A Design of a Virtual Agent that Facilitates a Spatial and Online Communication by Use of Social Particle Swarm Model

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Abstract

This paper aims at considering novel and practical applications of ALife techniques to design a co-creative social dynamics in an online and virtual space, which is becoming important because of the recent emergence of various types of online communication platforms due to outbreaks of COVID-19. Recently, spatial and online communication services, such as SpatialChat, have attracted more attention. Each participant is represented as an avatar or icon in a virtual 2D space. She can move it around in the space and listen to neighbors’ voices of which volume become louder as they get closer to her. However, the overall structure of communications tends to be deadlocked, which might make participants lose chances to communicate with many other people. We design and investigate a virtual agent, called “facilitator agent,” as a study towards realization of practical agents that facilitate novel and cooperative interactions in a spatial and online communication by giving human participants opportunities to communicate with many others cooperatively. We adopt a Social Particle Swarm (SPS) model to simulate group dynamics in this type of communication service. We assume several behavioral patterns of a facilitator agent with fixed game-theoretical strategies and several movement strategies. We discuss how incorporating a single facilitator agent into the space can increase novel and cooperative interactions in several behavioral settings of the facilitator agent. We also report on a preliminary experiment on designing a facilitator agent using a deep reinforcement learning technique.

Introduction

The impact of the COVID-19 has changed our daily life dramatically. Our face-to-face communication has been limited and instead, opportunities for online communication at work and school have increased. As well as standard online meeting services such as Zoom, Teams and Google meet, spatial and online communication services such as SpatialChat and oVice have attracted attention. Recently, IJCAI2020, one of the largest conference on AI, has been held on such a virtual venue on gather.town. In these services, each participant is represented as an avatar or icon in a virtual 2D space, and she can move it around the space. She can listen to neighbors’ voices of which volume becomes louder as they get closer to her. We can expect some groups talking with each other emerge spontaneously. However, there are also some issues. For example, each group tends to be isolated from one another once some groups are formed. Also, it is not easy for participants to figure out a timing to leave the group when the group size is small. As a result, the overall structure of communications tends to be deadlocked, which might make participants lose chances to communicate with many other people. Such a lack of opportunities for novel social behaviors to occur could be due to the limitation of channels in online communications, and thus we believe that a mechanism that can compensate for the low relational mobility would be necessary.

There has been increasing attention in designing a hybrid society composed of humans and virtual agents to be cooperative or pro-social (Paiva et al., 2018). For example, the performance of group behaviors can be improved when a bot is put into a group of humans performing cooperative or collective tasks. Shirado and Christakis conducted experiments involving a networked color coordination game in which human participants interacted with bots and showed that bots acting with small levels of random noise improved the collective performance of human groups (Shirado and Christakis, 2017). They also showed cooperative relationships could also be improved by incorporating bots into a networked population playing public-goods game (Shirado and Christakis, 2020).

This paper aims at considering novel and practical applications of ALife techniques to design a co-creative (i.e., mutually cooperative and creative) social dynamics in an online space, which is becoming important because of the recent emergence of various types of online communication platforms. Specifically, we design and investigate a virtual agent, called “facilitator agent,” as a study towards realization of practical agents that facilitate novel and cooperative interactions in a spatial and online communication by giving human participants opportunities to communicate with many others cooperatively. As a first step toward this re-
search direction, we adopt a Social Particle Swarm (SPS) model to simulate group dynamics in this type of communication service. Nishimoto et al. proposed the SPS model to represent and discuss continuously changing psychological and social relationships using a self-driven particle system \cite{nishimoto2013,nishimoto2014}, which will be explained in detail later. This model showed that the emergence and collapse of cooperative clusters occurred repeatedly, and similar dynamics were also observed in an online experimental framework with human participants \cite{ito2018}. We regard the two-dimensional space in the SPS model as a virtual space in online communication services, and regard cooperative behavior as a contribution to discussions among neighboring participants.

In this paper, we assume several behavioral patterns of a facilitator agent with fixed game-theoretical strategies and several movement strategies. We will discuss how incorporating a single facilitator agent into the space can increase novel and cooperative interactions in several behavioral settings of the facilitator agent.

We also report on a preliminary experiment on designing a facilitator agent using a deep reinforcement learning technique.

