Towards Automatic StarCraft Strategy Generation Using Genetic Programming

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***Abstract*—Among Real-Time Strategy games few titles have enjoyed the continued success of StarCraft. Many research lines aimed at developing Artificial Intelligences, or "bots", capable of challenging human players, use StarCraft as a platform. Several characteristics make this game particularly appealing for researchers, such as: asymmetric balanced factions, considerable complexity of the technology trees, large number of units with unique features, and potential for optimization both at the strategical and tactical level. In literature, various works exploit evolutionary computation to optimize particular aspects of the game, from squad formation to map exploration; but so far, no evolutionary approach has been applied to the development of a complete strategy from scratch. In this paper, we present the preliminary results of StarCratfGP, a framework able to evolve a complete strategy for StarCraft, from the building plan, to the composition of squads, up to the set of rules that define the bot's behavior during the game. The proposed approach generates strategies as C++ classes, that are then compiled and executed inside the OpprimoBot open-source framework. In a first set of runs, we demonstrate that StarCraftGP ultimately generates a competitive strategy for a Zerg bot, able to defeat several human-designed bots.**

I. Introduction

Real Time Strategy (RTS) games are a sub-genre of tactical videogames where the action takes place in real time, i.e., there are no turns. Players must manage units, production structures and resources in order to, normally, win a battle against a rival. Some famous and successful RTSs are Age of Empires™, Warcraft™and StarCraft™. The latter has also become very popular among the scientific community, as it is considered the unified test-bed for several research lines [1], such as Machine Learning, content generation, and optimization.

StarCraft [2] was developed by Blizzard Entertainment in 1998. It is a space strategy game in which three different races fight to dominate the galaxy: *Terran*, humans with futuristic weaponry; *Protoss*, aliens with highly advanced technology and powerful but expensive units; and *Zerg*, insect-like monsters that usually aim at overrunning the opponent with swarms of small units. A good part of StarCraft's success is due to an excellent balance between the three species, the complexity of units and buildings, and the existence of many different viable strategies.

A huge research community is centered on the creation of agents that play this game [1], also called "bots" (short for robots), with several periodic StarCraft AI competitions [3] held at annual conferences such as CIG or AIIDE, that encourages researchers to improve their methods and create stronger bots.

There are normally two levels of Artificial Intelligence (AI) in RTS games [4]: the first one takes decisions over the whole set of units (for instance, workers, soldiers, machines or vehicles), plans a build order, and generally defines a high-level direction of the match. The second level concerns the behavior of each unit, or small subsets of units. These two levels can be considered *strategic* and *tactical*, respectively. This paper focuses on the strategic part of the AI engine.

Although most of the development of StarCraft bots is focused on manually writing an AI, or improving the parameters on which its behavior depends on using Machine Learning techniques [5], the automatic creation of complete strategies from scratch has not been addressed so far.

This paper presents a framework for the automatic generation of strategies for StarCraft, using *Genetic Programming* (GP) [6]. GP belongs to the category of *Evolutionary Algorithms* [7], optimization techniques inspired by natural evolution, and it is commonly used to create solutions internally encoded as trees or linear graphs [8], but it has also been used for the generation of Turing-complete programs. These algorithms are normally used to generate computer programs to perform an objective task, optimizing a metric or objective functions called *fitness*. This technique can produce combinations of conditions and actions that are potentially very different from what a human programmer could design, making it possible to obtain competitive bots from scratch, i.e. without adding human knowledge. This introduces a high difference with respect to the usual improvement of behavioral models by mean of EAs [9], [10], [11], which is based on the optimization of parameters that guide the bots behavior, and consequently constrained to a human-designed model and its possible limitations.

The proposed approach directly writes the candidate strategies as C++ classes, that are then compiled in the open-source

bot *OpprimoBot* [12]. Since the focus of this contribution is on high-level strategies, the tactics of units and squads are left to be managed by OpprimoBot's default AI. The fitness function used to drive the evolutionary process is based on a series of actual matches against properly selected opponent. The resulting statistics are then analyzed and parsed to obtain a numerical metric. Even if a military victory is always considered the most important result, two different functions are tested:

1) Victory: the default final score returned by StarCraft at the end of one match against each of 12 different opponents;
2) Report: a more complex metric, aiming at separating military success from in-game economy development, using different rewards, computed after 3 matches against each of 4 different opponents.

The aim of these trials is to obtain indications on which kind of fitness metric could prove more beneficial: whether the result of a match can be generalized to multiple matches against the same opponent; and whether evaluating a candidate against a smaller variety of tactics could still return a strategy able to play well against new opponents.

The best strategies obtained after the evolutionary runs are then validated against different human-designed bots, also based on OpprimoBot: since the tactical low-level aspects of these bots are the same, theoretically the comparison should mainly concern the efficiency of the respective high-level strategies. Preliminary results show that the proposed approach can generate competitive Zerg bots, able to effectively tackle new opponents not used during training or never seen before, opening promising perspectives for future works.

The rest of the paper is structured as follows: after a background in computational intelligence in RTS in Section II, the proposed methodology is shown in Section III. Then, the experimental results are explained in Section IV. Finally, the conclusions and future work are presented.

II. Background

A. Genetic Programming for bot generation

GP [6] belongs to a wide class of probabilistic optimization techniques, loosely inspired by the neo-Darwinian paradigm of natural selection. The algorithm is defined by a set (population) of candidate solutions (individuals) for a target problem, a selection method that favors better solutions, and a set of operators (crossover, mutation) that act upon the selected solutions. After an initial population is created (usually randomly), the selection method and operators are successively applied, produce new solutions (offspring) that might replace the less fitted. In fact, at the end of each iteration (generation), the candidate solutions are compared on their goodness (fitness), and the worst ones are removed. Through this process, the quality of the individuals tends to increase with the number of generations.

