Formation of Cooperation Structure by Interaction Network in Directed Multi-Agent

Kosuke Sekiyama
Department of Human and Artificial Intelligence Systems, University of Fukui
3-9-1 Bunkyo, Fukui, Japan
sekiyama@dis.his.fukui-u.ac.jp

Yukihisa Okade
Department of Human and Artificial Intelligence Systems, University of Fukui
3-9-1 Bunkyo, Fukui, Japan
okade@dis.his.fukui-u.ac.jp

ABSTRACT

A directed agent implies an agent with high constraints in both recognition and motion. Because of the embodied restrictions, the directed agent perceives a sense of subjective distance according to its position and direction, which is not asymmetry unlike the physical distance. The directed agent can take advantage of this asymmetry of this sense of distance, synthesizing *Interaction Network*, which is introduced to represent a cooperative and competitive form based on the directed graph network. Each node corresponding to the agent has a variable number of links to the neighboring nodes depending on the internal state and local interactions characterized by activation and inhibition. Simulation results illustrate an efficient team play and analysis.

Categories and Subject Descriptors

H.4 [**Information Systems Applications**]: Miscellaneous; D.2.8 [**Software Engineering**]: Metrics—*complexity measures, performance measures*

General Terms

Theory

Keywords

multi-agent, directed agent, cooperation, interaction network

1. INTRODUCTION

Cooperative or competitive relationship in multi-agent systems is often depicted by a graph, which features a collective behavior. The collective behavior has been analyzed under a specific form of interaction, such as a team play in the soccer agents and a formation in multi-robot systems [1, 2]. However, a relational structure among agents is generally specified in advance. While, some research represents a relationship in the group organization by evolutionary graph network [3, 4, 5], where the functional interpretation of graph is not explicitly discussed. We have proposed *Interaction Network* in order to stress a functional meaning of the graph and provide an evolutionary mechanism of cooperation structure [6]. Also, it has been extended to a model of the mobile nodes, which can exhibit dynamic adaptation of the cooperation form in multi-agent behavior [7]. In this paper, we further extend *Interaction Network* to a directed multi-agent model. One of the examples for the directed agent is a canoe polo player. Canoe polo is a kind of canoe sports, which is like handball on the water. Unlike soccer and handball players, the motions of canoe polo player is strictly restricted because of the water resistance and strongly directed shape of the canoe. For this reason, it is especially important to realize a team play rather than individual play to win the game. Many of the conventional works have modeled the multi-agent as points, hence, positioning and motion are primary factors of the discussion [8, 9, 10]. On the other hand, in the canoe polo player, the motion and positioning are influenced not only the position but also the direction of the player. For this reason, the notion of directed agent is introduced. Also, due to the embodied constraints, sense of the distance in directed agent is considered to be subjective depends on the direction of agent. Even if the physical distance between the agents is equivalent, sense of the distance will not be symmetric. In this paper, we describe the subjective distance which is subjectively perceived by the directed agent, and present a model *Interaction Network* to deal with a team play in the collective game for the directed agents, where decision-making mechanism to enhance efficient organized behavior is discussed. We also evaluate the tradeoff between the team play and the individual play through some simulations.

2. DIRECTED AGENT

2.1 Definition of Directed Agent

We firstly define the directed agent in the motif of the canoe polo player. The directed agent has state of position and direction. Let U_i be a directed agent i, and the position of U_i at step t is defined by vector $\boldsymbol{p}_i(t)$ which is represented in the absolute coordinate system, and the direction of U_i is also defined by unit vector $\boldsymbol{u}_i(t)$. We assume here that the directed agent changes its position and direction by one motion per one step. We consider nine motions shown in

AAMAS'05, July 25-29, 2005, Utrecht, Netherlands.

Table 1: Motion of directed agent

k	Motion(k)	velocity v_k[m/step]	angular velocity ω_k[rad/step]
1	stop	0	0
2	spin left	0	$\pi/6$
3	spin right	0	$-\pi/6$
4	forward	2	0
5	back	-1	0
6	spin left	0	$\pi/3$
7	spin right greatly	0	$-\pi/3$
8	forward greatly	3	0
9	back greatly	-2	0

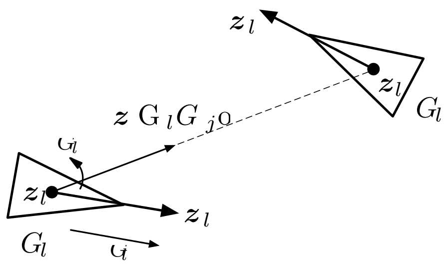


Figure 1: Relationship of position and direction between U_i and U_j.

