Agent Coordination by Trade-off between Locally Diffusion Effects and Socially Structural Influences

Yichuan Jiang
Department of Social Informatics
Kyoto University
Yoshida-Honmachi, Kyoto 606-8501, Japan
jiangyichuan@yahoo.com.cn

Jiuchuan Jiang
Department of Computer Science & Technology, Nanjing University of Aeronautics and Astronautics.
Nanjing 210016, China
jcjiang@163.com

Toru Ishida
Department of Social Informatics
Kyoto University
Yoshida-Honmachi, Kyoto 606-8501, Japan
ishida@i.kyoto-u.ac.jp

ABSTRACT

There were always two separated methods to make agent coordination: individual-local balance perspective and individual-society balance perspective. The first method only considered the balance between individual agents and their local neighbors; the second method only considered the balance between individual agents and the whole multi-agent society. However, in reality, the agents will be diffused by their local neighbors as well as influenced by their social contexts simultaneously; therefore, it is necessary to deal with the social performance as well as local performance. To address such problem this paper presents an agent coordination method in an integrative model where we combine the two perspectives together and make trade-off between them. With our presented model, the individual, local and social concerns can be balanced well in a unified and flexible manner. Moreover, the experimental results show that there are often situations in which the two coordination perspectives aren't conflictive but often bring out the better in each other.

Categories and Subject Descriptors

I.2.11 [**Distributed Artificial Intelligence**]: Multiagent Systems.

General Terms

Theory, Design, Performance, Experimentation.

Keywords

Multiagent System, Coordination, Local Diffusion, Social Influence, Unification Trend.

1. INTRODUCTION

A strategy is the action that agent adopts to behave in the multi-agent society; it is necessary to make coordination among agent strategies [1]. In multi-agents, there is an interesting phenomenon which can be called *unification trend*: when many agents operate concurrently in the system, they will incline to adopt an average strategy which can make the system be more unified [3][4][5][6].

An agent doesn't require being aware of every agents in the society, it may only know its local neighbors and the counterparts within its social contexts. Therefore, 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 [5][6][7][8]; 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 [9].

Until now almost all related work on multi-agent coordination 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 [5][6][7][8], which 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 [9], which may get the social performance but ignore the local effects. Moreover, the control on the whole agent society is sometimes difficult to achieve. Therefore, in this paper we provide an integrative model for agent coordination by trade-off between locally diffusion effects and socially structural influences. With our model, the individual, local and social concerns can be balanced well in a unified and flexible manner. Moreover, the experimental results show that the two perspectives aren't conflictive but often bring out the better in each other.

2. LOCALLY DIFFUSION EFFECTS

In [5], Reynolds initiated a research to explore the simulation for a flock of birds who coordinate with each other by a local control strategy to adopt a common average heading. 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" [6-8]. In the local diffusion effects, agents adjust their social strategies over time by myopically imitating the average strategy within their own neighborhoods.

Now, we make balance between the agent's initial strategy and the average one of neighbors. Let $s_i(t)$ denote the strategy of agent a_i at time t, L_i be the local interaction region of agent a_i, when we make balance between individual agent and the locally diffusion effects of neighboring agents, the new strategy of agent a_i will be:

$$s_i^L(t+1) = \alpha s_i(t) + \beta \frac{1}{|L_i|} \sum_{j \in L_i} s_j(t) \quad (2.1)$$

Where α is the inertia factor of the strategy of agent a_i, β is the influence factor of L_i to a_i, $\alpha+\beta=1$.

978-81-904262-7-5 (RPS) ©2007 IFAAMAS

3. SOCIALLY STRUCTURAL INFLUENCE

An agent is in some social contexts or organizations [2], the agent strategy is influenced not only by the local neighbors but also the counterparts within the social contexts.

Now, let agent a_i be in a social organization structure, the social strategy of a_i will be influenced by all agents in its contexts. So a_i will go toward to the average of all socially structural influences of its contexts regarding their respective influence strengths.

$$s_i^S(t+1) = \sum_{j\in\sum\Theta_i} \left(s_j \frac{I_{j\to i}}{\sum_{x\in\sum\Theta_i} I_{x\to i}}\right) \tag{3.1}$$

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, $\sum\Theta_i$ denotes the social contexts of a_i, $I_{j\to i}$ denotes the social influence strength of a_j to a_i.

4. BALANCE BETWEEN TWO PERSPECTIVES

4.1 Trade-off

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

$$s_i(t+1) = \lambda_L s_i^L(t+1) + \lambda_S s_i^S(t+1)$$
$$= \lambda_L\left(\alpha s_i(t) + \beta \frac{1}{|L_i|}\sum_{j\in L_i} s_j(t)\right) + \lambda_S \sum_{j\in\sum\Theta_{a_i}} \left(s_j \frac{CI_{j\to i}}{\sum_{x\in\sum\Theta_{a_i}} CI_{x\to i}}\right) \tag{4.1}$$

The different concern tendencies can be realized by the variations of combination of the four parameters ($\alpha,\beta,\lambda_L,\lambda_S$), which determine the relative importance of the three concerns:

- $\alpha+\beta=1$: determine the trade-off between 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.
- $\lambda_L+\lambda_S=1$: determine the trade-off between 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.

4.2 Performance Index

For the unification trend said in Section 1, each agent will try to be gregarious to its local neighbors or socially contexts. Therefore, we can define the following two performance indexes.