A candidate solution in GP is usually internally modeled as a tree or as a linear graph [8]. In μGP [13], the framework used in this contribution, each node in the internal representation (genome) corresponds to a user-defined macro, eventually with a set of parameters. The operators can modify a macro's parameters or even the structure of the genome, adding or removing nodes and subtrees. As the genome of an individual can be constrained in several ways, the resulting solutions can feature a considerable complexity. When applied to AI in games, GP solutions have been encoded as sets of rules or finite-state machines. Being non-human is, in fact, one of the main advantages of GP: the candidate solutions proposed by this algorithm can be very far from human intuition, and still be competitive.

Thus, GP has been used to generate autonomous playing agents (bots) in different types of games, such as famous case studies in Game Theory [14], simple board games [15], strategy games involving Assembly programs [16] and even First Person Shooters [17]. Bots created using GP have sometimes obtained higher rankings than solvers produced by other techniques, defeating even high-ranking human players (or human-designed solutions) [18]. In the case of RTS, some works are focused on the *Planet Wars* game, as it is a extremely simplification of an RTS. In this case, genetic programming was proved as a valid way to generate bots that can outperform optimized hand-made bots [19]. Different fitness functions have been compared, being the ones that compare individuals using victories the ones that produce more aggressive bots [20]. These promising results are a good motivation to apply GP to a more complex commercial game, such as StarCraft.

B. AI in StarCraft

Thanks to BWAPI, an open-source API developed by fans[1] of the game, StarCraft has become a challenging test-bed for research in RTS, with tens of publications on the subject[2]. Different research lines targeted different aspects of this game, ranging from building order definition, micro-management optimization, strategy prediction, efficient map navigation, or maximizing resource production.

In [21] Togelius et al. used a multi-objective evolutionary algorithm to automatically generate maps taking into account aspects such as playability, skill differentiation and fairness. But, is the creation of bots where the most of efforts are being focused. Ontañón et al. recently presented a survey on research in this topic [1], and also proposed a classification of the bot's AI taking into account the problems to address: strategy, tactics and reactive control. Different techniques have been used to generate (or optimize) AIs for this game: Hagelbäck [12] combined potential field navigation with the A* algorithm for the behavior of the squads, while Churchill and Buro [22] used a Branch & Bound algorithm to optimize the building order of the structures and units in real time.

EAs have been used to optimize StarCraft bots at different levels: for example, Othman et al. evolved the parameters of hand-coded high level strategies [5], while Liu et al. [23] optimized the 14 parameters of the micro-management tactics for units. However, these methods require a hand-coded base to optimize their numerical values, and human expertise to design the bots in the first place. To the best of our knowledge, no other authors have used GP to automatically generate strategies for StarCraft from scratch.

[1] https://github.com/bwapi/bwapi
[2] https://github.com/bwapi/bwapi/wiki/Academics

III. Proposed approach

In the proposed evolutionary framework (depicted in Figure 1) the evolutionary core (the algorithm) receives a set of code constraints used to automatically generate the code of the bots by means of GP. For each individual in the population, a .cpp file is generated, compiled by the external evaluator and compared against a set of enemies in several StarCraft matches, to ultimately obtain its fitness. The fitness value associated to an individual will later influence its probability to reproduce, creating new derived solutions, and to survive in future generations of the algorithm.

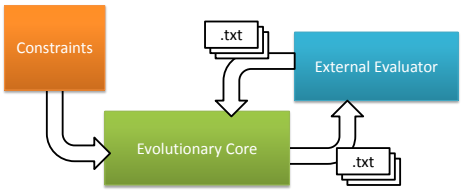


Fig. 1. High-level scheme of the proposed approach. Following user-defined constraints, the evolutionary core creates individuals encoded as C++ classes. The obtained files are then sent to an external evaluator, that will return a fitness value. The fitness values will be then exploited by the evolutionary core to create better and better solutions.

The next subsections will detail the encoding of the individuals in the population, and the two fitness functions used.

A. AI encoding

Each individual in the proposed framework represents the AI that manages the strategy of a StarCraft bot, and is encoded as a C++ class inside such a bot. The class features two methods: a constructor, defining the initial building plan (which units/structures will be built in which order) and the initial squads (groups of units with a specific role, such as attacker or defender); and a method called every frame to compute new actions (such as adding units to a squad, creating new squads, modifying the building plan) on the basis of the current situation. It is important to notice that only the strategy is evolved, while the tactics (e.g. the behavior of a single unit) are managed by other classes inside the bot, unchanged during the process.

Producing compilable C++ code through a GP-like evolutionary toolkit is not a trivial task: the structure of an individual is considerably complex, and relies upon the concepts of *Section*, *Subsection* and *Macro*. In the following, a *Section* is defined as a part of the individual that contains several *Subsections* and appears exactly once in the genome; a *Subsection* can appear multiple times and contain several *Macros*, but *Subsections* strictly follow the order in which they are declared, and all their instances appear before or after the instances of other *Subsections*; finally, a *Macro* represents a single instructions, or block of code, and *Macro* instances can appear in any order inside the *Subsection* they belong to. Using this block hierarchy, a properly defined structure guarantees that every individual produced by the algorithm will compile without errors.

As the class features two methods, the structure of an individual is divided into two *Sections*, here called `initialization` and `computeActions`. A scheme for the individual's structure is reported in Figure 2.

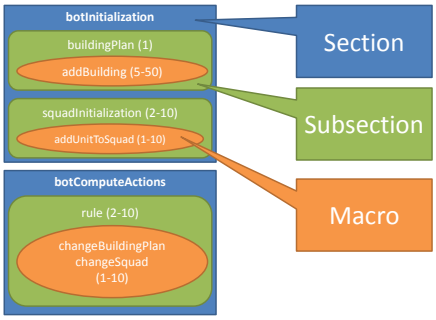


Fig. 2. Individual structure: *Sections* appear only once; *SubSections* can appear multiple times, always in the same order; *Macros* can appear multiple times, in any order.

