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Nonlinear Model-Based Fault Detection for a Hydraulic Actuator

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This paper presents a model-based fault detection algorithm for a specific fault scenario of the ADDSAFE project. The fault considered is the disconnection of a control surface from its hydraulic actuator. Detecting this type of fault as fast as possible helps to operate an aircraft more cost effective and can help to avoid an undetected increase in fuel consumption. The method proposed here uses an Adaptive Extended Kalman Filter (A-EKF) to detect the disconnection using only local measurements (control signal to the actuator and actuator rod position). For this purpose, an accurate physical model of the hydraulic actuator is needed and the fault is detected by parameter estimation. It is shown that the A-EKF performs better than the regular Extended Kalman Filter (EKF) for this application.

I. Introduction

In this paper the application of an A-EKF for the purpose of fault detection through parameter estimation is demonstrated for a nonlinear hydraulic actuator model. This model-based approach is applied on a fault scenario of the ADDSAFE benchmark, i.e., the disconnection of a control surface from the hydraulic actuator. The goal of the Advanced Fault Diagnosis for Sustainable Flight Guidance and Control (ADDSAFE) project is to research and develop model-based Fault Detection and Diagnosis (FDD) methods for aircraft flight control systems, mainly sensor and actuator malfunctions. Improving the fault diagnosis performance of the aircraft's flight control system allows to optimize the aircraft structural design, resulting in weight savings, which in turn helps improve the aircraft's performance and decrease its environmental impact. This last advantage also satisfies the newer societal imperatives toward an environmentally friendlier aircraft.

There are numerous examples where the EKF is used for FDD.[1,2,3,4] In the case of hydraulic actuators, the EKF is often used to estimate different parameters that influence the performance of the hydraulic system, e.g., oil bulk modulus, leakage parameters or friction coefficients.[3,4] By monitoring these slow varying parameters a reduction in the performance of the actuator can be detected. For the EKF it is known that the estimated states will converge to the real state as long as the initial estimate lies in the neighborhood of the real initial state and no unpredicted state jumps occur.[5]

However, the goal of this paper is the detection of the disconnection of the actuator from the control surface, which can be considered to be a large jump in the state of the actuator system. In order to account for this state jump, a adaptive modification can be performed to the EKF. In the EKF algorithm, the covariance matrices of the process noise and measurement noise, usually referred to as Q and R respectively, play an important role in tuning the filter.[6] A large Q or small R means that the filter has a high bandwidth, which means that the state and parameter estimates will follow the measurements accurately and rely less on the model information. On the other hand, a small Q or large R means a low bandwidth of the filter, and therefore more "emphasis" is put on the a priori knowledge of the model than on the measurements to perform the state estimation. To perform the fault detection in a fast and reliable way, a combination of both situations is preferred. Instead of making a trade-off by tuning the Q and R matrices, an adaptive

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algorithm is proposed such that the Q matrix is updated online during the parameter estimation, depending on the innovation of the EKF.

First, the fault scenario considered in this paper is introduced and its relevance is explained. Furthermore, the specific difficulties in detecting these type of fault is highlighted. In the next section, the nonlinear actuator model and aerodynamic force model that are used in the model-based approach are explained. In Section IV the actual fault detection method is introduced, after which the results for the hydraulic actuator are presented.

II. Fault Scenario

The fault scenario investigated is the physical disconnection of an actuator from the control surface, due to a mechanical breakage of the hinge or another part of the mechanical system. Due to this disconnection, the control surface will move to its null hinge moment, which is not necessarily at 0°. In this fault scenario, where the fault is applied to the left inboard aileron, the null hinge moment is at $\delta_a = -12°$. The actuator rod sensor measures the position of the rod correctly. Furthermore, in this scenario there is no control surface deflection sensor. Therefore, the only signals known are the control input to the actuator and the measured rod position. As a result of this failure, the other control surfaces on the aircraft will compensate for the fault and also the disconnected actuator will be given a command to compensate. Because of this automatic compensation performed by the Flight Control Computer (FCC), the drag of the aircraft is increased which results in higher fuel consumption. Detecting this type of fault in time gives the pilot the opportunity to take appropriate actions to counter any problems occurring from this increased fuel consumption.