**Social Particle Swarm Model**

The SPS model, designed for analyzing continuously changing social dynamics, is a system of self-driven particles whose behavior is defined based on game theory \cite{nishimoto2013,nishimoto2014}.

In this model, human individuals are represented as $N$ particles, which are placed in a two-dimensional ($W \times W$) and toroidal space representing their social and psychological space. The distance between two particles reflects their social closeness. In the original model, it was assumed that this space approximates structures of all possible communication channels, including both physical (i.e., face-to-face) and online (i.e., SNS) social networks. Here, we regard this space as a virtual space in the spatial online communication tools (e.g., rooms, venues).

Each particle has a strategy (cooperate or defect) for the prisoner’s dilemma (PD) game and moves according to the payoffs received from neighbors in the game. We regard that cooperative particles represent that they are contributing to discussions among neighboring individuals by providing useful or intriguing information for them. Defecting particles also represent individuals who are not interested in the topic or only exploiting the knowledge provided by others (or simply boring). The strong simplification of possible state of the strategy (C or D) might reflect the limitation of communication channels in online communications.

The behavior of the particles in each step consists of two phases, strategy selection phase and movement phase, as follows.

**Strategy Selection Phase**

All particles simultaneously decide whether to select cooperation or defection in the current steps in a tit-for-tat fashion based on the strategies of their neighbors as follows (Figure 1). Each particle has a cooperation threshold $c$ representing its tendency to select cooperation strategy. Each particle recognizes other particles within a radius of $R$ around itself as its neighbors. It calculates $r_c$ (the ratio of cooperators among the neighbors in the previous step) and then, it selects cooperation as the strategy for the current step if $r_c \geq c$, and otherwise selects defection (Figure 1).

In addition, the selected strategy is flipped with a small probability of $p$, accidentally.

![Figure 1: Strategy selection phase. Each particle selects the strategy for the next step according to the current proportion of cooperators in its neighbors.](image)

**Movement Phase**

Each particle $i$ receives attracting or repulsive forces from a game theoretical relationship (payoff) defined in Table 1 with each neighbor $j$, shown in Figure 2.

![Table 1: Payoff matrix. $P(s_i, s_j)$: a payoff value that a player $i$ with the strategy $s_i$ receives from a game theoretical relationship with a player $j$ with a strategy $s_j$.](image)

<table>
<thead>
<tr>
<th>player $i$</th>
<th>Cooperate</th>
<th>Defect</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cooperate</td>
<td>$R$ (=1)</td>
<td>$S$</td>
</tr>
<tr>
<td>Defect</td>
<td>$T$</td>
<td>$P$ (=1)</td>
</tr>
</tbody>
</table>

If a payoff value that a player $i$ receives from a player $j$, $P(s_i, s_j)$, is positive (or negative), $i$ receives a force that attracts $i$ to $j$ (or pushes $i$ away from $j$). The magnitude of each force is defined by

$$p(i, j) = \frac{P(s_i, s_j)}{|d_{i,j}|},$$

where $d_{i,j}$ is the vector from $i$ to $j$. This equation means that the magnitude is scaled inversely with the distance between them, representing that the shorter the distance is, the stronger their relationship is and thus the greater the effect of the relationship becomes. In other words, participants get closer to their close neighbors who are contributing to discussions but get away from those who do not in the context discussed in this paper.
Eqs. 2 and 3 show that the velocity vector of $i(\vec{v}_i)$ is the resultant force from all neighbors $(\vec{c}_i)$ but its speed is set to a constant value $v$.

$$\vec{c}_i = \sum_{j \in \text{neighbor}} p_{i,j} \frac{d_{i,j}}{|d_{i,j}|},$$  \hspace{1cm} (2)

$$\vec{v}_i = \frac{v}{|\vec{c}_i|} \vec{c}_i,$$ \hspace{1cm} (3)

All particles move on the basis of the calculated velocity vector in parallel (Figure 2). The particles without neighbors move in random directions.

**Facilitator Agent**

We incorporate a single “facilitator agent” into the SPS model. The facilitator agent is designed to act according to a-priori game and movement strategies, which are different from other normal particles in the SPS model. We also expanded her degree of influence on neighboring particles.