1) `initialization`*:* This part of the individual defines the initial building plan and the starting groups of units. The *Subsection* `buildingPlan`, that appears only once, lists between 5 and 50 instances of the *Macro* `addBuilding`, the instruction that adds a building to the queue of structures to be built. The *Subsection* `squadInitialization` defines a squad: between 2 and 10 squads can be created by the strategy. The *Macro* `addUnitToSquad` adds 1 to 5 units of a certain type to the squad, so a squad can initially feature between 1 and 50 units. Figure 3 shows an example of a building plan generated by the proposed approach.

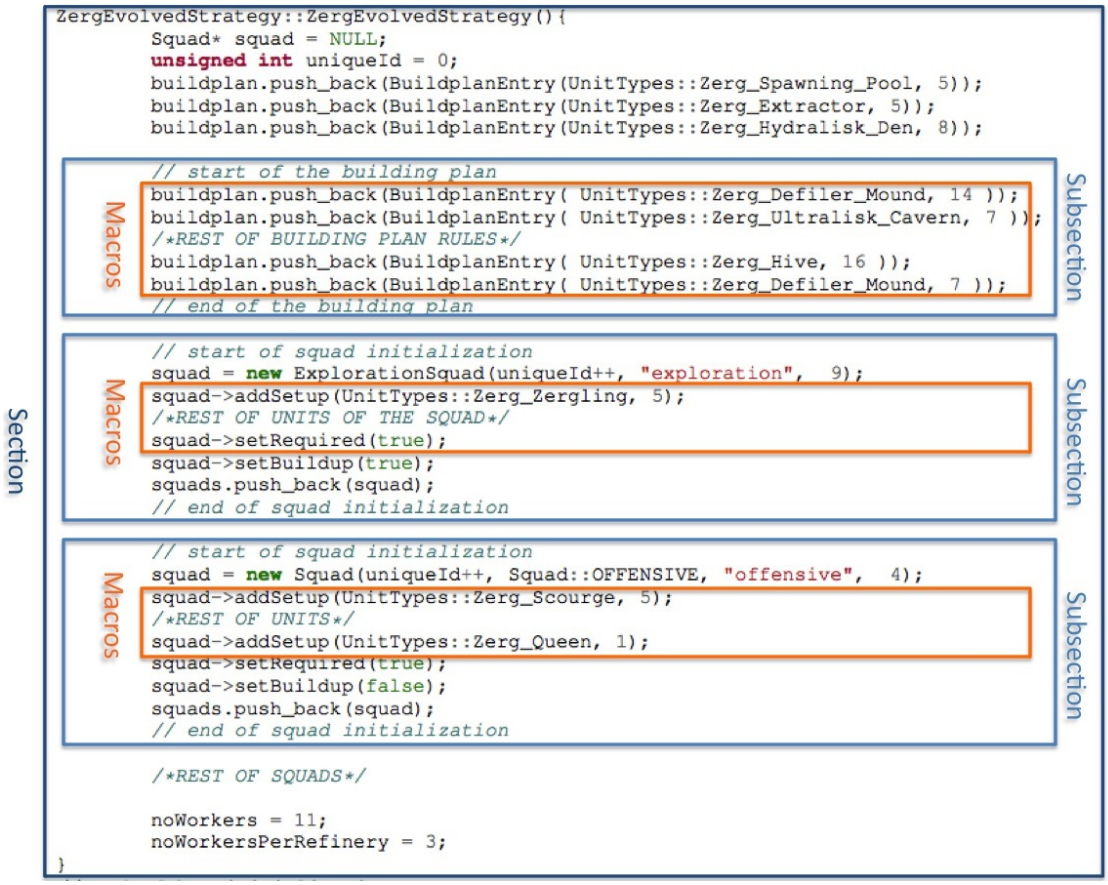
2) `computeActions`*:* This *Section* represents a method encoding a set of rules that will change the behavior of the bot during the execution, depending on the current situation. Figure 4 shows an example of a generated computeActions method.

B. Genetic Operators

Different genetic programming operators are used to cross and mutate the structure of the individuals. `onePointImpreciseCrossover` and `twoPointImpreciseCrossover` can combine two individuals, cutting their structures in one or two points, respectively. `subGraphInsertionMutation`, `subGraphRemovalMutation` and `subGraphReplacementMutation` can add, remove or replace an instance of a Subsection, respectively. `insertionMutation`, `removalMutation` and `replacementMutation` can add, remove or replace an instance of a Macro, respectively. `singleParameterAlterationMutation` and `alterationMutation` act on a Macro instance, randomizing one or all its parameters, respectively. These operators are part of the μGP framework, and are illustrated in more detail in [13].

C. Evaluation

The efficiency of a StarCraft strategy can be easily measured by matching it against different opponents. This fitness




```
ZergEvolvedStrategy::ZergEvolvedStrategy(){
        Squad* squad = NULL;
        unsigned int uniqueId = 0;
        buildplan.push_back(BuildplanEntry(UnitTypes::Zerg_Spawning_Pool, 5));
        buildplan.push_back(BuildplanEntry(UnitTypes::Zerg_Extractor, 5));
        buildplan.push_back(BuildplanEntry(UnitTypes::Zerg_Hydralisk_Den, 8));

        // start of the building plan
        buildplan.push_back(BuildplanEntry( UnitTypes::Zerg_Defiler_Mound, 14 ));
        buildplan.push_back(BuildplanEntry( UnitTypes::Zerg_Ultralisk_Cavern, 7 ));
        /*REST OF BUILDING PLAN RULES*/
        buildplan.push_back(BuildplanEntry( UnitTypes::Zerg_Hive, 16 ));
        buildplan.push_back(BuildplanEntry( UnitTypes::Zerg_Defiler_Mound, 7 ));
        // end of the building plan

        // start of squad initialization
        squad = new ExplorationSquad(uniqueId++, "exploration",  9);
        squad->addSetup(UnitTypes::Zerg_Zergling, 5);
        /*REST OF UNITS OF THE SQUAD*/
        squad->setRequired(true);
        squad->setBuildup(true);
        squads.push_back(squad);
        // end of squad initialization

        // start of squad initialization
        squad = new Squad(uniqueId++, Squad::OFFENSIVE, "offensive",  4);
        squad->addSetup(UnitTypes::Zerg_Scourge, 5);
        /*REST OF UNITS*/
        squad->addSetup(UnitTypes::Zerg_Queen, 1);
        squad->setRequired(true);
        squad->setBuildup(false);
        squads.push_back(squad);
        // end of squad initialization

        /*REST OF SQUADS*/

        noWorkers = 11;
        noWorkersPerRefinery = 3;
}
```

