FUZZY CONTROLLED COOPERATIVE BIO-INSPIRED ALGORITHM FOR BINARY OPTIMIZATION

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Abstract: Previously a meta-heuristic approach Co-Operation of Biology-Related Algorithms for solving binary-parameter optimization problems (COBRA-b), the basic idea of which consists in a cooperative work of different bio-inspired algorithms, was developed. Its performance was evaluated on a set of benchmark problems, and it was established that the idea of the algorithms' cooperative work is useful. However, it is still unclear which algorithms should be included in the cooperation and how many of them. Therefore, a fuzzy logic controller was introduced for solving this problem. The experimental results obtained by the two types of fuzzy-controlled COBRA-b are presented and their usefulness is demonstrated.

Keywords: bio-inspired algorithms, cooperation, fuzzy controller, binary optimization, comparison.

1. INTRODUCTION

Co-Operation of Biology-Related Algorithms (COBRA) is a meta-heuristic approach developed for solving real-parameter optimization problems [1]. Its basic idea consists in the cooperative work of different biology-inspired algorithms, which were chosen due to the similarity of their schemes. The following well-known nature-inspired heuristics were used as component-algorithms: the Particle Swarm Optimization Algorithm (PSO) [2], the Wolf Pack Search Algorithm (WPS) [3], the Firefly Algorithm (FFA) [4], the Cuckoo Search Algorithm (CSA) [5], the Bat Algorithm (BA) [6] and also the Fish School Search Algorithm (FSS) [7].

An examination of the efficiency of these six heuristics was conducted on a set of different test functions. Performance analysis showed that all of them are sufficiently effective for solving optimization problems, and their workability has been established. However, there are still various other algorithms which can be used as components for COBRA, and furthermore, even the bio-inspired algorithms already chosen can be combined in different ways. Therefore, an earlier controller based on fuzzy logic was implemented for COBRA to determine COBRA's components [8].

All the above-listed heuristics are similar bio-inspired optimization methods originally developed for continuous variable space. However, many applied problems are defined in discrete valued spaces where the domain of the variables is finite. For this purpose, the binary modification of COBRA, namely COBRA-b, was developed [9]. Later the migration operator of the Biogeography-Based Optimization (BBO) algorithm [10] was implemented to COBRA-b in an attempt to decrease the number of function evaluations during the solving of a given optimization problem [11]. Experiments showed that the proposed modification of the COBRA-b method works successfully and exhibits high performance.

Therefore, in this study fuzzy logic controllers were also implemented to the stated modification of the COBRA-b approach. Thus, in this paper firstly the COBRA meta-heuristic approach and its variations are described, and then a description of the fuzzy controller is presented. In the next section, the experimental results obtained by the two types of fuzzy controller are discussed, and after that the implementation of the best obtained fuzzy controller to COBRA and its experimental results are demonstrated. Finally, some conclusions are given in the last section.

2. CO-OPERATION OF BIOLOGY-RELATED ALGORITHMS

The original version of the meta-heuristic approach called Co-Operation of Biology-Related Algorithms or COBRA [1] was developed based on five optimization methods listed in the previous section except for the Fish School Search algorithm. FSS was later added as a component-algorithm of COBRA [12]. The basic idea for the development of a cooperative meta-heuristic was to use the cooperation of these biology-inspired algorithms instead of any attempts to understand which one is the best for the problem in hand.

The proposed meta-heuristic approach called COBRA is a self-tuning algorithm, whereby the number of individuals for each component-algorithm was determined by a specific tuning technique. First of all, one population was generated for a component. Then these populations were executed in parallel, cooperating with each other. The number of individuals in the population of each algorithm can increase or decrease depending on the fitness values: if the overall fitness value was not improved during a given number of iterations, then the size of each population increased, and vice versa.

There is also one more rule for population size adjustment, whereby a population can "grow" by accepting individuals removed from other populations. The population "grows" only if its average fitness value is better than the average fitness value of all other populations. Therefore, the "winner algorithm" can be determined as an algorithm whose population has the best average fitness value. This can be done at every step.

