SIMULATION-BASED FILTERING APPROACH FOR IN-FLIGHT MONITORING OF CONTROL SURFACES

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Abstract

In this paper, an approach to monitor the state of an aircraft's control surfaces employing a simulation-based filtering algorithm is presented. The implementation of such an algorithm and the application of an existing dynamic model for this purpose is outlined in this paper. While it is straightforward to estimate the coupled effects of a damaged control surface actuator and a degraded control surface itself, the attribution of a fault to its actual source (actuator or control surface) is not possible without a modification of the standard particle filtering process. Simulations have shown that the estimation performance can be substantially enhanced by the integration of an adaptive filtering step, enabling the simultaneous, instantaneous observation of a coupled control surface and actuator fault.

1 Nomenclature

1.1 Abbreviations

AoA	Angle of attack
DLR	*Deutsches Zentrum für Luft- und Raumfahrt,* German Aerospace Center
EKF	Extended Kalman Filter
FDI	Fault Detection and Isolation
FOD	Foreign Object Damage
FTC	Fault-tolerant control
PDF	Probability Density Function
SIR	Sampling Importance Resampling
SMC	Sequential Monte-Carlo Method
coeff.	coefficient

1.2 Variables

C_l	Rolling moment coefficient
C_{l0}	Aerodynamic bias parameter
$C_{l(.)}$	Nondimensional rolling moment derivatives
$C_{l\xi}$	Rolling moment coeff. due to aileron deflection
$C_{l\zeta}$	Rolling moment coeff. due to rudder deflection
C_n	Yawing moment coefficient
C_{n0}	Aerodynamic bias parameter
$C_{n(.)}$	Nondimensional yawing moment derivatives
$C_{n\xi}$	Yawing moment coeff. due to aileron deflection
$C_{n\zeta}$	Yawing moment coeff. due to rudder deflection
V	True airspeed
W_k	Process noise covariance matrix
m	Mean
num	Number of particles
q	Pitch rate
r	Yaw rate
s	Half of wing span
t	Continuous time
$\vec{u}_k$	System input vector

$\vec{v}_k$	Measurement noise vector
$\vec{w}_k$	Process noise vector
$wp^i_{(.)}$	Particle weights
$\vec{x}_k$	System state vector
$\vec{x}^i_k$	Particle vector of system state
$\vec{y}_k$	System output vector
$\vec{z}_k$	Measurement vector
$\vec{\Xi}_k$	Variable system parameter vector
α	Angle of attack
β	Sideslip angle
ζ	Rudder deflection
ξ	Aileron deflection
ξ_{com}	Commanded aileron deflection
ξ_e	Normalized aileron control surface efficiency
ξ^i_e	Particle vector of normalized aileron control surface efficiency
ξ_{eff}	Effective aileron deflection
ξ^i_{eff}	Particle vector of effective aileron deflection
ξ_Δ	Offset to commanded aileron deflection
ξ^i_Δ	Particle vector of aileron deflection offset
σ	Standard deviation

1.3 Indices

i	Particle index
k	Discrete time variable
m	Measured

2 Introduction

With the increasing complexity inherent to modern technical systems it becomes more and more important to be able to monitor the health of components and subsystems in order to prevent failures of parts or modules from resulting in malfunctioning of the whole system. This holds especially true for systems that are required to meet the highest safety standards such as modern aircraft. A common approach to determine the state of an aircraft's vital components such as control surfaces is to attach sensors to the relevant control assemblies and directly measure the surface deflection. This, however, can cover only a limited range of possible failure scenarios as it will effectively monitor the state of the surface actuators; damage to the control surfaces themselves as well as to the airframe cannot be detected by deflection sensors.

