EKF AND NEURAL NETWORK BASED AIRCRAFT ICING DETECTION AND IDENTIFICATION APPLIED TO F-16 FLIGHT DYNAMICS

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The recent improvements and research on aviation have focused on the subject of aircraft safe flight even in severe weather conditions. As a type of such weather conditions, aircraft icing has been found considerably negative effect on the aircraft flight performance. Furthermore, this phenomenon has resulted in several fatal accidents. Ice may occur on wings, control surfaces, horizontal and vertical stabilizers, fuselage nose, landing gear doors, engine intakes, fuselage air data ports, some sensors and drain system outputs. This study examines the wing icing occurrences in flight.

In early 1990, in [1] very useful data was obtained regarding the effects of aircraft icing to aircraft stability and control. As soon as aircraft icing was announced as a prior issue on 1997, NASA established a team called Icing Research Group. In [2] aircraft icing from several different viewpoints was investigated and a Smart Icing System was proposed. Ribbens and Miller [3] tried to detect tail icing by evaluating the decrease of elevator effectiveness via Failure Detection Filter. In [4], these researchers used a state estimator as a type of Luenberger Observer. These studies showed that icing detection via statistical error analysis of states was more effective than online parameter estimation. With NASA support, Ratvasky and Zante examined experimentally and analytically the effects of tail icing [5]. In [6-7] H-infinity algorithm to icing identification problem was applied. It was claimed that proposed method is better than least square estimation methods and Extended Kalman Filter (EKF) methods. Schuchard, et al. have worked on tail icing detection and classification by estimating icing affected parameters and sensor information via neural network (NN) [8]. Johnson and Rokhsaz have proposed a method detecting icing via neural networks and Kohonen Self Organizing Maps (SOMs). By observing NN connection weights' changes, they have tried to find iced and clean aircraft model via SOMs. In that research, the effects of atmospheric turbulence and elevator input signal to icing identification were presented [9].

In this work, icing identification based on EKF and NN is applied to F16 aircraft.

Design of the EKF for the F16 aircraft model estimation

In-flight icing detection and identification is applied to an unstable MIMO model of an AFTI/F-16 fighter. The fighter is stabilized by means of a linear quadratic optimal controller. The model of the fighter is as follows [10]:

$$\mathbf{x}(k+1) = \mathbf{Ax}(k) + \mathbf{Bu}(k) + \mathbf{F}(\mathbf{x}(k)) + \mathbf{Gw}(k) \quad \ldots(1)$$

where **A**, **B**, **G**, and **F** are system matrix, control distribution matrix, process noise distribution matrix, and matrix containing nonlinear terms, respectively. The aircraft state variables are:

$$\mathbf{x} = \begin{bmatrix} v & \alpha & q & \theta & \beta & p & r & \phi & \psi \end{bmatrix}^T$$

where, v is the forward velocity, α is the angle of attack, q is the pitch rate, θ is the pitch angle, β is the side-slip angle, p is the roll rate, r is the yaw rate, ϕ is the roll angle, and ψ is the yaw angle.

The fighter has six control surfaces and hence six control inputs are:

$$\mathbf{u} = \begin{bmatrix} \delta_{HR} & \delta_{HL} & \delta_{FR} & \delta_{FL} & \delta_C & \delta_R \end{bmatrix}^T$$

where δ_{HR} and δ_{HL} are the deflections of the right and left horizontal stabilizers, δ_{FR} and δ_{FL} are the deflections of the right and left flaps, δ_C and δ_R are the canard and rudder deflections. **w**(k) is the zero mean process noise vector.

In order to obtain efficient train samples by decreasing noise effects, EKF is used in this study. Below the EKF to estimate the F-16 aircraft motion is designed. Let us define the parameters vector as $\mathbf{U}(k) = \mathbf{x}(k)$ and apply the EKF to estimate this vector. The measurement equations can be written as:

$$\mathbf{z}(k) = \mathbf{HU}(k) + \mathbf{v}_m(k) \quad (2)$$

where **H** is the measurement matrix, $\mathbf{v}_m(k)$ is the measurement disturbance, and its mean and correlation matrix respectively are:

$$E[\mathbf{v}_m(k)] = 0; \quad E[\mathbf{v}_m(\mathbf{v}_m^T(j)] = \mathbf{R}(k)\delta(kj).$$

