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Adaptation using hybridized genetic crossover strategies

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Abstract

We present a simple game which mimics the complex dynamics found in many natural and social systems. Players modify their strategies periodically, depending on their performances. We propose that the agents use hybridized one-point genetic crossover mechanism, inspired by genetic evolution in biology, to modify the strategies and replace the bad strategies. We study the performances of the agents under different conditions and investigate how they adapt themselves in order to survive or be the best, by finding new strategies using the highly effective mechanism we proposed. We introduce the measure of total utility of the system and use it to study the efficiency and dynamics of the game.

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Keywords: Complex systems; Adaptation; Minority game; Genetic crossover

1. Introduction

The behaviour of most of the complex systems found in natural and social environments can be characterized by the competition among interacting agents for scarce resources and their adaptation to the environment [1–5]. The agents could be diverse in form and in capability, for example, cells in an immune system to great firms in a business centre. In these dynamically evolving complex systems the nature of agents and their manners differ. In order to have a deeper understanding of the interactions of the large number of agents, one should study the capabilities

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of the individual agents. An agent's behaviour may be thought of as a collection of rules governing "responses" to "stimuli". For example, if one sees a predator, then one should run, or if the stock indices fall then one should take immediate action, and so on. Therefore, in order to model any complex dynamically adaptive system, a major concern is the selection and representation of the stimuli and responses, since the behaviour and strategies of the component agents are determined thereby. In a model, the rules of action are a straightforward way to describe agents' strategies. One studies the behaviour of the agents by looking at the rules acting sequentially. Then one considers "adaptation", which is described in biology as a process by which an organism tries to fit itself into its environment. The organism's experience guides it to change its structure so that as time passes, the organism makes better use of the environment for its own benefit. The timescales over which the agents adapt vary from one system to another. For example, adaptive changes in the immune system take hours to days, adaptive changes in a firm take usually months to years, and adaptive changes in the ecosystem require years to several millennia.

In complex adaptive systems, a major part of the environment of a particular agent includes other adaptive agents. Thus, a considerable amount of an agent's effort goes in adaptation to the other agents. This feature is the main source of the interesting temporal patterns that these complex adaptive systems produce. For example, in financial markets, human beings react with strategy and foresight by considering outcomes that might result as a consequence of their behaviour. This brings in a new dimension to the system, namely rational actions, which are not innate to agents in natural environments. To handle this new dimension, game theory is used. It helps in making decisions when a number of rational agents are involved under conditions of conflict and competition [6]. However, game theory and other conventional theories in economics, study patterns in behavioural equilibrium that induce no further interaction. These consistent patterns are quite different from the temporal patterns that the complex adaptive systems produce.

In this paper, we study a simple game which has most of the discussed features of a complex adaptive system. The "mixed" strategies which the agents use to decide the course of action must be good, especially when the agents have to be the best in order to survive—similar to the idea of "survival of the fittest" in biology. So just as an organism adapts itself in the natural environment, we propose that "intelligent" agents in the game adapt themselves by modifying their strategies from time to time, depending on their current performances. We also borrow the concept of "hybridization" from biology and use it to modify the strategies in the course of the game, in the same way as in genetic algorithms [7–9]. Therefore, our game is a variant of the intelligent minority game introduced in [10], based on the basic minority game [11–15]. In the game we study here, we use the mechanism of hybridized genetic crossover where the two best strategies of an agent serve as the "parents" which it uses to create two new "children" using one-point genetic crossover [9,10] and then replaces two of its worst strategies with the children.

2. Model

Our game consists of an odd number of agents N who can perform only two actions denoted here by 0 or 1, at a given time t. For example, the two actions could be "buying" and "selling" commodities/assets. An agent wins the game if it is one of the members of the minority group. All the agents are assumed to have access to finite amount of "global" information: a common bit-string "memory" of the m most recent outcomes. With this there are 2^m possible "history" bit-strings. Now, a "strategy" consists of two possible responses, which in the binary sense are an action 0 or the opposite action 1 to each possible history bit-strings. Thus, there are 2^{2^m} possible strategies constituting the whole "strategy space". In our study, we use the "reduced strategy space" by picking only 2^m uncorrelated strategies, i.e., strategies which have Hamming distance $d_{\mathrm{H}} = \frac{1}{2}$ [16]. The Hamming distance indicates how similar two strategies are. It is calculated as the ratio of the number of different bits between two strategy bit strings and the total length of the strategy bit string.

