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Hybridizing Particle Swarm and Brain Storm Optimizations for Applications in Electromagnetics

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Abstract

This paper compares the performance of two global optimization algorithms: particle swarm optimization (PSO) and brain storm optimization (BSO). We observe that BSO has clear advantage in the speed of global exploration from a random initialization, while PSO outperformed in the accuracy of local exploitation with a predefined initialization. The possibility of hybridizing PSO and BSO is then investigated with an example of patch antenna circuit model determination. It is shown that the BSO-PSO hybrid algorithm could benefit from the advantages of both PSO and BSO, and therefore outperforms single optimization methods within the same number of iterations.

1 Introduction

Utilization of global optimization schemes has evolved as a popular strategy in solving complex electromagnetic problems. Particle swarm optimization (PSO) is a nature-inspired global optimization algorithm that has been proven advantageous comparing to many other techniques because of its inherent simplicity and robustness in solving multidimensional engineering problems [1]. Brain storm optimization (BSO) is a relatively new optimization algorithm that was recently introduced into electromagnetics applications [2]. It is a swarm intelligence optimization scheme inspired by the collective behavior of human beings in searching optimal idea for problem solving. The interested readers are encouraged to review [1] and [2] for many other relevant references on these topics. In this paper, we compare the performance of the two optimization algorithms in a benchmarking function with different initializing conditions. We observe advantage of BSO in the speed of global exploration from a random initialization, and PSO in the accuracy of local exploitation with a predefined initialization. A hybrid of PSO and BSO is then investigated with an example of patch antenna circuit model determination. It is shown that the hybrid algorithm of PSO initialized with BSO could benefit from the advantages of both single algorithms, and therefore outperforms both PSO and BSO in finding minimum fitness within the same number of iterations.

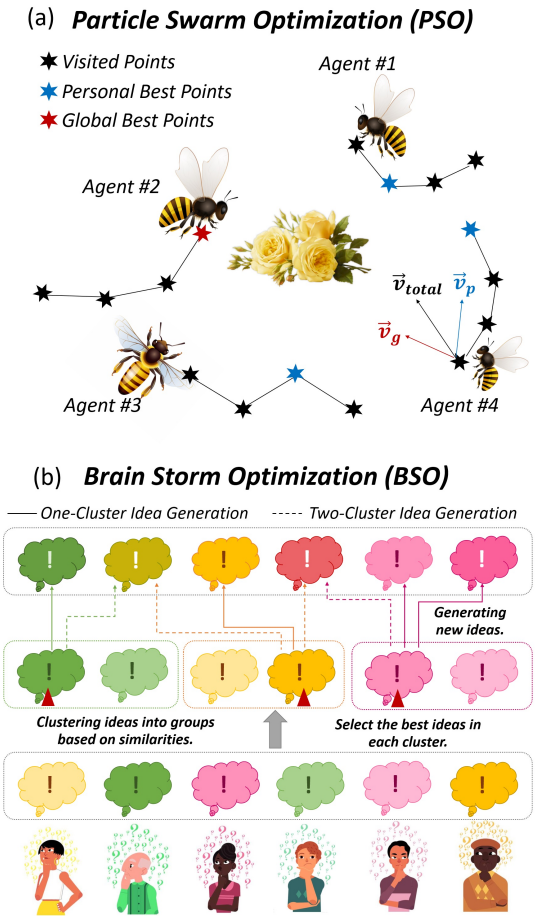

Figure 1. Principles of particle swarm optimization (PSO) brain storm optimization (BSO). (a) describes a swarm of bees searching for flowers with the previous visited points marked on the paths for each agent (bee). (b) illustrates the concept of idea generation in BSO by clustering the ideas. Both processes typically continue until reaching the maximum number of iterations.

2 Backgrounds of PSO and BSO

PSO and BSO are both evolutionary global optimization techniques based on the movement and intelligence of swarms. Both of the two techniques start by assigning a number of agents (also referred as populations in BSO) into the defined solution space. The agents move through the solution space, evaluate their positions using the fitness func-

tion, and update their positions (also velocities in PSO) at the end of each iteration.

