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Data Fusion Method for Constructing Fighter Aircraft Aerodynamic Database Using Variable Fidelity and Space Mapping Techniques

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Abstract
Aerodynamic database (DB) is one of the most important components of the flight simulation. To maintain high accuracy of the simulation, the DB should be constructed using high-fidelity analysis methods which requires a lot of time and cost. In this research the aerodynamic data fusion method (DF) is introduced to reduce the DB generation cost while preserving accuracy. Combination of space mapping and variable fidelity modeling is presented in this paper. Demonstration of the method is shown for 2D airfoil and 3D fighter aircraft DB. The method shows that the prediction errors improved 19%.

1. Introduction

Modern flight simulation is used in various fields. From entertain games to simple descriptions of flying, to precise simulation to training pilots, it is used for a variety of purposes. The flight simulation consists of look-up-tables, and the precision of the flight simulation depends on the precision of the tables. In the case of flight simulation for fun, a small look-up-table may be used, or performed based on simple calculations that do not consider aerodynamics.
However, flight simulation for pilot training and aircraft development must have very high precise precision. These high fidelity aircraft flight simulation is a very important technology in a modern aircraft's lifecycle. Simulation is used during aircraft design, certification and pilot training stages. Simulation for certification and pilot training should describe the exact same flight characteristic as the actual flight. An aerodynamic database plays a very important role in accurately describing actual flight. Wind tunnel experiments or high fidelity aerodynamic analysis data are used to construct these important aerodynamic DB. But the process of obtaining data is quite expensive and time-consuming work. Many methodologies have been developed to reduce such time and cost.

2. Data Fusion

One of them, data fusion method, combines data of various fidelity to produce one high fidelity data. Among such data fusion methods, Variable Fidelity Modeling (VFM) is a method of predicting high fidelity data based on scaling. Since the method making scaling function depends on the Gaussian Process (GP), it is difficult to predict the region that GP cannot predict well. The method of reducing the error of the VFM technique is the same as the method of reducing the GP prediction error. In this study, to reduce non-linearity of GP prediction, Space Mapping (SM) was proposed before performing VFM.

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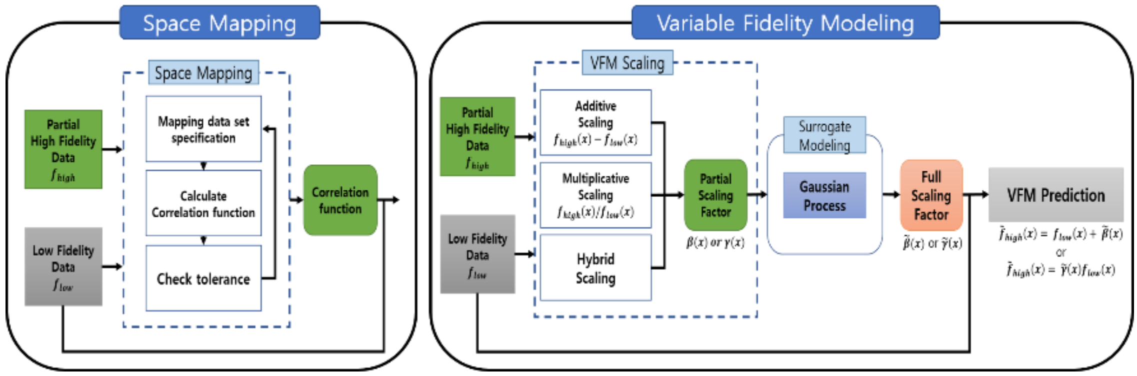

Figure 1 : SM & VFM process [5]

2.1 Space Mapping Technique

Space mapping (SM) is one kind of surrogate model. It is used for finding optimum points or min / max points. SM is more suitable to find a minimum / maximum point at specific area of interest rather than constructing global surrogate model. Most other surrogate model method match the high fidelity data with low fidelity data through modification of the response values. But the SM achieves same purpose by modifying the input variables.

There are two major steps performing SM. The first step is to obtain correlation factor that maps peak points of low fidelity samples to peak points of high fidelity samples. And second step is to perform the global SM after expanding the correlation factor to whole design space.

In the first step, the process of obtaining the correlation factor begins with the definition of input variable as following low fidelity and high fidelity sample points.

$$\boldsymbol{\Phi}_{HF} = \{\boldsymbol{\phi}_{h1}, \boldsymbol{\phi}_{h2}, \ldots\ldots, \boldsymbol{\phi}_{hl}\}^T \qquad \textbf{(1)}$$

$$\boldsymbol{\Phi}_{LF} = \{\boldsymbol{\phi}_{l1}, \boldsymbol{\phi}_{l2}, \ldots\ldots, \boldsymbol{\phi}_{lk}\}^T \qquad \textbf{(2)}$$

The response of this input variables is represented as $R_{HF}(\phi_{HF})$, $R_{LF}(\phi_{LF})$, respectively. And assume that there is relationship between Φ_{LF} and Φ_{HF} as follow

$$\boldsymbol{\Phi}_{\mathrm{LF}} = \boldsymbol{P}(\boldsymbol{\phi}_{HF}) \qquad \textbf{(3)}$$

