A Study of Agents with Self-awareness for Collaborative Behavior

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Abstract. In the history of artificial intelligence (AI), primary agent focuses have been external environments, outside incentives, and behavioral responses. Internal operation mechanisms (i.e., attending to the self in the same manner as human self-awareness) have never been a concern for AI agent. We propose to address this core AI issue by proposing a novel agent cognitive learning model (ACLM) having similarities with human self-awareness, and to apply the proposed model to the Iterative Prisoner's Dilemma (IPD) in cellular Automata networks. Our goal is to show the ability of a cognitive learning model to improve intelligent agent performance and support collaborative agent behavior. We believe additional simulations and analyses will indicate enriched social benefits, even in cases where only a few agents achieve limited self-awareness capabilities.

Keywords: Agent, self-awareness, Iterative Prisoner's Dilemma.

1 Introduction

The term self-awareness refers to experiences in which an individual's attention is pointed to the self [1]. Eastern and western philosophers and psychologists have studied the self-concept for many years [2-5] and have made self-awareness a central issue in cognitive science and educational psychology [6, 7].

Simulations and artificial societies are being used to develop and test Artificial Intelligence (AI) learning models (e.g., machine learning, neural networks, and evolutionary computing), to mimic human cognitive and behavioral models, and to establish intelligent agents [8-10]. However, most models offered to date focus on outer environments rather than inner operations, with some addressing the relationship between outside incentives and behavioral responses. Our research plan is to analyze the benefits of self-awareness mechanisms for AI agents.

Our goal is to refine and introduce an agent-cognition learning mechanism (ACLM) to overcome deficiencies in traditional AI learning approaches that emphasize self-schema for internal learning. Furthermore, we will address the artificial societal conflict between the public good and private interests resulting from agent environments and goals when proposing an agent self-awareness model that is consistent with cognitive learning models. Finally, we will discuss how self-awareness resolves the problem of collective irrational behaviors and establish model validity and stability via analyses of individual performances and collaborative behaviors.

2 Agent Cognition Learning Model (ACLM)

We use the world model Learning — putting the learning focus (Attention) at the outer environment to discuss the inadequacy of Russell's [11] general model of learning agents. Doing so requires addressing the importance of self-learning in order to narrow the gap between AI agent and human intelligence. Our proposed cognition learning model is based on using self-schema as an agent's internal learning focus, which can be compatible with existing agent systems. According to our proposed model, agents attend to both their world model and self-schema; achieving inner learning via self-schema awareness moves agents closer to human intelligence. The model also offers a unique design concept to solve the high-level intelligence challenges that agents based on the world model are incapable of solving.

2.1 The Proposed Model: ACLM

We modified our design concept as a result of our analysis of the world model, using Russell's general agent model to propose a new agent cognition learning model composed of three elements: performance, world model learning, and self-schema cognition (Fig. 1). The performance element is responsible for selecting external actions. The world model learning element is in charge of integrating traditional learning components (whose focus is limited to external environments) in order to improve learning efficiency. World model learning requires knowledge about the learning element and feedback on agent performance, which it uses to determine how the performance element should be modified for better performance in the future. The self-schema cognition element (which uses prior experiences to add information to a knowledge structure) can help agents understand, explain, and predict self-behavior. Our model supports coordination between world model learning and self-schema cognition to present the most favorable method for improving performance. Agents eventually possess both external and internal learning concepts. According to our proposed ACLM, agents will be capable of self-discovery and self-awareness via the addition of various schemas that can improve and promote efficiency by means of co-ordination between external learning and internal cognition, thereby moving closer toward a human intelligence model.

