Analysis of Scaling for Fitness Landscape Learning Evolutionary Computation based on CMA-ES*

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ABSTRACT

In order to reduce the number of fitness evaluations, the novel surrogate model called Rank Space Estimation (RSE) model and the surrogate-assisted EC with RSE model called the Fitness Landscape Learning Evolutionary Computation (FLLEC) have been proposed. In this paper, we analyze the scarling effect for CMA-ES with RSE model with support vector machine(SVM). The performance of CMA-ES with RSE model by using adequate scarling is shown by computer simulation taking k-table problem as an example.

CCS CONCEPTS

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

KEYWORDS

evolutionary computation, support vector machine, surrogate model, scarling

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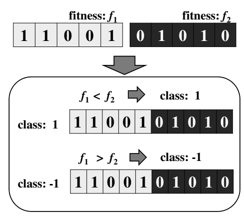

Figure 1: Outline of SVM for RSE model

1 INTRODUCTION

Lots of surrogate-assisted Evolutionary Computation (EC) have been proposed in order to reduce a large number of fitness evaluations. A novel surrogate model named the Rank Space Estimation (RSE) model has been proposed[2]. This model utilizes a Support Vector Machine (SVM) to estimate fitness landscape. The effectiveness of a framework for EC using the RSE model called the Fitness Landscape Learning Evolutionary Computation (FLLEC) framework has been reported. The RSE model has been introduce to an Evolution Strategy with Covariance Matrix Adaptation[1] (CMA-ES) in order to extend FLLEC concept to continuous optimization problem and reported that scarling is important to obtain high search performance. In this paper, we analyzed novel scarling method for CMA-ES with RSE model.

2 RANK SPACE ESTIMATION (RSE) MODEL

In RSE model, since the ranks is calculated by relative evaluation between two individuals, estimation quality of this method is superior to that of existing models by evaluating only one individual. This model is different from in terms of utilizing the ranks of two individuals, that is, relative evaluation. Besides, most surrogate models predict a fitness function directly, whereas this model only focuses on the order of two individuals. Complete prediction of a fitness function is sometimes more difficult than finding an optimum solution. By contrast, ranking of two individuals results in only three types: high, low or equal. If we ignore the equal ranks of different genotypes, it is sufficient to consider only two results.

The RSE model utilizes SVM as the training method. The input to SVM is the genotype information for two individuals and the output concerns their class and their ranks. Fig. 1 shows an outline of our SVM.

3 SCARLING FOR CMA-ES WITH RSE MODEL

CMA-ES with RSE model has been proposed[2]. In this section, we show the scarling method for CMA-ES with RSE model.

3.1 Logistic Approximation Scaling

The scarling[2] in which a normal distribution in CMA-ES sampling is approximated as a logistic distribution has been proposed. A sigmoid function is utilized for that scaling and the elements of input data for SVM are mapped onto a sigmoid function. Then, scaling method considering the biased population density is as follows.

$$\boldsymbol{x'} = \boldsymbol{B}^{\mathrm{T}}(\boldsymbol{x} - \boldsymbol{m}). \tag{1}$$

$\boldsymbol{B}^{\mathrm{T}}$ rotates $\boldsymbol{x} - \boldsymbol{m}$ into the coordinate axes. That is, the principal axes of the distribution $\mathcal{N}(\boldsymbol{0}, \boldsymbol{C})$ are rotated into the coordinate axes.

$$\boldsymbol{x''} = (f_1(x'_1), f_2(x'_2), \cdots, f_i(x'_i))^{\mathrm{T}}. \tag{2}$$

where $f_i(x'_i)$ represents the elements mapping from an SVM input vector. It is considered that the above scaling enables surrogate models to learn a fitness landscape efficiently.

3.2 Covariance Scaling

In the CMA-ES, individuals are generated according to

$$\begin{aligned} x_i^{(g+1)} &\sim \boldsymbol{m}^{(g)} + \mathcal{N}(\boldsymbol{0}, (\sigma^{(g)})^2 \boldsymbol{C}^{(g)}) \\ &\sim \sigma^{(g)} (\boldsymbol{C}^{(g)})^{-\frac{1}{2}} \mathcal{N}(\boldsymbol{0}, \boldsymbol{I}),\ (i = 1, 2, \sim, \lambda) \end{aligned} \tag{3}$$

where $\boldsymbol{C}$ is a covariance matrix for a normal distribution. In order to flatten the bias caused by $(\boldsymbol{C}^{(g)})$, we utilized following scarling:

$$\boldsymbol{x'} = \sigma^{-1} \boldsymbol{C}^{-1/2} (\boldsymbol{x} - \boldsymbol{m}). \tag{4}$$

σ^{-1} is multiplied for numerical stability.

4 EXPERIMENTS AND RESULTS

In this section, the effectiveness of the CMA-ES with RSE model and scaling algorithm are demonstrated. For the comparison experiment, the following methods are prepared.

- CMA-ES:original.
- CMA-ES with RSE model:using a Logistic Approximation scaling.
- CMA-ES with RSE model:Covariance scaling.

The k-tablet function is used as the benchmark functions in our experiment. Table 1 shows the experimental conditions.

Table 1: Experimental Conditions (Experiment 1)

Population size	100
Dimension size	10
Number of trials	30
Evaluations in each generation	50
Training data size(N_{ts})	1000
Kernel function of the SVM	Polynomial (cubic)

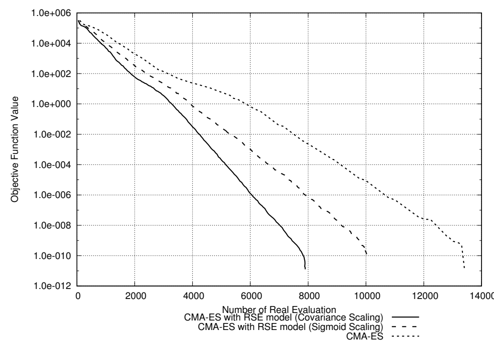

Figure 2: Bestever Objective Function Value with Fitness Evaluations

Figure 2 shows the average bestever objective function value with the number of fitness evaluations. The abscissa shows the number of fitness evaluations and the ordinate is a logarithmic scale axes and shows the objective function value. From this figure, the CMA-ES with the RSE model (Covariance Scaling) obtains the best search performance.

5 CONCLUSION

In this paper, we analyzed effect of scarling for CMA-ES with RSE model. The performance of CMA-ES with RSE model is the best by using adequate scarling. Introduce deep learning into FLLEC is an important future work.

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