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HYPERPARAMETERS OPTIMIZATION FOR ADAPTIVE DESIGN OF EXPERIMENT APPLIED TO WIND TUNNEL TESTING

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Abstract

A traditional experimental approach for wind tunnel testing called 'One Factor at a Time' has been widely used for modelling aerodynamic coefficients of aircraft, which has a disadvantage in terms of high resource consumption. The design of experiment (DoE) technique has been used for wind tunnel testing to overcome this disadvantage with well-designed constructed experimental plans. An adaptive DOE technique utilizes not only predetermined experimental plan based on the information on the model and facility but also acquired experiment results during the test in real time. Additional experimental points are determined using the Gaussian Process (GP) with the previously acquired experimental results, and this procedure continues until the stopping criterion – primarily in terms of modeling error – is satisfied. This paper introduces a method to optimize the hyperparameters characterizing the Gaussian Process applied to adaptive DOE based wind tunnel testing for modeling aerodynamic coefficients of an aircraft. The proposed optimal hyperperameter selection procedure reflects the confidence intervals of measuring device, improving the GP process and its termination condition. All of possible local optima of hyperparameters are investigated and the best available option to improve developed model is selected. Three cases with different aircraft configuration are presented to demonstrate the effectiveness of the proposed method.

1 Introduction

The design of Experiments (DoE) is a procedure to select experimental points that can minimize resource consumption while securing the accuracy level of the obtained results. The procedure pursues to find the best ways to conduct experiments and analyze the results for efficient modeling [1]. The DoE was first used for agricultural applications, and is currently used for various fields involving experiments. In the wind tunnel testing area, the DoE has been used since the end of 20th century by the DeLoach group of NASA Langley research center [2, 3] and it is extensively studied to model aerodynamic characteristics of aircraft [4, 5]. The wind tunnel testing is very cost-intensive task that accounts for a large portion of the verification and validation procedure of an aircraft. Hence, the use of DoE that can reduce the number of experiments and/or the experimental time would be an effective approach to save the research and development (R&D) of an aircraft.

In this paper, we introduced an adaptive design of experiment procedure that can be applied to the wind tunnel testing based aerodynamic coefficient modeling. The introduced procedure is different from traditional DoE methods in that the acquired data will be analyzed real-time to select next experiment points. Since the experiment points are selected after partial data is collected, the whole experiment plan is not fixed when we start the experiment. We used Gaussian Process (GP) [6] to model multiple aerodynamic coefficients of aircraft. The advantage of the GP is that it can calculate uncertainties of unexplored experiment region. Thus, the most uncertain point can be pointed out as next experiment point to improve the regression model efficiently.

The Gaussian Process regression model uses hyperparameters: the characteristic length-scale (ℓ) and noise variance (σ_n) to specify a model. The accuracy and shape of the model can vary depending on the hyperparameters, therefore, their selection is very important when we use the Gaussian Process model.

The rest of this paper is organized as follows. Section 2 introduces the detailed methodology of proposed adaptive design of experiment. Section 3 provides experimental setup and aerodynamic coefficients modeling results. The conclusions and discussions are represented in Section 4.

2 Methodology

The objective of the experiment considered in this paper is modeling of two aerodynamic coefficients: the normal force coefficient (C_N) and the pitching moment coefficient (C_m) of a vehicle. Detailed explanation about modeling methodologies which are the three-phase adaptive DoE procedure and length-scale optimization are presented as following sub-sections.

2.1 Three-Phase Adaptive DoE Procedure

The proposed adaptive DoE approach is composed of three steps. The first step is Initial Test which make initial design points and regression model. The second step is Adaptive Test which determine to execute more test or not and where to add next experiment point. After two steps, the Confirmation Test is needed to check the generated model is accurate or not. The explanation about each steps is as follows.