The original COBRA's migration operator can be described as "communication between populations". More specifically, populations exchange individuals in such a way that a part of the worst individuals of each population is replaced by the best individuals of other populations. Thus, the group performance of all algorithms can be improved, and it can help to prevent their preliminary convergence to their own local optimum.

Later, the algorithm COBRA-b, which is the modification of COBRA, was developed for solving optimization problems with binary variables [9]. COBRA was adapted to search in binary spaces by applying a sigmoid transformation to the velocity component (PSO, BA) and coordinates (FFA, CSA, WPS) to squash them into a range [0,1] and force the component values of the positions of the particles to be 0's or 1's. The basic idea of this adaptation was taken from [13]; the sigmoid function is also given in [13]. Finally, the migration operator of the Biogeography-Based Optimization (BBO) algorithm [10] was implemented to COBRA-b instead of its original migration operator [11].

The performance of the COBRA algorithm and its modifications was evaluated on a set of different benchmark problems. Experiments showed that these algorithms work successfully, are reliable on this benchmark and demonstrate competitive behaviour.

3. FUZZY LOGIC CONTROLLERS

The main idea of using a fuzzy controller was to implement a more flexible tuning method, compared to the original COBRA tuning algorithm. Fuzzy controllers are well known for their ability to generate real-valued outputs using special fuzzification, inference and defuzzification schemes. More specifically, fuzzy logic has applications in various areas, for example [14] or [15].

Previously, fuzzy controllers were implemented to the original version of the meta-heuristic approach called COBRA [8]. In the current study, components' success rates were used as inputs and population size changes as outputs. Similar fuzzy logic controllers were also implemented to the COBRA-b algorithm with a biogeography-based migration operator.

The fuzzy controller had 7 input variables, including 6 success rates, one for each component (the FSS algorithm was included in the collective), and an overall success rate. There were two types of success rate evaluation for all input variables except the last one: the component's success rate was evaluated as the average fitness value of its population or as the best fitness value of its population. In addition, the fuzzy controller had 6 output variables, i.e. the number of solutions to be added to or removed from each component. The last input variable was determined as the ratio of the number of iterations, during which the best found fitness value was improved, to the given number of iterations, which was over a constant period. Thus, the process of population growth was automated by the fuzzy controller.

The Mamdani-type fuzzy inference was used to obtain the output values. The rule base contained 21 fuzzy rules, which had the following structure: each 3 rules described the case when one of the components gave better results than the others (as there were 6 components, 18 rules were established); the last 3 rules used the overall success of all components (variable 7) to add or remove solutions from all components, in order to to regulate the computational resources.

The input variables were always in the range from 0 to 1, and fixed fuzzy terms of triangular shape were used. In addition to the three classical fuzzy sets, the "Don't Care" (DC) condition and a term with the meaning "larger than 0" (opposite to the first one) were also used to decrease the number of rules and make them simpler. The fuzzy terms used for the inputs are shown in Fig. 1.

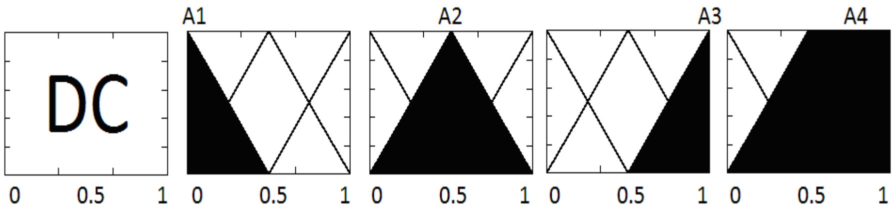

Fig. 1. Fuzzy sets for inputs

For the outputs, three fuzzy terms also of triangular shape, shown in Fig. 2 (as examples, the values 10 and 25 are demonstrated), were used.

