

Comparison of Evolutionary Algorithms and their Hybrids Applied to Mario AI

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Abstract—Researchers have been applying artificial/computational intelligence (AI/CI) methods to computer games. In this research field, further researches are required to compare AI/CI methods with respect to each game application. In this paper, we report our experimental result on the comparison of evolution strategy, genetic algorithm and their hybrids, applied to evolving controller agents for Mario AI. GA revealed its advantage in our experiment, whereas the expected ability of ES in exploiting (fine-tuning) solutions was not clearly observed. The blend crossover operator and the mutation operator of GA might contribute well to explore the vast search space.

Keywords—Evolutionary algorithm, autonomous game controller agent, neuroevolutions, Mario AI

I. INTRODUCTION

RESEARCHERS have been applying artificial/computational intelligence (AI/CI) methods to computer games, and reporting their research results in conferences including IEEE Conference on Computational Intelligence and Games (CIG)¹ and IEEE Congress on Evolutionary Computation (CEC)². In these conferences, competitions on autonomous game AI agents have been held. For example, competitions on Simulated Car Racing³, Mario AI⁴, Ms. Pac-Man⁵, etc., were held in CIG 2011⁶. To develop high performance agents, AI/CI methods such as artificial neural networks, fuzzy sets, evolutionary algorithms, swarm intelligence and enforcement learning have been applied. In this research field, further researches are required to compare AI/CI methods with respect to each game application: to investigate which methods can derive better agents than others for which application and why.

In this paper, we report our experimental result on the comparison of two evolutionary algorithms (evolution strategy (ES) [1], genetic algorithm (GA)[2]) and their hybrids, applied to evolving controller agents for Mario AI. We select ES and GA because these are the representatives of evolutionary algorithms.

II. MARIO AI

We selected Mario AI as the game application because the competition provided sample controller agents (written in Java) on the web⁷. The sample agents were neural network based ones: we expect sample agents will perform well as we tune values of their unit connection weights and unit biases.

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¹<http://www.ieee-cig.org/>.

²<http://cec2011.org/>, for example.

³http://cig.ws.dei.polimi.it/?page_id=175

⁴<http://www.marioai.org/>

⁵<http://cswww.essex.ac.uk/staff/sml/pacman/PacManContest.html>

⁶http://cilab.sejong.ac.kr/cig2011/?page_id=100

⁷<http://julian.togelius.com/mariocompetition2009/gettingstarted.php>

We apply evolutionary algorithms to the tuning of the weights and the biases. Training neural networks by means of evolutionary algorithms is known as neuroevolutions[3],[4]. Unlike training with the back propagation algorithm, neuroevolutions do not require training data sets and gradient information of error functions.

Fig. 1 shows a screenshot of Mario game played by a Mario AI agent. An autonomous agent controls Mario to “win as many levels (of increasing difficulty) as possible.”⁷



Fig. 1 Screenshot of Mario AI game play

A starter kit has been provided on the web⁸. Samples of Mario controller agents are included in `marioai/classes/ch/idsia/ai`. The agents are provided as Java classes. Source codes of the agents are also provided. We experimentally utilized the agent `SmallSRNAgent(marioai/classes/ch/idsia/ai/agents/ai/SmallSRNAgent.class)` in this research.

The following command starts game play simulation⁷:

```
> javach/idsia/scenarios/Play evolved.xml
```

The argument of the `Play` class, `evolved.xml`, is an XML-formatted file. The XML file includes an `<object>` element with which the agent class used as the controller in the simulation is specified. For example, the following example of description:

```
<object
type="ch.idsia.ai.agents.ai.SmallSRNAgent
" id="0">
```

denotes that the class `ch.idsia.ai.agents.ai.SmallSRNAgent` is used as the controller agent.

This `SmallSRNAgent` is implemented with a recurrent multi-layer perceptron (RMLP): as the input, the RMLP receives data of environmental state captured by Mario sensors, and the RMLP outputs data to actuate (control) Mario. Values of RMLP weights and biases are specified with `<array>`

⁸<http://julian.togelius.com/mariocompetition2009/marioai.zip>

elements in the XML file. Thus, better SmallSRNAgents will be evolved as the values of <array> elements are tuned. We experimentally compare the ability of evolutionary algorithms and their hybrids on this SmallSRNAgentneuroevolutions.

III. APPLYING EVOLUTIONARY ALGORITHMS TO MARIOAI CONTROLLER

A solution of the optimization problem in our research is a 405 dimensional real vector $\vec{x} = (x_1, x_2, \dots, x_{405})$. Each x_i is a variable for an <array> element in the XML file.

A. Evolution Strategy

The steps of evolution by means of ES in our research are shown in Fig.2.

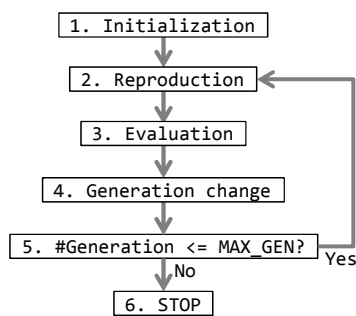


Fig. 2 Steps of evolution by means of ES

1. Initialization

First, μ solutions $\vec{x}^1, \vec{x}^2, \dots, \vec{x}^\mu$ are randomly generated. Values of x_i^j ($i=1,2,\dots,405$; $j=1,2,\dots,\mu$) are sampled from the normal Gaussian distribution with mean=0 and S.D.=1.