Fig. 3. Example of a generated `initialization` method.

evaluation, taking into account victories as primary target to improve, has been successfully used in previous works to generate agents for RTS games using GP [19]. Obtaining a reliable global assessment of a strategy's strength, however, requires a considerable number of evaluations [20]: not only some game plans are more effective on specific maps, due to their shape or size; but it is well-known that some strategies can be used as a counter to specific plans (for example, an early attack could be efficiently blocked by a defensive deployment); and finally, the game uses some random elements (e.g. amount of damage inflicted) that, while reasonably constrained between thresholds, can still influence the development of a match, so two games between the two same strategies on the same map could lead to two different outcomes. However, extra information may also help to guide the evolution, for example differencing military and economic victories to generate more aggressive bots.

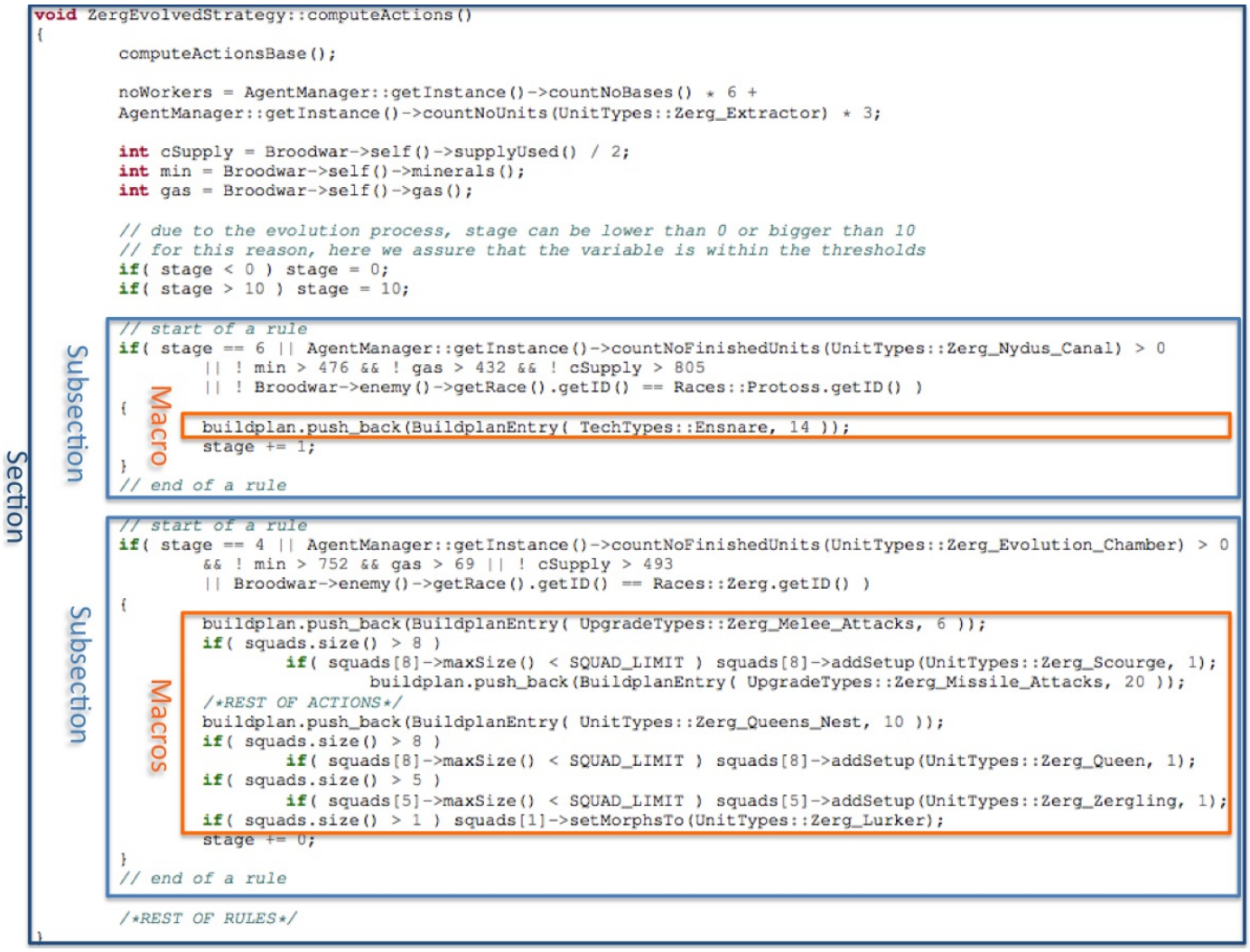
1) Victory-based fitness: This fitness compares, in lexicographical order, a vector of the number of victories against 4 different tiers of opponents in different tiers of strength. The tiers have been created through a preliminary tournament between the 12 considered strategies. In order to save computational time, a candidate bot accesses a tier if it won at least once against an opponent from the lower one. The final position of the vector is a ratio between the average StarCraft score obtained by the bot over the score obtained by the opponents.

