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Co-evolutionary learning with strategic coalition for multiagents

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Abstract

In a dynamic system, such as social and economic systems, complex interactions emerge among its members. In that case, their behaviors become adaptive according to changing environment. In this paper, we use the iterated prisoner's dilemma (IPD) game, which is simple yet capable of dealing with complex problems, to model the dynamic system, and propose strategic coalition to obtain superior adaptive agents and simulate its emergence in a co-evolutionary learning environment. Also, we introduce the concept of confidence for agents in a coalition and show how such confidence helps improving the generalization ability of the evolved agents using strategic coalition. Experimental results show that co-evolutionary learning with coalition and confidence can produce better performing agents that generalize well against unseen agents.

Keywords: Prisoner's dilemma; Coalition; Co-evolution; Multiagents; Evolutionary learning

1. Introduction

Evolutionary computation has been adopted for many branches of mathematics, social science and computer science. This plays a key role to make an adaptive system as a part of machine learning techniques. However, rapid changes in social situation and economic environment require some improvement in evolutionary technique. Game-theoretic approach has been used extensively to solve such problems [5]. In this paper, we use the iterated prisoner's dilemma (IPD) game to model dynamic systems as one of the game-theoretic methods, and propose strategic coalition to achieve superior adaptive agents in the game with co-evolutionary learning process.

In biology, co-evolution refers to the evolution of multiple species that affect one another. As one species evolves, it changes the relationship that it has with surrounding species. In game theory and evolutionary game, the IPD game and its variants have been used to study co-evolutionary learning under various conditions. It has also been used widely

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to model various social and economic phenomena, where the primary purpose is not to model a dynamic system, but to study how co-evolution can be used in learning novel strategies [10,18]. For example, co-evolutionary learning of strategies for the N-player ($N > 2$) IPD games has been studied extensively [8,12,19].

Cooperation among autonomous agents may be mutually beneficial even if the agents are selfish and try to maximize their own expected payoff [14]. As a method of cooperation, coalition that is motivated to get more payoff or survive for long time, consists of better performing agents extracted from a population. When agents form coalition, each agent in the coalition has his own confidence (i.e., weight) which influences the agent's impact in determining the next move for the coalition. Agent's confidence is evolved automatically through evolutionary learning process. It is not pre-defined or fixed.

In this paper, we investigate how the evolved agents using strategic coalition generalize well against unseen agents. Also we provide an analysis of how the evolved agents play against well-known test strategies in the prisoner's dilemma game [3]. As a result, the generalization ability of the evolved agents is improved outstandingly in the comparison of the results against test agents.

The rest of this paper is organized as follows: Section 2 introduces the prisoner's dilemma game and co-evolutionary approach to it. In Section 3, we propose strategic coalition in the IPD game and explain how it is formed in evolutionary process. Also, we describe how to evolve agent's confidence within a coalition so that the generalization ability of the coalition can be improved. Section 4 presents the experimental results and analyzes the results. Finally, Section 5 concludes with a brief summary and a few remarks.

2. Background

2.1. Iterated prisoner's dilemma game

In the prisoner's dilemma game, each player can choose one of two choices, defection (D) or cooperation (C). Table 1 shows an example of the payoff matrix table of the game. The prisoner's dilemma game is non-zero sum and non-cooperative game. That is, one player's gain may not be the same as the other player's loss and there is no communication between two players.

Table 1
Axelrod's payoff matrix for the two-player IPD game

Own move	Opponent's move	
	Cooperation	Defection
Cooperation	Player: R (3 points) Opponent: R (3 points)	Player: S (0 point) Opponent: T (5 points)
Defection	Player: T (5 points) Opponent: S (0 point)	Player: P (1 point) Opponent: P (1 point)

It must satisfy following conditions: $T > R > P > S$; $2R > T + S$.

According to the conditions given in Table 1, if the game is played for one round only, the optimal strategy is definitely defection. However, if the game is played for many rounds, mutual defection may not be the optimal strategy. Otherwise, mutual cooperation guarantees more payoff than mutual defection for two players. There has been a great deal of work in game theory investigating the optimal strategy for the two-player IPD (2IPD) game under various conditions. In this paper, we focus mainly on co-evolutionary learning and the generalization ability of learned strategies using strategic coalition among players.

2.2. Evolution of strategy

Generally, the IPD game has three steps such as selecting action, moving and updating history. After enough numbers of the IPD games have been played in each generation, each player's fitness is evaluated according to his total score obtained during the game. After evaluating fitness, superior players survive to the next generation by genetic operation. The evolutionary selection is made autonomously among the players in the population. After the evaluation and selection, the players' strategies are evolved according to genetic operators and the procedure repeats over and over.