2.1.1 Initial Test

In the initial test, the experimental points to initialize regression model. We adapt Latin Hypercube Design (LHD) [1] to make initial experimental points for the initial test. The traditional DoE method is useful when we want to get a rough idea about given experiment range since it sporadically distributes experimental points over the whole experiment variables. Since the data at corner points are highly important in generating Gaussian Process regression model, we forced to include the corner points in initial points making.

2.1.2 Adaptive Test

The second phase is Adaptive Test which is the process to add one point at a time with analysis of acquired data. In this step, we need to optimize hyperparameters which are length-scale and noise variance. Then, a decision whether to continue the experiment or not should be made at this step. The two factors which are 95% confidence interval of measuring device (CI_{DAQ}) and regression model (CI_{GP}) generated with Gaussian Process are used to determine the more experiment should be executed or not. When the ratio of two confidence intervals (CI_{GP}/CI_{DAQ}) are smaller than predefined threshold value, the regression model can be considered as good enough to represent overall behavior of actual aerodynamic coefficients.

If the regression model is not sufficiently good to terminate the experiment, one more experiment point should be added. The worst case degradation approach is used to select next experiment point. Since the objective of this research is to model two aerodynamic coefficients at the same time, we should select which coefficients are considered when choosing next experiment point. This is based on the ratio of confidence intervals (CI_{GP}/CI_{DAQ}) which is used for previous decision process. The coefficient which has bigger ratio is selected then the location where largest uncertainty is occurred. The uncertainty can be calculated stochastically with Gaussian Process.

2.1.3 Confirmation Test

The final step of proposed adaptive DoE approach is Confirmation Test. In this step, we randomly select additional experiment points which are not chosen in the previous two steps and gather data at the points to confirm the generated regression model is well accord with the confirmation points. This procedure is only for verifying that how the model is well fitted with unexplored region. The data acquired in this step is not used for refining the regression model.

The figure 1 represents the flowchart of three steps and brief explanation about them.

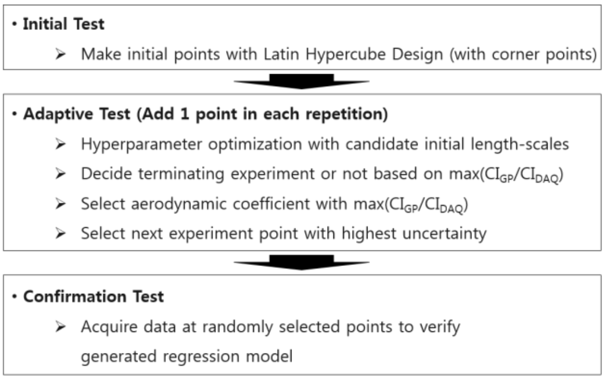

Fig. 1. Illustration of Three-phase Adaptive DoE Procedure

2.2 Hyperparameters Optimization

The hyperparameters optimization process is essential in the step of Adaptive Test for more efficient experiment execution. There are two important hyperparameters that influence the accuracy of the Gaussian Process regression model. The first one is characteristic length-scale(ℓ). The value of length-scale determines how relevant the data with its neighbor regions. As length-scale bigger, the data has more influence on far region and has less influence in the case of smaller value. The second hyperparameter is noise variance (σ_n). The value represents how much noise is included in the regression model. The width of confidence interval become large when the noise variance is big and so on. The default value of noise variance is set as noise level of measuring device but it should be optimized with maximum marginal likelihood method.

The important point when finding optimal hyperparameters is that there can be several local optimal values along the experiment region. When the initial value of length-scale and noise variance is determined, searching optimal value is done with conjugate gradient method maximizing marginal likelihood with GPML Toolbox [7]. However, the result of optimality searching can be different according to initial values due to the reason previously mentioned. Therefore, we added a step to compare the different local optimal values to find out best regression model among the various result.

In this step, we set the candidate initial length-scales within the possible feasible values then execute optimizing for each initial values. The initial values should be assigned to each experimental variables, so it could be matrix form when two or more experimental variable exist.

