# The Best Evolutionary Solution to the Iterated Prisoner's Dilemma 

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#### Abstract

In this paper we discuss the methodology and program which won the contest of the Iterated Prisoner's Dilemma (IPD) which was held during the Congress on Evolutionary Computation 2000 (CEC2000) in San Diego, California in July of 2000. This results were recognized as the best during the congress but have not been published before. In the first part of the paper we make an introduction to the IPD problem. In the second part we describe the algorithm we used to tackle the problem. This algorithm is based on a co-evolutionary Genetic Algorithm (GA). In the third part we present our conclusions and possible lines of future research.


Keywords. Cooperation, dilemma, genetic algorithms, co-evolution, CEC2002.

## 1 Introduction

In this paper we address a classical problem from game theory which sheds new light on several problems which have been discussed by philosophers and politicians [1], [2] throughout history. The interest it has generated allows to even propose ethical problems which may be found in the Web [3], [4]. This problem refers to a situation in which we are to decide which is the rational option of an individual as part of a group and for the group in its entirety. It helps us understand how such dilemmas may be solved to obtain the greatest individual and collective benefit and its implications reach far beyond a mere game: under the light of the IPD, it has been possible to analyze the problem of the arms race [5], the adequate selection of providers of goods and services in an open economy [6] and the policies of funding for science and technology [7], among others.

### 1.1 The iterated prisoner's dilemma

The iterated prisoner's dilemma takes its name from the following hypothetical situation:
"In a cell the police keeps two political prisoners. The interrogator is trying to convince them to confess their liason with an illegal opposition party. The prisoners know that if neither confesses, the investigator will not be able to press charges but he may continue his interrogation for three months without setting them free. If one of them confesses implicating the other, the one who confessed will be immediately released and the
other one will be put in jail for eight months. On the other hand, if both confess their help will be considered and they will only be in jail for five months. The prisoners are questioned in isolation; they do not know whether the other one has confessed but both know about the deal that is being offered. The dilemma is: What is the best strategy? To confess (defect) or not to confess (cooperate)?"

This dilemma (PD) may be thought of as a "game" in which players are graded according to the following table. Depending on the mutual responses, each player will receive a number of points. In the case

| Play |  | Points |  |
| :---: | :---: | :---: | :---: |
| Player 1 | Player 2 | Player 1 | Player 2 |
| Cooperate | Defect | 8 | 0 |
| Cooperate | Cooperate | 3 | 3 |
| Defect | Defect | 5 | 5 |
| Defect | Cooperate | 0 | 8 |

Table 1. Grading Table for the PD
just described, the grade reflects the losses arising from any given answer, as shown in Table 1. in this case the objective is to minimize the losses. Alternatively, the problem may be defined in terms of a benefit in which case we would try to maximize it.

This problem is called the "Iterated Prisoner's Dilemma" if the process is repeated several times. The true interest of this problem lies, precisely, in iterating
the actions as described. When this happens it is that the players may learn to adjust their behavior depending on the behavior of the other player. The points of each player ared the sum of those he obtained in each play. Thus, a game between two players may be as follows:

| Plays | $\mathbf{1}$ | $\mathbf{2}$ | $\mathbf{3}$ | $\mathbf{4}$ | $\mathbf{5}$ | $\mathbf{6}$ | $\mathbf{7}$ | $\mathbf{8}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Player 1 | C | D | C | C | D | C | C | D |
| Player 2 | D | D | C | C | C | D | C | D |
| Plays | Loss |  |  |  |  |  |  |  |
| Player 1 | $8+5+3+3+0+8+3+5=35$ |  |  |  |  |  |  |  |
| Player 2 | $0+5+3+3+8+0+3+5=27$ |  |  |  |  |  |  |  |

Table 2. An Example of a Sequence of IPD
In the iterated version we wish to find the strategy which minimizes the damage (or maximizes the profit) given that we redmember the last $n$ plays. In the example of table 2 player 1 receives a damge of 35 whereas player 2 only receives a damage of 27 : player 2 has won.

