Research on Crow Swarm Intelligent Search Optimization Algorithm Based on Surrogate Model

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1. Introduction

The complex engineering optimization is actually a computationally expensive optimization problem. Swarm intelligence algorithm can be used to increase calculation efficiency and the accuracy. However, these complex engineering optimization problems often need to use the simulation model to replace the real model. The swarm intelligence algorithm needs a lot of callings of the real function in the optimization process, which make the cost sharply increase in expenses. Some scholars have introduced the surrogate model into the swarm intelligence algorithm to effectively reduce the number of real function calls. However, in the existing research, the surrogate model and the swarm intelligence algorithm are only two independent tools to solve the optimization problem.

2. Body of abstract

In order to improve the optimization efficiency and further reduce the number of real function calls, this paper proposes the Surrogate-assisted Crow Search Algorithm(SACSA) by combining the characteristics of swarm intelligence algorithm and surrogate model. The proposed algorithm uses the initial samples to construct the initial surrogate model. The initial samples are applied as the initial crow population, then the current best solution is obtained by the improved Crow Search Algorithm (CSA). If the minimal distance limitation is met, the best solution will be added to the initial sample set. Then the surrogate model is updated with new sample set. The proposed method integrates CSA and surrogate model as an organic whole. Finally, the proposed method is compared with EGO, MSSR, ARSM-ISES, AMGO and SEUMRE, MPS, HAM algorithms by using 9 classical test functions. The results show that the proposed method can find global optimality with fewer samples and is beneficial to improve computational accuracy and efficiency.

3. Crow search algorithm

The crow search algorithm is a new swarm intelligence algorithm, which is derived from the study of the living habits and intelligent behavior of the crow population. Crows are considered to be one of the smartest birds[1]. They have demonstrated self-awareness in testing, has the ability to make and use tools and to communicate in complex ways. Crows also can find hidden spots of food after a few months and prevent food from being stolen by observing food hiding points.The key of CSA is generating new crow which have two states as shown in Eq. (1).

$$X^{i,iter+1} = \begin{cases} X^{i,iter} + r_i \times fl^{i,iter} \times (m^{j,iter} - X^{i,iter}) & r_i \geq AP^{j,iter} \\ a\ Random\ Position & otherwise \end{cases} \tag{1}$$

4. The Kriging Surrogate Model

The Kriging Surrogate Model was proposed by geologist Danie in 1951[2]. The Kriging model[3-4] not only utilizes the data information of the samples but also fully considers the correlation features between the samples. Thus an approximate function which more accurately describe the object problem can be established. The established approximate function can predict the function value at any point. The Kriging model has a good approximation ability to the nonlinear function with a unique error estimation function, which is widely used in the optimization field.

5. The Surrogate-assisted CSA

In order to integrate the CSA with the surrogate model, combined with the characteristics of the surrogate model, the CSA is improved. The surrogate model needs to call the real performance function to obtain the response samples during the construction process. These response samples are usually expensive and time consuming. The initial population of the swarm intelligence algorithm is often composed of the approximate response values based on the established surrogate model. The initial samples which used to establish the surrogate model are incorporated into the initial population of the CSA, which can make full use of the information of the search space obtained by the real performance function. As the number of iteration increases, the initial sample and the crow population are dynamically updated. The accuracy of surrogate model can be continuously improved, which can lead to more accurate search of the CSA. The Flow chart of the Surrogate-assisted improved CSA is show in Fig.1.

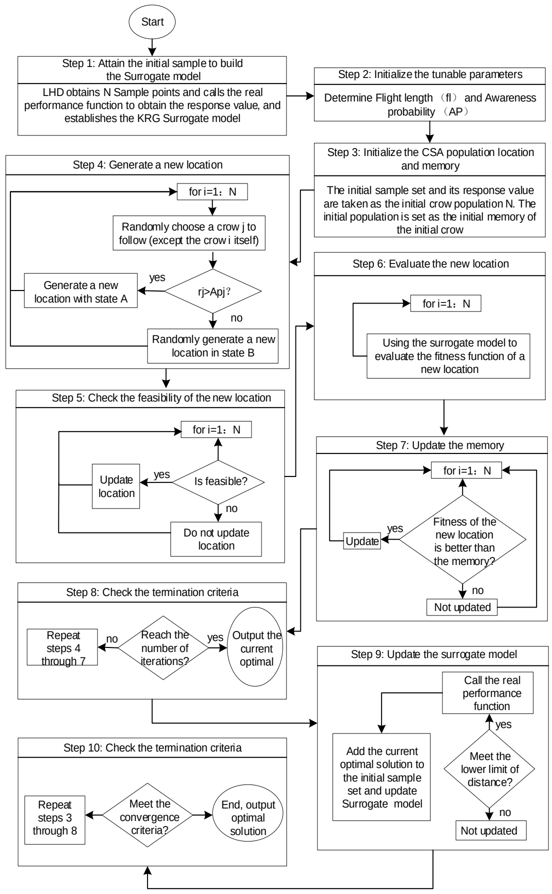

Fig.1 Flow chart of the Surrogate-assisted improved CSA

6. Test function validation

In this section, nine typical test functions are applied to verify the proposed SBCSA algorithm. The characteristics of nine test functions are described in Tab.1. Each function is tested with 10 different sets of initial samples. The optimization results are compared with some well-known optimization algorithms such as EMU[5], MSSR[6], ARSM-ISES[7], AMGO[8], and SEUMRE,MPS and HAM algorithms[9].

Table 1 Table caption must be centered

Test function	dimension	optimal value
Briainin	2	0.3979
Sasena	2	-1.4565
Goldstein_price	2	3.0000
Six_hump Camel	2	-1.0316
Booth	2	0
Hartman3	3	-3.8628
Hartman6	6	-3.3224
Trid4	4	-16.0000
Trid8	8	-112.000

7. Conclusions

In this paper, considering the characteristics of the CSA algorithm and the optimization of the surrogate model modeling, a new surrogate-assisted intelligent algorithm is proposed by combining CAS algorithm and Kriging method. The nine test functions are applied to test the proposed method. In order to verify the feasibility of the proposed method, several existing typical algorithms are compared with the proposed method. The optimization results show the effectiveness of the proposed algorithm.

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