Expert Systems with Applications 36 (2009) 4443–4450

Contents lists available at ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

Compatibility between the local and social performances of multi-agent societies

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ARTICLE INFO

Keywords:
Multi-agent Society
Social performance
Local performance
Compatibility
Coordination
Unification trend

ABSTRACT

To realize a harmonious multi-agent society, in previous work there are always two separated methods to make agent coordination: individual-local balance perspective and individual-society balance perspective. The two separated methods may bring out the conflicts between local and social performances. To achieve the compatibility between the local and social performances, this paper combines the two perspectives together and makes trade-off between them. With our presented model, the individual, local and social concerns can be balanced well in a unified and flexible manner. The experimental results show that there are often situations in which it is better for the local performance if the globally social performance is improved, and vice versa; thus the two coordination perspectives are not conflictive but often bring out the better in each other. Therefore, it concludes that the local and social performances in multi-agent societies can be compatible if we combine the two coordination methods together.

1. Introduction

Each agent will select its own social strategy which is the action that agent adopts to behave in the multi-agent society; however, the strategies among different agents may produce conflict. Therefore, in the multi-agent system, it is necessary to make coordination among agents (Bratman, 1992; Jiang & Jiang, 2005; Karrass, 1970; Weiss, 2000). In the coordination for the strategies of multi-agents, there is an interesting phenomenon which can be called *unification trend*: when many agents operate concurrently in the agent system, the agents will incline to adopt an identical average social strategy which can make the system be more unified (Jiang & Ishida, 2006, 2007, 2008; Jadbabaie, Lin, & Stephen Morse, 2003; Reynolds, 1987). With the unification trend, each agent will try to be gregarious to the community. The research for agent unification trend was initiated in the flocking behavior where many gregarious birds often go toward to an identical heading (Reynolds, 1987). Such phenomenon is also familiar in real human society where people always tend to select a common social strategy which will make the society be more harmonious.

In reality, an agent does not require being aware of every agents in the society, it may only know its local neighbors and the counterparts within its social organization. Therefore, with the unification trend of agents, the social strategy of an agent will be determined by: (1) *Locally diffusion effects*: the agent strategies will diffuse to each other in the local area, and agents will incline to the average strategy within neighboring region (Jadbabaie et al., 2003; Reynolds, 1987; Vicsek, Czirok, Ben Jacob, Choen, & Schochet, 1995; Zhiyun, Broucke, & Francis, 2004); (2) *Social influence*: agents will also be influenced by its social contexts especially the socially structural counterparts, therefore, agents will also incline to the consensus-strategy within the social contexts (Bandura, 2001; Carley & Newell, 1994; Hogg & Jennings, 2001).

Until now almost all related work on coordination in multi-agent society can be mainly categorized as falling into one of two general classes: *individual-local balance perspective*; *individual-society balance perspective*. In the first class, they only consider the balance between individual and local concerns (Jadbabaie et al., 2003; Jiang, Jiang, & Ishida, 2007; Reynolds, 1987; Vicsek et al., 1995; Zhiyun et al., 2004), which may get the local convergence but global polarization (Axelrod, 1997). Moreover, we may not get the globally social performance if we only consider the balance between individual and local concerns. Whereas, in the second class, they only consider the balance between individual and social concerns (Axelrod, 1976; Bandura, 2001; Carley & Newell, 1994; Hogg & Jennings, 2001), which may get the social performance but ignore the local effects. Moreover, the control on the whole agent society is sometimes difficult. Therefore, in related work, the local and social performances may be conflictive in agent societies.

To build a real robust multi-agent system, we should make the local and social performances be compatible. Therefore, in our research we provide an integrative model for agent coordination by trade-off between locally diffusion effects and socially structural

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doi:10.1016/j.eswa.2008.05.006

influences (Some preliminary results can be seen in our conference poster Jiang et al., 2007). On the base of our preliminary model in Jiang et al. (2007), we explore the compatibility between the local and social performances of multi-agent societies in this paper. With our model, the individual, local and social concerns can be balanced well in a unified and flexible manner. The experimental results shown that there are often situations in which it is better for the local performance if the globally social performance is improved, and vice versa; thus the two perspectives are not conflictive but often bring out the better in each other. Therefore, this paper concludes that the local and social performances in multi-agent societies can be compatible if we make a good trade-off between the two coordination methods.

2. Related work and scenarios

In Reynolds (1987), Reynolds initiated a research to explore the simulation for a flock of birds in flight; the birds fly as a flock and coordinate with each other by a local control strategy to adopt a common average heading. Moreover, Jadbabaie,Vicsek, and Lin presented that the agent's strategy is often updated using a local rule based on the average of its own strategy plus the strategies of its "neighbors" (Jadbabaie et al., 2003; Vicsek et al., 1995; Zhiyun et al., 2004). Agents will often make inferences from the social strategies of other agents at the adjacent places, which may lead naturally to some form of imitation. In the local diffusion of agent social strategy, each agent often interacts with a small set of social 'neighbors', and agents adjust their social strategies over time by myopically imitating the average strategy within their own neighborhoods. With the time goes, the agents' strategies in a local scope will inline to an identical point and achieve a locally harmonious behavior, such phenomenon can be called as local convergence in Axelrod (1997) or unification trend in Jiang and Ishida (2006).

