Social Impact and Optimization

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ABSTRACT: This paper proposes some ideas and suggestions describing application of dynamic theory of social impact (SI) simulations for optimization. This connection could lead to development of a novel psychologically inspired optimization scheme. The main aim is to use some macro level phenomena emerged from micro level SI theory in optimization. This aim is reached by introduction of fitness evaluation to SI simulation framework. For demonstration of optimization abilities of SI simulation, some preliminary experiments are presented.

KEYWORDS: Social psychology, optimization, social impact theory, nature-inspired, population based.

INTRODUCTION

For a long time, there has been a gap between natural sciences and humanities. One of many issues is the difference between technical and social science. Naturally, it could seem quite difficult to imagine some common elements shared by these two different areas. However, recently, the cross influences and inspirations are turning to be much more frequent day by day. One of the relatively wide area of these connections is the use of artificial intelligence methods in social science. An example is the building of mathematical models of cognitive processes, where computer simulations and cognitive sciences are encountering ([1], [2]). Some of these sociological simulations were based on models of individual actors realized simply by cellular automata. For instance, Thomas Schelling [3] was awarded with the Nobel Prize “for having enhanced our understanding of conflict and cooperation through game-theory analysis.” His checkerboard model is very similar to cellular automata models. Among others, it is regarded to be one of examples of good explanation in social sciences [4] or one of the predecessors of agent based computer models [5].

The examples mentioned above originate from sociology. However, this paper will be much more related to social psychology issue and its psychological point of view. It describes the modification of computer simulation, modelling the processes investigated by social psychology. The original simulation was described in [6] and was based on Latanés’ dynamic theory of social impact [7]. We have modified some parts of the simulation to investigate the ability of society to optimize.

PRECURSORS?

SOCIAL PSYCHOLOGY

Social psychology deals with perceiving, influencing and relating of individuals to each other. It attempts to understand and explain how the thought, feeling and behavior of individuals is influenced by the actual, imagined or implied presence of others. First of all, it is important to define some principal ideas and notions to come out of the field of social psychology:

Attitude is a learned, global evaluation of a person, object, place or issue that influences thought and action. The simplest definition is that attitudes are likes and dislikes [11]. In this work, the simulations will work with multiple 2-state attitudes which enable us to represent each member of society by a binary string.

Cognitive dissonance is a feeling of unpleasant arousal caused by noticing an inconsistency among cognitions. Cognitive dissonance is most apparent when a discrepancy has been noticed between one's self-concept and one's behavior. It typically leads to a change in attitude, a change in behavior, or a rationalization of behavior. In the current paradigm, the cognitive dissonance will be the main mechanism driving the optimization process.

Persuasion is a method of influence that attempts to guide people toward the adoption of an attitude, idea, or action by rational and/or emotive means. Persuasion relies on appeals rather than strong pressure or coercion. In our simulations, the persuasion will be the most important process giving optimization ability to the society.

SOCIAL IMPACT THEORY AND SIMULATIONS

According to Latané [7], social impact is any of the great variety of changes in physiological states and subjective feelings, motives, and emotions, cognitions, and beliefs, values and behavior, that occur in an individual, human or animal, as a result of the real, implied, or imagined presence or actions of other individuals. Dynamic social impact theory tries to describe and predict the diffusion of beliefs through social systems. It views society as a self-organizing complex system composed of interacting individuals each obeying simple principles of social impact. It states that the likelihood that a person will respond to social influence will increase with three factors: strength, immediacy and number.

Strength says how important the influencing individuals are to you.

Immediacy represents the spatial closeness of the influencing individuals

Number describes how many individuals are influencing the actual one.

This structure was simulated by Andrzej Nowak and Chris Szamrej in 1990 [6]. The simulations represented each individual as four parameters: the individual's attitude, two indicators of strength (persuasiveness and supportiveness) and its location in the social structure. The organization of simulations was following:

The **attitude** (opinion) was binary parameter and, could take only one of two values, regardless of interpretation. (Possible interpretation could be that the people are for or against a given idea – "guilty/not guilty", "supporting EU/not supporting EU".) Note that each person in that simulation had just one dimensional, binary attitudes, which will be generalized in present paper.

Strength factors were **persuasiveness** (0-100), the ability to persuade people with opposing beliefs to change their minds, and **supportiveness** (0-100), the ability to provide social support for people with similar beliefs. The persuasiveness and supportiveness were reassigned randomly after each attitude change. The two properties were independent, which will not be true in our preliminary experiments.

The concept of **immediacy** was established by organizing the group (or society) into a square matrix, where each cell represented one individual. The immediacy of two individuals was calculated as the Euclidean physical distance between the corresponding cells. It is clear, that the immediacy is an attribute of a pair of individuals.

During each iteration, two social impacts are computed from the parameters, from immediacy, represented as Euclidean distance and from number of individuals with the same or opposite attitude respectively. The first social impact is the total persuasive impact on a single individual of a set of N opposed sources differing in strength and immediacy:

$$\hat{l}_p = N_0^{1/2}[\sum (p_i / d_i^2) / N_0], \tag{1}$$

where $\hat{l}_p$ is persuasive impact, N_0 the number of individuals with an opposing view (sources), p_i the persuasiveness of source i, and d_i the distance between source i and the recipient. The supportive impact was given by

$$\hat{l}_s = N_s^{1/2}[\sum (s_i / d_i^2) / N_s], \tag{2}$$

where $\hat{l}_s$ is supportive impact, N_s the number of individuals sharing the individuals view (supporters), s_i the supportiveness of source i, and d_i has the same meaning as before.

