An IoT-based Framework for Understanding Continuous Social Dynamics in a Face-to-Face and Spatially Situated Environment

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Abstract: Interactions in human social environments are more continuously changing these days due to the recent progress in social networking services (SNS) in two senses: The temporal continuity in interactions and continuity in the closeness of social relationships. Nishimoto et al. constructed a simple computational model for investigating such continuously changing social relationships termed the Social Particle Swarm (SPS) model [1], showing repeated emergence and collapse of cooperative clusters of individuals. However, it is still not clear how face-to-face interactions can affect such dynamic social behaviors while the issues of COVID-19 clarify that human face-to-face interactions are essential even at the age of SNS. We propose an IoT-based framework for investigating face-to-face interactions which involve real human participants communicating with Raspberry Pi Zero devices through Bluetooth radio signals the strength of which reflects the social closeness between two given participants. The participants can press a button attached to the device to change their interaction strategy between cooperation or defection, and the devices have a screen that displays the current strategy in color, as well as the current accumulated score which is updated in real-time. We can simulate a similar situation to the SPS model in which the participants try to maximize their accumulated payoff by getting closer or away from others through an experimental trial. As a proof of concept, we introduce the whole framework and report that it worked properly as expected by showing two series of experiments. One was mainly to see if the framework can capture the dynamics of the social relationships such as the emergence and collapse of cooperative clusters. The second one compared the results against a web-based and anonymous version of online experiments to see the differences in the behavioral patterns of the participants between the two conditions.

Keywords: Social Particle Swarm, Prisoner's Dilemma, Real-time and face-to-face interactions experiments with human participants, Raspberry Pi, IoT devices

1. Introduction

Our social networks are transcending the physical boundaries and progressively embracing the virtual world. These networks are steadily increasing in size and encompass inherently continuous social interactions. In particular, contemporary online social networks provide continuities in two senses: The first one is the temporal continuity in that we stay connected to each other all the time through our handheld devices. The second is the continuity in the degree of social closeness, as we use various social networking services (SNS), each with a different topology of interactions that contains various channels of communication.

Based on the concept of self-driven particles models, Nishimoto et al. constructed a simple computational model for investigating such continuously changing social relationships termed the Social Particle Swarm (SPS) model [1]. They assumed individuals as particles in a two-dimensional social or psychological space, and each particle can switch a strategy for the prisoner's dilemma game, and also can get closer to (resp. away from) neighbors from which she obtains positive (resp. negative) payoffs. They observed repeated occurrences of explosive dynamics that consisted of formations and collapes of altruistic clusters, which reflects the dynamic aspects of real social networks. See Section 3, [1] or [2] for detail.

The concept of the original SPS model has been extended in order to understand the continuous social dynamics in different contexts using hybrid approaches [3]. Elhamer et al. analyzed the continuous social dynamics in a large-scale population such as SNSs by implementing a large-scale and 3D version of the SPS model using FlameGPU (Flexible Large Scale Agent Modelling Environment for the GPU) [4]. They found that the high information update rate about the strategies of the neighbors was essential for the emergence of dynamic and cooperative social relationships in a large-scale society composed of 100,000 agents [3].

Also, real-time decision making is getting much attention in experimental studies with human participants [5], [6], [7]. Suzuki et al. analyzed the continuous social dynamics in real human groups by implementing a web-based and multi-player game based on the SPS model in which human participants, represented as anonymous particles in a 2D and shared space, can change

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their positions and game-theoretical strategies in real-time, according to the benefits or costs arising from social relationships with neighboring players [8]. They found that the formation and collapse of cooperative clusters emerged in parallel, participants tended to be cooperative and tended not to be moving when the proportion of neighboring cooperators was high. This fact supports the validity of the behavioral rule of particles adopted in the SPS model.

Despite today's technological advancement which has reinforced our reliance on remote communication tools for interaction, various studies have demonstrated that face-to-face communication is no less important than these tools [9], [10], [11]. Several research groups have been developing new approaches for the study of close-proximity interactions [10]. In addition, the issues of COVID-19 clarify that human face-to-face interactions are essential even at the age of SNS [12].

