Co-Evolutionary Optimization of Autonomous Agents in a Real-Time Strategy Game

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Abstract. This paper presents an approach based in an evolutionary algorithm (EA), aimed to improve the behavioral parameters which guide the actions of an autonomous agent (bot) inside a real-time strategy game (RTS) named Planet Wars. Specifically the work describes a co-evolutionary implementation of a previously presented method, which yielded successful results.Thus, it's analyzed the effects of considering several individuals to be evolved (improved) at the same time in the algorithm, the use of 3 different fitness for measure the goodness of each bot in the evaluation, and the variance of use an EA with and without previous knowledge for the training. To this end, 4 on 4 matches have been considered. Two variants are presented without previous knowledge (where the 4 bots belongs to the population) and with (2 bots of the population versus 2 previously studied with good results bots). For the fitness, 3 methods are studied: one based in turns and result position, and another two based in the survey of the percentage of ships that belong each bot in each turn of the battle, using linear regression or area calculation. In this paper we set several aims for using co-evolution: First, to reduce the time needed for training in behavior with a huge time of evaluation. Second, to improve best bots for used in 4 on 4 battles. Third, to study the significant different between the training with and without previous knowledge. And finally, to study alternatives fitness for co-evaluations.

1 Introduction

Autonomous agents (or *bots*) in videogames have become very popular in the last years, because they can increase the challenge and lasting appeal of the game, by competing or cooperating with the human player. Thus, designing a good behavioural engine for them is one of the main topics of interest in the actual videogame development task. They have been widely used in Fisrt Person Shooter games (FPSs) from the nineties, but in this paper we will work with them on a Real-Time Strategy game (RTS). RTSs are a sub-genre of strategy-based video games in which the contenders control a set of units and structures distributed in a playing area and combat using them for conquering the scenario or defeating the opponent. Command and Conquer™, Starcraft™, Warcraft™ and Age of Empires™ are some examples of these type of games.

The RTS considered in the paper in named *Planet Wars*, and it was used a platform in the Google AI Challenge 2010. In this contest, 'real time' is sliced in

one second *turns*, with players receiving the chance to play sequentially. However, *actions* happen at the *simulated* same time.

This paper describes a Co-Evolutionary [1] approach for improving the decision engine of a bot that plays that RTS. This engine consists in a set of rules previously designed and evolved by the authors in [2] , using an regular Genetic Algorithm (GA) [3]. We applied an offline evolution (i.e., not during the match, but prior to the game battles) of the parameters on which the behavioural rules depends.

The evaluation of the quality (fitness) of each set of rules in the population was made by playing the bot against predefined opponents, being a pseudo-stochastic or *noisy* function, since the results for the same individual evaluation may change from time to time, yielding good or bad values depending on the battle events and on the opponent's actions. We have dealt with this noisy nature [4] by means of a reevaluation phase of all the individuals every generation, along with an average calculation of the fitness value of every individual after five combats (in five different an representative maps).

The aim is that the co-evolutionary scheme improves the fitness convergence of the population, since the individuals cooperate in their evolution.

Thus, we have considered matches with four players, with two of the contenders the individuals being evolved at a specific generation, and the other two opponents with a fixed AI engine, namely the competition sparring *GoogleBot* in one of the experiments, and our best individual to date, baptised as *Genebot-8*, in the other one.

2 State of the Art

Video games have become one of the biggest sectors in the entertainment industry; after the previous phase of searching for the graphical quality perfection, the players now request opponents exhibiting intelligent behaviour, or just human-like behaviours [5].

Most of the researches have been done on relatively simple games such as Super Mario [6], Pac-Man [7] or Car Racing Games [8], being many bots competitions involving them.

RTS games show an emergent component [9] as a consequence of the cited two level AI, since the units behave in many (and sometimes unpredictable) ways. This feature can make a RTS game more entertaining for a player and maybe more interesting for a researcher. There are many research problems with regard to the AI for RTSs, including planning in an uncertain world with incomplete information; learning; opponent modelling and spatial and temporal reasoning [10].

