A Novel Multimodal Optimization Algorithm for the Design of Electromagnetic Machines

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The optimal shape and parameter search during the design of an electromagnetic machine is a nonlinear, multivariable and multimodal optimization problem that incurs a great deal of computation time when calculating electromagnetic fields. To overcome these problems effectively, this paper proposes a new evolutionary multimodal optimization algorithm based on the Big Bang-Big Crunch method and aided by a surrogate model using the theory of compressed sensing. Its efficiency is demonstrated by assessing the optimization results for test functions. Moreover, to evaluate the feasibility of its application to an electromagnetic problem, a permanent magnet machine is designed using the proposed algorithm. The obtained results confirm that the proposed method is more effective and efficient than other existing approaches.

***Index Terms*—Electromagnetic machine design, evolutionary algorithm, multimodal optimization, surrogate model**

I. Introduction

IN THE AREA of electromagnetic machine design, there are many design parameters to be determined, and their nonlinear behaviors must be considered as well to obtain reliable results. Furthermore, given that the structures of up-to-date electromagnetic machines are more complex than those of traditional machines, more accurate electromagnetic field analysis methods, such as 3D FEM, are needed. Therefore, electromagnetic machine designs are highly nonlinear, multivariable and multimodal optimization problems. Moreover, the actual computation time and costs associated with optimization increase significantly depending on the number of objective function evaluations [1].

To find effective solutions to such problems, it is often desirable to obtain not only the global optimum but also the local optima because various solutions provide insight into the nature of the target space and suggest alternative solutions under limited conditions [2]. This makes multimodal optimization the most feasible approach to solve these problems.

In recent years, many multimodal optimization algorithms based on evolutionary algorithms have been widely studied [3]-[4]. Most conventional evolutionary optimization algorithms, such as genetic algorithms, evolutionary strategies, and particle swarm optimization methods, find only a single global solution in what is known as a genetic drift. To solve this problem, many practical studies involving modifications of evolutionary algorithms have been done to find multiple solutions to multimodal optimization problems [5]-[6].

The Big Bang-Big Crunch (BB-BC) algorithm has been recently introduced as a new heuristic search algorithm which relies on the theory of the evolution of the universe [7]. Because the BB-BC algorithm has a low computational cost and a high convergence speed, it is very efficient when the number of optimization parameters is high. The BB-BC method has shown good performance in actual engineering optimization problems [8]-[9].

Unfortunately, like other evolutionary algorithms, the BB-BC algorithm tends to converge towards the global optimum solution. Therefore, the standard BB-BC algorithm cannot simultaneously search for multiple solutions to multimodal problems. Thus far, research to develop a BB-BC algorithm to handle multimodal optimization problems has not been conducted. This paper deals with this problem, with several modifications applied to the standard BB-BC algorithm.

In this paper, we propose a new multimodal optimization algorithm based on the BB-BC algorithm and assisted by a surrogate model using compressed sensing (CS) theory. We use a surrogate model to determine the niche and its niche radius adaptively. The proposed algorithm reduces the computation time and cost significantly by eliminating the need for a large number of function evaluations, and the niche radius is adjusted adaptively according to the optimization results.

II. Brief Overview of the BB-BC Algorithm

The BB-BC algorithm consists of two main steps. The first step is the Big Bang phase, where candidate solutions are randomly distributed over the search space, and the next step is the Big Crunch phase, where a contraction procedure calculates a center of mass for the population [7]-[8].

The BB-BC algorithm can be summarized by the pseudo-code in Fig. 1.

Initialize population, x_i
Do While (Stop condition is not satisfied)
    Compute fitness function values, f_i
    Determine the center of mass, x_{cm} (Big Crunch Phase)
    Generate new candidate positions, x_i^{new} (Big Bang Phase)
End Do

Fig. 1. Pseudo-code of the BB-BC algorithm.

