Abstract—We considered that self-driven particles system (SDP) can be applied to the analysis of social dynamics and proposed a social model based on SDP. Each of particles represents an individual in society and has a strategy as a state. Each particle moves according to the payoff defined by the combination of strategies of both itself and neighbors, the payoff matrix to represent the social interaction among them and the distance between them. Specifically, it approaches to the others which brings a benefit and get away from the others who suffers a loss. In this work, we adopt Prisoner’s Dilemma as an payoff matrix and conducted the simulations to analyze the social dynamics represented by the movement of particles. The results showed that the cycle process between the formation of an altruistic cluster and its collapse with explosive dispersal of particles from the cluster. In addition, we found that the diversity of the parameter to decide the cooperation tendency of each plays an important role to the occurrence of cyclic dynamics.

I. INTRODUCTION

Collective motion is a widespread phenomenon in biological systems. Vicsek described each individual in the collective motion as a self-driven particle and investigated the emergence of self-ordered motion in systems of particles with biologically motivated interaction [1]. Since then, self-driven many-particle systems have been studied actively to understand the collective behavior of humans (e.g. crowd dynamics of pedestrians [2], [3]) and animals (e.g. schools of fishes [4] and flocks of birds [5], [6]) in the discipline of physics, biology and ALife. Transitions have also been observed in traffic models consisting of cars which can also be interpreted as self-driven particles.

Reynolds constructed a SDP model Boids to simulate the flocking behavior of birds [5]. Each particle follows the three simple rules: (1) Collision Avoidance: avoid collisions with nearby particles (2) Velocity Matching: attempt to match velocity with nearby particles (3) Flock Centering: attempt to stay close to nearby particles. With only these simple rules, his model succeeded in simulating complex behavior of birds such as flocking and obstacle avoidance.

By extending Reynolds’ Boids, where each particle follows the same kinetic rules, Sayama proposed a new SDP framework named EvolutionarySwarmChemistry [7]. In his model, a particle has some kinetic parameter sets (i.e. radius of local perception range, normal speed, maximum speed and so on) and move in a two-dimensional space according to one of them. The kinetic rules of one particle are propagated to another and mutate with a small probability when they collide. They showed the intriguing phenomenon, that is the emergence of macroscopic coherent structures from particles and its growth and replication.

We consider SDP can be applied to analyze the social dynamics and propose SocialParticleSwarm where particles move according not to their kinetic interaction based on their positions and velocities as the previous works, but to their social interaction based on the particles’ states and positions. Social interactions among particles are modeled using the game theory; therefore the states of particles represent the strategies in the game. A particle approaches to other ones which bring the profits in order to obtain more profits and gets away from ones whom it suffers a loss from in order to reduce losses. Each has a threshold parameter, and changes its strategy (state) based on the threshold and the proportion of the states of nearby particles. These describe the dynamics of relationships which changes according to the results of social interactions and dynamics of an individual condition affected by the surroundings, respectively.

Adopting Prisoner’s Dilemma (PD) as a model of social relationships among particles, we conducted simulations as an example of Social Particle Swarm. It showed that the system reached an intriguing state where clustering and dispersing of cooperative and defective particles are repeated. We analyzed the social dynamics observed in this process from the view point of the coevolution between cooperation and structures of relationships which has been studied actively in the discipline of adaptive network [8], [9], [10],[11].

II. MODEL

We assume $N$ particles (= individuals) in a two-dimensional plane. Each of individuals has a strategy and they generate forces decided by the payoff of PD. Each particle moves based on the resultant of the forces. The distance between two individuals represents the closeness between them in a relationship. When one approaches to another, the game result between them has greater influence on them.

The movement of particles in this model are based on human behavior in social environment as follows: 1. An individual reinforces the relationship with (= get close to) others who bring profits and try to gain more profit. 2. An individual weakens the relationship with (= get away from) others whom she suffers a loss from, and try to avoid more loss.
The structure of relationships and strategy distribution of nearby individuals (positions and states of particles) decides the games between them. Moreover, the results and the positions of individuals decide the movement of each individual, which changes their structure of relationships and strategies (Fig. 1). Specifically, each individual’s action consists of the two processes as follows.

1) Decide strategy
Each individual recognizes the individuals which exist in a radius of $R$ around herself as neighbors. We use parameter cooperative threshold $c_t$ which represents a tendency of cooperation for an individual. Each individual calculates the ratio of cooperators among her neighbors at the previous step $r_c$, then she selects cooperation as the strategy at the current step when $(1-r_c) < c_t$. When the parameter $r_c$ does not satisfy this condition, the individual selects defection. This process describes decision making according to the strategies of neighbors, which can be interpreted as an generalized Tit-For-Tat. Each individual reverses her strategy with a probability of $p_m$ (mutation).