At the beginning of the game, each agent randomly picks s strategies which constitutes its pool. Each time the game has been played, time t is incremented by unity and one "virtual" point is assigned to a strategy that has predicted the correct outcome and the best strategy of a player is one which has the highest virtual point score. The performance of the player is measured by the number of times the player wins, and the strategy, which the player uses to win, gets a "real" point. The number of agents who have chosen a particular action, say 1, is denoted by $A_1(t)$ and varies with time. The total utility of the system can be defined as

$$U(x_t) = (1 - \theta(x_t - x_M))x_t + \theta(x_t - x_M)(N - x_t), \tag{1}$$

where $x_M = (N-1)/2$, x_t is either equal to $A_1(t)$ or $A_0(t)$ and so $x_t \in \{0, 1, 2, \ldots, N\}$, and

$$\theta(x) = \begin{cases} 0 & \text{when } x \leqslant 0, \\ 1 & \text{when } x > 0. \end{cases}$$

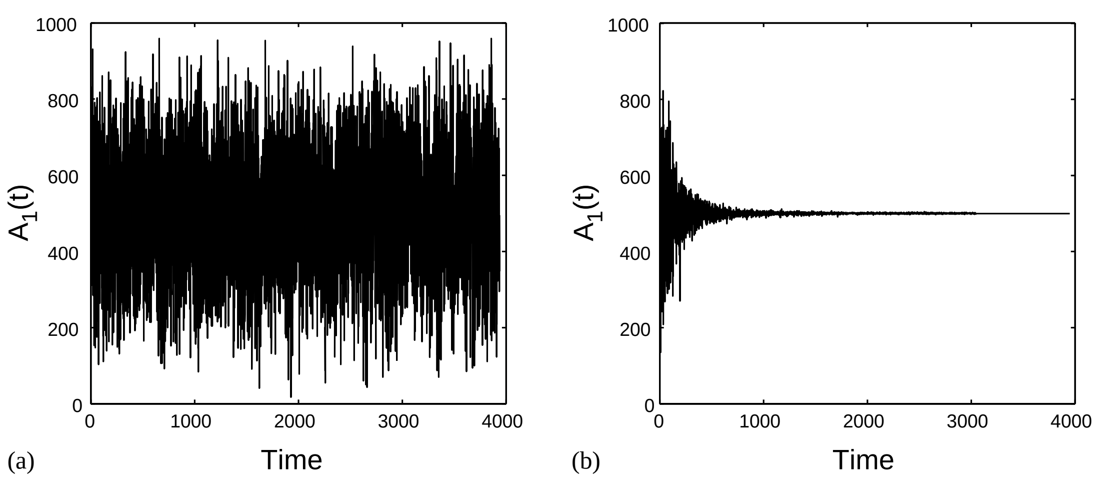
When $x_t \in \{x_M, x_M + 1\}$, the total utility of the system is maximum $U_{\max}$ ($= U(x_M) = U(x_M + 1)$) as the highest number of players win. The system is more efficient when the deviations from the maximum total utility $U_{\max}$ are smaller, or in other words, the fluctuations in $A_1(t)$ around the mean become smaller.

The players examine their performances after every time interval τ. If a player finds that he is among the fraction n (where $0 < n < 1$) who are the worst performing players, he adapts himself and modifies his strategies. The mechanism by which the player creates new strategies is that of hybridized one-point genetic crossover, whereby he selects the two best strategies ("parents") from his pool of s strategies. Then using one point genetic crossover [9,10], he creates two new strategies ("children") and replaces his two worst strategies with the children. It should be noted that our mechanism of evolution of strategies is considerably different from earlier attempts [11,17,18]. Here, the strategies are changed by the agents themselves and even though the strategy space evolves continuously, its size and dimensionality remain the same.

3. Results

The time variations of the number of players $A_1(t)$ who choose action 1 are plotted in Fig. 1. We observe large fluctuations around the mean for the basic minority game in Fig. 1(a). In Fig. 1(b), we observe the effect of hybridized genetic crossovers on the fluctuations around the mean. Interestingly, the fluctuations disappear totally and the system stabilizes to a state where the total utility of the system is at maximum, since at each time step the highest number of players win the game. As expected, the behaviour depends on the parameter values for the system. For example, as we increase m it is more unlikely that the system stabilizes. Also, we have to increase s, the size of the pool of strategies, in order that the system stabilizes. The dependence of the system's stability on these parameters is being studied in details in [19]. So the important fact here is that the behaviour is totally different from the behaviour of the basic minority game, where increasing s usually leads to larger deviations [11,12]. It is also interesting to note that starting from a situation, similar to what is shown in Fig. 1(a), simply allowing the agents to adapt themselves by modifying their strategies using the mechanism we have proposed, drives the system towards a state where the total utility is optimized.

