32nd Congress of the International Council of the Aeronautical Sciences
September 6-10, 2021
Pudong Shangri-La, Shanghai, China

FEEDBACK ERROR LEARNING WITH ENHANCED SAMPLING: NEURAL FAULT TOLERANT CONTROLLER OF AIRCRAFT

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Abstract

Neural adaptive controller trained by feedback error learning enhanced with additional sampling from estimated model is investigated. Generally, tuning of the adaptive controller takes a single sampled data every time step. It is not enough information value to train the multiple layer neural network to use the active fault tolerant control, and cause low convergence and stability of the control. To improve the sampling efficiency, the estimate network is adapted to estimate the system model of control target in real time. The additional information of the current system model is obtained by the online control simulation using the estimated model. And the additional samples are utilized with real samples for training of the neural controller to enhance the convergence.

Keywords: Fault Tolerant Control, System Estimation

1. introduction

Aircraft failures have caused many lethal accidents, i.e. JAL123 caused by full loss of hydraulics, UA 232 caused by full loss of hydraulics, and NA85 caused by rudder herd over. There are studies to achieve a fault tolerant control by actively changing the control law when any failure happens. Several methods, i.e. model reference control [1], L1 adaptive control [2], simple adaptive control [3], and adaptive control with feedback error learning [4], are proposed in the aeronautics community.
A feed forward adaptive controller (FFC) is introduced in the feedback error learning (FEL) method [5]. FFC can be just attached in parallel to the conventional feedback controller. FFC acquires an inverse model of the target system, and becomes an ideal feed forward controller. Therefore FEL control system is easily combined with other control methods. A linear adaptive controller, which can be recognized as a simple perceptron, is used in FEL adaptive control. So the linear control with non-linear system always connotes the control errors. A multiple layer perceptron known as a neural network is used to address the control error caused by the non-linearity of the target system. Neural networks can easily treat non-linear system, in other hand, the convergence of the controller becomes worse than linear controller.
In the adaptive control scheme, generally a single sample can be used to tuning of the adaptive law in every single control step. A large learning rate contributes to accelerate the convergence speed, however a stability of the control law gets worse. This problem is known as the low sample efficiency problem of reinforcement learning in the machine learning community. Using too old samples effects accuracy of the learning of the controller, because the control results greatly depends on the control law at that time. So re-sampling is required at every step, and learning efficiency is decreased.
These years, to tackle the low sampling efficiency, some method using the system estimator consisted with neural networks is proposed [6]. The short simulation with the estimated model provides the additional samples depending on the current control low. In these studies the target model is acquired before control low training and does not change during the learning of the controller. However in the fault tolerant control problem, the target model will be changed during the controller training. Therefore the online system estimation is required in the FTC problem.

In this paper, the fault tolerant controller trained by feedback error learning method with enhanced sampling by the system estimator is investing. The online system estimator is adapted to obtain additional sample to improve the convergence of the neural FFC. This system consisting of two control loops and two adaptive laws. These components are described following order as below: L1) a control loop, A1) a system estimation, L2) a simulation loop, A2) a FEL adaptation. L1) the control loop is a control of the aircraft with the neural FFC; A1) the control target system model is estimated by using the samples obtained in the control loop; L2) the simulation loop is a short simulation of the control of the estimated model with the current neural FFC; and A2) the neural FFC is trained by using the combined samples, the real samples from the control loop and the predicted samples from the simulation loop.

We call this method as the feedback error learning method with enhanced sampling, FELES. The convergence and stability of FELES for some aircraft failure will be discussed in this paper.

2. Background

2.1 Aircraft Model

The commercial aircraft Boeing 747 is utilized as the control target model. The model of the aircraft is described as a linear state space equation as below:

$$\dot{x}_t = Ax_t + Bu_t \tag{1}$$

where the x_t and u_t is a state vector and input vector, A and B is a state matrix and input matrix of B747, respectively. And this model can be discretized as:

$$\begin{aligned} x_{t+1} &= (I - \Delta t A)x_t + \Delta t B u_t \\ &= A_d x_t + B_d u_t \end{aligned} \tag{2}$$

where Δt is a control time step.