Zhang presented that each agent is in some social contexts or organizations (Stephens Merx, 1989). So the strategy of an agent is influenced not only by the local neighbors but also the counterparts within the social organization. Social influence in multi-agent society is the ability of some agents to modify the social strategies of other agents within the social contexts. The social influence often occurs according to some structures. For example, Wasserman presented that the social influence can be shown by many interpersonal relationships within social networks (Wasserman & Faust, 1997). Generally, the social influences among agents can be shaped as the form of network in which the vertices denote the agents and the edges denote their influence relations. To consider the effect of social influence, the balance between individual and society concerns is required to ensure that the overall system, as well as the individual agents, is able to function in an effective manner. In related work, Hogg and Jennings provided the concept of socially responsible agents which can make balance between individual and overall system perspectives (Carley & Newell, 1994), and proposed a framework for making socially acceptable decisions based on social welfare functions (Hogg & Jennings, 2001).

From above, we can see that the social strategies of agents can be self-propelled, locally-propelled or socially-propelled. However, the three propelled measures may produce conflicts among the three concerns (individual, local and social concerns), which may lead to the possibility of un-gregariousness of some agents in the society. In the related work, they only separately consider the individual-local balance, or the individual-society balance.

The following scenario is a common instance that can demonstrate this phenomenon.

Scenario 1.

(1) Smith has a family (local diffusion region), and he is also an employee in Beta Corporation (social organization).
(2) Smith does not like smoking and drinking, but he can tolerate such living habits of other people.
(3) The family members of Smith like drinking at home; The colleagues of Smith like smoking in the office.
(4) If Smith is completely self-propelled, he will reject smoking and drinking both at home and in the office. Now, the family members and colleagues of Smith will be unhappy. (Self-interested).
(5) If Smith is locally-propelled, he will permit drinking at home, but reject smoking in the office. Now, the family members are happy, Smith can tolerate the drinking, but the colleagues of Smith will be unhappy (Only individual-local balance).
(6) If Smith is socially-propelled, he will permit smoking in the office, but reject drinking at home. Now, the colleagues are happy, Smith can tolerate the smoking, but the family members will be unhappy (Only individual–society balance).
(7) Therefore, Smith should combine the two perspectives together, and permit drinking at home and smoking in the office. Now, the family members and colleagues are both happy, and Smith can also tolerate the smoking and drinking (Combination of individual-local balance perspective, and individual-society balance perspective).

Therefore, our contribution in this paper is to combine the two separated perspectives (individual-local balance perspective, individual-society balance perspective) in an integrative framework, and explore how to make trade-off between locally diffusion effects and socially structural influences to get the good social performance as well as good local performance.

3. Locally diffusion effects

In real society, each actor interacts always with a small set of local "neighbors", and individuals will adjust their behaviors over time by myopically imitating the average strategy within their own neighborhood (Jadbabaie et al., 2003; Reynolds, 1987; Vicsek et al., 1995; Zhiyun et al., 2004). A social strategy accepted by collective agents may diffuse to others easily (Jiang & Ishida, 2007); therefore, each agent will be influenced by the diffusion of the average strategy within the local neighboring region.

Then, how to define the local interaction region for an agent? In this paper, we mainly adopt geographical distance to define the local interaction region, and identify one parameter-the interaction radius of an agent.

Definition 3.1. *Local interaction region* of agent a_i is defined as:

$$L_i = \{a_j | d(a_i, a_j) \leqslant r\} \tag{3.1}$$

where r is a predefined value which denotes the local interaction radius and can be adjusted according to the actual situation; $d(a_i, a_j)$ denotes the geographical distance between a_i and a_j.

Obviously, Let A be the set of agents, the local interaction region of agent a_i satisfies:

(1) $a_i \notin L_i, \quad \forall a_i \in A$;
(2) $a_i \in L_j \Leftrightarrow a_j \in L_i, \quad \forall a_i, a_j \in A$.

The above characteristics denote that an agent is not attributed to its own local interaction group, and the local interaction relation is symmetrical.