The major difference between PSO and BSO lies in the position updating schemes. In PSO, the positions are updated based on their movement over a discrete time interval (Δt) with Δt usually set to 1 [1]:

$$\vec{x_n}^{k+1} = \vec{x_n}^{k} + \vec{v_n}^{k+1}\Delta t \tag{1}$$

$$\vec{v_n}^{k+1} = w^k \vec{v_n}^{k} + c_1 r^k_{1,n}(\vec{p_n}^{k} - \vec{x_n}^{k}) + c_2 r^k_{2,n}(\vec{g_n}^{k} - \vec{x_n}^{k}) \tag{2}$$

where subscript n and superscript k denote the nth agent in the kth iteration. $\vec{v_n}^{k}$ is the velocity, w_k is the inertial weight evolving through the iterations, $\vec{p_n}^{k}$ and $\vec{g_n}^{k}$ are the locations of the personal best and global best fitnesses, c_1 and c_2 the weighting coefficients, and $r^k_{1,n}$ and $r^k_{2,n}$ are random variables within the range of $\{0,1\}$. For BSO, the populations are grouped into clusters and the new positions (also referred as ideas) are generated based on either one cluster or two clusters controlled by a random parameter. For one cluster generation, the ideas are updated as [2]:

$$\vec{x_{new}}^{k+1} = \vec{x_{select}}^{k} + \vec{\xi}^k \cdot \vec{N}^k \tag{3}$$

$$\vec{\xi}^k = \alpha r^k \exp\left(1 - \frac{K}{K-k+1}\right) \tag{4}$$

where $\vec{N}^k$ is a Gaussian random vector with mean of 0 and variance of 1, and $\vec{\xi}^k$ is a weighting coefficient of $\vec{N}^k$ that also contains a random variable r^k and evolves with iterations. K is the maximum number of iterations, and k is the number of current iteration. Inspection of the updating schemes of the two algorithms reveals BSO's inherent capability in diverse searching, because of the involvement of more random variables, which could be advantageous especially during the initial iterations.

3 PSO and BSO with Random and Predefined Initializations

In this section, the benchmarking Griewank function is used to compare the performance of PSO and BSO. Griewank function is expressed as:

$$F_{gr}(\vec{x}) = \frac{1}{4000}\sum_{i=1}^{D}[x_i^2] - \prod_{i=1}^{D}[\cos(x_i/\sqrt{i})] + 1 \tag{5}$$

which has a global minimum of 0 and is evaluated within the solution space of $x_i \in [-600, 600]$, $\forall i = 1, 2, ...D$. 15 dimensions and $4D+1 = 61$ agents are assigned with a maximum of 1000 iterations, resulting in a total of 61000 function evaluations for both PSO and BSO. For PSO, social weights c_1 and c_2 are set to 2.0, inertial weight w^k is linearly decreasing from 0.9 to 0.4 through the iterations. For BSO, the number of clusters is set as 12 (about $1/5$ of the number of agents), which has been proved to yield optimal performance [2]. Finally, invisible boundaries are used for both two algorithms, which erases the agents outside the boundaries from performing fitness evaluations.

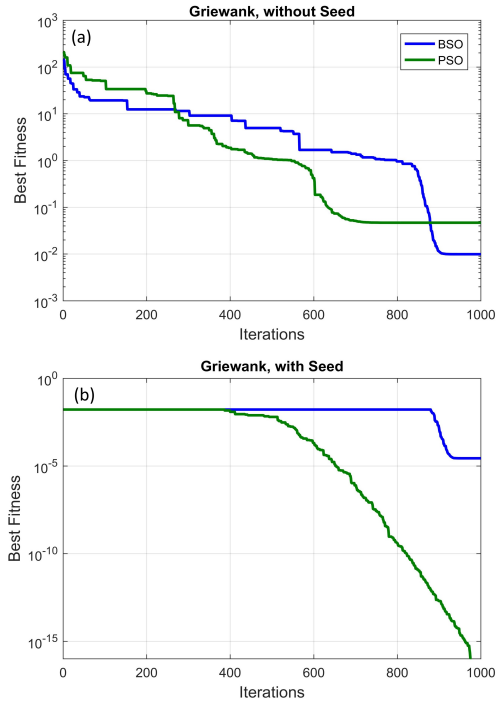

Figure 2. Best fitness in optimizing the 15-D Griewank function using PSO and BSO, with (a) random initialization and (b) predefined seed assigned to one of the agents at $x_i = 1$, $\forall i = 1, 2, ...D$.

The most commonly adopted swarm initialization in studying optimization techniques is the random initialization, in which the initial position of each agent is generated as:

$$\vec{x_n} = \vec{x_{min}} + \vec{r_n} \cdot (\vec{x_{max}} - \vec{x_{min}}) \tag{6}$$

where $\vec{x_{max}}$ and $\vec{x_{min}}$ are the specified maximum and minimum within the solution space, and $\vec{r_n}$ is random vector with value between 0 and 1 in each dimension. In many practical cases, however, the optimization could aim at fine tuning with a reasonable initial guess (referred as seed), which can be achieved by feeding the predefined seed to one of the agents while the rest of them remain random.