The purpose of this study is to propose an experimental framework for studying the continuous social dynamics in face-to-face interactions, by further extending the hybrid approaches of the SPS model. We develop a framework for a social experiment with human participants in which they interact with others through Bluetooth messages assuming similar game-theoretical and spatial relationship to the original SPS model. We will be seamlessly discuss whether and how the specific assumptions in experimental and modelling settings extended from the SPS model can affect the social dynamics, including face-to-face conditions.

In this paper, we briefly introduce the original SPS model and introduce the proposed framework in detail. Then, as a proof of concept, we report experimental results to show that the framework worked as expected, and the participants exhibit emergent dynamics of cooperative clusters. We also discuss the behavioral differences of participants between the face-to-face and a web-based (anonymous) environment.

2. The Social Particle Swarm Model (SPS)

The Social Particle Swarm model is inspired by self-driven particles systems and is developed to model social interactions in the context of the prisoner's dilemma game. **Fig. 1** shows an image of the behavioral rule of a particle, see [1] for details. They assumed that individuals were in a two-dimensional and toroidal plane. This represents a social or psychological space in which the proximity between two individuals reflected their social or psychological closeness. Each particle has a strategy for the prisoner's dilemma (PD) game, and moves according to the force vector generated from the payoffs in the game. The behavior of the particles in each step consists of two sequential processes: First, all particles simultaneously decide whether to select cooperation or defection in the current step in a tit-for-tat fashion based on the proportion of cooperators among its neighboring agents within a fixed range in the previous time step. If this proportion is larger than an attribute value of each individual, termed cooperation threshold, the focal individual cooperates, and otherwise, it defects. Second, each individual receives attractive (repulsive) force from each neighbor who gives a positive (negative) payoff according to the payoff matrix of the PD game, whose magnitude is proportional to the payoff value and inversely proportional to the distance between the focal individual and the neighbor. Then, each individual moves toward the direction of the resultant vector of all forces at a fixed speed.

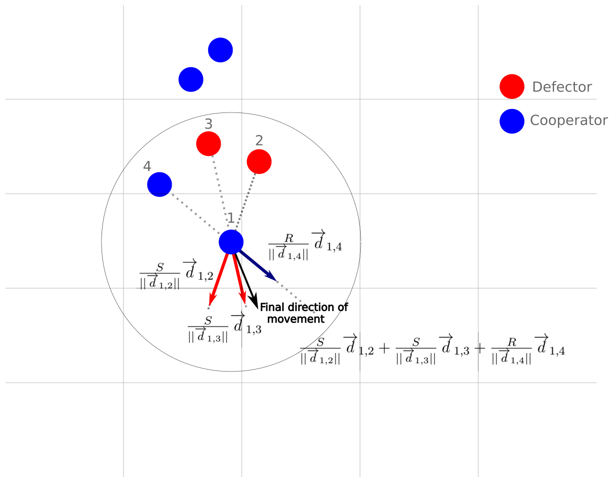

Fig. 1 Movement of social agents in the SPS model. $\overrightarrow{d_{a,b}}$ represents the vector from the agent b to a. R, T, S and P represent the payoff values of a standard prisoner's dilemma.

3. A Framework for a Face-to-Face Social Experiment

We developed a framework for a face-to-face and spatial social experiment with human participants. Each participant has a Raspberry Pi Zero device which has an integrated beacon that uses Bluetooth Low Energy technology to exchange signals with devices of others. Each participant shares their current game-theoretical strategy with the neighboring participants on a small LCD screen mounted on the device. They are asked to maximize their accumulated score which is summed from all the payoffs received from the neighbors, scaled by how far apart they are, meaning that the distance between the participants reflects their social closeness. Here, we explain each component of the framework in detail.

3.1 Hardware and Software Platform

We used Raspberry Pi Zero WH (Raspberry Pi Foundation) with an LCD hat and a set of buttons (ASHATA) as an interaction device (**Fig. 2**). The system was operated with DietPi (Linux) *1, and runs the program for an experiment written in Python. The codes are available upon request.

Each device with a unique ID holds a state of the strategy of the focal participant (cooperate or defect) that can be changed at any moment through the button press, and the accumulated score of the participant through a session. There are four types of information that are displayed on the device's screen (**Fig. 3**):
(1) The accumulated score over the session.
(2) The neighbors with the status of their strategy.
(3) The current strategy of the focal participant.
(4) The change rate in the received total score.