2.2 Feedback Error Learning

Feedback Error Learning (FEL) is proposed as a training algorithm of parameterized adaptive controller, such like neural network, which mimicking the motor nerve learning system of human brain [7]. Originally, a neural feed forward controller is attached in parallel to the feedback controller, i.e. PID controller, state feedback controller. Then the control inputs are generated as the following form:

$$u_t^{fel} = F_\theta(r_t) \tag{3}$$

$$u_t^{fb} = C(r_t, x_t; K) \tag{4}$$

$$u_t = u_t^{fb} + u_t^{fel} \tag{5}$$

where F_θ is a multiple layer neural controller parameterized by θ, C is a conventional feedback controller with gain K, and r_t is a filtered reference signal. The order of the filter for the reference signal is much to the relative order of the target system. The adaptive controller is trained to acquire the inverse model of the target object, and then it becomes an ideal feedforward controller. If the feedforward controller is the ideal controller for target plant, feedback controller output can be set to 0. Therefore the loss function of FEL consists of the feedback controller output with Eq.(5) as below:

$$\mathscr{L}_t^{fel} = \frac{1}{2}(u_t^{fb})^2 = \frac{1}{2}(u_t - u_t^{fel})^2 \tag{6}$$

The parameters of the neural controller are tuned by minimizing the loss function using the stochastic gradient descent with output of the feedback controller [5].

2.3 System Estimator

System estimation is utilized in several studies of reinforcement learning to obtain the additional information of target dynamics and/or to compensate the difference between the simulation model and the physical model [8], [6]. The estimator is consisted with multiple layer perceptron (MLP), generally called neural network. The network estimates the next time step states from current states and control inputs. Then the estimator network prediction and loss function can be written as below:

$$x^p_{t+1} = P_\phi(x_t, u_t) \tag{7}$$

$$\mathscr{L}^P_t = \frac{1}{2}\left(x_{t+1} - P_\phi(x_t, u_t)\right)^2 \tag{8}$$

where x_t is a state vector at time t, x^p_t is a predicted state, P_ϕ is a neural network function parameterized by weight parameters ϕ, and u_t is an action, which means control input. Recent N_e steps observations and actions are used as the learning data, and they are applied in few times N_{eL}.

3. FEL with Enhanced Sampling

To improve the sampling efficiency, an online simulation with estimated model is performed.

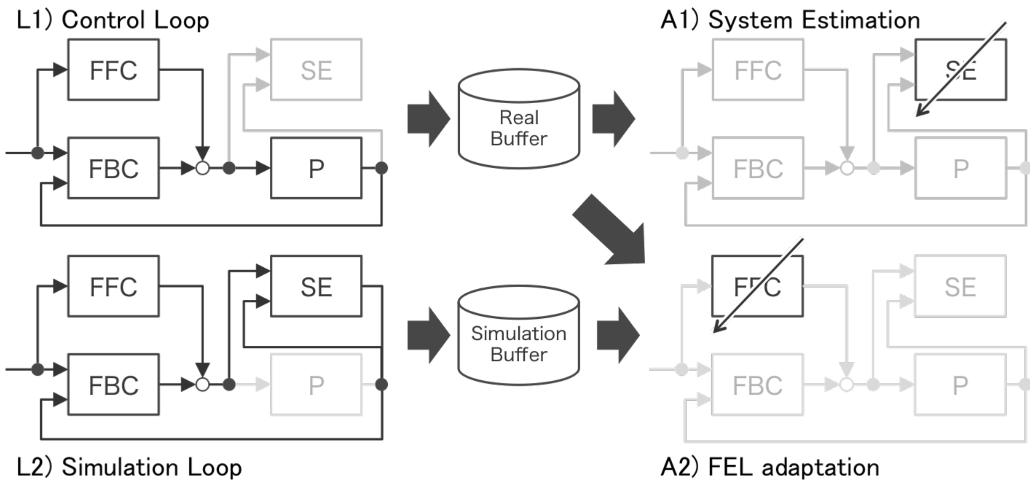

Figure 1 – FELES diagram

L1) Control loop

The control loop is implemented in the same way to the conventional FEL control scheme as Eq.(9) - (12). Then the set β^R_t of an action and observations, (the state x_t, the control input u_t, the next state x_{t+1}, and the reference r_t), are stored into the sampling buffer $\mathscr{B}_R$ at every control step as Eq.(13).