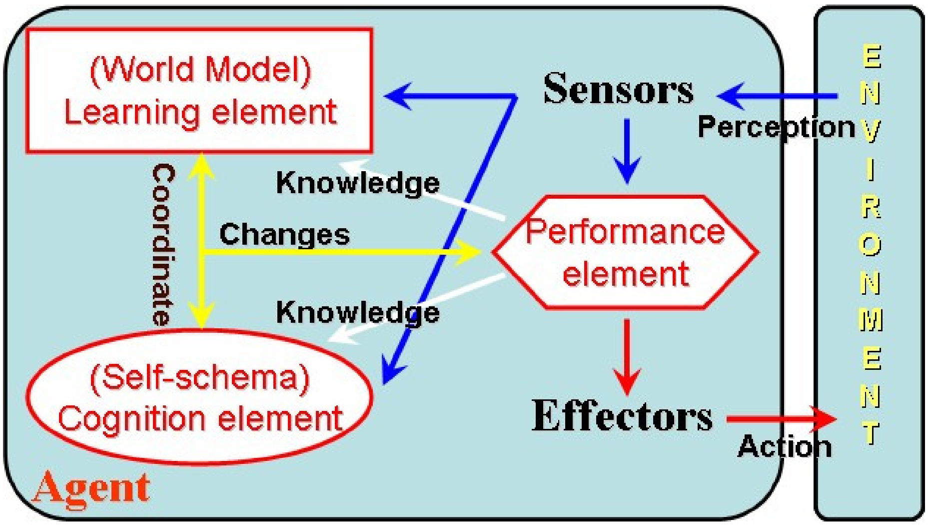

Fig. 1. Agent cognition learning model.

3 Experimental Design

The environment that any agent exists in will have many other agents, therefore the designer of a specific agent must refrain from dominating resources or profits in a manner that causes harm to the overall agent population. In response to this conflict between collective and individual agent goals, we propose an agent learning model in which the superego focuses on self-awareness achievement, based on our belief that any agent who owns self-awareness can make its life better by acting on its private interest, which in turn will benefit other agents in the form of cooperative behavior. This rational behavior has been observed among IPD strategic agents, therefore for our research platform we adopted an IPD environment with social networks that correspond to our experiment is aimed at observing the acts of learning agents with self-awareness and the effects of those actions on performance results.

3.1 Simulation Model

The simulation model shown in Figure 2 uses the two-layer concept, in which the combination of the IPD game and social networks serves as the research platform. The upper layer is the IPD (adopting the evolutionary computing approach) and the lower layer consists of the cellular automata social networks. Each upper agent adopts a pure strategy—that is, it uses the same policy for all coworkers. Besides, the Memory-1 deterministic strategy on its memory ability, there are 16 strategies can be chosen. To support observations of the emergent behaviours of strategic agents, each agent has its own unique colour. For lower-layer social networks, the cellular automata creation method made use of 2-D spatial relations in which each agent establishes links with its adjacent cells. When those links extend k steps it is called a "radius-k neighbourhood" consisting of surrounding coworkers. Subsequently, the radius-k neighbourhood of any agent can be modified by breaking off a fraction of its original links. This creates an equal number of new links (shortcuts) and randomly adds to the neighbourhood a set of individuals taken from the entire system.

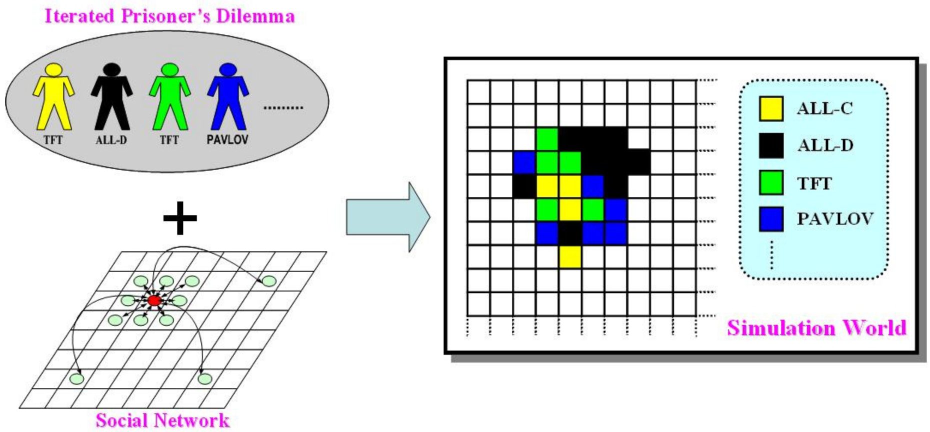

Fig. 2. Simulation model.

