Hybridizing Artificial Bee Colony with Simulated Annealing

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Abstract

A new hybridized Artificial Bee Colony (HABC) algorithm is presented. The exploration/exploitation balancing strategy of Simulated Annealing is incorporated into the original ABC algorithm to improve its search efficiency and reduce its computational cost. The algorithm begins with a high exploration rate and minimal exploitation effort and gradually switches to higher exploitation rates as the promising areas of the search space are identified. The proposed algorithm is applied to a number of benchmark problems. Comparison of the results indicates that in most cases the hybridized algorithm outperforms the other two algorithms.

Keywords: *Optimization; Hybrid Algorithm; Simulated Annealing; Artificial Bee Colony*

1. Introduction

Optimization plays a very significant role in different applications. There are many algorithms offered by different authors in the literature for this task. Artificial bee colony, Simulated annealing and Genetic algorithm are of this category. Each of these algorithms has some advantages and disadvantages which may make them work well in some problems and not work well in some others. With hybridizing these algorithms with each other, they may be able to cover each other's weaknesses and have a better performance than both of them.

In this case, Klepeis, Pieja and Floudas [1] introduced the novel classes of hybrid global optimization methods, termed alternating hybrids, for application as a tool in treating the peptide and protein structure prediction problems. Juang [2] created a hybrid of genetic algorithm (GA) and particle swarm optimization (PSO), and was thus called HGAPSO. HGAPSO was applied to recurrent neural/fuzzy network design. The performance of HGAPSO was compared to both GA and PSO in those recurrent networks design problems, demonstrating its superiority. Chen, Yang and Wu [3] combined discrete particle swarm optimization (DPSO) with global search and local search to search for the optimal results. Xia and Wu [4] studied a dual-resource constrained job shop scheduling problem by designing a hybrid genetic algorithm based on Genetic Algorithm (GA) and Simulated Annealing (SA). The results of numerical simulations, which were compared with those of other well-known algorithms, showed better performance of the proposed algorithm. Liu, Abraham and Clerc [5] designed a hybrid meta-heuristic fuzzy scheme, called as variable neighborhood fuzzy particle swarm algorithm (VNPSO), based on fuzzy particle swarm optimization and variable neighborhood search to solve the QAP. The performance of the proposed approach was evaluated and compared with other four different algorithms. Empirical results illustrated that the approach can be applied for solving quadratic assignment problems effectively. Balsa-Canto, Peifer, Banga, Timmer and Fleck [6] proposed a new hybrid global method, based on the combination of an evolutionary search strategy with a local multiple-shooting approach, which offered a reliable and efficient alternative for the solution of large scale parameter estimation problems. The presented new hybrid strategy offered two main advantages over previous approaches: First, it was equipped with a switching strategy which allowed the systematic determination of the transition from the local to global search. This avoided computationally expensive tests in advance. Second, using multiple-shooting as the local search procedure reduced the multi-modality of the non-linear optimization problem significantly. Because multiple-shooting avoided possible spurious solutions in the vicinity of the global optimum it often outperformed the frequently used initial value approach (single-shooting). Thereby, the use of multiple-shooting yielded an enhanced robustness of the hybrid approach. Niu and Li [7] presented a new hybrid global optimization algorithm PSODE combining particle swarm optimization (PSO) with differential evolution (DE). To demonstrate the effectiveness of the proposed algorithm, four benchmark functions were performed, and the performance of the proposed algorithm was compared to PSO and DE to demonstrate its superiority. Cao and Yang [8] studied a dual-resource constrained job shop scheduling problem by designing a hybrid genetic algorithm based on Genetic Algorithm (GA) and Simulated Annealing (SA). The results of numerical simulations, which were compared with those of other well-known algorithms, showed better performance of the proposed algorithm. Farshbaf, Feizi-Derakhshi and Roshanpoor [9] combined Pareto front method and cellular learning automata to exploit the potentiality of both in the hybridized algorithm. The proposed methods used to improve the performance addition to hybridization, were using an optimized method in generating reinforcement signal vector and considering the solutions of each non-dominated set as neighbours. A simulation research was carried out to investigate the effectiveness of the proposed hybrid algorithm. The simulation results confirmed the effectiveness of the proposed method. Gao, Wang, Ovaska and Zenger [10] a hybrid optimization approach is proposed and studied, in which the HS is merged together with the opposition-based learning (OBL). The modified HS, namely HS-OBL, has an improved convergence property. Optimization of 24 typical benchmark functions and an optimal wind generator design case study demonstrate that the HS-OBL can indeed yield a superior optimization performance over the regular HS method. Niknam [11] combined a fuzzy adaptive particle swarm optimization (FAPSO) algorithm with Nelder–Mead (NM) simplex search called FAPSO-NM. In the resulting hybrid algorithm, the NM algorithm was used as a local search algorithm around the global solution found by FAPSO at each iteration. Therefore, the proposed approach improved the performance of the FAPSO algorithm significantly. The algorithm was tested on two typical systems consisting of 13 and 40 thermal units whose incremental fuel cost functions took into account the valve-point loading effects. Yildiz [12] developed a novel hybrid optimization algorithm entitled hybrid robust differential evolution (HRDE) by adding positive properties of the Taguchi's method to the differential evolution algorithm for minimizing the production cost associated with multi-pass turning problems. The proposed optimization approach was applied to two case studies for multi-pass turning operations to illustrate the effectiveness and robustness of the proposed algorithm in machining operations. The results revealed that the proposed hybrid algorithm was more effective than particle swarm optimization algorithm, immune algorithm, hybrid harmony search algorithm, hybrid genetic algorithm, scatter search algorithm, genetic algorithm and integration of simulated annealing and Hooke-Jeevespatter search.