Detecting this type of fault without analyzing the flight dynamics of the aircraft can be a challenging problem, because the actuator is still fully functional and the rod sensor measures the position of the actuator rod correctly. The approach that is proposed in this paper is to detect this fault through parameter estimation. Using an accurate model of the hydraulic actuator combined with an aerodynamic model of the hinge moment created by the control surface, it becomes possible to detect this fault. In the next section, the models used are presented.

III. Actuator Model

The methods proposed here make use of an accurate physical model of a hydraulic actuator. Instead of using a pure mathematical model, the physical approach gives the advantage of using parameter estimation based fault detection techniques, because the variables in the model are related to real physical parameters of the actuator. The hydraulic actuator can accurately be modeled by the following equations[7,8] :

$$\dot{\boldsymbol{x}} = \boldsymbol{f}(\boldsymbol{x}, u), \qquad y = h(\boldsymbol{x}) \tag{1}$$

with:

$$\boldsymbol{f}(\boldsymbol{x}, u) = \begin{cases} x_2 \\ \frac{1}{M}\left(A_p P_s x_3 - B x_2 + F_{ext}\right) \\ \frac{2EV_m}{V_m^2 - A_p^2 x_1^2}\frac{A_p}{P_s}\left(\frac{\phi_n}{A_p}\sqrt{1-\text{sign}(u)x_3}\,u - Lx_3 - x_2\right) \end{cases} \qquad h(\boldsymbol{x}) = x_1 \tag{2}$$

where x_1 represents the position of the actuator rod, x_2 the velocity and x_3 the pressure difference between the actuator chambers. Furthermore, A_p is the piston area, B a damping coefficient, P_s the reservoir oil pressure, ϕ_n the maximum valve flow, V_m the mean actuator chamber volume, E the oil bulk modulus, M the mass of moving system and L the normalized leakage parameter. This is a generic hydraulic actuator model which omits the effects of the transmission lines and the servo-valve dynamics. The term F_{ext} represents the external force acting on the actuator piston, in this case the force due to the aerodynamic moment on the control surface.

Furthermore, this moment is considered to be known and can easily be modelled. The model used in this work is based on Mulder[9] and is described by:

$$H = \bar{q} C_H S \tag{3}$$

where H is the control surface hinge moment, $\bar{q} = \frac{1}{2}\rho V^2$ is the dynamic pressure, C_H the moment coefficient and S the control surface area. C_H is modelled as:

$$C_H = C_{H_0} - C_{H_\alpha}\left(\alpha - \frac{2y_m}{b}\frac{pb}{2V_{TAS}}\right) + C_{H_\delta}\delta_a \tag{4}$$

where α is the angle of attack, y_m the span wise position of the aileron, b the span wise, p the rolling rate of the aircraft, V_{TAS} the true airspeed and δ_a the control surface deflection angle. These values are always available in the Electronic Fligth Control System (EFCS) of an aircraft, and are therefore considered to be known. From this moment the force on the actuator rod can easily be calculated. The force now acts as an extra input to the system, while there is also a part that is dependent on the actuator rod position (δ_a).

IV. Proposed Approach

As already explained in the fault scenario description, detecting the disconnection using only *local* measurements (the command signal and measured rod position) can be a challenging problem. In the event of a fault, the actuator rod will still move to the commanded position. The method proposed here will take advantage of the physical model. Instead of using a *global* approach, involving the analysis of the flight dynamics of the aircraft, the idea here is to use parameter estimation to perform the fault detection. The state vector of system (2) can for this purpose be augmented with an extra parameter that models the fault.

The detection of the fault is then achieved by performing the joint state and parameter estimation of the nonlinear system using an A-EKF. The A-EKF is based on the work of Boizot et al.[10] It is a combination of a high-gain nonlinear observer and an EKF. This way, it combines the advantages of both type of observers. The EKF has very good noise filtering properties and is a good local observer, while the high-gain observer has a high reactivity to sudden jumps in system states, because they are nonlinear converging observers. However, this type of observers has not such good properties in the presence of noise.