3.2 Agent Self-Awareness Model Using Superego Idea

Based on an analysis of intelligent agent and learning agent personalities using Freud's Three Components of Personality, we concluded that they do not have what we would consider ids or superegos. If an agent did in fact have a superego, it would support an understanding of societal expectations and the earlier emergence of collaborative behaviour. We therefore view superego as an awareness goal to resolve conflicts between collective and private interests in artificial societies. We therefore adjusted the personality model for agents in our proposed ACLM in favor of a learning model that regards the superego as a self-aware goal according to the concepts of external learning and internal cognition—in other words, to add the self-schema cognition element to the ACLM.

As shown in Figure 3, our version of superego awareness consists of four sequential steps: self-observation, self-recognition and social expectation analysis, rational calculation, and self-adjustment. To test our idea we established an experimental model using the superego awareness unit and a control unit that go through an elementary evolutionary process (Fig. 4). The experiment consisted of eleven steps:

1. Establish environmental parameters (e.g., strategy color maps, social network parameters, interaction rules) and evolutionary parameters (e.g., population size, selection rules, mutation rate and rules, crossover rate and rules).
2. Randomly generate populations and establish two kinds of social networks.
3. Select coworkers.
4. Calculate fitness scores with coworkers.
5. Use evaluation rules to give reputations to coworkers.
6. If any coworkers have not yet been selected, go to step 3. Once all coworkers have been selected, go to step 7.
7. Collect agent recognition information from coworkers. (reputation)
8. Perform social expectation analysis to determine what coworkers expect from agents (social expectations).
9. Use rational calculations to determine the degree of matching between reputation and social expectations. If below an established threshold, do nothing; otherwise perform self-adjustment.
10. Use self-adjustment procedure to select a suitable social expectation strategy.
11. Select candidate agents for the next generation and reset reputation and expectation values to zero.

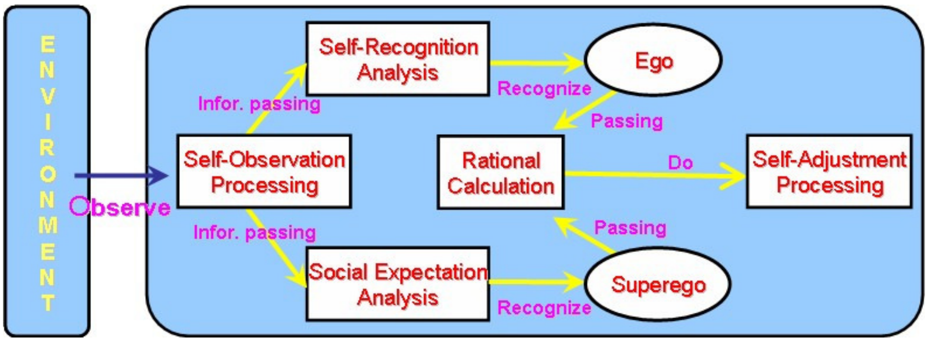

Fig. 3. Agent self-awareness model.

4 Results

We used cellular automata social networks in our experiments. In social networks, the control group is the elementary evolutionary IPD model (no self- aware agents), and the experimental group had self-aware agents in the simulated environment) at ratios of 1.0, 0.5, 0.3, and 0.1 (i.e., a ratio of 1.0 means that all agents are self-aware).