Assuming that the relation p(x) has an inverse function, it can be written as follows.

$$\textbf{Min } (\| \mathbf{R}_{\mathbf{HF}}(\boldsymbol{P}(\boldsymbol{\phi}_{LF})^{-1}) - \boldsymbol{R}_{LF}(\boldsymbol{\phi}_{LF}) \|) \qquad \textbf{(4)}$$

Where ‖.‖ is the Euclidean distance. Finding the $P(x)$ function satisfying above equation is the core of SM. In this study, simple linear relation function was used as follow. In first step, we can calculate the correlation factor at two peak points.

$$\boldsymbol{\Phi}_{\mathrm{LF}} = \boldsymbol{a\phi}_{HF} \qquad \textbf{(5)}$$

For example, for cl max peak points, in case of low fidelity sample's cl max is located Angle of attack 14, but in case of high fidelity sample's cl max is located Angle of attack 10.

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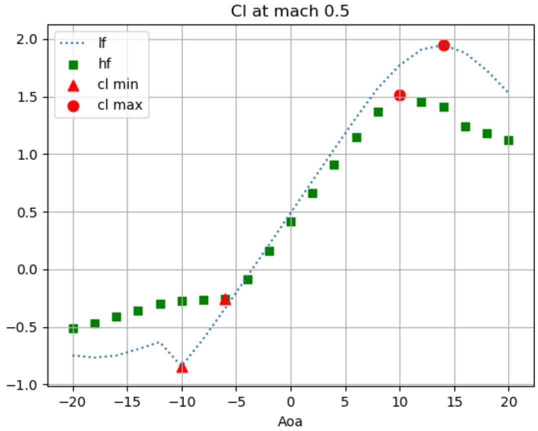

Figure 2 : SM example sample points

With Eq. (5), and peak point locations (14 deg for low fidelity, 10 deg for high fidelity), we can calculate a correlation factor $\boldsymbol{a}$ for cl max peak point. With this method, calculate correlation factor for two peak points.
The second step is to extend the correlation factor to whole design space. Since each peak point is mapped, all points that are not mapped yet should be adjusted to match the peak point mapping result smoothly. This process is the process of compressing and stretching the input variables. As you can see above, for cl min peak point should move to -6 deg from -10 deg, for cl max peak point should move from 14 deg to 10 deg. In that means low fidelity samples points between -10 deg to 14 deg are should compressed. And the sample points at both ends (below -10 deg, upper 14 deg) should stretched.

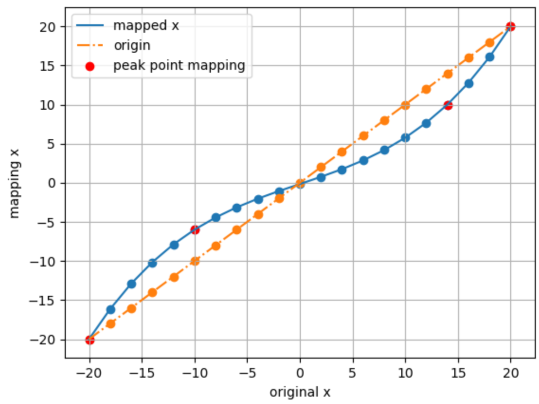

Figure 3 : SM example full mapping with Lagrange interpolation

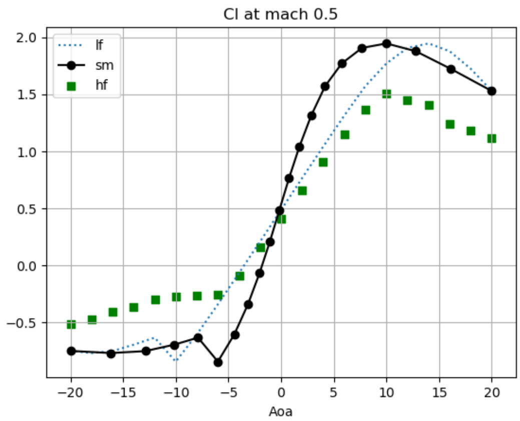

Figure 4 : SM example result [5]

With two end points and peak points, Lagrange interpolation is used to link unmapped points to smoothly with mapped peak points. Full mapping was performed as above figure. In above figure, x axis are original input variables and y axis are mapped input variables. As you can see, peak points are well mapped from -10 deg to -6 deg and 14 deg to 10 deg. And the other points are mapped smoothly. As you can see above right figure, low fidelity's peak points are mapped well to location of high fidelity's peak points.

2.2 Variable Fidelity Modeling

Variable Fidelity Modeling (VFM) is a kind of data fusion technique. It is a technique to produce high fidelity data by fusing various fidelity data. Generally, it takes a lot of time and effort to obtain high fidelity data. On the other hand, low fidelity data can be obtained relatively easily and quickly. The advantages of such high & low fidelity analysis are can be gathered through data fusion technique. Among data fusion method, the VFM is a method of obtaining data by combining the advantages of the precision of high fidelity analysis and fast time of low fidelity analysis.