With the agent locally diffusion effects, each agent will go toward to the average strategy of neighbors. Therefore, we should make balance between the agent's initial strategy and the average strategy of neighbors. Let $s_i(t)$ denote the strategy of agent a_i at time t, when we make balance between individual agent and the locally diffusion effects of neighboring agents, the new strategy of agent a_i will be:

$$s_i^L(t+1) = \alpha \cdot s_i(t) + \beta \cdot \frac{1}{|L_i|} \sum_{j \in L_i} s_j(t) \tag{3.2}$$

where α is the inertia factor of the strategy of agent a_i, β is the influence factor of L_i to a_i, $\alpha + \beta = 1$. $|L_i|$ is the agent number of the local interaction region of a_i. We can set the values of α and β to determine the relative importance of the two strategies in the trade-off according to the actual situation.

4. Socially structural influence

4.1. Social influence structure

Social influence in multi-agent society is the ability of some agents to modify the strategies of other agents within the social contexts. The social influence often occurs according to some socially organizational structure (Hosking & Morley, 1991), e.g., the social influence of the colleagues on Smith is endowed according to the corporation organization in Scenario 1. The influence relations among all agents will form an influence structure; the influence structure can be shaped as the form of network in which the vertices denote the agents and the edges denote their influence relations (Wasserman & Faust, 1997).

There are many influence relations in multi-agent systems, among which the cause–effect relations are always seen (Axelrod, 1976; Chaib-draa, 2002). The social cause–effect influence relation between two agents denotes that the source agent will influence the social strategy of the target agent. The causal influence structure governs the way the agent society's members are organized by cause–effect relations and the influence strengths among agents.

The cause–effect relations among agents can be represented as a weighted directed graph where the vertices denotes the agents, the edges denote the cause–effect relations, and the weight with each edge denotes the influence strength from the source agent to the target agent. For agent *a*, it's "in" interaction relations denote the influence causes from other agents and the "out" interaction relations denote its influence effects to other agents.

Definition 4.1. *Social influence strength*. Social influence strength of agent a_i to a_j can be a function: $r_{ij} \to [0,1]$. If the social influence strength from agent a_i to a_j is r_{ij}, then agent a_j will go toward to the strategy of agent a_i with the probability r_{ij}.

Definition 4.2. *Social influence structure*. The social influence structure in a multi-agent system is a weighted directed graph: $N = \langle A, R, C \rangle$, where A denotes the set of agents, R denotes the set of cause–effect influence relations, $\langle a_i, a_j \rangle \in R$ denotes there is a causal influence relation from a_i to a_j, C is the set of influence strengths associated to all influence relations. As said in Definition 4.1, the causal social influence strength of agent a_i to a_j can be a function: C: $\langle a_i, a_j \rangle \to [0,1]$, $\forall \langle a_i, a_j \rangle \in R$.

The social influence structure can also be represented as an adjacent matrix: $I = [r_{ij}]$, $1 \leqslant i,j \leqslant n$, $0 \leqslant r_{ij} \leqslant 1$, where n denotes the number of agents in the system, $r_{ij} = 0$ denotes that there are no immediate causal influence relation from agent a_i to a_j, $r_{ij} \neq 0$ denotes that there is a immediate causal influence relation from agent a_i to a_j with the strength of r_{ij}. It is assumed that each agent can influence itself fully, so we have $r_{ii} = 1$.

If agent a is the source of a directed social influence relation $r \in R$, then we can denote it as $a \odot r$; If agent a is the destination of a directed social influence relation $r \in R$, then we can denote it as $a \otimes r$. In the social influence structure, the social strategies of some agents will be influenced by the ones of other agents.

Definition 4.3. *The causal sub-structure of an agent* in the social influence structure is defined as the set of "in" relations of linking this agent with other agents. Let the social influence structure be $N = \langle A, R, C \rangle$, then the *1-order causal sub-structure* of an agent is the union of its immediate "in" links, i.e., the immediate causal relations:

$$CS_{a_i} = \{\langle a_j, a_i \rangle \mid a_j \in A \wedge \langle a_j, a_i \rangle \in R\} \tag{4.1}$$

In reality, the social influence can be transferred from one actor to another actor. For example, if *a* can influence *b*, *b* can influence *c*, then *a* may also influence *c* with some degree. Therefore, we will address the *more-order causal sub-structure* of agent.

Obviously, the *2-order causal sub-structure* of an agent can be defined as:

$$CS(CS_{a_i}) = \{\langle a_k, a_j \rangle \mid a_j \in A \wedge a_k \in A \wedge \langle a_j, a_i \rangle \in R \wedge \langle a_k, a_j \rangle \in R\} \tag{4.2}$$

Therefore, we can define the *n-order causal sub-structure* of an agent as:

$$\begin{aligned}\prod\nolimits_n CS_{a_i} = \overbrace{CS(CS(\cdots(CS_{a_i})\cdots))}^{n}\{\langle a_n, a_{n-1}\rangle | a_1 \in A \wedge a_2 \\ \in A \wedge \cdots \wedge a_n \in A \wedge \langle a_n, a_{n-1}\rangle \in R \wedge \cdots \wedge \langle a_2, a_1 \rangle \\ \in R \wedge \langle a_1, a_i \rangle \in R\}\end{aligned} \tag{4.3}$$

We can compute the causal sub-structure of an agent continuously until such causal process cannot go any more. Now the all-orders causal structure can be denoted as: $\prod_\infty CS_{a_i}$.

