Suppression of Wing Rock of Slender Delta Wings
Using a Single Neuron Controller
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Abstract—Wing rock is a highly nonlinear phenomenon in which the aircraft undergoes limit cycle roll oscillations at high angles of attack. A single neuron control scheme for suppression of wing rock of slender delta wings is presented. The effectiveness of the control scheme is demonstrated through software simulation and real-time control experiments in a wind tunnel on a 80° swept back wing. The suppression of the limit cycle is achieved in presence of control saturation. The robustness of the scheme is demonstrated by the suppression of the wing rock at various initial conditions and different angles of attack.

Index Terms—Delta wing, nonlinear, real time, saturation, single neuron, wing rock.

I. INTRODUCTION

Wing rock is a highly nonlinear aerodynamic phenomenon, in which limit cycle roll oscillations are experienced by aircraft with slender delta wings and pointed forebodies at high angles of attack. Generally the frequency and magnitude of the limit cycle oscillations are strongly dependent on the aircraft configuration, angle of attack, and other flow conditions. The combat effectiveness of fighter aircraft operating at high angles of attack can be seriously affected due to wing rock.

The limit cycle roll oscillations seem to occur due to asymmetric vortex shedding and vortex bursting. Pamadi et al. [1] have listed out various explanations of mechanism of wing rock, but the primary mechanism causing and sustaining wing rock is still not very clear. It can be approximated by a single degree of freedom phenomenon [2]. However, a perfect mathematical model of wing rock has yet to be established.

Singh et al. [3] have presented a direct adaptive and neural control of the wing rock. The first method of adaptive control makes use of the structure of nonlinearity of the plant, while the second method proposes the use of radial basis function neural network. The second method adaptively arrives at the weights associated with the neural network used in the control of wing rock and the final size of the network arrived has 441 neurons in the hidden layer. Both control schemes were demonstrated through software simulation. A rule-based fuzzy controller for wing rock has been presented by Tarn and Hsu [4]. They have compared the results with a data-based fuzzy controller. Only three term sets have been employed for the fuzzification of the control variables. Numerical results have been presented to demonstrate the robustness of the fuzzy controller at two angles of attack for small initial conditions (in the small). An optimal feedback control using Beecham–Titchener’s averaging technique for wing rock is presented by Luo and Lan [5]. The results show that an effective way to suppress wing rock is to control the roll rate. Optimal control-based on Hamilton–Jacobi–Bellman equation is employed by Shue et al. [6] to suppress wing rock. Simulation results have been presented using both linear
and nonlinear feedback. The nonlinear controller is shown to be asymptotically stable in the large which is important for nonlinear systems.

The present work presents a simple rule-based controller to suppress the limit cycle behavior of the wing rock. The rule base is constructed to be linearly separable. Using this, a simple neural controller with a single neuron is trained. This reduces the training time significantly compared to a multilayered neural controller. Also, real-time implementation of a single neuron is not difficult. This single neuron controller is shown to exhibit the robustness properties by effectively suppressing the wing rock not only in the software simulation (for different angles of attack and initial conditions) but also in the (real-time) experiments conducted in a wind tunnel at...
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A. Rule-Based Controller

A rule-based controller specifies the required control input based on the past experience of the operator or the expert. The expert would have derived some rules of his or her own (defined in the different domains of the state space), owing to a rigorous study, or a continuous acquaintance with the process. Once the rule base has been derived, one can formulate

- a nonlinear or linear, domain-based controller which is directly derive from the linguistic expressions in the rule base.

The implementation of rule-based controllers can be done using a “lookup table” or an “evaluating the rules on-line” approach. If one is to implement the former, then one has to face the problem of memory constraints. On the other hand, on line rule evaluation is time consuming although there are no memory overheads. Apart from this, to have a smooth control input variation, a larger set of rules have to be formed. In effect the quantization levels of the input have to be high.

