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Agent-based Social Simulation Model for Analyzing Human Behaviors using Particle Swarm Optimization

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Abstract—**The recent spread of personal digital assistants capable of connecting to the network has made Internet access a commonplace activity, enabling anyone to exchange all sorts of information via the network. As in the real world, a wide variety of human values exist on the Internet, which is a place where people can communicate and interact with each other. In this way, analyzing behavior when information propagates from one person to another during inter-personal exchanges on the Internet would be important for creating new social systems, but it has been difficult to represent complex human values in conventional agent-based simulations. With the aim of simulating how differences in human value systems can affect exchanges between people, this paper proposes an agent-based information-propagation model for an Internet society using particle swarm optimization (PSO), which is a type of swarm-intelligence algorithm. This model facilitates the representation of diverse human values in the real world and the evolution of human society driven by changes in values, and makes it possible to analyze the effect of different value systems on information propagation. Simulation experiments reveal how differences in the community environments that exchange information and the features of their value systems affect the process of information propagation.**

Keywords-intelligence algorithm; social simulation; particle swarm optimization; agent-based modeling

I. INTRODUCTION

The recent spread of network-capable personal digital assistants, such as personal computers, mobile phones, and smartphones, has brought us into close contact with the Internet. This has also enabled people around the world to exchange a huge range of information easily, through word-of-mouth sites, Q&A communities, social networking services (SNSs) such as Twitter and Facebook, and consumer generated media (CGM) called blogs, and the Internet is expanding dramatically. New systems called clouds have recently appeared, further enriching the social lives of businesses and people and leading to a state in which business cannot be done without a network [1]. These CGM sites on the Internet provide places where people can acquire information easily and communicate with each other [2].

The distinctive feature of the Internet society can be seen as: "People gather together to form communities, and each person behaves in various ways by interacting with the other people within the community." In addition, if we view a CGM in community units, the ease of acquisition of information that is helpful to the searcher and a state in which information propagates from person to person will differs for each community the searcher belongs to. Furthermore, since the Internet is accessed from all over the world, we can assume that there are people having a number of different value systems, and these people will interact with each other through CGMs and acquire information that is helpful to themselves. Since these people have different value systems, whether or not a certain bit of information is interesting will differ between people. In other words, even with the same information, the value of that information will depend on the recipient.

We can consider Web searches as an example of considering human value systems over the Internet. When using the Internet to search for certain information, the searcher can only search from the standpoint of his or her own knowledge and experience, which often makes it a struggle to reach the desired information or the search efficiency will deteriorate. At this point, the searcher could obtain search results of highly accurate information efficiently by receiving pointers on keywords or URLs from an expert who has extensive knowledge and experience. However, even if the expert receives guidance from an inexperienced searcher who has limited knowledge and experience, the search efficiency could still deteriorate because of delays or the mixing in of obscure keywords.

Thus, analysis of the effects on information propagation generated by differences in the value systems held by people is also important in comprehending social phenomena and constructing better social systems. In this manner, there has been a great deal of research recently into social simulations using agents, as methods of analyzing social phenomena such as the propagation of information from person to person [3][4][5]. People think and act on things on the basis of their own value systems, and their value systems change and grow every time they gain experience. When we model a society with humans as the constituent elements, it is necessary to define and describe complicated social behaviors and various different value systems. However, since the various different value systems and behaviors of humans are complicated, reflecting them as agents is not simple.

To that end, this study perceives that "human value systems are expressed in actions", and has focused on the swarm intelligence algorithm of an optimization method that is a model representing the motions of a swarm and particle swarm optimization (PSO) [6]. In PSO, we express the "action" of a person by a motion vector of an individual particle (search point). We also define a gathering of particles to be a swarm, and express a human value system as an "evaluation function" that evaluates the motion vector of each individual particle and the location at the end of the particle's motion. PSO is a model in which the surrounding particles are all associates and the particles cooperate with each other and search efficiently by behaving as a swarm. This is similar to the process in a real-life society in which each person obtains information that is helpful to him or her, while competing to communicate through the Internet with other people. Taking advantage of these features of PSO, we construct an environment such as the Internet in which people interact by exchanging information as a social simulation model, using an improved version of PSO in which the concept of selection (natural selection) has been incorporated [7], express the diverse value systems of people in the Internet society by using various different evaluation functions, and analyze how the process of information propagation is affected by differences in the value systems of other people who are exchanging information.

The structure of this paper is as follows. In Section II, we introduce research relating to social simulation. In Section III, we introduce the algorithm of PSO that is used in this research. Section IV gives specific description of a social simulation model proposed by this paper. Section V discusses information propagation in environments containing a number of agents having different evaluation functions. In Section VI, we discuss the conclusions obtained in this paper and future challenges.

II. SOCIAL SIMULATION

Multi-agent based simulation (MABS) is a method that has recently been used for analyzing information propagation [8]. An object that is given a certain number of rules and behaves autonomously on the basis of those rules is called an agent. MABS is a simulation method for executing various rules simultaneously and progressively on a number of agents, then analyzing the social actions that occur due to interactions between the agents. This is effective in the bottom-up analysis of social phenomena where it is not possible to imagine just the movements of individual agents, and research is underway as an approach to problems that center on human decision making, in areas such as social, economic, and cultural, where experimentation was difficult in the past [9]. This form of MABS is known collectively as social simulation [10] and is attracting attention as a means of comprehending social phenomena and creating social systems, to enable preliminary estimation of the effects of regulations and rules that have not yet been tested, where there are unknown precedents or few precedents that could not be determined previously. The recent spread of mobile devices and communications services on the Internet has led to increased opportunities for information circulation by individual people. Understanding the behavior of information circulation by individual people is important for marketing strategies, and various studies such as field investigations, substantive experiments, and service log analyses are under way. However there are various problems such as the fact that such investigations and experiments are time-consuming and costly, and that it is difficult to grasp how circulation changes when the elements (individual people) of the crowd have changed. To address these problems, a method has been proposed by which the attributes of the environment and agents (individual people) are laid out freely and information circulation between individual people in an artificial society are simulated [11].