In Fig. 2, we further analyze some measures related to the simulation in Fig. 1(b). If we plot the performances of the agents in a basic minority game, we find that the distribution of the performances is quite symmetric around the mean and the performances of the players do not vary remarkably during the game [11]. However, in our model the competition is very stiff and there are lots of ups and downs in the performances, and finally, when the system reaches an optimal state, the players can be divided clearly into two groups depending on their performances, as shown in Fig. 2(a). The performances in all cases are scaled such that the mean performance is zero at every time step, so that we can compare them easily. Fig. 2(b) shows the



(a) (b)

Fig. 1. Plot to show the time variations of the number of players A_1 who choose action 1, with the parameters $N = 1001$, $m = 5$, $s = 10$ and $t = 4000$ for (a) basic minority game and (b) our game, where $\tau = 25$ and $n = 0.6$.

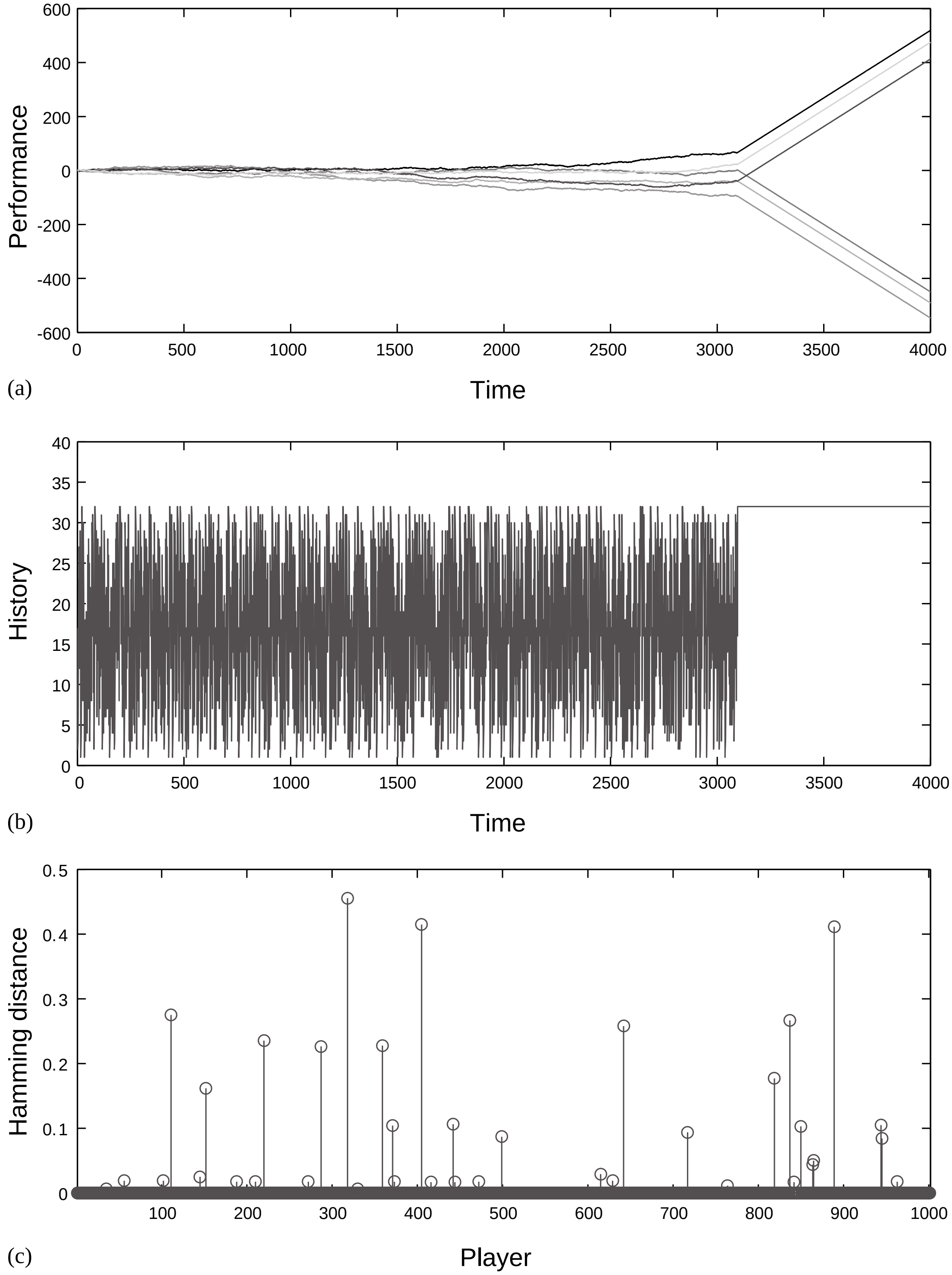