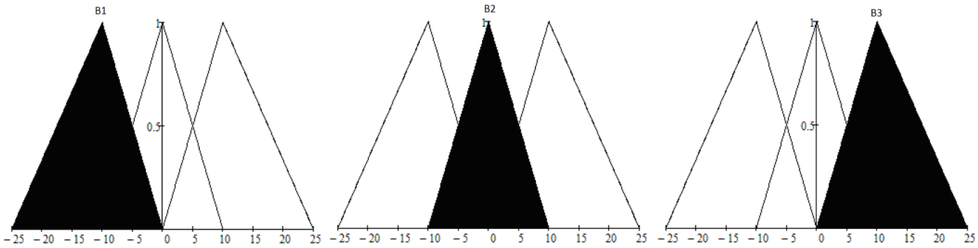

Fig. 2. Fuzzy terms for all 6 outputs

The output fuzzy terms were symmetrical, and the positions and shapes were determined by two values, encoding the left and right position of the central term, as well as the middle position of the side terms in one value, and the left and right positions of the side term in another value. These two values were optimized using the PSO algorithm. The defuzzification procedure was performed by calculating the centre of mass of the shape received by fuzzy inference.

4. EXPERIMENTAL RESULTS

In this study, the following 6 benchmark problems with the number of variables from 2 to 6 were used in experiments: Rosenbrock's function, the Sphere function, Ackley's function, Griewank's function, the Hyper-Ellipsoidal function and Rastrigin's function. The listed problems are real-parameter test optimization problems. Therefore, each real-valued variable was represented by a binary string whose length was equal to 10. Consequently, the number of variables while solving the above-mentioned test problems by the optimization method COBRA-b with the biogeography-based migration operator and its modifications varied from 20 to 60. These benchmark functions were considered to evaluate the robustness of the fuzzy controlled COBRA-b. However, firstly they were used to determine the best parameters for the two fuzzy controllers.

The standard Particle Swarm Optimization algorithm was used for this purpose. Therefore, the individuals were each represented as parameters of the fuzzy controlled COBRA, or more specifically, the positions of the output fuzzy terms. The objective function optimized by the PSO algorithm was the average best fitness over $T = 10$ runs and all functions. Thus on each iteration all test problems were solved T times by a given fuzzy controlled COBRA and then the obtained results were averaged. Calculations were stopped on each program run if the number of function evaluations exceeded $10000D$. The population size for the PSO algorithm was equal to 50 and the number of iterations was equal to 100; calculations were stopped on the 100-th iteration for the PSO heuristic.

When the successfulness of the component-algorithms was evaluated as the best average fitness value, the following parameters for the fuzzy controller were obtained: [-18; -10; 8; 9]. Finally, when the successfulness of the component-algorithms was evaluated as the best solution found by the component-algorithm, the obtained parameters were [-10; -8; 10; 20].

Fig 3 shows the change of the COBRA-b component population sizes during the optimization process on two functions, Rastrigin's Function (3b, 3d and 3f) and the Hyper-

Ellipsoidal Function (3a, 3c and 3e) with the best found fuzzy controller parameters and the COBRA-b meta-heuristic with the biogeography-based migration operator. These functions were chosen as they represent two cases: Rastrigin's function has many local minima and is quite difficult to optimize, while the Hyper-Ellipsoidal Function has a more simple landscape. Fig. 3a and 3b demonstrate the standard COBRA-b tuning procedure behaviour, 3c and 3d – the fuzzy controller with the component's success rate as the average fitness, 3e and 3f – the maximum fitness. In Fig. 3, the number of function evaluations is on the horizontal axis and the number of individuals in each population is on the vertical axis.