An alternate approach, that has gained increasing interest in both research and industry in recent years, addressing the problem of monitoring vital components is to analyze the system dynamics of the aircraft, employing a dynamic model of the aircraft's motion to estimate the states of the relevant parts and systems such as actuators and control surfaces, comparing these estimated states to the commanded or expected states and declaring a fault in case the deviation of expected, nominal condition system states and estimated system states exceeds a certain, predefined threshold. This approach, which can be employed utilizing the existing sensor infrastructure, is known as Analytical Fault Detection (figure 1).

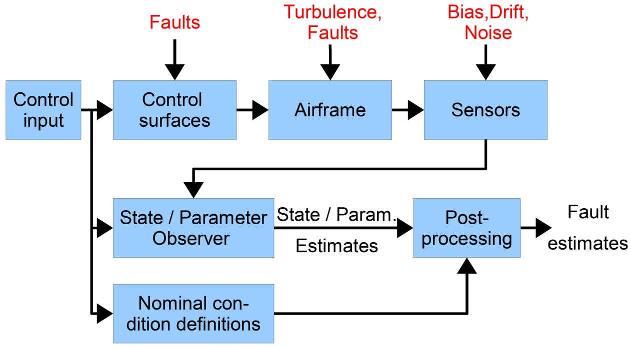

Fig. 1 Analytical Fault Detection using observers

The information gathered using this technique can be used to inform the operator (in this case, the pilot) about the change in system state and behaviour to increase situational awareness as well as to adapt control laws automatically in order to keep the system operational and safe, a concept which forms an important part of fault-tolerant control (FTC).

The critical task in analytical fault detection is to estimate the non-measurable system states and parameters, which can be challenging as there are other effects from external disturbances such as turbulence, that heavily influence aircraft dynamics. In addition, the influence of different faults can be coupled, making it difficult to correctly identify the source of the fault. The coupling of fault effects often results from the dependence of measurements on a system state and its interdepending parameter, requiring simultaneous state and parameter estimation techniques to correctly attribute the fault effects to the actual source. This paper addresses the detection and identification of these types of coupled faults, employing a simulation-based observer approach, widely known as the particle filter.

Several observer concepts have been applied to the domain of fault detection in aicraft systems. These comprise algorithms such as the Extended Kalman Filter (EKF) [1], H^∞ observation techniques [2], Fourier analyis [3] and multiple-model estimation algorithms [4]. A common method to simultaneously estimate states and parameters is to use a bank of dynamic models with varying parameters and apply different methods to select the most suitable model. The approach chosen in this paper is similar to the multiple-model concept, however the varying parameters are dynamically generated according to a dynamically adapted probability density function. This variation in parameters results in a non-Gaussian distribution of process noise, which encourages the application of particle filters due to the ability to handle arbitrary noise distributions.

3 Faults in Aircraft Systems

Taking the definition of [5], a *fault* occuring in a dynamical system is a deviation of the system structure or the system parameters from the nominal case, which results in the deviation of the plant's input/output characteristics from its designed or specified ones, hence changing the performance of the closed-loop system and eventually resulting in a *failure*, the loss of the system function. The effects of faults are similar to the influence of disturbances or model uncertainties, with the main difference being that the latter influence is known to exist and therefore is considered during the design of the system controller, whereas faults are more severe changes, whose effects on the plant behaviour cannot be suppressed by the nominal system controller.

3.1 Fault types

Faults can be categorized according to the affected components and to the kind of effects that a faulty dynamic system exhibits. Figure 2 depicts possible types of faults that a dynamic system can be exposed to; additionally, the corresponding aircraft systems are given as reference. Faults can influence **actuators**, the **plant** or **sensors**, the effects on the system dynamics can be additive or multiplicative (or both). In the case of additive faults, the system states are directly affected, which can be represented by additional unknown inputs to the system. Multiplicative faults occur when the system's structure is affected, resulting in a deviation of the system parameters from the nominal case.