By using quasi-linearization method let us linearize the model equation of the fighter by replacing **x** with **U**:

$$\mathbf{U}(k) = f[\hat{\mathbf{U}}(k-1)] + \mathbf{F}_u[\mathbf{U}(k-1) - \hat{\mathbf{U}}(k-1)] + \mathbf{B}(k-1)\mathbf{u}(k-1) \quad \ldots (3)$$

where $f[\hat{\mathbf{U}}(k-1)]$ is right hand side of (1) when the parameters are replaced by their estimated values, and $\mathbf{F}_u = \left.\frac{\partial f}{\partial \mathbf{u}}\right|_{\hat{\mathbf{U}}(k-1)}$ .By using the previously proposed method [10], the following recursive EKF algorithm for the state vector of the F-16 aircraft motion is obtained as

$$\hat{\mathbf{U}}(k) = f[\hat{\mathbf{U}}(k-1)] + \mathbf{P}(k)\mathbf{H}^T\mathbf{R}^{-1}\{\mathbf{z}(k) - \mathbf{H}f[\hat{\mathbf{U}}(k-1)\} \quad \ldots(4)$$

$$\mathbf{P}(k) = \mathbf{M}(k) - \mathbf{M}(k)\mathbf{H}^T[\mathbf{R} + \mathbf{HM}(k)\mathbf{H}^T]^{-1}\,\mathbf{H}\,\mathbf{M}(k) \quad \ldots(5)$$

$$\mathbf{M}(k) = \mathbf{F}_u\,\mathbf{P}(k-1)\,\mathbf{F}_u^T + \mathbf{B}\,\mathbf{D}_u\,\mathbf{B}^T + \mathbf{GD}_\delta\mathbf{G}^T \quad \ldots(6)$$

where **P**(k) is the covariance matrix of the estimation error, **M**(k) is the covariance matrix of the extrapolation error, $\mathbf{D}_u$ is the covariance matrix of the control input error; **G** is the transfer matrix of the system disturbance, $\mathbf{D}_\delta$ is the covariance matrix of the system disturbance.

Since the aircraft is unstable, it is stabilized by the linear quadratic control technique. The performance index to be minimized is as follows:

$$\mathbf{J}_P = \int_0^t \left[\mathbf{x}^T\mathbf{Q}\,\mathbf{x} + \mathbf{u}^T\mathbf{R}\,\mathbf{u}\right]dt \quad (7)$$

where **Q** is a semi-positive definite symmetric matrix and **R** is a positive definite symmetric matrix. The control input is computed as:

$$\mathbf{u} = \mathbf{R}^{-1}\mathbf{B}^T\mathbf{K}\mathbf{x} \quad (8)$$

where K matrix is computed from the following Riccati equation:

$$\mathbf{A}^T\mathbf{K}+\mathbf{KA}+\mathbf{Q}^T\mathbf{Q}-\mathbf{KBR}^{-1}\mathbf{B}^T\mathbf{K}=0 \qquad (9)$$

Aircraft icing

In-flight icing decreases the aerodynamic quality of aircraft such that aircraft weight increases, drag increases, lift decreases, and hence the effectiveness of angle of attack and pitch angle changes. The experimental studies have showed that, in the result of wing icing, drag may increase to values of 500%, and lift may decrease to values of 40%. The effect on moments may vary. Accordingly, the effectiveness of control surfaces may decrease [11-12]. All these directly affect aircraft safe flight. As well as this subject is clearly important in the respect of aviation safety, by taking into account extra fuel consumption due to icing, it is important for economical reasons.

It is clearly obvious that military aircraft have to fly at all places on air and weather conditions as possible. On the other hand, intensive air traffic has forced the aircraft could fly at all weather conditions. Civil aviation authorities and other organizations such as Federal Aviation Authority, FAA, and Joint Aviation Authority, JAA, which provide aircraft certificates and quality assurances, have restricted the flight of the aircraft which are not installed anti-icing system and icing detection system. In order to make sure that whether aircraft is safe on icing weather conditions, or not, the flight tests are mandated by these organizations prior to first aircraft approval. These flight tests are too time-consuming and expensive. Instead of these tests, flight simulations of exactly modeled iced aircraft by using modern technology products would be better for aircraft manufacturers. At least, these simulations could support to flight tests data.