The set of agents within the 1-order causal sub-structure of agent a_i (called as *1-order causal agents*) is:

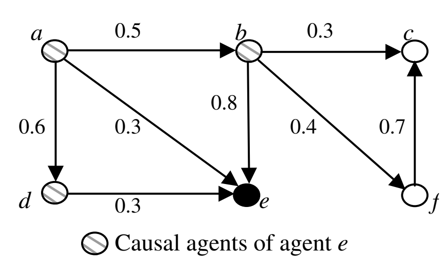
$$\mho_{a_i} = \{a_j | a_j \in A \wedge \langle a_j, a_i \rangle \in CS_{a_i}\} = \{a_j | a_j \odot r \wedge r \in CS_{a_i}\} \tag{4.4}$$

The set of all agents within the *all-orders* causal sub-structures of agent a_i is:

$$\sum \mho_{a_i} = \bigcup_{k=1}^{\infty} \left\{ a_j | a_j \odot r \wedge r \in \prod_k CS_{a_i} \right\} \tag{4.5}$$

Obviously, the social strategy of agent a_i will be influenced by its all-orders causal agents.

Example 4.1. Fig. 1 (i) is an example of social influence structure; Fig. 1 (*ii*) is the representation by adjacent matrix. In Fig. 1 (ii), we can see the causal sub-structure of agent *e*. The set of 1-order



(*i*)

$$\begin{pmatrix} 1 & 0.5 & 0 & 0.6 & 0.3 & 0 \\ 0 & 1 & 0.3 & 0 & 0.8 & 0.4 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0.3 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0.7 & 0 & 0 & 1 \end{pmatrix}$$

(*ii*)

Fig. 1. An example of social influence structure.

causal agents is: {a, b, d}, the set of 2-order casual agents is: {a}, the set of all-orders causal agents is: {a, b, d}. Obviously, the social strategy of e will be influenced by the agents in its causal sub-structure: {a, b, d}.

4.2. Social influence path and strength

As said in Section 4.1, the social influence can be transferred, and the social influence between two agents may proceed through some other agents. Therefore, we present the concept of social influence path.

Definition 4.4. *Social influence path.* The social influence path from agent a_i to a_j can be defined as: If there is a directed path from a_i to a_j in the social influence structure, we can say that there is a social influence path from a_i to a_j. The social influence path from agent a_i to a_j can be denoted as $CP_{i\to j}$.

Definition 4.5. Cumulative influence strength. If there is a path from a_i to a_j, then the cumulative influence strength from a_i to a_j is the multiplication value of the influence strengths for all immediate causal influence relations along the path, which can be denoted as $CI_{i\to j}$. Therefore, we have:

$$CI_{i\to j} = \prod_{\langle i,j\rangle \in CP_{i\to j}} r_{ij} \tag{4.6}$$

Theorem 4.1. *From Definitions 4.3 and 4.4, we can see that if there are no social influence paths from a_i to a_j, then a_i is not in the causal sub-structure of a_j, so the cumulative influence strength from a_i to a_j is 0.*

Example 4.2. In Fig. 1, there are three social influence paths from agent a to e: {⟨a, b⟩,⟨b, e⟩}, {⟨a, e⟩}, {⟨a, d⟩,⟨d, e⟩}; the corresponding cumulative influence strengths for the three paths are: 0.4, 0.3, 0.18.

From the above example, we can see that the cumulative strength through other agents may be higher than the immediate influence strength directly associated the two agents.

There may be several social influence paths between two agents. Then, how can we determine the ultimate influence strength if there are more than one social influence paths between two agents? In this paper, if there are more than one causal influence paths from a_i to a_j, then we can select *the social influence path with the strongest influence strength*. Such phenomenon is also always seen in real society. The following scenario is a common instance that can demonstrate such criterion.

Scenario 2.

(1) There are two departments in Beta Corporation: Department of Product Research, Department of Product Service. King is the president of Beta Corporation; Smith is an employee of the Department of Product Research; Alice is the head of the Department of Product Research; Bob is the head of the Department of Product Service.
(2) One day, the Department of Product Service finds that there are some bugs with a product from the feedback information of clients, and the product was developed by Smith.
(3) Now, Bob (the head of the Department of Product Service) may have three ways to deal with such problem:
  - Bob can directly ask Smith (the employee of the Department of Product Research) to improve the product, but Smith may not fully obey the request of Bob since Bob is not his boss. (Immediate social influence).
  - Alternatively, Bob can forward the information to Alice (the head of the Department of Product Research); if Alice accepts the request of Bob, then Alice will order Smith to improve the product; now Smith has to fully obey the request of Alice since Alice is his boss. However, if Alice cannot accept the request of Bob, then the product won't be improved (Intermediate social influence).
  - Otherwise, Bob can report the problem to King (the president of Beat Corporation); King will certainly order Alice to solve such problem, then Alice will have to obey the request of King; then Alice will order Smith to improve the product, so Smith will have to obey the request at last (Intermediate social influence).

