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A data assimilation methodology for reconstructing turbulent flows around aircraft

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ABSTRACT

This paper proposes a new approach for the study of complex turbulent flows of aeronautics that integrates experimental fluid dynamics (EFD), employing methods such as wind tunnel experiments, and computational fluid dynamics (CFD) by using a data assimilation technique. The approach aims at representing complex turbulent flows more properly than conventional EFD and CFD approaches by estimating the proper angle of attack, the proper Mach number, and the proper turbulent viscosity, which are the three uncertainty factors in EFD and CFD. To this end, the ensemble transform Kalman filter (ETKF), a sequential advanced data assimilation method, is employed for the estimation and applied to transonic flows around the RAE 2822 airfoil (two-dimensional flow) and transonic flows around the ONERA M6 wing (three-dimensional flow). The results computed using the angles of attack, Mach numbers, and turbulent viscosities estimated by the ETKF diminish the discrepancies between the results of standard computations and experiments. These findings show the effectiveness of this approach, which combines EFD and CFD using data assimilation to represent complex turbulent flows.

1. Introduction

Experimental fluid dynamics (EFD), employing methods such as wind tunnel experiments, and computational fluid dynamics (CFD) are major tools used for aerodynamic design in the field of aeronautical engineering. EFD and CFD aim at representing flows around flying aircraft or spacecraft in wind tunnel facilities and numerical space. Nevertheless, EFD and CFD cannot represent the flows perfectly, because EFD and CFD involve many uncertainty factors intrinsic to them.

Typical examples of uncertainty factors are the angle of attack and the Mach number of wind tunnel experiments, which are important boundary conditions. In most cases, wind tunnel walls affect flows in wind tunnels, and wind tunnel wall interference correction methods are applied to wind tunnel test data. In such methods, angles of attack and Mach numbers of experiments are corrected to eliminate wind tunnel wall interferences effects and represent those in free air situations. Several approaches [1] are available for the correction, but it is not guaranteed that the values corrected by them are the same. Therefore, there always exists a possibility that the corrections employed may be insufficient to obtain the proper angle of attack and the proper Mach number to represent flows around flying aircraft or spacecraft in free air situations.

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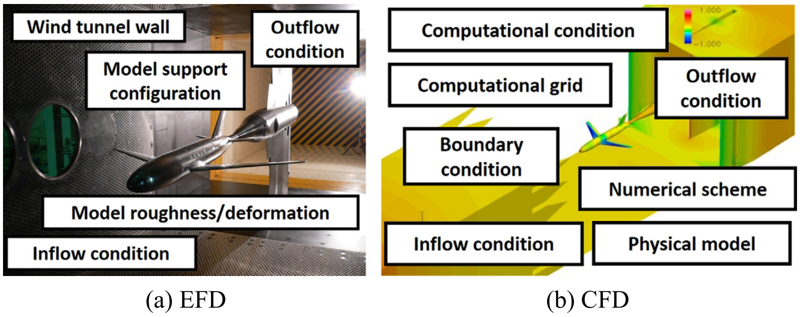

Fig. 1. Various examples of uncertainty factors in EFD and CFD.

Another example of an uncertainty factor is the chosen turbulence model. A turbulence model is used in CFD to represent turbulent flows with reasonable accuracy and efficiency. To date, several turbulence models have been proposed, and their effectiveness has been demonstrated. However, under complex conditions, these turbulence models tend to predict different turbulent flows, and the choice of turbulence model has significant effects on the computed results.

EFD and CFD involve many uncertainty factors in addition to the angle of attack, the Mach number and the turbulence model, such as model roughness and model support configurations of EFD, and initial and boundary conditions, qualities of discrete computational grids and numerical schemes of CFD. Fig. 1 illustrates various examples of the uncertainty factors of EFD and CFD.

Recently, evaluation and understanding of complex turbulent flows have become increasingly important in the design of high-efficiency aircraft and spacecraft. However, current experimental and computational approaches encounter difficulties in accurately evaluation and understanding of complex turbulent flows. This situation arises mainly from two reasons. One of the reasons is relevant to the lack of high accuracy of these approaches. Then to increase their accuracy is indispensable for properly representing complex turbulent flows. Another is relevant to uncertainty factors involved in EFD and CFD. They become obstacles to accurate estimation of aerodynamic characteristics when studying complicated flow fields. Therefore, an approach that focuses on uncertainty factors will be an important tool for representing complex turbulent flows more properly than conventional EFD and CFD approaches.

The Kalman filter [2] is one of the representative methods for considering uncertainties in both measured and computed data. The Kalman filter is based on the Bayesian estimation in which an underlying stratum of accurate data is estimated from measured and computational data that suffer from inaccuracies owing to conditions such as uncertainties.

In the field of earth science, data assimilation methodology has received considerable attention [3,4]. It has been widely used to estimate initial and boundary conditions for complex numerical analyses involving weather prediction by incorporating measured data into a computational weather system model, with the aid of the Kalman filter. In the field of weather analysis, as well as aeronautical design, the Navier–Stokes equations are employed as a system model. Hence, the data assimilation methodology is expected to be applicable to the analysis of complex flow problems in the field of aeronautical engineering. Specifically, it is highly probable that the new methodology based on the combination of data of EFD and CFD can present more realistic complex turbulent flows and contribute to aerodynamic design.

This study proposes a data assimilation-based approach to represent complex turbulent flows. In this approach, an advanced sequential data assimilation technique, the ensemble transform Kalman filter (ETKF) [5], is employed. The ETKF is an advanced data assimilation method, which is one of extended methods of the Kalman filter for nonlinear system models. The ETKF can be effective for aeronautical flow-field analyses that require massive computational costs, because the ETKF is a method of low calculation costs in ensemble-based data assimilation methods [6]. This new approach is applied to two test cases of turbulent flows, two-dimensional transonic flow around the RAE 2822 airfoil and three-dimensional transonic flows around the ONERA M6 wing consisting of three-dimensional flow, in which the discrepancies between EFD and CFD remain to be resolved.

This study focuses on the angle of attack of EFD, the Mach number of EFD and the turbulence model of CFD as uncertainty factors. In this study, the aim of data assimilation is to estimate corrected angles of attack and Mach numbers more properly than original ones, and turbulent viscosities more properly than those determined by eddy-viscosity-type turbulence models. The angles of attack and Mach numbers estimated by the present method will be helpful for designing a more reliable wind tunnel wall interference correction method. In addition, the estimated turbulent viscosity will be useful for improving the current turbulence models of eddy-viscosity-type. On the other hand, the uncertainties other than these three and those of measured data are not considered, as the first basic step to show the effectiveness of the present approach. The approach enables us to avoid discussions about the reliability of data reconstructed by data assimilation under conditions where both measured and computed data are uncertain. Moreover, the data reconstructed in light of the measured data becomes an important indicator of the effectiveness of the data assimilation method.

The rest of the paper is organized as follows. Section 2 gives the problem setting. Section 3 describes the method. The data assimilation procedure is shown in Section 4. Section 5 presents the results. The conclusions are given in Section 6.