2020 国际制导、导航与控制学术会议

2020 International Conference on Guidance, Navigation and Control

2020 年 10 月 23-25 日 中国•天津

October 23-25, 2020 Tianjin, China

程 序 册

Final Program

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ICGNC 2020

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Integrated Flight/Propulsion Optimal Control for DPC Aircraft based on GPR-PSO

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Abstract. The distributed propulsion configuration (DPC) is a new aircraft design concept proposed for the future and the design causes the tight coupling between aerodynamics, flight and propulsion system and creates the redundancy of control input. Therefore, an integrated optimal control that can improve flight performance is required. In this paper, particle swarm optimization (PSO) based on Gaussian Process Regression (GPR) (GPR-PSO) is proposed to solve the optimization control problem. GPR has obvious advantages in small sample, high dimensional, and non-linear modeling problems. GPR is used to model L/D and control inputs based on sample data. PSO is a global optimization method with high accuracy and fast speed. The model given by GPR is used as the objective function for PSO to search for the optimal solution in the feasible region, and a control allocation strategy can be determined based on the optimization result. Simulation results of example and flight/propulsion integrated optimization control show that GPR-PSO leads better accuracy compared to PSO based on piecewise linear interpolation and their convergence speed is similar.

Keywords: Distributed propulsion configuration, Integrated flight/propulsion optimal control, Gaussian Process Regression, Particle swarm optimization.

1 Introduction

In recent years, the world's aviation industry has focused on economics and environmental protection. The distributed propulsion configuration (DPC) is a new aircraft design concept proposed for the future. Its characteristics are: the blended wing body (BWB) layout can significantly improve the lift/drag characteristics; the use of several sets of semi-buried propulsion system distributed throughout the airfoil can take the initiative to change the field characteristics, to achieve active adjustment of aerodynamic and load distribution [1] [2]. This design makes the flight, aerodynamics and propulsion more closely coupled, creates more control variables and leads to the redundancies of control. Therefore, the space of control allocation optimization is large with many optimization variables and physical constraints. The control allocation problem is one of the core difficulties in solving the control problem of the new configuration aircraft. It requires high levels on speed and accuracy of the optimization algorithms.

Because of the actuator redundancies, the integrated control problem of DPC aircraft can turn into a control allocation problem. The research has experienced the development from static to dynamic, from direct allocation to optimal allocation and from linear optimization to non-linear optimization. Integrated flight/propulsion optimization is a constrained optimization problem without explicitly expression, there is no exact function of the objective function and constraints, and only a large number of input and output observation samples obtained through numerical simulation. Traditional allocation methods, such as pseudo-inverse method and tandem chain method perform poorly in optimization [3]. And some intelligent optimization methods have also been applied in this field. [4] use genetic algorithms to solve the control allocation problem. [5] give and compare the simulation results of control allocation based on particle swarm optimization, ant colony algorithm and RBF neural network. [6] introduce the deep learning method to solve the nonlinear control allocation problem of space reentry vehicle. [7] introduce the research results of control allocation are discussed respectively from three aspects of static, dynamic and nonlinear control allocation. [8] use dynamic allocation method in the aircraft with thrust vector and prove dynamic property and steady property of the algorithm. [9] use quadratic optimal control that takes amplitude and velocity constraints into consideration to deal with the control redundancy. [10] propose a combination of genetic algorithm and mathematical planning method to solve the control allocation problem. [11] apply particle swarm optimization to the design of generalized inverse control allocation method. Most of these methods perform mediocrely in speed, and the modeling of the objective function through samples also has a large deviation, which makes the optimization result dissatisfied.

Compared with the traditional interpolation method used to process flying data, Gaussian Process Regression (GPR) has smaller modeling bias and reduces overfitting when dealing with high-dimensional small sample data modeling problems. It can make the model of objective function more accurate and improve the optimization efficiency and accuracy. Particle swarm optimization (PSO) is a global optimization algorithm on random search. The advantages of PSO are faster optimization speed and breakthrough of local optimization through parameter adjustment to reach more accurate global optimization results.

This paper researches the DPC aircraft, describes its optimization problem and features and introduces how to solve the problem by GPR modeling the objective function and PSO searching the optimal solution. Compared with traditional modeling optimization methods, an example is used to explain the advantages of the combined optimization method. Finally, the method is combined with experimental data to solve the integrated flight/propulsion optimization problem and analyze the results.