Obviously, the third way is the most effective sine which has the highest cumulative influence strength. Therefore, in the Beta Corporation, when Bob finds there are some bugs with the product from the feedback information of clients, he will always adopt the third way to deal with the problem.

Therefore, given a social influence structure, we should compute the strongest cumulative influence strength between all agents, seen as Algorithm 1.

Algorithm 1. Compute the strongest influence strength between all agents.

InputI = $[r_{ij}]$;/* the matrix representation of social influence structure*/
for (*k* = *1*; *k* < = *n*; *k*++)
  for (*i* = *1*; *i* < = *n*;*i*++)
    for (*j* = *1*; *j* < = *n*; *j*++)
      if $r_{ij} < r_{ik} \cdot r_{kj}$ *then* $r_{ij} = r_{ik} \cdot r_{kj}$;
Output I.

Example 4.3. Now we use Algorithm 1 to compute the strongest influence strengths between all agents in Fig. 1, see as the followings:

$$\begin{pmatrix} 1 & 0.5 & 0.15 & 0.6 & 0.4 & 0.2 \\ 0 & 1 & 0.3 & 0 & 0.8 & 0.4 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0.3 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0.7 & 0 & 0 & 1 \end{pmatrix}$$

Now, let agent a_i be in a social influence structure, so the social strategy of agent a_i will be influenced by all agents in its causal sub-structure. We can combine the social influences of its causal agents together. So agent a_i will go toward to the average of all socially structural influences of its causal agents regarding their respective influence strengths.

$$s_i^S(t+1) = \sum_{j\in\sum \mho_{a_i}} \left(s_j \frac{CI_{j\to i}}{\sum\limits_{x\in\sum \mho_{a_i}} CI_{x\to i}} \right) \tag{4.7}$$

where s_j denotes the social strategy of agent a_j, $s_i^S(t+1)$ denotes the new social strategy of a_i if it fully obeys the social influence.

5. Balance between two perspectives

5.1. Trade-off

Therefore, to make trade-off between locally diffusion effects and socially structural influences, the strategy of agent a_i can be changed as:

$$s_i(t+1) = \lambda_L s_i^L(t+1) + \lambda_S s_i^S(t+1)$$
$$= \lambda_L(\alpha \cdot s_i(t) + \beta \cdot \frac{1}{|L_i|}\sum_{j \in L_i} s_j(t)) + \lambda_S \sum_{j \in \sum \mho_{a_i}} \left(s_j \frac{CI_{j \to i}}{\sum_{x \in \sum \mho_{a_i}} CI_{x \to i}} \right) \tag{5.1}$$

The different concern tendencies can be realized by the variations of combination of the four parameters (α, β, λ_L, λ_S), which determine the relative importance of the three concerns:

- $\alpha + \beta = 1$: these two parameters are to determine the trade-off between the individual concern and local concern in locally diffusion effects. If $\alpha > \beta$, the agent will incline to its own strategy more than the locally average strategy; if $\alpha < \beta$, the agent will incline to the locally average strategy more than its own strategy; if $\alpha = \beta$, the agent will place equal concern between its own strategy and the locally average strategy in the diffusion effects.
- $\lambda_L + \lambda_S = 1$: these two parameters are to determine the trade-off between the locally diffusion effects (include the individual concern and local concern in locally diffusion) and socially structural influence. If $\lambda_L > \lambda_S$, the agent will incline to the locally diffusion effects more than the socially structural influence; if $\lambda_L < \lambda_S$, the agent will incline to the socially structural influence more than the locally diffusion effects; if $\lambda_L = \lambda_S$, the agent will place equal concern between the locally diffusion effects and the socially structural influence.

5.2. Performance index

Since the inclination for unification trend said in Section 1, after the locally diffusion effects and socially structural influences, each agent will go toward to the average one of local region or socially structure. Therefore, we can define the following two performance indexes.

5.2.1. Local gregariousness of individual agents

With the unification trend of multi-agents, each agent will incline to be gregarious to the local neighbors when it is diffused by them.

The average strategy value within the local region of agent a_i is:

$$\overline{s_{L(i)}} = \frac{1}{1+|L_i|}\left(s_i + \sum_{j \in L_i} s_j\right) \tag{5.2}$$

The local gregariousness of agent a_i in its local region can be defined as

$$\sigma_{L(i)} = 1 - \frac{|s_i - \overline{s_{L(i)}}|}{\overline{s_{L(i)}}} \tag{5.3}$$

Therefore, the average local gregariousness of all individual agents in the agent set A can be defined as

$$\overline{\sigma_A} = \frac{1}{|A|}\sum_{i \in A}\sigma_{L(i)} = \frac{1}{|A|}\sum_{i \in A}\left(1 - \frac{|s_i - \overline{s_{L(i)}}|}{\overline{s_{L(i)}}}\right) \tag{5.4}$$

Higher values of $\overline{\sigma_A}$ indicate that better average local gregariousness performance of all agents can be gotten.

