Evolving ANTS game agents' strategies

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Abstract. This work studies the performance and the results of the application of Evolutionary Algorithms (EAs) for evolving the decision engine of a program, called in this context *agent*. This game was chosen for the Google Artificial Intelligence Challenge in 2011, and simulates battles between teams of ants in different types of maps without saving information between games. This restriction makes unable to implement an Evolutionary Algorithm inside the agent. In this paper, this engine has been evolved off-line by means of an extra Genetic Algorithm (GA), used for tuning a set of constants, weights and probabilities which directs the rules. To conduct the evolution (in the evaluation step), every candidate agent in the population has combated against three different enemies (in two different approaches): a deterministic agent who finished in rank 993, and two very competitive agents which got position 1 and 165. The results show that, although the best agents are difficult to win, a very simple agent tuned with the GA is possible to beat the agent that finished 1000 positions above it.

1 Introduction

Real-Time Strategy (RTS) games are a sub-genre of strategy-based videogames in which the contenders control a set of units and structures that are distributed in a playing arena. The game objective is normally eliminating all the enemy units. It is usually possible to create additional units and structures during the course of the game, at a cost in resources. Another usual feature is their real time nature, so the player is not required to wait for the results of other players' moves as in turn-based games. Starcraft^{TM}, Warcraft^{TM} and Age of Empires^{TM} are some examples of RTS games.

The 2011 edition of the Google AI Challenge [4] was conducted with an RTS named ANTS, in which the players control a set of ants that must 'fight' against the colonies of the rest of players in a grid with labyrinthine paths. The ants must gather food for generating new individuals and get an advance over the rivals. The fighting between ants is solved following some rules, but as a thumb rule, the higher number of ants are grouped, the easier will be to win a fight.

Thus, this is a RTS where the AI must be implemented at both commented levels: on the one hand, the ants must be grouped and specialized (explorers,

fighters, gatherers), on the other hand each individual should have a particular behaviour to get a global emergent behaviour.

As a first approximation, a behavioural engine (for both levels) was designed by defining a set of states and rules guided by several parameters. This agent participated in the contest and finished in position 2076. Then, in this paper, the initial engine has been improved by means of EAs [2], as some other authors have previously done in other RTSs . The agent is compared to other participants, and a good improvement has been attained.

The rest of the work is structured as follows: after the state of the art, we present the developed algorithms and experimental setting. Then, the results of the experiments are shown (Section 5), followed by conclusions and suggestions for future work.

2 State of the art

AI in games has become the most interesting element in actual games from the player's point of view, once the technical components (graphics and sound) have reached almost an upper bound. They mostly request opponents exhibiting intelligent behaviour, or just better human-like behaviours [8].

Researchers have also found it an interesting area from the early nineties, so this scope has presented an exponential grown in several videogames and fields, mainly starting with the improvement of FPS Bot's AI, the most prolific type of game [7, 10], and following with several games such as Super Mario [17], Pac-Man [9] or Car Racing Games [12], to cite a few.

The RTS games research area presents an emergent component [16] as a consequence of the commented two level AIs (units and global controllers). RTS games usually correspond to vast search spaces that traditional artificial intelligence techniques fail to play at a human level. As a mean to address it, authors in [13] proposed to extract behavioural knowledge from expert demonstrations which could be used to achieve specific goals. There are many research problems involving the AI for RTSs, including: planning with uncertainty or incomplete information, learning, opponent modelling, or spatial and temporal reasoning [1].

However, most of the RTS games in industry are basically controlled by a fixed script (i.e. a pre-established behaviour independent of inputs) that has been previously programmed, so they are predictable for the player some combats later. Falke et al. [3] tried to improve the user's gaming experience by means of a learning classifier system that can provide dynamically-changing strategies that respond to the user's strategies.

Evolutionary Algorithms (EAs), have been widely used in this field [14, 6], but they are not frequently used on-line (in real-time) due to the high computational cost they require. In fact, the most successful proposals for using EAs in games corresponds to off-line applications [15], that is, the EA works previously the game is executed (played), and the results or improvements can be used later during the real-time game. Through off-line 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. For instance, in [11] an agent trained with an EA to play in the previous Google AI Challenge is presented.