2.3. Representation of strategy

The representation of strategy may influence various aspects of evolutionary study such as distribution of behaviors in initial population of players, recombination and mutation. Several different types of representation schemes have been proposed

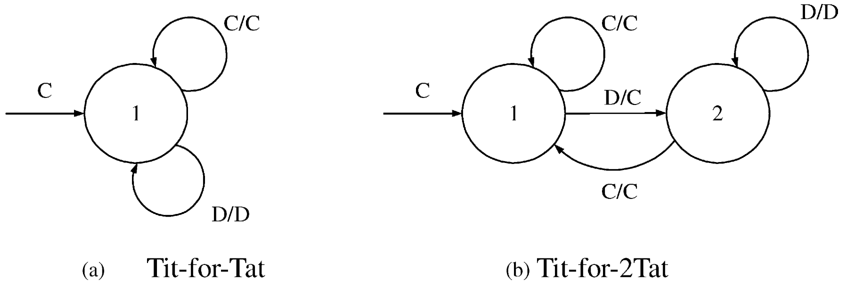


Fig. 1. Finite state machine examples.

for the IPD game such as finite state machine, logic tree, If-Skip-Action (ISAc) [2], Markov chain, and neural nets.

In this paper, we use the bit string representation that is generally used for the convenience of computer-based simulation. Figs. 1 and 2 describe the examples of finite state machine and bit string representation schemes, respectively.

Each genotype in bit string representation is projected to a look-up table that covers every possible action according to history table as shown in Fig. 2. History table that includes each player's action is represented as a binary string of $2l$ bits, where the first l bits represent the player's own previous l actions, and the other l bits represent the previous actions of the other player.

3. Strategic coalition

The strategies evolved with general evolutionary algorithm play well against other players in the same population. However, they may overfit to the population and perform poorly against unseen opponent' strategies that are not present in the population [6,7]. One effective approach to remedy this problem and improve the generalization ability of co-evolutionary learning is to learn automatically with a group of cooperative strategies. In particular, each player in the group becomes a specialist in dealing with an unseen opponent with similar genotype. Therefore, the whole group becomes robust and generalizes well [7,13]. Such a group including specialists is formed autonomously in cooperative way and it evolves like a single player. This approach can be regarded as a method of automatic design of modular systems, where each module consists of similar specialists. Fig. 3 depicts the proposed system using strategic coalition to improve the generalization ability of the players in this paper. Hereafter, we define the strategic coalition in the IPD game and describe how coalition forms and evolves.

3.1. Definitions

Coalition is an important way for cooperation in multiagent environment [15,16]. Allsopp [1] and Tate et al. [17] have applied coalition formation to model future scenarios in international military coalition as a part of DARPA's Control of Agent-Based Systems (CoABS) program. They have demonstrated how agent technologies support the rapid, coordinated construction of a coalition command system.

To form coalition among agents, two main principles must be resolved in advance. One is how autonomous agents coordinate their actions and form coalition. The other is among all possible coalition structures which coalition structure gives the best performance and what reasons and processes will lead the agents to form that particular coalition

	Strategy Table	History Table
Tit-for-Tat	0 0 1 1 1 1 0 1 1 0 0 1 1 0 0 1	1 0 0 1
CDCD	0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1	1 1 0 1
AllD	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	0 1 0 1

Fig. 2. Bit string representation examples.

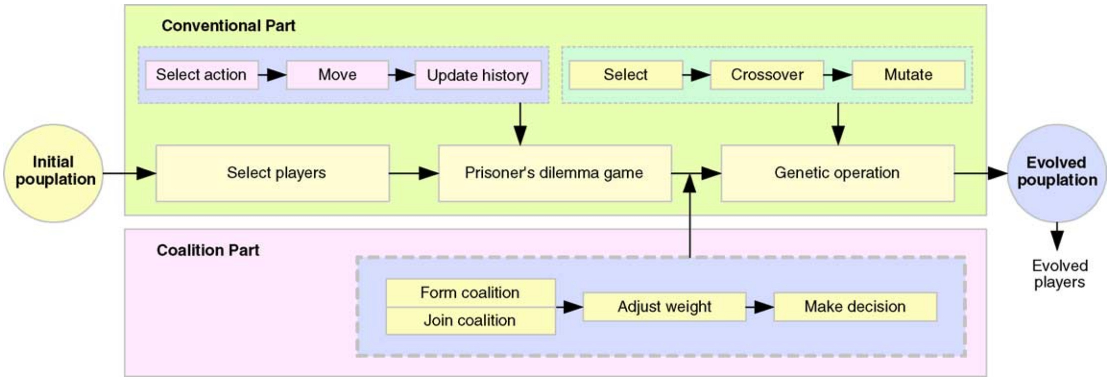


Fig. 3. Proposed system to improve the generalization ability of agents in the IPD game.