However, the reality in the industry is that in most of the RTS games, the bot is controlled by a fixed script that has been previously programmed (following a finite state machines or a decision tree, for instance). Once the user has learnt how such a game will react, the game becomes less interesting to play. In order to improve the users' gaming experience, some authors such as Falke et al. [11]

proposed a learning classifier system that can be used to endow the computer with dynamically-changing strategies that respond to the user's strategies, thus greatly extending the games playability.

In addition, in many RTS games, traditional artificial intelligence techniques fail to play at a human level because of the vast search spaces that they entail [12]. In this sense, Ontano et at. [13] proposed to extract behavioural knowledge from expert demonstrations in form of individual cases. This knowledge could be reused via a case-based behaviour generator that proposed advanced behaviours to achieve specific goals.

Evolutionary algorithms have been widely used in this field, but they involve considerable computational cost and thus are not frequently used in on-line games. In fact, the most successful proposals for using EAs in games correspond to off-line applications [14], that is, the EA works (for instance, to improve the operational rules that guide the bot's actions) while the game is not being played, and the results or improvements can be used later during the game. Through offline evolutionary learning, the quality of bots' intelligence in commercial games can be improved, and this has been proven to be more effective than opponent-based scripts.

This way, in the present work, an offline GA is applied to a parametrised tactic (set of behaviour model rules) inside the Planet Wars game (a basic RTS), in order to build the decision engine of a bot for that game, which will be considered later in the online matches.

3 Problem Description

In this paper works with a simplified version of the game Galcon, aimed at performing bot's fights which was used as base for the Google AI Challenge 2010 (GAIC)[1].

A Planet Wars match takes place on a map (see Figure 1) that contains several planets (neutral, enemies or owned), each one of them with a number assigned to it that represents the quantity of ships that the planet is currently hosting.

The aim of the game is to defeat all the ships in the opponent's planets. Although Planet Wars is a RTS game, this implementation has transformed it into a turn-based game, in which each player has a maximum number of turns to accomplish the objective. At the end of the match the winner is the player live, or owning more ships if more than one survives.

There are two strong constraints which determine the possible methods to apply to design a bot: a simulated turn takes *just one second*, and the bot is *not allowed to store any kind of information* about its former actions, about the opponent's actions or about the state of the game (i.e., the game's map).

Therefore, the goal in this paper is to study the improve of a bot, ———- according to the state of the map in each simulated turn (input) returns a set

[1] http://ai-contest.com

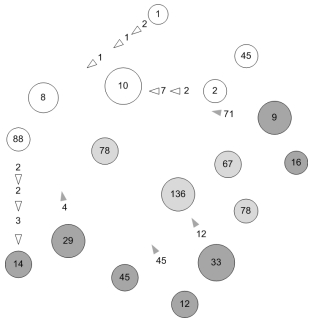


Fig. 1: Simulated screen shot of an early stage of a run in Planet Wars. White planets belong to the player (blue colour in the game), dark grey belong to the opponent (red in the game), and light grey planets belong to no player. The triangles are fleets, and the numbers (in planets and triangles) represent the ships. The planet size means growth rate of the amount of ships in it (the bigger, the higher).

of actions to perform in order to fight the enemy, conquer its resources, and, ultimately, win the game. In the original game, only two bots are faced but in this paper it's studied what happen when we simulated 4 on 4 battles, it's mean, when 4 bots are fighting in the same map.

4 Cooperative and Competitive Evolution: Co-evolution

There are two types of co-evolutions, attend of the interaction between the individuals of the population: cooperative and competitive. In this paper, it's described an co-evolutionary algorithm that has the two sides.

For one hand, it's simulated 4 on 4 battles where several bots will fight for the same goal, win the battle. That means that the bots are competing against each other. Also, the individuals are competing in the GA for perpetuate their species.

In the other hand, the cooperative side come because the 4 on 4 battle is *all versus all*, so a single individual may receive help of others for *kill* a temporally mutual rival. But beware, it is sure that at the end, can be only one. Additionally, the individuals are sharing *knowledge*, because they are *living* (and fighting) together. If the population is each time better, and the new individuals are *born* of these population, the new individuals will be better and better.

One of the major problems founded in the use of EAs for training bots in this behavior, was the huge time needed for the evaluation, because we have to simulated fulls battles, in several maps, several times... Additionally when dealing with a noise and stochastic problem like this, it's forced to use re-evaluation between generations.