Some icing sensors in nose sections are used on some modern aircraft to detect in-flight icing. However, these sensors only show an indication or a possibility for icing when it comes to some levels. They do not measure the icing effects. It is impossible to evaluate the degradation of aircraft performance due to in-flight wing and tail icing. Hence, the existing sensors do not provide enough information to pilot or autopilot.

Parameters affected by the icing

As explained above, icing results in decreasing aircraft aerodynamic performance, which are affected by changes in lift, drag and pitch moment, and their effectiveness with regard to aircraft position angles and velocities. In common representatives of aircraft linearized dynamic equations, variation of stability and control derivatives may reflect this effect. Especially, the researches in NASA Icing Research Group and Icing Institute of Illinois University have showed that the most affected parameters from in-flight wing icing are following [6]:

$$C_{D_\alpha}=\frac{\partial C_D}{\partial \alpha},\; C_{L_\alpha}=\frac{\partial C_L}{\partial \alpha},\; C_{L_q}=\frac{\partial C_L}{\partial q},$$
$$C_{M_\alpha}=\frac{\partial C_M}{\partial \alpha},\; C_{M_q}=\frac{\partial C_M}{\partial q}$$

As well as ice accumulation generally increases the drag parameters (C_{D_α}), it decreases moment and lift parameters (C_{L_α}, C_{L_q}, C_{M_α}, and C_{M_q}). In this study, as being in the previous research on icing, the changes of other derivatives are assumed small and negligible. When the matrix form of aircraft equations are examined, the relevant five stability derivatives are the terms of the matrix A as follows

$$\mathbf{A}(1,2)=k_1(C_{D_\alpha}-C_L) \qquad (11)$$

$$\mathbf{A}(2,2)=k_2(C_{L_\alpha}+C_D) \qquad (12)$$

$$\mathbf{A}(2,3) = k_3 C_{L_q} \quad (13)$$

$$\mathbf{A}(3,2) = k_4 C_{M_\alpha} \quad (14)$$

$$\mathbf{A}(3,3) = k_5 C_{M_q} \quad (15)$$

where constants k_i , i = 1,2,3,4,5, depend on the following parameters; dynamic pressure, the reference wing area, aircraft trim speed, wing chord length and aircraft inertial moment per aircraft pitch axis. These constants can be assumed as fixed for approximately 60 sec for cruise. These constants may be calculated from certain flight conditions such as take off, climb, cruise, and landing.

Icing detection by the innovation approach

Innovation is defined as a process of the differentiating between the actual system output and the predicted output based on past outputs. In order to detect the faults, which change the mean of the innovation process, the below statistical function is used [14].

$$\beta(k) = \sum_{j=k-M+1}^{k} \tilde{\mathbf{\Delta}}^T(j)\tilde{\mathbf{\Delta}}(j) \quad (16)$$

Here $\tilde{\mathbf{\Delta}}$ is the Kalman filter normalized innovation process, and M is the window length. This statistical function has Ms degree of freedom where s is the number of measurements. This function has $\chi 2$ distribution properties. There are two hypotheses; H_0 is the the case that the system works in normal conditions, and H_1 is the case that the system is faulty. When hypothesis H_1 is correct, then α-reliable $\chi 2$ probability level for H_1 is higher than the level for H_0.This can be expressed as follows:

$$H_0 : \beta(k) \leq \chi^2_{\alpha,Ms} \qquad \forall k$$
$$H_1 : \beta(k) > \chi^2_{\alpha,Ms} \qquad \exists k$$

This study considers the wing icing in flight as a fault.

NN model for icing parameter estimation

NNs have increasingly been shown as viable tools for mapping nonlinear systems and for the purpose of parameter identification. It is very efficient method in the analysis of nonlinear and complex models if enough data are available for its training phase. Unfortunately, icing in flight occurs in many different ways, and there is no enough training data available regarding stability and control derivatives. There are little data only for a few research aircraft obtained from tunnel test or flight test. This study aims to find the stability derivatives of clear and iced configuration. By monitoring the flight data, changes in these derivatives are found, and a fault signal can be built up according to change level.

In this study, since there are nine states measured and five parameters to be estimated, a NN structure having nine inputs and five outputs is presented. One hidden layer having tangent activation function is proposed. In the output layer, linear activation function is used. This NN is trained with the estimates of EKF previously proposed.