[14]. In order to form strategic coalition in the IPD game, two assumptions are given as follows.

Assumption 1. Players communicate each other to check intention about forming coalition. This assumption can be achieved by comparing each payoff after the IPD game between players.

Assumption 2. Coalition forms autonomously. That is, any external supervision should be blocked. Under this condition, players can negotiate each other to form coalition autonomously.

The IPD game is a good example to observe coalition formation procedure. In real society, strategic coalition like the IPD game can be shown easily—between individual and individual, individual and group, and group and group.

Let $I = \{A_1, A_2, \ldots, A_n\}$ be the collection of agents in a population that participate in the IPD game. Let $C = \{A_i, A_j, \ldots, A_k\}$, $|C| \geq 2$ be the strategic coalition that can be formed among those agents. The coalition, C, is the element of the agent group, I: $C \subseteq I$, $|C| \leq |I|$. Every agent has his own payoff, p_i, that earns from the IPD game against his opponents. Then, coalition has the vector, $C = \langle S_c, N_c, f_p, D_c \rangle$. Here, S_c, N_c, f_p and D_c mean the sum of players' payoff, the number of players in the coalition, payoff function, and decision of the coalition, respectively. Now we can define the strategic coalition as follows.

Definition 1 (*Coalition value*).
Let ω be the weight vector for each agent's payoff. The payoff of coalition, C_p, is the average payoff by the corresponding weight of agents that participate in the coalition.

$$C_p = \frac{S_c}{|C|} \tag{1}$$

where $S_c = \sum_{i=1}^{|C|} p_i \omega_i$ and $\omega_i = p_i / \sum_{j=1}^{|C|} p_j$.

Definition 2 (*Payoff function*).
Agents belonged to coalition get payoff with a given function. In general, the two-player IPD game follows Axelrod's payoff table [4].

Definition 3 (*Coalition identification*).
Each coalition has its own identification number. This number is generated when coalition is made with given conditions, and it may be removed when the coalition exists no more. This procedure is made autonomously according to evolutionary game process.

Definition 4 (*Decision making of coalition*).
Coalition must have one decision that is combined by participants. The decision reflects the intention of whole participants. There are several decision-making methods: weighted voting, Borda function, Condorcet function, and so on. We use weighted voting method for decision making of coalition in this experiment. Decision making of coalition, D_c, is determined by function with each participant' payoff and weight.

$$D_c = \begin{cases} 0\,(\text{cooperation}) & \text{if} \quad 1 < \dfrac{\sum_{i=1}^{|C|} C_i^{C} \omega_i}{\sum_{i=1}^{|C|} C_i^{D} \omega_i} \\[2ex] 1\,(\text{defection}) & \text{if} \quad 0 < \dfrac{\sum_{i=1}^{|C|} C_i^{C} \omega_i}{\sum_{i=1}^{|C|} C_i^{D} \omega_i} \leq 1 \end{cases} \tag{2}$$

Definition 5 (*Payoff distribution*).
Coalition get payoff after the game against other player or coalition. This payoff is distributed to each agent belonging to the coalition with a given function according to its weight.

$$p_i = \omega_i \frac{S_c}{|C|} \tag{3}$$

In the above definitions, coalition is a collection of agents that participate in the IPD game. In our experiment, the coalition may be formed autonomously while the IPD game plays repeatedly, and the coalition survives to the next generation without transformation.

3.2. Coalition formation

General procedure of coalition formation includes three activities: (1) generating coalition structure; (2) solving the optimization of each coalition; and (3) dividing the fitness value of the generated solution among agents [11]. In this paper, however, we propose a different method for coalition formation. It uses not coalition structure generation but autonomous coalition formation. While the IPD game is played, each player negotiates with his opponent to form coalition. Payoff is an important factor for negotiation. If the coalition formation conditions are satisfied, players participate in a coalition with confidence (i.e., weight) corresponding to own payoff. Player's confidence is not pre-defined and fixed, but evolved. A player may have different confidence in dealing with an opponent. In other words, a player takes part in deciding the next move of coalition at the rate of his confidence.