In the present work, EAs are also used, and an off-line Genetic Algorithm (GA) is applied to improve a parametrised behaviour model (set of rules), inside a RTS named ANTS.

3 The Google AI Challenge

This section describes the game scenario where the bots will play. The ANTS game was used as base for the Google AI Challenge 2011 (GAIC)[4] [5]. An ANTS match takes place on a map (see Figure 1) that contains several anthills. The game involves managing the ant community in order to attack the maximum number of enemy hills. Initially, game players have one or more hills and each hill releases the first ant. Then, the bot has to control it in order to reach food and generate another ant. Game is based on a turn system (1000 turns in official games). For each turn, participants have a limited time to develop a strategy with the ant community. Before turn time-over, bot should return a witness indicating that tasks have been finished. If the witness is not sent before time-over, the player receives the 'timeout' signal. Receiving a timeout' signal carries penalty points and the inability to make more movements until game finish. However, this does not entail game disqualification. If player has accumulated enough points before timeout, she could win. For each captured hill, the player receives two points and if one of our hills is captured, he lose a point.

There are two strong constraints (set by the competition rules) 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* between games about its former actions, about the opponent's actions or about the state of the game (i.e., the game's map). In order to achieve evolution has been added an extra layer that allows us to store best individuals parameters and let to evolve the population in future generations. During the competition, evolution take place offline locally in our computers and after obtaining the best individual, a new bot agent is generated and uploaded to the official online platform. Therefore, the goal in this paper is to design a bot agent using that extra GA layer that, according to the state of the map in each simulated turn (input) returns a set of actions to perform in order to fight the enemy, conquer its anthills, and, ultimately, win the game.

4 Algorithms and Experimental Setup

In this section the strategy to evolve is presented. A Genetic Algorithm (GA) is used to improve parameters of a basic agent. In order to improve the agent two different type of fitness and six different maps have been used.

[4] http://ants.aichallenge.org/

4.1 Strategy parameters

The basic strategy to our agent is based in a Greedy strategy to prioritize multiple tasks entrusted to the ants:

- If enemy hill in sight, attack the hill, else
- If food in sight, pick up the food, else
- If enemy ants in sight, attack the ants, else
- If unknow zone in sight, explore the area randomly.

The second strategy, Lefty, is based on follow a straight line until water is found, and then, walks to the left bording the water.

The parameters to optimize are:

- *food_distance*: Maximum distance to go get food, i.e. ants ignores food that is at a distance greater than this value.
- *time_remaining*: Margin time we have for one turn to finish without a 'time-out penalty'. Higher values indicate that more actions are performed, but as previously explained, the player receives a penalty.
- *distance_my_ant_attack* and *distance_hill_attack*: These parameters are used to determine the attack priority. Distance_my_ant_attack means that we have one ant partner close enough to take advantage when attacking enemy ants. In this situation, the distance_hill_attack is taking into account in order to change ant objective. If another enemy ant is close to our hill, our ant give priority to this more dangerous situation for our interest. In this case an ant is sacrified to keep alive our anthill.
- *turns_lefty*: Maximum number of consecutive turns in which an ant Lefty strategy can be used. After that number of turns, ants community change to Greedy strategy.

4.2 Genetic algorithms

A Genetic Algorithm is used to evolve the previously presented parameters. The **Fitness function**, which determines the individual's adaptation to the environment is based on launching a game against several opponents, in a certain number of turns and a specific map. The score for the agent after that game will determine the degree of kindness and individual adaptation to the problem we want to solve, know the individual that maximizes the score. Two different fitness functions have been studied:

- Basic fitness: Only takes into account the score obtained by our agent in the battle.
- Hierarchical fitness: The fitness is a tuple of the following elements in order: My score, enemy score (negative), number of my own ants and number of enemy ants (negative). A lexicographical order is applied to compare two individuals.