Fig. 2. Plots to show: (a) the performances of the players in our game for the best player, the worst player and four randomly chosen players, (b) the time variation of the history and (c) the Hamming distances for the final pool of strategies for all the players. The parameters used for simulations are $N = 1001$, $m = 5$, $s = 10$, $t = 4000$, $\tau = 25$ and $n = 0.6$.

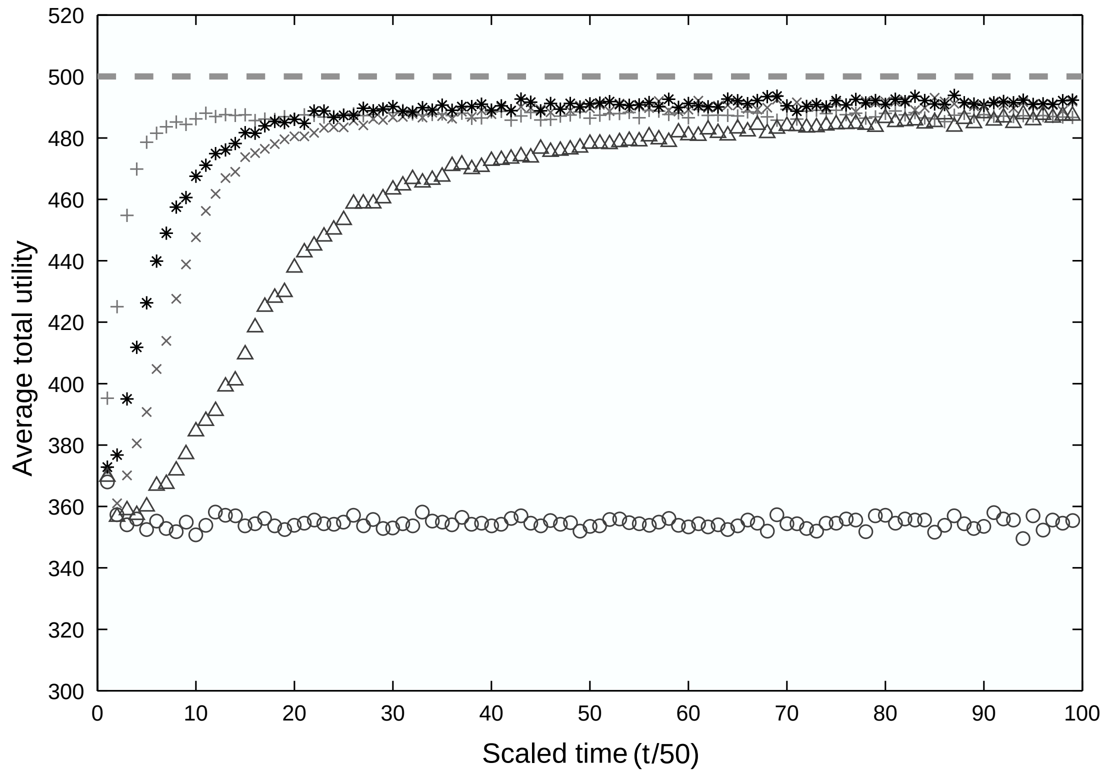


Fig. 3. Plot to show the variation of total utility of the system with time for the basic minority game for $N = 1001$, $m = 5$, $s = 10$, $t = 5000$, and our game, for the same parameters but different values of τ and n. Each point represents a time average of the total utility for separate bins of size 50 time-steps of the game. The maximum total utility $(=(N-1)/2)$ is shown as a dashed line. The data for the basic minority game is shown in circles. The plus signs are for $\tau = 10$ and $n = 0.6$; the asterisk marks are for $\tau = 50$ and $n = 0.6$; the cross marks for $\tau = 10$ and $n = 0.2$ and triangles for $\tau = 50$ and $n = 0.2$. We have taken ensemble average over 70 different samples, in each case.