4.2.1. Local Gregariousness of Individual Agents

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

$$\overline{s_{L(i)}} = \frac{1}{1+|L_i|}\left(s_i + \sum_{j\in L_i} s_j\right) \tag{4.2}$$

The local gregariousness of agent a_i in its local region is:

$$\sigma_{L(i)} = 1 - \frac{|s_i - \overline{s_{L(i)}}|}{\overline{s_{L(i)}}} \tag{4.3}$$

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

$$\overline{\sigma_A} = \frac{1}{|A|}\sum_{i\in A}\sigma_{L(i)} = \frac{1}{|A|}\sum_{i\in A}\left(1 - \frac{|s_i - \overline{s_{L(i)}}|}{\overline{s_{L(i)}}}\right) \tag{4.4}$$

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

4.2.2 .Social Gregariousness of Individual Agents

The average strategy value of the agent society A is:

$$\overline{s_A} = \frac{1}{|A|}\sum_{i\in A} s_i \tag{4.5}$$

The social gregariousness of agent a_i in the whole society A is:

$$\omega_{A(i)} = 1 - \frac{|s_i - \overline{s_A}|}{\overline{s_A}} \tag{4.6}$$

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

$$\overline{\omega_A} = \frac{1}{|A|}\sum_{i\in A}\omega_{A(i)} = \frac{1}{|A|}\sum_{i\in A}\left(1 - \frac{\left|s_i - \frac{1}{|A|}\sum_{i\in A}|s_i|\right|}{\frac{1}{|A|}\sum_{i\in A}|s_i|}\right) \tag{4.7}$$

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

5. EXPERIMENTS

Our aim is to evaluate the effectiveness of the model for different concern tendencies (individual, local and social concerns) under varying agent distributions. The different concern tendencies can be realized by the variations of combination for ($\alpha,\beta,\lambda_L,\lambda_S$). By referring to [9], here we use the following values:

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

5.1 Tests for Varying Agent Distributions

We test the model in 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 results are shown in Table 2.

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	\	\	0.9965	0.9961	0.9991	0.9977	0.9994	0.9987

5.3 Analyses for the Test Results

- When λ_L,λ_S are fixed, the higher α is, the lower the two performance indexes are. Therefore, we can conclude that:
  The higher value of self inertia factor α will produce low local gregariousness and social gregariousness; so the selfish agents aren't gregarious with their local neighbors as well as the whole society.
- Whenλ_L,λ_S are fixed, the higher β is, the higher the two performance indexes 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 the two performance indexes 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.
- Whenα,β are fixed, the higher λ_L is, the higher the two performance indexes are. Therefore, we can conclude that:
  The higher value of social balance factor λ_L can increase the social gregariousness; moreover, it can also increase the average local gregariousness accordingly..
- Certainly, 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.
- As a conclusion, we can find an interesting phenomenon: ***the two agent coordination perspectives (individual-local balance and individual-society balance perspectives) are not conflictive but often bring out the better in each other***.

6. CONCLUSION

The paper provides an agent coordination method by balancing the two perspectives in an integrative framework where 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, the experiments show that there are often situations in which it is better for the local performance is the globally social performance are improved; therefore, the two perspectives are not conflictive but sometimes bring out the better in each other.

7. REFERENCES

[1] Yi-Chuan Jiang, J.C.Jiang. A Multi-agent coordination model for the variation of underlying network topology. *Expert Systems with Applications*, 2(29): 372-382, 2005.

[2] Xiaoqin Zhang, Victor Lesser, and Tom Wagner. Integrative negotiation among agents situated in organizations. *IEEE Transactions on Systems, Man, and Cybernetics-Part C: Applications and Reviews*, 1(36): 19-30, 2006.

[3] Yichuan Jiang, Toru Ishida. Concurrent agent social strategy diffusion with the unification trend. *The Agent Computing and Multi-Agent Systems: PRIMA 2006*. LNAI 4088, pp.256-268, Springer-Verlag, Heidelberg.

[4] Yichuan Jiang, Toru Ishida. A model for collective strategy diffusion in agent social law evolution. *Proceedings of The 20th International Joint Conference on Artificial Intelligence (IJCAI-07)*, Hyderabad, India, Jan 2007.

[5] Craig W. Reynolds. Flocks, birds, and schools: A distributed behavioral model. *Computer Graphics*, 4(21): 25-34, 1987.

[6] Ali Jadbabaie, Jie Lin and A.Stephen Morse. Coordination of groups of mobile autonomous agents using nearest neighbor rules. *IEEE Transactions on Automatic Control*, Vol.48, No.6, 2003, pp.988-1001.

[7] T.Vicsek, A.Czirok, E.Ben Jacob, I.Choen, and O.Schochet. Novel type of phase transitions in a system of self-driven particles. *Physics Review Letter*, 1995, Vol.75, pp.1226-1229.

[8] Zhiyun Lin, Broucke, M., Francis, B. Local control strategies for groups of mobile autonomous agents. *IEEE Transactions on Automatic Control*. Vol.49, No.4, 2004, pp.622 – 629.

[9] L.M.J.Hogg and N.R.Jennings. Socially intelligent reasoning for autonomous agents. *IEEE Transactions on Systems, Man and Cybernetics-Part A: Systems and Humans*, Vol. 31, No.5, 2001, pp.381-393.