2 Description of optimization problem

2.1 Integrated Flight/Propulsion Optimization Control Program

There is a strong coupling effect between propulsion system and aerodynamic as the result of the DPC, called Boundary layer ingestion (BLI). Propulsion system and aerodynamic significantly influence each other by BLI. BLI can improve the aircraft aerodynamic. It also leads to the control of the propulsion system, such as the boost ratio and the area of the tail nozzle, which will directly affect the aerodynamic of the aircraft and change the force and torque on the aircraft. In this study, a 3-dimensional model of a 3-engine DPC aircraft is built and divided the mesh for integrated modeling, especially for propulsion system modeling. Using the boundary conditions provided by the propulsion system model, run numerical simulation of BLI by CFD calculation [6]. Based on the integrated flight/propulsion model and simulation data, GPR is used to model the hidden relationship between control variables and flight performance. Then PSO algorithm is used to find the solution of optimal control allocation, which maximizes flight performance while meeting constraints.

2.2 Mathematical form of Optimization Problem

The control allocation problem can be stated as follows:

$$B\mathbf{u} = \mathbf{v}$$

$$s.t.\,\mathbf{u}_{\min} \leq \mathbf{u} \leq \mathbf{u}_{\max}$$

$$\max C_{LD}(\boldsymbol{u}) \tag{1}$$

In these formulas, $\mathbf{u} = [\pi_{kl}^*, A_{8l}, \pi_{km}^*, A_{8m},\ \pi_{kr}^*, A_{8r}, \alpha]$, parameters represent the boost ratio, tail nozzle area of the three groups of engines and angle of attack in turn, $\mathbf{v} = [L_C, M_C, N_C, T_C]^T$, parameters represent expected roll, pitch and yaw moment and thrust in turn. max $C_{LD}(\mathbf{u})$ means maximizing the L/D. $\mathbf{u}_{min}, \mathbf{u}_{max}$ is the lower and upper limits of input.

Aerodynamic data of the DPC aircraft is given by CFD numerical simulation under different flight conditions, angle of attack, and control parameters of the propulsion system. According to the flight/propulsion mechanical model, we obtain the force and moment required by the aircraft under different cruise conditions. The optimization aims at improving the flight performance by maximizing the L/D on the premise of meeting control requirements and physical constraints.

The optimization variables have 7 dimensions without restrictions and the relationship between the target L/D and the input is a constraint optimization problem without explicit expression. So, GPR is used to model the objective function based on the data of input and L/D from CFD calculation then optimize the agent model by PSO. At last the optimal control allocation can be determined by the solution of PSO.

3 Model and Optimization based on GPR-PSO

3.1 Model based on GPR

GPR fits a Gaussian process on the set of known data samples. It describes objective function with a multivariate joint Gaussian distribution and predict the distribution of new point of function. Gaussian process consists of arbitrary finite random variables with a joint Gaussian distribution. Its properties are completely determined by the mean function and covariance function, that is:

$$m(x) = E[f(x)] \tag{2}$$

$$k(x,x') = E[(f(x) - m(x))(f(x') - m(x'))] \tag{3}$$

where x, x' are random variables, so Gaussian process can be defined as:

$$f(x) \sim GP(m(x), k(x,x')) \tag{4}$$

The model of L/D is set to $C_{LD} = f(\mathbf{u})$,where $\mathbf{u}$ is the control input and f($\mathbf{u}$) is unknown. We sample the control input uniformly in the feasible region into the set X and put their corresponding L/D from CFD simulation into set y. x_* is prediction point of control input and f_* is the corresponding prediction L/D. Generally, for convenience, the mean function is preprocessed to 0 then we get the joint distribution of y and f_*: $\begin{bmatrix} y \\ f_* \end{bmatrix} \sim N(0, \begin{bmatrix} K(X,X) + \sigma_n^2 I_n & K(X,x_*) \\ K(x_*,X) & k(x_*,x_*) \end{bmatrix})$, where $K(X,X) = K_n = (k_{ij})_{n*n}$ is a n*n order symmetric positive covariance matrix, $k_{ij} = (x_i, x_j)$ measures the correlation between x_i, x_j, $K(X,x_*) = K(x_*,X)^T$ is the n*1 order covariance matrix of x_* and X, I_n is n*n order identity matrix. Then, after factorizing the joint distribution using the Schur complement for the joint Gaussian, the posterior distribution of L/D at the prediction point can be calculated as $f_*|X, y, x_* \sim N(\bar{f}_*, cov(f_*))$, where