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VFM technique is a scaling based prediction technique. Scaling can be classified into three types.
First, Additive scaling, assuming that high fidelity function is sum of low fidelity samples and scaling factor function $\tilde{\gamma}(x)$ as below equation.

$$\tilde{f}_{high}(x) = f_{low}(x) + \tilde{\gamma}(x) \quad \textbf{(6)}$$

Second one is multiplicative scaling, assuming that high fidelity function is made of multiply of low fidelity and scaling factor function $\tilde{\beta}(x)$.

$$\tilde{f}_{high}(x) = \tilde{\beta}(x) f_{low}(x) \quad \textbf{(7)}$$

Last one is hybrid scaling, it is combined method of additive & multiplicative with weight factor w as below Eq.

$$\tilde{f}_{high}(x) = w\,\tilde{\beta}(x) f_{low}(x) + (1 - w)(f_{low}(x) + \tilde{\gamma}(x)) \textbf{(8)}$$

3. Data Fusion For 2D Airfoil Aerodynamic DB

3.1 High & Low fidelity sample data for 2D Airfoil Aerodynamic DB

The sample data to be used for the numerical examples of VFM and SM are shown below.

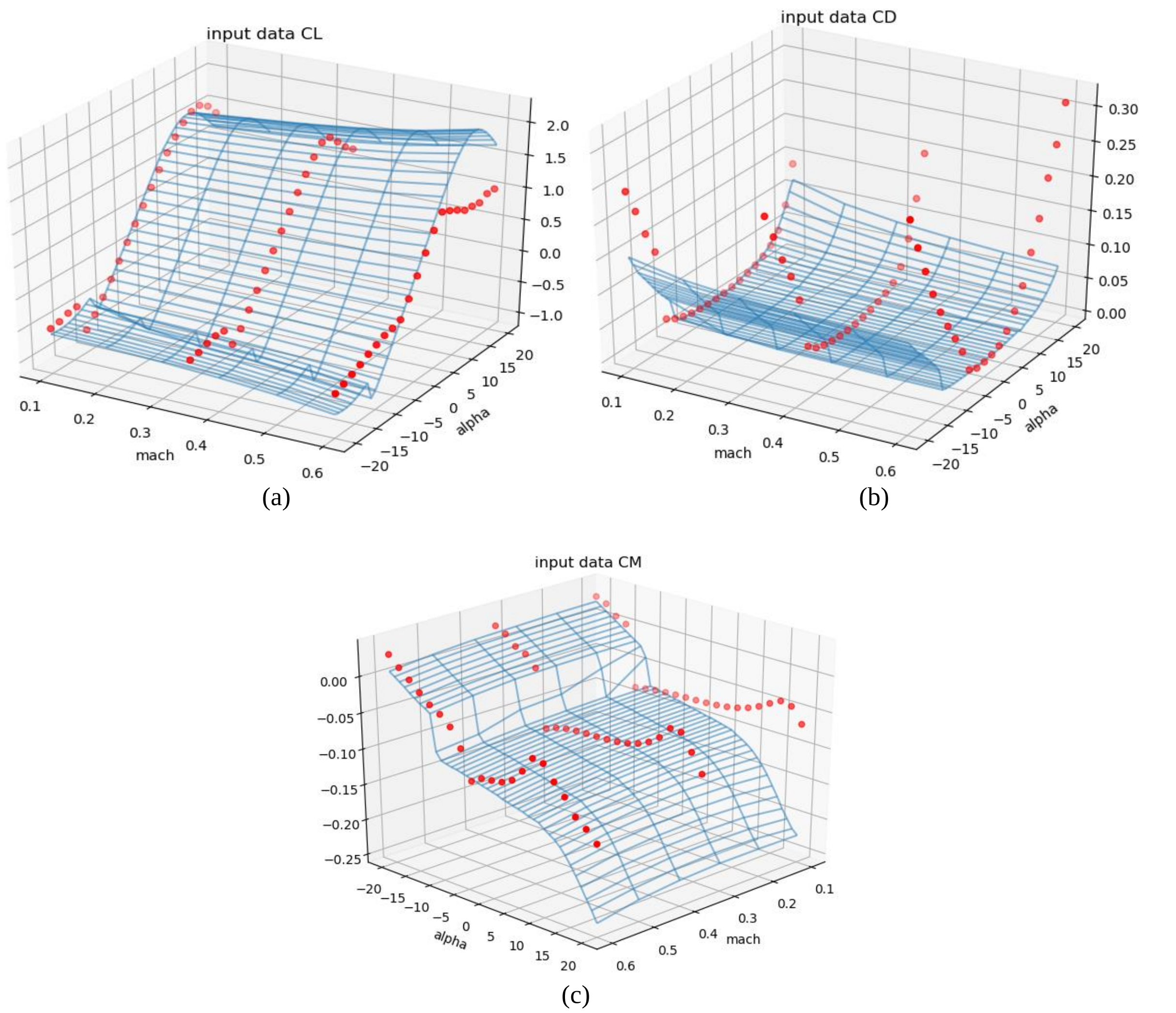

Figure 5 : Lift coefficient (a), Drag coefficient (b), Moment coefficient (c) input airfoil coefficient

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For the numerical example, the Clark Y airfoil was selected which is relatively simple to analysis rather than the full size aircraft configuration. As low fidelity data, Java Foil which is based on the panel method was used. Because Java Foil is a tool consider compressibility correction according to Karman and Tsien, analysis result can be inaccurate at high mach number. Ansys Fluent, one of the computational fluid dynamic analysis tools commonly used to get aerodynamic data, was used for high fidelity data. 301x100 C type mesh with the RANS solver, Yplus 1.0, and Spalart Allmaras turbulence model was used.