At the beginning of simulation, the attitudes are randomly distributed in the population. The values of p_i and s_i are also randomly initialized in the range (0,100). At each iteration, an individual changes its attitude if the persuasive impact is greater than the supportive impact. In case of attitude change, the values representing strength are randomly reinitialized. During simulation, all individuals change their attitudes and the process leads to equilibrium state. The equilibrium state is defined as the state without any attitude change. The Figure 1: depicts an example of result taken over from the original simulation. The initial random distribution of opinions evolved into an equilibrium state after 18 iterations. The results show the two emergent group phenomena – the shifting of attitudes towards incompletely polarized equilibria, which was connected with decreasing frequency of attitude changes and the formation of coherent clusterings of subgroups with deviant attitudes. The minority subgroups survived mainly on the margin of the matrix.

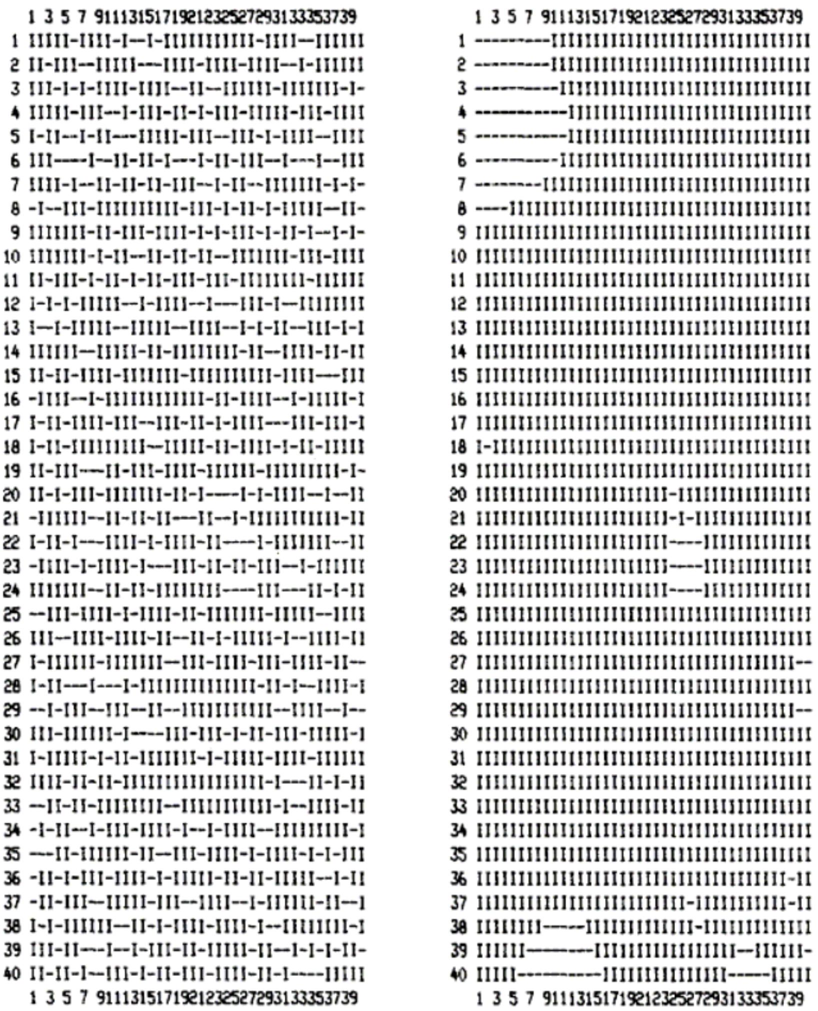

Figure 1: Example of results from [6]. Random starting configuration of attitudes (left) and attained equilibrium 18 steps later (right). Each cell represents an individual. Vertical bars represent the majority opinion; horizontal bars represent the opposing viewpoint. Source: [6]

The experiments described above show that the society of mutually influencing individuals is capable to develop certain forms of self-organization which relies on multiple interactions. Recently, it is known, that the human society embodies some forms of self-organization, which is also related to self-organizing behavior of social animals and the self-organization of simple mathematical structures. The self-organization is also associated with a notion of intelligence in the principle of collective intelligence which appears in many forms in bacteria, animals, humans and computers. Collective intelligence emerges from the collaboration and competition of many individuals. In nature, this phenomenon was observed in ants, termites, bees, fish and birds and inspired some artificial intelligence scientists, who developed the optimization algorithms like ant colonies [12] or particle swarm optimization [13]. The following section aims to examine possible optimization abilities of the society simulated by dynamic theory of social impact.

INTRODUCING OPTIMIZATION ABILITY

In this section, we propose some modifications, which enable us to introduce an optimization ability to the social simulation. There are three main modifications:

Multiple attitudes

The first modification is to add more attitudes to each individual. This makes it possible to represent optimization problems with more than one dimension. The attitudes of society are thus no longer represented by 2-dimensional matrix of binary numbers, but each individual is represented by binary vector and the attitudes of the whole society correspond to 2-dimensional matrix of binary vectors.

Elimination of supportiveness

The dynamic theory of social impact proposes the important fact that individuals differ. The difference is partly in attitudes and spatial positioning, and partly in the strength factor. The term strength was used to refer to the net of all the individual factors making a person influential. In the original simulation, the strength of each individual was represented by persuasiveness and supportiveness, two independent properties. We propose to use just one parameter which will be used in computation of social impacts. The first reason to do that is the simplification of the computational process. The second reason is that there is no special reason to consider persuasiveness and supportiveness independent. These two properties are complex functions of many components (e.g. physical size, intellect, wealth), and they evidently differ, but are not independent. That is why we use just one parameter – strength, for computation of both the supportive and persuasive impact. In the light of the original simulations described above, each individual i has the strength property q_i and the following assumption holds: $q_i = s_i = p_i$.

