Sample Efficiency Improvement on Neuroevolution via Estimation-Based Elimination Strategy

(Extended Abstract)

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ABSTRACT

In this paper, we propose *estimation-based* elimination strategy, which improves sample efficiency of NeuroEvolution (NE) algorithms. The fitness of new individuals was estimated using fitness of individuals evaluated in the past generations. The estimation was achieved by taking average fitness of individuals with high correlation with the new individual. Estimation-based elimination strategy avoids evaluating individuals with low estimated fitness. We adapt estimation-based elimination strategy for state-of-the-art NE algorithms: CMA-NeuroES and CMA-TWEANN. From the experimental results of pole-balancing benchmark tasks, we show that the proposed strategy improves sample efficiency of the NE algorithms.

Categories and Subject Descriptors

I.2.6 [**Artificial Intelligence**]: LearningConnectionism and Neural Nets; I.2.6 [**Artificial Intelligence**]: Robotics

General Terms

Algorithms, Design, Experimentation

Keywords

Fitness Estimation, Neuroevolution, Evolutionaly Computation

1. INTRODUCTION

In this paper, we propose *estimation-based* elimination strategy, which improves sample efficiency of NeuroEvolution (NE) algorithms. In evolutionary computation including evolutionary algorithms and NEs, the optimization of fitness function is achieved by random search that emulates natural evolution; first selecting the surviving individuals, and then from those individuals somehow generating the next generation. In nature, only part of the population is used as parents of the next generation at the selection phase. Therefore, there are always unused individuals in the population.

In this research, we focus on the correlation between the individuals to estimate the fitness of a newly created individual. Because the fitness between similar individuals is considered to be close, the fitness is estimated by taking average of high correlation individuals' fitness. In order not to evaluate redundant individuals, we avoid evaluating individuals with low estimated fitness in the generation. We apply our *estimation-based* elimination strategy to two state-of-the-art NE algorithms: CMA-NeuroES [2] and CMA-TWEANN [3]. The experimental results on pole balancing problems showed that our estimation-based elimination strategy significantly improves sample efficiency of each algorithm.

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2. METHOD AND APPLICATION

2.1 Estimation-Based Elimination Strategy

We propose *estimation-based* elimination strategy. This strategy based on two ideas. One is to reduce evaluation of redundant individuals in the evolution process of NE. The other is that individuals with high correlation are prone to obtain similar fitness.

In this research, we use correlation as the metric to find neighboring individuals and estimate the fitness of new individuals. We define the correlation metric with $\frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i-\bar{y})^2}}$. In this equation, n is the number of connection weights in ANNs, and x_i and y_i are the connection weights of the same edge. And $\bar{x}$ and $\bar{y}$ are the average values of all parameters in vector $\mathbf{x}$ and $\mathbf{y}$, respectively. For a connection weight x_i which has no counterpart y_i due to topology augmentation, we assign 0 to y_i.

The estimation-based elimination strategy is summarized in Algorithm 1. In this paper we only depict the evaluation part. *EvaluationRate* (*ER*) stands for the rate of individuals who are evaluated. Those evaluated individuals are put to an archive along with its evaluated fitness. In "other operations" in Algorithm 1 the evolutionary process of selection, mutation and augmentation of topology is performed. In this strategy, k and *ER* are user defined parameters.

We apply our strategy to two NE algorithms: CMA-NeuroES

Table 1: The results of pole balancing problems. The number in each box stands for the average number of episode cost to achieve each problem. If there is significant difference between with and without our strategy, we marked * ($p < 0.03$).

Algorithms	Single, Full	Single, Partial	Dobule, Full	Double, Partial
CMA-NeuroES	91	192	585	1141
CMA-NeuroES in our implemantation	36.1 (23.9)	52.2 (27.3)	521.4 (232.2)	902.9 (499.1)
CMA-NeuroES with proposed strategy	**29.0*** (20.9)	**41.4*** (20.4)	**400.8*** (178.3)	**716.6*** (333.8)
CMA-TWEANN	27.5 (21.5)	29.4 (19.4)	335.6 (189.6)	676.8 (863.3)
CMA-TWEANN in our implemantation	36.1 (23.6)	41.4 (17.2)	461.1 (269.8)	559.7 (1013.2)
CMA-TWEANN with proposed strategy	**27.8*** (19.1)	**33.8*** (12.5)	**356.8*** (212.9)	**421.7** (340.0)