B. Artificial Neural Networks

The last decade brought to light the ability of artificial neural networks (ANN’s) to learn from examples, with advantages such as fast computation, fault tolerance, nonlinear mapping ability and robustness [7]. Thus the rule-based systems are based on human experience and intelligence in decision making and control, while ANN’s are a rhetoric for parallel
distributed computing used in biological nervous systems to achieve real-time and reliable implementation scheme of the natural processes. So, integration of rule-based controller and ANN’s appears to be a promising approach with the view of combining the two aspects of human intelligence [8]. The rule-based systems have advantages like explanation capability, possibility of expert’s intervention, but they need a longer time for the knowledge acquisition. The ANN-based systems lack in explaining the logic behind their action but are fast computational paradigms. The unified approach of formulating a rule-based controller and implementing this using ANN overcomes the disadvantages associated with both ANN’s and rule-based systems.

II. CONTROL OF WING ROCK

The approximate model presented by Nayfeh et al. [2] for 80° swept back wing is given by

$$\ddot{\phi} + \omega^2 \phi = \mu_1 \dot{\phi} + b_1 \dot{\phi}^3 + \mu_2 \dot{\phi}^2 \ddot{\phi} + b_2 \dot{\phi} \dot{\phi}^2 + u$$  \hspace{1cm} (1)

where $\phi$, $\dot{\phi}$, and $\ddot{\phi}$ are roll angle, roll rate, and roll acceleration, respectively. $u$ is the control input. Also

$$\omega = -c_1 a_1, \quad \mu = c_2 a_2 - c_2, \quad b_1 = c_3 a_3, \quad b_2 = c_4 a_4, \quad c_1 = 0.354, c_2 = 0.001.$$

The various coefficients in the equation are dependent on the constants $c_1, c_2$, and the variables $a_1$ to $a_5$. Variables $a_1$ to $a_5$ vary with angle of attack, which is depicted in Table I. This model represents a 80° swept back wing constrained to roll only. Since, one of the aims of the present study is to experimentally verify the controller’s effectiveness, this model is employed for simulation rather than the nonlinear model representing the complete aircraft dynamics.

As can be seen that the equation is second order with cubic nonlinear terms. The control objective here is to suppress the wing rock, i.e., maintain the 80° delta wing model at zero roll angle ($\phi$) and zero roll rate ($\dot{\phi}$) condition. So in effect it becomes a regulator problem i.e., $\phi$ becomes the error “$e$” and $\dot{\phi}$ becomes rate of change in error “$\dot{e}$” for the controller.
Fig. 11. The block diagram of the experimental setup.

Fig. 12. Controlled response from experiment at $\alpha = 30^\circ$ and $\beta = 0^\circ$.

Fig. 13. Controlled response from experiment at $\alpha = 30^\circ$ and $\beta = 0^\circ$.

Fig. 1(a) shows the phase plot for (1). Limit cycle oscillations are reflected in the phase plot.

A typical time history is depicted in the Fig. 1(b). The amplitude of the stable limit cycle depicted is roughly 37$^\circ$ and the frequency is about 3 Hz for 25$^\circ$ angle of attack.

The state space being two dimensional (in “e” and “$\dot{e}$”), we can formulate the rule base on the familiar two axes Cartesian coordinate system. In Fig. 2, the error is depicted on the X axis and the Y axis depicts the error rate. Quadrant I would reflect that portion of the state space where the error and rate of change of error are positive. So the control input in this region has to be largely negative. By similar logic the quadrant III requires a positive control input. For quadrants II and IV a trial and error method was adopted to form a rule base which suppresses the wing rock effectively.

The rule base was tuned in the following way.

- The magnitude is given by
  \[ u = k_1(\text{abs}(e) + \text{abs}(\dot{e})) \]  \hspace{1cm} (2)

- The sign of the control input is derived from
  \[ \text{sgn}(-\dot{e} - k_2e) \]  \hspace{1cm} (3)

where $k_3$ takes the values $-10$, $-5$, $10$, and $-5$, respectively, in the I, II, III, and IV quadrants and $k_2 = 0.1$.

The constants “$k_1$” and “$k_2$” are iteratively arrived at, to form the rule base. The maximum amount of the control input that can be provided is 44.6 rad/s$^2$. This constraint is dictated by the torque that can be provided by the servomotor actuator installed in the experimental setup. Thus a practical constraint is accounted in the controller design. The rule base is linearly separable and is learned by a single neuron, to form the single neuron controller (SNC).

