



# Attitude coordination with potential game approach by learning algorithm SAP



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FL09\_19\_1  
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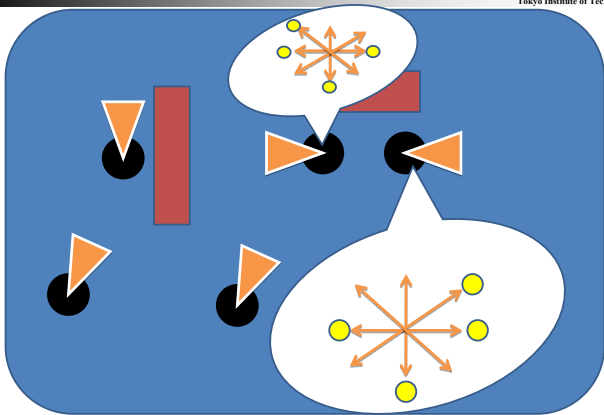


## Outline

- Background
- Outline of Oscillator
- Review of Potential game (RSAP)
- Adapt Potential game to Oscillator Problem
- Simulation Result
- Experimental Result
- Summary and assignment



## Background

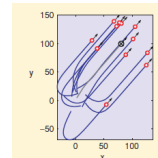


## Outline of Oscillator

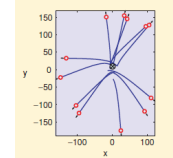
### Oscillator Models and Collective Motion

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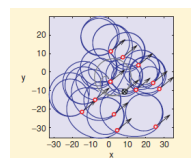
SPATIAL PATTERNS IN THE DYNAMICS OF ENGINEERED AND BIOLOGICAL NETWORKS



synchronized



balanced

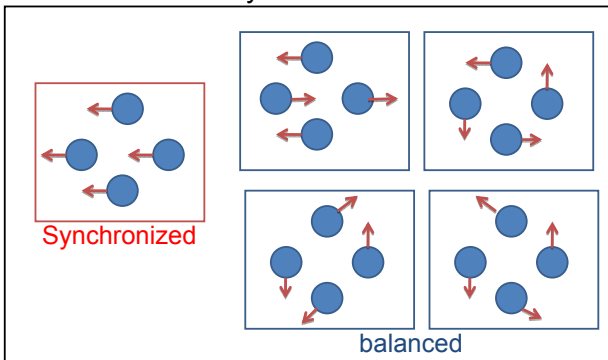


Synchronized with natural frequency



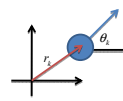
## Synchronized, balanced

### symmetric



## Oscillator

### Particle model



$$r_k = x_k + jy_k$$

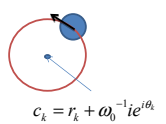
$$\dot{r}_k = e^{i\theta_k}$$

$$\dot{\theta}_k = u_k(r, \theta)$$

$$u_k = 0$$



$$u_k = \omega_0$$



$$c_k = r_k + \omega_0^{-1} e^{i\theta_k}$$

### Control law

$$u_k = \omega_0 + u_k^{pac}(r, \theta) + u_k^{ori}(\theta)$$

Spacing control  
Natural frequency Orientation control

Not consider the position

$$u_k = \omega_0 + u_k^{ori}(\theta)$$

Depend only on relative phase

$$\theta_{ij} = \theta_i - \theta_j$$



### Oscillator

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$$\theta_k = \theta_j \quad \text{Agent } j \text{ and } k \text{ is parallel position}$$

Phase order parameter

$$p_\theta = \frac{1}{N} \sum_{j=1}^N e^{i\theta_j} \quad 0 \leq |p_\theta| \leq 1$$

$|p_\theta|=1$  → synchronized   $|p_\theta| = \left| \frac{1}{3}(e^{i\pi/4} \times 3) \right| = |e^{i\pi/4}| = 1$

$|p_\theta|=0$  → balanced   $|p_\theta| = \left| \frac{1}{3}(e^{i\pi/2} + e^{i7\pi/6} + e^{i13\pi/6}) \right| = 0$

$p_\theta = \dot{R}$   $p_\theta$  is equal to the velocity of R  $R \triangleq \frac{1}{N} \sum_{j=1}^N r_j$ . Center of mass

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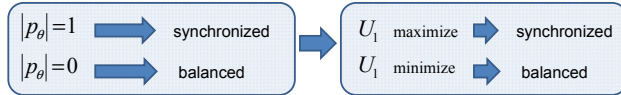