Addition of fitness function

The simulation proposed by Nowak and Szamrej [6] has one interesting point. How to handle the two strength factors? In the original work, the persuasiveness and supportiveness were initialized randomly for each individual and changed only when the individuals' attitude changed. However, there was uncertainty, how the two parameters should change. Therefore, the change was set always randomly after every change of attitude. We propose a modification of the behavior of strength, based on addition of one more parameter to each individual – the value of a fitness function. The motivation to do it is the following. The fitness function should evaluate each individual in terms of a binary optimization problem and the change of strength factors (factor, in our case) should be influenced by the actual fitness value and its past behaviour. Before proposing a suitable function for updating the strength the strength q (we can consider just one particular individual and remove the subscript), some limitations must be described. The first limitation is, that the value of q must take the values from a certain range (to be able to compare the individuals). Originally, the strange factors could take random values from $\langle 0,100 \rangle$. We will consider the range for the strength factor to be from $\langle 0,1 \rangle$. Further, the particular type of optimization task has to be considered. We will assume the minimization of fitness function, which implies, that the strength of an individual must be inversely proportional to its fitness. With regard to previous ideas, we propose the following formula:

$$q = \frac{f_{\max} - f}{f_{\max} - f_{\min}}, \tag{3}$$

where q is the strength of actual individual, the f is the fitness value of the individual and $f_{\max}$, $f_{\min}$ are the maximum and minimum values of fitness function in population respectively. This equation assigns zero strength to the individual with the maximum fitness value and strength equal to one to the individual with minimum value of fitness. This way of handling with the strength corresponds to real behavior of people, where more successful (fitter) people have higher influence to others.

TOWARDS A BINARY OPTIMIZER

The main goal of the experiments described in the next section was to examine the capability of the society model based on dynamic social impact theory to optimize. The algorithm used is described in Table I:. First, all individuals in the society initialize their binary attitudes randomly from uniform distribution (P(0)=0.5, P(1)=0.5). At each iteration, individuals evaluate their attitudes using a fitness function (line 4) and compute their strength using Equation (3). Next, each individual, considering its predefined neighbourhood, computes the two social impacts (lines 12,13).

Algorithm used in experiments

```
  1 Initialize attitudes by random assigning binary values from 0,1 to
    society.attitudes

  2 Iter=0

  3 While (iter<max_iter) do,
  4       society.fitness=evaluate(society.attitudes);

  5       fmax=max(society.fitness); fmin=min(society.fitness);

  7       society.strength=(fmax-society.fitness)/(fmax-fmin);

          iter=iter+1;

  8             For each individual i and each dimension d do:

  9                   Find sources and supporters in neighborhood of i

 10                   Compute number of sources and supporters (No,Ns) in
                      neighborhood of individual i with respect to
 11                   dimension d

 12                   Compute total persuasive impact lp
                       (according to Equation (1))
 13                   Compute total supportive impact ls
                       (according to Equation (2))

14a                   If lp>ls, invert the attitude of individual i in
                      dimension d

14b                   If lp>ls, invert the attitude of individual i in
                      dimension d WITH PROBABILITY 1-κ
                      Else, invert the attitude of individual i in
                      dimension d WITH PROBABILITY κ
                End (for)
    End (while)
```

Table I:. Algorithm of optimizing society

The individuals do not use the contributions of all individuals in the society, but just the square neighbourhood with predefined size. It reduces time requirements. The influence of the radius of this neighbourhood will be further examined in current experiments.

One can notice, that except the initialization of attitudes, the algorithm described so far is fully deterministic. However, this is not the case in real life, where complex mixture of additional random processes takes place and influence the evolution of society. Furthermore, in terms of optimization, stochastic element can improve the explorative capability and prevent loss of diversity. For these reasons, in some experiments, the following modification is made. The change of an attitude can occur even if the persuasive impact is less than the supportive one. On the other hand, if the persuasive impact predominates, the change may not occur. It is enabled by additional probabilistic parameter κ, which represents the probability of spontaneous attitude change. Thus, if the persuasive impact is greater, the change takes place with probability $1-\kappa$, else the change takes place with probability κ.

EXPERIMENTS

The main goal of experiments was to simulate societies with different settings and to explore the capability of the algorithm described in previous section to minimize a fitness function. For all experiments, the society was represented as square grid of different sizes (sizes of society). There was relatively simple optimization task used for these preliminary experiments. The fitness function was defined as Hamming distance of the D-dimensional attitude position from a point $\vec{c}$ in D-dimensional space, divided by the dimension D. It is unimodal function with constant gradient and minimum in the point $\vec{c}$ (D-dimensional sphere with centre $\vec{c}$). The function suffices for preliminary experiments, where the main task is not to test the new optimization algorithm, but only to explore the possible optimization abilities. If $H(\vec{x},\vec{c})$ represents the Hamming distance of the point $\vec{x}$ (binary vector of attitudes) from the centre $\vec{c}$, the fitness function to be minimized is as following:

$$f(\vec{x}) = H(\vec{x},\vec{c}) / D. \tag{4}$$

For all experiments, the binary vector $\vec{c}$ was created in the same manner. Its first half consisted of 0s and the second part were purely 1s. However, the form of this vector is not important for results (it is just reference point).