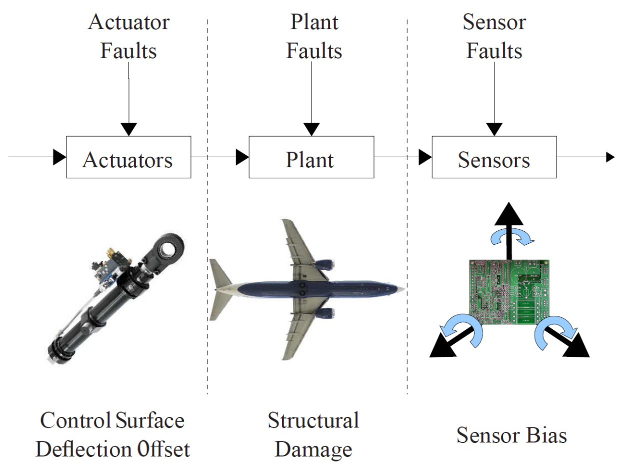

Fig. 2 Examples for different fault types relevant to aircraft systems

Actuator faults In the case of actuator faults, the plant properties are unchanged, whereas the control input to the plant is modified or even unavailable. For aircraft systems this means that the deflection of control surfaces or thrust do not match the commanded values. This type of fault is prevalently modelled as an additive fault.

Plant faults Deviations of a system's dynamic input/output characteristics from the nominal case are considered as plant faults. This type of fault results (for aircraft systems) from structural damage to the aircraft control surfaces or other parts of the airframe, which changes the parameters of the dynamic model. For this reason, plant faults are mostly modelled as multiplicative faults.

Sensor faults The class of sensor faults is mostly relevant to closed-loop systems. The open-loop system's dynamic behaviour remains unchanged, whereas the sensor readings exhibit considerable errors. Both additive (bias) or multiplicative faults can occur in the context of sensor faults.

Faults that occur while processing data in avionic components are beyond the scope of this paper, as these type of faults cannot be accounted for by observer concepts based on dynamic models.

3.2 Coupled effects of disjunct fault sources

In the case of aircraft accidents or incidents that were caused by physical degradation of aircraft components, the damage to the affected components frequently results in multiple different faults. This holds especially true for the case of foreign object damage (FOD), which mostly results in structural damage to the airframe, but which can also affect flight controls when control surfaces are hit by debris. Therefore, from a system dynamics point of view, FOD can simultaneously result in additive and multiplicative faults. While it seems obvious that FOD is an issue mainly for military applications, several reports suggest that FOD to the flight controls resulted in a substantial amount of civil aircraft losses [6].

The impact of a simultaneous damage to an actuator and the corresponding control surface on the aircraft's motion is coupled, which enhances the challenge to identify the location and the severity of the fault. This coupling can be seen from the equations of moment coefficients (1),(2), shown here only for the lateral aircraft motion and neglecting the influence of secondary control surfaces, ground effect and landing gear. The following explanations apply to a fixed-wing aircraft and will assume an aileron fault, affecting both actuator and control surface.

$$\begin{aligned} C_l &= C_{l0} &+& C_{l\Sigma} \\ &+ (C_{l\xi} + C_{l\xi\alpha}\alpha)\xi &+& C_{l\zeta}\zeta \end{aligned} \tag{1}$$

The influence of additional rolling and yawing moment derivatives not relevant to the explanations is summarized as $C_{l\Sigma}$ and $C_{n\Sigma}$.

$$\begin{aligned} C_n &= C_{n0} &+& C_{n\Sigma} \\ &+ C_{n\xi}\xi &+& C_{n\zeta}\zeta \end{aligned} \tag{2}$$

An actuator fault will result in a deviation of the aileron deflection ξ from its commanded value ξ_{com}, while a control surface degradation will result in a deviation of $C_{l\xi}$, $C_{l\xi\alpha}$, $C_{n\xi}$ from their corresponding nominal values. It is evident that for the estimation of either the actuator state or the associated moment coefficient, the value of the corresponding state or parameter has to be known. Numerous approaches to system identification in the domain of aircraft modelling exist, e.g. as presented in [7]. However, it is generally assumed that the system states are properly determined, for example by appropriate measurement equipment and pre-processing of flight test data. These approaches can identify system parameters with high accuracy, whereas for FDI the timely availability of on-line state and parameter estimates has priority over estimation accuracy.