Theoretically, the use of a co-evolution allows to reduce the number of simulations needed, because the population is evaluated in *groups*. That's, if there are a population of 100 individuals, in a classic GA it's needed make 100 evaluations, once for each individual, for each generation, times for the number of maps and the re-evaluation or others factors. In co-evolution case, for example, if it's used 2 bots of the population for the co-evolution it's only need 50 evaluations for the Co-GA. It's likely that simulations with 4 bots will take more time that a simulation with 2 bots, but the question is if the time taken for a $4 - simulations$ is less that the time taken for two $2 - simulation$. In that case, the co-evolution will decrease the time needed for the training.

The use of 2 individuals or 4 individuals of the population in the experiments depends of the use (or not) of previous knowledge.

4.1 Previous Knowledge vs Auto-generated Knowledge

It has a best training bot, which has proved its worth in 1vs1 battles. The question is if can be used the previous knowledge for improve (faster) better bots in a similar problem. Or maybe, if it's best don't use previous knowledge and allow fight versus individuals of the population; that theoretically (as the bases of the GAs) will be better and better in each generation. To answer this question, were making two types of experiments.

Co-evolution with previous Knowledge In this case, will be simulated battles between two individuals of the population versus two of the best bots (in 1vs1 contest). It's expected that the co-bots can learn the bases of the best bots, and improve for be better in 4 on 4 battles. It's desirable that this type of co-evolution prize bots that at least can win in a battled of the previous best bots.

Talcking about the time needed for the execution, it's not expected an huge reduction of the time needed for the training of the bots, but it's desirable that happen. It's something that will be increased in the next co-evolution method.

Co-evolution with Auto-generated Knowledge In this case, will be simulated battles between four individuals of the population. It's not used previous knowledge of previous works, but the bots were improving for be better versus bots every time betters (because it's expected that the population will better in each generation).

Talcking about the time, this method would reduce the time needed near to 50% that the previous method, because it reduced the number of evaluations to the half.

4.2 Fitness

In previous works, it's evaluated a single bot of the population versus always the same bot (an reference-bot). For fitness function, the bot was evaluated several

times (in different maps). The fitness function was defined depending of the result of the battle (if the bot wins all his battles or loses in someone) and the numbers of turns needed for end the game. For two bots A and B the fitness is defined like show in Fig.**??** .

Fitness based in Position and turns This fitness it's an natural evolution of the previous, applied to 4 bots battles. Again, the evaluations are in several maps. In this case, it's studied the position (1^{th}, 2^{th},..) of the bot in the 4-battle and the number of turns. For a bot that wins all the battles (it's 1^{th} in all) it's call $ferocity$ to the sum turns, in previous works was found that a bot that wins in less turns it's best that other that takes more turns in win too. In other case, the sum of turns it's call *sturdy*, and opposite to the $ferocity$, it's desirable a bot that take more turns in be defeated. In fig**??**()there are an formal description of this fitness.

```
A, B ∈ Population
if A WINs always then
    if B LOSEs some battle then
        A is better than B
    else if A take less turns than B then
        A is better than B
    else
        B is better than A
    end if
else
    if B WINs always then
        B is better than A
    else if A take less turns than B then
        B is better than A
    else
        A is better than B
    end if
end if
```

(a) Fitness used in battles of 2 bots

```
A, B ∈ Population
if A average position < B average position then
    A is better than B
else if A average position > B average position then
    B is better than A
else
    if A,B is always 1^th then
        if A take less turns than B then
            A is better than B
        else
            B is better than A
        end if
    else
        if A take less turns than B then
            B is better than A
        else
            A is better than B
        end if
    end if
end if
```

(b) Fitness used in battles of 4 bots

Fig. 2: Fitness based in turns and positions

In this fitness, we are only interesting in the final result: position and turn. We aren't student how the bot reach it. However, two variables are involved in the calculation of the fitness. That difficult the operation with severals evaluations, because the fitness can't be easily sum o averaged. In the next fitness, it's used another metric to define the goodness of the bots. The percentage of the ships that in each turn belong to each player.

For study the ships, it's taken from the simulation how many ships belong to each player in each turn, normalized at total ships in game for that turn (including neutrals ships in neutral planets). For each player, we have a *cloud* different like in Fig.5b. Below, see two alternatives to deal with this cloud of points for the fitness function: using slopes and areas.