evolution of the history. Since $m = 5$, there are $2^m = 32$ possible history bit strings denoted by a number between 1 and 32. Before the system reaches the optimal state, histories vary over the whole range of possible outcomes as shown in Fig. 2(b). But after reaching the stable state, the history is restricted to one value. So, one group wins while the other loses continuously, depending on the strategy spaces of the players. To study the differences in the strategies of each players' pool after the system has reached the stable state, we have calculated the average Hamming distance over all the strategy pairs in the players' pools. Results are shown in Fig. 2(c). If all the strategies in a pool are the same, average Hamming distance is zero, for uncorrelated strategies, it is $\frac{1}{2}$ and for totally anti-correlated strategies 1. Surprisingly, we find that for most of the players the average Hamming distance calculated for the whole pool is zero, which implies that the players have evolved their strategies and found only one strategy for use.

In order to study the efficiency of the system and its dynamics, we have introduced the study of the variation of the average total utility of the system $U(x_t)$ with time t. The results are shown in Fig. 3. We find that for the basic minority game the total utility does not change much throughout the course of the game. However, in the game we study, we can clearly see that the total utility of the system increases as the time passes on and eventually saturates (or becomes practically constant). We can define a characteristic time λ, during which the total utility reaches a saturation point. As intuitively expected, this characteristic time depends on the parameters of the system. It is interesting to note that this utility measure is very effective in characterizing the dynamics of an adaptive game. We calculate the mean of $U(x_t)$ when it has become practically constant or saturated, and denote it by U_{sat}. We then observe the asymptotics of the quantity $(U_{sat}-U(x_t))$, i.e., how this quantity approaches zero after a long time (t is large or even infinity). The asymptotics display very interesting dynamical behaviour. For example, when $N=1001$, $m=5$, $s=10$, $t=5000$, $\tau=50$ and $n=0.2$, the asymptotics suggest that eventually the behaviour is that of a power law with an exponent of about -1.5. We defer the detailed studies and results for a future communication [19].

In order to demonstrate that the "intelligent" players who adapt themselves in the course of the game, by modifying their strategies using the hybridized one-point genetic crossover, perform better than "normal" players, who do not adapt themselves, we have tested the players in two different situations. The first situation is where all the players play the basic minority game but later we select the worst player and allow it to adapt itself and thus modify its strategies. We find that the player starts winning immediately and eventually comes out to be a winner as shown in Fig. 4(a). Further, we choose two other worst players at two different times and allow them to modify their strategies also. These two players too begin to perform very well. We find that the performances of these chosen "intelligent" players are much better compared to the "normal" players of the basic minority game. The second situation consists of ten "intelligent" players who are capable of modifying their strategies and the rest are "normal" players who simply play the basic minority game. We find that the intelligent players perform extremely well in comparison to the other normal players, and form a separate group, as shown in Fig. 4(b). The competition amongst themselves is very stiff as can be seen from the inset of Fig. 4(b).

These two situations and the results clearly show how effective the adaptation of agents can be in a complex adaptive system. The mechanism of modifying the strategies is also very successful as it allows a player to find new strategies which maximizes the players' individual utility. However, the total utility of the system does not change much as the fraction of adaptive players is very small in both cases. It would be interesting to study the variation of the total utility of the system with the fraction of adaptive players.

4. Summary

In summary, we have proposed a game where the players adapt themselves to continuously changing environment, thus reproducing interesting temporal patterns that are usually created by complex adaptive systems in nature. The mechanism of adaptation we have introduced here seems to be very effective in all the cases we have studied, as can be seen from the individual performances of the players or from the measure of