Contributions from other domains for the simultaneous estimation of system parameters and states are available, such as employing methods like joint Kalman filtering [8], but these methods require complementary data sources, a prerequisite that usually is not fulfilled.

4 Filtering Algorithm

4.1 Particle filtering

Particle filtering is an observer concept that has found widespread use in several engineering applications since it was first presented at the beginning of the 1990s [9]. Shortly after its introduction, different modifications under designations such as bootstrap filter, SIR-filter or the condensation algorithm [10] have emerged. These methods follow an identical approach and are commonly referred to as *Sequential Monte-Carlo* methods (SMC). Particle filters employ a classical two-step approach for state estimation; based on the non-linear, time-discrete model (3)

$$\begin{aligned} \vec{x}_k &= f(\vec{x}_{k-1}, \vec{u}_{k-1}) + \vec{w}_k \\ \vec{y}_k &= h(\vec{x}_k, \vec{u}_k) + \vec{v}_k \end{aligned} \tag{3}$$

a set of state samples or *particles* $\vec{x}^i_{k-1}$ is propagated to time step k. The samples are generated with respect to the probability density function (PDF) of $\vec{w}_k$. In the following estimation step, particle weights $wp^i_{(.)}$ are derived by comparing measurements $\vec{z}_k$ with the propagated particle output $\widetilde{\vec{y}} = h(\vec{x}^i_k, \vec{u}_k)$. An additional resampling step is required to prevent the degeneration of samples, which, in practical terms, means that after a number of propagation/estimation steps a single particle accumulates most of the importance weight. This has the effect that most of the other particles do not contribute to the estimation process. To prevent the problem of degeneration, particles are drawn from the current particle set with probabilities proportional to their current weight and are assigned equal weights. This approach is one of many, but the most common method for resampling.

The main advantage of SMC methods over the EKF is that by means of sampling the system state's PDF using a set of particles, no assumptions regarding the nature of the applicable PDFs have to be satisfied.

4.2 Fault modelling

As outlined in section 3.2, estimating the state of actuators and control surfaces basically requires simultaneous state and parameter estimation of the aircraft model. For this reason, the model as of (3) has to be rewritten to account for the varying system parameters $\vec{\Xi}$ (4).

$$\begin{aligned} \vec{x}_k &= f(\vec{x}_{k-1}, \vec{\Xi}_{k-1}, \vec{u}_{k-1}) + \vec{w}_k \\ \vec{y}_k &= h(\vec{x}_k, \vec{u}_k) + \vec{v}_k \end{aligned} \tag{4}$$

A common approach for estimating these varying parameters is to enhance the dynamic model [11]; this is not feasible for the application of particle filters as it would require a substantial amount of particles, thus slowing down the estimation process considerably. For this reason, an alternative approach was chosen which does not require to estimate the full aircraft state vector. Instead, only fault states are estimated by the particle filter, whereas the required aircraft states are measured. The fault influence is modelled as an offset ξ_Δ to the commanded aileron deflection ξ_{com} and as a factor ξ_e representing the normalized control surface efficiency. By employing these definitions, an effective aileron deflection ξ_{eff} is defined as:

$$\xi_{eff} = \xi_e(\xi_{com} + \xi_\Delta), \qquad \xi_e = [0..1] \tag{5}$$

Offset ξ_Δ and normalized control surface efficiency ξ_e form the observer state vector $\vec{x}_e$.

$$\vec{x}_e = \begin{bmatrix} \xi_\Delta \\ \xi_e \end{bmatrix} \tag{6}$$

During the propagation step of the particle filter the unaltered dynamic aircraft model is used, with the actuator state ξ replaced by the effective actuator state ξ_{eff}. The set of particles of size *num* is generated by first generating a process noise sample $\vec{w}^i_k$ using a Gaussian PDF $\mathcal{N}(m, \sigma^2)$ with mean m and variance σ^2 (7).

$$\vec{w}^i_k \sim \mathcal{N}(\vec{0}, W_k) \qquad i = 1..num \tag{7}$$

The samples are added to the current values of ξ_Δ and ξ_e, generating the particle samples $\vec{x}^i_k$ which are propagated to the next time step by the dynamic aircraft model.

