in Wireless Sensor Networks with Adjustable Sensing Ranges. Proceedings of the 2005 IEEE International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob-05), Montreal, Canada 2005.

[14] Seow, K. T.—Sim, K. M.–Kwek, S. Y. C.: Coalition Formation for Resource Coallocation Using BDI Assignment Agents. IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews, Vol. 37, 2007, No. 4, pp. 682–693.

[15] Tabuada, P.—Pappas. G. J.—Lima, P.: Motion Feasibility of Multi-Agent Formations. IEEE Transactions on Robotics, Vol. 21, 2005, No. 3, pp. 387–392.

[16] Zhang, W.—Hu, J.: Optimal Multi-Agent Coordination Under Tree Formation Constraints. IEEE Transactions on Automatic Control, Vol. 53, 2008, No. 3, pp. 692–705.

[17] Jiang, Y.—Jiang, J.—Ishida, T.: Compatibility between the Local and Social Performances of Multi-Agent Societies. Expert Systems with Applications, Vol. 36, 2009, No. 3 – Part 1, pp. 4443–4450.

[18] Jiang, Y.—Jiang, J.: Contextual Resource Negotiation-Based Task Allocation and Load Balancing in Complex Software Systems. IEEE Transactions on Parallel and Distributed Systems, Vol. 20, 2009, No. 5, pp. 641–653.

[19] Jiang, Y.—Jiang, J.—Ishida, T.: Agent Coordination by Trade-off Between Locally Diffusion Effects and Socially Structural Influences. Proceedings of the Sixth International Joint Conference on Autonomous Agents and Multi-Agent Systems (AAMAS-07), Honolulu, Hawaii, May 14–18, 2007,pp. 520–522.

[20] Li, X.—Wan, PFrieder, O.: Coverage in Wireless Ad Hoc Sensor Networks. IEEE Transactions on Computers, Vol. 52, 2003, No. 6, pp. 753–763.

[21] Ma, K.—Zhang, Y.—Trappe, W.: Managing the Mobility of a Mobile Sensor Network Using Network Dynamics. IEEE Transactions on Parallel and Distributed Systems, Vol. 19, 2008, No. 1, pp. 106–120.

[22] Carle, J.—Simplot, D.: Energy Efficient Area Monitoring for Sensor Networks. IEEE Computer, Vol. 37, 2004, No. 2, pp. 40–46.

[23] Chen, A.—Kumar, S.—Lai, T. H.: Local Barrier Coverage in Wireless Sensor Networks. IEEE Transactions on Mobile Computing, Vol. 9, 2010, No. 4, pp. 491–504.

[24] Shu, T.—Krunz, M.: Coverage-Time Optimization for Clustered Wireless Sensor Networks: A Power-Balancing Approach. IEEE/ACM Transactions on Networking, Vol. 18, 2010, No. 1, pp. 202–215.

[25] Jiang, J.—Xia, X.: Prominence Convergence in the Collective Synchronization of Situated Multi-Agents. Information Processing Letters, Vol. 109, 2009, No. 5, pp. 278–285.

[26] Meguerdichian, S.—Koushanfar, F.—Potkonjak, M.—Srivastava, M. B.: Coverage Problems in Wireless Ad-Hoc Sensor Networks. Proceedings of the 21st Annual Joint Conference of the IEEE Computer and Communications Societies (INFOCOM-02), New York, USA 2002.

[27] Helbing, D.—Farkas, I.—Vicsek,T.: Simulating Dynamical Features of Escape Panic. Nature, Vol. 407, 2000, pp. 487–490.

[28] Helbing, D.—Molnar, P.: Social Force Model for Pedestrian Dynamics. Physical Review E, Vol. 51, 1995, No. 5, pp. 4282–4286.

[29] Reiman, J. H.: The Rich Get Richer and the Poor Get Prison: Ideology, Class, and Criminal Justice. 6th edition, Allyn and Bacon 2000.

Jiuchuan Jiang received the bachelor's degree in communication engineering from Xiangtan University, Xiangtan, China, in 2004, and the master's degree in computer science from Nanjing University of Aeronautics and Astronautics, Nanjing, China, in 2009. He is currently a PhD student in the Department of Computer Science, Aalborg University, Aalborg, Denmark. His main research interests include multiagent systems, social networks and complex systems.

Yungui Zhang received his bachelor's and master's degrees from Tsinghua University and China Iron and Steel Research Institute group (ARIM) in 1988 and 1991, respectively. He is currently a Professor in automation research and design at the Institute of Metallurgical industry (ARIM). His main research interests include industrial automatic control system and intelligent embedded equipments.