2. Reproduction

New λ offspring solutions are produced by using the current μ parent solutions. Fig.3 shows the steps of reproduction by means of ES.

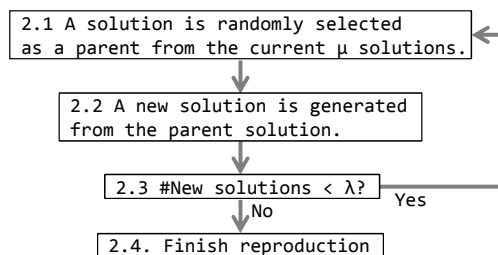


Fig. 3 Steps of reproduction by means of ES

In the step 2.2 in Fig.3, a new offspring solution \vec{x}_c is generated from the parent solution \vec{x}_p as:

$$\vec{x}_c = \vec{x}_p + \vec{d}, \quad (1)$$

where, \vec{d} is also a 405 dimensional vector ($\vec{d} = (d_1, d_2, \dots, d_{405})$)

and d_i s are small random real values. In our experiment, d_i is sampled from the normal Gaussian distribution with mean=0 and S.D.=1.

3. Evaluation

In this step, fitness of each solution is evaluated. The fitness in this research is the score of Mario game played by the controller agent in which values of x_i ($i=1,2,\dots,405$) is utilized as the associated <array> values in the XML file. In our experiment, we obtain the fitness score by utilizing the `ch.dsia.scenarios.CompetitionScore` class. This class gives us the total score of the games with level 0, 3, 5 and 10 stages⁹.

4. Generation change

In this step, next-generation μ solutions are selected from the population of the current μ solutions and the newly generated λ solutions. Two different methods for this selection are known as $(\mu+\lambda)$ -ES and (μ,λ) -ES [1]. As the next-generation solutions, $(\mu+\lambda)$ -ES selects the best μ solutions among the $\mu+\lambda$ solutions, while (μ,λ) -ES selects the best μ solutions among the new λ solutions. We experimentally applied both methods and found that, for the optimization problem in this research, $(\mu+\lambda)$ -ES was likely to evolve better solutions than (μ,λ) -ES did.

The steps 2 to 5 in Fig.2 are repeated MAX_GEN times where MAX_GEN is a predefined number of generations.

B. Genetic Algorithm

The steps of evolution by means of GA in our research are shown in Fig.4.

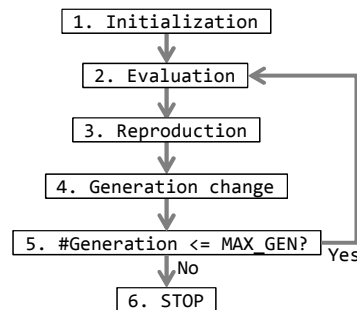


Fig. 4 Steps of evolution by means of GA

The steps 1, 2, and 5 are the same as those for ES.

1. Reproduction

Figs.5 and 6 show the steps of reproduction and crossover by means of GA respectively. New $(1-e)*\lambda$ offspring solutions are produced by using the current λ parent solutions. Note that $e*\lambda$ solutions are copied from/to the current generation by the elitism operation (so that the reproduction process produces only $(1-e)*\lambda$ new solutions).

⁹marioai/src/ch/idsia/scenarios/CompetitionScore.java

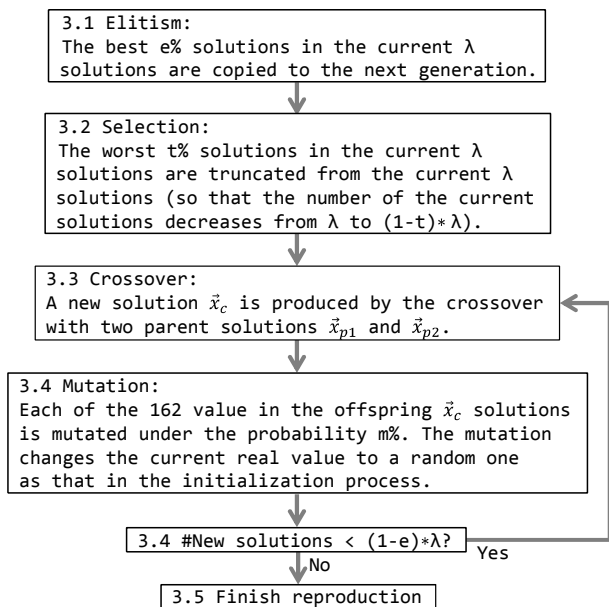


Fig.5 Steps of reproduction by means of GA

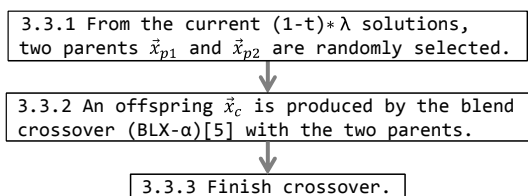


Fig. 6 Steps of crossover by means of GA

C. ES&GA Hybrids

As hybrids of ES and GA, we switch the application of the two algorithms between the first/last half of the total generations. For example, GA is applied in the first half of the total generations, and then ES takes over from GA in the last half of the total generations.