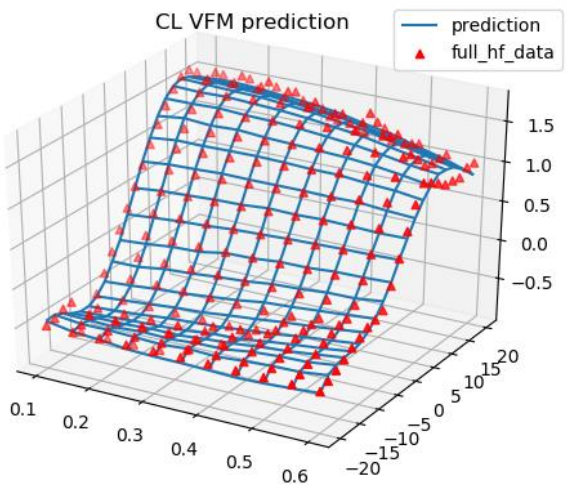
For low & high fidelity data, because of limitation of compressibility of Java foil, from mach 0.1 to 0.6 with 0.1 step, from Angle of Attack(AOA) -20 deg to +20deg with 1 deg step data was used for prediction as represented wireframe surface in above figure.

For high fidelity data, from mach 0.1 to 0.6 with 0.05 step, from AOA -20 deg to +20 deg with 2 deg step.

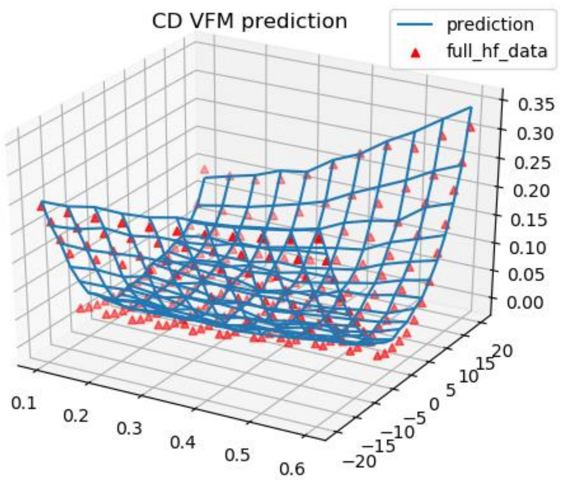
For numerical validation of the data fusion method, only data of mach 0.1, 0.35 and 0.6 was used and represented dot in above figure. And it was used for comparison between prediction and full high fidelity data

3.2 Variable Fidelity Modeling Airfoil Aerodynamic Data Fusion

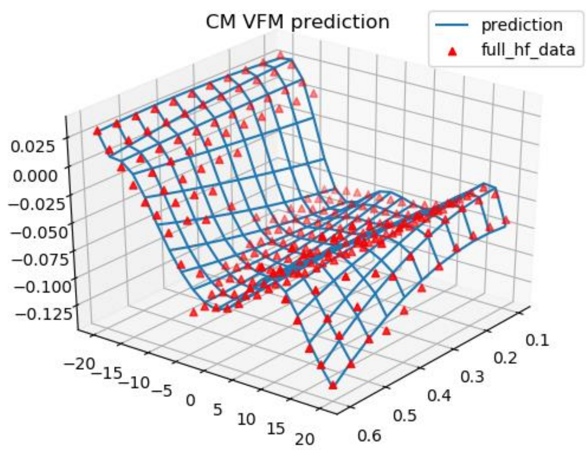
The results of the data fusion using VFM for the high fidelity data prediction with mach 0.1, 0.35, 0.6 and low fidelity data at mach from 0.1 to 0.6 are as shown below



(a)



(b)



(c)

Figure 6 : Lift coefficient (a), Drag coefficient (b), Moment coefficient (c) VFM prediction result

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The Mean Absolute Error(MAE) and the maximum error are shown in the following table. Errors are calculated with VFM prediction and already known total CFD data.

Table 1 : VFM Prediction Error

	MAE	Max. Error [%]
C_l	7.65×10^{-2}	0.2313 [14.4%]
C_d	1.114×10^{-2}	0.0235 [17.4%]
C_m	0.758×10^{-2}	0.0371 [127.2%]

As you can see above table, the prediction result of list and drag coefficient are relatively better than moment coefficient. The size of the error is also important but should also pay attention to where the maximum error occurs. The part where the error mainly occurs is where the data has a peak. As shown in the figure below, the maximum prediction error occurs at max peak or min peak for cl and cm.