2) Move
Each individual generates forces depending on her social relationship with her neighbor decided by the payoff matrix (TABLE I) and the relative position of that neighbor from the focal individual. The direction of the force from the individual $i$ to $j$ depends on the sign of the payoff which the individual $i$ receives from her neighbor $j$. The pulling force towards the individual $j$ is generated when the payoff is positive and, in contrast, the pushing force away from the individual $j$ is generated when it is negative. Each individual receives a payoff from her neighbor defined in TABLE I according to their strategies but its value is scaled by the inverse of the interaction radius of $N$ individuals $R = 150$, the temptation of defection $\alpha = 1.4$, the probability to reverse strategy $p_m = 0.04$ and the constant speeds of individuals $v = 10$. The value of $c_t$ of each individual is randomly selected from $[0, 1]$. The initial placement and the strategy of individuals are set randomly at the beginning of a simulation. When we conducted the simulations for 2000 time steps, it turned out that the system reaches one of the three quasi-stable states (Fig. 3) as below.

$$
\bar{c}_i = \sum_{j \in \text{neighbors}_i} \frac{P(s_i, s_j)}{|d_{i,j}|} \vec{d}_{i,j}, \quad (1)
$$
$$
\vec{v}_i = \frac{v}{|\vec{c}_i|} \vec{c}_i, \quad (2)
$$
$$
tp_i = \sum_{j \in \text{neighbors}_i} \frac{P(s_i, s_j)}{|d_{i,j}|}, \quad (3)
$$

III. Results
We conducted simulations using a $700 \times 700$ two-dimensional torus plane under the following conditions: the number of individuals $N = 700$, the interaction radius of individuals $R = 150$, the temptation of defection $\alpha = 1.4$, the probability to reverse strategy $p_m = 0.04$ and the constant speeds of individuals $v = 10$. The value of $c_t$ of each individual is randomly selected from $[0, 1]$. The initial placement and the strategy of individuals are set randomly at the beginning of a simulation. When we conducted the simulations for 2000 time steps, it turned out that the system reaches one of the three quasi-stable states (Fig. 3) as below.

<table>
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<tr>
<th>TABLE I</th>
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<td>Payoff matrix</td>
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Fig. 1. Concept diagram of Social Particle Swarm.

Fig. 2. Movement of a particle.
- State 1: More than half of the all individuals select *defection* and move around in the space repelling each other.
- State 2: Most of all individuals select *cooperation* and get together in some clusters attracting each other. We sometimes observed some individuals moved out of a cluster and *migrated* to another one.
- State 3: The three-step process ((a) formation of a cooperative cluster → (b) invasion by defectors → (c) collapse of a cluster and explosive dispersal of individuals) is repeated in the system. The proportion of cooperators oscillate and does not remain constant.

They are not necessarily steady states. The system sometimes transfer from one state to another. We focus on the State 3 and analyze the dynamics of the system.

A. The proportion of cooperators and the average number of neighbors

Fig. 4 (top) shows an example of the trajectory of the population in the space of the proportion of cooperators and the average number of neighbors in a typical trial that showed the large-scale formation and collapse in the state 3. Fig. 5 shows the time series of proportion of cooperators, the average number of neighbors and the average total payoff for the same time steps. Each process in the State 3 corresponds to (a) ~ (c) in Fig. 4 (bottom) and 5. We explain the details of each process.

(a) Formation of a cooperative cluster

Individuals who have relatively high $c_t$ (high tendency to cooperate) attract each other, and start to form a cluster. The cluster continues to enlarge because it attracts neighboring individuals near it. The distance between individuals narrows, and thus the average number of neighbors increases. Moreover, the proportion of cooperators and the average of an individual’s total payoff increases because the individuals who originally have the defection strategy change their strategies to cooperation due to the affection by the majority (cooperators) near him (Fig. 5 (a)).

(b) Invasion by defectors

When the cluster becomes larger gradually, the number of the defectors in the cluster who have relatively low $c_t$ increases. The individuals with extremely low $c_t$ can keep their defection strategy even if they are surrounded by the cooperators. When the number of defectors in the cluster increases to some extent due to the invasion by low $c_t$ individuals and mutations, some individuals with relatively high $c_t$ also begin to reverse their strategies from cooperation to defection. The reverse of the strategy propagates from the low $c_t$ individuals to high $c_t$ individuals, which causes the increase of defectors. Moreover, the average total payoff falls sharply because of the mutual defections and the exploitation of cooperators by defectors (Fig. 5 (b)).