IV. EXPERIMENTAL EVALUATION

To fairly compare the algorithms, we should make consistent the total number of solutions being generated and tested by an algorithm. In our experiment, the total number of generations was set to 500, and the population size (the value of λ) was set to 20. Thus, the total solutions being tested was 10,000 (= 20*500). The value of μ for (μ+λ)-ES was experimentally set to 4, and the parameter values for GA were experimentally set to:

- Blend crossover: α=0.5,
- Elitism: e=10%,
- Truncation: t=60%, and
- Mutation: m=1%.

These values performed better than other values in our experiment.

In the case of GA → ES switch, GA with the above setting was applied in the first 250 generations, and the offspring 20 solutions by GA in the 250th generation were taken over to ES as the parent solutions in the 251th generation (the best 4 solutions among the 20 inherited solutions were actually used as the parents because we utilized (4+20)-ES). Similarly, in the case of ES → GA switch, ES with the above setting was applied in the first 250 generations, and the offspring 20 solutions by GA in the 250th generation were taken over to GA as the parent solutions in the 251th generation.

Fig.7 and Table I show the result for comparing ES, GA and the two switches (ES → GA and GA → ES), where the fitness scores are the best onesso far at each generation (e.g., the fitness scores at the 250 generation in Fig.7 and Table I show the best scores during the 1st-250th generations) by the respective method.

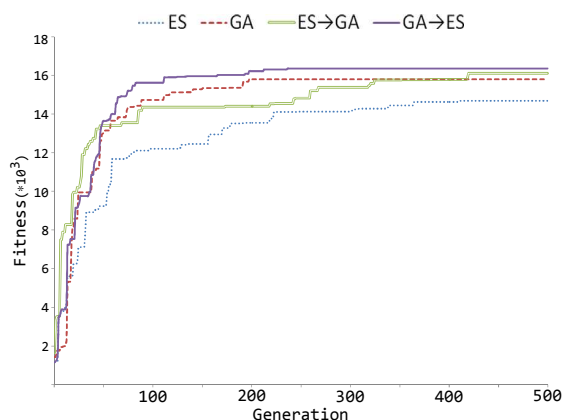


Fig. 7 Result of evolutions by the four algorithms

TABLE I
FITNESS SCORES BY THE FOUR ALGORITHMS

Generation	ES	GA	ES→GA	GA→ES
1	1152	1426	1654	1155
25	7101	9948	10212	9284
50	9239	13001	13405	13642
100	12206	14729	14355	15618
200	13540	15793	14398	16218
250	14122	15793	14822	16358
300	14122	15793	15384	16358
400	14625	15793	15791	16358
500	14686	15793	16104	16358

Fig. 7 and Table I revealed the followings.

- In the total 500 generations, GA → ES switch found a better solution than the other three algorithms. Note that the score by GA → ES was not improved in the last half of generations. Thus, the best score 16,358 was a result of GA, not of the GA → ES switch.
- At the 250th generation, the scores were better for GA and GA → ES than for ES and ES → GA. Thus, GA outperformed ES in the first half of generations.

These might due to the highdimensionality of the search space and the nature of ES/GA. In our application, the search space is a 405 dimensional real valued one (\mathbf{R}^{405}) so that the search efficiency by an algorithm will depend much on its ability of exploration in the early stage of generations. The blend crossover operator might contribute for GA to explore broader area in the search space, because the operator could not only exploit between the two parents but also explore outside of the two parents. The mutation operation might also contribute for GA to explore the space. On the contrary, the search by ES is neighborhood oriented (due to its reproduction process) so that ES was likely to contribute better for exploitation than for exploration.

We expected that GA \rightarrow ES would perform the best among the four algorithms, because GA \rightarrow ES would first explore promising area by GA and then exploit the promising area by ES, but the result was not consistent with the expectation. Further investigations are required on balancing the exploration and exploitation by mixtures of evolutionary algorithms. Recently, hybrid uses of evolutionary algorithms and local search algorithms have been researched, known as memetic algorithms [6]-[8]. Our future work includes application and evaluation of the memetic algorithms.

V. CONCLUSION

In this paper, we evaluated effectiveness of ES, GA, and their switching hybrids (ES \rightarrow GA and GA \rightarrow ES) on the optimization problem of the neuro-based Mario AI controller. GA revealed its advantage in this optimization problem, whereas the expected ability of ES in exploiting (fine-tuning) solutions was not clearly observed. The blend crossover operator and the mutation operator of GA might contribute well to explore the vast search space. Future work includes application and evaluation of memetic algorithms and other AI/CI methods to this optimization problem.

ACKNOWLEDGMENT

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