A Kriging-Assisted Light Beam Search Method for Multiobjective Electromagnetic Inverse Problems

Siguang An[1], Shiyou Yang[2], and Osama A. Mohammed[3], *Fellow, IEEE*

[1]Department of Electrical Engineering of China Jiliang University, Hangzhou, 310018 China, annsg@126.com
[2]College of Electrical Engineering of Zhejiang University, Hangzhou, 310027 China, shiyouyang@yahoo.com
[3]Department of Electrical and Computer Engineering, Florida International University, Miami, FL 33174 USA, mohammed@fiu.edu

A kriging-assisted light beam search method is proposed to solve multi-objective inverse problems. To reduce the computational burden and to increase the convergence speed, a kriging model is introduced into the evolutionary procedure of the light beam search method. To guarantee the accuracy of the final Pareto solutions, a dynamic detecting strategy is used in the light beam search method. To reflect the preference of a decision maker in decision making, a boundary control mechanism is proposed to assure all the obtained Pareto solutions are well-distributed within the preference of the decision maker. To testify the accuracy of the proposed method, a series of test functions and a benchmark inverse problem TEAM Workshop Problem 22 are solved. The numerical results demonstrate the effectiveness and efficiency of the proposed method.

***Index Terms*—Decision making, inverse problems, Pareto optimization, surrogate modeling**

I. Introduction

IN DESIGNS of an electromagnetic device, conflict objectives are often involved which cannot be optimized at the same point. Therefore, a lot of excellent multi-objective optimization methods, aiming to find complete and even Pareto solutions, have been developed successfully in recent years. However, computations of the objectives in inverse problems are always implemented by numerical methods such as finite element analysis (FEA) which is overwhelmingly time-consuming. The unendurable optimization calculation time has become one of the most important and difficult obstacles for current multi-objective optimization algorithms to be used wildly in the practical designs. Therefore, endeavors have been made to reduce the FEA calculations and increase the convergence speed of the algorithm by balancing the exploration and exploitation, and modifying the evolutionary procedures of the optimization method. Among these strategies, the kriging model is a promising tool due to its explicit mathematical concept and performance in surrogating the nonlinear objective space. Typical optimization methods based on kriging model are summarized in [1]-[4]. In [1], a novel multi-objective evolutionary algorithm based on kriging surrogate models is applied to the design of a surface-mounted permanent magnet motor. The kriging-assisted multi-objective evolutionary algorithm is proved to have the potential of providing good solutions with a limited computation time budget. In [2], a dynamic Taylor kriging is combined with a multi-objective differential evolution algorithm to solve electromagnetic inverse problems. In this paper, the bias function of kriging is not fixed but optimally selected to minimize the fitting error. In [3], a kriging-assisted adaptive weighted expected improvement with rewards approach is proposed. In [4], a combination method with adaptive Taylor kriging and particle swarm optimization is given. All these algorithms can obtain Pareto solutions successfully and reduce the calculation of FEA effectively. There are mainly divided into two categories: searching for one Pareto solution [3] [4] and searching for a whole Pareto solutions [1] [2] [5]. However, from a practical engineering perspective, only one solution for the design is presumptuous and a whole Pareto front of a multi-objective design problem may not always necessary. In some cases only a special part of the Pareto front is attractive for a decision maker (DM). It is essential that the algorithm could use the knowledge of the DM to guide the iterative search process to minimize nonproductive explorations of the objective space [6]. In this regard, a kriging-assisted light beam search method [7] is proposed to obtain any fraction of the whole Pareto front under the preference of a DM with less FEA calculations.

II. Kriging-assisted Light Beam Search Method

A. Dynamic Detecting Strategy

Most of the current kriging-assisted optimization algorithms are to build an accurate kriging model firstly and then use this model in an optimization method to predict the objective function value. Building a precise kriging model needs lots of sampling points and the completely uncoupling process of modeling and optimization is not beneficial to decrease the number of FEAs. In this regard, in the proposed method the kriging model is updated within the light beam search method using a dynamic detecting strategy. After every hundred iterations, a detecting procedure is triggered to measure the accuracy of the kriging model. In the detecting section, an individual is picked up randomly in the current population and its objective value is computed using FEA. Compare the predicted value given by the kriging model and the objective value of the designated point and record the difference as e. A *Flag Index* I_F is defined as:

$$I_F = \exp(-(e-e_0)/T) \tag{1}$$

where, e_0 is the maximum tolerance error; T is a control parameter. If the value of the *Flag Index* is smaller than a random number r generated in [0,1], the kriging model is need to be updated. In order to make the full use of the current information, the new sampling points to update the kriging model are based on the current population instead of a random sampling. Because although the model is not as accurate as demanded yet, the current individuals are still the superior solutions to some extent.

B. Boundary Control Mechanism

In the light beam search method [7], the searching direction is defined by using a reservation point and aspiration point, and the middle point is the intersection of the searching direction and Pareto front. A veto threshold is defined as the maximum change based on the middle point. The boundary of the searched Pareto segment is based on the middle point and the veto threshold. The middle point is unknown at the beginning of the searching process, and is evolved through the iteration procedure of the algorithm. Therefore, the original light beam search method suffers a poor performance in terms of robustness performances. Once the middle point is shifting, the Pareto segment is deviating. The searched Pareto solution can not represent the preference of DM precisely. To reflect the preference of the DM more strictly, a boundary control mechanism is proposed. The boundary of Pareto solutions searched is detected in iterations. If the boundary is overpass the preference of DM, a new division of the subdomains onto the utopia plane will be complemented which is related with the boundary and distribution of the Pareto solutions.

