Online Identification of Pilot Adaptation to Sudden Degradations in Vehicle Stability

Plaetinck, Wouter; Pool, Daan; van Paassen, Rene; Mulder, Max

DOI
10.1016/j.ifacol.2019.01.020

Publication date
2019

Document Version
Final published version

Published in
IFAC-PapersOnLine

Citation (APA)
Plaetinck, W., Pool, D., van Paassen, R., & Mulder, M. (2019). Online Identification of Pilot Adaptation to Sudden Degradations in Vehicle Stability. IFAC-PapersOnLine, 51(34), 347-352. https://doi.org/10.1016/j.ifacol.2019.01.020

Important note
To cite this publication, please use the final published version (if applicable). Please check the document version above.

Copyright
Other than for strictly personal use, it is not permitted to download, forward or distribute the text or part of it, without the consent of the author(s) and/or copyright holder(s), unless the work is under an open content license such as Creative Commons.

Takedown policy
Please contact us and provide details if you believe this document breaches copyrights. We will remove access to the work immediately and investigate your claim.
Online Identification of Pilot Adaptation to Sudden Degradations in Vehicle Stability

W. Plaetinck, D.M. Pool, M.M. van Paassen and M. Mulder *
* Control and Simulation Section, Aerospace Engineering, Delft University of Technology, 2629 HS, Delft, The Netherlands (e-mail: d.m.pool@tudelft.nl).

Abstract: Time-varying pilot control identification is essential for better understanding of how pilots respond when faced with sudden changes in the dynamics of the vehicle they control, such as when automatic control and stabilization systems disengage or undergo a mode transition. This paper presents the results of a human-in-the-loop experiment performed at TU Delft to test a promising online pilot identification method, based on recursive low-order ARX identification, developed in earlier work. In the experiment, eight skilled participants performed tracking tasks with time-varying vehicle dynamics, where at an unpredictable moment during each tracking run a sudden degradation in vehicle stability was induced. In addition to controlling the time-varying vehicle, participants were asked to indicate when they detected the change in the vehicle dynamics with a button push. This paper compares the effectiveness of two different approaches to detect the moment when pilot adaptation occurs from online identified pilot parameter traces. Overall, the results indicate that the lag in this detection of identified pilot adaptation is equivalent to the subjective detection times, or less. This implies that these online techniques have clear potential for ensuring timely and effective changes in adaptive pilot support systems.

© 2019, IFAC (International Federation of Automatic Control) Hosting by Elsevier Ltd. All rights reserved.

1. INTRODUCTION

While most of our current knowledge about how pilots control dynamics systems is valid only for time-invariant task conditions (McRuer and Jex, 1967), it is in fact pilots’ capacity for quick, time-varying, control adaptations that is of critical importance for many real-life control tasks (Young, 1969; Mulder et al., 2018). Of special interest in the aerospace domain are pilots’ interactions with time-varying controlled vehicle dynamics, which for instance may occur due to aircraft damage and sudden autopilot or stabilization system mode switches or disengagement (Hess, 2009, 2016; Zaal, 2016; Farjadian et al., 2016). Due to the often safety-critical nature of such cases, which can require significant time-varying pilot adaptation, a better quantitative understanding of the nature of such adaptations is needed (Mulder et al., 2018). Furthermore, accurate online detection and characterization of time-varying pilot adaptations – i.e., in real time – has great potential for, for instance, the detection of reduced attention or distraction and the design of adaptive pilot support systems and interfaces.

Traditionally, two perspectives on quantitative analysis of time-varying pilot behavior are followed: the development and testing of empirically-derived logic rules for the adaptation (Hess, 2009, 2016; Farjadian et al., 2016), or the explicit identification, using system identification methods, from collected pilot-in-the-loop data. For the latter, significant progress has been made towards developing time-varying identification methods suitable for offline, a posteriori, identification: e.g., methods based on Kalman filters (Schwiess and Roland, 1975; Boer and Kenyon, 1998; Popovici et al., 2017), wavelets (Thompson et al., 2001), linear parameter varying (LPV) models (Duarte et al., 2017), or explicit modeling of time-variations (Zaal, 2016). In the current state-of-the-art, however, a validated online identification approach, together with a tested algorithm for detecting pilot adaptations from identified time-varying parameter traces, is still missing.