Algorithm 1 Estimation-Based Elimination Strategy

$p_i \in \mathbf{P}(i = 1 \cdots \lambda)$
repeat
  for i = $1 \to \lambda$ **do**
    Calculate correlation between $\mathbf{p}_i$ and all individuals in *archive*
    Sort individuals in *archive* according to correlation
    for j = $1 \to k$ **do**
      $\mathit{EstimatedFitness}_i$ = Fitness(arv_j) $/k$
    end for
  end for
  Sort individuals in $\mathbf{P}$ according to *EstimatedFitness*
  for i = $1 \to \lambda * \mathit{EvaluationRate}$ (ER) **do**
    Evaluate($\mathbf{p}_i$)
    AddIndividualToArchive($\mathbf{p}_i$)
    continue
  end for
  other operations
until a task is achieved

and CMA-TWEANN. These two algorithms are both based on Covariance Matrix Adaptation Evolutionary Strategy (CMA-ES) [1]. In CMA-NeuroES, calculating correlation between individuals is straightforward because the number of edges is fixed. In CMA-TWEANN, the number of edges will eventually increase due to the addEdge and the addNode operation. In such case, we assign 0 as a connection weight to calculate the correlation.

3. EXPERIMENTAL SETUP

In this paper, we use pole balancing problems [3] as benchmarks to evaluate our correlation-based elimination strategy. We assign the number of episodes required to solve the problem as the score of each trial. The performance of each algorithm is measured by the average score of 100 trials.

3.1 Parameters Settings

The parameters of CMA-NeuroES and CMA-TWEANN are obey that of [1], except for initial step-size parameter ($\sigma_{initial}$). The initial step-size parameter ($\sigma_{initial}$) and topological mutation parameters obey that of [3].

In correlation-based elimination strategy, users have to decide two parameters: k and ER. For them, we try following combinations:

$$\begin{aligned} k &= \{1, \cdots, 7\}, \\ ER &= \{0.6, 0.65, \cdots, 0.95\}. \end{aligned}$$

We show the best parameter combination for each algorithm.

3.2 Results of Single Pole Balancing

In single pole balancing problems, it is known that they can be solved within a small number of episodes. The fitness estimation is likely to be inaccurate in early steps of episodes due to insufficient entries in the archive. Inaccurate fitness may mislead the direction of evolution, and results in sample inefficiency. Therefore, there is a possibility of our elimination strategy hindering the performance in pole balancing problems.

The experimental results show, however, that the correlation-based elimination strategy significantly improves the sample efficiency of both algorithms ($p < 0.03$), even in cases where the archive is small. The results show that in average CMA-NeuroES solved the problems with 29.0 for full information problem and 41.4 for partial information problem respectively, and CMA-TWEANN did so with 27.8 and 33.8 respectively.

3.3 Results of Double Pole Balancing

Double pole balancing problems are much more challenging than the single pole balancing problems. In full information problem, CMA-NeuroES and CMA-TWEANN with correlation-based elimination strategy solved them in 400.8 and 356.8 respectively, in average. The performance improvements are statistically significant ($p < 0.01$).

In partial information problem, with our strategy, CMA-NeuroES and CMA-TWEANN achieved the performances of 716.6 and 421.7. Because original algorithm has large standard deviation at its performance, collected data was not enough to achieve a statistic significance for CMA-TWEANN. Across all runs, the maximum number of episodes required for CMA-TWEANN to solve the task with and without our strategy are $2,091$ and $7,955$ respectively. This results in large average performance difference (137.0 episodes) between CMA-TWEANN with and without our strategy. From the experimental results of all pole balancing problems, estimation-based elimination strategy statistically improves sample efficiency of CMA-NeuroES and CMA-TWEANN.

4. CONCLUSION

In this paper, we proposed estimation-based elimination strategy, which improves sample efficiency of NE algorithms. From the experimental results of pole balancing problems, the application of our strategy to CMA-NeuroES and CMA-TWEANN successfully outperformed the sample efficiency of original algorithms. We conclude that estimation-based elimination strategy can improve sample efficiency of NE algorithms.

5. REFERENCES

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