The minimax solution given by game theory looks to minimize the maximum damage an opponent may inflict. This is determined by comparing the maximum damage under cooperation againts the maximum damage under defection. If the first player cooperates (C,-) the greatest damage is when the second player defects (CD) yielding a damage of 8 for the first player. If the first player defects ( $\mathrm{D},-$ ), the greatest damage occurs, again, when player 2 defects (DD). Now the damage to player 1 is 5 . Therefore, the first player minimizes his losses by defecting always. This line of reasoning is symmetric so that (DD) is the best minimax solution. It is easy to see, however, that the best strategy is the one in which both players cooperate. For example, in a sequence of length 4 (4 iterations) minimax strategy indicates that the best strategy would be DD;DD;DD;DD. The loss for player 1 (and for player 2 as well) is $5+5+5+5=20$. But, clearly, strategy $\mathrm{CC} ; \mathrm{CC} ; \mathrm{CC} ; \mathrm{CC}$ induces a loss for player 1 of $3+3+3+3=12$; much better than minimax's.

It is more common to set the cost table of the IPD as one of gains rather than losses. In such case, it is possible to generalize the game with a table of variable values which, to preserve the spirit of the game, ought to comply with the constraints shown in table 3. This constraints are identified with the following first letters: $C$ (cooperate); $L$ (low); $H$ (high) and $D$ (defect).

| Player's move | Opponent's <br> move | Grade |
| :---: | :---: | :---: |
| C | C | $C$ |
| C | D | $L$ |
| D | C | $H$ |
| D | D | $D$ |
| $L<D<C<H ; \quad H+L<=2 C$ |  |  |

Table 3. Grading table for the IPD with variable values
For instance, the values $\mathrm{C}=3, \mathrm{~L}=0, \mathrm{H}=5$ and $\mathrm{D}=1$ indicate that player 1 will win 3 points if both players cooperate (CC), 0 points if only he does (CA), 5 points if he defects and player 2 cooperates (AC) and 1 point if both defect. Here, obviously, $0<1<3<5$ and $5+0<6$, fulfilling the constraints. For this table the minimax strategy of permanent defection translates into constant gains of 1 point. In the example ( 4 iterations) each player wins 4 points. With a strategy of constant cooperation, on the other hand, would yield 12 points for each player. Several variations to this problem have been studied [3]. For example, when there are several moves per player, a non-symmetric grading in the table, multiple players, etc.

### 1.2 Strategies

We call a "strategy" to a set of one or more rules which tell us how to play the IPD. Some strategies are "Always cooperate" (AC) or "Always Defect" (AD). One common and simple strategy is called "Tit-for-Tat" (TT). In it the player starts cooperating; thereafter he or she repeats the opponents last move. Surptisingly, TT shows to be very efficient. If we play games with 5 iterations using TT, AD and AC with the values $\mathrm{C}=3$, $\mathrm{L}=0, \mathrm{H}=5$ and $\mathrm{D}=1$, we would get results as in table 4 .

| Strategy |  |  |  | Action/Points |  |  |  |  | Total |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| TT | C | 0 | D | 1 | D | - |  | D | 1 | D | 1 | 4 |
| AD | D | 5 | D | 1 | D | 1 |  | D | 1 | D | 1 | 9 |
|  |  |  |  |  |  |  |  |  |  |  |  |  |
| TT | C | 3 | C | 3 | C | 3 |  | C | 3 | C | 3 | 15 |
| AC | C | 3 | C | 3 | C | 3 |  | C | 3 | C | 3 | 15 |
|  |  |  |  |  |  |  |  |  |  |  |  |  |
| AD | D | 5 | D | 5 | D | 5 | D | 5 | D | 5 |  | 5 |
| AC | C | 0 | C | 0 | C | 0 | C | 0 | C | 0 |  | 0 |

Table 4. Confrontation of Strategies TT, AD and AC.

Another strategy is Pavlov's (PS) and is show in figure 1 as a two-state automaton.


Figure 1. Pavlov's Strategy.
This strategy calls for "C" as long as the previous plays (both from the player and his/her opponent) are alike. A 5 iteration game, with grading table 3, where PS and AD face each other would be as follows:

| Strategy |  |  |  |  | Action/Points |  |  |  |  |  | Total |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| AD | D | 1 | D | 5 | D | 1 | D | 5 | D | 1 | 13 |  |  |
| PS | D | 1 | C | 0 | D | 1 | C | 0 | D | 1 | 3 |  |  |

Table 5. Results of Confronting Strategies AD and PS
There are many strategies [8] and software with which one may build original strategues and play tournaments between them. For instance, the program WINPRI may be gotten from [8].