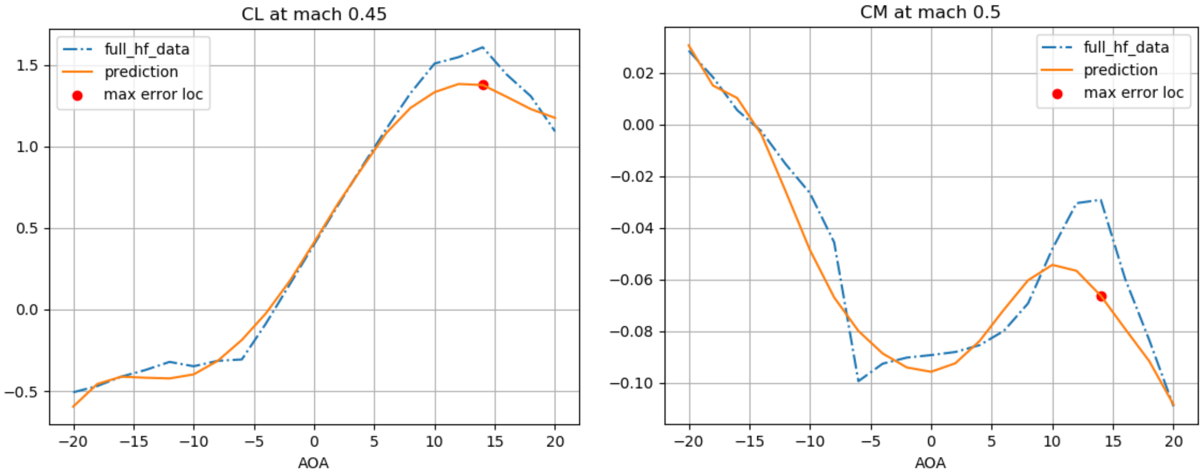

Figure 7 : Cl (left), Cm (right) Max. Error

Those kinds of error can be occurred when predicting scaling factor function with GP model which is one of the surrogate model that are the basis of VFM

It can be assumed that this error is due to the difficulty in predicting scaling factor function with dramatic changes due to the nature of GP. Thus, to reduce these errors, the peak point can be matched first with SM, and then the VFM prediction can be performed.

3.3 Space Mapping & Variable Fidelity prediction

The above prediction using only VFM confirmed that the GP did not predict well for when the sample data has sudden changes. In order to reduce this error, after matching peak point with SM, VFM was performed as follow.

Table 2 : SM + VFM prediction error

	MAE	Max. Error [%]
C_l	5.563×10^{-2}	0.2674 [16.6%]
C_d	0.709×10^{-2}	0.0222 [8.8%]
C_m	0.614×10^{-2}	0.0328 [112.5%]

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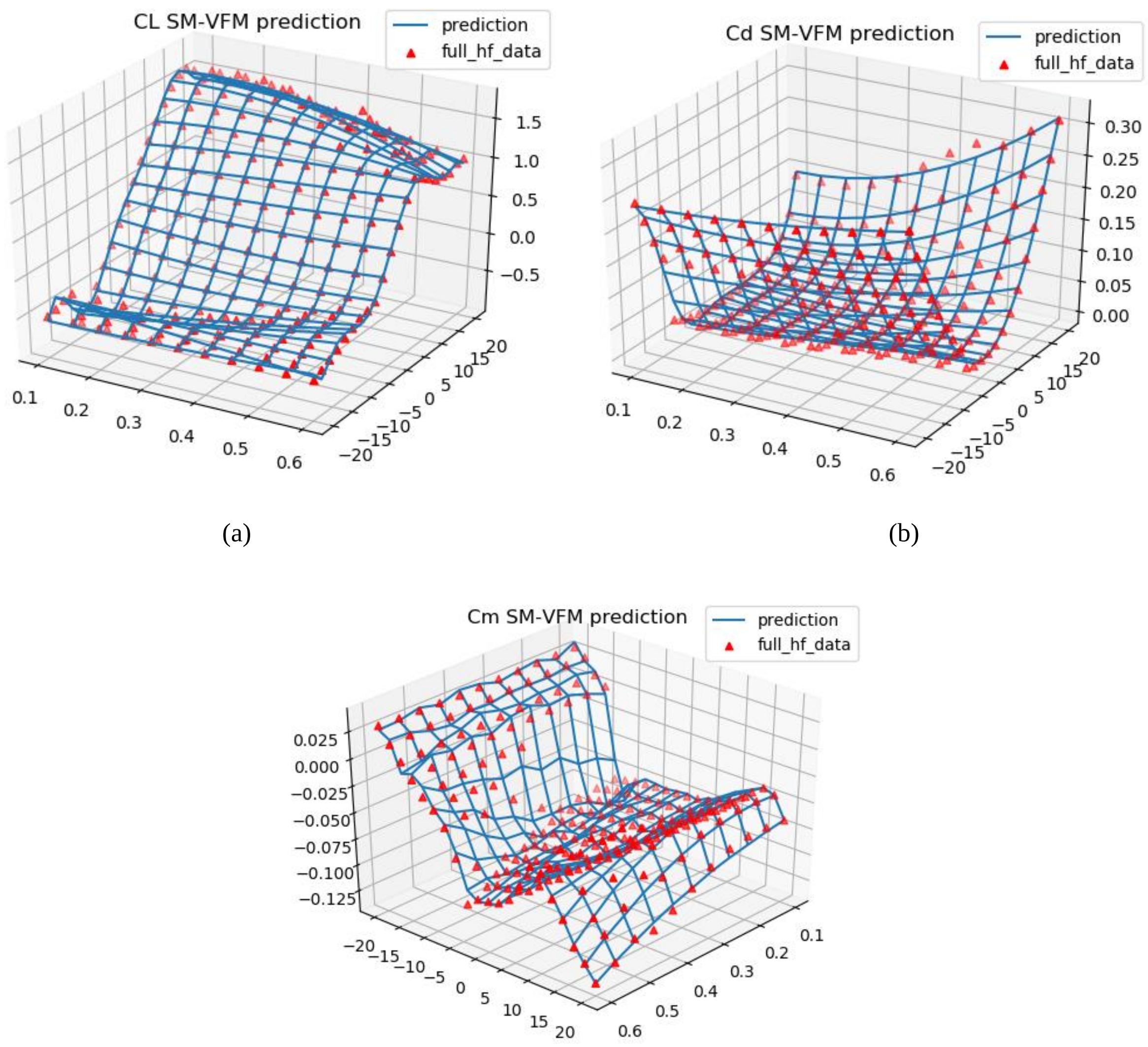
In the case of cl, maximum error was increased, but MAE was decreased. In case of cd, maximum error and MAE was decreased. However, in case of cm, the MAE and maximum error are reduced, but the error is still quite large. It is too large to use as coefficient. The error was caused by the fact that the trend of the low fidelity data and high fidelity data do not match at all. The VFM method has a characteristic that it follows the trend of low fidelity data in prediction other than the region where high fidelity data exists. Due to the characteristics of the VFM, the prediction results are improved with SM-VFM, but it can be confirmed that is still insufficient.