Table1 as a motion of the directed agent. When U_i chooses the motion(k) from Table1, its position and direction in next step are determined respectively as follows,

$$\boldsymbol{p}_i(t+1) = \boldsymbol{p}_i(t) + v_k \boldsymbol{u}_i(t), \tag{1a}$$

$$\boldsymbol{u}_i(t+1) = \begin{bmatrix} \cos\omega_k & -\sin\omega_k \\ \sin\omega_k & \cos\omega_k \end{bmatrix} \boldsymbol{u}_i(t). \tag{1b}$$

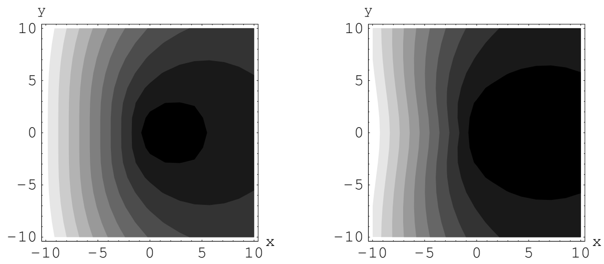
2.2 Definition of Subjective Distance

Interactions are dependent on the direction of agent. Even if the physical distance is equivalent in the agents, the sense of distance is not necessarily the same. For example, an agent placed in front is perceived much closer than the agent in the back. We define the subjective distance perceived by the directed agent U_i in the position $\boldsymbol{p}$ as follows,

$$D(\boldsymbol{p}_i, \boldsymbol{p}) = \|\boldsymbol{p} - \boldsymbol{p}_i\| \exp(-\kappa(\boldsymbol{u}_i \cdot \boldsymbol{P}(\boldsymbol{p}_i, \boldsymbol{p}))), \tag{2a}$$

$$\boldsymbol{P}(\boldsymbol{p}_i, \boldsymbol{p}) = \frac{\boldsymbol{p} - \boldsymbol{p}_i}{\|\boldsymbol{p} - \boldsymbol{p}_i\|}, \tag{2b}$$

where, $\kappa > 0$ is coefficient. Figure2 illustrates the subjective distance by a contour map, where the position vector and the direction vector of specific directed agent are set to $(0, 0)$ and $(1, 0)$ respectively. The black portion in fig.2 indicates that the subjective distance from specific directed agent is close. Eq.(2a) implies that the subjective distance in front of the directed agent is closer to the agent in the back. The value of κ relates to the directivity of agent; if it takes larger value, the directivity becomes stronger. Appropriate value should be verified with the actual players, but it is not a scope of this paper.



(a) $\kappa = 1.0$. (a) $\kappa = 1.5$.

Figure 2: Result of calculation of subjective distance.

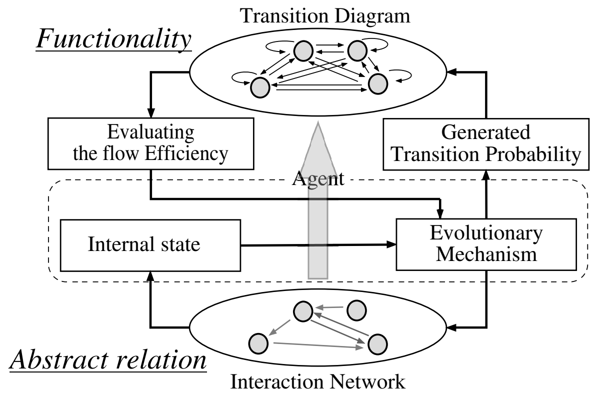


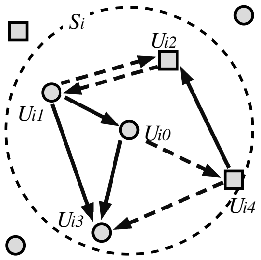
Figure 3: Concept of *Interaction Network* and Transition Diagram

3. INTERACTION NETWORK

Interaction Network is defined as a relational structure representing cooperation and competition in collective agent systems, which is formulated by bidirectional directed simple graph with N nodes. Nodes indicate autonomous directed agents, and directed links correspond to the interactions between agents. Figure 3 depicts the conceptual diagram of proposed model, where Transition Diagram represents flow in the system by the relational structure. Features of *Interaction Network* are summarized as follows:

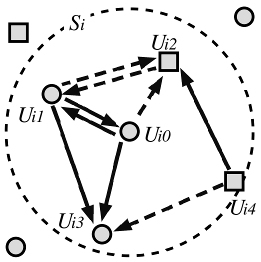
- The internal state of the node is determined by interactions from the neighborhood nodes and the graph structure of local *Interaction Network*.
- Action attribute named activation and inhibition is given in the interaction between nodes. Activation enhances the internal state of the connected agents, on the other hand, inhibition weaken the internal state.
- The variable number of interactions (out-degree of node in graph theory) are defined in each agent dependent on the level of the internal state of agent.
- Each agent updates its graph structure of local *Interaction Network* by changing the interaction agents, where the number of interactions is also variable according to a situation.

We define some notations for formulation. Firstly, surrounding condition of the agents is recognized by the subjective



$$\begin{pmatrix} 0 & 0 & 0 & 1 & -1 \\ \hline 1 & 0 & -1 & 1 & 0 \\ 0 & -1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & -1 & 0 \end{pmatrix}$$

(a) *Interaction Network* before updating.



$$\begin{pmatrix} 0 & 1 & -1 & 1 & 0 \\ \hline 1 & 0 & -1 & 1 & 0 \\ 0 & -1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & -1 & 0 \end{pmatrix}$$

(b) *Interaction Network* after updating.