2) Report-based fitness: There are several in-game metrics that can be exploited to provide a smoother slope towards good solutions, such as the number of enemy units destroyed, the amount of resources gathered, the number of units produced, etc. In particular, the following have been chosen as fitness values, to be maximized and evaluated in lexicographical order:

1) **Military victory**: each time the candidate strategy is able to defeat an opponent before the alloted time runs out, this score is incremented by 1.
2) **Economic victory**: if the alloted time runs out, but the in-game score for units and structures of the candidate strategy is higher than the opponent's, this score is incremented by 1.
3) **Relative destruction**: the average score for units and structures destroyed, over the same score for the opposing strategy.
4) **Time to loss**: the average time the candidate strategy resisted before losing against the opponents it was not able to defeat.
5) **Relative economy**: the average score for units and structures built, over the same score for the opposing strategy.

IV. Experimental evaluation

Given the consideration in Subsection III-C, it is easy to see how the number of evaluations needed for the assessment of a




```
void ZergEvolvedStrategy::computeActions()
{
        computeActionsBase();

        noWorkers = AgentManager::getInstance()->countNoBases() * 6 +
        AgentManager::getInstance()->countNoUnits(UnitTypes::Zerg_Extractor) * 3;

        int cSupply = Broodwar->self()->supplyUsed() / 2;
        int min = Broodwar->self()->minerals();
        int gas = Broodwar->self()->gas();

        // due to the evolution process, stage can be lower than 0 or bigger than 10
        // for this reason, here we assure that the variable is within the thresholds
        if( stage < 0 ) stage = 0;
        if( stage > 10 ) stage = 10;

        // start of a rule
        if( stage == 6 || AgentManager::getInstance()->countNoFinishedUnits(UnitTypes::Zerg_Nydus_Canal) > 0
                || ! min > 476 && ! gas > 432 && ! cSupply > 805
                || ! Broodwar->enemy()->getRace().getID() == Races::Protoss.getID() )
        {
                buildplan.push_back(BuildplanEntry( TechTypes::Ensnare, 14 ));
                stage += 1;
        }
        // end of a rule

        // start of a rule
        if( stage == 4 || AgentManager::getInstance()->countNoFinishedUnits(UnitTypes::Zerg_Evolution_Chamber) > 0
                && ! min > 752 && gas > 69 || ! cSupply > 493
                || Broodwar->enemy()->getRace().getID() == Races::Zerg.getID() )
        {
                buildplan.push_back(BuildplanEntry( UpgradeTypes::Zerg_Melee_Attacks, 6 ));
                if( squads.size() > 8 )
                        if( squads[8]->maxSize() < SQUAD_LIMIT ) squads[8]->addSetup(UnitTypes::Zerg_Scourge, 1);
                                buildplan.push_back(BuildplanEntry( UpgradeTypes::Zerg_Missile_Attacks, 20 ));
                /*REST OF ACTIONS*/
                buildplan.push_back(BuildplanEntry( UnitTypes::Zerg_Queens_Nest, 10 ));
                if( squads.size() > 8 )
                        if( squads[8]->maxSize() < SQUAD_LIMIT ) squads[8]->addSetup(UnitTypes::Zerg_Queen, 1);
                if( squads.size() > 5 )
                        if( squads[5]->maxSize() < SQUAD_LIMIT ) squads[5]->addSetup(UnitTypes::Zerg_Zergling, 1);
                if( squads.size() > 1 ) squads[1]->setMorphsTo(UnitTypes::Zerg_Lurker);
                stage += 0;
        }
        // end of a rule

        /*REST OF RULES*/
}
```

Fig. 4. Example of a generated `computeActions` method.

candidate strategy quickly explodes: considering a minimum of 3 matches in the same conditions to obtain a reliable average, evaluating a candidate strategy against 10 opponents on 10 different maps would require $3 \cdot 10 \cdot 10 = 300$ matches; and a match long enough to be significant would last at least 10 wall-clock minutes, even at maximum in-game speed. Thus, a self-evident disadvantage of the proposed approach is the sheer quantity of computational power necessary to evaluate the individuals. For this reason, in this proof-of-concept experimental evaluation, the focus is on a limited number of strategies, evaluated on a single map: overfitting the final strategy on these conditions is almost a given, but the objective is not to obtain a tournament-competitive player, but rather to assess whether the approach is viable.

The most competitive bots in current championships usually implement Protoss and Terran [1] strategies, meaning that they are probably easier to manage for hand-coded AIs. For our first runs, we choose to evolve a Zerg strategy to assess whether a GP engine can more successfully manage this faction.

A. Setup

The experiments have been performed on a group of 8 VirtualBox[3] virtual machines (VMs), one Master and 7 Clients, running Windows XP (see Figure 5). The Master VM runs the evolutionary algorithm μGP [4] [24], that creates the strategy classes following the constraints specified in Subsection III-A. The algorithm is configured with the parameters reported in Table I. These parameters have been chosen because they have been used successfully in other works that use GP for RTS bot generation [19]. It is important to notice that the 30 generations set as a stop condition correspond to about 5 days (120 hours) of computation, on the hardware used for the experiments. Candidate strategies are then compiled inside the OpprimoBot[5] framework [12], v14.12, obtaining a DLL with the complete bot. Finally, the DLL is sent to the TournamentManager[6] software, that distributes the matches to be played among the Client VMs and collects the results.

[3] http://www.virtualbox.org/
[4] http://ugp3.sourceforge.net
[5] http://code.google.com/p/bthai/
[6] http://webdocs.cs.ualberta.ca/~cdavid/starcraftaicomp/tm.shtml

A Python 2.7 script directs the execution of all the involved programs, and parses the TournamentManager files to obtain the fitness values.

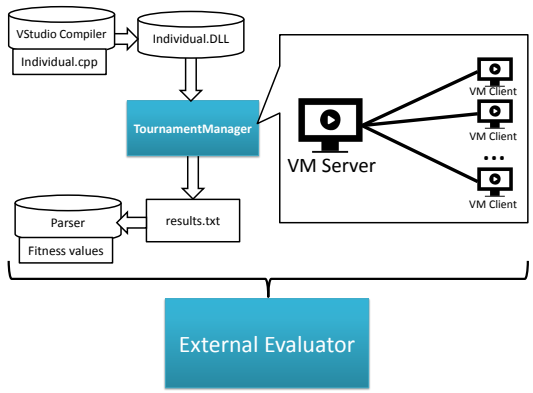


Fig. 5. Evaluator used during the evolutionary process. The candidate strategy, a C++ class, is compiled in the OpprimoBot framework, obtaining a DLL. The DLL is then sent to the TournamentManager software, to run several matches on virtual machines connected over a virtual network. Lastly, the results are parsed to obtain the fitness values.