There is also agent-based modeling (ABM), which is a method of activating a number of agents simultaneously, and replicating complicated phenomena by simulating their interacting statuses [12]. Candidates for ABM are often abstract, but specific descriptions of human social behaviors are rarely seen. One reason is that if the ABM candidates become complicated, it becomes difficult to analyze the cause-and-effect relationships between the attribute values of the model and the simulation results. Human value systems are an abstract concept, but it is necessary to map value systems specifically in some way, in order to model human societies. Since such models are too complicated, it is not simple to reflect human social value systems in ABM which handles abstract candidates.

III. PARTICLE SWARM OPTIMIZATION

A. Overview

The particle swarm optimization (PSO) method developed by Kennedy and Eberhart in 1995 is a heuristic optimization method (metaheuristic) based on swarm intelligence, to solve problems such as function optimization. This addresses an extremely universal problem class that is confronted daily in various different fields and at various different locations in industrial applications and science and technology, such as the analysis, control, design, and operation of systems [13].

Swarm intelligence is a generic term for algorithms that focus on the social actions of living creatures such as insects and animals [13]. With a swarm intelligence, each individual that makes up the swarm does not exhibit particularly complicated behavior, but by becoming a swarm they act as if they are a single living organism having sophisticated intelligence. In this manner, the way in which local interactions between individuals result in overall behavior is considered to be an important element in the attraction of swarm intelligence. The basic principle of PSO is based on the hypothesis that "information is shared by the entire swarm" which has been derived from research into the behavior of swarms of creatures such as birds or fish when searching for food. With PSO, each of a number of search points (particles) has information on its own position and velocity and exchanges that information within the swarm, and the entire swarm searches for information on the best solution while sharing.

Since the PSO algorithms are extremely simple ones constructed from repeating basic numerical operations, they are applied to various different problems such as electrical power systems, design systems for control systems, and wireless communications system, and their validity has been confirmed [14][15][16].

B. Algorithm

PSO is a method that was originally developed from processes that simulate the movements of swarms in two-dimensional space, but PSO can be expanded in an multi-dimensional space as an optimization method. In the next-generation optimization problem, each particle that forms part of the swarm has a current position $\boldsymbol{x_i}$ and velocity $\boldsymbol{v_i}$ in its own state space. In this case, i is the particle number (where $i = 1, 2, ..., m$). In addition, each particle records its own best position information $\boldsymbol{pbest_i}$ that it has discovered up to that point and the related evaluated value $f(\boldsymbol{pbest_i})$. Furthermore, the best position information $\boldsymbol{gbest}$ and its evaluated value $f(\boldsymbol{gbest})$ that are shared by the entire swarm are recorded. The most general PSO model in which the best position information is shared by the entire swarm in this manner is called the gbest model. We describe these models below. Note that if $\boldsymbol{x_i}$, $\boldsymbol{v_i}$, $\boldsymbol{pbest_i}$, and $\boldsymbol{gbest}$ are expressed by using vector components, we obtain Equations (1) to (4). In this case, j is a vector variable component (where $j = 1, 2, ..., n$).

$$\boldsymbol{x_i} = \left(x_{i1}, \dots, x_{ij}, \dots, x_{in}\right)^{\boldsymbol{T}} \tag{1}$$

$$\boldsymbol{v_i} = \left(v_{i1}, \dots, v_{ij}, \dots, v_{in}\right)^{\boldsymbol{T}} \tag{2}$$

$$\boldsymbol{pbest_i} = \left(pbest_{i1}, \dots, pbest_{ij}, \dots, pbest_{in}\right)^{\boldsymbol{T}} \tag{3}$$

$$\boldsymbol{gbest} = \left(gbest_1, \dots, gbest_j, \dots, gbest_n\right)^{\boldsymbol{T}} \tag{4}$$

With PSO, each particle searches with the aim of obtaining the optimized solution of the target function that it wants to optimize, by using $\boldsymbol{pbest_i}$ and $\boldsymbol{gbest}$ to amend its velocity and update its position. From its current position $\boldsymbol{x_i^k}$ (where k is the number of iterations), each particle updates its current velocity ($\boldsymbol{v_i^k}$) to ($\boldsymbol{v_i^{k+1}}$) as a weighted linear linkage between the vector towards the best solution that it has recorded itself ($\boldsymbol{pbest_i^k}$ - $\boldsymbol{x_i^k}$) and the vector towards the best solution shared by the entire swarm ($\boldsymbol{gbest^k}$ - $\boldsymbol{x_i^k}$), and moves to its next position $\boldsymbol{x_i^{k+1}}$. A schematic view of this process is shown in Fig. 1.

The velocity update calculation is shown in Equation (5) and the position update calculation is shown in Equation (6).

$$\boldsymbol{v}_i^{k+1} = w\boldsymbol{v}_i^k + c_1\mathrm{rand}_1\left(\boldsymbol{pbest}_i^k - \boldsymbol{x}_i^k\right) + c_2\mathrm{rand}_2\left(\boldsymbol{gbest}^k - \boldsymbol{x}_i^k\right) \tag{5}$$

$$\boldsymbol{x}_i^{k+1} = \boldsymbol{x}_i^k + \boldsymbol{v}_i^{k+1} \tag{6}$$

In this case, w, c_1, and c_2 are weighting parameters for the corresponding terms and rand_1 and rand_2 are uniform random numbers from 0 to 1.