Figure 4: Correspondence of the updating local *Interaction Network* to adjacency matrix. The full line arrow and the dashed line indicate activation and inhibition respectively.

distance. A set of agents within R-neighborhood of U_i is given by,

$$S_i(t) = \Big\{ U_j \;\; D_i(\boldsymbol{p}_j(t)) < R, i \neq j \Big\}. \qquad (3)$$

Since every relation of the interactions is locally recognized from the viewpoint of U_i, we introduce the local description of *Interaction Network*. Assuming that there exist $N_i(t)[= |S_i(t)|]$ agents within the neighborhood of U_i, we define U_{ij}, $(j = 1, \cdots, N_i(t))$ as the jth nearest agent from U_i, where U_i recognizes itself as U_{i0}. Then, the interaction between U_{ij} and U_{ik} is defined as follows,

$$a_{i,jk}(t) = \begin{cases} +1 & \text{activation,} \\ -1 & \text{inhibition,} \\ 0 & \text{no interaction.} \end{cases} \qquad (4)$$

Note that we consider $N_i = N_i(t)$ in the following argument. The graph structure of local *Interaction Network* of U_i is represented by adjacency matrix $\boldsymbol{A}_i(t)$,

$$\boldsymbol{A}_i(t) = \begin{pmatrix} 0 & a_{i,01}(t) & \cdots & a_{i,0N_i}(t) \\ a_{i,10}(t) & 0 & \cdots & a_{i,1N_i}(t) \\ \vdots & \vdots & \ddots & \vdots \\ a_{i,N_i0}(t) & a_{i,N_i1}(t) & \cdots & 0 \end{pmatrix}. \qquad (5)$$

In this model, we do not consider activation and inhibition to itself, hence, the diagonal part of $\boldsymbol{A}_i$ is set to 0. Moreover, U_i can change a target of interactive agent as well as action attributes. The change of interactions corresponds to the change of the first row in $\boldsymbol{A}_i$. An example is depicted in fig.4. The internal state $E_i(t)$ of agent U_i is decided by received activation and inhibition actions from the neighborhood agents in $S_i(t)$ as follows,

$$E_i(t) = \Phi \left[\sum_{j=0}^{N_i} a_{i,j0}(t) + E_{\text{base}} \right], \qquad (6a)$$

$$\Phi(\xi) = \begin{cases} E_{\max} & \text{if } \xi > E_{\max}, \\ E_{\min} & \text{if } \xi < E_{\min}, \\ \xi & \text{else.} \end{cases} \qquad (6b)$$

where, E_{base} is default value of the internal state, and $E_{\max}$ and $E_{\min}$ are maximal and minimal internal state respectively. $E_i(t)$ determines the upper bound of the number of interactions to the neighborhood agents. The actual number of interactions is called as the interaction degree of freedom (interaction DOF) $b_i(t)$ which takes integer value set $\{0, 1, \cdots, E_i(t)\}$ according to a surrounding situation. If the agent receives more activating interactions, it can take larger interaction DOF, while if the agent receives more inhibiting interactions, it can be reduced to zero. Using these variable $E_i(t)$ and $b_i(t)$, the index $x_i(t) \geq 0$ is defined to represent the remaining level of autonomy, the resource to be used for own actions as follows,

$$x_i(t) = E_i(t) - b_i(t). \qquad (7)$$

Larger value of $x_i(t)$ implies higher ability of autonomous behavior, however, it may reduce the variation of interactions to the neighborhood agents. Under the constrain of $E_i(t)$, the balance of $b_i(t)$ and $x_i(t)$ is a primary concern for the effective graph network.

4. SIMULATION MODEL

4.1 Design of collective game by Interaction Network

Formation play is a straightforward model to exemplify functional connectivity. In this paper, a simple collective game is considered employing *Interaction Network*. Suppose that there are one ball and N agents on the game field, and agent $U_i, (i = 1, \cdots, N)$ belong to one of the two groups $G^{(1)}$ and $G^{(2)}$. Each agent moves on the field and passes the ball to the goal area, and also it prevents plays of the opponent group. One game will be over if either team takes 20 point at first. As shown in Fig.3, we define Transition Diagram which is generated by *Interaction Network* as a destination of ball transition. If agent U_i holds the ball, the destination of ball is decided stochastically from the neighborhood of U_i. We denote in the meaning that $\boldsymbol{p}_i = \boldsymbol{p}_i(t)$ in the following discussion. Let $\boldsymbol{z}^{(l)}$ be position vector of the goal point for the group $G^{(l)}, (l = 1, 2)$. In the case of $U_i \in G^{(l)}$, the intentional pass direction $\boldsymbol{m}_i(t)$ for U_i is decided as follows,

$$\begin{aligned} \boldsymbol{m}_i(t) &= \frac{\boldsymbol{z}^{(l)} - \boldsymbol{p}_i}{\|\boldsymbol{z}^{(l)} - \boldsymbol{p}_i\|^2} + M_1 \sum_{U_{ij} \in G^{(l)}} \frac{\boldsymbol{p}_{ij} - \boldsymbol{p}_i}{\|\boldsymbol{p}_{ij} - \boldsymbol{p}_i\|^2} \\ &- M_2 \sum_{U_{ik} \notin G^{(l)}} \frac{\boldsymbol{p}_{ik} - \boldsymbol{p}_i}{\|\boldsymbol{p}_{ik} - \boldsymbol{p}_i\|^2}. \end{aligned} \qquad (8)$$

where $M_1, M_2 > 0$ are constant respectively. Here, the first term denotes vector of the goal direction, and the second term indicates vector of the direction of supporter agents and the third term indicates avoiding vector from the opponent agents. So the intentional pass direction is decided by the linear combination of these three vectors as shown in