$$u^{fel}_t = F_\theta(r_t) \tag{9}$$

$$u^{fb}_t = C(r_t, x_t; K) \tag{10}$$

$$u_t = u^{fb}_t + u^{fel}_t \tag{11}$$

$$x_{t+1} = P(x_t, u_t) \tag{12}$$

$$\mathscr{B}_R \leftarrow \mathscr{B}_R \cup \beta^R_t \tag{13}$$

Stored samples are utilized to update networks, the system estimator and the FFC. Using old sample, the current system can not be correctly reflected into networks. Therefore, the data sampled before T_R step is removed from the buffer, T_R is a hyper parameter to be defined by trainers.

A1) System Estimation

The control target model is estimated with the data sets sampled in L1. To reflect newer information of the target model, a decay factor $\gamma < 1$ is multiplied the estimation error. The objective function of the system is described as below:

$$\mathscr{L}^{est} = \frac{1}{2}\gamma^k\left(x_{t-k+1} - P_\phi(x_{t-k}, u_{t-k})\right)^2 \tag{14}$$

$$\min_{\phi} \quad \mathbb{E}_{\mathscr{B}_C}\left[\mathscr{L}_t^{est}\right] \tag{15}$$

where k denotes data sampled k steps before. To enhance model adaptation speed, the input of the estimator P_ϕ, the state x_t and control input u_t, shall be normalized between -1 $\sim$ 1 with its assumed maximum values if the values are quite small or the value range have large gap among the state or control input values, because smaller values cause the small update values. If the input values are normalized, the estimated states must be denormalized.

L2) Simulation loop

The online short simulation with the estimated model is performed to obtain additional information of the target system. The estimated model is used as the control target. And the samples β_τ^s are stored into the simulation data buffer $\mathscr{B}_S$. Therefore Eq.(12) and (13) are changed as follows:

$$x_{k+1} = P_\phi(x_k, u_K) \tag{16}$$

$$\mathscr{B}_S \leftarrow \mathscr{B}_S \cup \beta_k^s \tag{17}$$

The reference signal r_τ is generated by using filtered constant value. The constant reference values are randomly selected from a normal distribution $\bar{r} \sim \mathscr{N}(0,1)$ bounded by the available range of the state. The filter is same to the reference filter W. Then the initial value of the reference is set to the current state.

$$r_{k+1} = W(\bar{r}, r_k) \tag{18}$$

$$r_0 = x_t \tag{19}$$

Multiple times of the short simulation with different reference values is executed to enrichment the additional information of the estimated dynamics. This simulation state values are vertically stacked like $\mathrm{x}_k = \left[x_{1k}^{\mathrm{T}}, \cdots, x_{ik}^{\mathrm{T}}, \cdots, x_{N_{\mathrm{sim}}}^{\mathrm{T}}\right]^{\mathrm{T}}$ and multiple simulation should be computed in parallel to enhance the simulation speed.