We describe the mechanism of Equation (5) below, focusing on each of the terms. The first term on the right side denotes the state in which the particle continues to move in the same direction with the velocity it had up to that point (inertia).

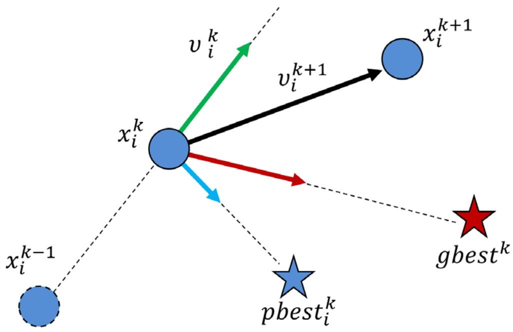

Figure 1. Schematic view of PSO.

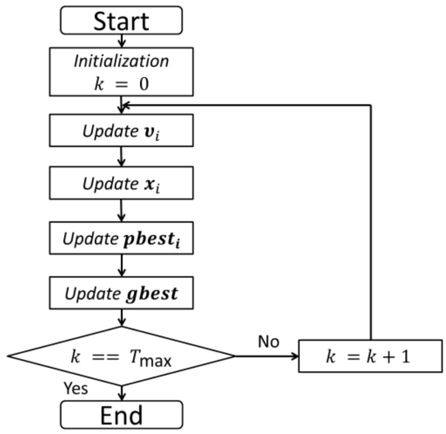

Figure 2. Flowchart of Gbest model.

The second term on the right side is a linear attractive force that varies with a random number coefficient towards the particle's own best position $\boldsymbol{pbest_i}$. The third term on the right side is a linear attractive force that varies with a random number coefficient towards the best position $\boldsymbol{gbest}$ discovered by all the particles within the swarm. Thus PSO is characterized in that each of the particles that make up the swarm integrates its own unique information with information that is common to the entire swarm, and the swarm acts to obtain the optimum solution in accordance with fixed rules.

We will now demonstrate the general PSO search algorithm with respect to an unconstrained minimization problem, with reference to the flowchart of Fig. 2.

Step 0 [Preparation]:
Provide a number of particles m; weighting parameters w, c_1, and c_2; and a maximum number of iterations $T_{\max}$; and set $k = 0$.

Step 1 [Initialization]:
Provide an initial position $\boldsymbol{x_i^0}$ and initial velocity $\boldsymbol{v_i^0}$ for each particle. Provide $\boldsymbol{x_i^0}$ at random within the executable region and $\boldsymbol{v_i^0}$ at random. In addition, set $\boldsymbol{pbest_i^0} = \boldsymbol{x_i^0}$ and $\boldsymbol{gbest^0} = \boldsymbol{pbest_{ig}^0}$.

However, ensure that $i_g = \arg\min_i f(\boldsymbol{pbest}_i^0)$.

Step 2 [Update of velocity]:
Update the velocity $\boldsymbol{v}_i^k$ by Equation (5).

Step 3 [Update of position]:
Update the position $\boldsymbol{x}_i^k$ by Equation (6).

Step 4 [Update of ***pbest*** and ***gbest***]:
Compare the current evaluated value $f(\boldsymbol{x}_i^{k+1})$ of each particle with its previous best value $f(\boldsymbol{pbest}_i^k)$, and update $\boldsymbol{pbest}_i^k$ accordingly.

if $f(\boldsymbol{x}_i^{k+1}) < f(\boldsymbol{pbest}_i^k)$
then $\boldsymbol{pbest}_i^{k+1} = \boldsymbol{x}_i^{k+1}$
else $\boldsymbol{pbest}_i^{k+1} = \boldsymbol{pbest}_i^k$

In addition, substitute: $\boldsymbol{gbest}^{k+1} = \boldsymbol{pbest}_{ig}^{k+1}$.

However, ensure that $i_g = \arg\min_i f(\boldsymbol{pbest}_i^{k+1})$

Step 5 [Completion condition]:
If the number of iterations k reaches the maximum number of iterations $T_{\max}$, the processing ends with the optimized solution being $\boldsymbol{gbest}^{k+1}$ and the optimum value being $f(\boldsymbol{gbest}^{k+1})$. Otherwise, the processing returns to **Step 2** with $k = k + 1$.

C. Swarm information exchange formats

In PSO, each particle exchanges and shares best-solution information between itself and the particles having an adjacency relationship. This interaction between particles is called the swarm information exchange format. Typical information exchange formats are the Gbest model and the Lbest model. The Gbest model the most basic model in which the best solution discovered by the entire swarm is shared by the entire swarm as ***gbest***. The Gbest model has the advantage that convergence is quick, but the defect that it can easily get trapped at a local solution, depending on the function that is the target of the optimization.

In the Lbest model, on the other hand, the swarm is divided into a number of groups and the best solution discovered by each group is shared only within that group as ***lbest***, but not to the entire swarm. The groups each search in mutually different regions, but since the groupings of particles overlap, it is not that there is absolutely no information sharing with the entire swarm but ultimately the solution converges on the best value (***gbest***) from among the ***lbest*** values of each group. For that reason, the Lbest model takes longer to converge on the solution than the Gbest model, but since it is less likely to fall into the trap of a local solution, the possibility of discovering the optimized solution is higher.

