A Multi-space Interrelation Theory for Correlating Aerodynamic Data from Hypersonic Ground Testing

Z. Jiang and C. Luo

Abstract Prediction of aerodynamic force/heating acting on hypersonic vehicles in flight conditions with experimental data is a critical yet challenging step in developing hypersonic vehicles. A multi-space interrelation (MSI) theory and its correlation algorithms have been presented. MSI considers the flight condition as an ideal wind tunnel and then aims at detecting an inherent invariant of aerodynamic data from different wind tunnels. The invariant detection is carried out by special supervised self-learning schemes, adaptive space transformation (AST), and/or parse-matrix evolution (PME). The invariant is then used to predict the aerodynamic force/heating coefficients. The study indicates that the multi-space interrelation theory agrees well with physical phenomena. The correlation algorithm can make use of hypersonic wind-tunnel experimental data effectively, and the correlation function is capable of unifying all the experimental data in an analytical form. With the proposed theory and algorithm, one can expect to find a reliable correlation formula with high accuracy based on plenty of wind-tunnel experimental data, provided that the physical condition has not essentially changed.

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1 Introduction

Hypersonic vehicles hold the mission to flying faster, higher, and further, which is always a dream of mankind. With increasing flying speed, the drag reduction and thermal protection become two primary issues to consider when designing a new hypersonic vehicle.

During the last decades, many wind tunnels of different types have been built up and operated all over the world to study the aerodynamic force/heating behaviors of hypersonic vehicles. A huge number of experimental data have been collected for different vehicles in different conditions. However, the prediction of aerodynamic force/heating acting on hypersonic vehicles in flight conditions with experimental data is still a challenging step in developing hypersonic vehicles. In fact, from subsonic to supersonic and hypersonic, with the quantitative change of flight speed, the flow medium outside the edge of the vehicle has changed qualitatively, and the boundary layer is dominated by shocks and thermal reactions of air and featured with nonlinear, multi-scale, and nonequilibrium behaviors. Even worse, limited by the experiment capability of wind tunnels, only a part of flight parameters such as Mach number M_∞ and/or Reynolds number Re_∞ could be simulated with conventional hypersonic wind tunnels, and the limitation is imposed on the accurate prediction of vehicle performances in flight conditions [1].

Great efforts have been devoted to study the correlations of ground testing data and the flight flying conditions. A number of methods have been proposed in the past decades. These methods fall into two categories: (I) simplification and correction and (II) approximation and extrapolation. The simplification might be geometry simplification or theoretical simplification. For geometry simplification, the target hypersonic vehicles are divided into a combination of simple shapes, e.g., cones, cylinders, flat plates, spheres, and wedges, for which analytical solutions are available [2]. This method is easy to understand and have physical basis, but it ignored the effect of interaction of simple shapes, so the predicted results are not acceptable, especially in the area of interactions. For theoretical simplification, some assumptions are made, and only one or two so-called key parameters are considered to get a scale factor for prediction [3]. A common limitation of the method in category I is that its performance depends heavily on the experience of engineers.

A number of approximation-based methods have also been presented for the aerodynamic-coefficient prediction including least squares regression [4], artificial neural network (ANN) [5], support vector machine (SVM) [6], and extrapolation [7]. We have also suggested an adaptive surrogate model [8] to improve the accuracy of approximation. In general, the prediction results of these methods are reliable within the convex hull of known data (interpolation). However, in many cases, as discussed above, the flight parameters could not be covered by wind tunnels. In the sense of mathematics, the prediction of flying condition with ground testing data is a kind of extrapolation problem. So the prediction needs to be done outside the convex hull (extrapolation). As a result, the methods in category II have poor performance on extrapolation, and their prediction results are not reliable.

In this work, we propose a multi-space interrelation (MSI) theory. It suggests analyzing the problem in a dimension-reducible, multidimensional space and could expect to reveal the underlying relationship of testing data among different wind tunnels. The MSI theory considers the flight condition as an ideal wind tunnel and then aims at detecting an inherent invariant of aerodynamic data from different wind tunnels. The invariant detection is carried out by a special supervised self-learning scheme, adaptive space transformation (AST) [9]. The invariant is then used to predict the aerodynamic force/heating coefficients.

2 Multi-space Interrelation (MSI) Theory

2.1 Physical Idea of MSI Theory

There are a variety of different types of hypersonic wind tunnels, even if the same kind of wind tunnel; simulation capacity is also very different, which increases the diversity and disorder of experimental data. Meanwhile, the flight corridor could not be covered by experiments due to limitations of wind tunnels. However, all the test results are still physical and inherently correlated if standing on a higher-dimensional space. In fact, although the experiment conditions might be different with the flight condition, far or less, as long as the results are reliable. The test data hold the information of physical mechanisms and eventually have contributions to the flight behavior predictions, more or less, depending on the degree of deviation from the flight corridor.