III. Proposed Algorithm

In this research, we propose a new multimodal BB-BC optimization algorithm assisted by a surrogate model using CS theory. Generally, in multimodal optimization algorithms, it is very difficult to determine a niche radius parameter which determines the size of the niche or species. Here, to ascertain the niche and its niche radius adaptively, we construct a surrogate model from selected samples and then find the peaks. The BB-BC algorithm is also utilized restrictively in the region within its niche radius.

The detailed process of the proposed algorithm is as follows.

Step 1—Generation of Initial Samples:

Generate initial samples randomly in the predefined search space and calculate their fitness function values.

Step 2—Construction of the Surrogate Model using CS:

Surrogate models are able to estimate approximately real objective functions. The spatial distribution on a predefined lattice region can be obtained through various interpolation methods, such as RSM and Kriging method. In this research, we apply a newly developed CS interpolation method. This interpolation method has the ability to reconstruct the objective function successfully with only a small number of selected samples. Consequently, it reduces the computational complexity more effectively.

Step 3—Finding Peaks:

In this step, the locations of local peaks are estimated on the points of a grid using the surrogate model.

Step 4—Calculating the Niche Radius using the Peaks:

The positions of the peaks in the present iteration calculated in step 3 are assigned as temporary niches, with each niche radius calculated based on the mutual distances of the peaks. The niche radius is determined by the Euclidian distance between the temporary niche and the nearest neighbor peak from it.

Step 5—Checking the Change of the Peaks:

The positions of the peaks in the present iteration calculated during step 3 are compared to those of the peaks one step behind and two steps behind the iteration. If all three step positions are nearly identical, the interpolation process is terminated and this algorithm goes to Step 10.

Step 6—Big Crunch Phase:

The Big Crunch is a convergence operator that has only one output, known as the center of mass x_{cm}, derived from (1):

$$x_{cm} = \sum_{i=1}^{N} \frac{1}{f_i} x_i \Big/ \sum_{i=1}^{N} \frac{1}{f_i} \tag{1}$$

The Big Crunch is applied to a predefined number of nearest neighbor samples of each peak within its niche radius. The position of the peak is updated if the fitness value of the center of mass is larger than the fitness value of the existing peak for a maximization problem, which is an elitism strategy between the existing peak and the new center of mass.

Step 8—Big Bang Phase:

Create new members to be used in the next iteration step. Spread new offsprings x_i^{new} around the peak (center of mass) using (2) within its niche radius

$$x_i^{new} = x_{cm} + \frac{r\alpha(x_{\max} - x_{\min})}{k} \tag{2}$$

where r is a random number from a standard normal distribution, α is the parameter limiting the size of the search space, and k is the number of iterations.

Step 9—Generation of Additional Samples:

Predefined numbers of samples are randomly generated in an unoccupied region. After selecting additional samples, the execution of this algorithm goes back to Step 2.

Step 10—Searching for Peaks in Detail within the Niche Radius:

To find the precise peaks in detail, an additional peak search process using the BB-BC algorithm is necessary. This process is performed within the niche radius of each peak (niche) obtained in step 4.

IV. Numerical Test and Result

To evaluate the performance of our algorithm, we applied it to test functions and electromagnetic machine designs. A detailed explanation will be presented in the full paper. Fig. 2 shows an example.

V. Conclusion

In this paper, a multimodal BB-BC optimization algorithm aided by a surrogate model using the theory of compressed sensing is proposed. The availability of this new algorithm is proved through comparisons with conventional methods, and it is applied to the design optimization of a permanent magnet machine.

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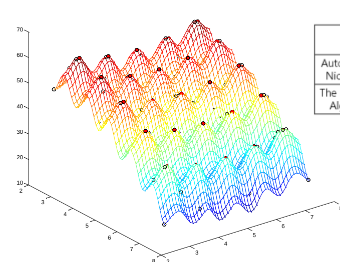

	Number of Peaks	Number of Function Call
Auto Tunning Niching GA	25	5039
The proposed Algorithm	25	837

Fig. 2. Optimization result on a test function.