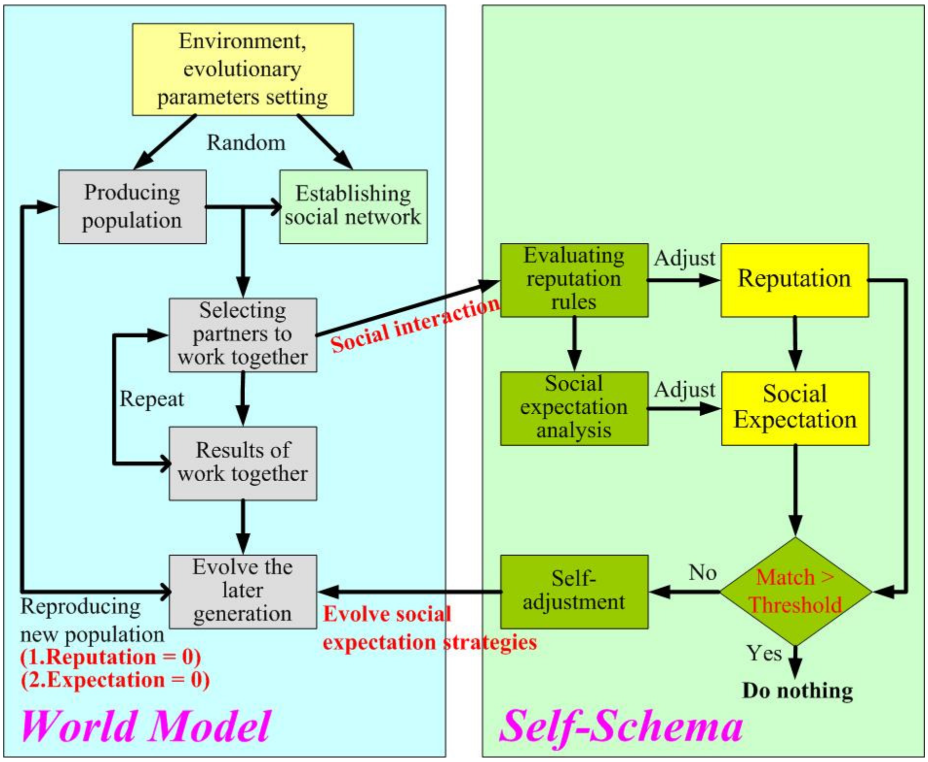

Fig. 4. Experimental procedure (world model plus self-schema).

4.1 A Few Agents with Self-Awareness that Can Improve Whole Interest

Experimental results for the first social network topology are shown in Figure 5. The five squares on the right side represent the ratios of self-aware agents. The black curve (CA: without any self- awareness agents) has some interesting implications: during early periods of evolution, individuals randomly choose strategies for working with their partners. After several generations, these individuals tend to betray their partners in order to maximize their own fitness; when most of the agents change their strategies to defection, the society falls into a self-destructive cycle that causes all social benefits to decrease rapidly. As these social benefits decreases, eventually so do private benefits, and after a few more generations, defection agents return to cooperation strategies, thereby matching the game theory concept that mutual cooperation is a better strategy for agents in iterative games. Renewed mutual cooperation triggers increases in social benefits, and the entire society moves toward an evolutionary equilibrium. According to the evolutionary dynamics of strategic agents in the control group, the simulation model matches the results of rational analysis in game theory, thus verifying the effectiveness of the simulation model.

According to the curve CA_Mix (1.0) on the figure 5, if all agents have self-awareness capabilities, all social benefits will increase and a group of agents will not fall into a destructive cycle that indicates distrust among agents. However, such an experimental setup is unrealistic. Instead, our goal is to add a limited number of self-aware agents into an existing agent system that lacks any self-aware agents, with the expectation that the introduced agents will speed up the process by which cooperative behavior emerges. Although CA_Mix (0.5), CA_Mix (0.3) and CA_Mix (0.1) may not achieve a stable state as quickly as CA_Mix (1.0), they will support a faster reduction in the chaos phenomenon, indicating that the proposed self-awareness model does produce improvement in overall social benefits. Using curve CA_Mix (0.1) as an example, even if only one agent among ten has self-awareness capability, both social and individual benefits eventually emerge at a time period that is sooner than if none of the ten agents had that self-awareness capability.