For a certain aircraft shape, the speed, static temperature, static pressure of free stream, model scale, and other aerodynamic parameters of wind tunnel constitute a complete multidimensional full-parameter space of experimental data. Note that the static pressure and height of the flight corridor have a restricted relationship $H(T, P)$. Hence the flight state is a special subspace of the full-parameter space.

2.2 Variations and Invariant

There are two levels of cognition for physical laws: variation trend and invariant (Fig. 1). The first level is to find the variation trend of objective value (e.g., coefficient of drag C_D) with respect to relevant parameters (e.g., M, Re, T_0, P_0, s, etc.). But a better way is to find some invariant to describe an object or system to make prediction. For example, there might be many ways to describe an ellipse. But only if an invariant relation such as “The sum of the distances from any point (P) on a given ellipse to its two foci (F_1, F_2) is a constant” is detected, its essential property is grasped.

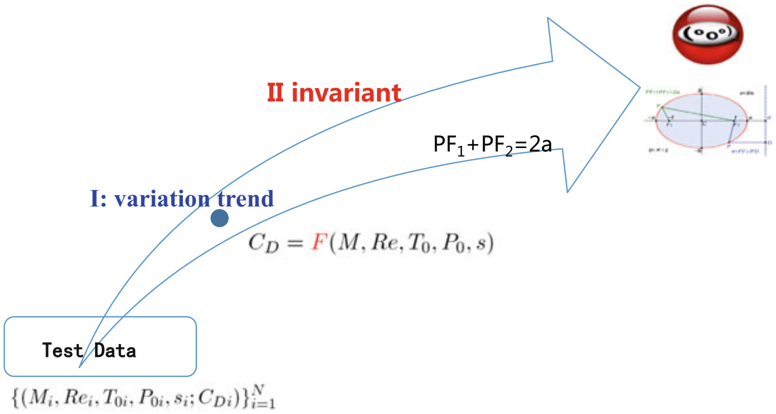

Fig. 1 Two levels of cognition for an object or system

The invariant relation has a great recovery capability. For example, once the above invariant relation is detected, it can help recover the entire ellipse from a small part of the ellipse. That is, although only a part of an ellipse (e.g., the lower-left 1/4 part) is known, we can predict (recover) the rest of it. The recover process is similar to data correlation, in which the objective is also to predict the unknown part by using the information of the known part.

2.3 Optimization Methods for MSI Correlation

An intelligent functional optimization, parse-matrix evolution (PME), is recommended to automatically select proper parameters (dimension reducing) and detect their analytical relationship with the target value (aerodynamic force/heating coefficient, coefficient of drag C_D for example). PME can optimize the function structure of model (f) as well as its parameters (e.g., λ_1, λ_2). That is, PME can determine which function structure such as power, exponential, logarithm, sine, their combinations, etc. is the best fit model according to the test data. No previous assumptions on the function structure are necessary any more. This makes it easy to use and rely little on the experience of practical engineers.

As discussed above, invariant is a better way for prediction. The MSI theory considers the flight condition as an ideal wind tunnel and then aims at detecting an inherent invariant of aerodynamic data from different wind tunnels (Fig. 4). To detect the underlying invariant of the test data from different wind tunnels, a special supervised self-learning scheme, adaptive space transformation (AST) [9], is proposed.

2.4 Philosophy of MSI Theory

Einstein's formulas of mass-energy equivalence ($E = mc$ˆ2), Newton's law of motion ($F = ma$), and Kepler's law of planetary motion (aˆ3/Tˆ2 $= K$) are all simple and elegant. In Chinese Taoist philosophy, there is a well-known principle that says "Great truths are always simple." As for the aerodynamic force/heating, the prediction model must not be too complex. The model of conventional modeling methods including spline fit, multivariate polynomial regression artificial neural network (ANN), and support vector machine (SVM) involves many hidden coefficients, which are adjusted to compromise the data variations, but too complex to describe a physical law.

In MSI methods (PME and AST), the model complexity is controlled in real-time in the functional optimization process of target model.

3 Implementation of MSI Correlation

There are three essential factors to implement the MSI: theory, data, and algorithm. The theory and algorithm have been presented in the above section. However, the data plays a decisive role in the process of variation trend (and/or invariant) detection. First, to get a reliable correlation model for prediction, the data must carry enough information to describe the variation trend brought by different physical mechanisms such as real-gas effect, scale effect, Reynolds effect, etc. Second, the accuracy of data is also decisive, which sometimes leads the MSI correlation to success or failure.