A2) FEL adaptation

The FFC network is updated with the samples from the real observation buffered in $\mathscr{B}_R$ and the simulated observation buffered in $\mathscr{B}_S$. The estimation loss $\mathscr{L}_t^{est}$ is used to remove the low accuracy samples from the simulation. And the decay factor γ_F is introduced same reason as Eq.(14). The objective function and FFC network is written as the followings:

$$\mathscr{L}_R^{feles} = \frac{1}{2}\gamma_F^k \left(u_{t-k} - F_\theta(r_{t-k})\right)^2 \tag{20}$$

$$\mathscr{L}_S^{feles} = \frac{1}{2}\exp\left(-\alpha \mathscr{L}_t^{est}\right)\left(u_\tau - F_\theta(r_\tau)\right)^2 \tag{21}$$

$$\min_{\theta} \quad \mathbb{E}_{\mathscr{B}_R}\left[\mathscr{L}_R^{feles}\right] + \mathbb{E}_{\mathscr{B}_S}\left[\mathscr{L}_S^{feles}\right] \tag{22}$$

where $\alpha \in \mathbb{R}$ is an adjust factor.
We mention this learning method as feedback error learning with enhanced sampling (FELES). The diagram of FELES is show in Fig.1

4. Simulation

4.1 Simulation settings

4.1.1 Models

For simulation, the linear model of the vertical motion of the commercial aircraft B747 is used as the control target. The state-space matrix and the input matrix are defined as below:

$$A = \begin{bmatrix} -0.0225 & 0.0022 & -32.3819 & 0 \\ -0.2282 & -0.4038 & 0 & 869 \\ 0 & 0 & 0 & 1 \\ -0.0001 & -0.0018 & 0 & 0.5518 \end{bmatrix}, \quad B = \begin{bmatrix} 0 \\ -0.0219 \\ 0 \\ 1.2394 \end{bmatrix} \tag{23}$$

and the state vector is $x = [u,\ w,\ \theta,\ q]$ forward speed, vertical speed, pitch angle, and pitch angle speed and the input is the elevator deflection $u = \delta_e$. In this experiment, the pitch angle θ is the control target, and the aircraft system is regarded as 1-input 2-output system. The reference filter is 2nd-order as below, because the the transfer function of the pitch motion is described as the transfer function which relative order is 2.

$$r_{t+1} = \left(I - \Delta t \begin{bmatrix} 0 & 1 \\ -\frac{1}{\tau^2} & t\frac{1}{2\tau} \end{bmatrix} \right) r_t + \Delta t \begin{bmatrix} 0 \\ \frac{1}{\tau} \end{bmatrix} \bar{r}_t, \tag{24}$$

where $\bar{r}_t$ is the original reference input, $\tau = 1.0$ is the filter time constant. The length of the short simulation is $T_R = 1.0$ and simulation time step is $\Delta t = 1/50$ sec. Feedback gain is tuned as the linear quadratic regulator.

As the fault, a gain reduction of the elevetor is asummed. This failure reduces the value of the input matrix B.

4.1.2 Netoworks

The FEL controller consists with the neural network, 16-16 units hidden layers with ReLU function, and the activation function of the output layer is tanh. The system estimator is also the neural netowork with 2-hidden layer that has 8-8 units and ReLU function. The networks are updated by stochastic gradient decent algorithm, and the learning lates are 0.05 for the FEL controller and 0.15 for the system estimator. The inputs are normalized into -1 $\sim$ 1 by assumed maximum ranges, respectively. The output of system estimator is de-normalize to bring it in its actual scale. The decay factors are $\gamma = \gamma_F = 0.9$, adjust factor is $\alpha = 5 \times 10^3$.

4.2 Result

We show the simulation results of the fault tolerant control by the conventional FEL and FELES. Figure 2 show the control result of conventional controls, state feedback, FEL and proposed method FELES. The vertical red line indicate the time which the fault had occurred. In this simulation, effectiveness of the elevator is reduced by 70% . The upper panel is the reference (gray dashed line) and pitch angle response of the state feedback (blue), FEL (green), and FELES (orange). The middle panel shows the elevator command. And bottom panel indicates the control errors of each control method. FEL and FELES had shown quite better result in aspect of control error than state feedback control, and there is no large difference between these. However soon after the fault occurrence, the control error of FELES is 33.4% smaller than FEL. This advantage is achieved by the oversampling using the estimated model. Figure 3 show the state prediction result of the system estimator of FELES. Orange line show the predicted value of pitch angle in the ipper panel and pitch angle rate in the lower panel. Black line indicates the observed value of them.