For training method the Levenberg-Marquardt Backpropagation Algorithm (LMBA) is used to maintain second-order training speed without having to compute the Hessian matrix, which includes the second derivatives of the network output errors (**e**) per network weights and biases (**NW**). Error represents the difference between network output and actual or simulated value, i.e. desired value. NN model of the aircraft can be calculated as below:

$$\mathbf{NW}_{k+1} = \mathbf{NW}_k - [\mathbf{J}^T\mathbf{J}+\mu\mathbf{I}]^{-1}\mathbf{J}^T\mathbf{e}$$

where **J** is the Jacobian matrix that contains first derivatives of the network errors with respect to the weights and biases. The Jacobian matrix can be computed through a standard backpropagation technique. μ is the parameter of LMBA to make the network faster and more accurate every step forward. If μ is zero, the method becomes the basic Newton's optimization method. When μ is large, this becomes gradient descent with a small step size. Newton's method is quicker and more accurate near an error minimum. Therefore, the aim in LMBA is to shift towards Newton's method as quickly as possible.

Simulations

The proposed method is applied to several model configurations. Both training and validation is performed either only clean or only iced F16 model. Batch size for training is chosen such that icing can be detected within a certain time frame. All states are filtered through EKF so that measurement noise levels are considerably compensated.

Fig. 1 shows the icing parameters variation during 8min-simulation time frame. Note that no icing occurs between 0-1. Solid and dashed lines represent the clear and iced cases, respectively. Fig. 2 shows the variation of the EKF estimates for pitch angle. Solid and dashed lines represent actual or simulated states and EKF estimates, respectively. Fig. 3 shows the normalized innovation sequence for pitch angle. Threshold value (196) is obtained from 90% reliable χ^2 distribution properties. As shown increasing icing condition for one simulated flight is detected 3 min. later than the start of icing, i.e. the detection time is around min 4.

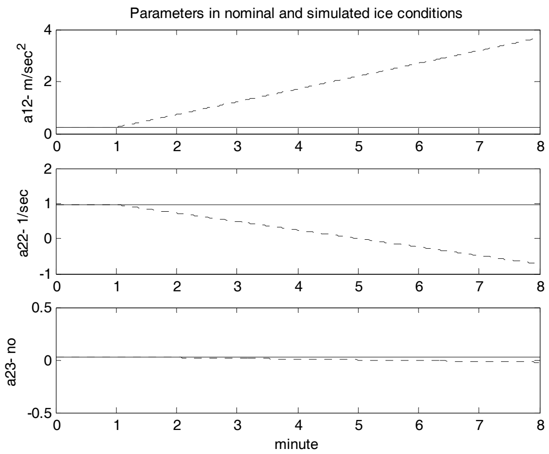


Fig. 1

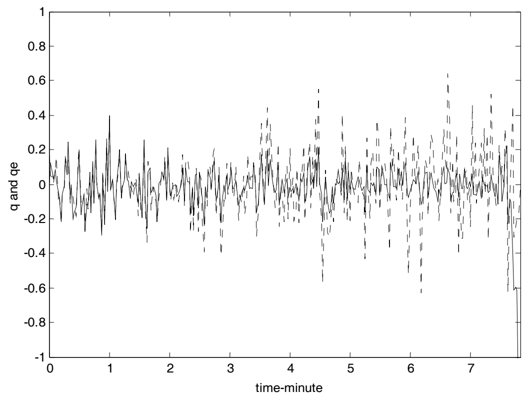


Fig. 2

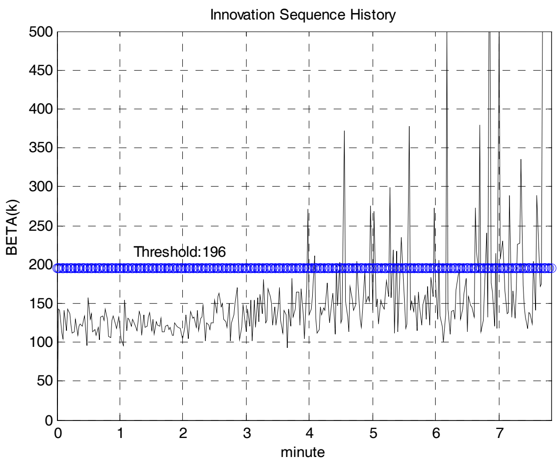
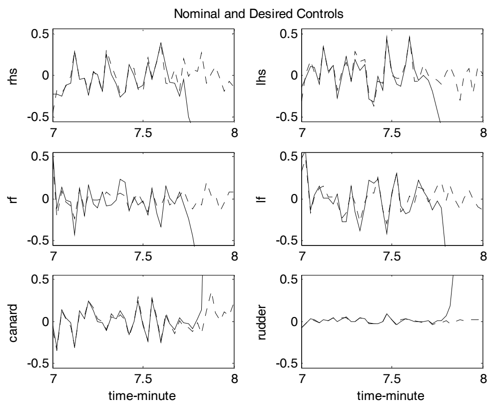