### Oscillator

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Phase potential

$$U_1(\theta) = \frac{N}{2} |p_\theta|^2$$



Gradient control

$$\frac{\partial U_1}{\partial \theta_k} = \langle i e^{i\theta_k}, p_\theta \rangle \rightarrow \begin{cases} K_1 < 0 \Rightarrow \text{synchronized} \\ K_1 > 0 \Rightarrow \text{balanced} \end{cases}$$

$$\langle x, y \rangle = \text{Re} \{ x^* y \}$$

Use all agents information

$$u_k = \omega_0 - k_1 \langle i e^{i\theta_k}, p_\theta \rangle$$

$$K_1 < 0 \Rightarrow \text{synchronized}$$
  
$$K_1 > 0 \Rightarrow \text{balanced}$$

$$u_k = \omega_0 + \frac{k_1}{N} \sum_{j=1}^N \sin \theta_{kj}$$

Kuramoto model

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### Oscillator

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Phase potential  $U_1(\theta) = \frac{N}{2} |p_\theta|^2$  Use all agents information

Laplacian Phase Potential  $W_1(\theta) = Q_L(e^{i\theta}) = \frac{1}{2N} \langle e^{i\theta}, L e^{i\theta} \rangle$

Laplacian quadratic form  $Q_L(x) = \frac{1}{2N} \langle x, Lx \rangle$   
 $\langle x, y \rangle = \sum_{j=1}^N \langle x_j, y_j \rangle$

Interaction is limited is OK

Graph is complete

$$\rightarrow W_1(\theta) = \frac{N}{2} - U_1(\theta)$$

$$W_1(\theta) = Q_L(e^{i\theta}) = \frac{1}{2N} \langle e^{i\theta}, L e^{i\theta} \rangle$$

$$= \frac{1}{2N} \sum_{k=1}^N (d_k - \sum_{j \in N_k} \langle e^{i\theta_k}, e^{i\theta_j} \rangle) \geq 0$$

$$W_1(\theta) = 0 \Leftrightarrow \text{synchronized}$$

minimize Synchronized phase  
maximize Balanced phase

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### Oscillator

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$$W_1(\theta) = Q_L(e^{i\theta}) = \frac{1}{2N} \langle e^{i\theta}, L e^{i\theta} \rangle$$

Laplacian Phase control (continuous)

$$\frac{\partial W_1(\theta)}{\partial \theta_k} = \frac{1}{2N} \langle i e^{i\theta_k}, (L+L^T)_k e^{i\theta} \rangle = \frac{1}{N} \langle i e^{i\theta_k}, L_k e^{i\theta} \rangle$$

$$u_k^{ori} = \frac{k_1}{N} \langle i e^{i\theta_k}, L_k e^{i\theta} \rangle \text{ (gradient control)} \quad \dot{\theta}_k = \omega_0 + u_k^{ori}$$

Simplified Kuramoto model

$$\dot{\theta}_k = \omega_0 + \frac{K_1}{N} \sum_{j \in N_k} \sin \theta_{kj}$$

Evolves monotonically

$$\dot{W}_1(\theta) = \frac{k_1}{N^2} \sum_{k=1}^N \langle e^{i\theta_k}, L_k e^{i\theta} \rangle^2$$

Invariance principle

Converge to largest invariant set for which  $\dot{W}_1(\theta) = 0$

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### Oscillator

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$$\dot{W}_1(\theta) = 0 \rightarrow \langle i e^{i\theta_k}, L_k e^{i\theta} \rangle = 0 \quad \dot{W}_1(\theta) = \frac{k_1}{N^2} \sum_{k=1}^N \langle e^{i\theta_k}, L_k e^{i\theta} \rangle^2$$

$\theta$  is stationary point  
(ex)  $e^{i\theta}$  is an eigenvector of L

$1^T$  is an eigenvector of L (from graph theorem)  
 $e^{i\theta} = 1^T$  synchronized  $K_1 < 0$

graph is circulant

$e^{i\theta} (1^T e^{i\theta} = 0)$  is an eigenvector of L (from graph theorem)  
 $1^T e^{i\theta} = 0$  balanced  $K_1 > 0$

circulant  $L = \begin{bmatrix} c_0 & c_{-1} & \dots & c_1 & c_0 \\ c_1 & c_0 & \dots & c_{-1} & c_1 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ c_{-2} & c_{-1} & \dots & c_0 & c_1 \\ c_{-1} & c_0 & \dots & c_1 & c_0 \end{bmatrix}$   
(ex) 

