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Strategy for robust gust response alleviation of an aircraft model

Yuting Dai[a,*], Chao Yang[a], Chaolei Wang[b]

[a] School of Aeronautic Science and Engineering, Beihang University, Beijing 100191, China
[b] Science and Technology on Special System Simulation Laboratory, Beijing Simulation Center, 100854, China

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ABSTRACT

The aeroelastic response to time-dependent gusts or turbulence should be considered in airplane design. A robust generalized predictive control law for gust response alleviation is designed and simulated on an aircraft model by using the real wind tunnel response and approximated gust input. Based on the open-loop response of an aircraft model at different test conditions, a nominal Auto Regressive (AR) model with parameter uncertainty is identified. Singular Value Decomposition is designed to reduce the dimension of the uncertainty matrix. Afterwards, with the identified online aeroelastic model and its uncertainty, a robust generalized predictive control (GPC) is applied to alleviate the wing tip acceleration at all test conditions, including varying flow velocities and varying gust frequencies. Finally, the alleviation effect of gust response at different test conditions is estimated based on the comparison of simulated closed-loop acceleration with an experimental open-loop one. The comparison indicates that after robust gust response alleviation control, the wing tip acceleration response can be reduced by up to 70% under all test conditions. Remarkably, the control law is robust to the parameter uncertainties and input uncertainties, which is applicable to the gust alleviation wind tunnel test.

1. Introduction

Gust response concerns with the structural response and strain in aircraft design (Karpel, Moulin, & Chen, 2005). It is a multi-disciplinary aeroelastic problem with the structural dynamics, aero-dynamics and the flight dynamics (Karpel, Moulin, & Presente, 2008; Marzocca, Librescu, & Chiocchia, 2001; Nguyen & Gatzhammer, 2015). To avoid large gust responses, gust response alleviation systems have been designed and validated by many wind-tunnel tests (Babbar, Suryakumar, & Strganac, 2015). In the wind tunnel test, the gust is usually generated by biplanes with reciprocating sinusoidal motion. In this case, the measurement in the wind tunnel test and the simulation by computational fluid dynamics finds that the gust disturbance is also similar as a discrete sinusoidal function (Babbar et al., 2015). The classical proportional-integral-derivative (PID) and linear quadratic Gauss (LQG) theories are widely used controllers for gust response alleviation (Chen & Wu, 2009; Wu, Chen, & Yang, 2013). Considering a parameter's perturbation, H_∞ optimal controller and μ synthesis are effective robust control methods to account for disturbance and variations in the mathematical model (Dharmayanda, Budiyono, & Kang). All of these control laws are based on a known or identified state-space aeroelastic model, named “model-based”. Model-based control laws are highly depending on the theoretical model. They may fail when the parameters of a theoretical aeroelastic model are not accurate enough. Alternatively, a data-based control law according to experimental input and output data can be designed. In this case, there is no need to construct the theoretical aeroelastic model. It can prevail over the modeling mismatch due to the strong nonlinear behavior. The first issue for data-based control is system identification, usually with ARMA model and least square identification algorithm (Dovetta, Schmid, & Sipp, 2016). In fact, the data-based generalized predictive control (GPC) is a good choice for aeroelastic active control (Martin-Sanchez, Lemos, & Rodellar, 2012; Salcedo, Martınez, & Ramos, 2005), both for gust load alleviation and flutter suppression (Kvaternik, Eure, & Juang, 2006; Lew & Juang, 2012). It has been applied to the gust response alleviation simulation of an aircraft model with rigid and elastic motions (Lew & Juang, 2012). In order to accommodate the disturbance and uncertainties, the GPC method has been modified for flutter suppression simulation of a Benchmark Active Controls Technology wind-tunnel model (Salcedo et al., 2005).

The authors conducted a gust response wind tunnel test in 2011. However, in the wind tunnel test, uncertainties are unavoidable, including the measurement noise, flow turbulence, and gust disturbance (Wu, Chen et.al., 2013; Wu, Dai et al., 2013). To apply data-based GPC to this wind-tunnel model, the unknown gust input and unknown uncertainties embedded in the output data have to be tackled with. The first problem has been solved in Ref. Dai and Yang (2015). Hence, based on the autho rs' former work, the uncertainty modeling of

* Corresponding author.
E-mail address: yutingdai@buaa.edu.cn (Y. Dai).