In this paper, Simulated annealing is hybridized with Artificial bees colony. In Section 2, Artificial bees colony is described. In Section 3, Simulated annealing is explained. In Section 4, exploration and explotation concepts in optimization algorithms are discussed and in Section 5, results for experiments on benchmark problems are presented.

2. Artificial Bee Colony Algorithm (ABC)

This algorithm is adopted from the food foraging behavior of honey bees in the nature. In every hive, there are some scout bees that are responsible for discovering promising flower patches with high quality nectar and pollen. After discovering those patches, they inform the colony about the quality of the patches, their distance from the hive and their directions. Based on the quality and the distance, more bees are sent to better patches (better patch means a patch with more high quality nectar and less distance).

This behavior is adopted to offer an algorithm for optimization applications. The algorithm is as follows: n initial random points are generated. m best points are selected among n points and e best points are selected among m points. nep bees are allocated for neighborhood search around the e points and nsp bees are allocated for neighborhood search around the m-e points. ngh is the radius of the neighborhood. Bees are allocated to search the neighborhood by a roulette wheel (in a roulette wheel, fitter points are more probable to be chosen).The pseudo code of the algorithm is shown by Pham, Ghanbarzadeh, Koc, Otri, Rahim and Zaidi [13] as following:

1. Initialize population with random solutions.
2. Evaluate fitness of the population.
3. While (stopping criterion not met)

   //forming new population

4. Select sites for neighborhood search.
5. Recruit bees for selected sites (more bees for best e sites) and evaluate fitnesses.
6. Select the fittest bee from each patch.
7. Assign remaining bees to search randomly and evaluate their fitnesses.
8. End While.