5.2.2. Social gregariousness of individual agents

With the unification trend of multi-agents, each agent will also incline to be gregarious to the whole society when it is influenced by the socially structural counterparts.

The average strategy value of the agent society is

$$\overline{s_A} = \frac{1}{|A|}\sum_{i \in A} s_i \tag{5.5}$$

The social gregariousness of agent a_i in the whole agent society can be defined as

$$\omega_{A(i)} = 1 - \frac{|s_i - \overline{s_A}|}{\overline{s_A}} \tag{5.6}$$

Therefore, the average social gregariousness of all individual agents in the agent set A is:

$$\overline{\omega_A} = \frac{1}{|A|}\sum_{i \in A}\omega_{A(i)} = \frac{1}{|A|}\sum_{i \in A}\left(1 - \frac{\left|s_i - \frac{1}{|A|}\sum_{i \in A}|s_i|\right|}{\frac{1}{|A|}\sum_{i \in A}|s_i|}\right) \tag{5.7}$$

Higher values of $\overline{\omega_A}$ indicate that better average social gregariousness performance of all agents can be gotten.

6. Experiments

6.1. The test environments

In our experiments, we consider agents distributed in a two-dimensional grid. Local diffusion interaction group in our experiments: let the position of agent a_i be (x_i, y_i) and the distance of each lattice be 1, then the local diffusion interaction group of agent a_i is composed of the agents that locate on the place of (x, y) which satisfies:

$$\sqrt{(x - x_i)^2 + (y - y_i)^2} \leqslant r \tag{5.8}$$

Therefore, if the local interaction radius r is set as $\sqrt{2}$, the local diffusion interaction group of an agent is the set of agents locating on its 8 geographically closest places, see Fig. 2.

About the agent system, we mainly have three parameters: m denotes the size of the two-dimensional grid, n denotes the number of agents, r denotes the radius of agent locally diffusion region.

Therefore, we will use two matrixes to denote the agent system and the social influence structure:

(1) $A = [a_{ij}], 1 \leqslant i,j \leqslant m$, where m denotes the size of the two-dimensional grid, $a_{ij} \neq 0$ denotes that there is an agent in place (i, j) whose initial social strategy is a_{ij}; $a_{ij} = 0$ denotes that there are no agents in place (i, j).

(2) From the top left to the bottom right in the grid, we can number the agent as $a_1, a_2, \ldots, a_n$. Now, we will use the following matrix to denote the social influence structure:

$$I = [r_{ij}], 1 \leqslant i,j \leqslant n, 0 \leqslant r_{ij} \leqslant 1.$$

As said in Section 4.1, n denotes the number of agents in the system, $r_{ij} = 0$ denotes that there are no direct causal influence relations from agent a_i to a_j; $r_{ij} \neq 0$ denotes that there is a immediate causal

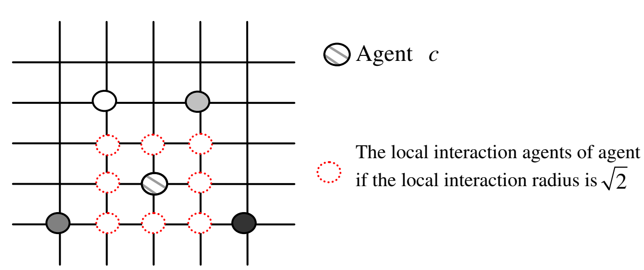


Fig. 2. The local region of experiment environment.

Table 1
Variations of the four weighting parameters

λ_L	λ_S	Tendency	α	β	Tendency
1	0	Fully local concern	1	0	Individual selfish
0.75	0.25	Local tendency	0.75	0.25	Individual tendency
0.5	0.5	Balanced	0.5	0.5	Balanced
0.25	0.75	Social tendency	0.25	0.75	Neighbor tendency
0	1	Fully social concern	0	1	Individual selfless

influence relation from agent a_i to a_j with the influence strength of r_{ij}; $r_{ii} = 1$.

6.2. The results and analyses

Our aim is to evaluate the effectiveness of the model for different concern tendencies (individual, local and social concerns) under varying agent distributions and agent system scales. The different concern tendencies can be realized by the variations of combination for the four parameters (α, β, λ_L, λ_S) (see Table 1). By referring to Hogg and Jennings (2001), here we use the following values:

6.2.1. Tests for varying agent distributions

There are always three kinds of agent distributions: (1) Cluster like agent distribution: there are some clusters in the grid, the agent distribution is dense within each cluster but is sparse between clusters; (2) Even agent distribution: the agents are evenly distributed in the grid; (3) Random agent distribution: the agents are distributed randomly in the grid.

