A Hybrid Approach to Understanding the Continuous Social Dynamics Based on a Large-Scale Modeling and a Face-to-Face Experiment

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Introduction

Online social networks make our social interactions continuous in two senses: The first being temporal, as we stay constantly connected in real-time in a non-discrete way using our hand-held devices, and the second being the degree of social closeness as we use various Social Networking Services (SNSs) and communicate with others at different frequencies. Contrarily, many studies highlighted the importance of face-to-face interactions, and developed new approaches for the study of close-proximity networks (Eagle and Pentland, 2006). The issues of COVID-19 also imply that human face-to-face interactions are essential even at the age of SNS (Ozili and Arun, 2020).

We have been investigating the continuous social dynamics using both a conceptual framework of social particle swarm (SPS) (Nishimoto et al., 2013), and anonymous web-based experiments with human subjects (Suzuki et al., 2018). It is still unclear however whether and how such cooperative relationships emerge in a large-scale or in face-to-face networks as mentioned above.

Our purpose is to further consider the continuous social dynamics under more extreme conditions extended from the SPS model; we implement a large-scale model using GPGPU (Elhamer et al., 2020a) and a face-to-face experiment using IoT devices (Elhamer et al., 2020b). In this paper, we briefly introduce both approaches, focusing on the effects of the information flow about strategies in both cases. Fig. 1 shows a schematic representation of our approach.

Large-Scale Social Particle Swarm Model

We consider \( N \) interacting agents in an abstract 3D toroidal space with periodic boundary condition, each with a position and a velocity (Fig. 2 and 3). Agents run three procedures at each time step: (1) cooperators estimation, (2) strategy update and (3) social relationship change. The first one entails estimating the ratio of cooperators among her neighbors using a formula: 

\[
e(t+1) = e(t) + (r(t) - e(t) \times I),
\]

\( I \in [0,1] \), where \( e(t) \) is the estimate at time \( t \) and \( r(t) \) is the actual ratio of cooperators at \( t \). \( I \) represents the information update rate about the neighbors, which can be small because of the limitation in cognitive abilities to social relationships in a large social network (e.g., Dunbar’s number). In strategy update, \( e(t) \) is compared against a cooperation threshold \( \text{thresh} \in [0,1] \), which is randomly assigned to each agent. If \( e(t) > \text{thresh} \), then the agent sets her strategy to cooperation, and to defection otherwise. The last process is expressed through steering forces, where an agent steers towards or away from the center of mass of her neighbors found within her interaction range depending on the sign of the total score obtained from her social relationship (see Fig. 2). The inverse of the distance represents the social closeness between players. Specifically, each agent receives the total score obtained from the payoff of the Prisoner’s
Dilemma game against all her neighbors divided by the distance between them. The generated steering force vector is obtained using Reynolds’s steering formula (Reynolds, 1999) (Fig. 2).

Simulations with 100,000 agents, using FlameGPU v1.5 (Richmond and Chimeh, 2017), yielded repeated emergence of spherical cooperative clusters followed by their explosion due to overpopulation by defectors (Fig. 3 (I)). On the other hand, when the update rate \( I \) was small (0.01), the population was dominated by many wandering defectors and cooperative clusters were few but consistent over time (Fig. 3 (II)), because cooperators tended to lose chances to form and grow clusters. This implies that the information update rate significantly contributed to the emergence of more dynamic and cooperative social relationships in a large-scale social environment represented by the formation of many cooperative clusters and an overall increase in the cooperation rate.

**Face-to-Face Experiments**

In an experimental room, each participant has a Raspberry Pi Zero WH with an LCD screen (Fig. 4 right), which simulates the game-theoretical situation to the SPS model in a physically grounded environment (Fig. 4 left). Players’ devices advertise their EddyStone UID via Bluetooth which comprises the ID of the player and her current strategy, which can be switched with a button by the player. The strategy can be shared via colors on the screen (red for defection; blue for cooperation) among players. Players can physically move in the room during the experiment. The score, which is accumulated throughout the session, changes according to both their strategy and the social closeness which is measured by the strength of the detected radio signal strength (RSSI) that reflects physical proximity between players. We adopted the same formula to the one in the 3D SPS model except that the social closeness was discretized (strong: 1.0, medium: 1/2, low: 1/3). Players were not notified of the end of the session. We ran four sessions with 5 players and discuss typical two sessions from them: In the first session, players were given instructions to hide their screen from others, and in the second one, they shared their strategies by showing their screen.

The strip plots in Fig. 5 show the dynamics in the number of close neighbors of which the social closeness was medium or high (black dots corresponding to values from 0 to 4 neighbors) of each player and her strategy (blue: cooperation, red: defection), and the average accumulated score and the average proportion of cooperators (black: low, white: high). In session 1, we see an overall tendency for players to alienate other players and to defect more often, which resulted in a low average accumulated score. On the other hand, session 2 shows a much-varied number of neighbors of individuals with transitory changes in their strategy while keeping the high proportion of cooperators, and thus resulted in a high accumulated score. This is expected to be attributed to being more responsive to others because access to the strategy information about them was possible via the LCD screen, and this facilitated chances of recognition and interaction with others.

**Conclusion**

We introduced two-extreme approaches for understanding the continuous social dynamics, and discussed the effects of information flow of others’ strategies on them. The results showed that the high information update rate in the large-scale model and visible information in the face-to-face experiment can bring about active social dynamics and contribute to cooperation. This work was supported in part by JSPS/MEXT KAKENHI JP17KT0001 and Topic-Setting Program to Advance Cutting-Edge Humanities and Social Sciences Research JP17J0011b.
References