Table 3 : Error Comparison

	VFM MAE	SM-VFM MAE	Improvement
C_l	7.65×10^{-2}	5.563×10^{-2}	27.6 %
C_d	1.114×10^{-2}	0.709×10^{-2}	36.4 %
C_m	0.758×10^{-2}	0.614×10^{-2}	19 %



(a) (b)

(c)

Figure 8 : Lift coefficient (a), Drag coefficient (b), Moment coefficient (c) SM-VFM prediction

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4. Constructing Fighter Aircraft Aerodynamic DB

4.1 Configuration of fighter aircraft

To obtain aerodynamic data for data fusion, the F-16C fighter aircraft, which is considered data publicly available than others, was selected. The configuration data of F-16C was completed through CATIA, one of the 3D CAD (Computer Aided Design) programs, by referring to NASA Technical Paper (TP) 3355 [3] written in 1998. Based on NASA TR 3355, 3D CAD model was created like below.

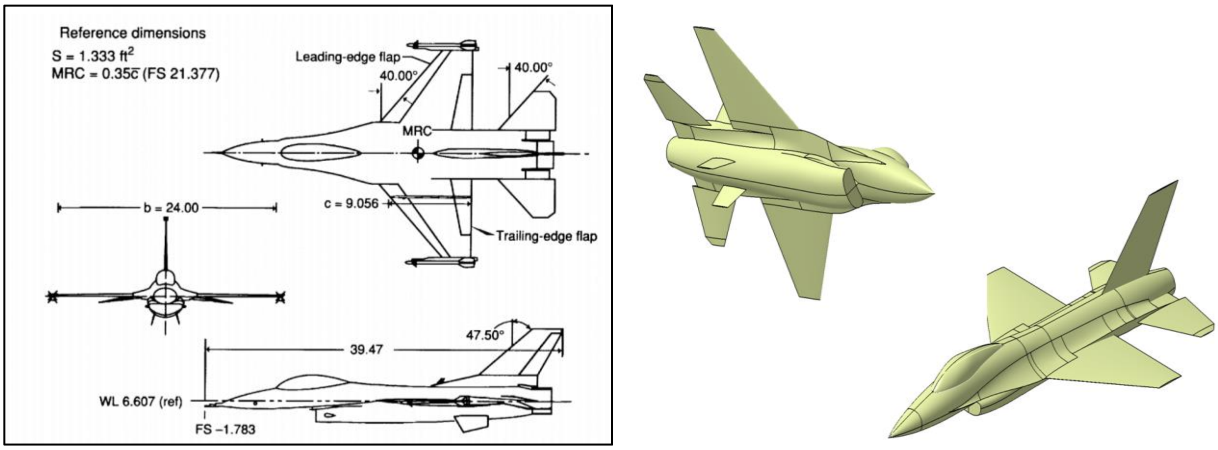

Figure 9 : F-16C NASA report(left) [3], F-16C CAD model(right)

4.2 High & Low fidelity sample data

High and low fidelity data generation for data fusion was computed using Ansys Fluent and DATCOM (Digital Data Compendium) analysis tool. In case of CFD, from -20 deg to +50 deg was selected for the angle of attack for subsonic, and from -6 deg to +6 deg was selected for supersonic region. The range of angle of attack was selected within F-16C operation area which is referred from F-16C's operational manual. In case of low fidelity data, subsonic and supersonic analysis data was obtained within range of -20 deg to +35 deg, because of the limitation of DATCOM analysis tool, the data of transonic (Mach 0.61 ~ Mach 1.09) region was excluded.
High Fidelity Analysis used 3D CAD model of F-16C that was transformed into unstructured mesh using Ansys ICEM CFD. With Yplus = 1, there are 72 layer of Prism mesh that grow from the initial height at the wall surface into the far field with the mesh ratio of 1.12.