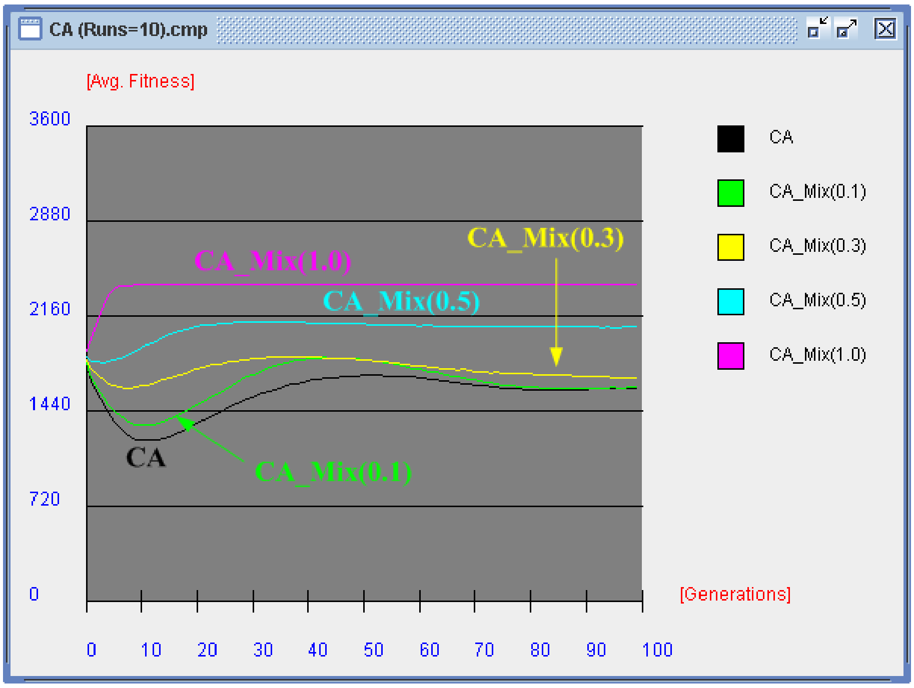

Fig. 5. Comparison with mixing partial self-awareness agents in cellular automata.

4.2 Emergence of Social Behavior

A total of sixteen single memory-strategy agents were used in our experiments. For investigating IPD model behaviour, all representative strategies that were analyzed and discussed can be classified as ALL-C, ALL-D, TFT, and PAVLOV, defined in an earlier section. We will discuss these four strategies/categories in terms of the two social networks used in the experiment.

Figure 6 illustrates reactions among the four strategies according to this topology. At the first evolutionary step, no significant difference was noted in terms of quantity. In the third generation we observed dramatic increases in ALL-D agent numbers and less dramatic decreases in the numbers of ALL-C and PAVLOV agents resulting from the growth in ALL-D agents. TFT agents, which began to emerge when ALL-D quantities achieved a certain level, checked and balanced the growth of ALL-D agents while coexisting with PAVLOV and ALL-C agents. After approximately 20th generations, TFT agents exceeded ALL-D agents; as the number of TFT agents increased, the number of ALL-D agents decreased rapidly. At approximately the 30th generation, the TFT versus STFT asynchronous memory problem began to emerge, thus triggering began the vicious circle of despiteful breach. At this point the number of PAVLOV agents started to increase because they do not suffer from memory synchronization failure. At the 60th generation the number of TFT agents becomes less than the number of ALL-D agents, and the ALL-D agents start to increase once again while the number of PAVLOV agents decrease. Finally, at the 80th generation the number of TFT agents once again exceeds ALL-D agents, and the artificial society achieves a dynamic equilibrium in which the numbers of PAVLOV and ALL-C agents remain stable (referred to as the evolutionary stable strategy, or ESS), while ALL-D and TFT continue to exist in a checks-and-balances relationship.

Cellular automata-associated results for our experiment group are shown in Figures 7 (1.0 mix ratio) and 8 (0.1 mix ratio). As shown in Figure 7, no ALL-D agents were observed at the beginning of the evolutionary process, since the cellular automata was filled with self-aware agents. Since ALL-D agents are not good matches for social good strategies, the self-aware agents quickly determine that an ALL-D existence is not permitted by their superegos, thus triggering the self-adjustment/ strategy modification mechanism of the self-awareness model. Evolutionary equilibrium is achieved at about the 3rd or 4th generation.