3 Results

3.1 Experiment Device

The 1:6.3 scaled Vympel R-73 shaped missile aircraft is used as the subject of aerodynamic coefficients modeling. The wind tunnel experiment was conducted in low speed wind tunnel at KAIST, Republic of Korea. Detailed specification of aircraft and wind tunnel is presented in figure 2.

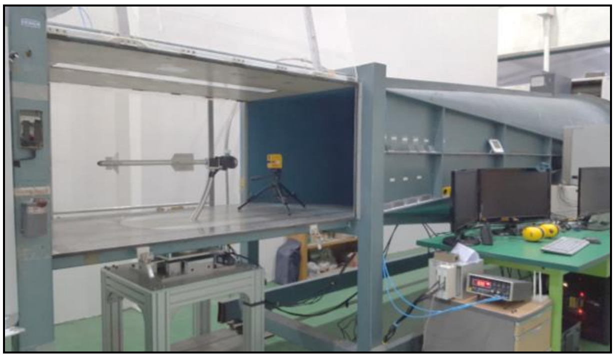

Fig. 2. Model aircraft installed in the wind tunnel

Table. 1. Specification of model aircraft and wind tunnel in KAIST.

Property of model aircraft	Value
Length (mm)	46.5
Diameter (mm)	26.19
Wingspan (mm)	80.95
Property of wind tunnel	**Value**
Dimensions of the test section	
Height (mm)	1016
Width (mm)	762
Wind tunnel type	Open loop / Suction type
Contraction ratio (-)	7.2:1
Wind speed range (m/s)	10 ~ 70

3.2 Aerodynamic Coefficients Modeling Results

The modeling results of two aerodynamic coefficients which are normal force coefficient and pitching moment coefficients is presented in this section. Experimental variables which can be changed by experimenter is set as angle of roll tab deflection, angle of attack and roll angle. The experiment range for angle of roll tab deflection is set as 0 to 20 degree with step of 10 degrees, 0 to 50 degree with 1-degree step for angle of attack, and 0 to 80 degree with 10-degree step for roll angle. The two variables which are angle of attack and roll angle can be changed during the wind on state but another variable which is angle of roll tab deflection should be changed in the wind off condition since the screws should be loosened and tightened to change the deflection. Total three run was executed with change of angle of roll tab. In each run, angle of attack and roll angle is set as design variables so the value of two variables are selected with the proposed adaptive DoE method. The terminate condition for adaptive test is set as 1.5 for the ratio of two confidence intervals (CI_{GP}/CI_{DAQ}) which means the size of average confidence for generated GP model should not exceed half as much again that of measuring device. For the hyperparameters optimization process, the candidate initial length-scales for two design variables are set as 0.1 to 0.9 with step of 0.4. The values are selected based on the idea that the influence of angle of attack and roll angle would not very big but relatively small. Consequently, there are three candidate initial length-scale for optimizing hyperparameters for each design variable than total nine possible combinations can exist. The value of initial noise variance is set as average noise level arise from measuring devices for all test points until the step. After the initial hyperparameters are determined, the values are optimized with conjugate gradient method. In each adaptive test repetition, a case when the biggest maximum likelihood values occur is selected for the GP model at the step.

The figure 3 to 5 represents modeling results of each run. The test points from Initial Test, Adaptive Test and Confirmation Test are denoted as different markers to classify the origin of the points among the three steps. Note that the number of experiment points is different for each run depending on how the generated model quickly fitted with data points.