The social influence structures are produced randomly. Now we test the multi-agent coordination, the results are shown in Table 2.

6.2.2. Tests for varying agent system scales

Now we test our multi-agent coordination model by increasing the scale of agent system step by step, then the agent distribution and social influence structure are random. The test results are shown in Table 3.

6.2.3. Analyses and conclusion for the test results

From Tables 2 and 3, we can see:

- When λ_L, λ_S are fixed, the higher α is, the lower $\overline{\sigma_A}$ and $\overline{\omega_A}$ are. Therefore, we can conclude that:The higher value of self inertia factor α of agent will produce low local gregariousness and social gregariousness; so the selfish agents are not gregarious with their local neighbors as well as the whole society. Therefore, if there are many selfish agents in the system, there may be many collisions both within each local region and throughout the whole system.
- When λ_L, λ_S are fixed, the higher β is, the higher $\overline{\sigma_A}$ and $\overline{\omega_A}$ are. Therefore, we can conclude that: When agents incline to go toward to the average strategy of their own local neighbors, then they will be more gregarious to their local region as well as the whole society.
- When α, β are fixed, the higher λ_L is, the higher $\overline{\sigma_A}$ and $\overline{\omega_A}$ are. Therefore, we can conclude that:The higher value of local balance factor λ_L can increase the local gregariousness; moreover, it can also increase the social gregariousness accordingly. Therefore, if we improve the local performances, it is also likely that the globally social performance is improved.
- When α, β are fixed, the higher λ_S is, the higher $\overline{\sigma_A}$ and $\overline{\omega_A}$ are. Therefore, we can conclude that:The higher value of social balance factor λ_S can increase the social gregariousness; moreover, it can also increase the average local gregariousness accordingly. Therefore, if we improve the globally social performance, it is also likely that the average local performance of all agents is improved.
- The effect of social balance factor on the social gregariousness is more than the one of local balance factor; the effect of local balance factor on the local gregariousness is more than the one of social balance factor. Therefore, we can conclude that:If we want to improve the globally social performance evidently, we should increase the weight of social concern; if we want to improve the local performance evidently, we should increase the weight of local concern.

As a conclusion, from our experiments, we can find an interesting phenomenon: the two agent coordination perspectives

Table 2
Test results for varying agent distributions

Local-society		Individual-neighbor		Performance indexes for varying agent distributions					
λ_L	λ_S	α	β	Cluster like distribution		Even distribution		Random distribution	
				$\overline{\sigma_A}$	$\overline{\omega_A}$	$\overline{\sigma_A}$	$\overline{\omega_A}$	$\overline{\sigma_A}$	$\overline{\omega_A}$
1	0	1	0	0.4889	0.4168	0.5757	0.4879	0.5589	0.6779
		0.75	0.25	0.6384	0.5542	0.7381	0.5929	0.6865	0.7249
		0.5	0.5	0.7735	0.6792	0.8524	0.6667	0.8022	0.7934
		0.25	0.75	0.8861	0.7742	0.8947	0.7049	0.8995	0.8821
		0	1	0.9045	0.7890	0.8499	0.6929	0.9172	0.9892
0.75	0.25	1	0	0.6295	0.5652	0.7084	0.6171	0.6763	0.7593
		0.75	0.25	0.7363	0.6675	0.8173	0.6955	0.7689	0.7943
		0.5	0.5	0.8343	0.7606	0.8976	0.7508	0.8536	0.8455
		0.25	0.75	0.9167	0.8313	0.9287	0.7792	0.9254	0.9118
		0	1	0.9299	0.8423	0.8973	0.7703	0.9384	0.9919
0.5	0.5	1	0	0.7590	0.7128	0.8139	0.7459	0.7875	0.8405
		0.75	0.25	0.8279	0.7803	0.8829	0.7980	0.8479	0.8636
		0.5	0.5	0.8917	0.8417	0.9343	0.8346	0.9034	0.8975
		0.25	0.75	0.9455	0.8881	0.9545	0.8534	0.9507	0.9414
		0	1	0.9541	0.8954	0.9343	0.8475	0.9592	0.9946
0.25	0.75	1	0	0.8837	0.8579	0.7099	0.8744	0.8951	0.9216
		0.75	0.25	0.9164	0.8926	0.9432	0.9002	0.9248	0.9328
		0.5	0.5	0.9473	0.9223	0.9680	0.9182	0.9522	0.9494
		0.25	0.75	0.9735	0.9446	0.9780	0.9274	0.9755	0.9710
		0	1	0.9777	0.9482	0.9681	0.9246	0.9797	0.9973
0	1	\ [a]	\ [a]	0.9965	0.9961	0.9991	0.9977	0.9994	0.9987

[a] If λ_L is 0, then the value of α and β do not take effects according to Eq. (5.1), so as done in Table 3.