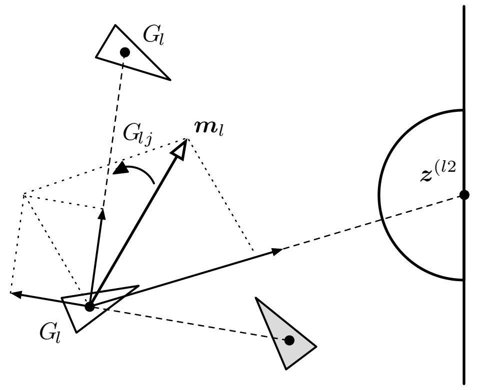


Figure 5: Relationship between the direction of pass $m_i(t)$ and the angle ψ_{ij}

fig.5. Then, the angle $\psi_{ij}(t)$ of agent $U_j \in S_i(t)$ from the pass direction $\boldsymbol{m}_i(t)$ is calculated as follows,

$$\psi_{ij}(t) = \arccos \quad \frac{\boldsymbol{m}_i(t) \cdot (\boldsymbol{p}_j - \boldsymbol{p}_i)}{\|\boldsymbol{m}_i(t)\| \|\boldsymbol{p}_j - \boldsymbol{p}_i\|} \quad . \tag{9}$$

The transition probability w_{ij} of the ball from U_i to U_j is generated by

$$w_{ij}(t) = \frac{\Psi_{ij}(t) \exp(x_j(t) - x_i(t))}{\sum_{U_k \in S_i(t)} \Psi_{ik}(t) \exp \quad x_k(t) - x_i(t)}, \tag{10a}$$

$$\Psi_{ij}(t) = \frac{1}{D(\boldsymbol{p}_j, \boldsymbol{p}_j)} \exp(-\sigma \psi_{ij}(t)^2). \tag{10b}$$

Where, $\sigma > 0$ is constant, and the transition probability to $U_k \notin S_i(t)$ is $w_{ik}(t) = 0$. The probability reflects influence of the directivity of pass direction and uncertainty due to the subjective distance between U_i. The cooperation structure becomes a variable node probability network, which is generated by the graph structure of *Interaction Network* and the agent distribution. Therefore, each agent attempts to reconfigure the cooperation structure *Interaction Network* so as to improve dominant rate of the ball. To do this, each agent behaves according to the following procedures:

(1) Agents are assigned to the Game Field.

(2) $U_i, (i = 1, \cdots, N)$ decides the interaction DOF b_i and remaining level of autonomy x_i, based on *Interaction Network*.

(3) The agent moves on the field, and updates the graph structure of *Interaction Network* within the neighborhood by $b_i(t)$.

(4) Transition probability is generated by $x_i(t)$.

(5) Destination of the ball is decided stochastically by transition probability.

Where (1) is an initialization of collective game. Then, repeat the procedure from (2) to (5) until either of group makes a score.

4.2 Decision-making Mechanism of Agent

4.2.1 Evaluation on Positioning

We consider the positioning of agent as a set of position and direction, and it changes according to own motions. Also it depends on the dominance rate of the ball. Let position of the ball be $\boldsymbol{r}$ and a candidate of the positioning of U_i be $(\tilde{\boldsymbol{p}}_i, \tilde{\boldsymbol{u}}_i)$. Then we define the evaluation function for positioning of agent $f_i(\tilde{\boldsymbol{p}}_i)$ using the subjective distance as follows,

$$f_i(\tilde{\boldsymbol{p}}_i, \tilde{\boldsymbol{u}}_i) = \begin{cases} \exp(-\alpha \ D(\tilde{\boldsymbol{p}}_i, \boldsymbol{z}^{(l)})^2) - V_i(\tilde{\boldsymbol{p}}_i), \\ \qquad \text{for } U_i \text{ has a ball,} \\ \exp(-\beta \ D(\tilde{\boldsymbol{p}}_i, \boldsymbol{r}(t))^2) - V_i(\tilde{\boldsymbol{p}}_i), \\ \qquad \text{for } U_i \text{ doesn't has a ball.} \end{cases} \tag{11a}$$

$$V_i(\boldsymbol{p}) = \sum_{j=1}^{N_i} \exp(-\gamma \ \|\boldsymbol{p}_{ij} - \boldsymbol{p}\|^2). \tag{11b}$$

Where $\alpha, \beta, \gamma > 0$ are constant, and V_i is the evaluation for collision avoidance to the neighborhood agents.