The IPD game including coalition is played according to the procedure given in Fig. 4. In each generation, the 2IPD game is played between two randomly selected players. A single player may play against a coalition. Also there may be the game

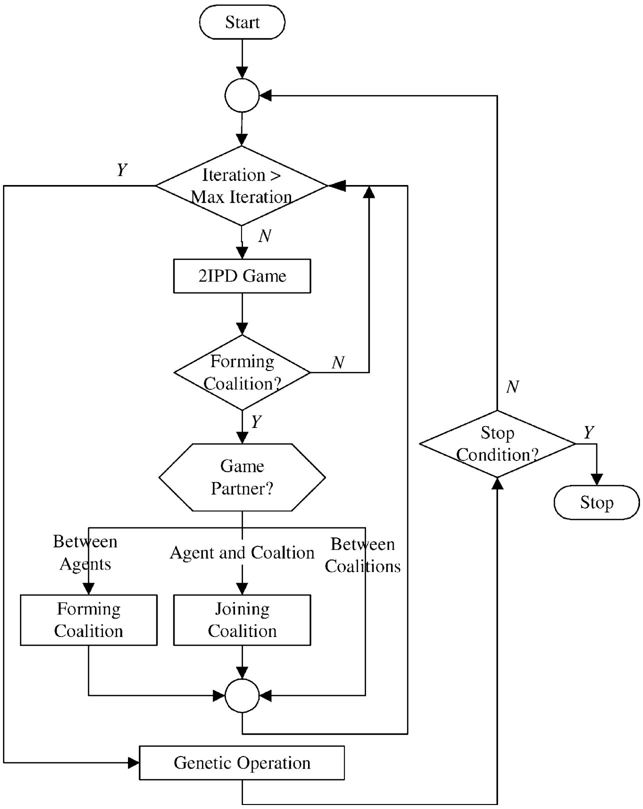


Fig. 4. The two-player IPD game allowing coalition.

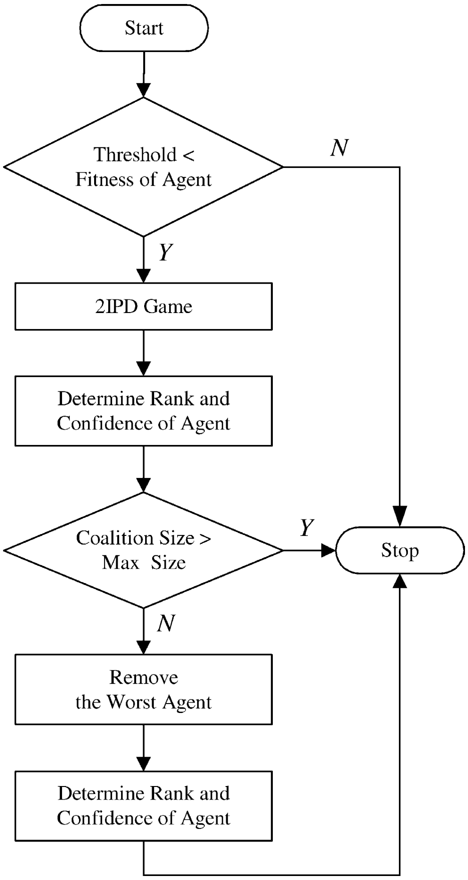


Fig. 5. Coalition formation procedure during evolution.

between coalition and coalition. After the game, players may form a new coalition or join an existing coalition if their fitness is higher than the coalition's payoff threshold. In the case of game between coalition and coalition, there is no change in each coalition structure except fitness.

Once a player has joined a coalition, players within the coalition (including the new player) will play the IPD game in round-robin way. For k players in a coalition, a total number of $k(k-1)/2$ games will be played. If the total number of players (i.e., k) is greater than a pre-defined maximum coalition size, the weakest player (in terms of the total payoff he/she obtained in all round-robin games) will be removed from the coalition as shown in Fig. 5. All players within a coalition are ranked (sorted) according to the total payoff. A player's confidence is assigned in proportion to his/her rank in the coalition. Here, the average confidence is 1.0 in real number. For example, if there are four players in a coalition, each player's confidence will be 0.8, 0.9, 1.1 and 1.2. Here, confidence plays an important role in determining the player's impact on deciding coalition's next move.