The devices exchange messages through Bluetooth Low Energy (BLE) radio signals. We used Google Eddystone Protocol

*1 https://dietpi.com

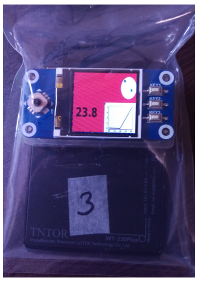

Fig. 2 The interaction device in action. Raspberry Pi Zero WH attached to TNTOR pocket-sized power bank

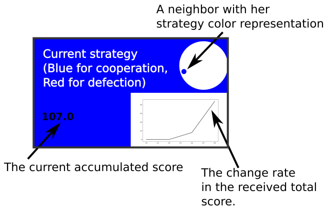

Fig. 3 The information on the LCD.

specification[*2] for defining the BLE message format which is broadcasted by the devices. These messages are represented in EddyStone-UID frames type[*3] which consists of a 16-bytes Beacon ID composed of a 10-byte namespace, and a 6-byte instance. It contains the ID and the strategy of a device.

3.2 Social Closeness

During the experiment, the players' devices are constantly scanning for each other and exchanging information which is encapsulated in Bluetooth messages. We divided the covered zones into three categories based on the strength of the received signal (RSSI) which represents how socially close the player is (**Fig. 4**), and assigned the social closeness factor (1, 1/2 and 1/3) to each category (strong, medium and weak).

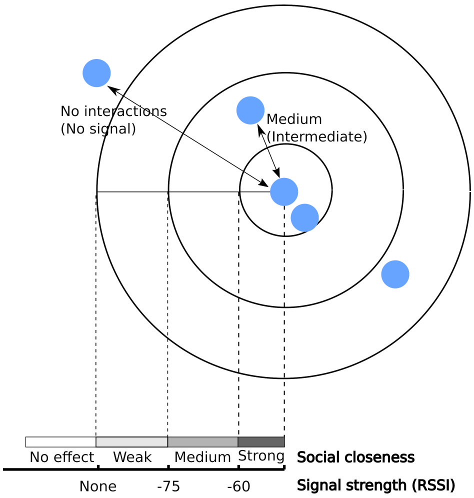

Fig. 4 The social closeness.

In order to determine the threshold values of the RSSI signal between closeness categories, we set up two Raspberry Pi Zero devices and put them apart at zero distance, and started recording the values of the received radio signals while gradually increasing the distance by fixing the location of one device, and moving the other device while maintaining the same height from the ground for both devices. After 500 trials, we obtained the graph shown in **Fig. 5** which shows the mean values of the RSSI strength with their standard deviations. **Table 1** highlights the different ranges of the signal strength and their corresponding social closeness factors. We adopted these threshold values because the higher signal values than around -60 were recorded at about 1 or 2 meter distance (immediate), and the values quickly became smaller and kept around -75 when the distance was near ($< 12m$). It should be noted that the RSSI values tended to fluctuate and become smaller during sessions due to the movement of devices. There are no social interactions between participants of which BLE signals were not detected (no signal).

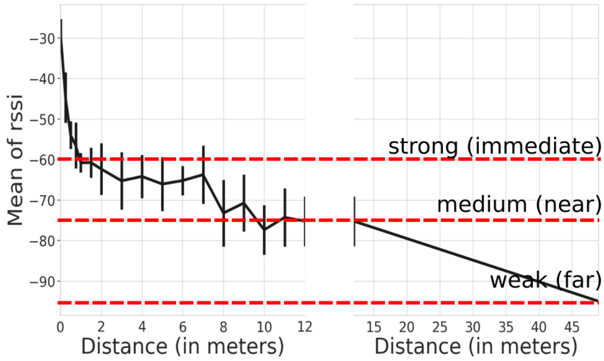

Fig. 5 The social closeness and the RSSI signal strength.

Table 1 Estimation of the social closeness based on the received radio signal strength values.