Figure 4 and 5 shows the control result with the random value rectangle reference input and system estimation results. In this case, FELES also has smaller control error at almost time step. However some point FEL control is better than FELES, i.e. t=170-180 sec. These time, system predict accuracy is low, in this simulation especially pitch speed estimation is not correct (Figure 5 middle), and then the training factor which shown as Equation (21). This low accuracy of system estimation can leads wrong adaptation of FEL training.

We can avoid these low quality simulation sample by setting the adjust factor high. However there is a trade off between sample quality and sample efficiency Figure 6.

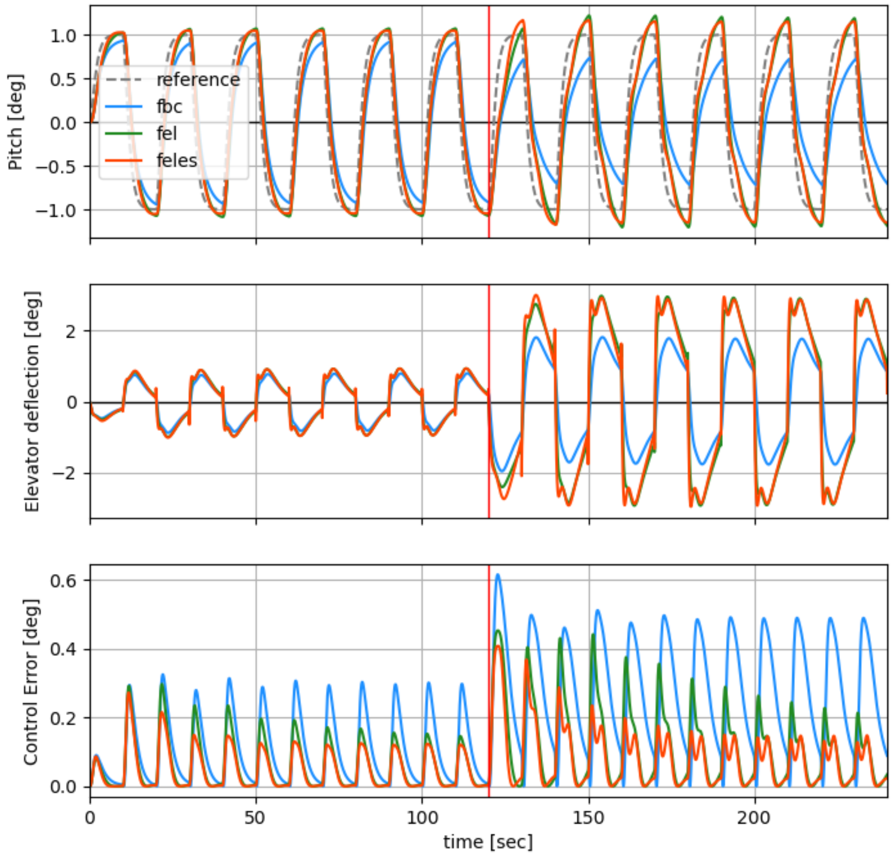

Figure 2 – Control result of FELES vs FEL with random reference

5. Conclusion

In this paper, the feedback error learning with enhanced sampling is proposed. This method is enhance sample by system estimation and online simulation powered by machine learning methods. FELES show high sample efficiency and better stability than conventional FEL method. But there is low quality sample problem invoked by low accurate system estimation. We have to remove these low quality sample more actively. However FELEs is a better choise than FEL for more stability-required system such like aircraft.