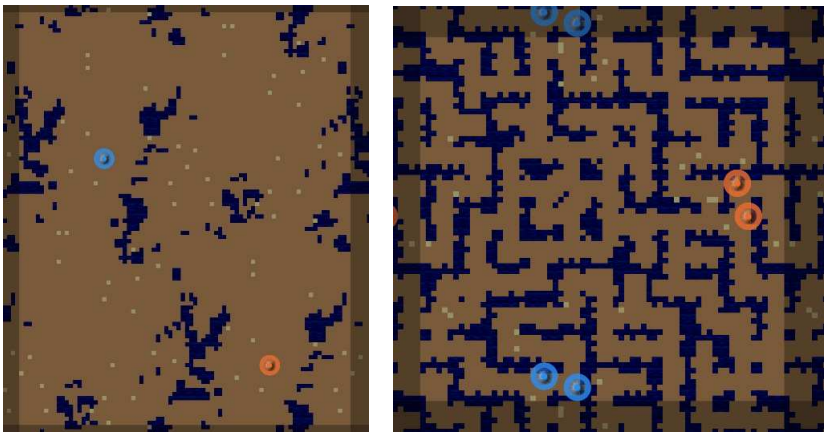
To represent each individual in the population, we chose to use a tuple of integers, where each number indicates the value of one of the parameters previously explained.

4.3 Maps to use

Six maps have been used to evolve the bot. All of them are provided by the competition organizers in tools package. Three maps are mazes with different grade of difficult and the other three have open walking areas. Figure 1 shows two different kind of maps. The circles mark hills positions with one colour for each team. The blue areas represent water and ants cannot walk on it, small points represent food and the rest are land where ants can walk. Other relevant information about maps are detailed in Table 1.

Table 1. Maps

	Name	Type	#competitors	Rows	Cols	#Hills
map1	random_walk_p02_01	Open	2	100	80	1
map2	random_walk_p02_05	Open	2	52	70	1
map3	maze_p02_05	Maze	2	66	66	2
map4	maze_p02_34	Maze	2	108	138	1
map5	maze_p02_42	Maze	2	72	126	2
map6	cell_maze_p02_10	Open maze	2	42	142	2



(a) Map 1: open map (b) Map 3: labyrinth type

Fig. 1. Two different maps used in the experiments.

4.4 Experimental setup

Once completed the design and implementation of the various versions of the genetic algorithm, we will show the performance of the two in each of the six

previous maps, with an initial size of population of 64 individuals. Crossover rate is 0.3, mutation rate is 0.1 and the stop criterion is fixed to 20 generations. The agent is evolved in the six maps 10 times.

5 Results and Analysis

This section explains the obtained results. Selected competitors have higher final ranking than our bot. Table 2 shows that our robot can not beat robots that are in positions 165 and 1. However, the evolution of the agent makes higher the number of own ants and decreases the number of enemy ants in a few generations. Genetic evolution of our agent wins on all maps to the robot that ended in ranking 993, more than 1000 position above the version without optimization. The number of ants is the main difference between basic fitness and hierarchical fitness, and this feature allows to use more effective attack technics. In maps 5 and 6, the score is lower than the obtained with basic fitness in some cases. However, the number of ants own doubles to those obtained with a basic fitness. This invites us to improve strategies maps in such type of maps to achieve a better use of the large community of ants generated. A remarkable result is found in the standard deviation (SD) value. SD is zero in many cases because variables have very few possible values (i.e. in maps with only two hills, max_score will be 0, 1 or 3 points) and after 20 generations the system evolves always to reach max score.

6 Conclusions and future work

This paper presents the design of an agent that plays in the RTS ANTS game proposed by Google AI Challenge. Starting with a combination of two basic behaviours (Lefty and Greedy) an Evolutionary Algorithm is used to set the parameters that modify the agent behaviour. This agent is evolved in the 6 maps provided by Google fighting three different bots that participated in the contest: the ones that finished in position 993, 165 and the winner. Results show that, even as evolving the parameters of two simple tasks, a fixed strategy agent is capable to win harder opponents. By the contrary, the same strategy is not affective against a middle bot, so it is clear that the enemy behaviour affects to the offline training algorithms with an specific strategy. Two different fitness functions have been tested: a basic function that only takes into account the final score (the number of conquered anthills in a run), and a hierarchical fitness, where the number of player's ants, turns, and enemy ants are also used to compare individuals. Genetic optimization is enough to beat a competitor who is above about 1000 positions in the ranking but, evolving a basic robot is not enough to beat robots with good strategies. We conclude that parameters optimization using GA significantly improves agent performance in RTS games and this technique obtains better results combined with good planning strategies.