$$\bar{f}_* = K(x_*,X)[K(X,X) + \sigma_n^2 I_n]^{-1} y \tag{5}$$

$$\text{cov}(f_*) = k(x_*,x_*) - K(x_*,X)\,[K(X,X) + \sigma_n^2 I_n]^{-1} K(X,x_*) \tag{6}$$

is the mean and variance of f_* at the corresponding x_* [13].

As the mean is set to 0, the focus of GPR is to determine the covariance function also called kernel function. Matern kernel and the Gaussian kernel are commonly used among kernel function [14]. For example, Gaussian kernel is used in this paper, it is defined as:

$$\kappa(x,x') = exp\left(-\frac{1}{2}(x - x')^T \Sigma^{-1} (x - x')\right) \tag{7}$$

where Σ is the kernel parameter matrix. When the kernel function is specified, the next job is to determine the parameters of the kernel function on the sample set, which is called the training hyperparameters for the GPR (or the process of GP model training and updating). The kernel parameters or hyperparameters can be estimated by empirical Bayesian methods. In order to reduce the computational complexity, many approximate method can be used [15].

3.2 Optimization based on PSO

PSO is a swarm intelligence optimization algorithm derived from the problem of bird predation.

First, PSO randomly generates several points in the feasible region as the initial swarm. Each particle of swarm represents a potential solution. The initialization process determines the size of the swarm, the initial position of each particle, and the initial moving speed. Then, PSO calculates fitness of each particle. Fitness indicates the quality of a particle. In this study, the fitness is calculated by the agent model that is established by GPR, fitness=$\bar{f}_*$(u). Next, PSO find the individual best fitness, which is the optimal value of individual historical fitness, and global best fitness, which is the optimal value of the swarm. At the beginning of each iteration, PSO updates the speed of each particle according to the speed update formula and then uses new speed to update the position [10].

Update formula is as follows:

$$V_{id}^{k+1} = \omega V_{id}^{k} + c_1 r_1 (P_{best}^{k} - \mathbf{u}_{id}^{k}) + c_2 r_2 (G_{best}^{k} - \mathbf{u}_{id}^{k}) \tag{8}$$

$$\mathbf{u}_{id}^{k+1} = \mathbf{u}_{id}^{k} + V_{id}^{k+1} \tag{9}$$

where V_{id}^{k} is the velocity of particle in the k-th iteration, $\mathbf{u}_{id}^{k}$ is the position of particle in the k-th iteration as well as a group of control input, r_1, r_2 are random numbers, c_1, c_2 are adjustable coefficients, P_{best} is the position of individual best fitness, G_{best} is the position of best fitness in the swarm.

In each iteration, algorithm calculates fitness of each particle, updates P_{best} and G_{best} by comparing the fitness until it finds the satisfied global best fitness. Algorithm stops when the situation that G_{best} doesn't change or change within range keeps until the set iteration is reached. Algorithm provides the last G_{best} as the optimal result.

In actual optimization, c_1, c_2, ω need to be adjusted to ensure the accuracy and efficiency of algorithm. For the problem in this paper, we set different ω in different periods of optimization. In the early, value of ω is large to keep the wide search range and avoid falling into local optimum. In later period, value of ω gets smaller and smaller to search exactly and converge fast. We decrease c_1 and increase c_2. Let the search to the global, and weaken the influence of a large number of existing local optimizations on the convergence speed and accuracy. Generally, the population size is set to n, the maximum number of iterations is N, and the time complexity of the algorithm is $O_{(n^2)}$.

4 Simulation and Analyze

4.1 Comparison of agent model and optimization

We select the function f(x)=$0.5 - \frac{sin^2\left(\sqrt{x^2+y^2}\right)-0.5}{[1+0.001*(x^2+y^2)]^2}$ as the example for modeling comparison. The function only reaches maximum value of 0 at one point, corresponding position (0,0). There are a large number of local optimums, and peaks and valleys alternate.