A standard SIR filter algorithm as presented in [12] was chosen for processing of particles with the number of particles set to 50. Simulations with varying numbers of particles were run, showing that additional particles result in slightly enhanced estimation performance while substantially increasing computational requirements.

As the normalized aileron efficiency ξ_e is unobservable without an excitation of control surfaces, a band-limited noise signal is added to the commanded aileron deflection. The standard deviation of the excitation signal was chosen to be $0.5°$; the low-pass filter was designed with a cutoff frequency of 1.5 Hz. The continuous application of this noise signal is considered to be impractical for real applications and should be activated only in case an indication of a potential failure condition exists. A potential condition for activating this signal can be the crossing of a threshold of the dynamically calculated process noise covariance matrix W_k as shown in section 4.3.

The properties of the aircraft model used during the simulations are shown in table 1. Simulations of the algorithm described above

Table 1 Simulation parameters

Aircraft Type	Twin-Engine Jet Transport
Aircraft Mass	18500 kg
VTAS	160 kts
Altitude	4900 m
Configuration	clean

were obtained and are depicted as figures 3 - 6. At simulation time $t = 1s$ an actuator fault occurs, resulting in an offset to the commanded aileron deflection of $\xi_\Delta = -10°$; at simulation time $t = 3s$ the control surface efficiency is reduced to $\xi_e = 0.5$. The resulting roll angle ϕ is depicted in figure 3. The aileron offset ($t = 1s$) has the effect of a strong decrease of the aircraft's roll angle, which is reduced at the instance when the aileron efficiency drops to $\xi_e = 0.5$ ($t = 3s$).

Simulations were generated for different process noise covariance matrices W_k; the initial value W_0 (8) of the process noise covariance matrix has already been used in a related work [13].

$$W_0 = \begin{bmatrix} 0.01^2 rad^2 & 0 \\ 0 & 0.1^2 \end{bmatrix} \tag{8}$$

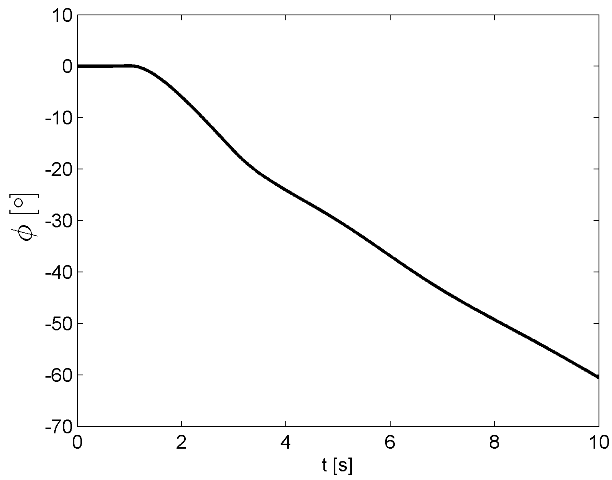

Fig. 3 Roll angle ϕ resulting from $\xi_\Delta = -10°$ at $t = 1s$ and $\xi_e = 0.5$ at $t = 3s$

Figure 4 depicts the real, effective aileron offset ξ_Δ and four aileron offset estimates using the standard SIR filter algorithm with different static values for W_k. For $W_k < W_0$ the convergence speed of the filter is very low. Using the reference covariance matrix W_0 results in an bias error, whereas values greater than W_0 exhibit substantial noise and estimation bias of the estimated ξ_Δ.