Signal interval	Signal category	Neighbor proximity	Social closeness value (s)
> -60	*Strong*	*Immediate*	1
$[-75, -60]$	*Medium*	*Near*	$\frac{1}{2}$
< -75	*Weak*	*Far*	$\frac{1}{3}$
no signal	no effect	non-neighbor	N/A

3.3 Experimental session

In each session, participants are interacting with each other in a confined physical space (**Fig. 6**), according to a PD game with the following payoff matrix: $\{T, R, S, P\} = \{1.8, 1.0, -1.4, -1.0\}$.

Fig. 6 A snapshot taken during the experiment.

The participants can read off their device's screen the status of their current accumulated score (increasing or decreasing), and check the detected neighbors as well as their strategy colors. We asked the participants to make their screen visible to the others so that they can see their strategy color (blue for cooperation; red for defection). Each participant's goal is to maximize their total

*2 `https://github.com/google/eddystone`
*3 `https://github.com/google/eddystone/tree/master/eddystone-uid`

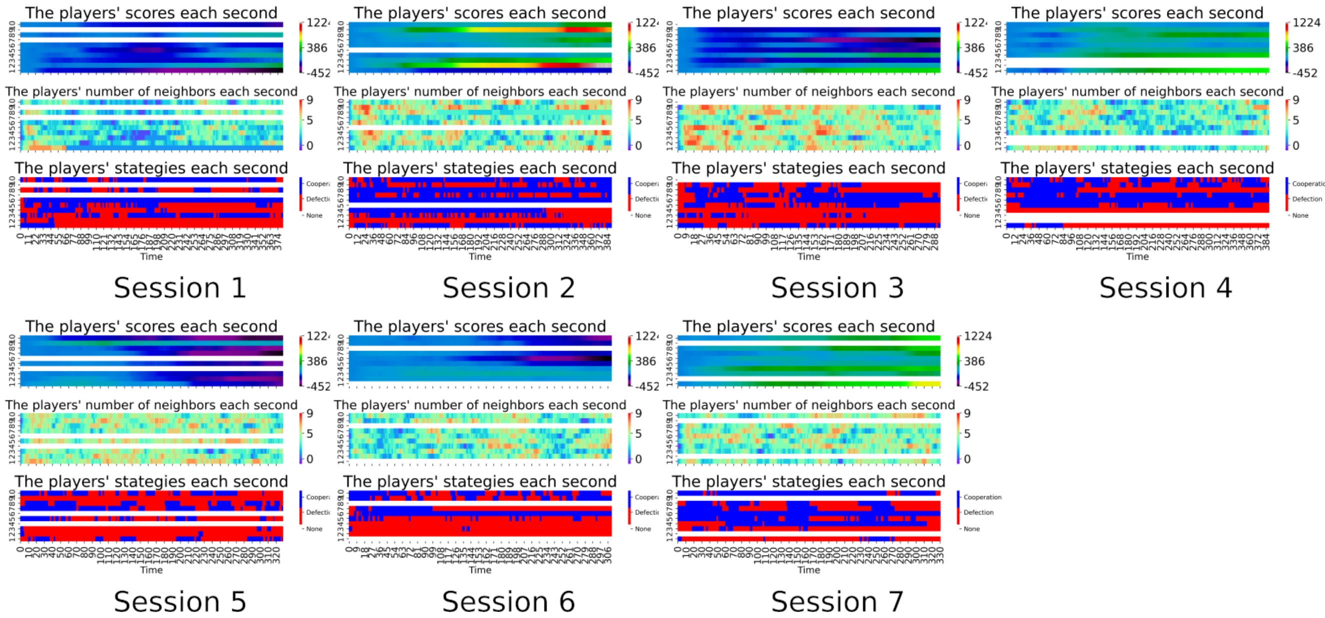

Fig. 7 Characterization of the tendencies of the players. The x-axis represents the time, the y-axis represents the ID of each player. The neighbors denote players who were detected within the strong and medium zones. White bars mean that the given player did not partake in this session

score using two mechanisms: (1) Either through a button press which switches the strategy between cooperation and defection, or through (2) physical displacement such as getting closer to those who offer benefit. The total score is obtained by summing the received payoffs from the PD game, scaled by the corresponding social closeness factors (s) as follows:

$$total\_score_i = \sum_{j \in neigh_i} pay_{(i,j)} \times s_i \tag{1}$$

where $pay_{(i,j)}$ is the the payoff player (i) receives from her neighbor (j). The total score of player (i) is the sum of all the payoffs she receives from her neighbors ($neigh_i$), scaled by the social closeness factors (s_i). Note that the update of the information of neighbors and the score calculation (accumulation) was conducted in intervals of a second during the session.

