A Surrogate-assisted Selection Scheme for Genetic Algorithms Employing Multi-layer Neural Networks

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ABSTRACT

In this paper, we propose a simple yet effective approach in surrogate-assisted genetic algorithms employing a neural network to estimate survival probabilities of individuals in selections to reduce computational cost of their fitness evaluations. A surrogate-assisted selection scheme we propose employs multi-layer perceptron to learn whether an individual is selected or not without fitness evaluations based on the observations of selections by fitness evaluations in the previous generations.

CCS CONCEPTS

• **Theory of computation → Evolutionary algorithms**;

KEYWORDS

genetic algorithms, surrogate model, neural networks, multi-layer perceptron

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1 INTRODUCTION

In evolutionary algorithms, fitness values are evaluated repeatedly to find the optimal solution.

In some real-world applications, a fitness evaluation may be costly by performing computationally expensive simulations, constructing physical products, interacting with people, and so on.

To solve computationally-expensive optimization problems such as design optimizations employing computer simulations in evaluating fitness values, surrogate models can be employed to approximate fitness functions. Surrogate models such as Kriging response surface models [2] are employed to approximate fitness landscape of airplane design space [1] involving computational fluid dynamics that needs computer simulations for hours or even several days to evaluate a single fitness value. Surrogates are employed not only to approximate fitness values but to capture characteristics of the target problems.

In case that we do not need an accurate model as surrogates, or difficult to obtain such models, we may take a straightforward approach to reduce computational overheads of the fitness evaluations by replacing selection with actual fitness evaluations by estimations with machine learning techniques whether the target individual should survive or not after selection. In this paper, we propose Surrogate-Assisted Selection in genetic algorithms by employing a neural network (Multi-Layer Perceptron).

Surrogate models are often adopted for evolutionary computation, where fitness function is approximated by surrogate models and the computational cost is reduced by using surrogate fitness function. When the fitness function is approximated by surrogate models, individuals and its fitness values are used to approximate it. In optimization with "Surrogate-Assisted Evolutionary Computation", both original fitness function and surrogate fitness function are used and a surrogate model is updated sequentially by the data obtained in the process of evolutionary computation. In our method, whether or not individuals were selected by genetic selection with real fitness evaluations are used to train neural network to construct surrogate selection model. Therefore it isn't necessary to calculate fitness value with approximated evaluation function.

We perform numerical experiments on test functions, and show the effectiveness of the proposed approach in reducing the number of fitness evaluations necessary to obtain optimal solutions.

2 THE PROPOSED METHOD

When applying the surrogate model to the evolutionary computation, the evaluation function is mainly approximated by. However, in the case of genetic algorithms, fitness values are used only to compare which individual is better to select and it is not necessary to calculate surrogate fitness value if we can capture the relationship between individuals.

In our proposed "A Surrogate-assisted Selection Scheme for Genetic Algorithms", genetic selection is carried out by a surrogate model.

The outline of the proposed algorithm is shown in **Figure 1**. This algorithm is similar to simple genetic algorithms but in genetic selection part, there are 2 ways. One is original genetic (tournament) selection, the other is surrogate selection. Surrogate selection decide which individuals to leave to the next generation. In surrogate selection, neural network (multi layer perceptron) is used as surrogate model to select individuals, and training data of

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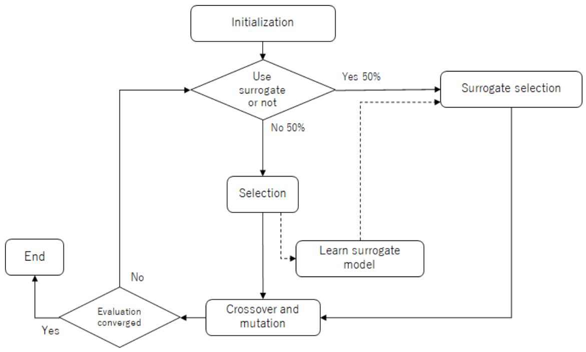

Figure 1: A sample black and white graphic.