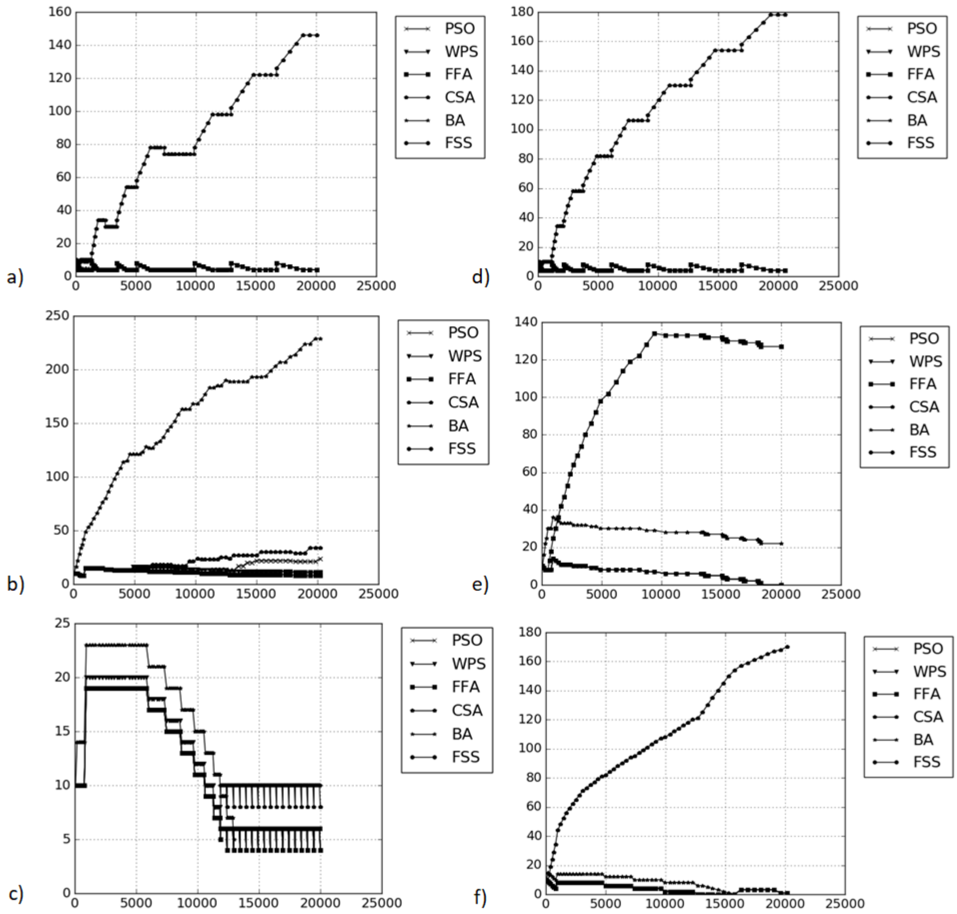

Fig. 3. Graphs of population size change

It was established that the population sizes are quite small while solving optimization problems with the fuzzy controlled COBRA-b algorithm and with the component's success rate as the maximum fitness value (except for the Rastrigin's function demonstrated in the Fig. 3f). On the other side, the population sizes increase significantly while solving optimization problems with the fuzzy controlled COBRA-b algorithm, with the component's success rate as the average fitness value and with the standard COBRA-b meta-heuristic.

On the following step, the obtained parameters were applied to the fuzzy controlled COBRA-b and it was tested on the above-listed benchmark functions. There were 51 program runs for each optimization problem; and calculations were stopped if the number of function evaluations was equal to 10000*D*.

In Table 1 and Table 2, the results obtained by the fuzzy controlled COBRA-b for the two types with the best parameters are presented. The following notations are used: the best found function value (Best), the function value averaged by the number of program runs (Mean), the standard deviation (STD) and the number of binary variables (Bit).

In Tables 1 and 2, the numbers in bold show the values which are better compared to the original COBRA in Table 3. For the case when the average fitness values were used for the successfulness evaluation in Table 1, better mean results were obtained for 5 cases out of 18, while for the best values used for the successfulness evaluation in Table 2, better mean results were received for 14 cases out of 18.

Table 1. Results obtained by the fuzzy controlled COBRA with average values for the successfulness evaluation