### 1.3 Design of a Strategy

A strategy may depend of N previous plays for integer $N$ and $N \geq 0$. Thus, AD and AC do not depend on the previous moves; TT depends only on the last response and PS depends both on the last response as well as on the latest (own) play.

A form of representing strategies is with a vector [9] where every position represents the answer that should be given in each case. For instance, if during the last 2 plays the sequence DCDC has been recorded, the response will be derived from the corresponding positions of the vector. Therefore, we need to assign to every response a number and the simplest form is in binary. Hence, if the two last plays have been DCDC we change the Cs into 1 s and the Ds into 0 s , getting the string 1010 (which corresponds to number 12 assuming traditional weighted binary encoding). We should, then, answer with the element of the vector whose index is 12 . In the case of PS we may represent the strategy as in table 6.

With this notation we may see that the answer of PS is CDDC. In the case of TT the answer would be DDCC. if it is deemed necessary to use strategies which depend on more (older) previous plays we may simply repeat the sequence. That is, the response for $A D$ corresponds to DDDD; it does not depend on any previous play. Therefore, the length of the string which represents a strategy depends on how many previous plays $(l)$ it takes into consideration and is given by $2^{2 l}$.

| Previous Plays <br> Player/Opponent | State | Vector's <br> Index | Response |
| :---: | :---: | :---: | :---: |
| DD | 2 | 1 | C |
| DC | 2 | 2 | D |
| CD | 1 | 3 | D |
| CC | 1 | 4 | C |

Table 6. Determining the Answers from a Vector

## 2 Solving the IPD using a Genetic Algorithm

Given the representation above, it is possible to use a Genetic Algorithm (GA) to solve the problem and find a strategy which solves the IPD [10]. The basic algorithm used to win in CEC200 is described in what follows.

1) Generate a set $S$ of $m$ strategies at random.
2) From i $\leftarrow 1$ to $6 \times 6 m$ make [from a) to c)]:
a) Select 2 strategies $s_{1}$ and $s_{2}$ from S randomly.
b) Confront $s_{1}$ and $s_{2}$ a predefined number of times.
c) Register the results for $s_{1}$ and de $s_{2}$.
3) From the $S$ strategies select the best $t$ (those whose average behavior has been best). We then take this set of strategies (T) as a baseis against which we must test the individuals of a GA (in the best T we conventionally include TT).
4) Generate a random initial population of $n$ candidate strategies (C)
5) While stopping criterion has not been met do
a) From i $\leftarrow 1$ to $n$.
i) Select strategy $c_{i}$ of C.
ii) From $\mathrm{j} \leftarrow 1$ to t
(1) Confront a $c_{i}$ against $s_{j}$
(2) Register the sum of the results as the fitness of population C .
b) From the $n$ individuals in the population plus the $t$ individuals in the bases set, select the best $t$. These will be the basis set for the next generation.
c) Obtain a new C using an EGA.
6) The best strategy is the best from set $T$.

This is a co-evolutionary algorithm because the set of best strategies (T) evolves at the same time as the set of strategies (C) which evolve with the GA. The GA we used is not conventional (we have called it an eclectic GA, or EGA). It includes full elitism, deterministic pairing and annular crossover. It also self-adapts the probability of mutation, the probability of crossover and the number of descendants. Finally, it is polyalgorithmic in that it alternates with a random mutation hill-climber. The detailed description of the EGA may be found in [11], [12].

The EGA has been used to solver the IPD and the corresponding software may be gotten from [10]. this software only needs the values of the grading table (which we denoted by L, D, C and H ) and the number of plays ( g ) which the strategy is to "remember". The output of the program is a string of size $2^{2 g}$ which encodes the resulting strategy.

### 2.1 International Contest CEC2000

The Congress on Evolutionary Computation held in San Diego, California, was hosted by the mathematics department of Iowa State University. It took place on July 16-19, 2000. As part of this congress four contests were presented to the international community:

1) Reason vs Evolution: Prisoner's Dilemma Competition
2) Time series prediction competition
3) Dow Jones Prediction Competition
4) Visualization Competition

The rules for each contest were specified in [13] and, in general, sought for the applications of evolutionary techniques to each of the listed problems. We describe the particular conditions fro the IPD.