neural network are design variables (input data) and its fitness values (output data). Therefore it is not necessary to calculate the fitness value with approximated fitness function like existing methods. In this algorithm, the surrogate model is updated for each generation by using training data obtained as the optimization progresses. After original genetic selection, data of individual and its fitness value is used to train the neural network. Therefore surrogate selection reflects a little bit the old original genetic selection. In training of neural network, we determine not to use too old genetic selection data. It is because too old data are not reflect recent genetic selection and it is necessary to reduce cost to train neural network. In this algorithm, data in recent 20 generation are used to train surrogate model because we found it enough in pre-reseach.

In this algorithms, which selection to use is determined with 50% probability chance.

3 EXPERIMENT

In this experiment, we compare the simple GA and the surrogate selection GA with 10-dimensional numerical function optimization problem. Evaluation items are the number of fitness evaluation taken until the optimal solution is found. GA population size is 400, individual's length is 100. We employed single-point crossover and flip bit mutation and their execution ratio are 0.8 and 0.01 respectively. Stopping criteria of this algorithm is to find the optimal solution. The numerical precision of optimal solution is 10^{-31}. The result is average data over 20 trails. The unit configuration of the neural network used in the surrogate model is five types, [20], [40], [40, 20], [40, 20, 10]. [20] represents one layer with 20 nodes and [40,20] represents two layer with 40 and 20 nodes respectively.

Figure 2 and **Figure 3** show the number of real fitness evaluation of Sphere function and Ackley function optimization for each unit configuration of neural network used in the surrogate selection model.

We successfully reduced the actual number of evaluations by 17 to 31% for Sphere function and 1 to 20% for Ackley function.

4 CONCLUSION AND FURTHER WORK

In this paper, we have presented a genetic algorithm based on surrogate selection.In the best case of our trials (sphere function with

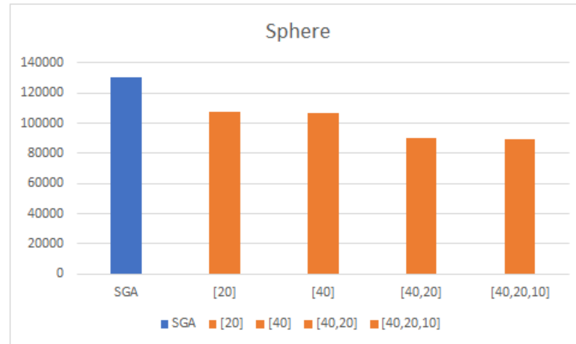

Figure 2: Number of fitness evaluation (Sphere function).

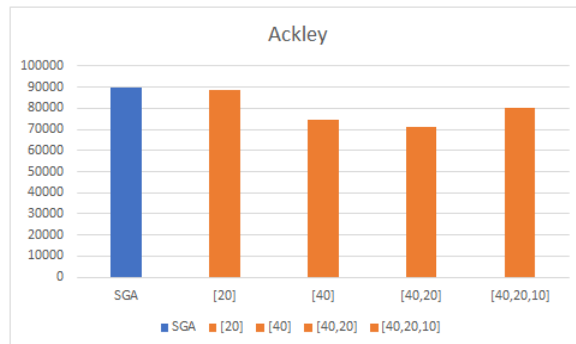

Figure 3: Number of fitness evaluation (Ackley function).

model type [40,20,10]), we succeeded to reduce the fitness evaluation number of GA by a factor of 31% by the proposed method.In the worst case (ackley function with model type [20]), the proposed method did not harm and could still slightly reduce the number of evaluation by 1%.

We are planning to test the proposal algorithms to more kinds of problems including real-world optimization problems and find out what kind of problems the proposal algorithms are effective against. We will also consider the appropriate neural network parameters according to the target problem. In this experiment, we decided whether or not to use the surrogate selection model with a probability of 50% for each generation, but we will reconsider the usage criteria of surrogate selection. We are planning to evaluate the correctness of surrogate assisted selection and use this evaluation to decide surrogate assisted selection usage.

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