Empirical Analysis of Cooperative Coevolution using Blind Decomposition

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ABSTRACT

How to decompose problems effectively and how to select appropriate collaboration methods for problems with particular separabilities have been discussed in Cooperative Coevolutionary Algorithms (CCEAs) research for many years. In most of the previous work, the prior knowledge of decomposition about the problems is obtainable. However, there could be some real problems that the information to conduct the decomposition of the problems is unclear. This paper offers a solution by decomposing the problems in a blind way. We provide an analysis if the blind decomposition is feasible and give some basic advice on how to implement the blind decomposition.

Categories and Subject Descriptors

I.2.8 [**Artificial Intelligence**]: Problem Solving, Control Methods, and Search – *heuristic methods.*

General Terms

Algorithms, Measurement, Performance, Experimentation.

Keywords

Cooperative coevolution, Function optimization, Natural decomposition, Blind decomposition.

1. INTRODUCTION

So far most of the existing applications of CCEAs implement a natural decomposition process, where each component represents one dimension of a problem. The one dimension could be a single variable in a function optimization, or could be a hidden neuron in an evolved artificial neural network. Although natural decomposition is straightforward and easy to implement, in real world there could be some problems that are difficult or somewhat unclear to determine the bounds of the problem dimensions. To implement a natural decomposition process will be infeasible, thus, one might have to try a blind way. Although some theoretical work has been done to analyze the CCEA models [1, 5], how the models perform using a blind decomposition mechanism has been unreported so far.

In this paper we apply a classic cooperative coevolutionary algorithm developed by Potter [2], and analyze how the blind decomposition affects the implementation of the CCEAs combining with three collaboration methods. We conduct our empirical studies on a suite of function optimization problems.

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2. EXPERIMENTAL SETUP

2.1 Optimization Problems

Since it is very simple to implement both natural and blind decomposition on function optimization problems, we chose the same function minimization problems, Rastrigin, Schwefel and Trid, as employed in our previous work [4]. We conducted our experimental studies with 6 variables for all cases.

2.2 Problem Decomposition

We implemented two kinds of decompositions, natural and blind, in our experiments. We applied a standard approach to identify a natural decomposition for our function optimization problems: a function of n variables was decomposed into n components.

We executed the blind decomposition by generating the number of components p at random for a problem. The problem was therefore evenly divided into p components. However, the last components could have a different size if the size of the problem cannot be divided exactly by p. Furthermore, our experiments subdivided the blind decomposition into two classes. We defined a coarsely blind decomposition when $p < n$, and a finely blind decomposition when $p > n$. An upper bound and a lower bound of p for the three blind decompositions were defined as follows: 1) $[n/2, 3n/2]$ for the blind decomposition; 2) $[n/2, n)$ for the coarsely blind decomposition; and 3) $(n, 3n/2]$ for the finely blind decomposition.

2.3 Evolutionary Characteristics

In our experiments, we employed three collaboration methods to produce three versions of the CCEAs, where CCEA-G used a greedy collaboration [2], CCEA-LG used a less greedy collaboration [2] and CCEA-RS used a reference sharing collaboration [4] combining with an even distributed sorting evaluation [3]. The genetic algorithm (GA) chosen for evolving each population of the CCEAs had the following characteristics.

representation:	binary of 16 bits per function variable
selection:	rank-based selection
genetic operators:	two-point crossover and bit-flipping mutation
mutation probability:	0.05
breeding individuals	30
reproduction strategy:	the 60 lowest individuals in the rank were replaced by offspring of the

	breeding pairs.
population size:	100
termination criteria:	100,000 function evaluations
archive size	3; only used in CCEA-RS

3. EXPERIMENTAL RESULTS

We carried out 50 independent runs for each type of evaluation. All the methods were compared based on the average results of our experiments.

We firstly show the comparative performance of different versions of the CCEAs using the blind decomposition with those using the natural decomposition (see table 1). Statistical significance has been verified using a Student's two-tailed t-test, assuming unequal variances at 95% confidence. From this table it is apparent that the CCEAs achieved similar results regardless of the decomposition methods in most cases when the same collaboration methods were employed, where only two of the comparative results were statistical significant. In general, the CCEA-RS was the best choice for all the three problems using the blind decomposition.

Secondly, we would like to know if there were performance differences between coarse and fine fashions when we decomposed a problem in a blind way. Table 2 illustrates the fitness differences of using the three kinds of blind decompositions from that using the natural decomposition after 1000,000 function evaluations. The values above 0 indicate better performance than using the natural decomposition, and vice versa. We can see that the coarsely blind decomposition was superior to the finely blind decomposition under the most conditions, and it was even better than the natural one when we applied the CCEA-G and CCEA-LG to the Trid problem.

Table 1. Average performance of different versions of the CCEAs using the natural and the blind decomposition

Methods	Decompose	Rastrigin	Schwefel	Trid
CCEA-G	Natural	0.0394	2.0220	-29.8448
	Blind	0.1377	13.5978	-29.5306
	P-values	0.0821	0.0517	0.9482
CCEA-LG	Natural	4.2E-06	0.6886	-45.2926
	Blind	0.1997	7.3444	-44.5312
	P-values	**0.0046**	0.0599	0.7083
CCEA-RS	Natural	0.0368	1.3283	-48.0151
	Blind	0.0394	4.4315	-42.7191
	P-values	0.9439	0.2549	**0.0098**

4. CONCLUSIONS

This work investigates the effects of the blind decomposition in CCEAs. Our experimental results showed, somewhat surprisingly, that the blind decomposition did not badly degrade the performance of CCEAs, but yielded similar convergence to the natural way in most cases when the same evolutionary properties of CCEAs were employed. On the contrary, by using the coarsely blind decomposition, the CCEAs could achieve better performance than using the natural decomposition for the nonseparable problem, the Trid. The primary work indicates that it is not a bad idea to decompose a problem in a blind way if no prior knowledge about the problem decomposition is available.

Table 2. Performance differences of using different blind decompositions from that using the natural decomposition

Methods	Decompose	Rastrigin	Schwefel	Trid
CCEA-G	Blind	-0.0984	-11.5758	-0.3141
	Coarsely	-0.2377	-2.0864	1.4524
	Finely	-0.2360	-12.0416	-6.280
CCEA-LG	Blind	-0.1996	-6.6558	-0.7614
	Coarsely	-0.3760	-9.3248	1.7955
	Finely	-0.2458	-12.3089	-0.9040
CCEA-RS	Blind	-0.0026	-3.1032	-5.2959
	Coarsely	-0.2786	-2.0208	-0.5203
	Finely	-0.1403	-3.8859	-6.9376

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