Fig. 6 shows how to combine players' confidence in a coalition to decide coalition's next move. In the figure, previous action indicates the history of opponent's and player's move in previous game. C_i, C_j, C_k and C_l are players belonging to a coalition. Coalition's next action is determined by the sum of the value of cooperation/defection that each player selects as the next action in proportion to each confidence

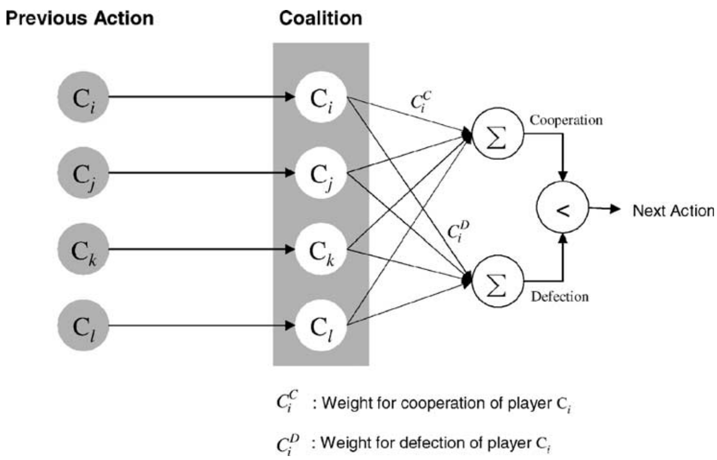


Fig. 6. How to make decision of coalition.

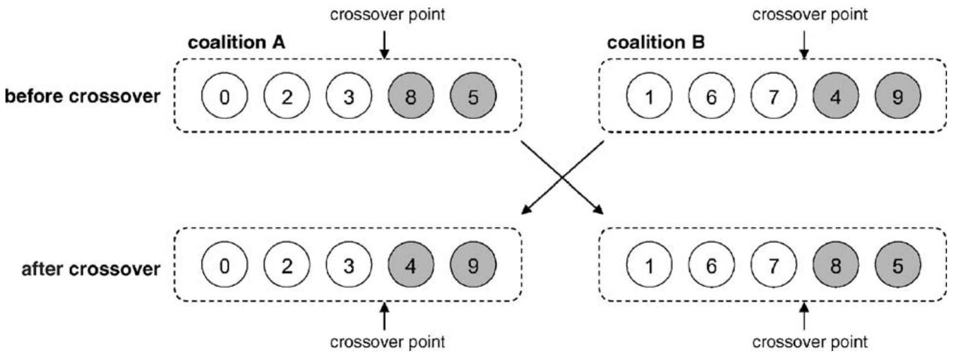


Fig. 7. Evolution of coalition using crossover.

(refer to Eq. (2)). For example, if the sum of cooperation value is greater than the sum of defection value coalition's next action will be cooperation.

3.3. Evolution of coalition

In this paper, coalition acts as a single player in evolutionary process. Therefore, coalition is also influenced by genetic operation. This makes the diversity of population improved so that players in population perform well against various opponents. Fig. 7 depicts how new coalition is generated by crossover of existing two coalitions. Crossover of coalitions is done by exchanging the same number of players with crossover.

4. Experimental results

In our experiments, we use population size of 50, crossover rate of 0.6, and mutation rate of 0.001. We adopt a genetic algorithm with one-point crossover and rank-based selection as evolutionary selection scheme [9]. For the two-player game, the history length is set to 2. The maximum coalition size is 10 and the maximum number of coalitions is one third of the population size (i.e., 16).

4.1. Coalition evolution

Coalition that is generated autonomously in a population evolves with co-evolutionary process. It participates in the IPD game like a single player and gets payoff after the game. Fig. 8 shows the average fitness of coalitions for four runs during evolution. In the beginning of generations, the average fitness of coalitions is above that of individual players in the population. This means that coalitions perform better than individual players. However, the difference decreases as time goes by, because individual players have gradually learned how to deal with coalitions. In other words, individual players also evolve to adapt to their environment.

Fig. 9 shows population convergence. Here, bias means the ratio of cooperation or defection in a specific bit position of a player's strategy table. For example, if bias is 0.7, 70% of players in the population select cooperation or 70% of players select defection. Convergence of bias 1 represents that most of the players select mutual cooperation or mutual

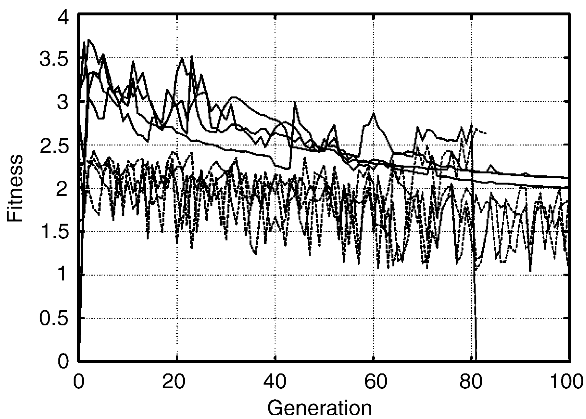


Fig. 8. Average fitness of coalition and individual players in the population. Solid lines represent coalition and dashed lines represent individual players.