In this paper, a previously developed recursive ARX identification technique (van Grootheest et al., 2018) is implemented in real time and tested for its capacity to online identify, and timely detect, time-varying pilot adaptation in response to a sudden degradation in vehicle stability. To test the method, a dedicated human-in-the-loop experiment was performed, similar to (Zaal, 2016), where eight participants performed tracking tasks with time-varying controlled element (CE) dynamics. To detect HC adaptation from identified traces of pilot response gains, two different detection methods were tested, which compared current values of these identified parameters against either an a priori estimated time-invariant condition average, or a moving average of the identified trace itself. For comparison with the identified adaptation detections, participants in the experiment were also asked to indicate, by means of a button push, when they detected a change in the CE dynamics during the tracking task.

2. METHOD

2.1 Control Task

A single-axis compensatory tracking task, based on the experiment of Zaal (2016), was used to evaluate the time-varying pilot identification and adaptation detection methods. A block diagram of this task is shown in Fig. 1. In this task, the pilot controls the time-varying controlled element (CE) dynamics $H_c(s, t)$ such that its output $y$
For the considered time-varying control task, it is known that the time-varying pilot control dynamics \( H_p(s, t) \) and the characteristics of the nonlinear remnant contribution \( H_n(s, t) \) are expected to vary due to a change in the CE. For the CE, a typical low-order approximation of aircraft dynamics is considered:

\[
H_c(s, t) = \frac{K_c(t)}{s^2 + \omega_c(t)s} \tag{1}
\]

To induce time-varying pilot adaptation, the parameters of the CE dynamics in Eq. (1) – i.e., the gain \( K_c \) and the break frequency \( \omega_c \) – were changed over time. To tie in with (Zaal, 2016), a sigmoid function was used to vary both parameters between an initial (i.e., subscript “I”) and a final (i.e., “F”) value, e.g., \( K_c(t) = K_{cI} + (K_{cF} - K_{cI})/(1 + e^{-G(t-M)}) \). The initial CE dynamics represent a highly stable and responsive vehicle, while the final CE dynamics are notably less stable and more sluggish and require pilots to generate lead (McRuer and Jex, 1967). As shown in Fig. 2, two different settings of the sigmoid rate of change parameter \( G \) were considered, 0.5 and 100 s\(^{-1}\), to include both instantaneous and more gradual changes in the CE. For consistent data collection, the CE variation was always centered on the midway point of the measurement interval \( T_m = 81.92 \text{s} \), i.e, \( M = 40.96 \text{s} \).

![Fig. 2. CE parameters scheduled by sigmoid function for a sudden \( (G = 100 \text{ s}^{-1}) \) and a gradual change \( (G = 0.5 \text{ s}^{-1}) \), located at \( M = T_m/2 \).](image)

For the considered time-varying control task, it is known that the time-varying pilot control dynamics \( H_p(s, t) \) are effectively quantified with a traditional linear pilot model for which (part of) the parameters are free to vary over time (Zaal, 2016; Duarte et al., 2017; van Grootheest et al., 2018), see Eq. (2). Note that to avoid identification ambiguities between the error response gain \( K_e \) and the lead time constant \( T_L \) normally present in models of this form (McRuer and Jex, 1967), an error rate response gain \( K_e(t) = K_e(t)T_L(t) \) is used for the parameterization:

\[
H_p(s, t) = (K_e(t) + K_v(t)s)e^{-\tau s}H_{nm}(s, t) \tag{2}
\]

\[
H_{nm}(s, t) = \frac{\omega_{nm}^2(t)}{\omega_{nm}^2(t) + 2\zeta_{nm}(t)\omega_{nm}(t)s + s^2} \tag{3}
\]

As previous work has found no evidence for time-varying adaptations of the pilot response delay \( \tau \) (Zaal, 2016) for the considered scenario, four time-varying pilot parameters are estimated. The pilot gains \( K_c(t) \) and \( K_v(t) \) capture how much proportional and derivative control is performed by pilots. The natural frequency \( \omega_{nm} \) and damping ratio \( \zeta_{nm} \) of the neuromuscular dynamics \( H_{nm}(s, t) \) (see Eq. (3)) account for time-varying neuromuscular adaptations.