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### Oscillator

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Pi/2 problem

$$\dot{\theta}_k = \omega_0 + \frac{K_1}{N} \sum_{j \in N_k} \sin \theta_{kj}$$

If  $\sin \theta_{kj} = 0$ , then  $\dot{\theta}_k = \omega_0$

When realizing synchronized

$$\sin(\pi/2 - (-\pi/2)) = 0$$

Evolution stop but not realize synchronized

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## Potential game

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Global planner  $\phi : A \rightarrow R$   
(potential function)

aligned

Player's objective function

$$U_i(a_i'', a_{-i}) - U_i(a_i', a_{-i}) = \phi_i(a_i'', a_{-i}) - \phi_i(a_i', a_{-i})$$

Changing in the player's objective function



Changing in the potential function

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## attention

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Consensus point



Nash equilibrium of the game characterized by the



Player's objective function  $U_i(a) = - \sum_{j \in N_i} \|a_i - a_j\|$



set of Consensus point  $\xrightarrow{A^c} \subset \xleftarrow{A^*}$  set of Nash equilibrium



Learning algorithm

Guarantees **probabilistic** convergence to a pure Nash equilibrium that **maximize the potential function**

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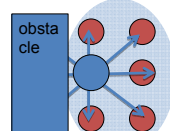
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## Restrictive Spatial Adaptive Play

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Issue of SAP  $\rightarrow$  Permit any action in its action set



$\rightarrow$  From mobility limitation, it's impossible

Restricted action set  $R_i(a_i(t-1))$

## Restrictive Spatial Adaptive Play

step1

Randomly choose one player  $P_i$   
(Another player do a same action)

step2

Player  $P_i$  selects **one trial action**  $\hat{a}_i$  from  $R_i(a_i(t-1))$ .  $z_i = \max_{a_i \in A_i} |R_i(a_i)|$

$$\Pr[\hat{a}_i = a_i] = 1/z_i, \quad a_i \in R_i(a_i(t-1)) \setminus a_i(t-1)$$

$$\Pr[\hat{a}_i = a_i(t-1)] = 1 - (|R_i(a_i(t-1))| - 1)/z_i$$

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## Restrictive Spatial Adaptive Play

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step3 Player  $P_i$  chooses its action at time t

$$\Pr[a_i(t) = \hat{a}_i] =$$

$$\frac{\exp\{\beta U_i(\hat{a}_i, a_{-i}(t-1))\}}{\exp\{\beta U_i(\hat{a}_i, a_{-i}(t-1))\} + \exp\{\beta U_i(a_i(t-1))\}}$$

$\rightarrow$  Choose trial action

$$\Pr[a_i(t) = a_i(t-1)] =$$

$$\frac{\exp\{\beta U_i(a_i(t-1))\}}{\exp\{\beta U_i(\hat{a}_i, a_{-i}(t-1))\} + \exp\{\beta U_i(a_i(t-1))\}}$$

$\rightarrow$  Don't move

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## Theorem

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### Theorem

Consider a finite n-player potential game with potential function  $\phi$

If restricted action set satisfy

$$a_i^2 \in R_i(a_i^1) \leftrightarrow a_i^1 \in R_i(a_i^2) \quad (\text{Reversibility})$$

$$\text{and } a_i^k \in R_i(a_i^{k-1}) \quad (\text{Feasibility})$$

then RSAP induce a **Markov process** over the state space A where the unique distribution  $\mu \in \Delta(A)$  is

$$\mu(a) = \frac{\exp\{\beta \phi(a)\}}{\sum_{\bar{a} \in A} \exp\{\beta \phi(\bar{a})\}}$$

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## Synchronized

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$$W_i(\theta) = \frac{1}{2N} \sum_{k=1}^N (d_k - \sum_{j \in N_k} \langle e^{i\theta_k}, e^{i\theta_j} \rangle) \rightarrow \text{minimize}$$

$$= \frac{1}{2N} \sum_{k=1}^N (d_k - \sum_{j \in N_k} \cos(\theta_k - \theta_j))$$

Synchronized phase

Potential game

$$\phi(\theta) = -\frac{1}{2N} \sum_{k=1}^N (d_k - \sum_{j \in N_k} \cos(\theta_k - \theta_j))$$