**Game strategies**

The game strategy of a facilitator agent is fixed to either cooperation or defection. In other words, it does not change the strategy in an experiment.

**Movement strategies**

We assume three types of movement strategies (random walk, Lévy flight and approaching neighbors) for the facilitator agent (Figure 4).

- **Random walk**
  The facilitator agent moves at a fixed speed $v_A$ in a random direction (chosen from eight directions) every step.

- **Lévy flight**
  The facilitator agent moves in a random direction in a manner similar to the random walk except that the speed follows a Cauchy distribution defined by the equation:

$$v_A = x_0 + \gamma \tan (\pi (p - 1/2)),$$ \hspace{1cm} (4)

where $p$ is a uniform distribution from 0 to 1. Since its speed follows a long-tailed distribution, the agent walks around the current position but occasionally jumps farther.

- **Approaching neighbors**
  The facilitator agent moves at a fixed speed $v_A$ every step and moves closer to the center of mass of all its neighbors. Thus, it moves toward a close group.

**The degree of influence on neighboring particles**

The facilitator agent has two additional parameters, which determine its degree of influence on neighboring particles: the difference in its interaction radius $R_A$ from those of the neighbors.
other particles \((R)\) and the payoff coefficient \(\beta\), as shown in Figure 5.

The facilitator agent is recognized by particles within a radius of \(R + R_A\) around the facilitator agent as a neighbor. Each neighbor receives a payoff \(\beta\) times larger than the corresponding normal payoff (received when playing with normal particles) from the facilitator agent.

![Figure 5](image)

Figure 5: The facilitator agent interacts with neighbors within a radius of \(R + R_A\) and neighbors receive \(\beta\) times of normal payoff.

### Degree of novel and cooperative communication (NC)

To quantify the degree to which novel and cooperative communication is facilitated, we defined the degree of novel and cooperative communication \((NC)\) as follows:

\[
NC = \frac{1}{N} \sum_{i} \frac{N_{nc}(i)}{N-1},
\]

where \(N_{nc}(i)\) represents the number of other particles with which a particle \(i\) kept playing cooperate-cooperate games more than \(n\) steps in an experiment. \(n\) reflects the depth of cooperative relationship required for establishing novel social relationships. This may vary according to the context of online communications or the individual difference in the purpose for participating communicative interactions. We adopt a fixed and shared \(n\) for simplicity in this paper.

The higher \(NC\) is, the larger number of novel other participants had opportunities to spend a certain amount of time to cooperatively communicate with. We expect that a population with high \(NC\) would be more co-creative in that they can exchange their ideas with many others constructively.

### Experiment and Discussion

#### Experimental settings

We used the default parameters as follows: \(N = 300\), \(W = 400\), \(R = 60\), \(v = v_A = 10\), \(p = 0.03\), \(n = 5\), \(S = -1.7\), \(T = 1.7\), \(x_0 = 5\), and \(\gamma = 1\). We adopted this setting as a typical situation in which the SPS model tends to exhibit Class 3 (Class1 : 24%, Class2 : 32%, Class3 : 37%). The position, strategy and \(c\) of each particle were initialized with random values. The variation in \(c\) represents the diversity in cooperativeness among particles, which can facilitate the emergence of Class 3 [Nishimoto et al., 2013]. We conducted experiments with all possible combinations of game strategies, movement strategies, and several values of \(R_A\) and \(\beta\). We measured the \(NC\) by conducting experiments 25 times \((t = 300\) steps\) in each setting. The source codes and data are available online.

#### Basic results

Figure 6 shows the average \(NC\) in each setting represented as the rate (%) of increase or decrease from the \(NC\) in the case without the facilitator agent (=0.46). The facilitator agent had a significant effect on the \(NC\) since it increased up to around 18% and decreased up to around 22% from the original condition.

We found two types of facilitator agents who could increase the \(NC\) when their degree of influence \((R_A\) and \(\beta\)) was high, as illustrated in Figure 7. One is a defecting agent following the Lévy flight or a random walk strategies, who repelled others. The other is a cooperating agent approaching the center of mass of neighbors, who attracts many neighbors.