### 2.3 Online Time-Varying ARX Identification

The goal of time-varying pilot identification is to use measured time traces of the tracking error \( e \) and the control signal \( u \) (see Fig. 1) to estimate time traces of all time-varying pilot model parameters. In this paper, for this a previously developed approach based on the “autoregressive with external input” (ARX) model structure is applied (van Grootheest et al., 2018).

**ARX Model Structure**

Eq. (4) gives the general single-input-single-output ARX model structure (Ljung, 1999) that is used in this paper:

\[
u(t) = \frac{B(q)}{A(q)}q^{-n_k}e(t) + \frac{1}{A(q)}\epsilon(t) \tag{4}\]

Eq. (4) represents a discrete-time model with time shift operator \( q \), such that \( q^{-n_k}e(t) = e(t - n_k) \) to model the pilot (input) delay. Pilot dynamics are approximated by the ratio \( B(q)/A(q) \) of the ARX polynomial models and the input data shift of \( n_k \) samples. Eq. (4) shows that the system and noise (remnant) dynamics are coupled through \( A(q) \) in the ARX model structure, which makes estimating its parameters a straightforward least-squares problem.

In this paper, second-order \( A(q) \) and \( B(q) \) polynomials were chosen to match Eq. (2). The resulting ARX model structure of Eq. (5) allows for estimating the vector of polynomial coefficients – i.e., \( \theta_1 = (a_1 a_2 b_0 b_1)^T \) – with RLS, but not the discrete input time shift parameter \( n_k \).

As was shown to be an allowable approximation by van Grootheest et al. (2018), the pilot time delay was set \textit{a priori} to \( \tau = 0.28 \text{s} \) (Zaal, 2016), corresponding to \( n_k = 28 \) for the 0.01 s timestep considered in the experiment.

\[
H_p(q) = \frac{B(q)}{A(q)}q^{-n_k} = \frac{b_0 + b_1q^{-1}}{1 + a_1q^{-1} + a_2q^{-2}}q^{-n_k} \tag{5}
\]
Recursive Least Squares An RLS algorithm with standard exponential forgetting factor was used to estimate and track the ARX coefficients over time (Ljung, 1999; van Grootheest et al., 2018). The forgetting factor, for the considered 100 Hz data rate, was set to $\lambda = 0.99609$ based on detailed tuning performed in previous work (van Grootheest et al., 2018). This value corresponds to a memory horizon of 2.56 s. The RLS algorithm estimated $\theta_i$ at every sample time step, starting at $i = 3$ s, as at earlier time instances insufficient data over the memory horizon are available, accounting also for the input time shift $n_k$. To start the RLS, default initial parameter and parameter covariance matrix settings of $\theta_0 = (-1.85 0.85 0.08 -0.08)^T$ and $P_0 = 10,000I_{1x4}$, respectively, were used.

Pilot Parameter Retrieval To retrieve the physical pilot parameters from Eq. (2), the estimated discrete-time ARX coefficients need to be converted. This is done by first converting the estimated ARX model to discrete-time transfer functions $H_p(z)$ using the $Z$-transform. The discrete transfer function estimated at each time step is then converted to the continuous-time equivalent, using a zero-order-hold conversion method. The pilot model parameters can then be retrieved from the converted ARX model parameters using the following relations, where the superscript “c” indicates that the ARX coefficients from Eq. (5) have been converted to continuous time first:

$$K_c = \frac{b_0^c}{a_2^c}, \quad K_e = \frac{b_0^c}{a_2^c},$$

$$\zeta_{nm} = \frac{\omega_{nm}}{2\sqrt{a_2^c}}, \quad \omega_{nm} = \sqrt{a_2^c}$$

(6)

It should be noted that this conversion is straightforward as long as the orders of the parameter and ARX models match. Otherwise, an order reduction technique would be required for the parameter retrieval.

2.4 Adaptation Detection

For the considered task, the main expected pilot adaptation is a reduction in the error gain $K_e$ and an increased error rate gain $K_e$ after the induced drop in vehicle stability (Zaal, 2016). For this reason, this paper tests two adaptation detection methods that perform the detection based on the time-varying estimates of these two parameters. Both proposed detection methods check for instances where the current estimate of the parameter (e.g., $K_e$) is outside of a range linked to an expected average value (e.g., $\bar{K}_e$) of the considered parameter and an accepted variability margin (e.g., $\delta K_e$). This principle is illustrated in Fig. 3, where the blue area indicates the reference average parameter range and the red line indicates the identified parameter trace.