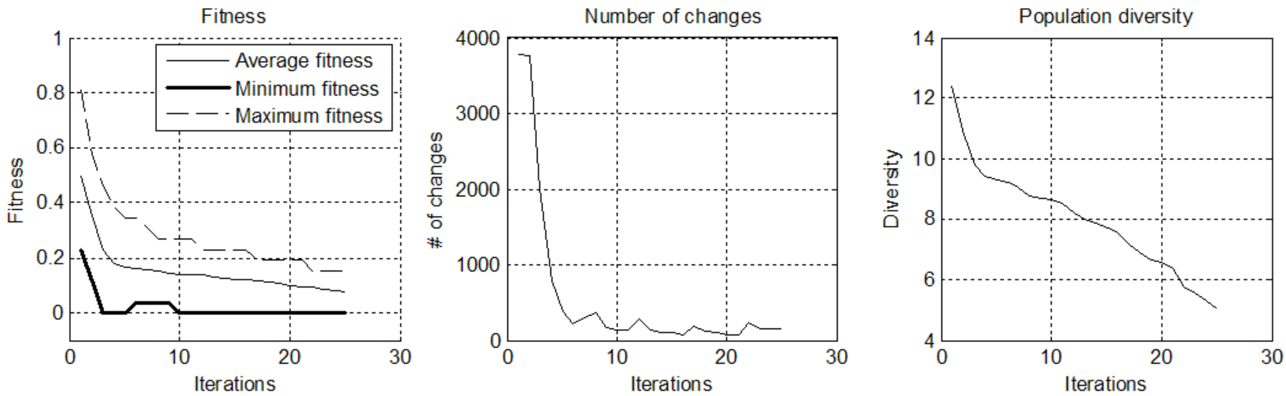

Figure 2: The result of one run of experiment with 30x30 individuals and 26-dimensional attitude space. The radius of the neighbourhood was 15.

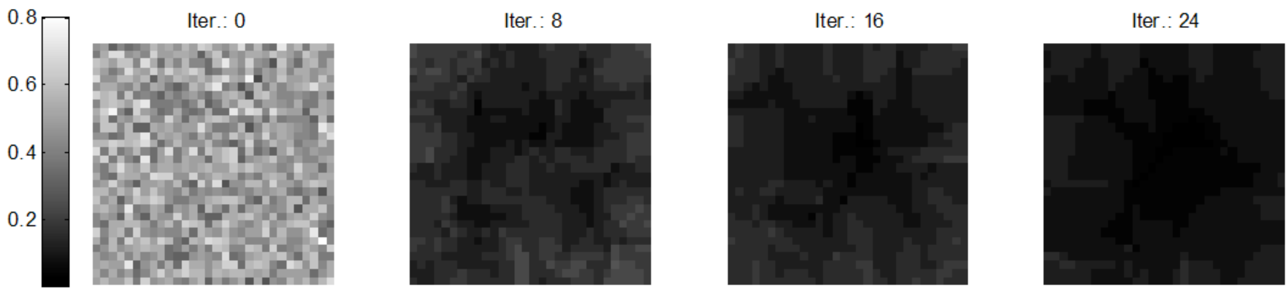

Figure 3: The maps of fitness values corresponding to four moments in simulation process from the Figure 2.

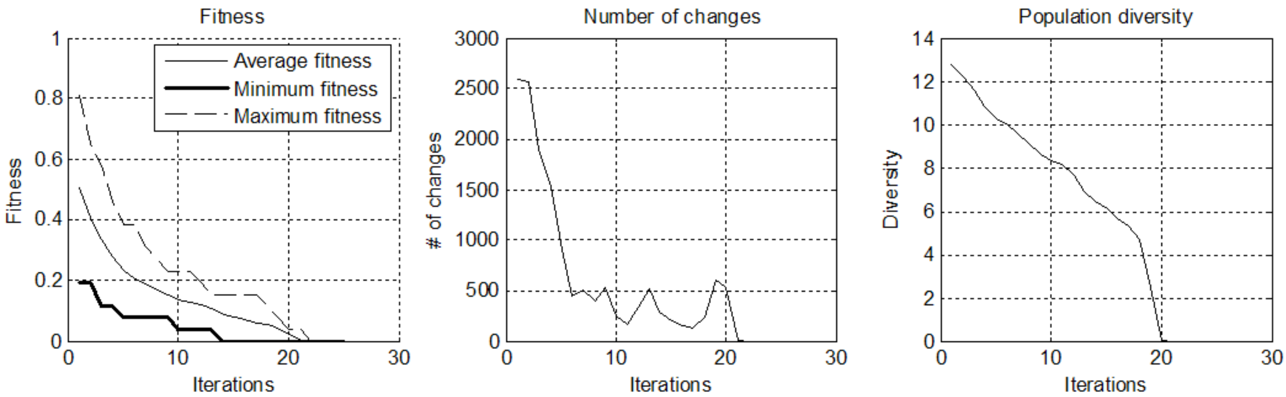

Figure 4: The result of one run of experiment with 30x30 individuals and 26-dimensional attitude space. The radius of the neighbourhood was 7.