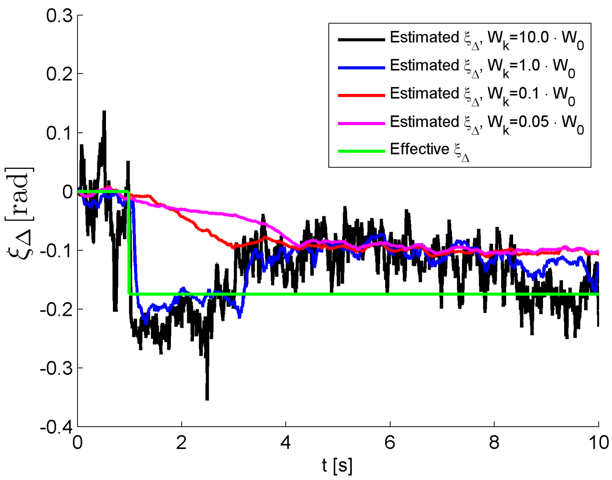

Fig. 4 Estimation of aileron offset with different static process noise covariance matrices W_k

The estimation bias is even better visible in the estimation results for the normalized aileron efficiency ξ_e (figure 5). Smaller values than W_0

result in slow convergence speed, while larger ones yield a large bias.

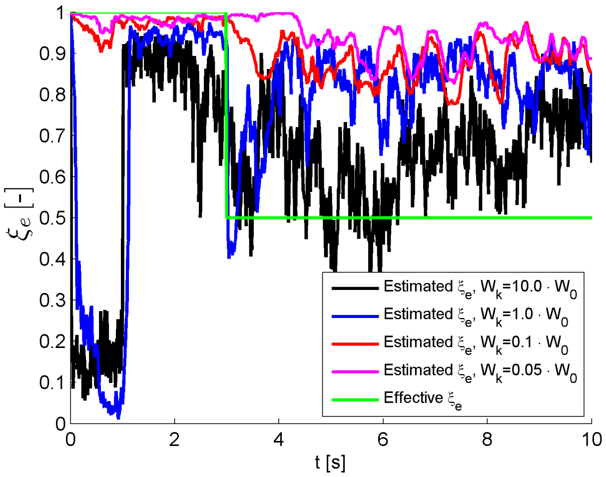

Fig. 5 Estimation of aileron loss of efficiency with different static process noise covariance matrices W_k

Further evaluation of the results shows that for appropriate values of the process noise covariance matrix W_k the combined actuator offset / control surface efficiency $\xi_\Delta \cdot \xi_e$ (figure 6) can be observed, whereas the attribution of the fault to the corresponding source appears to be questionable. Considering the influence of the process noise covariance during the different phases of the fault scenario it can be concluded that static covariance values result either in a slow convergence or even divergence of the estimation solution or in an unacceptably high estimation error.

4.3 Dynamic adaptation of covariance matrix

As outlined in section 4.2, particle samples are generated by generating samples of the process noise PDF. Therefore, the values of the process noise covariance matrix have an impact on the size of the explored state space. As a fault results in a considerable change of system states and / or parameters due to the deviation from nominal conditions, using assumptions of process noise optimized for nominal case conditions has the effect that state hypotheses close to the new, faulty system state will never be considered. On the other hand, using assumptions of process noise optimized for faulty conditions results in high estimation variance due to the anticipated estimation uncertainty.