4.2.2 Reconfiguration of the Graph Structure

As shown in fig.4, reconfiguration of local *Interaction Network* of U_i is conducted by changing only the first row of adjacency matrix $\boldsymbol{A}_i$ in eq.(5). So, a candidate of updated graph structure $\tilde{\boldsymbol{a}}_i$ and corresponding matrix $\widetilde{\boldsymbol{A}}_i$ are given as

$$\tilde{\boldsymbol{a}}_i = (\tilde{a}_{i,01}, \cdots \tilde{a}_{i,0N_i}), \tag{12a}$$

$$\widetilde{\boldsymbol{A}}_i(\tilde{\boldsymbol{a}}_i) = \begin{pmatrix} 0 & \tilde{a}_{i,01} & \cdots & \tilde{a}_{i,0N_i} \\ a_{i,10}(t) & 0 & \cdots & a_{i,1N_i}(t) \\ \vdots & \vdots & \ddots & \vdots \\ a_{i,N_i0}(t) & a_{i,N_i1}(t) & \cdots & 0 \end{pmatrix}. \tag{12b}$$

A candidate of updated graph structure is evaluated so that it can improve the dominant rate of the ball in the immediate future. In order to obtain such a *predicted condition* for each of candidate of the graph in a limited calculation, we employed the stationary solution of stochastic process produced by the local Transition Diagram. The agent U_i forms a local Transition Diagram according to the decision rule of the transition probability of eq.(10a). However, U_i cannot recognize the remaining level of autonomy and the path directions for $U_{ij}, (j = 1, \cdots, N_i)$ accurately because these are information based on the internal state of each agent. So, U_i estimates $x_{ij}(t)$ for $U_{ij}, (j = 1, \cdots, N_i)$ from eq.(6b), eq.(7), and eq.(12b) as follows,

$$x_{ij}(t) = \Phi \left[\sum_{k=1}^{N_i} a_{i,kj}(t) + \tilde{a}_{i,0j} + E_{\text{base}} \right] - \sum_{k=0}^{N_i} |a_{i,jk}(t)|. \tag{13}$$

The first term of eq.(13) relates to estimation from each agent's internal state based on eq.(6b), and the second term indicates interaction DOF from adjacency matrix $\widetilde{\boldsymbol{A}}_i$. Also, the pass direction $\boldsymbol{m}_{ij}(t)$ for U_{ij} is estimated by eq.(8), (9), and angle $\psi_{i,ij}(t)$ of the agent U_{ij} from the pass direction of $\boldsymbol{m}_{ij}(t)$ is calculated with eq.(9). Therefore, the transition probability $w_{i,jk}(t), (j, k = 0, \cdots, N_i)$ of the ball from U_{ij}

to U_{ik} is supposed by

$$w_{i,jk}(t) = \frac{\Psi_{i,jk}(t)\exp(x_{ik}(t)-x_{ij}(t))}{\sum_{n=0}^{N_i}\Psi_{i,jn}(t)\exp(x_{in}(t)-x_{ij}(t))}, \quad (14a)$$

$$\Psi_{i,jk}(t) = \frac{1}{D(\boldsymbol{p}_{ij},\boldsymbol{p}_{ik})}\exp(-\sigma\psi_{i,jk}^2). \quad (14b)$$

The local Transition Diagram of U_i is represented as the transition probability matrix $\boldsymbol{W}_i(\tilde{\boldsymbol{a}}_i)$ as follows,

$$\boldsymbol{W}_i(\tilde{\boldsymbol{a}}_i) = \begin{pmatrix} w_{i,00}(t) & w_{i,01}(t) & \cdots & w_{i,0N_i}(t) \\ w_{i,10}(t) & w_{i,11}(t) & \cdots & w_{i,1N_i}(t) \\ \vdots & \vdots & \ddots & \vdots \\ w_{i,N_i0}(t) & w_{i,N_i1}(t) & \cdots & w_{i,N_iN_i}(t) \end{pmatrix}. \quad (15)$$

Since $w_{i,jk}(t) > 0$ for $\forall j,k$ in $\boldsymbol{W}_i$, the transition process is modeled as regular Markov chain, therefore, we see that the unique stationary distribution exists for the transition process of W_i, which is given by

$$\boldsymbol{\pi}_i(\tilde{\boldsymbol{a}}_i) = \boldsymbol{\pi}_i(\tilde{\boldsymbol{a}}_i)\boldsymbol{W}(\tilde{\boldsymbol{a}}_i), \quad (16)$$

where, $\pi_{ij},(j=0,\cdots,N_i)$ is interpreted as expected value of the acquisition probability for U_{ij}. From location of the agents and evaluation on the efficiency of pass, evaluation function $h_i(\tilde{\boldsymbol{a}}_i)$ for $U_i \in G^{(l)}(U_i \notin G^{(L)})$ is defined by the followings according to both cases of offense mode and defense mode;

$$h_i(\tilde{\boldsymbol{a}}_i) = \begin{cases} \sum_{U_{ij}\in G^{(l)}} \pi_{ij}\exp(-\alpha\ D(\boldsymbol{p}_{ij},\boldsymbol{z}^{(l)})^2), \\ \qquad \text{for offense mode,} \\ \sum_{U_{ij}\in G^{(L)}} \frac{1-\pi_{ij}}{N_i-1}\exp(-\alpha\ D(\boldsymbol{p}_{ij},\boldsymbol{z}^{(L)})^2), \\ \qquad \text{for defense mode.} \end{cases} \quad (17)$$

Where, in the offense mode, evaluation value of eq.(17) becomes high when the acquisition probability of the ball is high for the agents in $G^{(l)}$ which is near the goal $z^{(l)}$.