TABLE I. PARAMETERS USED DURING THE EVOLUTIONARY PROCESS. ACTIVATION PROBABILITIES FOR THE OPERATORS AND SIZE OF THE TOURNAMENT SELECTION ARE SELF-ADAPTED DURING THE RUN, USING THE α INERTIAL PARAMETER TO SMOOTHEN THE VARIATION OF VALUES. THE GENETIC OPERATORS CAN REPEAT MUTATIONS ON THE BASIS OF THE σ PARAMETER.

Parameter	Value	Meaning
μ	30	Population size
λ	30	Number of genetic operators applied at each generation
σ	0.9	Initial strength of the mutation operators
α	0.9	Inertia of the self-adapting process
τ	(1,4)	Size of the tournament selection
MG	30	Stop condition: maximum number of iterations (generations)

Different strategies have been chosen as competition to test our approach and measure the fitness, taken from those available in OpprimoBot 14.12 [12], and one *Dummy* player, that essentially builds some structures and then keeps gathering resources, without producing offensive units or attacking. The Dummy's purpose is to smoothen the fitness values at the beginning of the evolution, allowing the evolutionary core to discriminate between individuals that show some good qualities and those who are just inert. Three matches are played against each strategy, on the map `Benzene.scx`, a very common map used in competitions, taken from those available in the 2014 AIIDE competition [7]: the map has been selected for its relatively small size and classical layout.

For the Victory-based fitness, the strategies chosen for evolution are:

- Tier 1 (Easy): OBTerranDummy, OBProtossReaverDrop1B, OBProtossDefensive, OBZergHydraMuta
- Tier 2 (Medium): OBProtossTemplarRush, OBProtossReaverDrop, OBTerranDefensiveFB, OBTerranDefensive
- Tier 3 (Hard): OBZergLurkerRush, OBTerranWraithHarass, OBTerranPush, OBTerranMarineRush

[7]http://webdocs.cs.ualberta.ca/~cdavid/starcraftaicomp/

For the Report-based fitness, the Dummy and three human-designed players from the difficult tiers have been used: OBTerranDummy, OBProtossReaverDrop, OBTerranWraithHarass, OBZergLurkerRush (repeating 3 times each one).

B. Results

As a StarCraft game requires real time to be executed (usually 10 minutes per match), even using 8 VMs in parallel, each execution of the algorithm requires several days. However, as this is a proof-of-concept, we analyze the only run we have performed for each fitness compared. The best individuals obtained are shown in Tables II and III.

TABLE II. FITNESS OF THE BEST INDIVIDUAL OBTAINED AND AVERAGE POPULATION FITNESS USING VICTORY-BASED EVALUATION.

	Best individual	Average population
Tier 3	4	1.73
Tier 2	3	1.83
Tier 1	3	2.93
Score ratio	0.0481	0.0378

TABLE III. FITNESS OF THE BEST INDIVIDUAL OBTAINED AND AVERAGE POPULATION FITNESS USING REPORT-BASED EVALUATION.

	Best individual	Average population
Military Victories	3	1.76
Economic victories	1	1.93
Relative destruction	400245	358172
Time to loss	1120	1380.7
Relative Economy	0.309	0.501

Evolution of the average individuals for both fitness approaches are shown in Figure 6 and Figure 7 (only the number of the victories of the fitness vector is plotted). It is interesting to remark, that both bots have been able to beat more than one strategy. As it can be seen, in both methods, the average population during all the run has lower values for the "difficult" type of victory (first value of the fitness vector), while the obtained best individuals (in Tables) have reached higher values for this number (Tier 3 victories and military victories, respectively). Therefore, the population is not stagnated for 30 generations, so more generations may lead to even better individuals.

C. Validation

After the evolution, and in order to validate the generated bots of the two different fitness approaches, a championship has been performed. The two generated bots have been confronted versus all the hand-coded strategies of OpprimoBot (including the ones not used for evolution, in the case of the Report-based fitness) and also against the complete OpprimoBot. Each bot has been confronted 10 times against each enemy. Table IV shows the number of victories (from 0 to 10) of our generated bots.

Results of this championship show that the first runs of our method generated bots able to defeat human-coded strategies, and even a complete complex bot (OpprimoBot). A comparison of the two generated bots shows a prevalence of the Victory-based fitness, that wins over more strategies, and more times. This can be explained because a greater number of bots has been used for the fitness value for this approach, instead of repetitions of only 4. It is interesting to notice that the Report-based fitness, although weaker, has been able

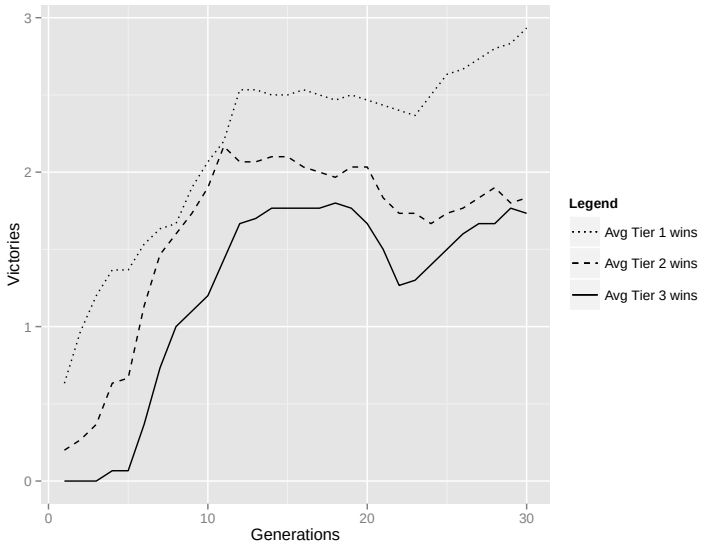


Fig. 6. Evolution of the average fitness value of the population during the run using the Victory-based fitness (only victories in each tier are shown)