Fitness based in Slope For this fitness, it's used the least squares regression analysis for resume the cloud of points to a simple line. A line is represented as $y = \alpha \times x + \beta$, where α and β are calculated as show the Fig. 8b according to least squares regression. For each bot in the simulation it's calculated α, that it's also call *slope*. This *slope* it's the fitness defined for each bot for that simulation.

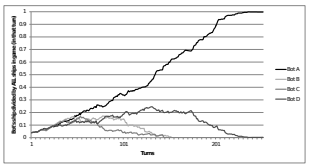
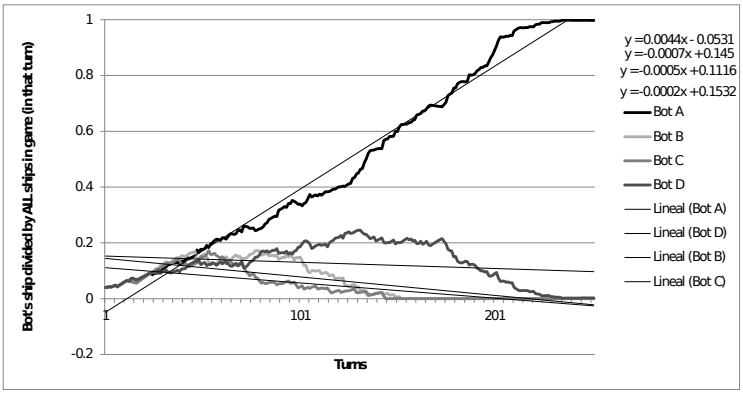


Fig. 3: Representation of the number if ships of each bot in each turn

$$\alpha = \frac{\sum_{i=1}^{n}(X_i - \bar{X_i})(Y_i - \bar{Y_i})}{\sum_{i=1}^{n}(X_i - \bar{X_i})^2} \quad (1)$$

$$\beta = \bar{Y} - \alpha\bar{X} \quad (2)$$

(a) Leats squares regression



(b) Representation of the number if ships of each bot in each turn

Can be establish an theoretical maximal an minimal values for this fitness. An hypothetical bot that wins in the first turn, will have an slope of 1, so this is the maximal value of our fitness. For other hand, an bot that loses in the first turn, will have an slope of -1. In addition, looking at the slope, can be known if the bot $WINs$ ($slope > 0$) or $LOSEs$ $slope < 0$. Finally, can be determined that when the slope was greater (and therefore closer to the maximum) should be better the bot.

Several evaluations in different maps was using, so it's need operate with fitness. In that case, only sum the slope of all the evaluations of the bot.

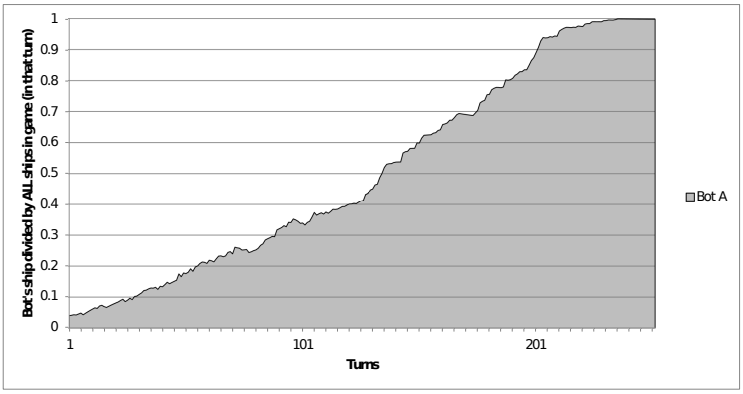
4.3 Fitness bases in Area

In these fitness, it's used the integral of the curve for calculate the area between it and the x-axis. This *area* is normalized to the number of turns, representing the average percentage of ships along the battle for each player. In the Figb

As before, can be established an theoretical maximal an minimal values for this fitness. An hypothetical bot that wins in the first turn, will have an area closer to 1, so this is the maximal value of the fitness. Furthermore, an bot that loses in the first turn, will have an area near to 0. In this case, can't be know by the fitness if the bot wins or loses the battle. In this scope, we are losing information.

$$area = \frac{\int_0^t \%ships(x)dx}{t} \quad (3)$$

(a) Calculus of the area



(b) Example of area under the curve

5 Experiments and Results

How there are something that it's studies in this paper, different experiment are development. The principal experiments is improve bots using the co-evolutionary algorithm. The parameters uses in the GA are show in table in Fig.6

Population Size	Generations	Crossover Factor	Mutation Factor	Elitism	Nts
100	200	0.6	0.1	20	2

Fig. 6: Table with the parameters used in the GA.