1. The code containing the set of strategies may be published in the WWW after the contest. It should be contained in a flat ASCII file and written in C++ with:

Definition of types/structures/global
variables
int firstact() \{ code which initializes the player and returns the first play \}
int pla (int lastact) \{ Code which processes the opponent's play "lastact" and returns the present play\}
2. Must use " 0 " to denote " C " and " 1 " for " $D$ ").
3. Strategies which require excessive memory or time will be disqualified.
4. All submitted strategies plus some previously designed will form a set. This set will be complemented with a C++ interface which may invoke any of the strategies.
5. Strategies will be added so that their number will be close to a multiple of ten to obtain a balance between evolutionary and non-evolutionary techniques.
6. 100 iterations will be performed following the next procedure:
a) The full set will be split in groups of 10 .
b) Random values for $L, D, C, H$ will be selected in a range between 0 and 10 .
c) $N$ rounds will be played; $N$ will be normally distributed with mean 300 and variance 25 .
d) 10 tournaments will be played in each group. Every pair of players will play $N$ round of IPD.
e) The player with the highest score in every group of 10 will receive 10 points, the next one 9 , and so on.
f) The winner will be determined by the total points scored.

A program which will be described in what follows was sent to the mentioned tournament. This program, as pointed out in the abstract, turned out to be the winner of the tournament.

### 2.1.1 Winning Program of the International IPD Contest in CEC2000

The strategy which we sent to this contest was found with the co-evolutionary algorithm described above. However, since the points assigned in each individual contest were, according to the tournament rules, variable we determined the following.

1. We used a memory of 4 plays. That is, the EGA considered the 8 last plies ( 1 ply is equal to one player's move) to determine its strategy. The search space, hence, consists of

$$
\begin{aligned}
2^{2^{8}} & =2^{256}=\left(2^{10}\right)^{25} \times 2^{6} \\
& \approx 64 \times\left(10^{3}\right)^{25} \\
& \approx 64 \times 10^{75}
\end{aligned}
$$

possible solutions. It is a tribute to the analytical capabilities of the EGA that it was able to find a good solution in reasonable time.
2. Since the program receives no information as to the values of $L, D, C$ and $H$ we generated all possible combinations of integer positive values which satisfied
the problem's conditions ( 250 in all) and selected 10 of these combinations at random (see ahead).
3. We evolved (using the co-evolutionary GA) the best solutions for each one of the parameter sets.

### 2.1.2 Considerations

The choices mentioned in the last section obey the following considerations:

1. We selected a memory of 4 plays ( $m=8 ; 8$ plies) because previous experiences [14] had found satisfactory behaviors for $m=6$. Evidently, we sought to improve on this record. On the other hand, the evolution time for this value are still practical.
2. We selected 10 combinations because an analysis of cluster determination using self-organizing maps (Kohonen's neural networks) indicated that the groups of parameters were sufficiently characterized considering 10 elements.
3. We assumed that, given the bases of the contest, it was reasonable to expect that the worst performances of each of the 10 opposing strategies, on the average, would be below ours, which were coevolved.

Thus, the program we sent chose at random from one of the 10 strings of length $2^{8}=256$ and the first 4 plays (when we still could not use the strategy for lack of information) were tackled with TT. Its appearance was deceptively simple and its workings practically unintelligible.