5. SEARCH ALGORITHMS

Agent U_i searches the best solution from candidates of positioning $(\tilde{\boldsymbol{p}}_i, \tilde{\boldsymbol{u}}_i)$ and the graph structure $\tilde{\boldsymbol{a}}_i$ employing the genetic algorithms (GA) for every time step. Firstly, ten individuals to candidate of $(\tilde{\boldsymbol{p}}_i, \tilde{\boldsymbol{u}}_i)$ and $\tilde{\boldsymbol{a}}_i$ are created respectively. Then, the adaptation value is calculated for the candidate set of individual. According to adaptation value, the selected candidate sets are reproduced in the next generation with the genetic operation. In this genetic operation's parameter, crossover probability and mutation probability are set to 0.5 and 0.1 respectively. The best solution is selected from candidate sets when the search is repeated until tenth generation; therefore, computation is light.

5.1 Adaptation Function for GA search

The positioning and pass-play are evaluated with eq.(11a) and eq.(17) respectively. The adaptation function is defined according to eq.(11a) and eq.(17) as follows,

$$y_i(\tilde{\boldsymbol{p}}_i, \tilde{\boldsymbol{u}}_i, \tilde{\boldsymbol{a}}_i) = \varphi_i h_i(\tilde{\boldsymbol{a}}_i) + (1-\varphi_i) f_i(\tilde{\boldsymbol{p}}_i, \tilde{\boldsymbol{u}}_i). \quad (18)$$

Where, $\varphi_i \in [0,1]$ is strategy parameter denoting tendency between team-play and individual play. If $y_i(\tilde{\boldsymbol{p}}_i^*, \tilde{\boldsymbol{u}}_i^*, \tilde{\boldsymbol{a}}_i^*)$ takes the largest value, it provides the best solution $(\tilde{\boldsymbol{p}}_i^*, \tilde{\boldsymbol{u}}_i^*, \tilde{\boldsymbol{a}}_i^*)$.

$\rho(1)$	$\cdots$	$\rho(k)$	$\cdots$	$\rho(n)$

(a) positioning

Agent Number :	$s(1)$	$\cdots$	$s(k)$	$\cdots$	$s(N_i)$
Connection :	$q_{s(1)}$	$\cdots$	$q_{s(k)}$	$\cdots$	$q_{s(N_i)}$

(b) graph structure

Figure 6: The genotype of positioning and graph structure

5.2 Individual Expression and Genetic Operation of Positioning

For calculating a best positioning, the binarly code as shown in fig.6-(b) is used as the genotype of GA. This genotype indicates the number of motion in Table1. The conversion rule of decimal number from the binary code $\boldsymbol{\xi}$ is represented as $\mathcal{D}(\boldsymbol{\xi})$, the decoding of a genotype is also defined as follows,

$$K \times \frac{\mathcal{D}(\boldsymbol{\rho})}{2^n} + 1, \quad (19)$$

where, K indicates the total number of motion ($K = 9$). When integral part eq.(19) is k, the candidate of positioning $(\tilde{\boldsymbol{p}}_i, \tilde{\boldsymbol{u}}_i)$ is given according to the motion(k) as follows,

$$\tilde{\boldsymbol{p}}_i = \boldsymbol{p}_i(t) + v_k \boldsymbol{u}_i(t), \quad (20a)$$

$$\tilde{\boldsymbol{u}}_i = \begin{matrix} \cos\omega_k & -\sin\omega_k \\ \sin\omega_k & \cos\omega_k \end{matrix} \ \boldsymbol{u}_i(t). \quad (20b)$$

Moreover, the uniform crossover and mutation of bit reversal are used as genetic operation of the reproducing individuals.

5.3 Individual Expression and Genetic Operation to Graph Structure

For calculation of the best graph structure with GA, a candidate of the graph structure is coded as shown in fig.6-(b). In this genotype, the number of agent which is able to interact with U_i, is assigned to $s(k),(k=1,\cdots,N_i)$ by random sequence, and lower row element $q_{s(k)}$ is defined by,

$$q_{s(k)} = \begin{cases} 1 & \text{for action to } U_{is(k)}, \\ 0 & \text{for no action to } U_{is(k)}. \end{cases} \quad (21)$$

As a constraint on the candidate of graph structure $\tilde{\boldsymbol{a}}_i$, interaction DOF of U_i is given according to the number of agents within its neighborhood and internal state E_i. Hence, the genotype$(s,\ q)$ is decoded by the algorithm with fig.7. In this genetic operator of crossover method, the partial matched crossing method is adopted, and new individuals to the candidate of graph structure X^* and Y^* are reproduced from the individuals X and Y (Fig.8-(a)). Also, the inversion is employed as a mutation method(Fig.8-(b)).

6. SIMULATION RESULTS

6.1 Simulation Conditions

Simulations are conducted to illustrate cooperative network formation in the directed multi-agent. Suppose $G^{(1)}$ and $G^{(2)}$ indicate the offense side and the defense side respectively, and one game will end when either $G^{(1)}$ or $G^{(2)}$ make a score. Figure9 shows the game field for the simulation, where the size of game field is 90[m] $\times$ 60[m].