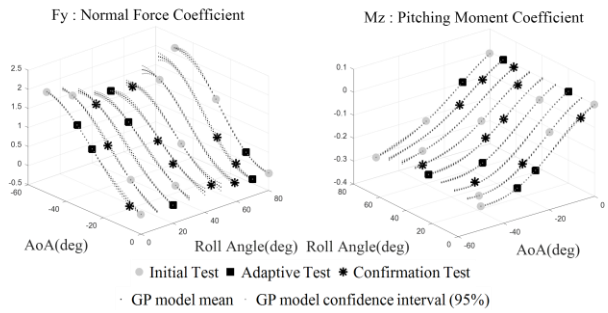

Fig. 3. Aerodynamic Coefficients Modeling Result (angle of roll tab = 0 deg)

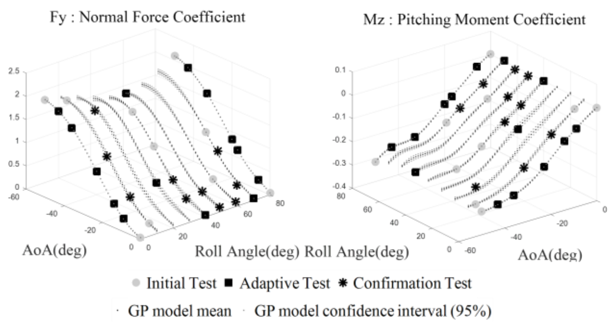

Fig. 4. Aerodynamic Coefficients Modeling Result (angle of roll tab = 10 deg)

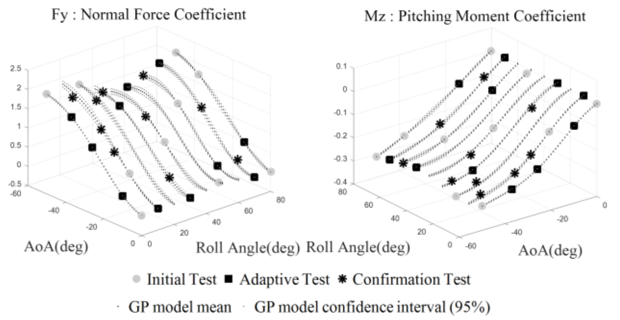

Fig. 5. Aerodynamic Coefficients Modeling Result (angle of roll tab = 20 deg)

The table 2 and 3 presents the optimized hyperparameters (ℓ and σ_n) and calculated accuracies for three cases, respectively. The average residual which is absolute average differences between generated model and confirmation points and relative residual which represents relative percentage of average residuals compared to range of each output variable.

Table. 2. Optimized values of hyperparameter for three cases

Angle of roll tab (deg)	Normal force coefficient (C_N)			Pitching moment coefficient (C_m)		
	ℓ_{AoA}	ℓ_{roll}	σ_n	ℓ_{AoA}	ℓ_{roll}	σ_n
0	1.0215	1.3162	0.0179	0.4700	2.3685	6.98e-04
10	0.7585	1.2618	9.39e-07	0.5734	0.4622	2.72e-05
20	1.0089	0.7145	5.20e-06	1.0479	0.9224	0.0017

Table. 3. Accuracy of Developed Regression Models

Angle of roll tab (deg)	Normal force coefficient (C_N)		Pitching moment coefficient (C_m)	
	Average residual (-)	Relative residual (%)	Average residual (-)	Relative residual (%)
0	0.0680	3.05	0.0052	1.67
10	0.0344	1.66	0.0050	1.55
20	0.0611	2.78	0.0078	2.47

4 Conclusions

The hyperparameters optimization process that can be used for three-phase adaptive DoE applied to wind tunnel testing based aerodynamic coefficient modeling is presented. The initial values of hyperparameters (length scale and the noise variance) are selected, and they are optimized using the conjugate gradient method. Among local optima of the hyperparameters, the value that yields the biggest maximum likelihood is selected.

The three aerodynamic coefficient modeling case studies for a missile with different roll-tab deflection angles are presented to demonstrate the effectiveness of the proposed approach. The study results indicate that the models were successfully created – with very low relative residual values (below 3%).

It is expected that required time to conduct wind tunnel testing could be more reduced when detailed cost elements for executing experiment are considered. Applying the proposed adaptive design of experiment method to more complex cases with many design variables should be also dealt with to demonstrate the general applicability of the proposed approach.

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