4 Applications

The MSI correlation methods have been applied to many practical aerodynamic force/heating prediction problems. Here two examples are presented. One is on aerodynamic force prediction, and the other is on aerodynamic heating prediction.

To predict the drag of a sharp cone with 10-degree half-angle, 200 learning cases are used for training AST, and another 800 cases are used to test the performance of AST, where most of test points lie outside of the convex hull of the learning data (blue in Figs. 2 and 3). The comparison results show that it has much better predictions than ANN and ε-SVR [9].

The second example is trying to detect an invariant for aerodynamic heating of a sharp cone, which can hopefully unify the data distributions from different type of wind tunnels. Two sharp cones with half-angle 7° are used for experiments. One is about 1.2 m long, tested in JF12. The freestream is typically calorically perfect gas. The other is about 0.6 m, tested in JF10. The freestream is typically chemical/thermal nonequilibrium. The original data distributions are separated

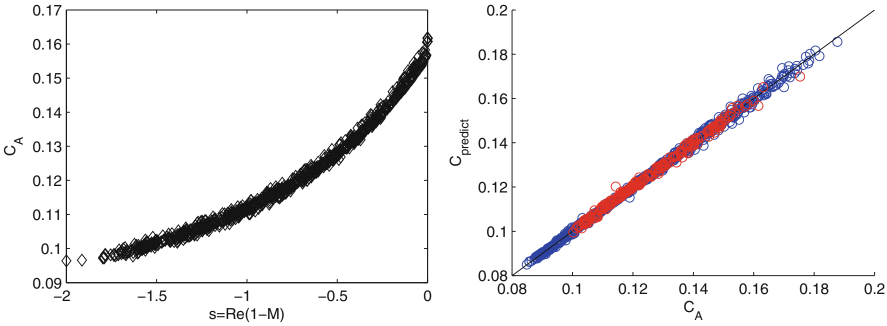

Fig. 2 A best correlation model by MSI and its performance on cone-drag prediction

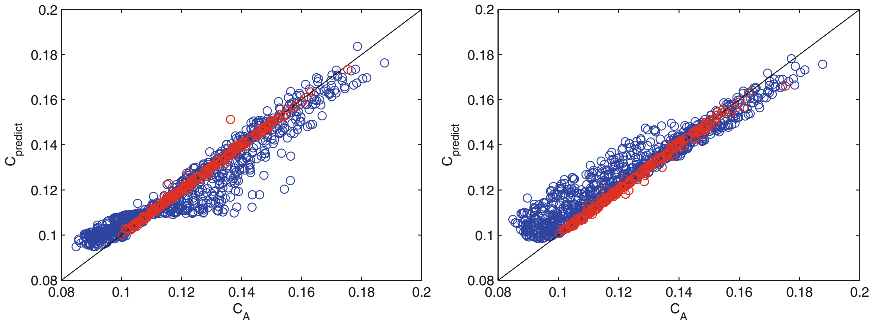

Fig. 3 Prediction deviation of ANN and ε-SVR, inside (red) and outside (blue) the convex hull

(Fig. 4a). In MSI method, 11 parameters including data distribution T_0, P_0, H_0, H_{w}, p, ρ, u, M, T, Re_{L}, and $\boldsymbol{Re_x}$ are set for inputs of PME, and the target is to find a best model to unify all these data. PME reached at a simple and elegant formula $\mathrm{St} = a + \frac{b}{c+\mathrm{Re}_x}$. With this correlation formula, the data distributions could be well unified (Fig. 4b). The correlation performance of MSI is much better than other existing methods in literatures (Fig. 5a, b) [10].

5 Conclusion

A multi-space interrelation (MSI) theory and its correlation algorithms have been presented. MSI considers the flight condition as an ideal wind tunnel and then aims at detecting an inherent invariant of aerodynamic data from different wind tunnels. The invariant detection is carried out by special supervised self-learning schemes, adaptive space transformation (AST), and/or parse-matrix evolution (PME). The invariant is then used to predict the aerodynamic force/heating coefficients. The study indicates that the multi-space interrelation theory agrees well with physical