Figure 8 presents the most important results for our experiment, in which we added self-aware agents to the cellular automata social network at a mix ratio of 0.1. We observed that at the beginning of evolution, the ALL-D strategy was not as vigorous as that noted for the control group in Figure 6. Furthermore, a comparison of peak ALL-D numbers (at approximately the 15th generation) in Figures 6 and 8 indicate 700 ALL-D agents in the control group out of 2,500 strategic agents in the simulation without self-aware agents and 550 ALL-D agents in the experimental group (0.1 mix ratio of self-aware agents)—a significant difference of 150 agents, and an indication that even the addition of a small number of self-aware agents can speed up the process toward achieving equilibrium. Another phenomenon we observed is that the number of PAVLOV agents exceeded ALL-D and TFT agents for a certain period of time, but then decreased, suggesting that PAVLOV agents are not successful when competing against ALL-D agents, even at small numbers of ALL-D agents.

5 Conclusion

In this paper we introduced an Agent Cognition Learning Model (ACLM) and Agent Self-Awareness Model that we hope will be useful to researchers in the fields of artificial intelligence (AI), cognitive psychology, economics, and social behavior. We used AI principles to increase the thinking capabilities of agents as a means of repairing the flaws of existing intelligent agents and learning agents whose learning focuses were established according to world model guidelines. Instead, we used principles from cognitive psychology to establish a personality model that allows agents to achieve self-improvement through self-awareness, using a Prisoner's Dilemma mathematical model to address the conflict between public good and private interest in an artificial society. We eventually hope to clarify the importance of uniting internal cognition with external learning, and to revise our ACLM to offer a new approach for intelligent agents.

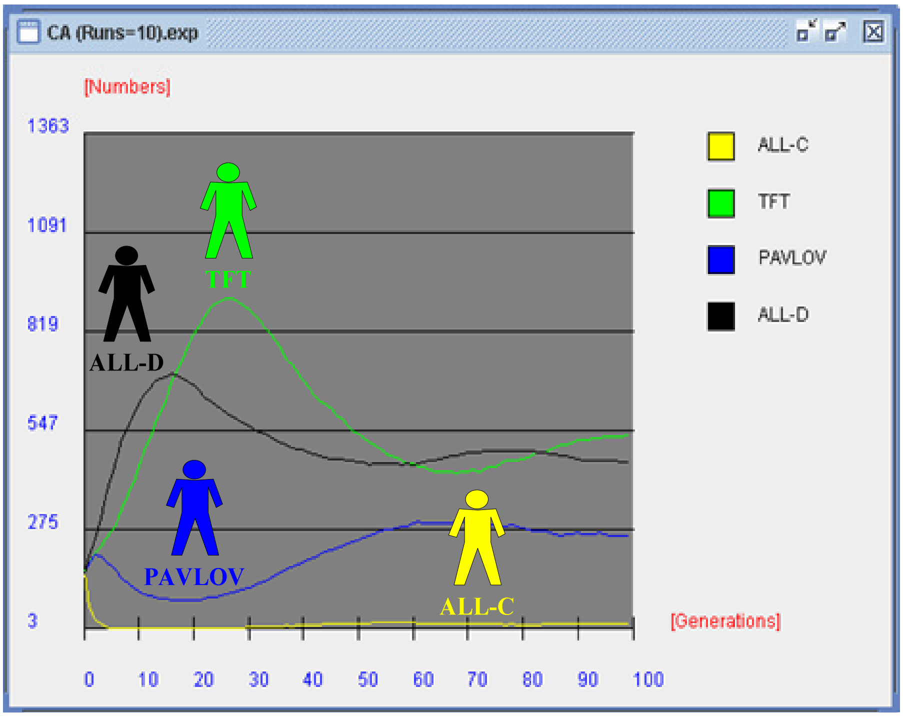

Fig. 6. Four well-known strategies in cellular automata.