Fig. 2 plots the global best fitness obtained by PSO and BSO versus the number of iterations, with random initialization in (a), and predefined seed at the position of $x_i = 1.0$, $\forall i = 1, 2, ...15$ in (b). With randomly generated initial agents, BSO and PSO are demonstrating comparable performances within 1000 iterations. BSO is showing advantage over PSO in the initial searching speed within the first few hundreds (around 300) of iterations, and also finishes the optimization with a slightly lower fitness (1×10^{-2} for BSO versus 4×10^{-2} for PSO). However, with a initial seed assignment at $x_i = 1$, $\forall i = 1, 2, ...D$, which gives an initial best fitness on the order of 10^{-2}, PSO significantly outperforms BSO in the capability of local exploitation based on the knowledge of a "good" initial position. At the end of 1000 iterations, PSO returns a fitness on the order of 10^{-16}, while BSO finishes with a best fitness around 10^{-5}. The advantage of BSO in initial searching speed fails to demonstrate with the knowledge of a "good" seed.

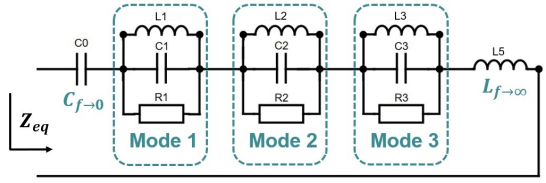

Figure 3. General topology of the equivalent lumped element circuit of rectangular patch antennas. The patch antenna input impedance is modeled by the series connection of parallel resonant RLC tanks, a low-frequency capacitor, and a high-frequency inductor.

4 Hybrid BSO-PSO in Patch Antenna Circuit Model Determination

Hybridizations of PSO with other optimization algorithms (e.g. genetic algorithm) have been studied in literature [3]. In this section, we investigate a hybrid of PSO and BSO, with the hope of benefiting from the advantages of both algorithms by switching from one to the other at certain number of iterations. The switching is done by taking the population of one algorithm and using it as the initial populations of the other algorithm. In this study, we perform PSO with BSO initialization, based on the observed advantages of initial exploration in BSO and local exploitation in PSO.

The example problem used in this section is the determination of circuit equivalence of a patch antenna. As shown in Fig. 3, a generalized circuit equivalence of patch antenna consists of the series connection of a low-frequency capacitor C_0, a high frequency inductor L_5, and parallel RLC tanks representing the orthogonal modes of resonance [4]. The input impedance of the equivalent circuit is written as:

$$Z_{eq} = j2\pi f L_5 + \frac{1}{j2\pi f C_0} + \sum_{i=1}^{M}\left(\frac{1}{R_i} + \frac{1}{j2\pi f L_i} + j2\pi f C_i\right)^{-1} \tag{7}$$

where M denotes the number of resonances in the frequency band of interest, R_i, C_i, L_i are the equivalent lumped resistance, capacitance and inductance for the ith number of resonant mode. The goal of this optimization is to find the circuit parameters C_0, L_5, R_i, C_i and L_i so that the difference between $Z_{eq}(f)$ computed from (7) and the $Z_s(f)$ generated from full-wave simulation is minimized. A normalized error function is therefore defined as the fitness:

$$\frac{1}{Z_0}\left(\frac{1}{N}\sum_{j=1}^{N}\{\mathrm{Re}[Z_s(f_j) - Z_{eq}(f_j)]^2 + \mathrm{Im}[Z_s(f_j) - Z_{eq}(f_j)]^2\}\right)^{\frac{1}{2}} \tag{8}$$

where Z_0 is the characteristic impedance of 50 Ω, N is the total number of frequency sampling, f_j is the frequency for the jth sample.

In this study, we choose two cases with $M = 2$ and $M = 3$, resulting in 8-dimensional and 11-dimensional optimization problems. The solution space is defined as $C_0, C_i \in [0, 50]$ (pF), $L_5, L_i \in [0, 10]$ (nH), $R_i \in [10, 200]$ (Ω), $\forall i = 1, 2, 3$. The number of agents are set as 33 and 45, with maximum iteration number of 2000, resulting in 66000 and 90000 fitness evaluations for the 8-dimensional and 11-dimensional cases. The intrinsic parameter setting for BSO and PSO are kept as stated in previous section, except number of clusters of BSO are chosen as 6 and 9 for the two cases (about $1/5$ of agents number). BSO, PSO and BSO-PSO hybrid are compared by the two cases, all with random initialization. In the BSO-PSO hybrid, BSO is used in the initial 300 iterations, and then switched into PSO for the rest 1700 iterations with the initial populations taken from BSO in the 300th iteration. Fig. 4 plots the best fitness versus number of iterations using BSO (blue), PSO (green), and BSO-PSO hybrid (red). The BSO-PSO hybrid outperforms both BSO and PSO alone within 2000 it-