In order to investigate the process from the increase of defectors to the collapse of the cluster, we conducted a simulation from a initial state where we set all individuals which have cooperation strategy at a point and they has been already clustered. Fig. 6 shows the time variation of the average distance from the center of the cluster to individuals with $c_t < 0.5$ and with $0.5 \leq c_t$. We see from Fig. 6 that the cluster expanded and contracted repeatedly (step 0 - 5). Then, the *segregation* happened that the individuals with low $c_t$ move into the center of the cluster, and the individuals
with high $c_t$ moves to the fringe area (step 5 - 9). This results from the avoidance behavior of cooperators with high $c_t$ from the defectors which moved into the center of the cluster to exploit. When the forces of cooperators to escape outwards from defectors in the center exceeds the attraction force between them, the cluster collapses and the individuals spread like an explosion (step 9-) (Fig. 7).

(c) Dispersion of individuals and reformation of a new cluster

The explosion is the phenomenon where defectors in the inside area chase the cooperators in the fringe area repelling each other, and the cooperators escape outwards from them. When it happens, the average degree and the proportion of cooperators decreases suddenly because the distance between individuals increases rapidly (Fig. 5 (c)). In such situation, it is only the high $c_t$ individuals that can keep the cooperation strategy. In addition, the particle density varies widely in the space immediately after the explosion because many particles move simultaneously. When individuals with high $c_t$ attract each other and create a cluster in a low density area, the cluster can be maintained even if it is surrounded by a few defectors. The small cluster grows gradually and draws surrounding individuals into itself, then the cluster will be formed again.

Fig. 4. The emergence of cycle between proportion of cooperation and average number of neighbors.

IV. DISCUSSION

The clusters that emerged in our simulations can be described as the altruistic groups where cooperators gather. This model draws the universal scenario: the formation and the expansion of altruistic groups → the invasion by defectors → the decrease of the group benefit → the segregation in the cluster between individuals with a cooperation tendency and with a defection tendency → the collapse of the altruistic

Fig. 5. The time series of proportion of cooperation, average number of neighbors and average payoff

B. The effect of the value of $c_t$

We changed the setting of the parameter $c_t$ which has been initialized randomly in each individual to a fixed value. We conducted ten trials with under the condition where all individuals have the same value of $c_t$. As a result, the system reaches to State 1 or State 2, not but State 3, in all trials.

Fig. 6. Time variation of average distance of particles from the center of the cluster.
groups and the dispersion of individuals, even though the rules are very simple.

It should be noted that such a dynamic social behavior closely related to the phenomena observed in several recent studies on adaptive networks. Cavaliere et al. [11] reported that the similar dynamics was observed in their PD model on adaptive network, which is the cycle of the formation and fragmentation of the network of individuals playing PD. We observed that the cycle between the strategy and the average number of neighbors of each individual emerged. In our model, the average number of neighbors can be interpreted as an average degree of the network if we assume that neighbors are connected by links. The emergence of the cyclic process between the average degree and the cooperative behavior was also observed in the evolutionary model proposed by Suzuki et al. where the network structure and individuals’ strategies coevolve [10]. The fact that the common phenomenon was observed in several different models tells us that the scenario emerged in our model is important for the dynamics of relationship in societies.

Also, our example model can be seen as an extended PD model with mobile agents. PD models with mobile agents have been studied by many researchers [12], [13], [14], [15], [16]. Chen et al. constructed a new model where agents play evolutionary PD moving together as flocks [12]. In their model, the evolutionary mechanism is introduced into the individual’s strategy, but the direction of its movement only follows the average direction of neighbors. In contrast, in our model, the movement is determined adaptively according to social interactions defined by a payoff matrix of PD, but the strategy of each individual is dependent on the strategy distribution of neighbors. From this point of view, our model and Chen’s model is speculated to be complementary to each other.

In addition, the simulations in section III (B) showed that the difference of $c_t$ among individuals is an important factor for the occurrence of the State 3. The value of $c_t$ describes the characteristic of each individual, thus it means that the diversity of individuals plays an important role to generate the dynamic cycle in the system.

V. CONCLUSION

In this paper, we proposed a new social model based on the self-driven particles where each particle represents an individual in society and each moves according to social interactions with others based on the positions and states of neighbors. Adopting Prisoner’s Dilemma as an example model of social interaction, we conducted the simulations. We classified the states of the system into three quasi-stable states and focused on the most dynamic state among them. In this state, we discovered that the cycle process between the formation of an altruistic cluster and its collapse with explosive dispersal of particles emerged. In addition, it enables us to understand visually the dynamics of the relationship among individuals as the movement of particles which has been represented as a network in previous works. Thus, we believe that our framework has a significant potential to discuss complex social dynamics. One of the future directions would be to investigate the particle dynamics under the different social interactions among particles in place of Prisoner’s Dilemma.

REFERENCES