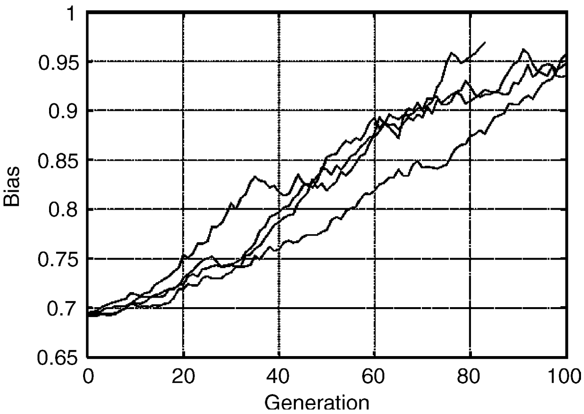


Fig. 9. Population convergence.

defection. As shown in the figure, the population has more or less converged to bias 1 at about 100 generation, which means that the evolved strategies cooperate mutually.

Coalition can survive or disappear depending on whether its average payoff exceeds the average payoff of individual players. Fig. 10 shows the number of coalitions during evolutionary process. In the figure, the maximum number of coalitions is limited to 16 because we set up the limitation with one third of population to prevent coalition from dominating population. In the beginning of generations, the number of coalitions grows up to the maximum. However, as individual players evolve gradually, the number of coalitions decreases in the end of generations.

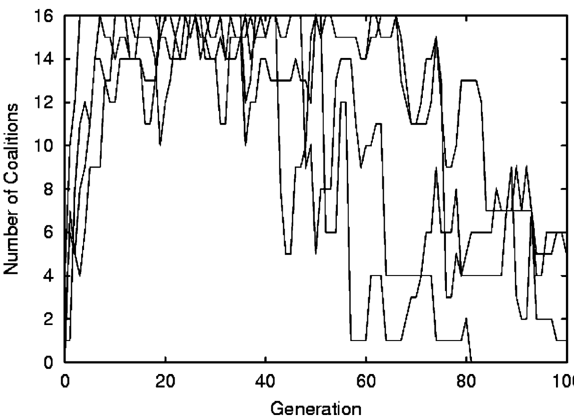


Fig. 10. The number of coalitions in evolution.

Table 2
Well-known test strategies with random strategy

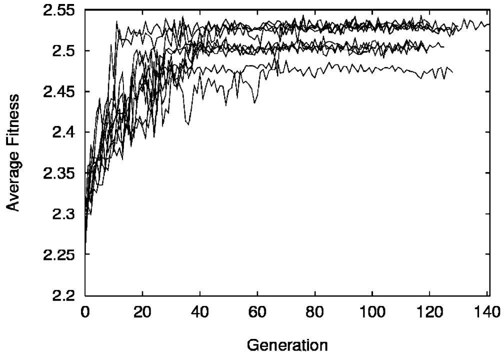
Strategy	Characteristics
TFT	Initially cooperate, and then imitate opponent's action
TF2T	Similar TFT, but defect for opponent 2's defection
Trigger	Initially cooperate. Once opponent defects, continuously defect
AllD	Always defect
CDCD	Cooperate and defect over and over
CCD	Cooperate and cooperate and defect
C10Dall	Cooperate before 10 rounds and always defect after that
Random	Random move

4.2. Generalization ability

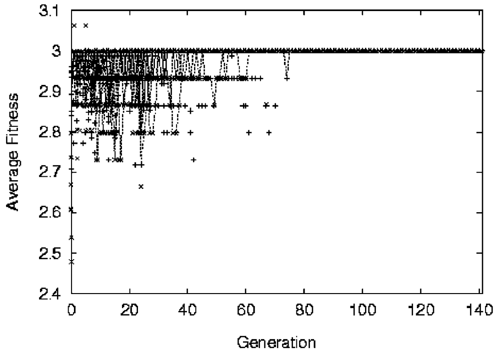
As mentioned in Section 3, we have proposed the strategic coalition to generate superior adaptive strategies in a population. Obviously, the evolved strategies using strategic coalition should perform well against unseen opponents. That is the problem of the generalization ability. In this subsection, we investigate how the evolved strategies generalize well against each test strategy. To experiment, we choose two types of test strategy sets. One is the set of well-known test strategies such as TFT, Trigger, CCD, and so on. These strategies are used frequently in the IPD game competition [3]. The other is the set of the top ranked 30 strategies in a random population of 300 strategies. Table 2 shows the characteristics of the seven well-known strategies and random strategy.