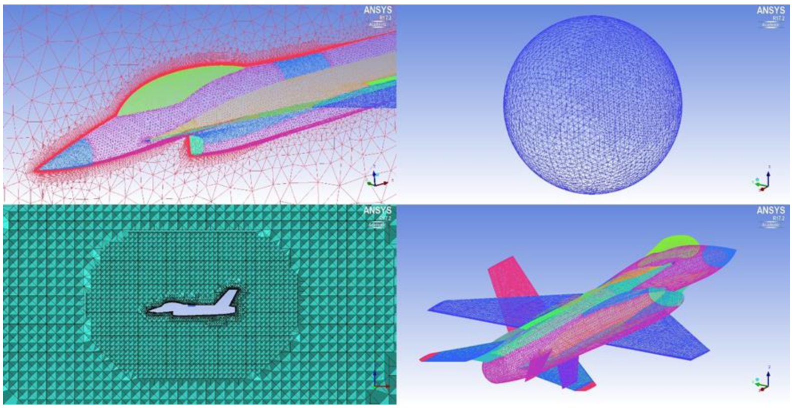

Figure 10 : Ansys analysis Mesh

The far field is made with spherical shape to ensure a considerable homogeneous distance from the far-field to the model for all required angle-of-attack and side-slip angle DOE of high-fidelity analysis. The total mesh for the full 3D model is 5,810,163. The numerical analysis is done with Ansys Fluent using RANS analysis method. Double precision 3D Density-based solver with kω-SST turbulence model is selected to solve both compressible and non-compressible cases of this analysis.

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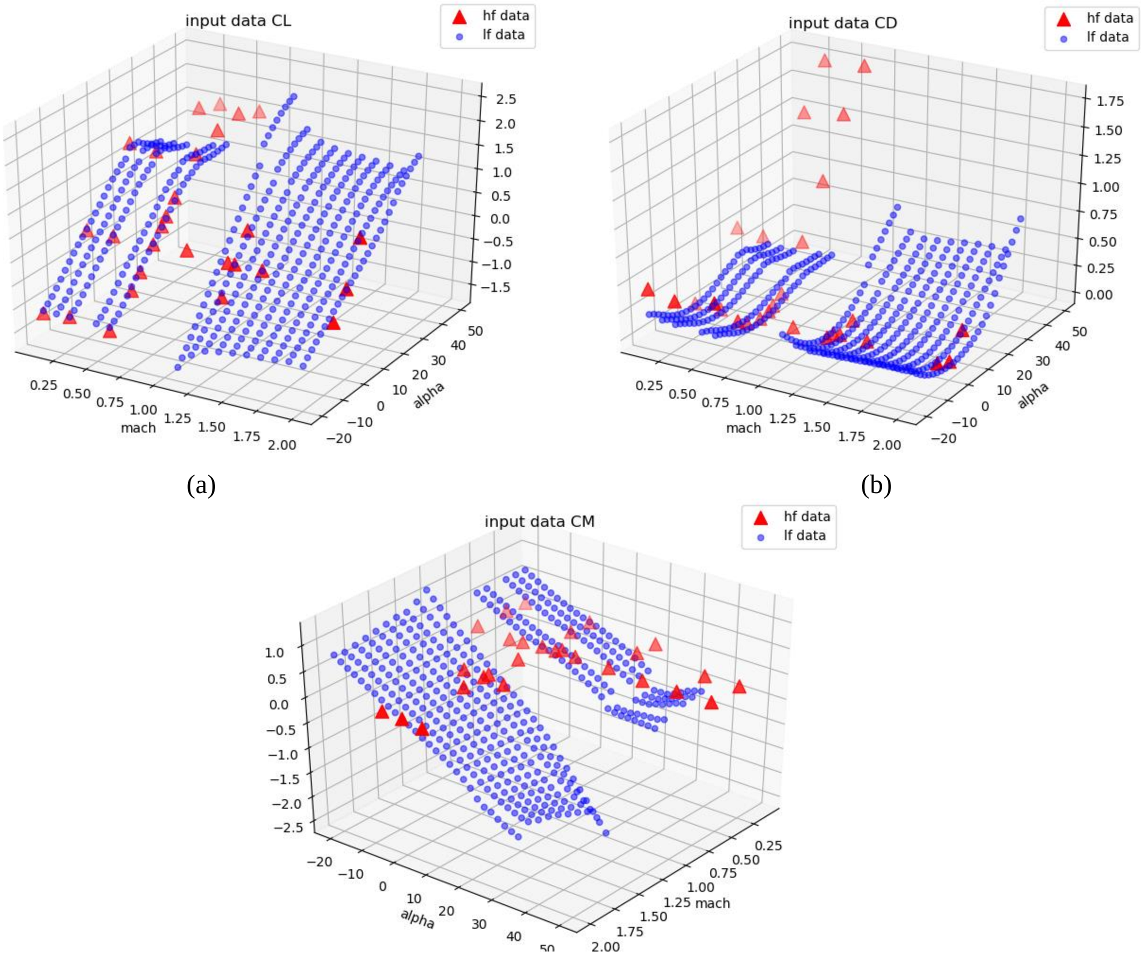