Algorithm Decoding of individual.
$sum \leftarrow 0$
for $k = 1$ to N_i **do**
  if $sum < E_i$ **then**
    $sum \leftarrow sum + q_{s(k)}$
    if $U_i, U_{is(k)} \in G^{(l)}$ **then**
      $\tilde{a}_{i,0s(k)} \leftarrow +1 \times q_{s(k)}$
    else
      $\tilde{a}_{i,0s(k)} \leftarrow -1 \times q_{s(k)}$
    end if
  else
    $\tilde{a}_{i,0s(k)} \leftarrow 0$
  end if
end for
$b_i \leftarrow sum$
end Algorithm

Figure 7: Decoding Algorithm of individual

Table 2: Parameter set for simulation

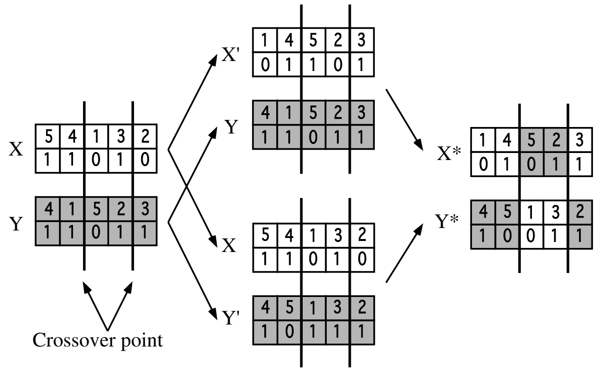
N	number of agent	8
$E_{\max}$	maximal internal state	5
$E_{\min}$	minimal internal state	0
E_{base}	default internal state	3
R	radius of neighborhood circle	20
R_v	maximal distance	5
α	evolution coefficient to goal	0.277×10^{-3}
β	evolution coefficient to ball	1.09×10^{-3}
γ	reflection coefficient to V_i	4.43×10^{-3}
σ	directivity parameter to w_{ij}	0.632

The result is evaluated based on the total score of $G^{(1)}$ in the consecutive 20 games. Also, we employ the average of 10 trials for later discussion. $\varphi^{(l)}$ defined in eq.(18) is parameter for decision-making of the agent in $G^{(l)}, (l = 1, 2)$, which implies tendency of the strategy; $\varphi^{(l)} = 1$ corresponds to team-play oriented strategy and $\varphi^{(l)} = 0$ corresponds to the individual play strategy. By changing the set of parameter values of $(\varphi^{(1)}, \varphi^{(2)})$, we compare the difference of performance of the collective game and evaluate cooperation structures. The other parameters are listed in Table2.

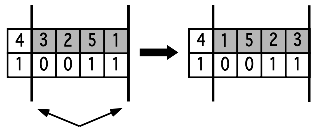
6.2 Evaluation of Cooperation Structure by Interaction Network

In this section, dependency of the strategy parameter φ is examined for various situations, which are made by the difference in the value of coefficient κ determining the feature of subjectivity distance in eq.(2a). Figure10 depicts two dimensional histogram for four conditions, where the value of each histogram indicates the average goal score of group $G^{(1)}$ according to the values of $(\varphi^{(1)}, \varphi^{(2)})$.

Figure 10-(c) shows simulation results in the case that the subjective distance is determined with $\kappa = 3$, where the agents have strong directivity in the recognition of the subjective distance in the collective game. From the simulation results as shown in fig.10-(c), in the case that the strategy parameter $\varphi^{(1)}$ takes large value, the goal score of $G^{(1)}$ tends to be larger. However, this does not mean that entire team play is the best strategy because strategy parameter of



(a) Partially Matched Crossover



(b) Inverse

Figure 8: GA Operator of individual

the best score is found to be $(\varphi^{(1)}, \varphi^{(2)}) = (0.7, 0.9)$. Also, figure 10-(b) shows the simulation results in the case that the subjective distance is determined with $\kappa = 2$. From this result, if the strategy parameter $\varphi^{(1)}$ takes intermediate value, the goal score of $G^{(1)}$ tends to be high. And, figure 10-(a) shows the simulation result when the subjective distance is determined with $\kappa = 1$. This situation means that the agents perceive the subjective distance with the weakest directivity compared to the other cases. As shown in fig.10-(a), in the case that strategy parameter $\varphi^{(1)}$ takes smaller value and $\varphi^{(2)}$ takes larger value, we can see that goal score of $G^{(1)}$ tends to be high. Therefore, when using directed agents which perceive the subjective distance with weak directivity, the individual play strategy becomes more effective than the team play strategy. The number of neighborhood agents seems to relate to the result. The front parts becomes very close in the subjective distance in the case that κ is large value, so the number of perceivable agents tends to be large, while it tends to be smaller in the case that κ is small value, which makes it rather difficult to achieve well organized team play.

On the other hand, figure 10-(d) shows the simulation result in the case of the subjective distance with $\kappa = 4$, which corresponds to the case of the strongest directivity. From the result of fig.10-(d), the combination of strategy parameter $(\varphi^{(1)}, \varphi^{(2)})$ seems to have little relevance to the score.