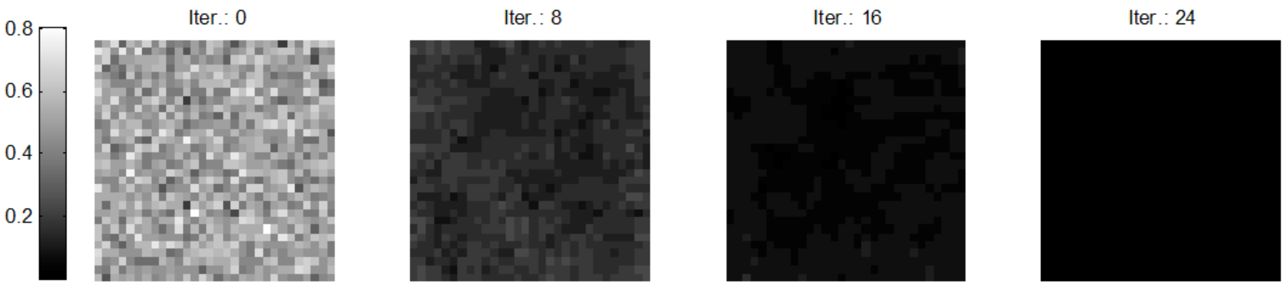

Figure 5: The maps of fitness values corresponding to four moments in simulation process from the Figure 4.

During the simulation process, the following measures were used: society's maximum, average and minimum value of the fitness function, number of attitude changes occurred in current iteration and finally, the population diversity measure. The diversity was estimated as follows: for each dimension $d = 1...D$, the standard deviation of attitudes was computed through the whole society and the population diversity was sum of these D standard deviations. It is obvious, that such diversity measure depends on the size of population. Finally, the colour map representing the distribution of values of the fitness function in society was used to demonstrate the structure of society in different moments of simulation.

For the first series of experiments, dimension D was 26, a society of 30x30 individuals was used and the algorithm with line 14a (without stochastic element) was launched. The Figure 2: and Figure 3: describe the result of simulation, where the neighbourhood radius was 15 and each individual used the information from all members of society. The Figure 4: and Figure 5: describe the result of simulation, where the neighbourhood radius was 7 and each individual used the information from part of society and ignored all individuals out of the neighbourhood. The Figure 6: and Figure 7: describe the other extreme, where the radius is 1 and each individual is influenced just by individuals in immediate vicinity.

The first and the most important feature of the results is that in all cases, the society found the minimum of fitness function. It is not surprising, because the task is really simple with small dimension and the number of individuals is 900. However, we will see later, that the society with much smaller size is also able to reach the optimum. It is also expected, that the wider the neighbourhood, the faster convergence is reached and the less time needed to reach the optimum. It is probably connected with the amount of information, which is accessible for each individual. In the case of small neighbourhood, the information and search process is much more distributed in the society. One has to consider the possibility of multimodal fitness function with more than one optimum, which could lead to problems with local optima. In such case, the society could even profit from the information inaccessibility. The graph of minimum fitness in the Figure 2: also shows that the minimum fitness function can even increase and thus the society can temporary lost the best-so-far solution.

Further, there is also an interesting phenomenon in behaviour of the number of changes per iteration. The most evident property is the oscillating character of the curve. One can observe that periods of increasing number of changes are alternating with periods when the number of changes is decreasing. These oscillations take place during the whole simulation and decay merely when the loss of diversity occurs. It seems that in comparison to original simulations

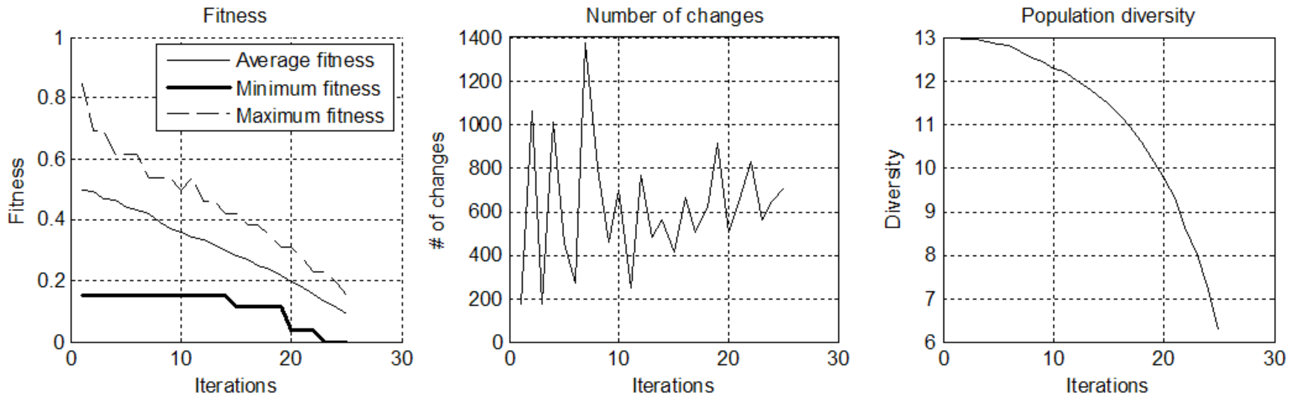

Figure 6: The result of one run of experiment with 30x30 individuals and 26-dimensional attitude space. The radius of the neighbourhood was 1.