The standard EKF can be described by the following equations. Consider the nonlinear system:

$$\begin{aligned} \dot{x}(t) &= f(x(t), u(t)) + G(x(t))w(t) \\ z(t) &= h(x(t)) \end{aligned} \tag{5}$$

With the discrete measurements $z_m(t_i) = z(t_i) + v(t_i)$. In these equations, $w(t)$ and $v(t)$ represent zero-mean white noise signals, with covariance matrices defined as $Q = E\left[w(t)w(t)^T\right]$ and $R = E\left[v(t)v(t)^T\right]$. $f(\cdot,\cdot)$ and $h(\cdot)$ are known functions, and $x \in \mathbb{R}^n$, $u \in \mathbb{R}^d$. The EKF consists of two steps. The first step is the one-step ahead prediction of the state and covariance, and calculated by:

$$\begin{aligned} \hat{x}(k+1|k) &= \hat{x}(k|k) + \int_{t_k}^{t_{k+1}} f\left(\hat{x}(t), u(t), t\right)\, dt \\ P(k+1|k) &= \Phi(k+1|k)P(k|k)\Phi(k+1|k)^T + \Gamma(k+1|k)Q(k|k)\Gamma(k+1|k)^T \end{aligned} \tag{6}$$

Where Φ and Γ are discretized versions of the Jacobian $F_x = \frac{\partial f}{\partial x}$ and G. The notation $(k+1|k)$ means the value of the variable at time $k+1$, knowing the measurement at time k. The second step of the EKF is the measurement update. In this step, the measurement of the output is used to correct the prediction of the state and the covariance matrix. This step is performed by:

$$\begin{aligned} K(k+1|k) &= P(k+1|k)H_x^\top(k+1|k)\left[H_x(k+1|k)P(k+1|k)H_x^\top(k+1|k) + R\right]^{-1} \\ \hat{x}(k+1|k+1) &= \hat{x}(k+1|k) + K(k+1|k)\left(z_m(k+1) - z(k+1|k)\right) \\ P(k+1|k+1) &= \left[I - K(k+1|k)H_x(k+1|k)\right]P(k+1|k)\left[I - K(k+1|k)H_x(k+1|k)\right]^\top \\ &\quad + K(k+1|k)\,R\,K(k+1|k)^\top \end{aligned} \tag{7}$$

Where K represents the Kalman gain and H_x is the Jacobian of the output function h.

In the case the EKF is used for parameter estimation using an augmented state, convergence of the estimated parameter to the real value can be achieved by using a pseudo-noise modification.[1] Changing the corresponding value in the Q matrix to a small value will make the parameter estimate more *rigid* because the related Kalman gain will be smaller. This makes the detection of a sudden change in the parameter, in this case a fault, more difficult and slower, increasing the chance for a missed detection. Increasing this value will make the parameter estimate more *flexible.* This reduces the detection time, but makes the estimation more sensitive to external disturbances and model-mismatches, and therefore increases the chance for a false alarm. To increase the performance of the fault detection using the EKF, there is a need for an automatic tuning of the Q matrix, and if possible, a adaptation algorithm that changes the related covariances in the Q matrix online. This can be achieved by implementing an adaptation algorithm into the EKF.

The method proposed here is mainly based on the work of Boizot et al.[10] By including an adaptive term in the Q matrix based on the innovation, the EKF can be made adaptive. The parameter is called θ and the new covariance matrix is calculated by:

$$Q_\theta = \theta \Delta Q \Delta \tag{8}$$

With $\Delta = \text{diag}\left(1,\, \theta(t),\, \theta(t)^2,\, \ldots,\, \theta(t)^{n-1}\right)$. Furthermore, θ is defined by:

$$\dot{\theta}(t) = F(\theta(t), \mathcal{I}(t)) \tag{9}$$

Where $\mathcal{I}$ is the innovation and defined as the integral of the squared error between the predicted output and the measured about over a certain time window T:

$$\mathcal{I}(t) = \int_{t-T}^{t} ||z_m(\tau) - \hat{z}(\tau)||^2 d\tau \tag{10}$$

The time window is tuned according to the speed of the dynamics of the system observed, and the required detection time for the fault. The actual update equation F should be chosen such that if the innovation increases (which indicates a certain increase in the model mismatch), the parameter θ increases, and vice versa. An example for such a function is given by:

$$F(\theta, \mathcal{I}) = \mu(\mathcal{I}) \cdot \mathcal{F}(\theta) + \lambda(1 - \mu(\mathcal{I})) \cdot (1 - \theta) \tag{11}$$

With $\theta(0) = 1$ and λ chosen such that θ returns to the value 1 at an appropriate speed. Furthermore:

$$\mathcal{F}(\theta) = \begin{cases} \frac{1}{T}\theta^2 & \text{if } \theta \leq \theta_1 \\ \frac{1}{T}\left(\theta - 2\theta_1\right)^2 & \text{if } \theta > \theta_1 \end{cases} \tag{12}$$

$$\mu(\mathcal{I}) = \begin{cases} 0 & \text{if } \mathcal{I} \leq \gamma_0 \\ \in [0;1] & \text{if } \gamma_0 < \mathcal{I} < \gamma_1 \\ 1 & \text{if } \mathcal{I} \geq \gamma_1 \end{cases} \tag{13}$$