Fig. 11 shows the average fitness of the evolved coalitions and each well-known test strategy when they play against each other. It is clear that the coalitions have learned to cooperate with cooperators (including TFT, Trigger and TF2T), retaliate against AllD, and beat the random player soundly. The coalitions also play well against C10Dall and CDCD by defeating or tying with them. Regardless of opponents, the coalitions could consistently achieve high fitness value.

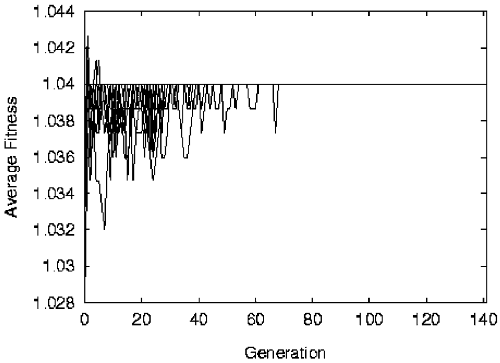
The next experiment to evaluate the generalization ability of coalitions is the IPD game against the second test set of the top ranked 30 players in a random population. Each player's bit string of the test set is given in Table 3. We have experimented to compare the performance between before and after evolution of the evolved coalition against the top ranked 30 test strategies. Then, we have conducted experiment to



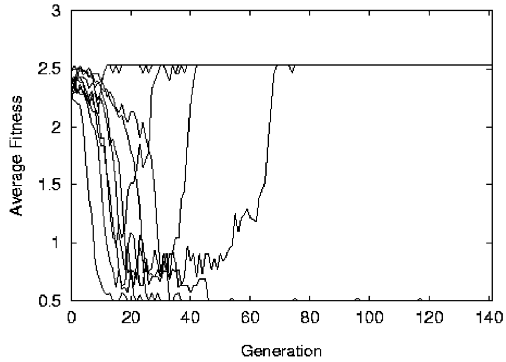
(a) Average fitness of the evolved coalitions.



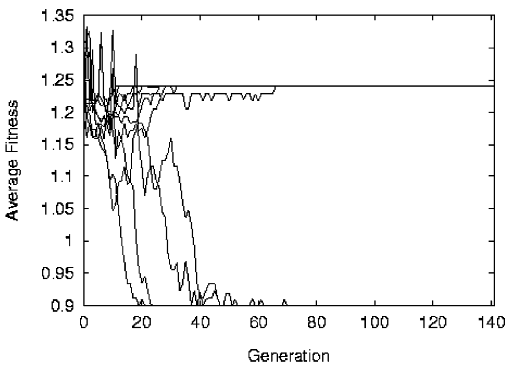
(b) Average fitness of cooperators such as TFT, Trigger and TF2T.



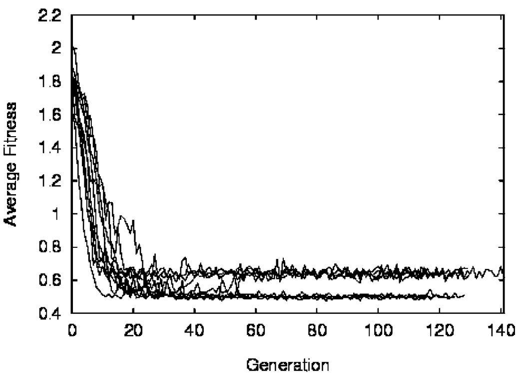
(c) Average fitness of AllD.



(d) Average fitness of CDCD strategy.



(e) Average fitness of C10Dall strategy.



(f) Average fitness of random strategy.

Fig. 11. Average fitness of the evolved coalition and each test strategy.

compare how well-known test strategies play against the top ranked 30 test strategies. Every experimental game is proceeded in round-robin way. We have repeated it for 10 runs to show the result of generalization ability.