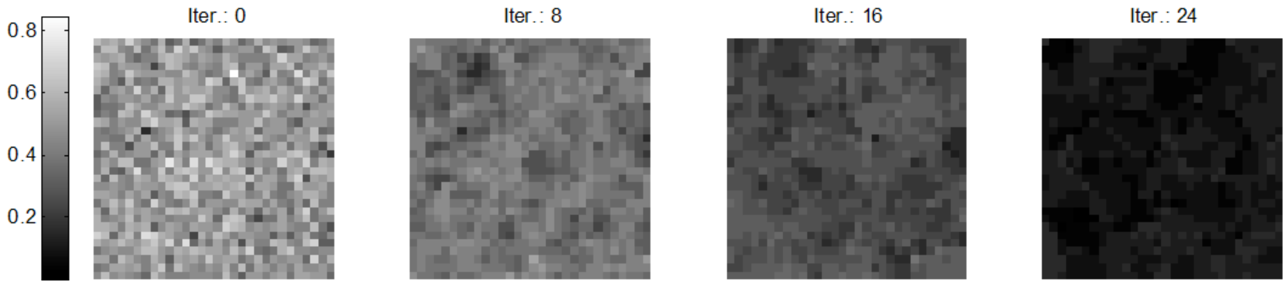

Figure 7: The maps of fitness values corresponding to four moments in simulation process from the Figure 6.

presented in [6], the only equilibrium our systems reached is the complete polarization of society where all individuals hold the same attitudes. However, any general conclusion cannot be made on the basis of one run of the system.

Finally, the question of diversity can be considered. The decreasing curves of population diversity are quite related to the maps of fitness value distribution acquired in 4 different moments. Each pixel in these maps represents one individual and the colours correspond to different values of fitness function. The darker the colour, the smaller the fitness value. The diversity of population is decreasing over the time and the range of fitness values in society is smaller. The fitness maps show interesting phenomenon, which is similar to formation of coherent clustering in original simulations (see Figure 1:). The system self-organizes itself in such a way, that the areas of similar fitness value can be observed (Figure 3:, Figure 5:, Figure 7:). The Figure 8: shows such another phenomenon (observed for higher dimension). Again, the maps represent the society, however, each subplot represents distribution of attitudes in one dimension. Only first 12 dimensions were depicted. Therefore, the figures have exactly the same interpretation as Figure 1:, and even show the same result. The result on Figure 8: was obtained after 25 iterations from experiment with dimension 82, where first 41 attitudes should find zero values. The zero attitudes were really taken by majority of individuals, but several other individuals holding the attitude 1 still remain. In the original simulations, the system converged to uncompletely polarized equilibrium. This is the fundamental difference of current simulations, where the pressure of fitness function leads to complete loss of diversity and completely polarized state (the reason why the complete polarization was not reached in some experiments was the fact that we stopped the optimization after predefined number of iterations, however after several more iterations, the system would lost the diversity). The second interesting point of Figure 8: is the clustering of some attitudes. The homogenous clusters of individuals with minority opinion were formed mainly on the margins of the society matrix. This seems to be analogy of small minority groups living on social margin.

The purpose of second series of experiments was to explore the behavior of society in case of greater dimension, to examine the importance of addition of the stochastic element (Table I:, line 14b) and to examine influence of size of the society. The dimension of space of attitudes was 82. The simulations were launched for 100 iterations. The Figure 9: and Figure 10: depict the result obtained from a society with 30x30 individuals. One can observe all phenomena, which were observed in previous experiments with smaller dimension. An important fact is that the society was also able to find the minimum value of fitness, although it took more time. In comparison to previous