Where θ_1 is a high enough value. Using these definitions, $F(\theta, \mathcal{I})$ has the following properties:

- if $\mathcal{I}(t) \geq \gamma_1$: θ increases toward $2\theta_1$ and is above θ_1 in a time less than T, for any $\theta_1 > 1$, and the corresponding value in Q_θ will increase, making convergence to the real state faster,
- if $\mathcal{I}(t) \leq \gamma_1$: θ decreases toward 1, at a rate set via the parameter λ, and the A-EKF returns to operate as a regular EKF performing as a local observer.

The function μ controls which part of F is engaged.

V. Application to the Hydraulic Actuator

To apply the adaptive algorithm presented in the previous section, the state vector of the system described in Equation (2) needs to be augmented with an additional parameter. The disconnection is modelled such that in the fault-free case, this parameter is equal to 1, in the faulty case it is equal to 0. Therefore, this parameter is considered constant and its derivative is equal to 0. The system equations become then:

$$\boldsymbol{f}(\boldsymbol{x}, u) = \begin{cases} x_2 \\ \frac{1}{M}\left(A_p P_s x_3 - B x_2 + x_4 F_{aero}(x_1)\right) \\ \frac{2EV_m}{V_m^2 - A_p^2 x_1^2} \frac{A_p}{P_s}\left(\frac{\phi_n}{A_p}\sqrt{1 - \text{sign}(u) x_3} u - L x_3 - x_2\right) \\ 0 \end{cases} \qquad h(\boldsymbol{x}) = x_1 \tag{14}$$

Where the additional state $x_4 = 1$ in the fault-free case and $x_4 = 0$ when the disconnection occurs. In this equation, the value of $F_{aero}(x_1)$ is calculated using the aerodynamic model for the hinge moment explained in Section III.

In order to be able to perform estimation of the parameter x_4, the observability of the augmented system has to be guaranteed. This can be achieved by checking that the system satisfies the following rank condition:[11]

$$\text{rank}\left\{d\left(L^j_{\boldsymbol{f}}h(\boldsymbol{x})\right) : 0 \le j \le n-1\right\} = n, \quad \forall x \in \mathbb{R}^n \tag{15}$$

Where $L^{\cdot}_{\boldsymbol{f}}$ represent the Lie derivatives of the system (14). When this condition is satisfied, the system is locally observable. From this analysis, it is shown that for the augmented system of the hydraulic actuator, this condition is satisfied as long as the actuator is moving. Although this appears to be a very restricting condition, it does not limit the use of the A-EKF as observer in this application. When the disconnection occurs, the FCC will react and control deflections will be send to the ailerons, both left and right. Therefore, when the identification of the extra state is needed, i.e., when the fault occurs, the actuators will always be moving, making the estimation of the parameter possible.

For the fault detection, we want the augmented state to converge to its real value. Therefore, the value corresponding to the fourth state will be made adaptive. This is done by changing the matrix Δ to:

$$\Delta = \text{diag}\,(1,\, 1,\, 1,\, \theta) \tag{16}$$

In this way, only the covariance of the augmented state related to the fault will be updated online. Furthermore, appropriate values need to be defined for the variables T, θ_1, λ, γ_0 and γ_1. In this case, $T = 0.3\,$s, allowing a fast detection time. γ_0 and γ_1 are based on the magnitude of the innovation $\mathcal{I}$ in the fault-free and the faulty case. θ_1 is chosen large enough such that a fast convergence is achieved when the fault occurs.