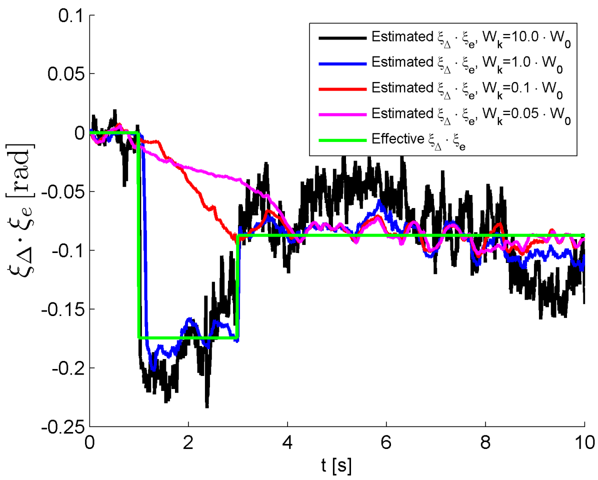

Fig. 6 Estimation of combined aileron offset / loss of efficiency with static process noise covariance matrix W_k

For this reason, an approach for adapting the process noise covariance matrix W_k has been implemented. The average error of each system state is calculated by adding the differences between each of the propagated state particles and the actual measurements. This average error corresponds to the current estimation accuracy and is used to re-initialize the process noise covariance matrix W_k. In the case of an aileron-related fault the process noise covariance for ξ_Δ is generated from the average error between measured roll angle ϕ_m and propagated roll angle particle set ϕ^i and for ξ_e from the average error between measured roll rate p_m and propagated roll rate particle set p^i (9),(10).

$$W_k(1,1) = \frac{1}{num} \sum_{i=1}^{num} \sqrt{(\phi_m - \phi^i)^2} \tag{9}$$

$$W_k(2,2) = \frac{1}{num} \sum_{i=1}^{num} \sqrt{(p_m - p^i)^2} \tag{10}$$

The complete algorithm including dynamic adaptation of the covariance matrix is shown in Listing 1.

Listing 1 Algorithm for estimating ξ_Δ and ξ_e

```
Initialize aircraft model
Initialize W_0
ξ_Δ = 0.0
ξ_e = 1.0
k = 0
start:
Add band−limited noise to input ξ_com
For each particle draw
   random numbers ~ N(0⃗, W_k)
Add random numbers to ξ_Δ and ξ_e
   x⃗_e^i = x⃗_e + w⃗_k^i
Calculate ξ_eff^i = ξ_e^i (ξ_com + ξ_Δ^i)
Propagate system state:
   x⃗_{k+1}^i = f(x⃗_k^i, ξ_eff^i)
k=k+1
Calculate new W_k
Calculate particle weights
   wp_(.)^i = f(z⃗_k, x⃗_k^i)
Calculate current ξ_Δ and ξ_e:
   ξ_Δ = 1/num Σ_{i=1}^{num} wp_{ξΔ}^i · ξ_Δ^i
   ξ_e = 1/num Σ_{i=1}^{num} wp_{ξe}^i · ξ_e^i
Resample particles
Jump to start
```

The simulation results of the modified estimation algorithm employing a dynamically adapted process noise covariance matrix W_k are shown in figures 7 and 8. The results show a sufficient match between real and estimated actuator state and control surface efficiency. Although the estimated efficiency (figure 8) fluctuates up to 10% of the nominal efficiency, it is expected that a compensating feedback controller or a human pilot is sufficiently robust to handle this inaccuracy. In addition, it is envisioned that the estimation variance of ξ_e can be further reduced by the application of more adequate excitation signals. It should also be noted that the settling time is around one second, which should be sufficiently low to enable a fault-tolerant controller to apply adequate countermeasures.

Figure 9 depicts the adaptation of the covariance matrix W_k to the systems's failure condition for the aileron offset state ξ_Δ. In times ($t = 1s$, $t = 3s$) of high deviation of expected from measured system state the covariance is raised, thus increasing the explored state space. As soon as the filter algorithm has adjusted the estimated fault states to the real states, the covariance is reduced, resulting in less noise of the state and parameter estimates.