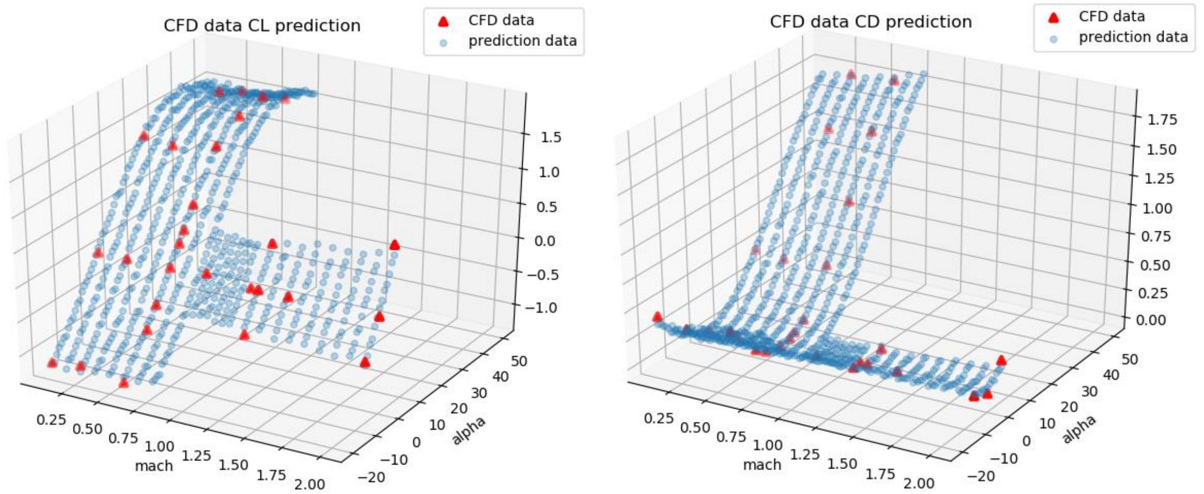
(a) (b)

(c)

Figure 11 : Lift coefficient (a), Drag coefficient (b), Moment coefficient (c) input F16C coefficient

4.2 Fighter aircraft aerodynamic Data Fusion

It can be confirmed that all coefficients except the two points of the moment coefficient which CFD calculation error occurred are well predicted. Extrapolation in the subsonic region over angle of attack +35 deg and extrapolation in the transonic region are also physically predicted well.



(a) (b)

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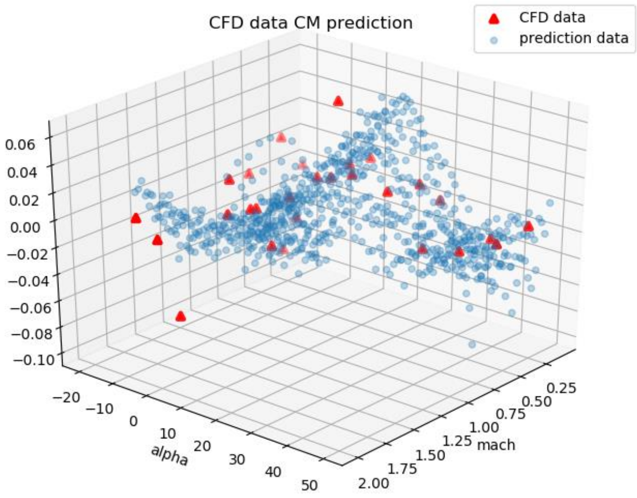

(c)

Figure 12 : Lift coefficient (a), Drag coefficient (b), Moment coefficient (c) Fighter aircraft data fusion result

5. Conclusion and Future plan

In this study, Space Mapping and Variable Fidelity Modeling was performed with airfoil and F-16C data. With small amount of high fidelity data, predicted data was created. It is confirmed with Clark Y airfoil data that the SM and VFM combined prediction has lower prediction error in Mean Absolute Error than VFM only result.

Using Clark Y airfoil data, In the prediction using VFM, MAE was 7.65×10^{-2}, 1.114×10^{-2} and 0.758×10^{-2}, respectively, and the SM-VFM was performed. As result, the MAE decreased to 5.563×10^{-2}, 0.709×10^{-2} and 0.614×10^{-2} which was 27.6%, 36.4%, 19%

Using F-16C data, data fusion was performed. The number of F-16C data was 420 in low fidelity and 28 in high fidelity. Although there is no data to verify the prediction result of F-16C, numerical comparison was not made, but it was confirmed that physically correct data was obtained with only 6.6% of high fidelity data.

Based on those kinds of method, we will construct full F-16C aerodynamic database including alpha, beta, mach sweep. With predicted aerodynamic database, flight simulation will be performing and compare the result with the certification regulations to see whether virtual flight certification is possible.

Acknowledgement

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