![Figure 6](image)

Figure 6: The degree of novel and cooperative communication \((NC)\) in each setting of facilitator agent. The value is represented as the rate (%) of increase (red) or decrease (blue) from the \(NC\) without a facilitator agent (0.46). The row and column of tables represent movement and game strategies, respectively. The row and column in each table represent beta and \(R_A\), respectively.

Figures 8 and 9 show typical behaviors of the former type of facilitator agent. In these cases, other particles tended to avoid the defecting facilitator agent, because they received a large negative payoff regardless of their game strategies. This modified the structure of close clusters directly and led to their collapse, which further led to formation of a new cooperative cluster later (Figure 8). In addition, we observed that the facilitator agent broke clusters indirectly in that repelled particles from the facilitator agent invaded into other clusters, making them collapse (Figure 9). The reason why the Lévy flight strategy was more effective to increase the \(NC\) than the random walk is that an occasionally occurring
Figure 7: Two types of the facilitator agents who increased the $NC$. Left: cooperating agents with random walk, right: defecting agent with approaching neighbors.

long jump allowed the facilitator agent to explore the whole space, making more groups collapse.

Figure 8: A typical behavior of a defecting facilitator agent with Lévy flight, who breaks a cooperative cluster directly. A video link: https://bit.ly/3rpfVtq

Figure 9: A typical behavior of a defecting facilitator agent with Lévy flight, who breaks a cooperative cluster indirectly. A video link: https://bit.ly/3bjPnnL

Figure 10 shows a typical behavior of the latter type of facilitator agent. Here, other particles were attracted to the cooperative facilitator agent because they received a large positive payoff regardless of their game strategies. Once it gathered many particles, it approached and joined a neighboring cooperative cluster. This further brought about an explosion of that large cluster due to the major change in the relationships in the group.

At the same time, the facilitator agents rather decreased the $NC$ in opposite combinations of settings in that the game strategy was flipped. This is expected that the overall behaviors to facilitate novel and cooperative communications explained above were strongly dependent on mutual effects of game-theoretical and movement strategies.

Figure 11: The degree of novel and cooperative communication ($NC$) in each setting of facilitator agent represented as the rate of increase from the $NC$ without the facilitator agent (0.45). Class 1 occurring condition ($R = 120$).

Figure 12: The degree of novel and cooperative communication ($NC$) in each setting of facilitator agent represented as the rate of increase from the $NC$ without the facilitator agent (0.45). Class 2 occurring condition ($R = 45$).

Effects of the basic dynamics in the SPS model on roles of the facilitator agent

The performance of the facilitator agent would depend on the basic dynamics emerging in the SPS model. The SPS model tended to be in Class 3 in the previous experiments. Here, we further investigate how the facilitator agent can affect the $NC$ under the conditions in which Class 1 or 2 occurs frequently. Since the previous study (Nishimoto et al., 2014) has shown that Class 1 and 2 occur more frequently when $R$ is large and small, respectively, we used $R = 120$ and 45 so that Class 1 (Class 1: 45%, Class 2: 18%, Class 3: 37%) and 2 (Class 1: 27%, Class 2: 52%, Class 3: 0.21%) occur more frequently without the facilitator agent, respectively.
Figure 12: The degree of novel and cooperative communication (NC) in each setting of facilitator agent represented as the rate of increase from the NC without the facilitator agent (0.39). Class 1 occurring condition ($R = 45$).

was much higher as a whole. This means that breaking cooperative clusters by the facilitator agent better contributed to the increase in the NC when particles tend to form stable clusters.

A facilitator agent based on a deep reinforcement learning

The behavior of the facilitator agents discussed so far was based on a combination of manually defined strategies. There has been a significant progress in the techniques to acquire behavioral rules for game playing using deep reinforcement learning techniques. It is still a challenge to design an adaptive behavior of individuals in terms of the global benefit (i.e., the increase in the NC) in a multi-agent and game theoretical situation, with such a learning framework.