In addition, we deployed an Ad-Hoc Wi-Fi network so that the devices can log their interaction data to a remote server which also acts as a control point that sends Start/Stop messages to the devices' screen to inform them about the start/end of the session.

4. Results and Discussion

4.1 Experiment 1

The experimental procedures were approved by the planning and evaluation committee in the Graduate School of Informatics, Nagoya University (GSIS-H28-3 and GSI-R2-3). We recruited ten voluntary graduate students and asked them to interact with each other using the Raspberry Pi devices in a room (Fig. 6). The players were incentivized through monetary rewards at the end of the experiment. Talking was prohibited during the experiment. We asked the players to hide their screen from each other in the first session only in Experiment 1, but asked to share it with neighbors in the other sessions.

We ran seven sessions while changing a couple of players at each session to avert biases. Each session lasted for approximately five minutes. We kept a log of the interactions (such as the number of neighbors of each participant, their accumulated scores at each time-step, as well as their selected strategies) during the experiment. Note that, we regarded participants as neighbors when their received signal is within the 'strong' and 'medium' signal categories (immediate and near neighbor) in this paper. Thus, the information about the neighbors in this sense was indicated on the LCD of each device, and the neighbors in the subsequent analyses represent others in these categories.

4.1.1 Data Collection of Social Dynamics

The primary purpose of this paper is to show that the proposed system works, and we were able to obtain data on the social dynamics of the participants. **Fig. 7** presents very basic data showing the fine-scale behavioral dynamics (the accumulated score, the number of neighbors and the strategy) of each individual in each session. We see that some participants actively switched their strategies while others kept cooperation or defection through the session. The number of neighbors varied strikingly throughout the experiment, marking the emergence and collapse of clusters. We also see the changes in the accumulated scores were either collectively increasing or decreasing on average.

4.1.2 Basic Analysis

Fig. 8 shows the average of the accumulated score, the average number of neighbors and the proportion of cooperators, as basic indices of global dynamics. We see that the average proportion of cooperators tended to fluctuate significantly while the number of neighbors tended to keep intermediate values. It also shows the changes in the distribution of clusters at a fixed time-step interval. A cluster comprises a group of participants who are recognized by at least one member of the focal group as neighbors. The proportion of cooperators in each cluster is indicated through the degree of the opacity of the color (plain green meaning a 100% cooperative cluster, and a fading color indicates a 100% defectors in the cluster). Throughout the sessions, the par-