$U_i(\theta) = \frac{1}{N} \sum_{j \in N_i} \cos(\theta_i - \theta_j)$

(Time-invariant interaction graph and undirected)

(proof)  $\phi(\theta) = -\frac{1}{2N} \sum_{k=1}^N (d_k - \sum_{j \in N_k} \cos(\theta_k - \theta_j))$

$$= -\frac{1}{2N} \sum_{k=1}^N (d_k - \sum_{j \in N_k} 2 \cos(\theta_i - \theta_j) - \sum_{j \neq i, k \in N_j} \cos(\theta_j - \theta_i))$$

Interaction fixed

$$\phi(\theta_i^*, \theta_{-i}) - \phi(\theta_i, \theta_{-i}) = \frac{1}{2N} \sum_{j \in N_i} 2 \cos(\theta_i^* - \theta_j) - \frac{1}{2N} \sum_{j \in N_i} 2 \cos(\theta_i - \theta_j)$$

$$= U_i(\theta_i^*, \theta_{-i}) - U_i(\theta_i, \theta_{-i})$$

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## Balanced

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$$W_i(\theta) = \frac{1}{2N} \sum_{k=1}^N (d_k - \sum_{j \in N_k} \langle e^{i\theta_k}, e^{i\theta_j} \rangle) \rightarrow \text{maximize}$$

$$= \frac{1}{2N} \sum_{k=1}^N (d_k - \sum_{j \in N_k} \cos(\theta_k - \theta_j))$$

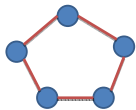
Balanced phase

Potential game

$$\phi(\theta) = \frac{1}{2N} \sum_{k=1}^N (d_k - \sum_{j \in N_k} \cos(\theta_k - \theta_j))$$

$U_i(\theta) = -\frac{1}{N} \sum_{j \in N_i} \cos(\theta_i - \theta_j)$

(Time-invariant interaction graph and undirected)



Graph is circulant

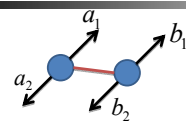
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## example

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2 agents  
2 actions

4 states

- $S_1 = (a_1, b_1)$
- $S_2 = (a_1, b_2)$
- $S_3 = (a_2, b_1)$
- $S_4 = (a_2, b_2)$

Transmission matrix

$$P = \begin{bmatrix} 1-p_{12}-p_{13} & \frac{1}{4} \frac{e^{\beta U_2(S_1)}}{e^{\beta U_2(S_1)}+e^{\beta U_2(S_2)}} & \frac{1}{4} \frac{e^{\beta U_1(S_1)}}{e^{\beta U_1(S_1)}+e^{\beta U_1(S_2)}} & 0 \\ \frac{1}{4} \frac{e^{\beta U_2(S_1)}}{e^{\beta U_2(S_1)}+e^{\beta U_2(S_2)}} & 1-p_{21}-p_{24} & 0 & \frac{1}{4} \frac{e^{\beta U_1(S_1)}}{e^{\beta U_1(S_1)}+e^{\beta U_1(S_2)}} \\ \frac{1}{4} \frac{e^{\beta U_1(S_1)}}{e^{\beta U_1(S_1)}+e^{\beta U_1(S_2)}} & 0 & 1-p_{31}-p_{34} & \frac{1}{4} \frac{e^{\beta U_2(S_1)}}{e^{\beta U_2(S_1)}+e^{\beta U_2(S_2)}} \\ 0 & \frac{1}{4} \frac{e^{\beta U_1(S_2)}}{e^{\beta U_1(S_1)}+e^{\beta U_1(S_2)}} & \frac{1}{4} \frac{e^{\beta U_2(S_2)}}{e^{\beta U_2(S_1)}+e^{\beta U_2(S_2)}} & 1-p_{42}-p_{43} \end{bmatrix}$$

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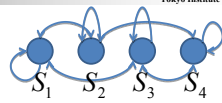