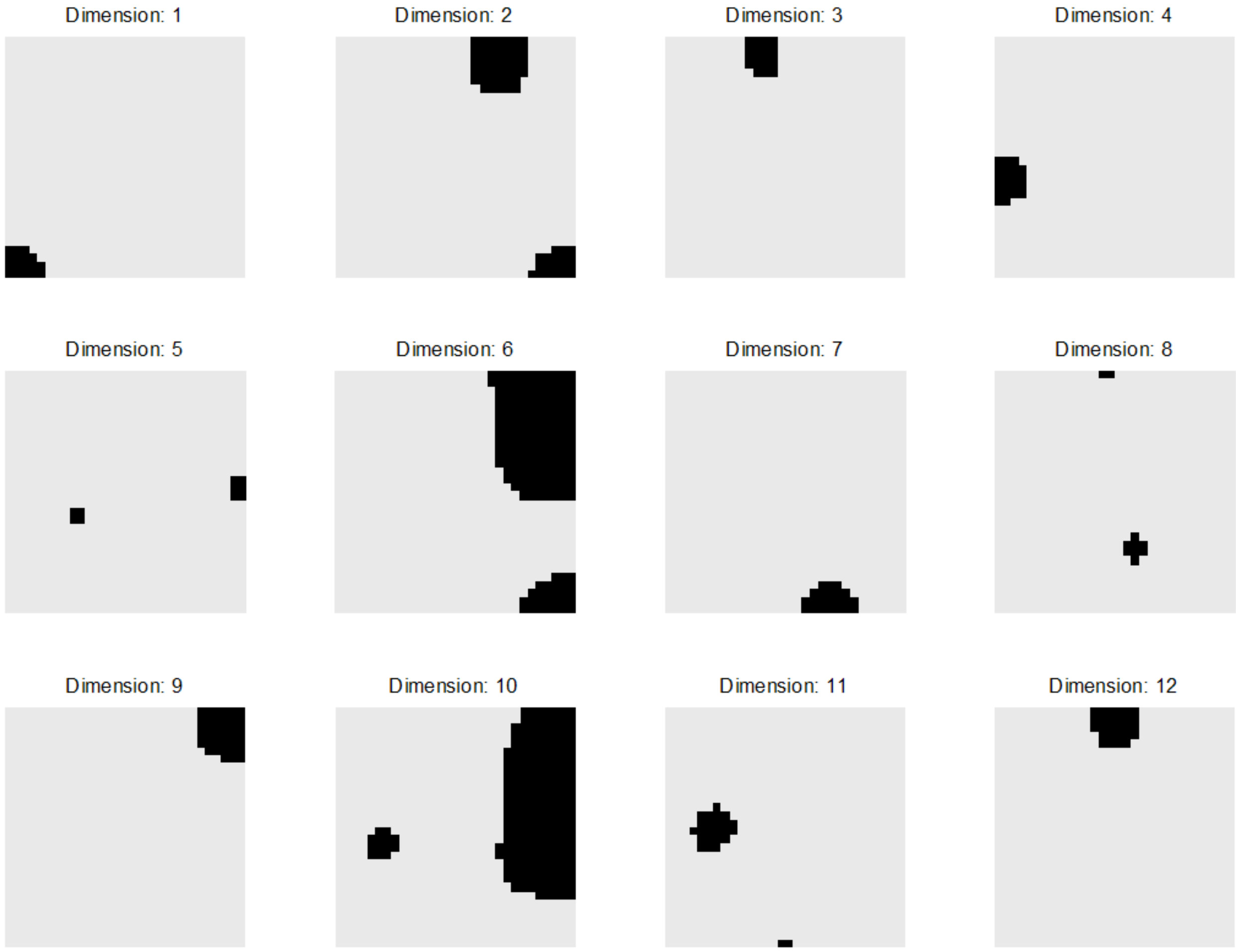

Figure 8: The attitude maps for first 12 dimensions of 82-dimensional attitude space, society size was 30x30, the radius of neighbourhood was 7. The optimal values are 0s. One can observe small minor groups with opinions 1 located on social margins.

observations, the only difference is the smaller range of fitness values in the society, which leads to a smaller contrast in the maps of fitness values (Figure 10:).

Obviously, the simulation process is becoming much more time consuming, as the dimension of attitude space is increasing. If one would like to use the optimization ability of the society for real binary optimization, it would be necessary to decrease the computational complexity as much as possible. The last series of experiments dealt with this topic. Four different sizes of societies were used, the society was organized in square matrix with 5x5, 10x10, 20x20 and 30x30 individuals and the neighbourhood radius was set 1, 2, 4 and 7 respectively. First, the non-stochastic simulation was launched (Table I:, line 14a) and then, the simulation with stochastic element was tested (Table I:, line 14b). The parameter κ decreased linearly over the time from the value 0.15 to 0.05 to ensure the explorative behaviour at the beginning and the exploitative behaviour at the end of the simulation. For each setting, ten runs of simulation were averaged. The average dependencies of the fitness function value on the time are depicted in the Figure 11:. It was already stated before, that the society of 30x30 individuals without stochastic element was able to find the minimal value of fitness function (Figure 6:) which is not surprising with regard to big number of individuals. The minimum was also found by the society with 20x20 individuals, however, for the two remaining sizes, the society prematurely converged to uniformity and did not find the optima. When the stochastic element was added to the update formula in the algorithm, one can observe two important things. First, the stochastic element slowed down the convergence. On the other hand, the minimum was found for all sizes of society. It seems, that the probabilistic update rule (Table I:, line 14b) plays fundamental role if one would like to utilize the optimization ability of societies for a real problem. It partly supports the exploration and partly prevents the premature loss of diversity. Finally, it is quite surprising, that the size of the society does not affect the speed of convergence in this case, however, other experiments should be done to be able to draw valid conclusions.

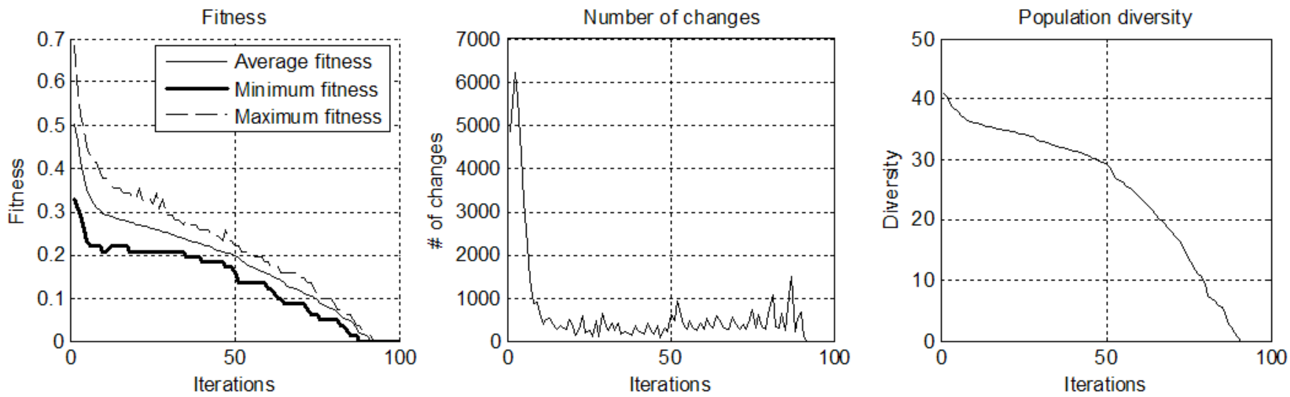

Figure 9: The result of one run of experiment with 30x30 individuals and 82-dimensional attitude space. The radius of the neighbourhood was 7.