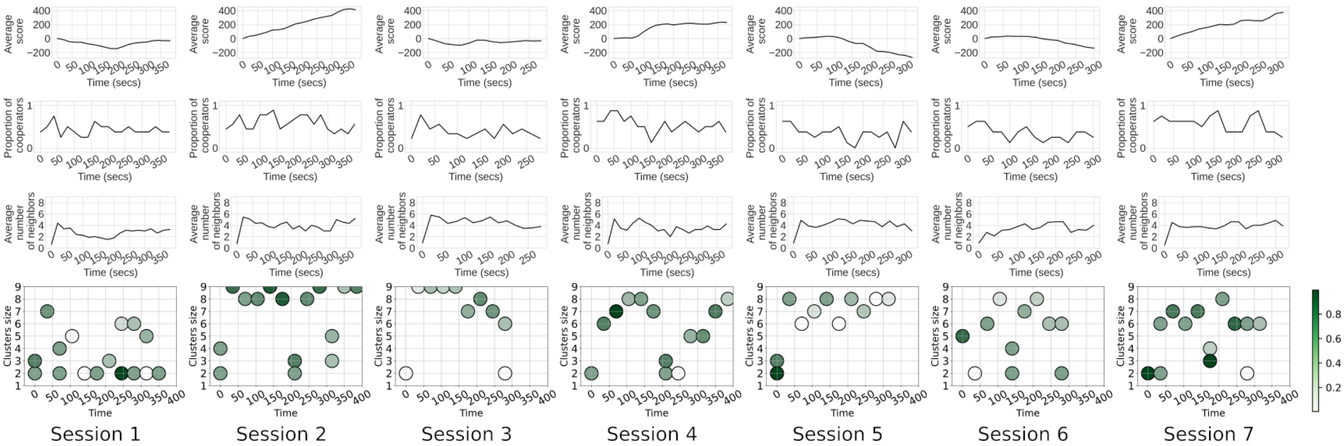

Fig. 8 From bottom to top: Time-lapse of the formation and dissipation of clusters in each session. The color intensity indicates the cooperation rate inside the cluster. Average number of neighbors. Average values of the proportion of cooperators. Average values of the accumulated scores of the players.

ticipants started off as several clusters such as in the sessions 1 and 2, and then they adapted to form solid clusters larger in size in general. Eventually, these groups did not last and dissipate due to being over-populated by defectors (i.e., the cluster color fades away before dissolution). This is denoted by the wave-like pattern of the plots, which is observed in the session 4 and 6. We also see that the large cluster contributed (or did not contributed) to the overall scores in the session 2 (or 5). Thus, the proposed system can observe various patterns of social dynamics in face-to-face conditions.

4.1.3 Behavioral Analysis

Further, we discuss the patterns of behavioral tendency, focusing on the correlations between several indices.

Fig. 9 shows a pair plot of the mutual relationships between the cooperation rate, the rate of strategy change, the rate of changing neighbors and the accumulated score. Each plot represents the corresponding value calculated over each session for each participant. The linear regression line with a confidence interval was also indicated.

We note that there exist weak correlations where a high tendency to change social relationships brings high scores while a high tendency to change strategies (which increases the cooperation rate) brings low scores. because of a weak positive correlation with a high cooperation rate. The degree of cooperation had a weak negative correlation with the scores while it varied among participants and sessions. This is expected to be due to the exploitation by defectors in cooperative clusters.

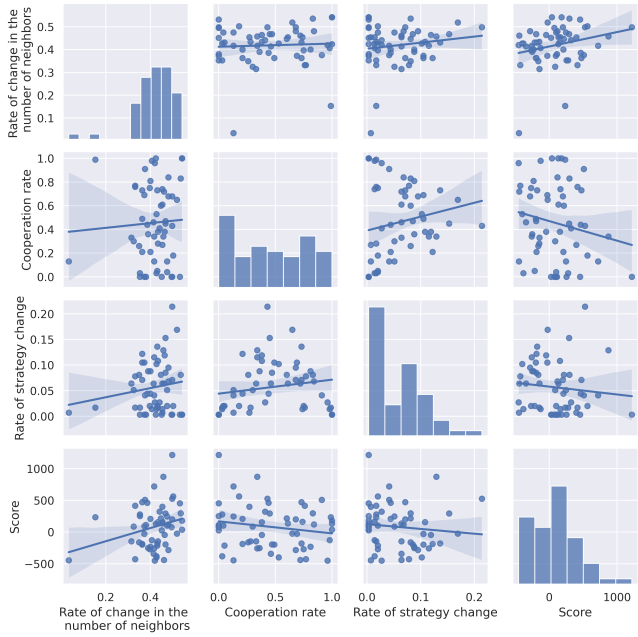

Fig. 9 A pair plot of the mutual relationships between the cooperation rate, the rate of strategy change, the rate of changing neighbors and the accumulated score.

4.2 Experiment 2

We conducted a face-to-face experiment and a web-based experiment with the same five graduate school students while keeping the same payoff matrix. The web-based experiment uses a framework developed by Suzuki et al. [8] based on the SPS model, which comprises human participants interacting with each other online. Each player is placed in a 500×500 px 2D torus as a small dot at the center with her strategy color (blue for cooperation; red for defection) and is assigned a handle. The dot is positioned inside a circle representing her interaction range. During the experiment, players can only see other players located within their interaction range and can move their virtual selves in all directions through the mouse by placing the mouse cursor outside their interaction circle which will make the focal player follow the mouse at a fixed speed. The players' strategy can be changed by pressing the '**C**' key from the keyboard. The radius of the interaction range and the moving speed is fixed for all the players. The score each player obtains from her interaction with a given neighbor is defined as the payoff from a PD game, which is divided by the distance between the focal player and the neighbor. The total score obtained from all the neighbors is accumulated with a short time interval of 0.5 seconds during the experiment. We ran three sessions, each one lasting for about five minutes.