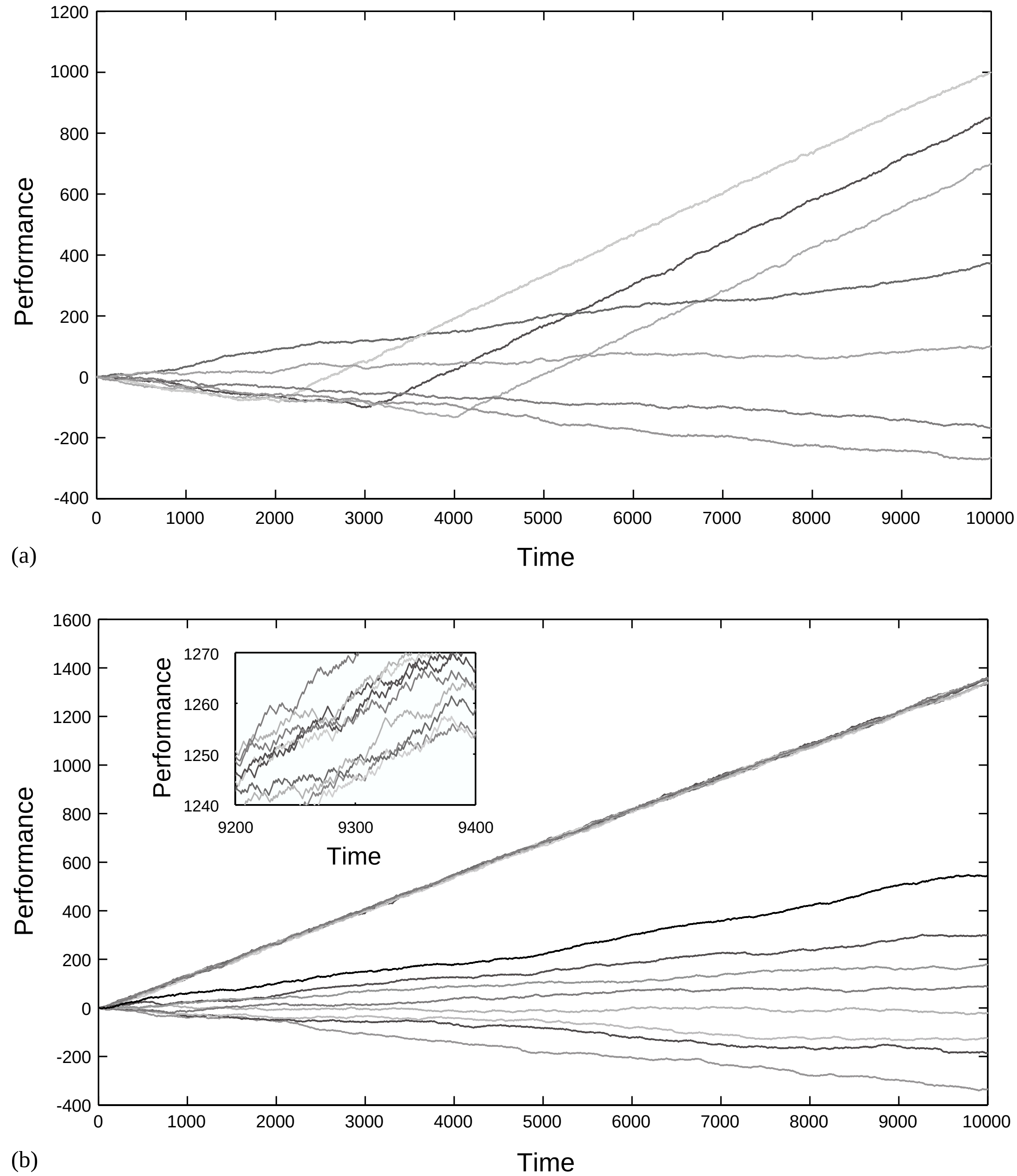


Fig. 4. Plots to show the performances of the players: (a) for three players who were the worst players in the basic minority game at different times but started winning once they started modifying their strategies using the hybridized genetic crossovers and the best "normal" player, the worst "normal" player and two randomly chosen "normal" players and (b) for the ten "intelligent" players who modify their strategies using the hybridized genetic crossovers and cluster together in the winning group and the best "normal" player, the worst "normal" player and six randomly chosen "normal" players. The inset of (b) shows performances of ten "intelligent" players who modify their strategies using the hybridized genetic crossovers and cluster together in the winning group in a magnified scale. The parameters used for simulations are $N = 1001$, $m = 5$, $s = 10$, $t = 10000$ and $\tau = 10$.

the total utility of the system. Here, we also introduced the total utility of the system varying with time, as a different measure than the usual σ^2/N, which can be used to study not only the efficiency of the game but its entire dynamics as well. The performances of the players in different conditions always seemed to be better when they adapted themselves compared to the players who did not. We conclude that using this mechanism one could increase remarkably the individual utility and the total utility of the system as well, if the fraction of adaptive players is significant.

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