Function	***Bit***	***Best***	***Mean***	***STD***
Sphere function	20	7.64432e-006	**1.37598e-005**	**1.22309e-005**
	40	1.52886e-005	0.000295071	**0.00048754**
	60	0.00283604	0.0290591	0.0380496
Griewank's function	20	2.90483e-005	0.000106251	0.000165582
	40	4.05784e-005	0.00096025	**0.00157851**
	60	0.00216486	0.0448933	0.0410031
Ackley's function	20	0.00802368	0.00959571	0.00374216
	40	0.00802368	0.0197203	0.0256664
	60	0.0467534	**0.250501**	**0.19103**
Hyper-Ellipsoidal function	20	3.82216e-006	**1.45242e-005**	**7.00613e-006**
	40	**2.2933e-005**	0.00121239	0.00146286
	60	0.00167793	0.0562018	0.044983
Rosenbrock's function	20	9.63228e-005	**0.000285254**	0.000377863
	40	0.00633962	0.165901	0.262342
	60	**0.00113475**	**1.37951**	**0.988972**
Rastrigin's function	20	0.00151655	0.00151655	0
	40	0.00303311	0.16205	0.352673
	60	**0.00303311**	0.902374	0.924889

Table 2. Results obtained by the fuzzy controlled COBRA with best values for the successfulness evaluation

Function	***Bit***	***Best***	***Mean***	***STD***
Sphere function	20	7.64432e-006	**7.64432e-006**	**0**
	40	1.52886e-005	**0.000111607**	**0.000365942**
	60	**0.000114665**	**0.00710004**	0.0111394
Griewank's function	20	2.90483e-005	**2.90483e-005**	**0**
	40	4.05784e-005	**0.000207498**	**0.000487303**
	60	**0.000171292**	0.0184986	0.0184049
Ackley's function	20	0.00802368	**0.00802368**	**0**
	40	0.00802368	0.201013	0.0176732
	60	**0.0124203**	**0.213764**	**0.215561**
Hyper-Ellipsoidal function	20	3.82216e-006	**7.64432e-006**	**1.06747e-005**
	40	**2.2933e-005**	**0.000340937**	0.000502775
	60	**0.00019493**	**0.0161624**	**0.0123844**
Rosenbrock's function	20	9.63228e-005	**0.000384319**	**0.0007001**
	40	0.000288968	0.034175	0.0642982
	60	0.0386962	**1.60835**	**1.2701**
Rastrigin's function	20	0.00151655	0.00151655	0
	40	0.00303311	**0.00424621**	**0.00309283**
	60	0.00454966	**0.720278**	**0.664165**

Thus, the comparison demonstrates that often the results obtained by the COBRA-b with six components without a controller are better than the results obtained by the fuzzy controlled COBRA with the first type of successfulness evaluation. However, the fuzzy controlled COBRA with the second type of success rate outperformed both of them. Therefore, it can be used for solving optimization problems instead of the stated algorithm's versions.

Table 3. Results obtained by COBRA with six component algorithms

Function	Bit	Best	Mean	STD
Sphere function	20	0	2.40796e-005	6.67413e-005
	40	1.52886e-005	0.000276724	0.000544196
	60	0.000206397	0.00901265	0.0101676
Griewank's function	20	2.90483e-005	5.62613e-005	6.1605e-005
	40	4.05784e-005	0.000821278	0.00189427
	60	0.000691558	0.0120674	0.0128442
Ackley's function	20	0.00802368	0.00959571	0.00374216
	40	0.00802368	0.0188514	0.0169323
	60	0.0157206	0.251521	0.236922
Hyper-Ellipsoidal function	20	3.82216e-006	0.000192637	0.000562536
	40	9.93761e-005	0.000455601	0.000480002
	60	0.0014486	0.0207276	0.0134696
Rosenbrock's function	20	9.63228e-005	0.000413515	0.00137837
	40	0.000288968	0.0319719	0.0539459
	60	0.0050697	1.7758	1.68727
Rastrigin's function	20	0.00151655	0.00151655	0
	40	0.00303311	0.0193946	0.0283402
	60	0.00454966	0.836051	0.753535

5. CONCLUSION

In this paper, a new modification of the meta-heuristic called COBRA-b, which was originally based on five nature-inspired algorithms, has been introduced. The proposed modification involves the usage of a fuzzy controller for the adjustment of the component-algorithm population sizes and the adjustment of the whole collective for COBRA-b. Besides, the Fish School Search algorithm was added as a potential component of the COBRA-b approach. These modifications were validated and compared. Simulations and comparison showed that the fuzzy controlled COBRA-b algorithm with the best fitness values used for the success rate evaluation is superior to the other versions.

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