3. Simulated Annealing (SA)

Simulated annealing is an optimization algorithm that is adopted from the annealing process of the metals. In this algorithm, a tempreture is defined for the system and is decreased with increasing the iterations. The algorithm parameters are neighborhood radius, initial temperature and temperature cooling strategy. The algorithm is as follows: in the first iteration, an initial random point is generated in the state-space which is named “particle”. In the next iteration, another random point is generated in the neighborhood of the particle and the temperature is decreased by the cooling strategy. The fitness of the two points is compared with each other. If the second point is fitter, the particle will move to it and this is called a downhill movement (because the particle moves towards a better point), else, dividing the current temperature on the initial temperature, a value larger than 0 and smaller than 1 is produced which is named the uphill movement probability. Then a random value between 0 and 1 is generated which is compared with the uphill movement probability. If it is larger, uphill movement will take place (uphill movement means moving towards a worse point hoping to find a fitter point in its neighborhood.). This continues till the stopping criterion is met. The stopping criterion can be the number of iterations or the temperature. The question is: what is the role of temperature in this algorithm? Maybe temperature is the most creative part of simulated annealing algorithm. It controls the exploitation and exploration capabilities at different stages of the search process.

4. The Hybridized Artificial Bee Colony (HABC) Algorithm

Every search algorithm applies two important capabilities to find the optimal or near optimal solutions. By exploration, it looks for promising areas, and by exploitation, it searches the discovered zones to find the optimal or near optimal solutions. If at the beginning of the search, the computational cost (computational cost in optimization problems is considered as the number of function evaluations) is spent for exploration process and with increasing the iterations, gradually, this cost gets spent for exploitation, the final result will be more optimum. This means, if at first, promising areas are discovered and then better zones are exploited, it is hoped more that more optimal solutions are obtained finally compared to the state that at first the computational cost is spent for exploitation and at the end it is spent for exploration or like most of the algorithms, these two capabilities remain steady from beginning to end.

In Simulated annealing, uphill movements fulfill the exploration capability and downhill ones play the role of the exploiter. Indeed, when there is a better point found around the particle, it will exploit it but if there is a worse point, if it moves to it, it means that it is losing the current good point hoping to find a better point around the worst point. This can be counted as the exploration capability. When the temperature is high, uphill movements are more likely to happen but with the gradual decrement of the temperature, they become less likely to take place. This means that the exploration is high and exploitation is low at first, but gradually this trend gets reversed with the decrement of the temperature. This is the main advantage of SA algorithm. To prove it, once the temperature was kept fixed and high, once more the temperature was kept fixed and low, in another experiment, the temperature was gradually decreased from high to low during the optimization process and the results were compared. Results indicated that temperature decrement was so effective.

In bee colony, in every iteration, the random search plays the role of the explorer and the neighborhood search plays the role of the exploiter and from beginning to end they are fixed. As a matter of fact, the principle of high exploration and low exploitation at the beginning and gradual conversion to high exploitation and low exploration is not considered in it. In this paper, the idea of variable exploration and exploitation which is noticed in SA is applied for Bee colony algorithm to improve its performance. A temperature is defined for the system which is high at first and is decreased gradually. With decrement of the temperature, the number of random points generated in every iteration is decreased and they are added to the points that are used for neighborhood search. This helps the algorithm to adjust the exploration and exploitation capabilities. The modified algorithm was tested by some famous benchmark problems and was compared with the original ABC. Results in table 1 indicate that the concept of applying a temperature for controlling the exploration and exploitation is useful. As it is clear, variable and decreasing temperature has had the best results and others have had unacceptable outcomes. This verifies the above mentioned concept.

Table 1. Results for Simulated Annealing with Various Initial Temperatures

Problem	Type	GO	VDT	LCT	HCT	VIT
De Jong	Max	3905.93	3903.87	3207.61	2568.24	2276.32
Goldenstein&price	Min	3	3.2	7.35	10.45	12.43
Branin	MIn	0.3977272	0.3982316	1.4738954	3.4535456	4.3439847

In Table 1, GO stands for Global optimum, VDT stands for variable decreasing temperature, LCT stands for low constant temperature, VIT stands for variable increasing temperature and HCT stands for high constant temperature.