The actual fault detection is performed when the value of $\hat{x}_4 \in [-\epsilon, \epsilon]$, where ϵ is represents a bound around 0. In this case, the value is set to $\epsilon = 0.02$. The results obtained with the A-EKF are compared to the results of the regular EKF and are shown in Figure 2 for a disconnection occurring at 10 s after the start of the simulation. The normalized actuator position and the aerodynamic force acting on the rod are shown for this simulation in Figure 1. Although the time until detection is the same for both the EKF and A-EKF, one can notice that the estimate is more constant for the A-EKF. This is due to a different initial Q matrix. For the case of the EKF, the matrix was tuned such that a good convergence was achieved in case of a fault, and found to be optimal for $Q_{\text{EKF}} = \text{diag}\left(10^{-5},\, 10^{-3},\, 10^{-3},\, 10^{2}\right)$. For the A-EKF, because of the adaptive scheme, there is no need to put a larger value for the fourth state, and the matrix is $Q_{\text{A-EKF}} = \text{diag}\left(10^{-5},\, 10^{-3},\, 10^{-3},\, 10^{-2}\right)$. If the same Q matrices would be used, then the estimate of the EKF would not converge to zero anymore, because the estimate would be too rigid due to a low pseudo-noise value, as is shown in Figure 3.

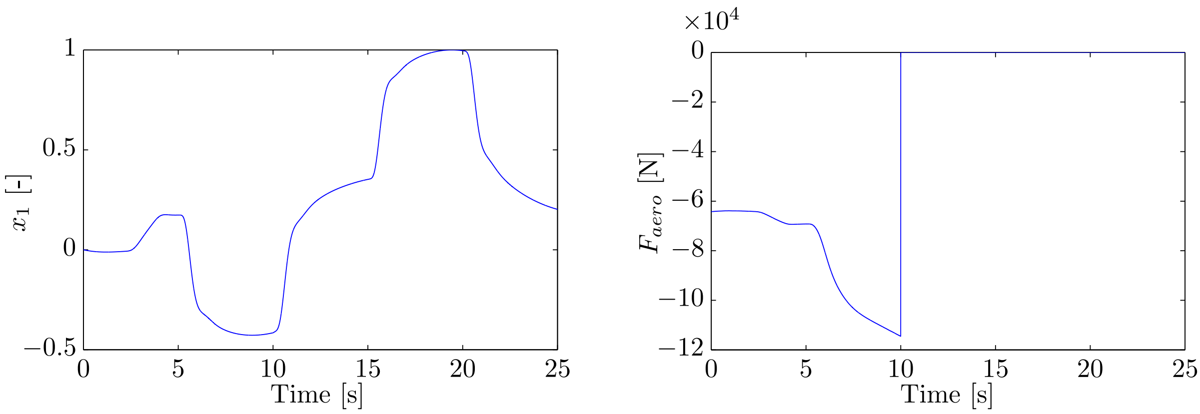
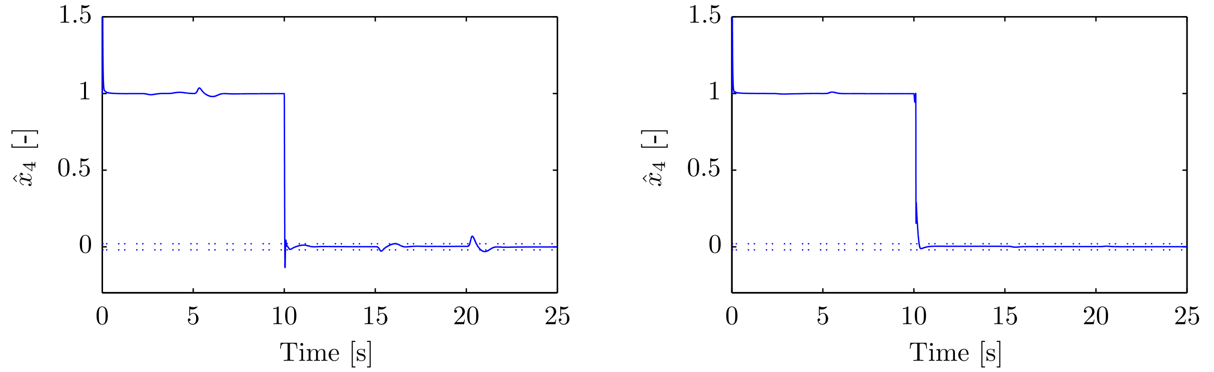


Figure 1. Normalized actuator rod position and aerodynamic force F_{aero}

In Figure 4 a detail is shown of the estimation error of x_4 at the time of the fault, together with the estimated covariance. This figure clearly shows that there is a small delay in the reaction of the A-EKF. This is due to the fact that the innovation $\mathcal{I}$ is calculated over a certain time window and θ also needs time to increase, ΔT. However, the figure also shows that the estimation error remains within the bounds of the estimated covariance $P(4,4)$, indicating the proper functioning of the A-EKF. In Figure 5 the value of θ is shown. At the time of the fault (10 s), it is clear that the adaptive algorithm is engaged and that θ increases and in this way increases the rate of convergence of the estimated parameter.