## example

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Transmission matrix P

irreducible  
aperiodic



Exist Stationary distribution

$$\mu(a) = \frac{\exp\{\beta \phi(a)\}}{\sum_{\bar{a} \in A} \exp\{\beta \phi(\bar{a})\}}$$

$$\beta \text{ const } \mu(a) p_{ab} = \mu(b) p_{ba} \text{ (detail balance)}$$

(ex)

$$\beta = 0 \rightarrow P = \begin{bmatrix} \frac{3}{4} & \frac{1}{8} & \frac{1}{8} & 0 \\ \frac{1}{8} & \frac{3}{4} & 0 & \frac{1}{8} \\ \frac{1}{8} & 0 & \frac{3}{4} & \frac{1}{8} \\ 0 & \frac{1}{8} & \frac{1}{8} & \frac{3}{4} \end{bmatrix}$$

Stationary distribution

$$\begin{bmatrix} \frac{1}{4} & \frac{1}{4} & \frac{1}{4} & \frac{1}{4} \end{bmatrix}$$

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## example

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(ex)

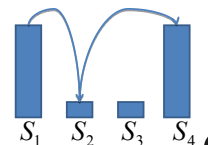
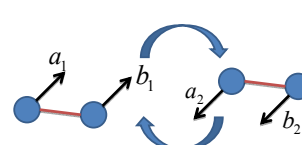
$$\beta = \infty \rightarrow P = \begin{bmatrix} 1 & 0 & 0 & 0 \\ \frac{1}{4} & \frac{1}{2} & 0 & \frac{1}{4} \\ \frac{1}{4} & 0 & \frac{1}{2} & \frac{1}{4} \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

Absorbed state

Not exist stationary distribution

SAP's features is not convergence one state!

If there are some consensus point, change the state during some consensus point.



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What degree is better for β?

The most largest probability from consensus point to another state is

$$\max_{i \in N} \frac{1}{nz} \frac{e^{\beta U_{i \max 2}}}{e^{\beta U_{i \max}} + e^{\beta U_{i \max 2}}}$$

Probability of changing the state from Consensus point is smaller than

$$\sum_{i \in N} (z'_i - 1) \times \max_{i \in N} \frac{1}{nz} \frac{e^{\beta U_{i \max 2}}}{e^{\beta U_{i \max}} + e^{\beta U_{i \max 2}}}$$

$z'_i$ : feasible action of  $i$



spec

Do small the probability of changing the state from Consensus point than p

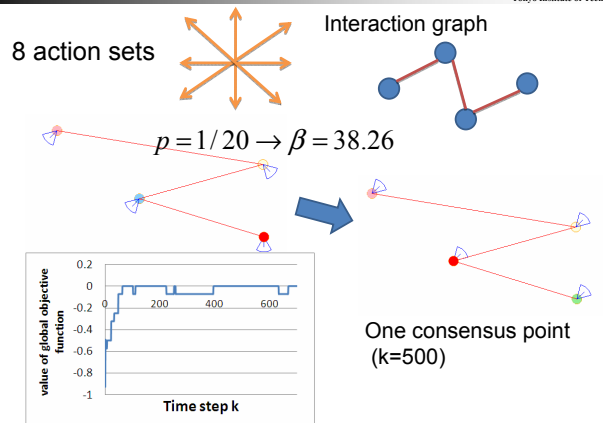
$$\sum_{i \in N} (z'_i - 1) \times \max_{i \in N} \frac{1}{nz} \frac{e^{\beta U_{i \max 2}}}{e^{\beta U_{i \max}} + e^{\beta U_{i \max 2}}} < p$$

$$\max_{i \in N} \frac{1}{U_{i \max} - U_{i \max 2}} \log \left( \frac{\sum_{i \in N} (z'_i - 1)}{pnz} - 1 \right) < \beta$$

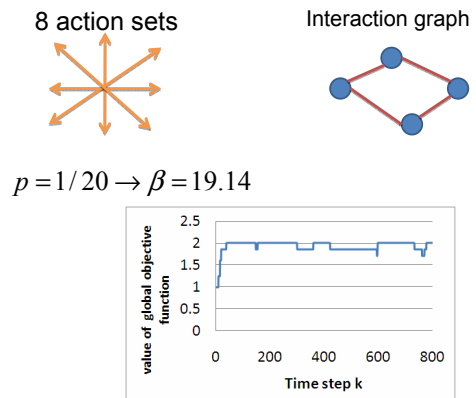
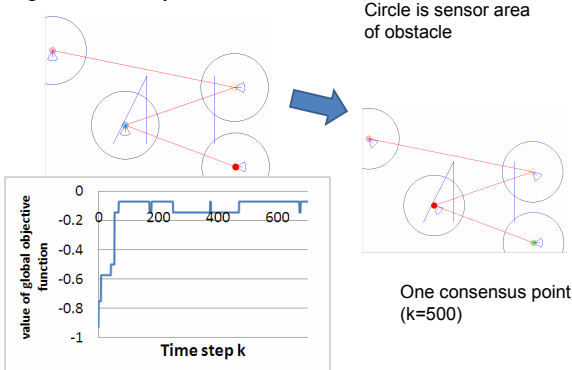
A little strict condition