7. CONCLUSIONS

This paper presented the subjective distance which is a sense of distance subjectively perceived for directed agent. The collective game is modeled using *Interaction Network*, and the decision-making mechanism is proposed based on the evaluation for the surrounding relation and self-behavior. From simulation results, we confirmed that effective cooperation structure is formed, when strategy parameter φ is large and κ is large. However, in the case that the coeffi-

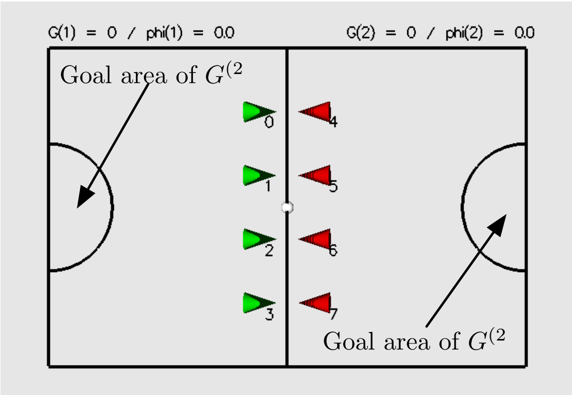
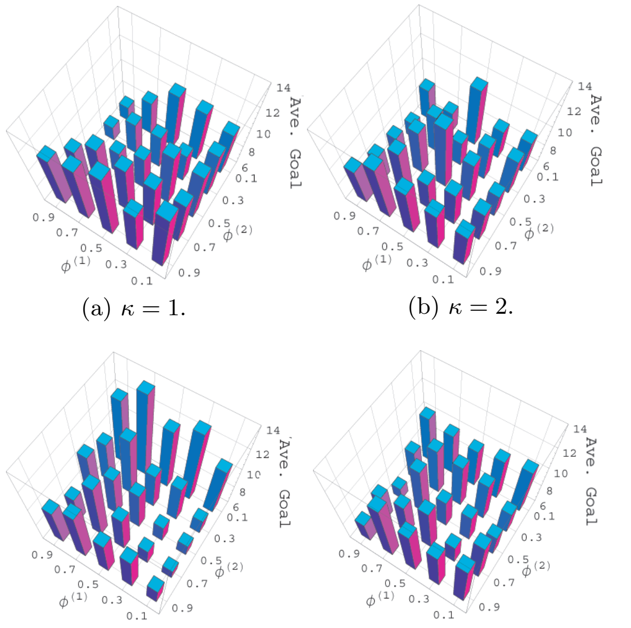


Figure 9: Game field of collective game. Left-hand cone and right-hand cone represent the directed agent belonging to $G^{(1)}$ and $G^{(2)}$ respectively.

cient κ of the cognitive distance is too large, we observed that a strategy parameter φ is rather meaningless. In the present work, agents cannot change φ dynamically depending on the game phase, so dynamical adaptation for team play strategy remains to be solved.



(a) $\kappa = 1$. (b) $\kappa = 2$. (c) $\kappa = 3$. (d) $\kappa = 4$.

Figure 10: Result of collective game for four situations.

8. REFERENCES

[1] J. Fredslund and M. Mataric. Robot formations using only local sensing and control. In *Proc. of IEEE International Symposium on Computational Intelligence in Robotics and Automation, 2001*, volume 2001, pages 308–313, 2001.

[2] T. Balch and R. Arkin. Behavior-based formation control for multi-robot teams. *IEEE Transactions on Robotics and Automation*, 14:926–939, December 1998.

[3] W. Aiello, Fan Chung, and L. Lu. Random evolution in massive graphs. In *IEEE Symposium on Foundations of Computer Science*, pages 510–519, 2001.

[4] S. N. Dorogovstsev and J. F. F. Mendes. Evolution of networks. *Advances in Physics*, 51:1079–1187, 2002.

[5] A.S.Mikhailov and V.Calenbuhr. *From Cells to Societies*, chapter 9, pages 233–277. Springer, July 2001.

[6] Kosuke Sekiyama and Yukihisa Okade. Variable interaction network based on activation and inhibition. In *IEEE International Symposium on Computational Intelligence in Robotics and Automation, 2003*, pages 1551–1556, 2003.

[7] Kosuke Sekiyama and Yukihisa Okade. Dynamical reconfiguration of cooperation structure by interaction network. In *Proceedings of the 7th Symposium on Distributed Autonomous Robotic System*, 2004.

[8] M. Tambe, J. Adibi, Y. Alonaizon, A. Erdem, G. Kaminka, S. Marsella, and I. Muslea. Building agent teams using an explicit teamwork model and learning. *Artifical Intelligence*, 110(2):215–239, 1999.

[9] Hitoshi Matsubara, Itsuki Noda, and Kazuo Hiraki. Learning of cooperative actions in multiagent systems: A case study of pass play in soccer. In *Working Notes for the AAAI Symposium on Adaptation, Co-evolution and Learning in Multiagent Systems*, pages 63–67, 1996.

[10] Peter Stone and Manuela M. Veloso. Task decomposition and dynamic role assignment for real-time strategic teamwork. In *Proc. of Agent Theories, Architectures, and Languages*, pages 293–308, 1998.