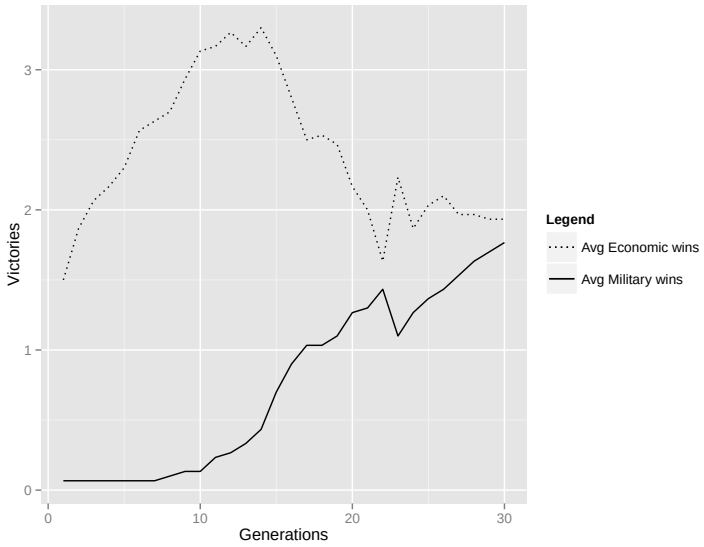


Fig. 7. Evolution of the average fitness value of the population during the run using the Report-based fitness (only victories are shown)

to generalize, defeating opponents it has never seen, such as OBProtossDefensive or OBProtossTemplarRush. Surprisingly, this bot beats the Victory-based 8 of 10 times.

Looking into the generated decision rules, the Victory-based bot has 9 different rules, while the Report-based only has 3. This can explain the different behavior of the two generated bots, being the first one more adaptive to different situations. In fact, analyzing the triggered rules of these bots, from the Victory-based fitness only 6 of the 9 rules have been triggered during the championship (in different proportions), while in the Report-based version 2 of the 3 rules are used, being these rules triggered almost the same amount of times.

TABLE IV. NUMBER OF VICTORIES OF THE GENERATED BOTS AGAINST HAND-CODED BOTS.

Bot	Victory-based	Report-based
OBTerranDefensiveFB	7	1
OBProtossTemplarRush	4	8
OBZergHydraMuta	10	1
OBZergLurkerRush	8	0
OBProtossDefensive	8	5
OBProtossReaverDrop1B	5	1
OBTerranDefensive	5	1
OBProtossReaverDrop	3	6
OBTerranMarineRush	7	0
OBTerranWraithHarass	5	0
OBTerranPush	6	3
OBTerranDummy	10	10
Victory-Based	*	8
Report-Based	2	*
OpprimoBot	6	1
TOTAL	86 of 140	45 of 140

The activated Victory-based rules basically generate exploratory squad with zerlglings, hydralisks and mutalisks, and an offensive one with Scourges, overlords and queens. Sometimes one of these types of squads are duplicated in the construction queue, and updated with Scourges or evolving units to Devourers and Lurkers. In the case of the Report-based, 6 different types of squads (offensive, rush and exploratory) are queued at first, and the two rules executed add hydralisks to existent squads, but no more squads are generated.

V. CONCLUSIONS

StarCraft has become a *de facto* test-bed for research on RTS games, as it provides different strategic levels for agent generation and optimization, well balanced types of races, and a huge community of players and researchers.

This paper proposes a preliminary study on the usage of Genetic Programming to automatically generate high-level strategies for StarCraft, using the StarcraftGP framework. Two different methods for evaluation of the bots during the evolution have been compared: a victory-based fitness and a report-based fitness, both using different number of enemies. The first run for each method has been able to automatically generate strategies that can defeat bots hand-coded by human experts. Results show that the victory-based fitness can generate better bots than the report-based method, winning more than half of the battles against hard-coded strategies.

Future works will address several improvements of the proposed methodology, for example using more fitness functions, more runs per method, or different maps. Also new experiments using more game information, or studying the optimization of the other two races of the game (Protoss and Terran) will be performed. Other aspects of the game will be also optimized using our framework, such as the squads behavior, or even the micro-management of each unit. Finally, other techniques can be used in conjunction with our method, for example, optimizing the learning and map analysis modules available in the literature.

ACKNOWLEDGMENT

The authors would like to thank Johan Hagelbäck and Dave Churchill for their help and the insight they provided. This

work has been supported in part by SIPESCA (Programa Operativo FEDER de Andalucía 2007-2013), TIN2011-28627-C04-02 and TIN2014-56494-C4-3-P (Spanish Ministry of Economy and Competitivity) and SPIP2014-01437 (Dirección General de Tráfico) and GENIL PYR-2014-17, awarded by the CEI-BioTIC UGR.

REFERENCES

[1] S. Ontañón, G. Synnaeve, A. Uriarte, F. Richoux, D. Churchill, and M. Preuss, "A survey of real-time strategy game AI research and competition in starcraft," *IEEE Trans. Comput. Intellig. and AI in Games*, vol. 5, no. 4, pp. 293–311, 2013. [Online]. Available: http://dx.doi.org/10.1109/TCIAIG.2013.2286295

[2] Wikipedia, "Starcraft," 2015, http://en.wikipedia.org/wiki/StarCraft.

[3] M. Buro and D. Churchill, "Real-time strategy game competitions," *AI Magazine*, vol. 33, no. 3, pp. 106–108, 2012.

[4] J. B. Ahlquist and J. Novak, *Game Artificial Intelligence*, ser. Game Development Essentials. Canada: Thompson Learning, 2008.