For future work, new combination of strategies will be studied and more different fitness will be analysed: for example, combining all maps in each fitness

Table 2. Results

	maxScore	maxMyAnts	maxEnemyAnts	meanTurns
Basic fitness vs. Bot993.				
map1	3,00 ± 0,00	84,08 ± 43,82	66,50 ± 49,20	416,87 ± 125,94
map2	3,00 ± 0,00	68,08 ± 39,10	60,67 ± 34,92	425,64 ± 90,26
map3	6,00 ± 0,00	39,91 ± 15,65	186,91 ± 63,74	318,28 ± 124,63
map4	1,00 ± 0,00	8,64 ± 0,67	12,00 ± 0,00	150,00 ± 0,00
map5	5,42 ± 0,51	36,00 ± 27,24	228,75 ± 89,91	428,93 ± 189,53
map6	6,00 ± 0,00	46,25 ± 59,21	111,25 ± 20,82	221,18 ± 104,35
Hierarchical fitness vs. Bot993.				
map1	3,00 ± 0,00	154,56 ± 28,84	2,67 ± 1,50	481,33 ± 48,26
map2	3,00 ± 0,00	97,67 ± 37,83	3,00 ± 2,18	486,78 ± 79,99
map3	6,00 ± 0,00	45,00 ± 8,85	118,33 ± 19,49	266,00 ± 55,57
map4	1,00 ± 0,00	9,22 ± 0,44	12,00 ± 0,00	150,00 ± 0,00
map5	4,67 ± 0,50	73,78 ± 71,10	226,89 ± 57,61	706,78 ± 262,88
map6	5,00 ± 1,15	104,11 ± 107,52	77,89 ± 58,10	519,44 ± 262,51
Hierarchical fitness vs. Bot165.				
map1	0,00 ± 0,00	33,58 ± 2,97	101,17 ± 7,83	183,42 ± 7,29
map2	0,17 ± 0,39	31,08 ± 8,54	122,00 ± 49,41	221,17 ± 86,06
map3	0,00 ± 0,00	35,33 ± 9,72	98,83 ± 10,99	186,50 ± 9,26
map4	0,00 ± 0,00	34,75 ± 9,75	99,17 ± 10,96	184,92 ± 9,11
map5	0,00 ± 0,00	32,50 ± 10,51	101,75 ± 12,19	186,25 ± 9,18
map6	0,00 ± 0,00	31,50 ± 10,91	103,10 ± 12,80	188,00 ± 9,08
Hierarchical fitness vs. Bot1.				
map1	0,00 ± 0,00	31,00 ± 34,00	109,00 ± 95,00	185,00 ± 198,00
map2	0,00 ± 0,00	17,00 ± 23,00	119,00 ± 132,00	156,00 ± 175,00
map3	0,00 ± 0,00	16,00 ± 17,00	118,00 ± 147,00	160,00 ± 186,00
map4	0,00 ± 0,00	14,00 ± 17,00	130,00 ± 120,00	166,00 ± 160,00
map5	0,00 ± 0,00	20,00 ± 31,00	112,00 ± 108,00	149,00 ± 147,00
map6	0,00 ± 0,00	21,00 ± 19,00	127,00 ± 131,00	172,00 ± 171,00

calculation. Because the stochastic behaviour of some robots also affects the fitness, an study of how this fitness is affected during the algorithm run will be performed. As demonstrated, the behaviour of the enemies is also a very important key to analyse for designing a all-terrain bot: an agent should adapt to these differents behaviours. Also, using a quick map analysis in each turn to set the parameters obtained in this work could be studied to adapt the agent accordingly. A map analysis could be performed, for example, counting the number of direction changes in a period of time. If many direction changes occurs by collisions with walls, means that bots are fighting in a map with maze pattern. Once map type has been detected, bot can choose suitable parameter group for the map. The combination of the Greedy and Lefty actions also will be studied in other RTS games, as the previous Google AI Contest games.

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