Fig. 3



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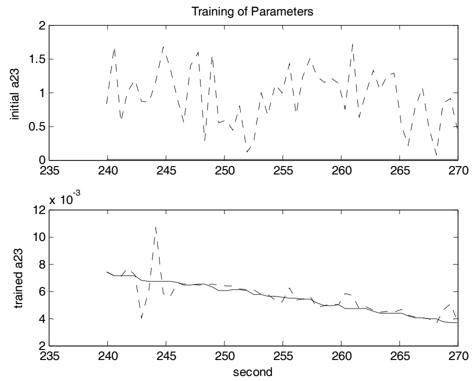

Fig. 5

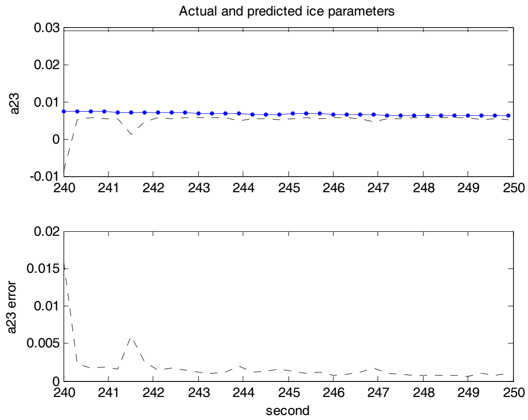

Fig. 6

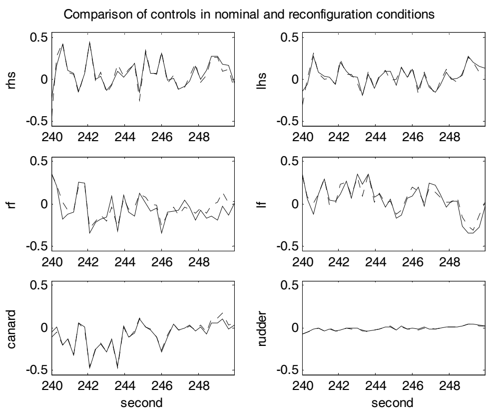

Fig. 7

Fig. 4 shows the control surface deflection at normal linear quadratic control rule. Note that the aircraft will not be controlled after around 7.8min. Fig 5 shows the outputs of NN model and simulated parameter values at training stage as dashed and solid lines, respectively. The error history is also given in the upper side of the figure. Figure 6 shows the outputs of NN model and simulated parameter values at the identification stage as dashed and solid lines, respectively.

Fig 7 shows the control surface deflections, as dashed lines, based on the identified NN model in terms of five icing parameters and linear quadratic control rule. Solid lines in the figure represent the normal control surface deflections shown in Fig 4.

Conclusion and comments

In-flight icing at aerodynamic surfaces such as wing affects several aircraft flight dynamic parameters. In order to capture icing effect on aircraft performance, these parameters have been calculated. Determination of stability derivatives affected by icing is very difficult experimentally or analytically. A suitable inverse NN modeling of flight dynamics could estimate uncertain stability derivatives related with icing effects. In this research, identification based on NN and EKF has been applied to F16 aircraft flight dynamic model. Inverse NN model of the aircraft flight dynamic model is produced for icing parameters' identification. In order to identify in-flight icing, aircraft should have sufficient dynamical properties or certain level model noises. As a nonlinear F-16 aircraft model is simulated in a time dependent manner by entering various stability derivatives for a certain time which ice is detectable, the necessary training samples can be collected. In this method training process of NN is off-line, and application is on-line. The more model noise exists, the less validation noise becomes, but the worse training performance gets.

In NN process, simulated data have been used. In future studies, the actual flight testing data will be used. The proposed icing identification method can be used as an analytical sensor to measure icing effects. Using of the existing ice detection sensors increases the reliability of the method.

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