Adaptive Evolution Control with P-I Similarity Index for Surrogate-assisted Evolutionary Computation

Taku Hasegawa, Kento Tsukada, Naoki Mori and Keinosuke Matsumoto
Graduate School of Engineering Osaka Prefecture University
1-1 Gakuencho, Sakai City, Osaka, 599-8531, Japan
{hasegawa@ss, tsukada@ss, mori@, matsu@}.cs.osakafu-u.ac.jp

ABSTRACT

Surrogate-assisted Evolutionary Computation provides us good results in real-world optimization. In this paper, we propose a novel adaptive evolution control using P-I similarity index for surrogate-assisted EC. The computational experiments are carried out to show the effectiveness of the proposed adaptive evolution control.

Categories and Subject Descriptors

I.2.8 [Artificial Intelligence]: Problem Solving—Control Methods, and Search

Keywords

Genetic algorithms, Surrogate model/fitness approximation

1. INTRODUCTION

Evolutionary computation (EC) has been applied to various kinds of problems, and several advantages to using EC have been reported. On the other hand, a large number of fitness evaluations is required in order to obtain satisfactory results with EC. It is therefore difficult to obtain adequate results when applying EC to real-world applications, owing to the high costs of fitness evaluations. As a result, there is a limit to the number of fitness evaluations that can be performed.

Surrogate-assisted ECs have been proposed in response to this problem, and a few methods have reported success[1]. In many cases, we cannot obtain an ideal surrogate model, owing to a lack of data. It is therefore important to use the original fitness function alongside the surrogate model. This process is termed "evolution control." We can improve the search performance with effective evolution control. However, effective evolution control depends on the respective problem.

In this paper, we propose a novel form of adaptive evolution control using a P-I similarity index [2].

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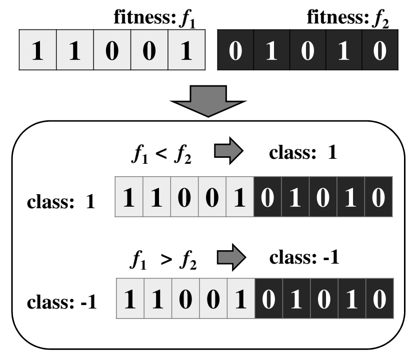

Figure 1: Outline of SVM

2. SURROGATE-ASSISTED EVOLUTIONARY COMPUTATION

Surrogate models generally estimate the fitness function and are directly used in fitness evaluations to reduce the number of fitness evaluations.

On the other hand, it is difficult to estimate the fitness function correctly due to the lack of data and high dimensionality of input space. Therefore, in many cases, both surrogate model and original fitness function should be utilized in search process of ECs. In [1], this is considered as issue of evolution control.

3. RSE MODEL AND FLLEC

We proposed a novel surrogate model based on the ranks of two individuals, and named it the Rank Space Estimation Model (RSE Model). Most surrogate models predict the fitness function directly, while our model only focuses on the ranks of the individuals. By limiting prediction in the model to the ranks of two individuals, we can exchange effective learning for a fitness value. 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 labels based on their ranks. Figure 1 shows an outline of our SVM.

We have also proposed a novel evolutionary computational framework, which introduces the RSE Model and which we have called Fitness Landscape Learning Evolutionary Computation (FLLEC)[3]. The population can evolve reducing the number of fitness evaluations using predictions from the RSE Model in FLLEC.

If we apply FLLEC to a problem, we have to decide which method is utilized as the EC part in the FLLEC. We adopt "Genetic Algorithms" and the RSE Model as a typical example of FLLEC. FLLEC with GA is called " Air GA "[3].

4. ADAPTIVE EVOLUTION CONTROL USING A P-I SIMILARITY INDEX

To use surrogate-assisted EC, the evolution control must be selected. We propose a novel form of adaptive evolution control using a P-I similarity index.

In surrogate-assisted EC that uses adaptive evolution control, the number of evaluations in a generation is controlled by the P-I similarity index.

4.1 P-I Similarity Index

The P-I similarity index tracks the similarity between an individual and a population. The symbols used in this section are as follows:

s: individual X: population
n: population size s_i: gene of individual s at locus i
L: chromosome length e_i: number of alleles at locus i
x_{i,s_i}: ratio of gene s_i at locus i in a population X

A cosine similarity $R(s,X)$ between the feature vectors with individual s and population X is obtained as follows:

$$R(s,X) = \frac{\frac{1}{L}\sum_{i=0}^{L-1}(e_i x_{i,s_i} - 1)}{\sqrt{\frac{1}{L}\sum_{i=0}^{L-1}(e_i x_{i,s_i} - 1)^2}} \quad (1)$$

$R(s,X)$ is the P-I similarity index. The value of the cosine similarity is not affected by the absolute values for the vectors. Rather, it is exclusively affected by the direction of the vectors. Therefore, the P-I similarity index evaluates the direction of positional bias based on the genotype of the individual s. The individual s has a strong positive correlation with population X when the value of the P-I similarity index approaches one, and the individual s has almost no correlation with population X when the index value approaches 0. In this work, let $e_i = 2 (i = 0, 1, \cdots, L-1)$. Thus, only problems with a binary domain are applied.

4.2 Adaptive Evolution Control with the P-I Similarity Index

In surrogate-assisted EC that uses adaptive evolution control, whether an individual is evaluated using original fitness function is controlled by the P-I similarity index.

An individual s is evaluated using original fitness function with a probability of P_s. P_s is decided as follows.

$$P_s = f_{\mathrm{sig}}(2(f_{\mathrm{pos}}(R(s,X)) - 0.5)) \quad (2)$$

$$\begin{aligned} \textit{where} \qquad f_{\mathrm{sig}}(x) &= \frac{1}{1+\exp(-x)} \\ f_{\mathrm{pos}}(x) &= \begin{cases} 1-x & (x \geq 0) \\ 1 & (\text{otherwise}) \end{cases} \end{aligned}$$

For this type of adaptive evolution control, the original fitness functions are used to evaluate some individuals from a given generation.

Table 1: Number of successful runs

	Number of evaluations				
	1000	1500	2000	3000	4000
I-Air GA	14	30	32	39	39
G-Air GA	5	20	31	38	40
A-Air GA	24	33	37	44	46

In surrogate-assisted EC that uses this type of adaptive evolution control, lots of individuals are evaluated using the original fitness function at the early stages of the searching process and using the surrogate model at the later stages of the searching process. Moreover, by deciding if an individual is evaluated based on P-I similarity index, this type of adaptive evolution control can consider the trade off between exploration and exploitation. This type of adaptive evolution control is not restricted to Air GA. It can be introduced in other surrogate-assisted ECs as well. Air GA with this type of adaptive evolution control is called A-Air GA.

5. EXPERIMENTS

In this section, we demonstrate the effectiveness of adaptive evolution control using the P-I similarity index. Air GA with individual-based evolution control is called I-Air GA and Air GA with generation-based evolution control is called G-Air GA. We compare the I-Air GA, G-Air GA and A-Air GA under each of the best parameters using the Nk problem ($N = 30$, $k = 2$) as example.

Table 1 shows the number finding optimal solution for each approaches. A-Air GA can achieve the best successful runs. From these results, our adaptive evolution control can improve the search performance.

6. CONCLUSION

In this paper, we proposed a novel form of adaptive evolution control using a P-I similarity index and showed the effectiveness of our adaptive evolution control by comparing each evolution control. Relearning method based on diversity of population is future work.

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