For each previously presented method, at least 3^2 executions of the co-evolution improve method are executed.

In addition, the time using for the evaluation in each generation it's measure, for comparing the average time needed.

Experiments with:

6 Conclusions and Future Work

Acknowledgements

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[2] In GA generally requires more executions, but executions are costly in time in our problem.

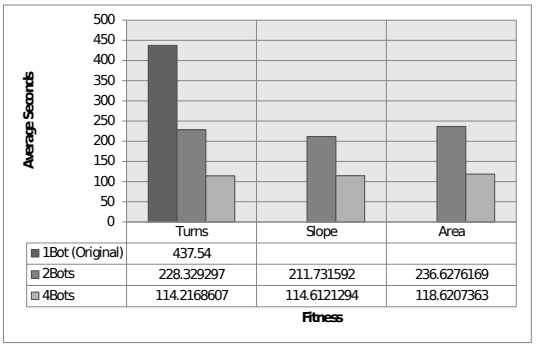

Fig. 7: Generation average time of execution to each fitness and knowledge method

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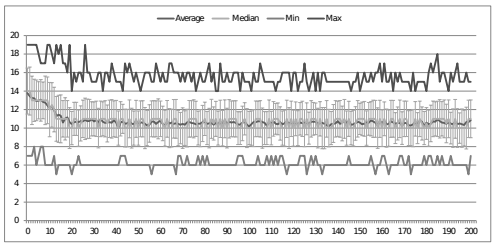

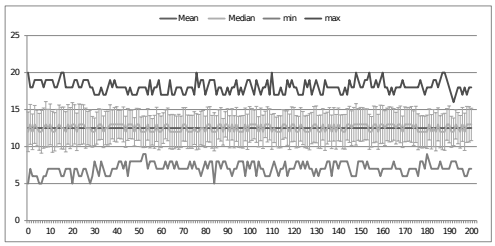

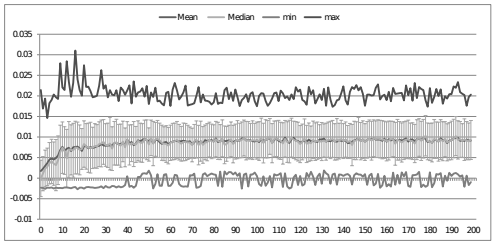

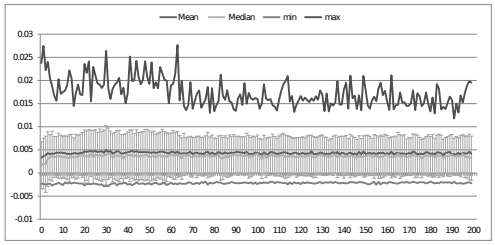

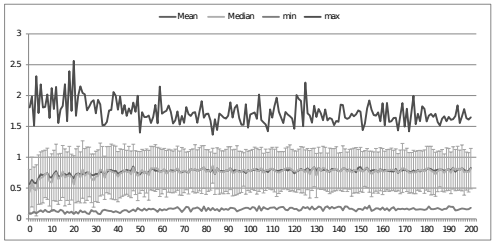

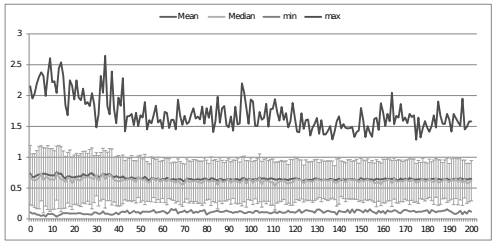

(a) Methods with previous knowledge

(b) Methods with autogenerate knowledge