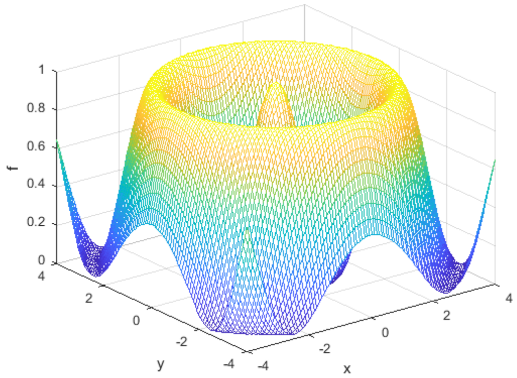

Fig. 1. Original function

As shown in Fig.1, we randomly and uniformly choose 100,00 points from original function and do grid drawing.

We randomly and uniformly choose 4,00 points as the sample for modeling. Based on the sample, GPR and Piecewise linear interpolation (PLI) is used for modeling, then predict 100,00 points selected before, plot and compare the errors.

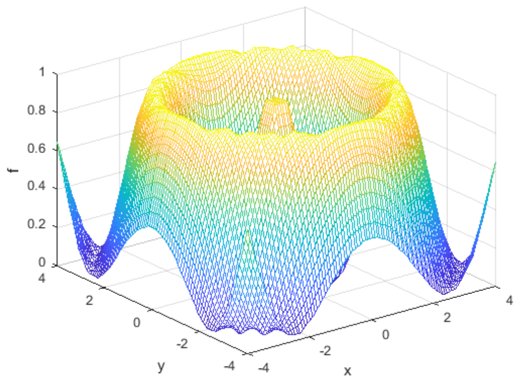

Fig. 2. Agent model generated by PLI

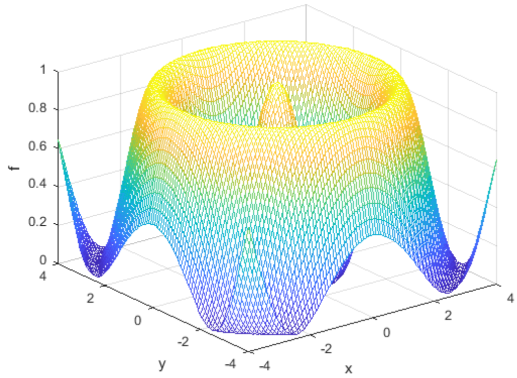

Fig. 3. Agent model generated by GPR

Fig2, Fig3 are the modeling results of GPR and PLI at 100,00 points selected. The sum of squared errors of GPR is 0.00085594, and the sum of squared errors of PLI is 4.8225. On the problem of fitting a large number of data to this small sample, PLI shows obvious overfitting, and the cumulative error is large. The model given by GPR has obvious advantages in these two aspects. Due to over-fitting in the model from PLI, the values fluctuate greatly within the interval, so subsequent optimization may be more likely to fall into a local optimum.

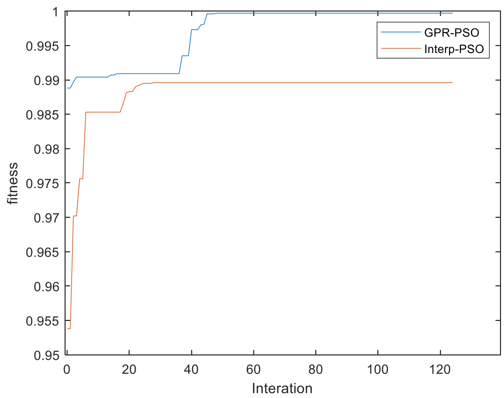

Fig. 4. Optimization results of GPR-PSO and Interp-PSO

PSO is used to optimize the two models (in this example, the optimization is to find the maximum value). The result is shown in Figure 2. The optimal value of GPR-PSO is 0.9997, corresponding position is (-0.000113, -0.000438). The optimal value of Interp-PSO is 0.9896, corresponding position is (-0.1839，-3.1579). PSO starts from same initial population in both searches, because of the difference between models, they lead different initial fitness. The optimal solution from the model given by GPR is closer to the true value and has obvious advantages. There are two main reasons. One is that model given by GPR has a smaller deviation and is closer to the real situation near the optimal value. Second, the over-fitting problem of the model given by PLI caused the optimization to fall into a local optimum.