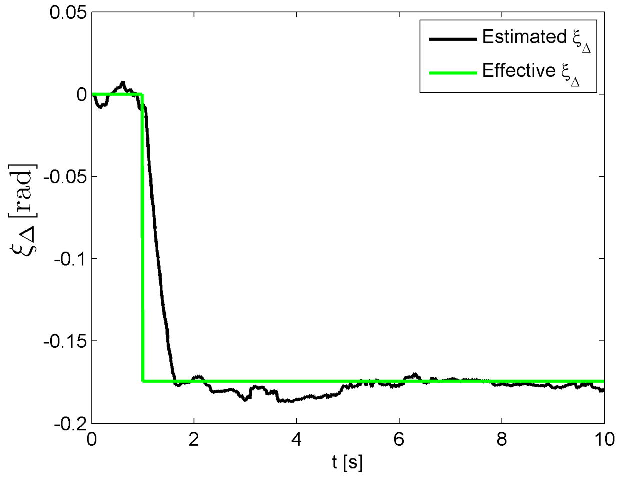

Fig. 7 Estimation of aileron offset ξ_Δ using dynamic process noise matrix

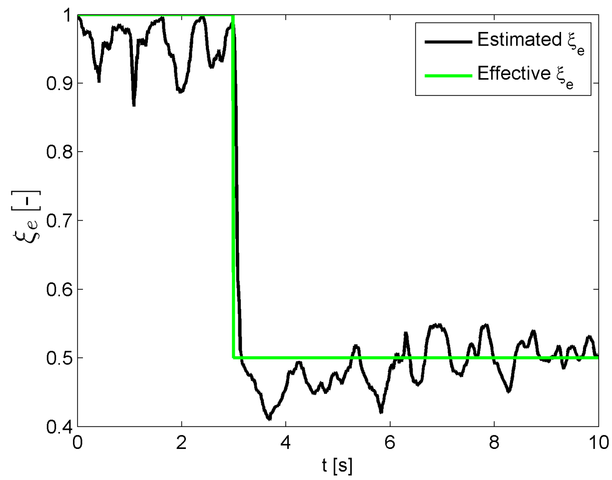

Fig. 8 Estimation of aileron efficiency ξ_e using dynamic process noise matrix

5 Summary

In this paper an approach for simultaneous estimation of system states and parameters with the application to fault detection in an aircraft's primary flight controls was presented. The applica-

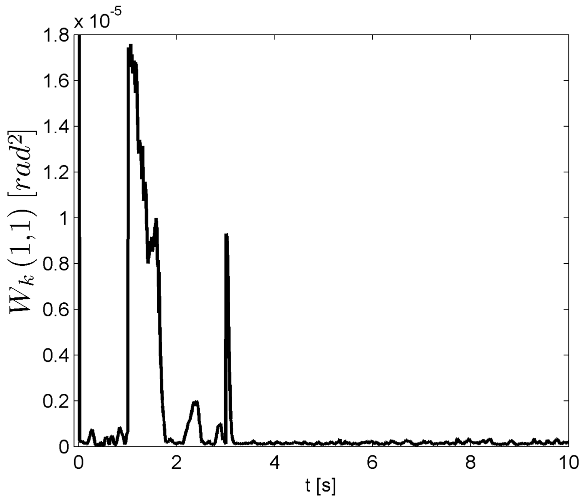

Fig. 9 Adaptation of process noise covariance matrix entry $W_k(1,1)$ (for ξ_Δ)

bility of Sequential Monte-Carlo methods for this purpose has been verified. The ability of SMC methods to estimate arbitrary PDFs offers an additional method for the simultaneous estimation of states and parameters, since for systems that are subject to varying parameters the assumption of Gaussian PDF cannot be maintained. Additionally, it has been shown that the dynamic adaptation of the assumptions regarding the process noise covariance can substantially improve estimation performance.

Further work in this field focuses on investigations on the automatic generation of signals for actuating control surfaces to enhance control surface efficiency estimation performance. In addition, the validation in flight tests is envisioned.

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