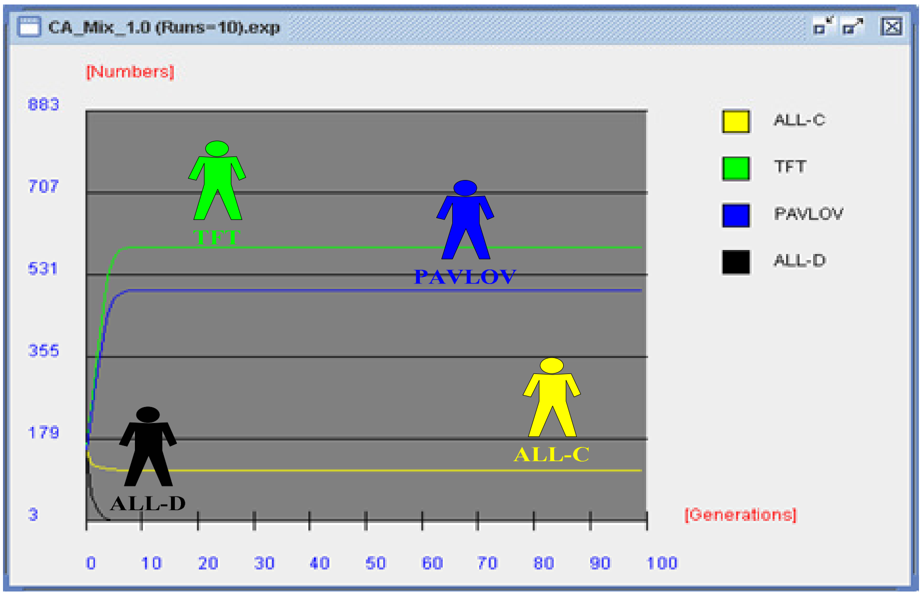

Fig. 7. Four well-known strategies in cellular automata (mixing self-aware agents with ratio 1.0).

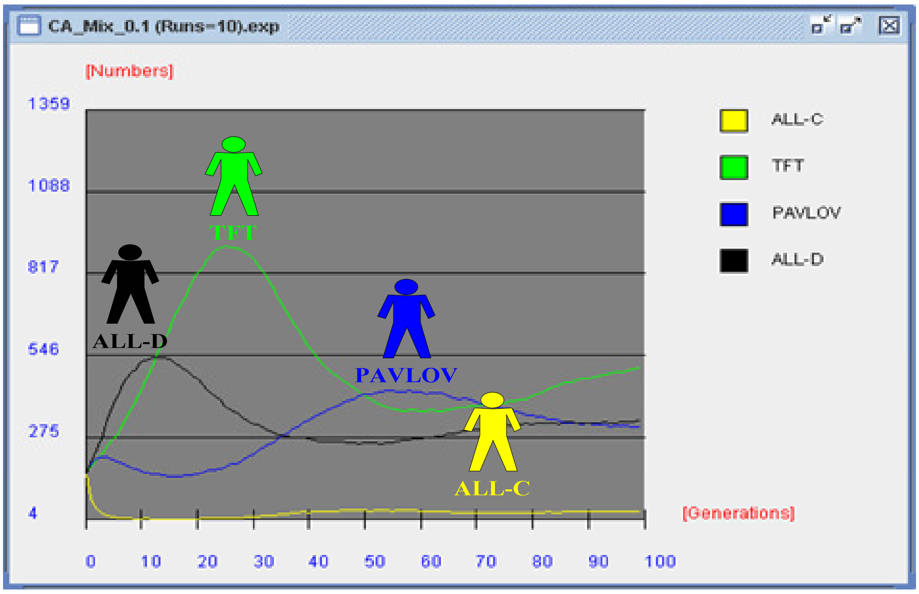

Fig. 8: Four well-known strategies in CA (Mixing self-aware agents with ratio 0.1)

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