Copyright Statement

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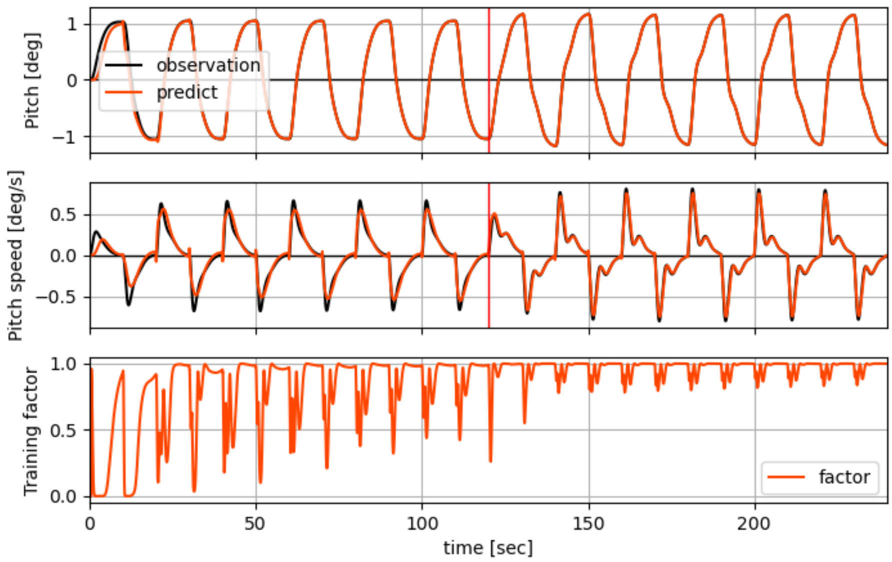

Figure 3 – Online state prediction by system estimator with random reference

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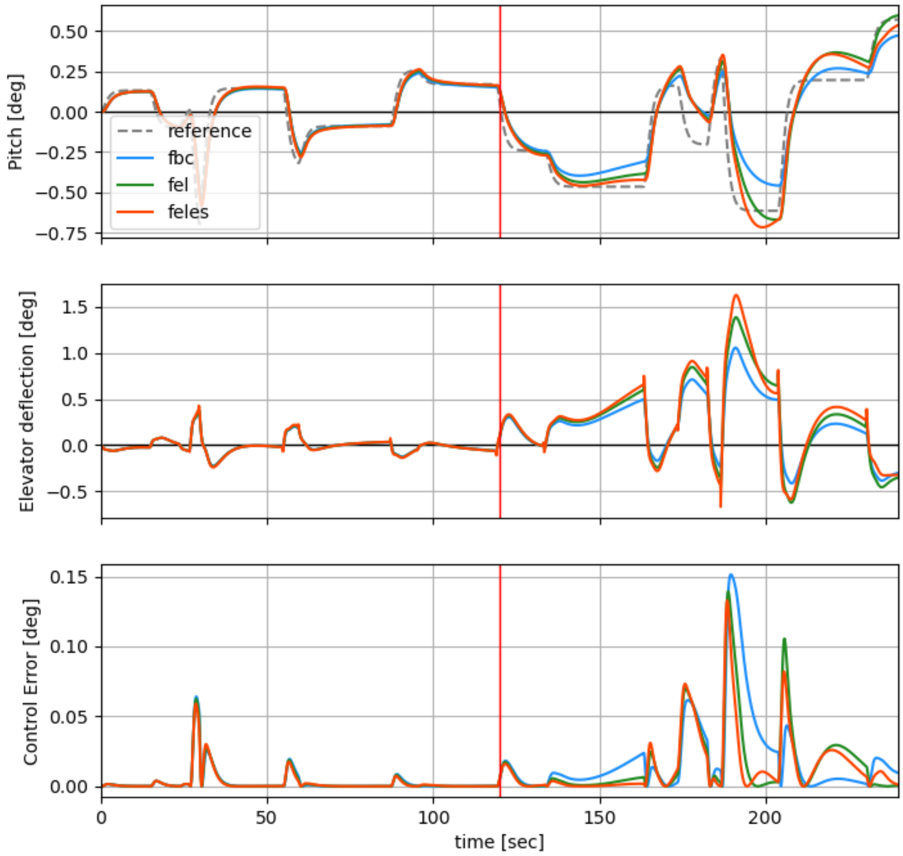