In the Lbest model, the equation for updating the velocity of each particle is Equation (7). Note that we use the same Equation (6) as that of the Gbest model for the position update equation.

$$\boldsymbol{v}_i^{k+1} = w\boldsymbol{v}_i^k + c_1\mathrm{rand}_1\left(\boldsymbol{pbest}_i^k - \boldsymbol{x}_i^k\right) + c_2\mathrm{rand}_2\left(\boldsymbol{lbest}^k - \boldsymbol{x}_i^k\right) \quad (7)$$

Interactions between particles in the Gbest model are shown in Fig. 3 and those in the Lbest model are shown in Fig. 4. In these figures, the circles indicate particles and the lines linking them indicate adjacency relationships (information propagation paths) between particles. In the Gbest model, each particle has an information propagation path to each of the other particles, and information is shared between all the particles. In the Lbest model, on the other hand, each particle has information propagation paths to only the neighboring particles, and information is shared only between some particles.

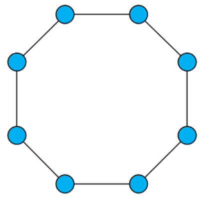

Figure 3. Gbest model.

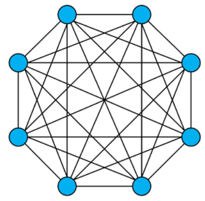

Figure 4. Lbest model.

IV. PROPOSED METHOD

A. Overview

In our research, we see that: “Human value systems are expressed in actions.” We define a human “action” as a particle and a gathering of particles as a swarm. A human value system is expressed as an evaluation function that evaluates a target value of the motion vector of each individual particle and the location at the end of the particle’s motion. In this study, we propose a social simulation model using an improved version of PSO that incorporates the concept of selection (natural selection) into PSO, which is an optimization method that utilizes swarm intelligence. Using the Gbest and Lbest models, which are information exchange formats in PSO, we construct communities where people exchange information through Internet societies. By turning particles into agents, we represent people who operate within communities in the Internet society and express the evolution of agents by the concept of selection. The evolution of agents represents the state in which humans develop.

There are many different people and they have different value systems, but there are certain tendencies in value systems due to factors such as environment, upbringing, and age. Therefore, since the behaviors of people in real-life societies are based on diverse value systems, the value of information will differ according to the recipient, even with the same information [17]. Since it is difficult to express individual human value systems suitably, in this study we classify the value systems that humans have by five evaluation functions. To classify them even more minutely, we express the diversity of human value systems by varying the values of c_1, and c_2. It is difficult to describe the ordinary social behaviors of people, but we can simply express value systems that form standards determining the relative merits of information, by using evaluation functions as the first step in our research. In other words, even with the same information, it is possible to express that the value of that information will vary according to the evaluation function of the agent doing the evaluation.

In this research, we assume the conditions described below. Within information, there is information that each person finds helpful (high value) and information that is unnecessary (low value). Each agent decides on the relative merits of information, based on its own evaluation function. Within the Internet society, there are many communities and each person belongs to a number of those communities. Through the Internet, each agent acquires information by conducting Internet searches and exchanging information with other agents, to acquire information that is valuable to itself.

The differences in evaluation functions of each agent can be seen as analogous to the diverse value systems of people in the Internet society. We classify them into five evaluation functions. This makes it possible to represent each of: a simple value system when there is a monomodal evaluation function, in which there is only one solution; a complicated value system when there is a multimodal evaluation function, in which there is a number of local solutions; a value system when there is a poorly-scalable evaluation function, in which relative weighting is applied to constituent elements of the information and the evaluation with respect to the information varies greatly depending on the constituent elements of the information; and a value system when the evaluation function has dependencies between variables, in which there are nonlinear dependency relationships between the constituent elements of the information. We demonstrate the constituent elements for any agent i in this model below.

1) Agent number: i

2) Evaluation function: f_i

3) Search vector: $\boldsymbol{v}_i$

4) Search information: $\boldsymbol{x}_i$

5) Agent's own previous best information: $\boldsymbol{pbest}_i$

6) Previous best information within the community: $\boldsymbol{cbest}$

7) Inertia towards search vector of previous step: w

8) Weighting of own information: c_1

9) Weighting of other agents' information: c_2

In this case, $\boldsymbol{x}_j$ (where $j = 1, 2, ..., n$) denotes the constituent elements of the information that the agent is searching for. For example, if the information $\boldsymbol{x}$ is "automobile", the constituent elements of that information are details such as "manufacturer", "design", "color", and "price". In addition, we assume that the value of the information is $f(\boldsymbol{x})$, evaluated by submitting the information x to an evaluation function f. Since this evaluation function will differ according to the recipient of the information, the same information will have different values, depending on the person. The information that "the body of the automobile labeled $\boldsymbol{x}_{red}$ is red" is high-value information to someone who likes red, but low-value information to someone who likes white. In other words, each agent evaluates the information it has retrieved by its own evaluation functions, and searches in order to obtain information $\boldsymbol{x}$ that has a high value to itself. In addition, each agent obtains information of value to itself from other agents, by exchanging information with the other agents within the community.

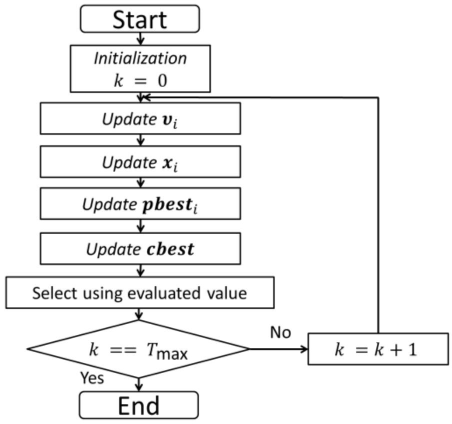

Figure 5. Flowchart of proposed method.