III. Numerical Results

To validate and demonstrate the advantages of the proposed algorithm, the test function MOP2 and the TEAM Workshop problem22 in [5] are solved.

The parameters of the proposed algorithm for solving MOP2 are set as: nd =5, z_r=[0 0], $z\_ v$=[1 1], v=[0.05 0.05], N=40, θ_0=[10 10 10], e=10^{-4}; while for solving the TEAM Workshop Problem 22 are set as: nd =10, z_r=[0 0], $z\_ v$=[0.08 0.08], v=[0.009 0.02] , N=40, θ_0=[10 10 10], e=10^{-4}. nd is the number of the desired Pareto solutions; z_r and z_v is the aspiration point and reservation point, respectively; v is the veto threshold; N is the number of the population; θ_0 is the initial parameter for the kriging model; e_0 is the maximum tolerance error. Fig. 1 and Fig. 2 give the searched Pareto front using the proposed method for MOP2 and TEAM Problem 22 respectively. Obviously, the proposed method can find a referenced segment within the whole Pareto frontier. Table I and Table II are the comparison of some key points of the original [7], the improved [8] and the proposed method for MOP2 and Workshop Problem 22. It is clear that the proposed method can find a preference part of Pareto front successfully while the iterative number of FEA is decreased dramatically.

References

[1] M. Li, F. Gabriel, M. Alkadri and D. Lowther, "Kriging-assisted multi-objective design of permanent magnet motor for position sensorless control," *IEEE Trans. Magn.*, vol. 52, no. 3, 7001904, Mar. 2016.

[2] B. Xia, N. Baatar, Z. Ren and C. Koh, "A numerically efficient multiobjective optimization algorithm: combination of dynamic Taylor kriging and differential evolution," *IEEE Trans. Magn.*, vol. 51, no. 3, 9400604, Mar. 2015.

[3] S. Xiao, M. Rotaru, and J. K. Sykulski, "Adaptive weighted expected improvement with rewards approach in kriging assisted electromagnetic design," *IEEE Trans. Magn.*, vol. 49, no. 5, pp.2057-2060 , May 2013.

[4] B. Xia, M. Pham, Y. Zhang and C. Koh, "A global optimization algorithm for electromagnetic devices by combing adaptive taylor kriging and particle swarm optimization," *IEEE Trans. Magn.*, vol. 49, no. 5, pp.2061-2064, May 2013.

[5] I. Voutchkov and A. Keane, "Computational intelligence in optimization," ALO 7, Y. Tenne and C. K. Goh, Eds. Springer-Verlag Berlin Heidelberg, 2010, pp. 155-175.

[6] S. L. Ho, Shiyou Yang, and Guangzheng Ni, *IEEE Trans. Magn.,* vol. 44, no. 6, pp. 1038-1041, June. 2008.

[7] K. Deb and A. Kumar, *IEEE Congress on Evolutionary Computation*, pp.2125-2132, Sept. 2007.

[8] Siguang An, Qing Li, Shiyou Yang, *IEEE Trans. Magn.,* vol. 52, no. 3, 7000904, Nov. 2015.

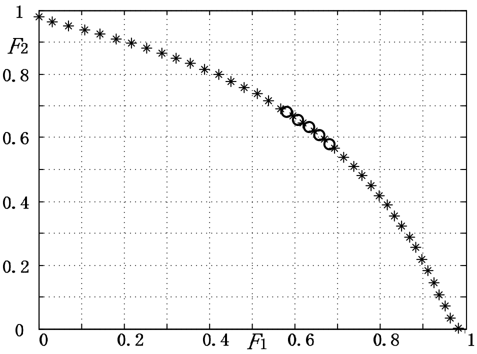

Fig. 1. The searched Pareto front of MOP2: ∗ the whole Pareto front obtained by a normal intersection method, ○ by the proposed method.

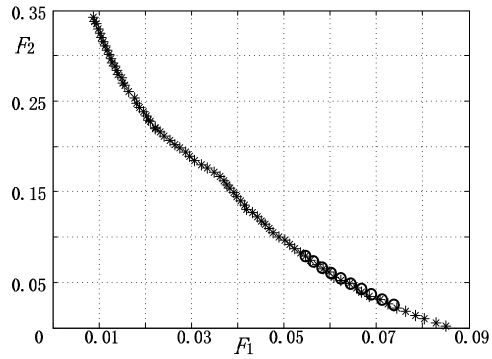

Fig. 2. The searched Pareto front of TEAM work 22: ∗ the whole Pareto front obtained by a normal intersection method, ○ by the proposed method.

TABLE I
Key Points of the Original and the Proposed Method on MOP2

algorithm	Middle point	Max-F_1-point	Max-F_2-point	No. of iterations
original	(0.632,0.632)	(0.681,0.581)	(0.580,0.680)	20000
improved	(0.491,0.491)	(0.681,0.581)	(0.581,0.681)	11649
proposed	(0.633,0.633)	(0.681,0.581)	(0.581,0.681)	390

TABLE II
Key Points of the Original and the Proposed Method on TEAM 22

algorithm	Middle point	Max-F_1-point	Max-F_2-point	No. of iterations
original	(0.0597,0.0610)	(0.0687,0.0350)	(0.0535,0.0810)	20000
improved	(0.0712,0.0712)	(0.0733,0.0335)	(0.0544,0.0790)	11361
proposed	(0.0649,0.0640)	(0.0740,0.0290)	(0.0567,0.0812)	587