Table 3
Test results for varying agent system scales

Individual-neighbor		Performance indexes for varying agent system scales							
α	β	$n = 25$		$n = 50$		$n = 75$		$n = 100$	
		$\overline{\sigma_A}$	$\overline{\omega_A}$	$\overline{\sigma_A}$	$\overline{\omega_A}$	$\overline{\sigma_A}$	$\overline{\omega_A}$	$\overline{\sigma_A}$	$\overline{\omega_A}$
$\lambda_L:\lambda_S = 1:0$									
1	0	0.5372	0.2508	0.5280	0.6635	0.5650	0.2502	0.5559	0.6599
0.75	0.25	0.6710	0.3898	0.6698	0.5931	0.6970	0.3163	0.6844	0.6597
0.5	0.5	0.7906	0.5335	0.7978	0.5788	0.8173	0.4121	0.7979	0.7030
0.25	0.75	0.8926	0.6790	0.9025	0.6157	0.9164	0.5326	0.8960	0.7663
0	1	0.9088	0.8087	0.9174	0.6951	0.9265	0.6688	0.9137	0.8227
$\lambda_L:\lambda_S = 0.75:0.25$									
1	0	0.6670	0.4413	0.6568	0.7476	0.6808	0.4402	0.6721	0.7439
0.75	0.25	0.7619	0.5459	0.7594	0.6956	0.7770	0.4896	0.7664	0.7444
0.5	0.5	0.8487	0.6547	0.8527	0.6854	0.8652	0.5612	0.8504	0.7773
0.25	0.75	0.9213	0.7615	0.9290	0.7131	0.9382	0.6510	0.9233	0.8250
0	1	0.9327	0.8574	0.9400	0.7723	0.9454	0.7524	0.9363	0.8674
$\lambda_L:\lambda_S = 0.5:0.5$									
1	0	0.7898	0.6286	0.7786	0.8308	0.7923	0.6288	0.7845	0.8274
0.75	0.25	0.8491	0.6992	0.8447	0.7972	0.8545	0.6618	0.8462	0.8287
0.5	0.5	0.9033	0.7718	0.9050	0.7909	0.9119	0.7092	0.9016	0.8512
0.25	0.75	0.9494	0.8424	0.9541	0.8095	0.9595	0.7686	0.9497	0.8834
0	1	0.9561	0.9053	0.9614	0.8487	0.9640	0.8355	0.9582	0.9120
$\lambda_L:\lambda_S = 0.25:0.75$									
1	0	0.9076	0.8127	0.8964	0.9132	0.9012	0.8160	0.8951	0.9106
0.75	0.25	0.9335	0.8498	0.9274	0.8976	0.9306	0.8326	0.9249	0.9126
0.5	0.5	0.9572	0.8868	0.9556	0.8953	0.9579	0.8561	0.9520	0.9248
0.25	0.75	0.9768	0.9218	0.9783	0.9049	0.9805	0.8853	0.9754	0.9416
0	1	0.9789	0.9522	0.9819	0.9244	0.9825	0.9180	0.9796	0.9563
$\lambda_L:\lambda_S = 0:1$									
\	\	0.9867	0.9998	0.9930	0.9987	0.9955	0.9980	0.9972	0.9980

(individual-local balance and individual-society balance perspectives) are not conflictive but often bring out the better in each other, the local and social performances can be compatible if we combine the two coordination perspectives together. Therefore, when we design an agent coordination mechanism, we should combine them together. Such phenomenon is often seen in real society, e.g., the following scenario is a simple demonstration for it.

Scenario 3.

- A selfish people is not welcomed by his neighbors as well as the whole society.
- The more likely a people is welcomed by his neighbors, then the more likely he is also welcomed by the whole society.
- The more likely a people is welcomed by the whole society, then the more likely he is also welcomed by his neighbors.

7. Conclusion

The local and global performances of a multi-agent system should be compatible. Therefore, it is necessary to make tradeoff between the locally diffusion effects and socially structural influences. This paper provides the agent coordination method by balancing the two perspectives in an integrative framework. Within the integrative framework, the locally diffusion effects and socially structural influences are combined together; and the individual, local and society concerns can be balanced well in a unified and flexible manner. At last, we make experiments for our coordination model; the test results show that our model is valid for varying agent distributions and agent system scales. The experimental results proved that there are often situations in which it is better for the local performance is the globally social performance are improved; thus the two perspectives are not conflictive but sometimes bring out the best in each other. Therefore, when we design a multi-agent system, the two perspectives can be combined well so as to achieve the compatibility between the local and social performances.

Acknowledgements

This paper is significantly extended version of our preliminary work in Jiang et al. (2007).

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