(a) EKF (b) A-EKF

Figure 2. Estimate of the augmented state x_4, for both EKF and A-EKF

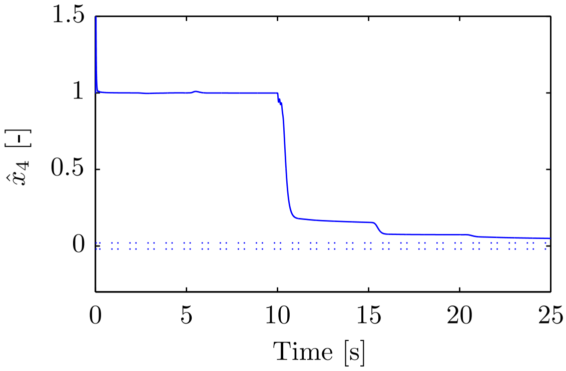


Figure 3. Estimate of the augmented state x_4 using EKF and $Q_{\text{A-EKF}}$

VI. Conclusion

A model-based approach using an Adaptive Extended Kalman Filter was presented to detect the disconnection of a control surface from the hydraulic actuator. First of all, an accurate nonlinear model of a hydraulic actuator is presented that suits our needs for the fault detectino. By augmenting the state vector of the hydraulic actuator system with an additional parameter, the disconnection fault was modelled. The detection of the fault was then performed by parameter estimation using an A-EKF. This approach was chosen because a regular EKF does not show the required performance to detect large jumps in parameters. In order to have fast and full convergence of the estimate of the parameter, the related variance in the Q matrix of the EKF algorithm needs to be high. However, this makes the estimate sensitive to model-uncertainties and external disturbances. Therefore, an adaptive scheme is used, such that in the event a fault is happening, the EKF is adapted such that fast convergence of the estimate parameter is made possible. Results show that the A-EKF presented in this paper shows beneficial performance over the regular EKF for this application.

Acknowledgments

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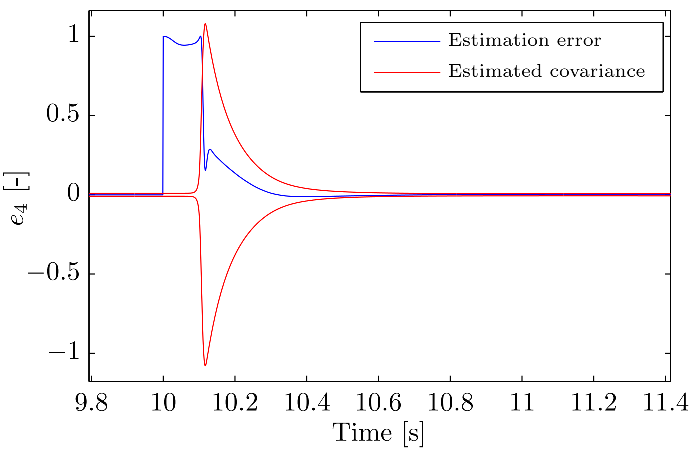

Figure 4. Detail of estimation error of $\hat{x}_4$, together with estimated covariance.

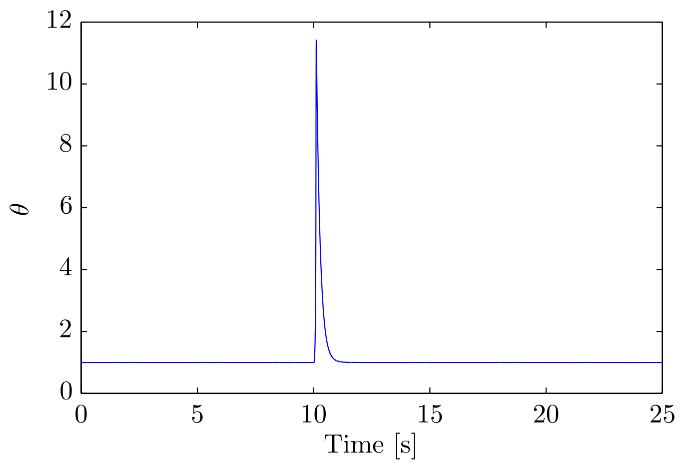

Figure 5. θ for simulation using A-EKF

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