In this manner, we express the diverse value systems of people in the Internet society by a social simulation model, and analyze information propagation in an interactive environment in which there is a number of agents having different evaluation function, by computer simulation using this model.

B. Algorithm

The algorithm of the proposed method is described below and shown in the flowchart of Fig. 5.

Step 0 [Preparation]:
Provide a number of particles m and a maximum number of iterations $T_{\max}$, and set $k = 0$.

Step 1 [Generation of weighting parameters]:
For each particle, generate the weighting parameters c_1 and c_2 at random, and provide w.

Step 2 [Initialization]:

Step 2-1: Provide $\boldsymbol{x}_i^0$ at random within the executable region and the initial search vector $\boldsymbol{v}_i^0$ at random.

Step 2-2: Substitute $\boldsymbol{pbest}_i^0 = \boldsymbol{x}_i^0$.

Step 2-3: Substitute $\boldsymbol{gbest} = \boldsymbol{pbest}_{ig}^0$.

However, ensure that $i_g = \arg\min_i f(\boldsymbol{pbest}_i^0)$.

Step 3 [Update of search vector]:
Update the velocity $\boldsymbol{v}_i^k$ by Equation (5).

Step 4 [Update of search information]:
Update the position $\boldsymbol{x}_i^k$ by Equation (6).

Step 5 [Update of $\boldsymbol{pbest}$ and $\boldsymbol{gbest}$]:
Compare the current evaluated value $f(\boldsymbol{x}_i^{k+1})$ of each particle with its previous best value $f(\boldsymbol{pbest}_i^k)$, and update $\boldsymbol{pbest}_i^k$ accordingly.

if $f(\boldsymbol{x}_i^{k+1}) < f(\boldsymbol{pbest}_i^k)$
then $\boldsymbol{pbest}_i^{k+1} = \boldsymbol{x}_i^{k+1}$
else $\boldsymbol{pbest}_i^{k+1} = \boldsymbol{pbest}_i^k$

Step 6 [Update ***cbest***]:

Substitute $\boldsymbol{cbest}^{k+1} = \boldsymbol{pbest}_{ig}^{k+1}$.

However, ensure that $i_g = \arg\min_i f(\boldsymbol{pbest}_i^{k+1})$.

Step 7 [Selection (natural selection)]:

Step 7-1: Elect the particle having the best evaluated value, from among all the particles.

Step 7-2: Elect 20% of all the particles with the worst evaluated values, from among all the particles.

Step 7-3: Replace the search information $\boldsymbol{x}_i^k$ and search vector $\boldsymbol{v}_i^k$ of the particles elected in **Step 7-1** into the particle elected in **Step 7-2**.

Step 8 [Completion condition]:

If the number of iterations k reaches the maximum number of iterations $T_{\max}$, the processing ends with the optimized solution being $\boldsymbol{gbest}^{k+1}$ and the optimum value being $f(\boldsymbol{gbest}^{k+1})$. Otherwise, the processing returns to **Step 2** with $k = k + 1$.

In this case, k is the number of iterations; i is the agent number; $\boldsymbol{x}$ is the search information; $\boldsymbol{v}$ is the search vector; ***pbest*** is the previous best information of the agent itself; ***cbest*** is the previous best information shared within the community; w, c_1, c_2 are weighting parameters for each term; and rand_1 and rand_2 are uniform random numbers. We refer to Document [7] for **Step 7**.

V. SIMULATION EXPERIMENTS

In this section, we describe simulation experiments we performed by the proposed method, using five evaluation functions.

A. Evaluation functions

We express real-life social value systems in five classifications as evaluation functions for the agents, by using five evaluation functions having different behaviors as evaluation functions for the agents: the monomodal Sphere function, the weakly multimodal Bohachevsky function, the strongly multimodal Rastrigin function, the poorly-scalable Weighted-Sphere function, and the inter-variable dependent Rosenbrock function.

We give details of each evaluation function below.

a) Sphere function

• Function expression

$$f_a(x) = \sum_{i=1}^{n} x_i^2 \tag{8}$$

• Features

This is the simplest monomodal function where there is only one extremely small value within the search space, irrespective of any dependency relationship between decision variables.

b) Bohachevsky function

• Function expression

$$f_b(x) = \sum_{i=1}^{n-1} (x_i^2 + 2x_{i+1}^2 - 0.3\cos(3\pi x_i) - 0.4\cos(4\pi x_{i+1}) + 0.7 \tag{9}$$

• Features

This is a weakly multimodal function having a large number of local solutions.

c) Rastrigin function

• Function expression

$$f_c(x) = \sum_{i=1}^{n} (x_i^2 - 10\cos(2\pi x_i) + 10) \tag{10}$$

• Features

This is a strongly multimodal function having a large number of local solutions in a matrix, with no dependency relationships between decision variables.

d) Weighted-Sphere function

• Function expression

$$f_d(x) = \sum_{i=1}^{n} i \cdot x_i^2 \tag{11}$$

• Features

This is a poorly-scalable function where the sensitivity with respect to the target function varies greatly according to the variables, because of the way in which the scaling of the coordinate system is different.

e) Rosenbrock function

• Function expression

$$f_e(x) = \sum_{i=1}^{n-1} \{100((x_i + 1)^2 - (x_{i+1} + 1))^2 + (1 - (x_i + 1))^2\} \tag{12}$$

• Features

This is an inter-variable dependency function where there are strongly dependent relationships between neighboring variables.