The single neuron equations are represented by

\[ A = W_1 \times e + W_2 \times \dot{e} \]  \hspace{1cm} (4)

\[ u = \frac{2}{(1 + e^{-A})} - 1. \]  \hspace{1cm} (5)

The schematic block diagram of the neuron is given in the Fig. 3. The neuron takes a weighted sum of the inputs (“e” and “$\dot{e}$”), and then processes it through the nonlinear activation function to produce the output $u$. The activation function should be monotonic and continuous for attaining the functional mapping ability exhibited by the neural networks [7]. The above used function is the popular tanh-sigmoidal function. The bias term has not been used. A backpropagation training algorithm was used to find the weights associated with the inputs of the SNC with the training samples derived from the rule base derived earlier. The final values of $W_1$ and $W_2$ are given by $-1.0$ and $-0.1718$, respectively. The value of the slope parameter $S_1$ is 6. The values were computed using 50 data points from the rule-based controller covering all the quadrants.

Thus effectively the neuron learns the examples taught by the rule-based controller and builds its own continuous model.
of the control strategy. The SNC can be practically realized by simulating it on a digital computer.

III. SIMULATION RESULTS

The (1) is simulated along with the forcing function to find the closed-loop responses with the rule-based controller and the SNC. The control input is multiplied by 44.6 before passing it onto the plant. The phase plane plots and the control input variations at 25° angle of attack are depicted in Figs. 4–6. It can be seen that the SNC has a better response both in terms of settling time and the smoothness in the control input. This shows that the SNC enhances the performance of the rule-based controller in the present case and is better suited for experimental implementation. To demonstrate the robustness properties of the SNC, responses for 25° and 22.5° angle of attack are presented in Figs. 7–9 for two different initial conditions. The closed-loop responses are found to be satisfactory and well behaved. These results have better settling time compared to the ones presented in [4] and [5]. Also, the controller is seen to behave properly even for large initial conditions. Since the results were encouraging in terms of performance and robustness, experimental investigation was taken up.

IV. EXPERIMENTAL SETUP

The free to roll rig is depicted in the Fig. 10 (given at the end). It consists of a “U” shaped metallic structure whose two ends are supported at the tunnel walls. One end is having a rack and pinion arrangement so that the angle of attack can be varied between 0–45°. The side slip angle can be varied in discrete steps of 5° up to 25°.

The control input $u$ (1) can be generated using various means like deflecting aerodynamic control surfaces or different types of aerodynamic blowing mechanisms in wind tunnel experiments. To demonstrate the control strategy in this experiment, a servo-motor aligned with the shaft of the wing is employed to generate the control moment. The 80° swept back wing is mounted on a shaft whose rear end is coupled with a Servo potentiometer (POT) used for position measurement. The dc servo motor used for control purposes is coupled with the help of belt and pulley arrangement to the main shaft. The belt used is the grooved tamer belt along with grooved pulleys which do not allow any slip during motion. The potentiometer is of single turn 10 KΩ wire wound type. The dc servo motor is a 15 V, 4.5 A, 4000 r/min, and 0.1 N-m torque capacity one.

The complete block diagram of the set up is shown in Fig. 11. Two loops can be seen in the block diagram. The inner loop is a current feedback loop consisting of the motor and a current control amplifier (CCA). The CCA is a simple proportional and integral controller. For power amplification, a complementary symmetry darlington pair is used. The controller is incorporated in a 40 MHz PC 386. The controller and the plant are interfaced by a data acquisition card, PCL 208.

V. RESULTS AND DISCUSSIONS

The plots in Figs. 12–14 present the closed-loop responses of the system from the experimental setup for representative angles of attack and side slip angles. All figs. show effective suppression of the limit cycle oscillations within 1.5 s.

The robustness of the controller is a result of the design methodology which does not require the exact plant parameters for the derivation of the controller. Since the input to the controller is error and change in error, it can also be used for tracking. Onboard practical implementation of the controller either in software or hardware form is very simple because of a single neuron employed here.

REFERENCES