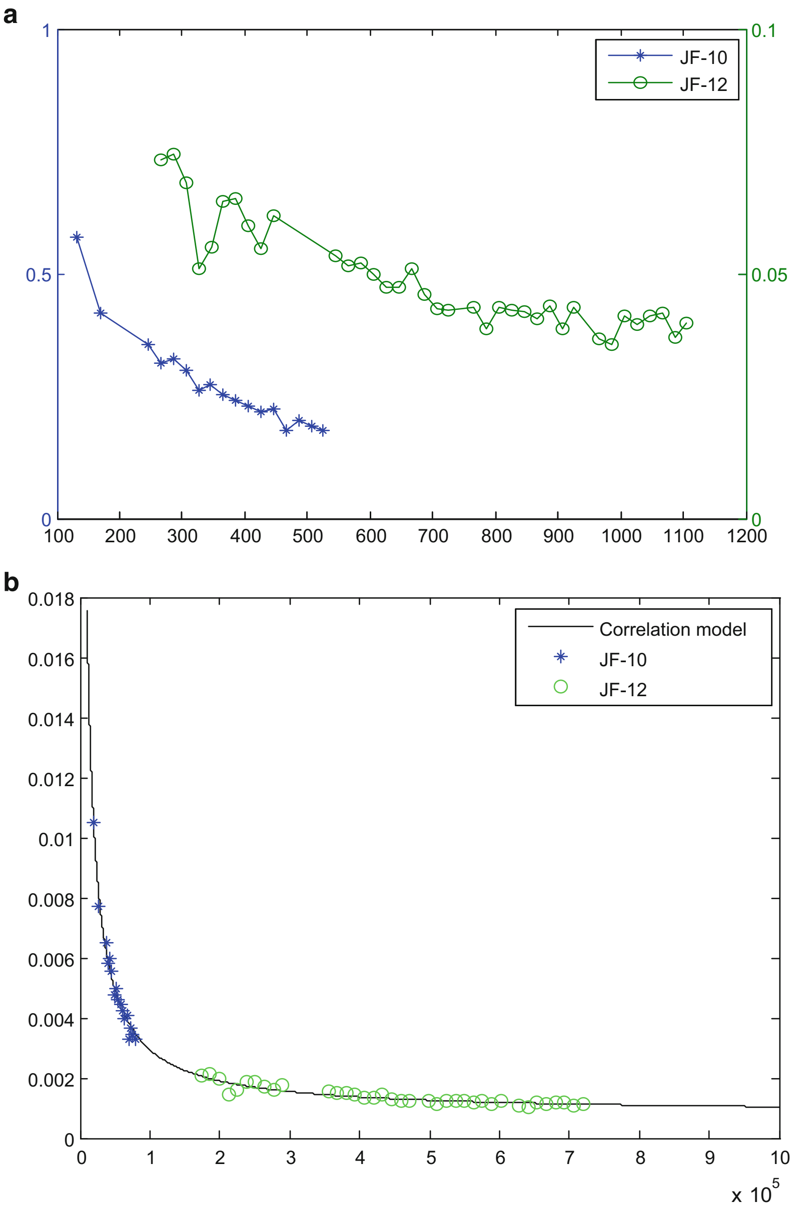

Fig. 4 Data correlation of test data from different wind tunnels. (**a**) Original data distribution; (**b**) correlated data distribution

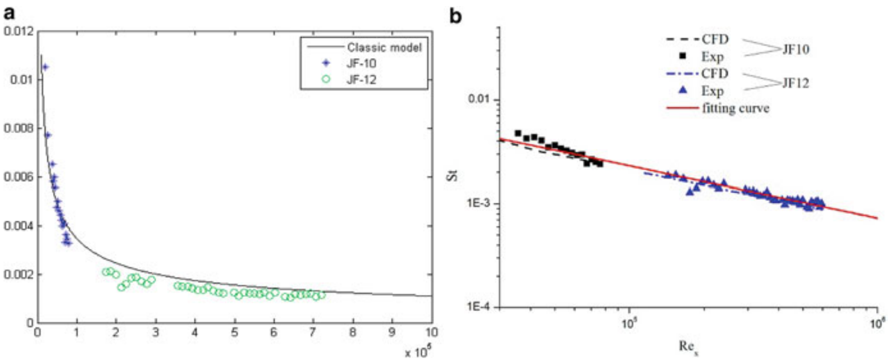

Fig. 5 Correlation performance of other methods. (**a**) Conventional method, $\mathrm{St}\ \mathrm{Re}_x^n = C$; (**b**) boundary layer out-edge method $\mathrm{St}_e\sqrt{\mathrm{Re}_x} = C$

phenomena. The correlation algorithm can make use of hypersonic wind-tunnel experimental data effectively, and the correlation function is capable of unifying all the experimental data in an analytical form. With the proposed theory and algorithm, one can expect to find a reliable correlation formula with high accuracy based on plenty of wind-tunnel experimental data, provided that the physical condition has not essentially changed.

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