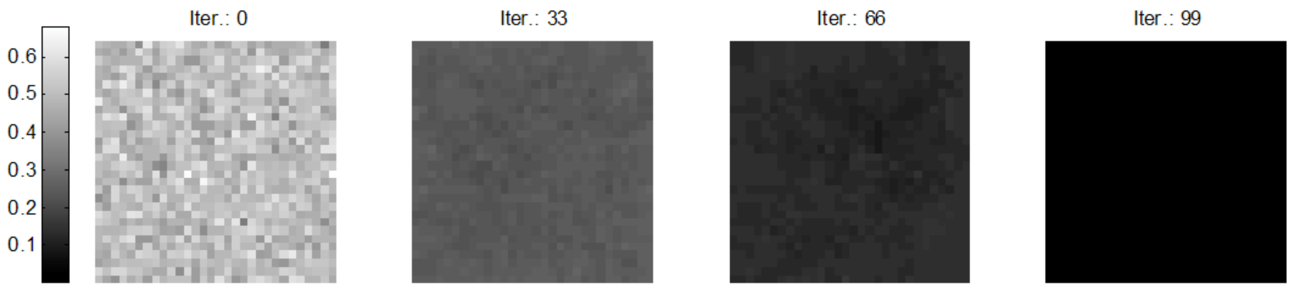

Figure 10: The maps of fitness values corresponding to four moments in simulation process from the Figure 9

CONCLUSION

In the present paper, we have shown, that the society simulated by dynamic social impact theory is able to optimize its attitudes in the sense of certain evaluation. This was enabled by addition of fitness function into the simulation mechanism. The addition was done quite intuitively using an inspiration in the real life, where successful persons have greater influence on others. However, the paper did not propose a new optimization algorithm. The testing function was too simple to draw some conclusions about global search properties or to do a comparison to some state-of-the-art optimization methods. Finally, one can notice, that the presented algorithm has many common features with binary particle swarm optimization [13]. It could be interesting to compare the properties and analyze, if it is possible to consider the binary particle swarm optimization as a particular case of more general, social impact theory based optimizer.

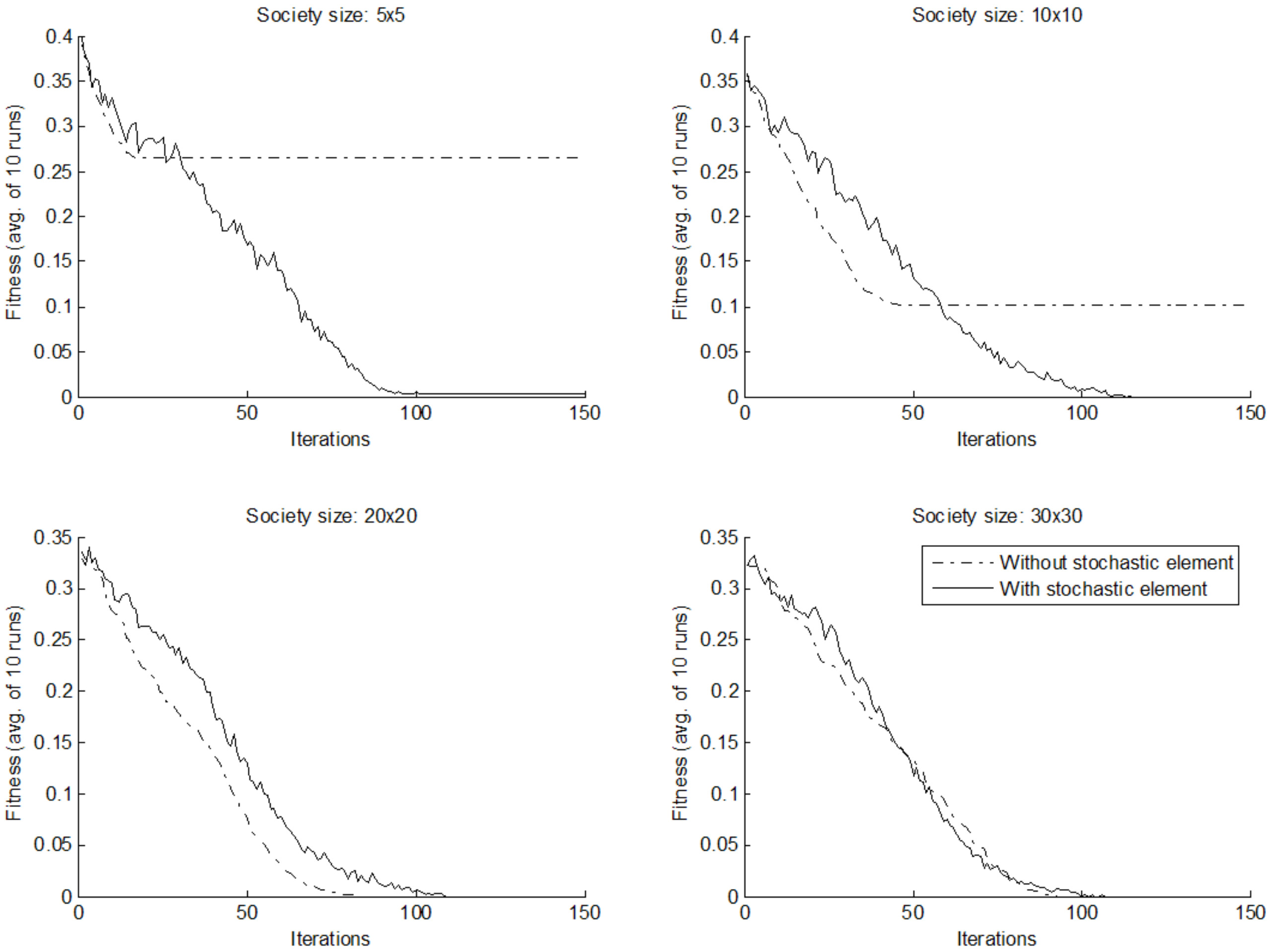

Figure 11: The evolution of fitness functions (averaged of 10 runs). The minimal fitness value corresponding to the on local global optima is 0.

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