Fig. 10 shows the network of the social interactions between the players during the three sessions in the face-to-face and the web-based experiments. We see that the network structure in the face-to-face experiment did not change much between the three sessions. For example, the edges between participants 1-5, 2-4, and 3-5 consistently existed through the sessions. This is because the participants preserved their relationships with some others in this small population. In the web-based experiment, the network showed larger variations between the participants over the sessions. This is expected to be due to the anonymity of the participants and that participants who were not detected by others provide no information about their locations and strategies to others. However, It is interesting that even in anonymous conditions, there exist consistent relationships between some participants, which is expected to be because they were able to create social patterns only from their own behaviors, while the face-to-face settings facilitated this process even more.

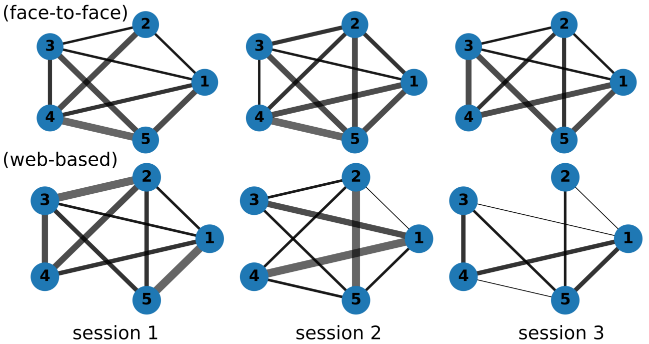

Fig. 10 Network layout of interactions in the face-to-face and the web-based experiments.

Fig. 11 summarizes the average values of the cooperation rate, the interaction rate, and the total score of each player in the three sessions in the face-to-face and the web-based experiments. We define the interaction rate as the proportion of participants who had at least one neighbor.

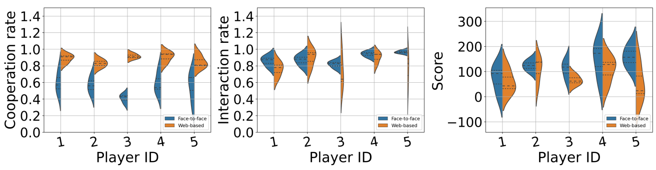

Fig. 11 The average cooperate rate, average interaction rate and the average score of each player across the three sessions in the face-to-face and the web-based experiments.

In comparison, cooperation rate in the face-to-face experiment was small while the scores were high. This could be due to the availability of information about the status of other players, such as spatial locations and strategies which facilitated being spotted and defected against, thus allowing for more defections which in turn brought about rapid changes in the spatial relationships. Conversely, limited information access in the web-based experiment promoted cooperation in the sense that limited information led to slow formation of cooperative clusters thus urging the players to choose cooperation to preserve their social relationships.

The observed difference between the face-to-face and the web-based experiments may be attributed to the difference in the information visibility within these conditions mentioned above, which is related to the information update rate about the proportion of neighboring cooperators in the 3D version of the SPS model [3].

5. Conclusion

In this paper, we proposed a framework for studying continuous social dynamics in the context of face-to-face interactions. We designed and implemented a physically bounded social interaction framework and adopt it for running two experiments. We successfully collected fine-scale data on the participants' behavior, which indicated that there existed personal differences in strategy selections, for example. The further analyses showed that similar dynamics of formation and dissipation of small cooperative groups observed in the SPS model were observed. Another experiment comprising five participants playing in two different settings: face-to-face and web-based, showed that access to information about the other players can quickly bring about dynamically changing cooperative interactions, while conversely, limited access to information can bring about steady cooperative relationships but slow to grow. This tendency was well-fitted with the findings obtained from a large-scale computational model. This implies that our framework can contribute to a better understanding of continuous and social dynamics which are becoming ubiquitous in both face-to-face and online communications.

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