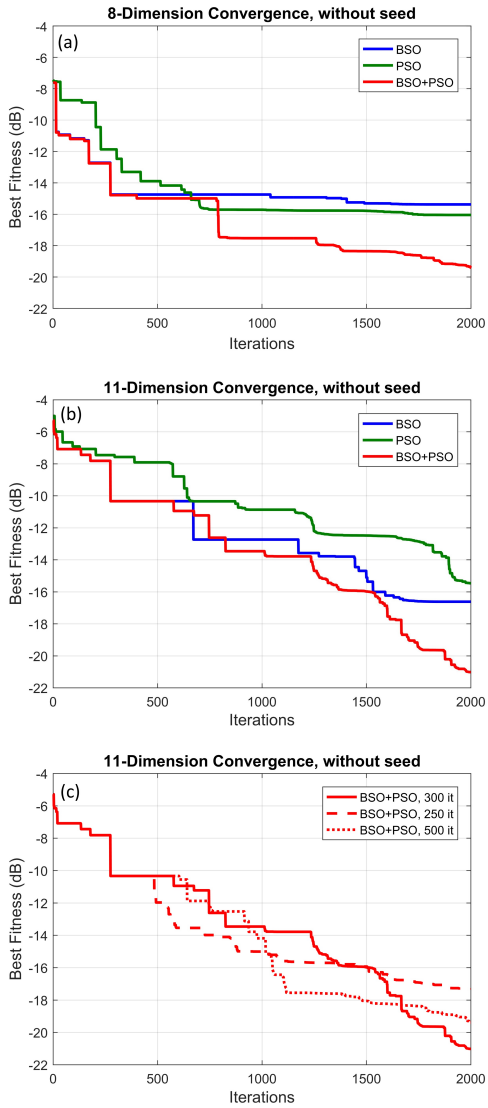

Figure 4. Best fitness in optimizing the circuit equivalence of patch antenna using BSO (blue), PSO (green), and the hybrid algorithm of PSO with BSO initialization (red). Two cases are studied, with (a) 8 dimensions and (b) 11 dimensions. The number of iteration for switching from BSO to PSO is varied in (c), for the 11-dimensional case.

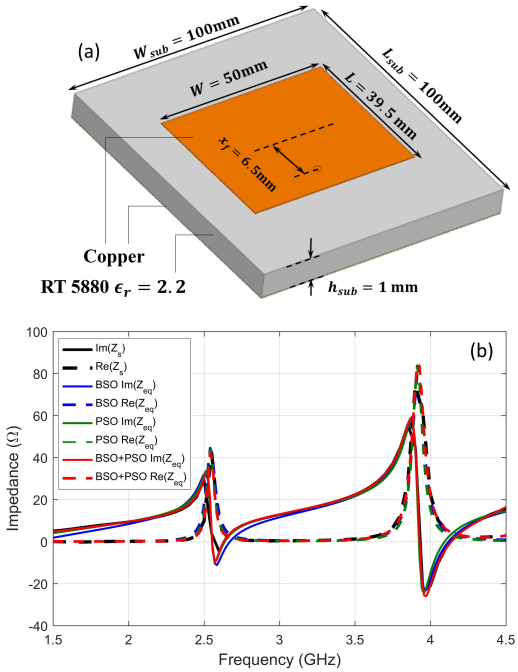

Figure 5. (a) Dimensions of the patch antenna used in the example of circuit model determination. (b) The simulated input impedance Z_s (black) and circuit equivalence impedance Z_{eq} of 11 dimensions obtained with BSO (blue), PSO (green), and hybrid of PSO with BSO initialization (red).

erations, for both 8-dimensional and 11-dimensional problems. The number of iteration for switching from BSO to PSO is varied in Fig. 4 (c). It is observed that fitness obtained by switching at 300th iteration is better than those at 250th and 500th iterations in this example. However, comparing to the results in Fig. 4 (b) with PSO or BSO alone, the hybrid method outperforms in all three cases with different switching points, returning lower fitnesses at the end of 2000 iterations.

Dimensions of the rectangular patch antenna used in the example of circuit model determination are illustrated in Fig. 5 (a). The simulated input impedance Z_s and circuit equivalence impedance Z_{eq} of 11 dimensions obtained with BSO, PSO, and hybrid of PSO with BSO initialization are shown in Fig. 5 (b). All three methods generate reasonably good results, with the closest agreement to simulation obtained using the hybrid BSO-PSO.

5 Conclusion

We perform comparison study regarding the performance of PSO and BSO. The advantages of the two algorithms are identified using a benchmarking function. Based on this observation, a hybrid of PSO and BSO is proposed and investigated with the example of patch antenna circuit model determination. We demonstrate that the BSO-PSO hybrid algorithm could benefit from the advantages of both PSO and BSO, and therefore outperforms single technique in some optimization problems.

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