We conducted an additional experiment to acquire an efficient behavior of the facilitator agent using a deep reinforcement learning. We assumed the settings as follows: The input information is an 84x84 grayscale image of a snapshot of the field around the facilitator agent. The image illustrates the positions and strategies of neighboring particles. We used a set of images of the previous 4 time steps as the whole input information at each time step. The output is a behavioral pattern chosen from a set of 16 patterns (i.e., 8 directional movement with the speed $V_A \times 2$ game strategies to keep or switch the current strategy). For each particle, we counted the number of other particles who satisfied a condition that it established mutual cooperation with the focal particle for $n$ time steps until the current step. The average of it over all particles was used as a reinforcement signal for the facilitator agent for each time step. We adopted PFRL (a deep reinforcement learning library that implements various state-of-the-art deep reinforcement algorithms in Python using PyTorch) [Fujita et al., 2019] for implementation and used Rainbow algorithm [Hessel et al., 2018] for a reinforcement learning, with default parameters for example defined in PFRL.

We assumed a small population composed of $N=50$ particles for simplicity, and used other parameters as follows: $W=400$, $R R_A = 60$, $v = v_A = 10$, $\beta=4.0$, $p = 0.03$, $n = 5$, $S = -1.5$ and $T = 1.5$. We conducted 20,000 episodes, each composed of $t=300$ time steps. We observed a steep increase in the NC until around 200th episode and exceeded 0.5 at until around 700th episode. However, it gradually decreased and converged to around 0.42, while it was higher than the one with no facilitator agent (around 0.37), which indicates that the algorithm settings have much room to improve. Fig. [13] shows an example behavior of the facilitator agent who acquired the best NC. It acquired a simple behavior that moves straight keeping the defection strategy (Fig. [13] (bottom)). This is simple but beneficial because the agent can scan or explore to find and break clusters over the whole space, by using the property of the space, which is toroidal. Simultaneously, the agent occasionally gathered other particles to create a cooperative cluster (Fig. [13] (top)) for a while from the initial time step, then switched to the above defection strategy. This behavior appeared to be beneficial to prevent the whole population from falling into Class 1 composed of repelling defectors. This implies our approach enables us to design more flexible behavior of facilitator agents.

Figure 13: An example behavior of the best facilitator agent acquired with a deep reinforcement learning. A video link: https://bit.ly/2N7zhEh

Conclusion

We examined novel and practical applications of ALife techniques to design a co-creative social dynamics in an online space, which is becoming important because of the recent emergence of various types of online communication platforms due to the outbreak of COVID-19. We investigated whether and how a novel and cooperative communication in a spatial and online communication service such as SpatialChat, as a minimal platform, can be facilitated by incorporating a virtual facilitator agent into the space.

We used the SPS model as a simulated population of com-
municating human participants. It should be noted that we observed similar patterns of emergence and collapse of cooperative clusters occurred in a web-based experiment with more than 20 participants, and their behavior showed a validity of the definition of the behavior of particles in the SPS model (Ito et al. 2018). In the model with a manually-designed facilitator agent, we found that the cooperating agent approaching neighbors and the defecting agent following the random walk or Lévy flight strategies facilitated novel and cooperative communication. This implies that two types of virtual agents can contribute in an online and spatial communication space (e.g. a room in SpatialChat) as follows: 1) A virtual agent who actively gathers participants by broadcasting an attractive information or topics for other participants to make them join an exiting cluster, further expecting its collapse, 2) a wandering agent who broadcasts not-so-interesting information or even noise can give existing participants to explore novel chances to communicate with other participants.

We also used a machine learning technique to design a behavior of an agent that can contribute to the benefit of the whole social dynamics. While still preliminary, our result showed a possibility that a more adaptive behavior (i.e., switching strategies) can be acquired by further investigations.

There exist limitations in the current approach. The state of humans in real communication might not be simply classified into two extreme states (i.e., cooperative or defective). A comparative and complementary approach based on both large-scale models and corresponding web-based/face-to-face experiments can contribute to the design of more natural representation of communication dynamics (Elhamer et al. 2020). We also believe using a generative model of text information such as GPT-2 (Radford et al. 2019) or GPT-3 (Brown et al. 2020) to simulate conversations among particles would be one of the promising research directions.

Furthermore, experiments with multiple facilitator agents or with a smaller $\beta$ (than 1) would be the situations to be investigated. While the difference in the cooperation threshold among particles reflects individual variation in cooperativeness, it would be important to consider effects of the variations in other factors that could affect real human behavior (e.g., culture, context, gender) on the social dynamics in the model. Incorporating a virtual facilitator agent into a real online communication system based on a virtual space is also another future work.

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**References**