Next we show the 10 strings sent to the contest. The values which appear as a commentary (//) correspond to the values of $L, D, C, H$. Notice that each string is 256 bits long. This is because, since $m=8$, the set of histories (sequences of foregoing plies of the opponent and ones own) is $2^{8}=256$. For the parameters (0-7-6-4), for instance, the historic sequence DDDDDDCC (index $=3$ ) triggers a response, on our part, of defection ( 0 or D ); but the historic sequence DDDDDCDD (index $=4$ ) triggers our response "cooperate" ( 1 o C $)$. On the other hand, and as a last example, we mention that for the parameters (1-9-7-5) the same sequences (indices $=3$ and 4) trigger the responses C and C .
"000010011100100000011110011000101010001001001 011000110111010101011010001111111101001010100 000110101101110101101111011000110110101110000 011010000111001010101100110111101100011100110 111011010100111000010101000001101101110110001 $11001011100101101010011100111011 / / / 0,7,6,4$
"11000001010101001100111001000001111110101100 101000110110000110110001000111011100001110010 100111010000111110111111110000111001100100001 101110000000111101000001101111000001011001000 001110110001011111000100001011001100111010000 10101011000111100001110110000000 " //1,8,5,2
"00001001101110011101111011000100100001111001 101001000010110110111010001010011010110100000 111110101011100010000100110110101011011110111 110101000101101100110111111101000100001001110 011110000001010111101011101101000100111010010 10010101110101101010111000111011 " //1,8,7,5
"11111000011010110001000100011110111000011110 001100011000011001011100010111100100011101110 011001100110111100101111110010000100100111111 100101000111101010110010010010110000110100111 110000100101101010000001011101010110100101101 01110101011111000010111110011001 "//1,9,7,5
"00110100000000001011101101111101010101100100 000001110001100001001011001010010000101010110 010010100001001001100011111110111000111111010 011101000000010110100101110000111101001001010 110110001010111110001000110100111100000111011 11110010100011111100010101001010 " //0,9,6,2
" 10111001010110011100001100010010110001101110 001100001100100010011011001000010001111101001 110100000101111110110001111100000010111101010 101010100010010011011000111101001001010011011 111110110101101111100010111101011001101000011 01101001101001101001100100101011 " //1,8,7,6
" 10111001010110011100001100010010110001101110 001100001100100010011011001000010001111101001 110100000101111110110001111100000010111101010 101010100010010011011000111101001001010011011 111110110101101111100010111101011001101000011 $01101001101001101001100100101011 \mathrm{l} / / 2,9,8,7$
" 11011100111000111000011100101101101010001101 010011000100100110010000100011101111101000000 000000011101110011111000000000100010101100100 100001001000011101000111000111000110010101010 111110111001001100000111011101010010101101001 11110100000100000111001100000010 " //3,9,7,5 "01000110001011100101001111000101010010101101 101110011101001100011101110100100010010101101 101001101100110100111111011000001111101000001 111100010111001011000000010001001111000110000 001100110111011111000101110111011100000010100 11110101001001100011000101000101 " //3,10,9,5 "11010110001001111001010011011001010010100111 111101001000100000111000111101001101101111101 000100100001001000110110111101101100100111001

101000010111101110010001001111001110011101101 011110100011110111000001100111000001011011010 $10011011010111010011001011001101 " / / 4,10,8,5$

## 3. Conclusions and Future Work

### 3.1 Implications

The fact that the international community was invoked to tackle the IPD using evolutionary techniques implies:
a) This problem's importance transcends the merely formal.
b) Although it is cast as a game, its implications hold interest outside game theory.
c) Evolutionary tools have succeeded where alternative techniques of analysis and heuristic search have failed
d) The international community which shows interest in artificial intelligence and its applications is ready to assimilate the importance of this kind of problems and tackle successfully the problems inherent to the purported solution of the IPD with GAs.

### 3.2 Future Lines of Research

To avoid the random selection of the possible combinations of $L, C, D, H$ it is possible to change the program that finds the strings [10]. Instead of adding the points which are gotten for eafch play we could keep a record of how many times we got an $L$ or a $D$ or some other value. Thus, the result of a contest between two strategies would not be a number but, rather, a linear combination of the values of $L, C, D, H$. Then using the 250 combinations of possible values we would know which of the two strategies would win for any value of the parameters. Afterwards we should perform a statistical analysis which compares the behavior of the string resulting from this new method against the program that won the contest to measure its performance.

### 3.3 Acknowledgements

It is interesting to mention that we have applied new concepts to solve this problem (non-conventional GAs; sampling selection of strategies) but relying on previous experiences and developments (the evolutionary methods themselves; the concept of co-evolution). Because of this we wish to acknowledge to those researchers who have preceded in the search for the best IPD algorithm: to John Holland for his initial work in the area of GAs, to Robert Axelrod for his initial motivation, to Douglas Hofstadter and others who have
sensitized the community about the implications of the IPD beyond the restricted scope of game theory, to Dan Ashlock for having proposed and supervised this international contest.

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