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Nomenclature

GPC	generalized predictive control
AR	Auto Regressive
SVD	Singular Value Decomposition
LQG	linear quadratic Gauss
PID	Proportional-integral-derivative
$\boldsymbol{y}(k\text{-}p)$	output of the AR model
$\boldsymbol{d}_g(k\text{-}p)$	gust disturbance
$\boldsymbol{u}_c(k\text{-}p)$	the deflections of control surfaces at the time step *k-p*
p	Order of the AR model
V_0	flow velocity
ω_i	gust frequency
h_p	Prediction steps
h_c	Command steps
$\boldsymbol{R}$, $\boldsymbol{Q}$	the output weighting matrices
$\bar{\mathbf{Y}}$	the vector of observer Markov parameters
$\boldsymbol{d}_{gp}$,$\boldsymbol{d}_{gf}$	The gust input for the past p time steps and the future h_p time steps
$\boldsymbol{u}_p$,$\boldsymbol{u}_{hc}$	The deflections of control surfaces for the past p time steps and the future h_c time steps
$\boldsymbol{y}_p$,$\boldsymbol{y}_{hp}$	The responses for the past p time steps and the future h_c time steps

turbulence and measurement noise is considered in this current work.

The sections of this paper are organized as follows. In section two, the nominal GPC control law for gust response alleviation is introduced. Afterwards, considering different test conditions, an uncertainty model is constructed and a robust GPC control law is designed to minimizing the variance of output uncertainties. In section three, the whole framework is validated by an aircraft aeroelastic model with open-loop gust response in the wind tunnel test.

2. Control law design for gust response alleviation

In this section, the theory for GPC is described according to Ref. Martin-Sanchez et al. (2012) and Ref. Kvaternik et al. (2006). The gust input is derived and standard GPC method for gust response alleviation is modified to adapt to different flow velocities. More details of this theory can be found in the authors' former work (Lew & Juang, 2012). Afterwards, the uncertainty is introduced to several different test conditions, including different flow velocities and gust frequencies. Based on the identified nominal model with quantified uncertainty, a robust GPC is designed not only to alleviate the predicted response of a nominal AR model but also to alleviate the variance of the predicted response due to uncertainty.

2.1. Gust response alleviation under different test conditions

The significant feature for GPC method is to identify an Auto Regressive (AR) model based on the open-loop input and output data (Kvaternik et al., 2006). It is similar as to deduce a theoretical model in the model-based method. Afterwards, control command is acted on the AR model to minimize a prediction of the system response in the future.

More details of the standard GPC method for gust response alleviation is seen in the authors' former work, see Ref. Dai and Yang (2015). Here, only some important expressions are given, which is convenient to understand for robust GPC method.

When an external excitation exists, a time-invariant multi-input-multi-output Auto Regressive model can be written as (Kvaternik et al., 2006; Dai and Yang, 2015):

$$\mathbf{y}(k) = \boldsymbol{\alpha}_1\mathbf{y}(k-1) + \boldsymbol{\alpha}_2\mathbf{y}(k-2)+\ldots+\boldsymbol{\alpha}_p\mathbf{y}(k-p) + \boldsymbol{\beta}_0\mathbf{u}_c(k) + \boldsymbol{\beta}_1\mathbf{u}_c(k-1)+\ldots+\boldsymbol{\beta}_p\mathbf{u}_c(k-p) + \boldsymbol{\gamma}_0\mathbf{d}_g(k) + \boldsymbol{\gamma}_1\mathbf{d}_g(k-1)+\ldots+\boldsymbol{\gamma}_p\mathbf{d}_g(k-p) \tag{1}$$

where integer p is called the model order. $\boldsymbol{y}(k\text{-}p)$ is the output of the model, and $\boldsymbol{d_g}(k\text{-}p)$ is the gust disturbance on the aircraft model in the wind tunnel test. $\boldsymbol{u}_c(k\text{-}p)$ is the deflections of control surfaces at the time step *k-p*. Gust response in the wind tunnel test is excited by a sinusoidal moving gust generator (Wu, Chen et al., 2013). In order to express the gust disturbance at different flow velocity and different sinusoidal frequency, the gust disturbance is written as a polynomial function