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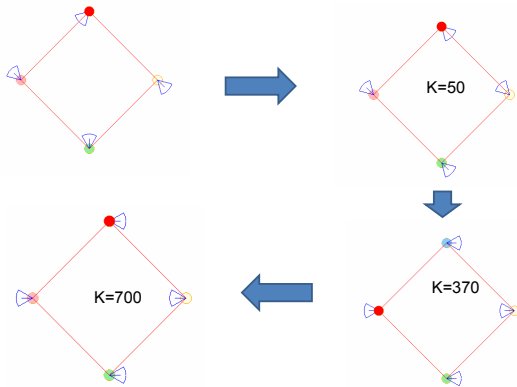


$$p = 1/20 \rightarrow \beta = 29.0$$



### Simulation Result (balanced with four agents)

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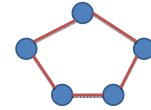
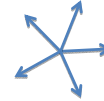
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### Simulation Result (balanced with five agents)

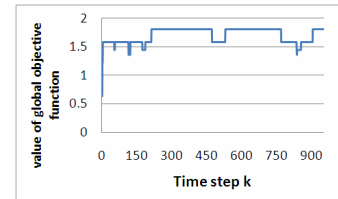
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5 action sets

Interaction graph



$$p = 1/80 \rightarrow \beta = 18.2$$

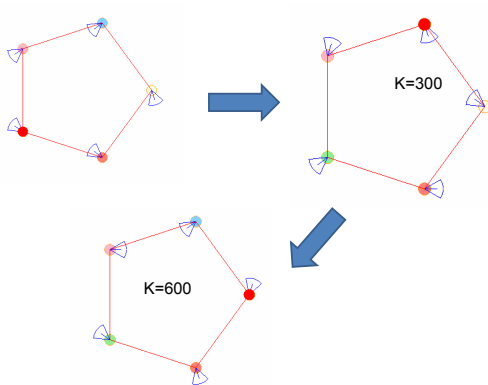


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### Simulation Result (balanced with five agents)

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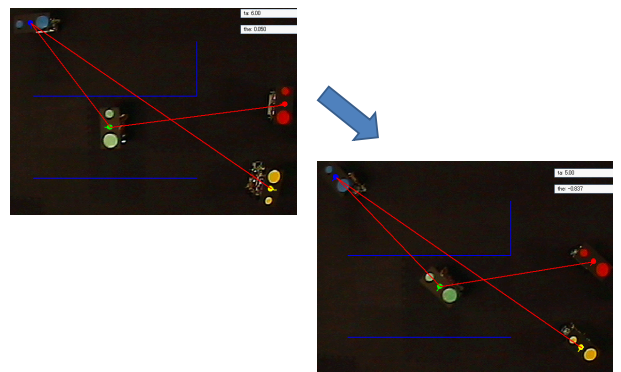


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### Experimental Result (synchronization)

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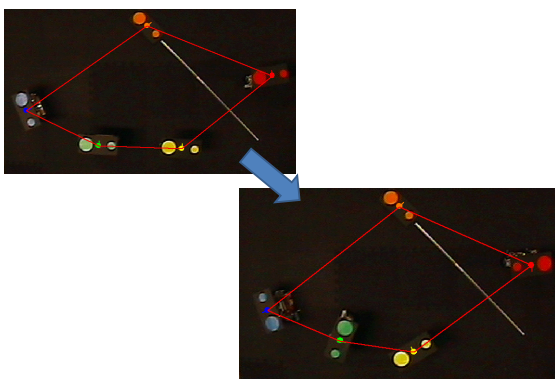


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### Experimental Result (balanced)

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### Summary and assignment

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- Can adapt potential game to oscillator
- RSAP can make Stationary distribution
- Some time change consensus state to another consensus point
- Can decide changing rate with exploration rate  $\beta$
- How to make suboptimal state high probability  
→using reinforcement learning ?
- How to decide  $p$   
→consider not consensus states

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