For example, assume that an agent is doing a Web search to obtain desired information from the Internet. If the agent's evaluation function is the Sphere function, we can express people where the desired information is clear. With the Bohachevsky and Rastrigin functions, we can express people where the desired information is obscure, and with the Weighted-Sphere and Rosenbrock functions, we can express people such that the value of the desired information changes according to keywords and their numbers.

The evaluated values of all of these five functions are zero or greater, and the best evaluated value by the global optimized solution $\boldsymbol{x}^* = (0, \ldots, 0)^T$ becomes zero. In other words, the value of the information increases as the evaluated value created by the evaluation function approaches zero.

Thus, the problem of solving by the evaluation function f_i of the agent is given by Equation (13).

$$\min_{x} f_i(x) \qquad (13)$$
$$\text{subj. to} -5.0 \le x_j \le 5.0, \;\; j = 1, 2, \ldots, \mathrm{n}$$

This means that each agent searches the solution space to look for the same information (global optimized solution), a model which represents a number of people searching for the same information in a real-life society. Note that we referenced Document [18] for the variance range of the search information $\boldsymbol{x}$.

B. Experimental environments

In our simulation experiments, we turned the following experimental environments into communities:

Single-value environment

An environment in which each agent exchanges shared information only with agents having the same evaluation function as itself.

Multi-value environment

An environment in which each agent exchanges shared information with all the agents.

Correlations (links) between agents in a single-value environment are shown in Fig. 6 and those between agents in a multi-value environment are shown in Fig. 7. In this case, agents of the same color have the same evaluation function, and the lines connecting agents represent links (communities) between the agents. In the single-value environment, each agent forms a community only with agents that have the same color as itself. In a multi-value environment, on the other hand, each agent forms a community with all of the other agents, including those of colors different from itself.

In this study, we performed two experiments to clarify the effects on information propagation due to the differences in the two community environments. The parameters of the experimental environments are listed in Table 1. Experiment 1 is a simulation experiment with a fixed number of agents in each evaluation function, focusing on the "number of agents per evaluation function", and Experiment 2 is a simulation experiment with a fixed number of agents in each swarm, focusing on the "number of agents per swarm". With Experiment 1, we can clarify the effects of information propagation in communities in which the overall scale is fixed, by making the total number of agents the same. However, since the number of agents in one swarm differs for each community, the amount of information exchange that each agent handles is different for each community environment. In this case, Experiment 2, in which the number of agents in one swarm is the same, enables us to analyze information propagation in an experimental environment in which each agent performs the same number of information exchanges regardless of community. We will discuss how the information propagation process is affected by differences between these community environments and experimental environments.

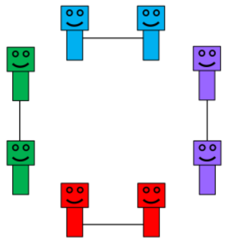

Figure 6. Single-value environment.

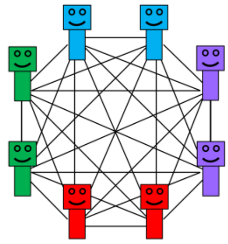

Figure 7. Multi-value environment.

TABLE I. EXPERIMENTAL ENVIRONMENT PARAMETERS

Experiment 1	Single-Value Environment	Multi-Value Environment
Number of agents per evaluation function	50	50
Number of swarms	5	1
Number of agents per swarm	50	250
Total number of agents	250	250
Experiment 2	**Single-Value Environment**	**Multi-Value Environment**
Number of swarms	250	50
Number of swarms	5	1
Number of agents per swarm	250	250
Total number of agents	1250	250

TABLE II. SIMULATION PARAMETERS

Next generation of evaluation functions	$n = 20$
Agent parameters	$w = 0.6$ $c_1 = 0.1$ to 2.0 $c_2 = 0.1$ to 2.0
Maximum number of steps	1000
Number of trials	1000

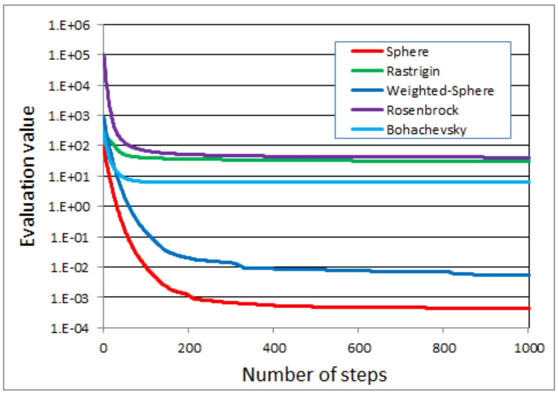

Figure 8. Single-value environment (Experiment 1).

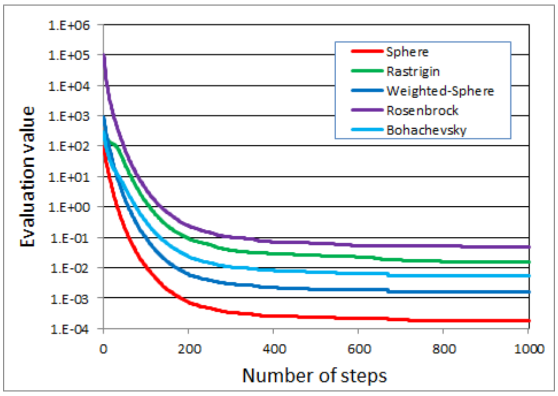

Figure 9. Multi-value environment (Experiment 1).