Table 4 shows the performance of the evolved coalition and each well-known test strategy against the top ranked 30 test strategies. The first column describes the results between before and after evolution with strategic coalition. In the result after

Table 3
Top ranked 30 test strategies from a population of 300 random players

Strategy table	History	Strategy table	History
0111101111101110	1000	1101111001110011	1111
1101111111110011	0100	0101100111010001	1100
1111111000000111	1000	0011111101010010	0111
0111111110110111	0111	0111011101010111	1111
0111001101010011	1100	0101101100111100	1111
1011111001011100	0001	1001110101010110	0111
0011010111111110	0001	0001000110011010	1101
0001110110110010	1100	1101110011111101	0010
1101110011011101	1000	1001100101011000	1001
1101101111000110	0010	1101000111101010	1000
1111101100011011	1111	1001011001110110	0110
0111010011011111	0110	0101111101110010	1011
1011010111111100	1010	0011110111011000	0001
1101000101011110	1101	0111010101110001	1110
1101011110111011	1100	0101011111110100	1011

Table 4
Performance against the top ranked 30 test strategies in a random population

Strategy	Wins	Ties	Average	Opponent average
Before	8.64 ± 4.9	6 ± 2.19	1.84 ± 0.28	1.75 ± 0.59
After	18.55 ± 0.5	4 ± 0.63	2.16 ± 0.07	0.92 ± 0.29
TFT	8	0	1.70	1.77
Trigger	30	0	2.13	0.80
TF2T	7	0	1.54	2.40
AllD	30	0	2.17	0.7
CDCD	0	0	1.05	2.75
CCD	0	0	0.91	3.34
C10Dall	27	0	1.97	1.12

evolution, winning rate and the average payoff is relatively better than before evolution. It means the evolved strategies generalize well against the top ranked test strategies in a random population. In general, the evolved strategies' winning percentage has increased significantly and losing percentage decreased. In comparison with each well-known strategy in the next column in Table 4, the evolved strategies' performance is much better than well-known strategies except AllD (notice that AllD strategy is impossible to win) against the top ranked 30 test strategies.

Fig. 12 compares the result of the payoff when the evolved strategies play against each well-known test strategy. In this figure, we know that the evolved strategies exploit well opponent's strategy. Specifically, in the game against random strategy, the evolved strategies select mostly defection to get T in payoff table because they know that defection guarantees more payoff than cooperation on average in random move. Whereas, in the game against TFT strategy, the evolved strategies cooperate mainly with TFT strategy because they know that mutual cooperation gives the

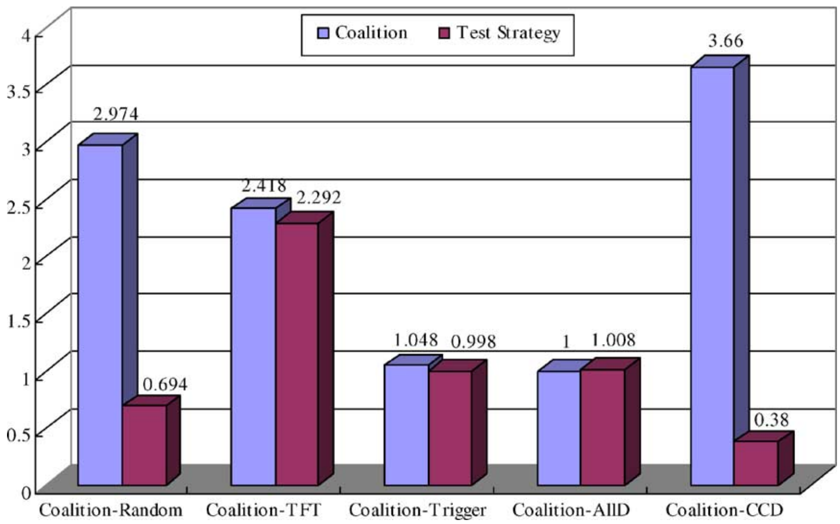


Fig. 12. Payoff comparison of the evolved strategies against well-known test strategies.

best performance, but they occasionally select defection to exploit the weakness of TFT strategy.

5. Conclusions

Combining multiple players in a group may be a very effective way of designing an evolutionary learning system that generalizes well. We have evolved coalitions consisting of a number of players in the IPD game. Each player in a coalition has a confidence which specifies how well he/she performs in dealing with an opponent.

Experiments have been carried out to compare the performance of generalization ability between with and without strategic coalition. In the above experiments, we can find that strategic coalition improves the generalization ability of the evolved strategies significantly. In other words, coalitions with adaptive player's confidence can deal soundly with various opponents regardless of whether they are cooperators.

Although we have used the two-player IPD game in this paper, some of the results we have obtained may be applicable to more complex games. It will be very interesting to study the evolution of coalitions and confidences in a real world environment. For example, it is interesting to investigate how coalitions can be formed among different countries in the world, how coalitions can be formed among different parties in a country, how coalitions can be formed in a commercial market, etc.

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