$$d_g = a_0 \sin\omega_i t + a_1 V_0 \sin\omega_i t + a_2 V_0^2 \sin\omega_i t \tag{2}$$

where a_0, a_1 and a_2 are the constant polynomial coefficients. To combine this expression for gust disturbance with the AR model in Eq. (1), the one gust input is augmented to three. They represent the constant gust, the linear gust with flow velocity and the quadratic gust with flow velocity, respectively. The expression is

$$\mathbf{d}_g(k) = \left[\sin\omega_i t(k), V_0 \sin\omega_i t(k),\ V_0^2 \sin\omega_i t(k)\right]^T \tag{3}$$

Until now, the decomposed gust disturbance is already known. Moreover, the response $\boldsymbol{y}$ and the deflection of control surfaces $\boldsymbol{u}_c$ are measured by the data acquisition system in the wind tunnel test. Hence, the inputs and outputs in Eq. (1) are known experimental open-loop data. Then the standard AR model in Eq. (1) can be rewritten as a regressive form

$$Y = \bar{Y}V \tag{4}$$

where $\mathbf{Y} = [\mathbf{y}(0), \mathbf{y}(1), \ldots, \mathbf{y}(l-1)]$ and $\boldsymbol{V}$ is formed from the time series of $\boldsymbol{u}_c$,$\boldsymbol{d}_g$ and $\boldsymbol{y}$. The expression for matrix $\boldsymbol{V}$ is shown in Ref. Dai and Yang (2015). Denote $\bar{\mathbf{Y}}$ as the vector of observer Markov parameters to be identified. Associating it with Eq. (1), $\bar{\mathbf{Y}}$ is composed of

$$\bar{\mathbf{Y}} = [\boldsymbol{\gamma}_0\ \ \boldsymbol{\beta}_0\ \ \boldsymbol{\gamma}_1\ \ \boldsymbol{\beta}_1\ \ \boldsymbol{\alpha}_1\ \ \boldsymbol{\gamma}_2\ \ \boldsymbol{\beta}_2\ \ \boldsymbol{\alpha}_2\ \ \cdots\ \ \boldsymbol{\gamma}_p\ \ \boldsymbol{\beta}_p\ \ \boldsymbol{\alpha}_p] \tag{5}$$

The solution of $\bar{\mathbf{Y}}$ is calculated by employing a least square algorithm. That is,

$$\bar{Y} = yV^+ = yV^T[VV^T]^{-1} \tag{6}$$

After the parameters of the AR model at the k time step in Eq. (1) are identified according to the past$l$time steps, the second step for GPC method is to design a control law. Assume the control law is switched on from the k+1 time step. The deflection of the control surface is still denoted as $\boldsymbol{u}_c$. Similar as the AR model in Eq. (1), in the future h_p time steps, the response of the future time step j can also be represented as a linear combination of three parts. Those are the response in the future j time steps and in the last p time steps, the deflection of control surface $\boldsymbol{u}_c$ in the future h_c time steps and in the last p time steps, and the gust disturbance in the future j time steps and in the past p time steps. The regressive relationship for the future predicted response is written as

$$\mathbf{y}(k+j) = \alpha_1^j y(k-1+j) + \alpha_2^j y(k-2+j)+\ldots+\alpha_p^j y(k-p+j) + \beta_0 u_c(k+j) + \beta_0^1 u_c(k-1+j)+\ldots+\beta_0{}^j u_c(k) + \beta_1{}^j u_c(k-1)+\ldots+\beta_p^j u_c(k-p) + \gamma_0 u_d(k+j) + \boldsymbol{\gamma}_0^1 u_d(k-1+j)+\ldots+\gamma_0^j u_d(k) + \gamma_1^j u_d(k-1)+\ldots+\gamma_p^j u_d(k-p) \tag{7}$$

Letting j in Eq. (7) range over the set of values j=1, 2, ..., h_p−1, the resulting equations can be assembled into a multi-step output prediction equation. That is,

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