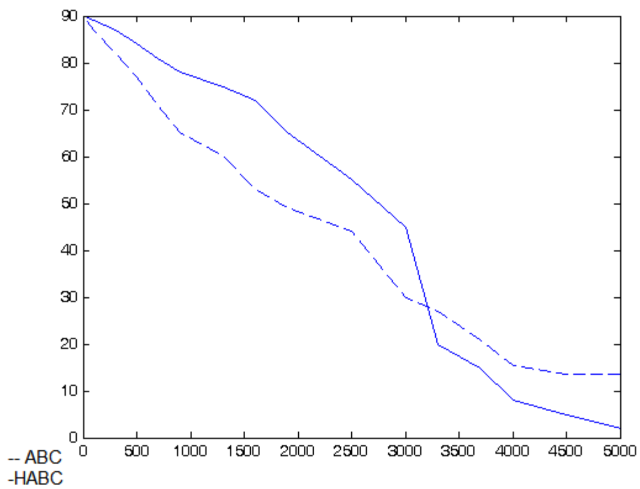

Figure 1. Optimization Graph of Martin and Gaddy Benchmark Function

In Figure 1, it is clear that the hybridized algorithm has spent its computational cost on exploration at the beginning to find the promising areas and gradually has exploited them and at the end, it has found better points than ABC. But ABC has spent the computational cost for exploiation from the beginning and it has been able to gain better results at first, but gradually the intial investment of the hybridized algorithm has helped to obtain better final solutions.

5. Results and Discussion

A series of experiments were conducted to investigate the applicability and efficiency of the proposed algorithm and the results were compared with those from original SA and ABC. The algorithm was applied to standard benchmark problems from [13] and the results were averaged over 100 runs. Each run was terminated when the difference between the population's best fitness and the global optimum fell below 0.1% of the global optimum or below 0.001, whichever came first. An initial temperature of 8000 with a linear cooling strategy was used with α=0.99. Results from original ABC and SA algorithms were taken from [13].

Table 2. Comparison of Results from HABC and Original ABC and SA Algorithms

Problem	HABC		ABC		SA	
	suc	fev	suc	fev	suc	fev
De Jong	100	687	100	868	*	*
Goldenstein&price	100	768	100	999	*	*
Branin	100	1578	100	1657	*	*
Martin&Gaddy	100	478	100	526	*	*
Rosenbrock (2D) a	100	589	100	631	100	4508
Rosenbrock (2D) a	100	2208	100	2306	100	5007
Rosenbrock (4D)	100	7987	100	28529	94	3053
Hyper Sphere	100	6876	100	7113	*	*
Griewangk	100	1186	100	1847	*	*

In the above table, the numbers in column “suc” represent the number of times the algorithm successfully found the global optimum out of 100 runs and the numbers in column “fev” represent average function evaluations to convergence. An asterisk in a column indicates that no results were available in published literature.

Comparison of the computational cost in terms of function evaluations in cases wherein results from both HABC and other algorithm(s) are available clearly shows the superiority of HABC. This can be attributed to the contribution of the algorithm’s SA-style exploration/exploitation balancing strategy. The strategy has proved effective in limiting the unnecessary exploitation efforts of the algorithm in its early search stages and allowing it to explore wider areas of the search space instead. As the algorithm identifies more and more promising areas, it is gradually encouraged to exploit its knowledge of the explored areas to close in on local/global optima.

6. Summary and Conclusions

A hybridized Artificial Bee Colony (HABC) algorithm was presented. The algorithm combines the exploration power of the original ABC algorithm with the exploration/exploitation balancing strategy of SA to improve its search efficiency and reduce its computational cost. The algorithm focuses mostly on exploration in its early search stages and allows higher levels of exploitation only when promising areas of the search space have been well identified. In this investigation, the variable exploration capability using a central temperature is adopted from SA to control the exploration and exploitation capability of the algorithm in different stages of the search process for improving its performance. The new algorithm was tested on some famous benchmark problems and was compared with some published results in the literature. Results from a series of experiments indicate that the proposed algorithm outperforms the original ABC and SA algorithms on most benchmark problems.

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