Figure 4 – Control result of FELES vs FEL with random reference

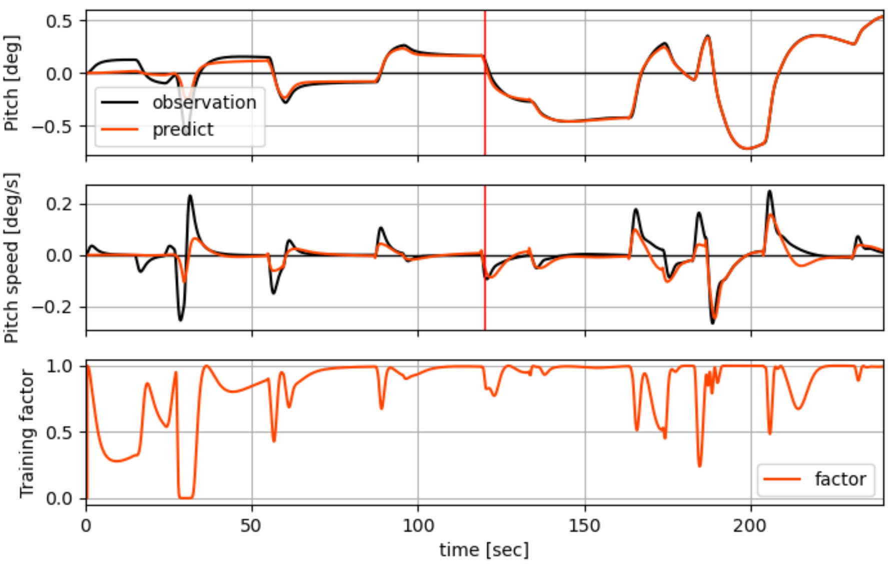

Figure 5 – Online state prediction by system estimator with random reference

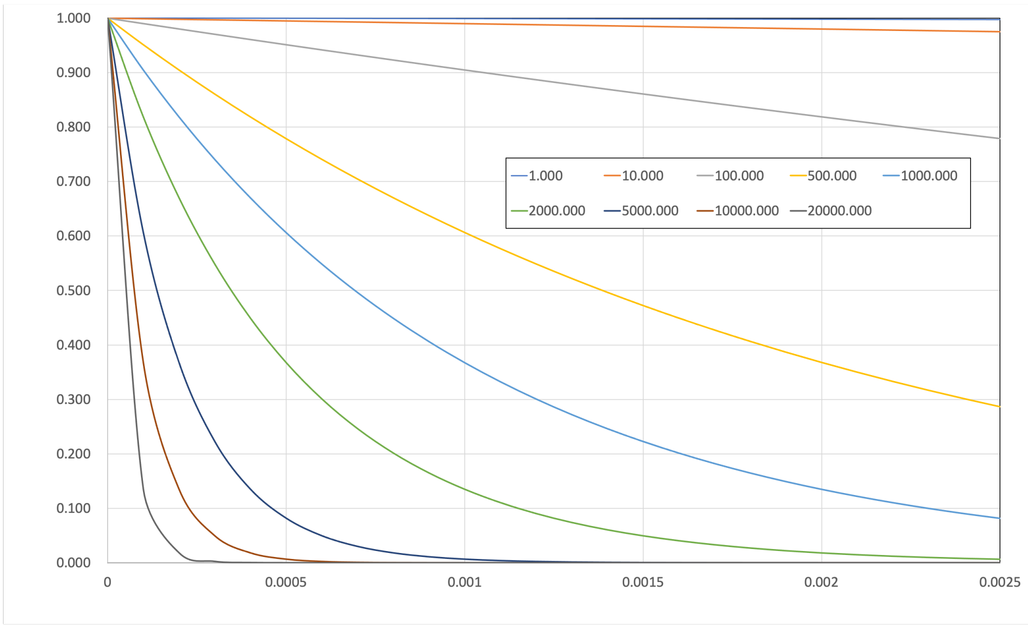

Figure 6 – Loss of system estimation vs training factor