As shown in Fig. 3, two different approaches were tested for defining the reference band, leading to two adaptation detection methods:

- **Time-Invariant Condition Average (TICA)**, Fig. 3(a): in this approach the reference parameter variation $\bar{K}_{e,TICA}$ and spread is defined a priori and derived from identified parameter traces of time-invariant task runs, i.e., with only the stable CE dynamics.
- **Moving Average (MA)**, Fig. 3(b): in this approach the center of the reference band $\bar{K}_{e,MA}$ is derived from the current identified parameter trace only, by taking a moving average over a past window of $n_s$ samples.

Both detection methods have several settings that should be tuned to minimize false-positive and false-negative detections. A false positive (FP) was defined as a detection made outside of the interval $M < t_d < 60$ s, with $M = 40.96$ s the moment of transition. A limit of 60 s was arbitrarily chosen since by then pilots should have adapted to the new situation and the identified parameters should be sufficiently converged to trigger a detection. A false negative (FN) occurs when no detection was made. This, for instance, can happen when the parameter trace is not outside the reference band for longer than $\Delta T$ seconds. The tunable settings (hyperparameters) of the detection methods, which should be tuned to avoid FP and FN, are:

- $\delta K_e$, $\delta K_e$: the accepted variability margin size. These parameters define the width of the reference band and quantifies the allowed (or expected) deviation of pilot parameter estimates from the average without leaving the reference band.
- $\bar{K}_e$, $\bar{K}_e$: the middle of the reference parameter band, defined following a different strategy for the TICA and MA methods, see Fig. 3.
- $\Delta T$: the minimum amount of time the current parameter trace should be outside of the reference band to be considered a detection.
- $n_s$ (for MA method only): the number of samples over which the reference moving-average parameter average is calculated, which directly influences the tracking speed of the moving average.

The TICA approach here is used as a reference, as for general applications detailed knowledge of parameter variations in equivalent time-invariant scenarios are not available. The MA approach requires less additional data to tune and is thus more promising for online implemen-
tation. In this paper, both methods are applied to the identified traces of both $K_e$ and $K_{\dot{e}}$.

3. EXPERIMENT SETUP

3.1 Apparatus

To evaluate the proposed methodology for detecting pilot adaptation to changes in the CE, a dedicated human-in-the-loop experiment was performed where participants performed the control task of Fig. 1. The experiment was performed in the fixed-base simulator setup of the Human-Machine Interaction Laboratory (HMILab) at the Faculty of Aerospace Engineering at TU Delft, see Fig. 4. The control task was implemented as a pitch attitude tracking task matching the experiment of Zaal (2016), where participants were asked to minimize pitch tracking errors shown as the vertical displacement between a (stationary) aircraft symbol and the (moving) horizon line, see Fig. 4(a).

Fig. 4. The experiment setup in the HMILab simulator (a) and the push button on control stick (b).

Participants provided their control inputs using a right-handed electro-hydraulic side-stick as shown in Fig. 4(a). The stick’s torsional stiffness was set to 2.5 Nm/rad, its damping to 0.22 Nm s/rad, and its inertia to 0.01 kg m$^2$ with a moment arm of 9 cm. The stick could only rotate around the pitch axis. Finally, a push button on the stick, see Fig. 4(b), was used by the participants to indicate when they detected the change in the task characteristics.

3.2 Forcing Function

The forcing function $f_t$ was defined as a sum of ten sinusoids with different frequencies, all defined as integer multiples of the base measurement frequency $\omega_m = 2\pi/T_m$ to avoid spectral leakage. The forcing function was identical to the signal used by Zaal (2016), however, it was shifted by 10.5 s backwards in time, by an adjustment to the phases. This was done to have a different part of the $f_t$ time trace align with the CE transition region.

3.3 Experiment Conditions

In the experiment, two variables were varied independently and all combinations were tested by all participants (within-subjects design). First, participants were subjected to both fast and gradual time-variations of the CE – referred to as TV12F and TV12S in the remainder of this paper – implemented with two values for the maximum rate-of-change parameter of the sigmoid function: $G = 100$ or 0.5 s$^{-1}$, respectively, see Fig. 2. In addition, to ensure that the time of the CE change occurred did not become predictable, the amount of run-in time added before the measurement window of $T_m = 81.92$ s was varied over three levels: 5 s, 10 s and 15 s. Finally, time-invariant reference data with the initial CE dynamics ($K_e = 90$, $\omega_c = 6$ rad/s) were also collected for each participant for implementing the TICA adaptation detection.