The simulation parameters for these experiments are listed in Table 2. In this case, c_1 and c_2 in the updated Equation (5) for each agents' search vectors are weighting parameters indicating the weightings for the agent's own information and for other information. We use different values of these weighting parameters c_1 and c_2 for each agent. If $c_1 > c_2$, for example, the search is done by focusing more on the person's own information than on that of other people, whereas if $c_1 < c_2$, the search is done by emphasizing other people's information over that of the person. This makes it possible to express differences in the ways in which information is considered, even with agents classified in the same evaluation function. In this case, we set the agent's weighting parameter w to 0.6 with reference to Document [3].

C. Results and discussion

Transitions in the average evaluated value of the best solution ***f(gbest)*** for each step of the agents having each of the evaluation functions are shown in Figs. 8 and 9, as results of the simulation experiments with single-value and multi-value environments, respectively.

First of all, we can confirm from the graphs of the simulation experiment results for Experiment 1 (Figs. 8 and 9) that all of the evaluation functions converge in both single-value and multi-value environments. In addition, we see that each agent is successful in searching for information that it considers to be better, when it conducts information search and information exchange.

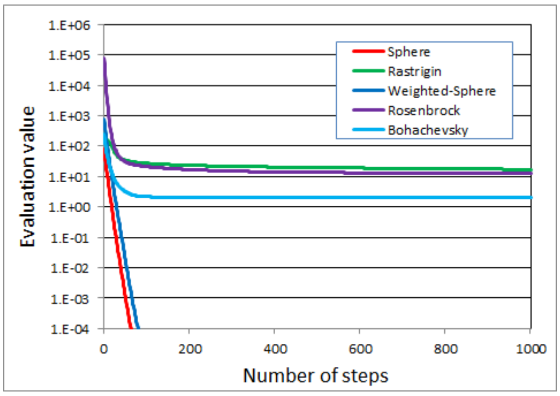

Figure 10. Single-value environment (Experiment 2).

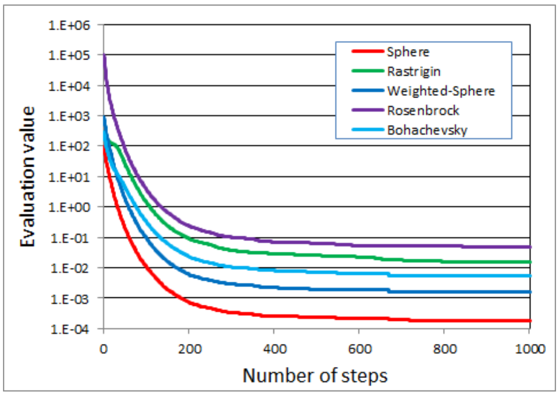

Figure 11. Multi-value environment (Experiment 2).

Next, we can confirm that, of all the evaluation functions, the Sphere function converges on the best value regardless of whether it is a single-value environment or a multi-value environment. This is because the Sphere function is the simplest monomodal evaluation function amongst the evaluation functions, so information searches are conducted efficiently. In addition, the Sphere function converges to substantially the same value, regardless of whether the environment is single-value or multi-value. This is thought to be due to the fact that although information exchange in a multi-value environment is done between agents having different evaluation functions, the Sphere function itself possesses the most helpful information, so the effect of agents having other evaluation functions is small.

Finally, we look at the evaluation functions other than the Sphere function. If we look at the Bohachevsky, Rastrigin, Weighted-Sphere, and Rosenbrock evaluation functions, we can confirm that convergence on a good value occurs more in a multi-value environment, which is an environment where there are a number of agents having evaluation functions that differ from that of the current agent. This is due to the effects of agents having the Sphere function, which has the highest evaluated value amongst the five evaluation functions, facilitating escape from local solutions. From this we can say that if there is an agent within the community that has a better evaluated value that another agent, the other agents are affected favorably, but if there is no agent with a better evaluated value, the other agents are completely unaffected.

Transitions to the average evaluated value of the best solution *f(**gbest**)* at each step of agents having each of the evaluation functions are shown in Figs. 10 and 11, as simulation results in single-value and multi-value environments, respectively.

First of all, we can confirm from the graphs of simulation experiment results in Experiment 2 (Figs. 10 and 11) that, of all the evaluation functions, the Sphere function succeeds in retrieving the best value, regardless of whether it is a single-value environment or a multi-value environment, in a similar manner to Experiment 1. We know that with a multi-value environment, all of the evaluation functions head towards convergence every time the search proceeds, whereas in a single-value environment, the Rastrigin, Rosenbrock, and Bohachevsky functions do converge but the Sphere and Weighted-Sphere functions do not converge. In addition, we can confirm that with the Rastrigin, Rosenbrock, and Bohachevsky functions, good search information is obtained more with a multi-value environment than a single-value environment. However, with the Sphere and Weighted-Sphere functions, good search information is obtained more with a single-value environment than a multi-value environment. For that reason, an agent with the Sphere and Weighted-Sphere functions can retrieve better information from information exchange between agents having the same evaluation function as itself in a single-value environment, where it is not affected by other agents, than in a multi-value environment.

In contrast, with the Rastrigin, Rosenbrock, and Bohachevsky functions, we found that good search information is obtained more with a multi-value environment in which information is exchanged between agents having different evaluation functions, than with a single-value environment, because better information is exchanged from the other agents.

From the results of the above Experiments 1 and 2, the following knowledge has been obtained:

1) Agents having simple evaluation functions, such as monomodal ones, obtain the best search results.

2) Differences in the evaluation functions of agents that are exchanging information affect the information propagation process. In particular, with agents having evaluation functions that often have many local solutions, such as in multimodal situations, each agent can escape from local situations by exchanging good information with agents having different evaluation functions from itself, making it easier to obtain good information.