[5] N. B. Othman, J. Decraene, W. Cai, N. Hu, M. Y. Low, and A. Gouaillard, "Simulation-based optimization of starcraft tactical AI through evolutionary computation," in *2012 IEEE Conference on Computational Intelligence and Games, CIG 2012, Granada, Spain, September 11-14, 2012*. IEEE, 2012, pp. 394–401.

[6] J. R. Koza, *Genetic Programming: On the programming of computers by means of natural selection*. Cambridge, MA: MIT Press, 1992.

[7] T. Back, *Evolutionary algorithms in theory and practice*. Oxford University Press, 1996.

[8] M. F. Brameier and W. Banzhaf, *Linear genetic programming*. Springer Science & Business Media, 2007.

[9] P. Spronck, I. Sprinkhuizen-Kuyper, and E. Postma, "Improving opponent intelligence through offline evolutionary learning," *International Journal of Intelligent Games & Simulation*, vol. 2, no. 1, pp. 20–27, February 2003.

[10] N. Cole, S. Louis, and C. Miles, "Using a genetic algorithm to tune first-person shooter bots," in *Evolutionary Computation, 2004. CEC2004. Congress on*, vol. 1, June 2004, pp. 139–145 Vol.1.

[11] A. Fernndez-Ares, A. M. Mora, J. J. Merelo, P. Garca-Snchez, and C. Fernandes, "Optimizing player behavior in a real-time strategy game using evolutionary algorithms," in *Evolutionary Computation, 2011. CEC '11. IEEE Congress on*, June 2011, p. accepted for publication.

[12] J. Hagelbäck, "Potential-field based navigation in starcraft," in *2012 IEEE Conference on Computational Intelligence and Games, CIG 2012, Granada, Spain, September 11-14, 2012*. IEEE, 2012, pp. 388–393.

[13] G. Squillero, "MicroGP-an evolutionary assembly program generator," *Genetic Programming and Evolvable Machines*, vol. 6, no. 3, pp. 247–263, 2005. [Online]. Available: http://dx.doi.org/10.1007/s10710-005-2985-x

[14] M. Gaudesi, E. Piccolo, G. Squillero, and A. Tonda, "Turan: Evolving non-deterministic players for the iterated prisoner's dilemma," in *Evolutionary Computation (CEC), 2014 IEEE Congress on*. IEEE, 2014, pp. 21–27.

[15] A. Benbassat and M. Sipper, "Evolving both search and strategy for reversi players using genetic programming," in *2012 IEEE Conference on Computational Intelligence and Games, CIG 2012, Granada, Spain, September 11-14, 2012*. IEEE, 2012, pp. 47–54. [Online]. Available: http://ieeexplore.ieee.org/xpl/mostRecentIssue.jsp?punumber=6361518

[16] F. Corno, E. Sánchez, and G. Squillero, "Evolving assembly programs: how games help microprocessor validation," *Evolutionary Computation, IEEE Transactions on*, vol. 9, no. 6, pp. 695–706, 2005.

[17] A. Esparcia-Alcázar and J. Moravec, "Fitness approximation for bot evolution in genetic programming," *Soft Comput.*, vol. 17, no. 8, pp. 1479–1487, 2013. [Online]. Available: http://dx.doi.org/10.1007/s00500-012-0965-7

[18] M. Sipper, Y. Azaria, A. Hauptman, and Y. Shichel, "Designing an evolutionary strategizing machine for game playing and beyond," *IEEE Transactions on Systems, Man, and Cybernetics, Part C*, vol. 37, no. 4, pp. 583–593, 2007.

[19] P. García-Sánchez, A. Fernández-Ares, A. M. Mora, P. A. C. Valdivieso, J. González, and J. J. M. Guervós, "Tree depth influence in genetic programming for generation of competitive agents for RTS games," in *Applications of Evolutionary Computation - 17th European Conference, EvoApplications 2014, Granada, Spain, April 23-25, 2014, Revised Selected Papers*, ser. Lecture Notes in Computer Science, A. I. Esparcia-Alcázar and A. M. Mora, Eds., vol. 8602. Springer, 2014, pp. 411–421.

[20] A. M. Mora, A. Fernández-Ares, J. J. M. Guervós, P. García-Sánchez, and C. M. Fernandes, "Effect of noisy fitness in real-time strategy games player behaviour optimisation using evolutionary algorithms," *J. Comput. Sci. Technol.*, vol. 27, no. 5, pp. 1007–1023, 2012. [Online]. Available: http://dx.doi.org/10.1007/s11390-012-1281-5

[21] J. Togelius, M. Preuss, N. Beume, S. Wessing, J. Hagelbäck, and G. N. Yannakakis, "Multiobjective exploration of the starcraft map space," in *Proceedings of the 2010 IEEE Conference on Computational Intelligence and Games, CIG 2010, Copenhagen, Denmark, 18-21 August, 2010*, G. N. Yannakakis and J. Togelius, Eds. IEEE, 2010, pp. 265–272.

[22] D. Churchill and M. Buro, "Build order optimization in starcraft," in *Proceedings of the Seventh AAAI Conference on Artificial Intelligence and Interactive Digital Entertainment, AIIDE 2011, October 10-14, 2011, Stanford, California, USA*, V. Bulitko and M. O. Riedl, Eds. The AAAI Press, 2011.

[23] S. Liu, S. J. Louis, and C. A. Ballinger, "Evolving effective micro behaviors in RTS game," in *2014 IEEE Conference on Computational Intelligence and Games, CIG 2014, Dortmund, Germany, August 26-29, 2014*. IEEE, 2014, pp. 1–8. [Online]. Available: http://ieeexplore.ieee.org/xpl/mostRecentIssue.jsp?punumber=6919811

[24] E. Sanchez, M. Schillaci, and G. Squillero, *Evolutionary Optimization: the GP toolkit*. Springer US, 2011. [Online]. Available: http://dx.doi.org/10.1007/978-0-387-09426-7_3