Multiobjective Multi Unit-Type Neuroevolution for Micro in RTS games

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ABSTRACT

We used multiobjective genetic algorithms with neuroevolution of augmenting topologies (NEAT) to evolve effective micro behaviors for opposing groups with heterogeneous compositions in StarCraft II, an RTS game. We used the Fast Nondominated Sorting Genetic Algorithm to maximize damage done and minimize damage received in a skirmish, and used this two objective fitness to guide NEAT to evolve the structure and weights of a neural network based controller. The evolved NEAT network controls the movement and attack commands for each unit. We show that non-dominated selection and NEAT can be used together to generate effective micro for groups with two types or three types of units on each side. The evolved micro also generalized well to random configurations, doing well along both objectives. We also manually co-evolved against the best performing individuals produced during a run for multiple cycles and show that this improves micro resulting in better performance against the default Starcraft II AI.

KEYWORDS

Multi objective, neural networks, evolution, NEAT, NSGAII, RTS

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1 INTRODUCTION

Real Time Strategy (RTS) games are a genre of computer games which can be played by multiple players at once. Players have to control tens to hundreds of units, while simultaneously moving the camera around, deciding which units or unit factories to build, selecting units, scouting, and exploring. Starcraft II (SCII), a popular RTS game, has a number of unit types, with each type different from another in movement speed, damage capacity, weapon range and others. This leads to different optimal tactics in skirmishes for groups depending on factors like types of units in one's group, types of units in opposing group and also on the quantity of different kinds of units in each group.

The complexity of RTS games has attracted much research and has seen application of multiple research approaches towards different aspects of RTS gameplay [4]. Reinforcement learning, tree search, and genetic algorithms (GA) among others have been used to automatically learn a competitive agent [5]. GA based approaches have been successful in evolving good tactics for micro scenarios consisting of multiple types of units in a group [2]. Another GA approach where both structure and connection of a neural network are evolved called NEAT [6], has also been shown to evolve strategies that generalize well against different number of units in a group [3]. In this paper, we extend NEAT to multiple types of units in a group and use multiple objectives to guide evolution [1].

In this paper, We show that NEAT combined with a non dominated sorting genetic algorithm can evolve networks for controlling heterogeneous group of units and can generalize to different numbers of units in each group. We also show that the evolved network is robust against different starting positions and that on each iteration of manual coevolution, manually coevolved individuals perform better against individuals from previous runs.

2 METHODOLOGY AND RESULTS

NEAT is a robust algorithm for evolving neural networks based on genetic algorithm principles, NEAT allows for continuous complexification by allowing crossover and mutation between network representation [6]. The Nondominated Sorting Genetic Algorithm II (NSGA) is a type of multiobjective evolutionary algorithm (MOEA) which can be used to optimize for problems with more than one objective [1]. Our network representation for NEAT is an extension to [3] with the addition of unit type inputs using a one hot representation.

We used different number of units of each type in a group, but keep the composition of the opposing group same as that of the friendly group in our experimental setup. We also manually coevolved better players by playing against the best player from the last run. That is, we selected the best individual from the evolved Pareto front, made it our opponent, and evolved against it for the next round. For group skirmishes containing two unit types, we had fifteen zealots and five stalkers in each opposing group, and for groups containing three type of units, we had ten Marines, six Marauders, and four Medivacs in each opposing group. All units were controlled by a single network with the only differentiating inputs being the unit identifying inputs.

From Figure 1a, and Figure 1d, we see that the Pareto fronts show good improvement for both two types and three types scenarios

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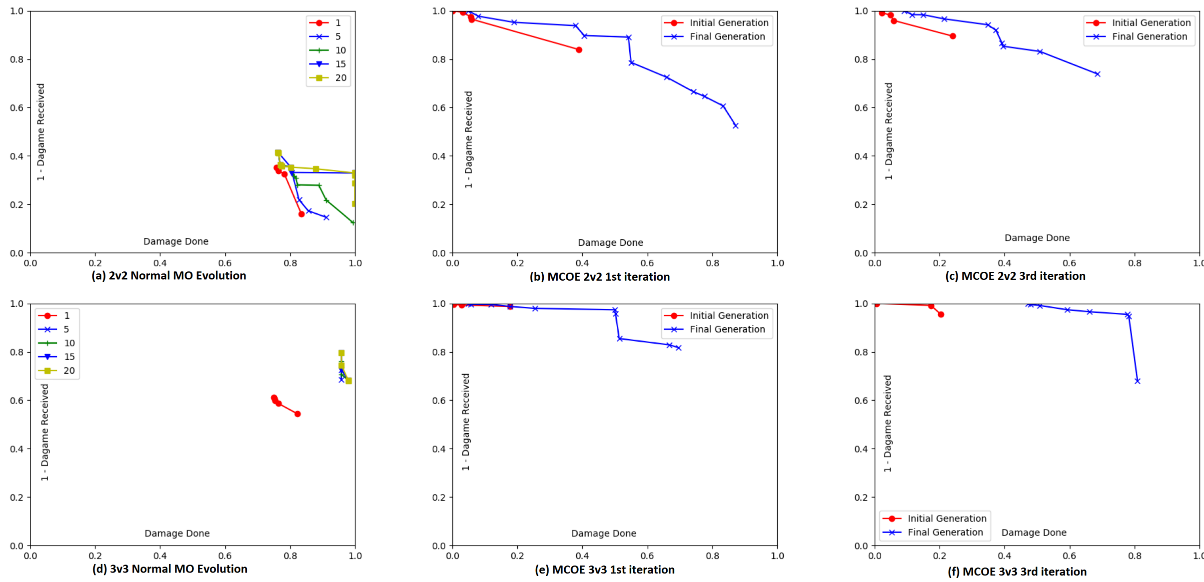

Figure 1: Pareto fronts for Normal Multiobjective (MO) and Manual Multiobjective Coevolution (MCOE)

Table 1: Comparison of between best individuals from normal evolution and Manual Coevolution (MCOE). ObjA is damage done and ObjB is 1-damage received.

Method	2v2 ObjA	2v2 ObjB	3v3 ObjA	3v3 ObjB
Normal	0.857966	0.376345	0.629189	0.122628
MCOE run-1	0.859106	0.381967	0.640296	0.124016
MCOE run-2	0.867881	0.382371	0.691048	0.250223
MCOE run-3	0.871826	0.386840	0.710296	0.280662

over twenty generations. We show the result of 1^{st} and 3^{rd} manual coevolution in sub-figures b, c, e and f in Figure 1. In each iteration, we see that the first (red line) and last (blue line) Pareto fronts show considerable improvement, which shows that we have more robust individuals than the previous iteration.

We tested one of the balanced network from the best Pareto fronts against 100 random scenario to test the performance of networks in novel scenarios. From Table 1 we see that the fitness values for all objectives increase monotonically from normal evolution to the 3^{rd} run of manual coevolution which reinforces the result from the Pareto graphs. We see greater improvement in three vs three scenario for both damage done (12%) and 1-damage received (where it was more than doubled) compared to two vs two as it was already doing very well. We can conclude that best performing network did get more robust against random testing scenario with each iteration of manual coevolution.

Our research focused on using Multiobjective Neuroevolution and manual coevolution to generate RTS micro agents. The agents evolving against the default SCII AI were able to control groups containing multiple type of units and quickly learned to beat the default SCII AI. We further used manual coevolution using the evolved AI as an opponent to generate more robust agents. We show that the evolved networks generalized well to different numbers of opposing units and different starting configurations. With a general neural network representation and with NEAT, we think that our approach can be effectively extended to more complex scenarios.

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