This example is similar to flight/propulsion parameters optimization problem in this paper. The optimization problem of the paper is higher in dimensionality and the sample points are sparser, the advantages of GPR will be more obvious

4.2 Integrated Flight/Propulsion Optimization Control based on GPR-PSO

Select the cruise state with H = 5000 m and Ma = 0.6 for simulation analysis. In this flight state, the aircraft is in a balanced flight state, and the residual force and moment are zero, $L_{Rc} = 0, T_{Rc} = 0, M_{Rc} = 0$. The control parameters of three groups of engines are the same, π_k^* and A_8 of all groups are the same. The adjustable range of π_k^* and A_8 is defined according to the thrust required range of the aircraft cruise. The integrated flight/propulsion optimization control problem can be stated as follows:

$$\max C_{LD}(\alpha, \pi_k^*, A8)$$
$$s.t.\, L_R(\alpha, \pi_k^*, A8) = 0$$
$$T_R(\alpha, \pi_k^*, A8) = 0,\, M_R(\alpha, \pi_k^*, A8) = 0$$
$$-2^o \le \alpha \le 8^o,\, 1.38 < \pi_k^* < 1.58,\, 1.4 < A8 < 1.56 \tag{10}$$

We establish the agent model with 210 random uniform samples and their corresponding L/D from CFD simulation by GPR. The agent model is used as the objective function for PSO. We take the intersection from the range of each control input and the balancing conditions of forces and moments as the search range.

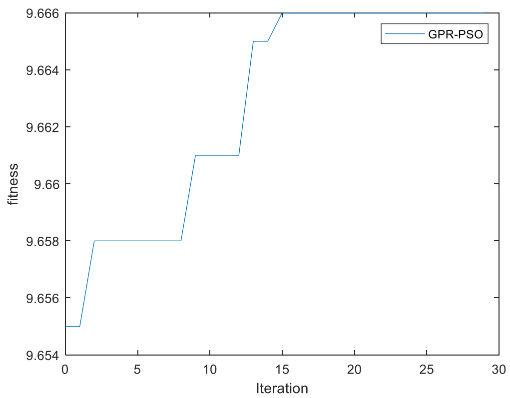

Fig. 5. Optimization result of GPR-PSO

The optimization process is shown in Fig.5.

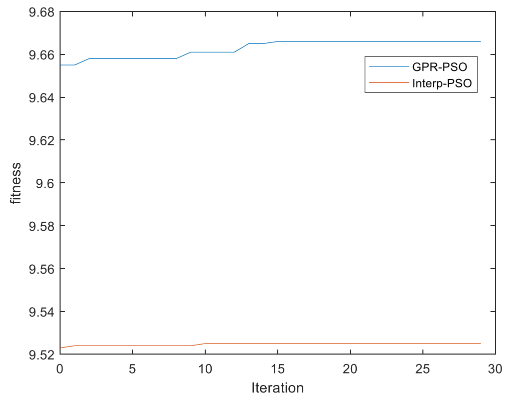

Fig. 6. Optimization results of GPR-PSO and Interp-PSO

Repeat the optimization with PLI instead of GPR and both results are shown in Fig.6.

The maximum L/D given by GPR-PSO is 9.666 and corresponding input is A8=1.4973, PiKStar=1.5149, alpha=4.8086. The maximum L/D given by Interp-PSO is 9.5251, corresponding input is A8=1.56, PiKStar=1.5, alpha=6.

Comparing the results of the above optimization, it is obvious that the optimization based on GPR leads better solution, and the optimization based on PLI falls into the local optimum. The model established by GPR is smoother and closer to reality, so the optimization results cross multiple local optimal solutions and better guides the process of optimization. They take similar time and GPR-PSO gives better optimization performance.

Compared with traditional optimization based on interpolation models, GPR-PSO achieves better optimization results with more accurate and smooth modeling when the efficiency is similar. The advantage of GPR-PSO is obvious under the small sample and high dimensionality.

5 Conclusion

This paper uses the advantages of GPR to deal with high-dimensional small sample modeling problems and the features of PSO for global optimization and fast convergence under appropriate parameter settings to solve the flight/propulsion integrated optimization control problem for the DPC aircraft and gets better result than traditional PLI modeling and PSO. The optimization time is basically controlled within an acceptable range. It also proves that BLI plays an important role in the performance improvement of the DPC aircraft, and there is huge development potential at the optimization level.

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