3) An agent having an evaluation function where there is no local solution, in situations that are monomodal or poorly scalable, finds it difficult to obtain good information by being affected by agents having different evaluation functions from itself.

From these results, we see an agent can conduct information exchange that is optimum from its own viewpoint and improve its search efficiency more, by selecting other people for information exchange from consideration of the evaluation functions of other agents.

VI. CONCLUSIONS

In this study, we have proposed an agent-based social simulation model created by an improved version of PSO in which the concept of selection is reflected into PSO, which is one swarm intelligence algorithm, in order to analyze how differences in human value systems in the Internet society affect the information propagation process. From the results of simulations, we found that the information propagation process varies according to the features of the evaluation functions and the environment of the community.

In the future, we will review the details given below in order to create a real-life model by the social simulation model proposed by this paper.

First of all, the simulation experiments we performed compare ***pbest***, which is the best information held by each agent, and makes the best value of that the best information for the community. However, in real-life societies, it often happens that the information that is most helpful (the global optimized solution) to the searcher differs from that which is helpful to other people. It is therefore necessary to review whether the concept of competition and the value systems of agents could not be reflected in the method of deciding ***cbest***, which is the best information within the community.

Since there are many different value systems in real-life societies, there are some parts that cannot be duplicated by just five evaluation functions. In addition, human value systems themselves do not occur superficially, so it is not possible to decide what kind of value system is held by the other person in an information exchange. It is therefore necessary to make it possible to decide what kind of evaluation function is held by an agent who is exchanging information, from the agent's behavioral history and similarities with other evaluation functions.

Finally, we will set differing values of global optimized solution for each evaluation function and perform simulation experiments after a review of factors such as the number of next generations and the number of evaluation functions. In addition, since differences in human value systems are linked to information leakage and information falsification, which are some of the various problems of the Internet [19], we will also review application of the method to information security.

REFERENCES

[1] C. C. Reyes-Aldasoro, and F. Kuhlmann, "Telecommunications and Internet in the future society: myths and realities,'' Proc. 2008 IEEE Symposium on Computers and Communications, pp. 49–55, July 1999.

[2] H. Ninomiya, B. Flanagan, E. Ito, and S. Hirokawa, "Near friends communication encouragement system using NFC and SNS," Proc. 2012 IIAI International Conference on Advanced Applied Informatics, pp. 145–148, September 2012.

[3] T. Takahashi, T. Yamada, and T. Terano, "Simulating information transmission mechanisms on a network through particle swarm optimization," Proc. Ninth Annual International Symposium on Applications and the Internet, pp. 292–293, July 2009.

[4] H. Kannabe, M. Noto, T. Morizumi, and H. Kinoshita, "Agent-based social simulation model that accommodates diversity of human values," Proc. IEEE International Conference on Systems, Man, and Cybernetics, pp.1818–1823, October 2012.

[5] A. Janecek, T. Jordan, and F. B. de Lima-Neto, “Agent-based social simulation and PSO,” Lecture Notes in Computer Science, vol. 7929, pp. 63–73, June 2013.

[6] J. Kennedy, and R. Eberhart, “Particle swarm optimization,” Proc. IEEE International Conference on Neural Networks, vol. 4, pp. 1942–1948, November 1995.

[7] P. J. Angeline, “Using selection to improve particle swarm optimization,” Proc. IEEE International Conference on Evolutionary Computation, pp. 84–89, May 1998.

[8] C. Derksen, C. Branki, and R. Unland, “Agent. GUI: A multi-agent based simulation framework,” Proc. IEEE Computer Science and Information Systems, pp. 623–630, March 2011.

[9] Y. Yamamoto, A. Notsu, H. Ichihashi, and K. Honda, “Agent-based social simulation based on cognitive economic efficiency,” Proc. IEEE Congress on Evolutionary Computation, pp. 1089–1094, June 2008.

[10] N. Gilbert, and K. G. Troitzsch, “Simulation for the social scientist,” Open University Press, 2005.

[11] S. Matsuyama, “Analysis of interpersonal information distribution by agent-based simulation,” Journal of The Japanese Society for Artificial Intelligence, vol. 24, no. 1, p. 115, January 2009.

[12] C. M. Macal, and M. J. North, “Tutorial on agent-based modeling and simulation,” Journal of Simulation, vol. 4, no. 3, pp.151–162, September 2010.

[13] J. Kennedy, and R. Eberhart, “Swarm intelligence” Morgan Kaufmann, March 2001.

[14] K. Pouya, and H. Lesani, “An angle-based PSO approach for reactive power management problem,” Proc. IEEE Power Systems Conference and Exposition, pp. 1–6, 2009.

[15] S. Li, D. Zhao, X. Zhang and C. Wang, “Reactive power optimization based on an improved quantum discrete PSO algorithm,” Proc. 5th International Conference on Critical Infrastructure, pp. 1–5, September 2010.

[16] C. Chen, M. Ho, C. Chiu, and S. Liao, “PSO and APSO evolutionary computing in indoor wireless communication,” Proc. The 6th International Conference on Genetic and Evolutionary Computing, pp. 204–206, August 2012.

[17] S. H. Schwartz, “Basic human values: theory, measurement, and applications,” Revue française de sociologie, vol. 47, no. 4, pp. 929–968, 2006.

[18] E. Aiyoshi, and E. Yasuda, “Metaheuristics and application,” The Institute of Electrical Engineers of Japan, October 2007.

[19] T. Morizumi, and H. Kinoshita, “Proposal of the security model that prevents information leakage and information falsification caused in social system,” Japan Society of Security Management Journal, vol. 20, no. 3, pp. 13–30, December 2006.