3.4 Participants and Experiment Procedures

Eight skilled participants volunteered to perform the experiment and provided written informed consent before participating. Participants were instructed to minimize the tracking error shown on the display and push the button whenever they noticed changed CE dynamics. They received no further briefing regarding nature of the tested experiment conditions. After an initial training consisting of at least one run of each condition, three further repeated measurements of each condition were collected for each participant, using a randomized order of presentation to balance out fatigue effects. After each run, participants received feedback of their performance (RMS of the error $e$) as motivation to perform consistently.

4. RESULTS

4.1 Time-Varying Pilot Identification Data

To illustrate the first step of our proposed procedure, Fig. 5 shows average recorded time traces from the control task ($f_t$, $y$, and $u$, see Fig. 1), as well as the time-varying estimates of the four free parameters of the pilot model of Eq. (2) for condition TV12F. As is clear from the top
triggered for the MA method. For error detection based on
a very early detection well before the actual CE change is
in
K parameter traces show the matching expected decrease
in vehicle stability and responsiveness. The estimated pilot
u increased control effort (larger 
e
K
variation
in
K
parameters
in
K
parameter traces across our dataset.

Here were obtained for an initial heuristic tuning of the

K
hyperparameters. Especially the MA method

(Figs. 6 and 7) show that adaptation detection based on
K
hyperparameters:

δKc = 0.06, δKε = 0.02, ∆T = 3 s.

Table 1. Error detection confusion matrix for both methods. Hyperparameters: δKc = 0.06, δKε = 0.02, ∆T = 3 s, ns = 1500.

| Condition | Method | Parameter | TP | FP | TN | FN |
|-----------|--------|-----------|----|----|----|----|
| TV12F     | TICA   | Kc        | 12 | 33 | 0  | 27 |
|           | MA     | Kc        | 0  | 15 | 0  | 57 |
| TV12S     | TICA   | Kc        | 6  | 30 | 0  | 35 |
|           | MA     | Kc        | 2  | 10 | 0  | 59 |

To demonstrate the adaptation detection performed with
the TICA and MA algorithms, Figs. 6 and 7 show example
results for a single tracking run of one subject for the
condition with a sudden change in the CE, i.e., TV12F.
Each figure consists of two sets of graphs – one set for
Kc and one for Kε – and for each set the top graph
shows the respective identification data, while the bottom
graph shows the derived detection results. Matching Fig. 3,
the identified parameter variation over time is the red
data, while the parameter range used for the adaptation
detection is indicated as a blue area. In the detection
graphs, blue data are the “raw” detections that represent
all instances when the parameter trace goes outside of the
reference band, while the green data indicates the
“final” result, i.e., the first detection that has a length
longer than ∆T. For reference, the subjective detection
(button press) is indicated in red. The results presented
here were obtained for an initial heuristic tuning of the
hyperparameters for both algorithms, based on inspection
of the nature and variability of the identified pilot param-
eter traces across our dataset.

Figs. 6 and 7 show that adaptation detection based on
Kc is more troublesome, as inherent parameter variations
unrelated to the CE change seem to be comparatively
larger than for Kε. Fig. 7 even shows a clear FP, as only
a very early detection well before the actual CE change is
triggered for the MA method. For error detection based
on Kε, the raw detection data show that both methods
are also clearly triggered due to local, short-duration,
varying adaptations in the neuromuscular parameters are
observed.

4.2 Adaptation Detection from Pilot Identification

To demonstrate the adaptation detection performed with
the TICA and MA algorithms, Figs. 6 and 7 show example
results for a single tracking run of one subject for the
condition with a sudden change in the CE, i.e., TV12F.
Each figure consists of two sets of graphs – one set for
Kc and one for Kε – and for each set the top graph
shows the respective identification data, while the bottom
graph shows the derived detection results. Matching Fig. 3,
the identified parameter variation over time is the red
data, while the parameter range used for the adaptation
detection is indicated as a blue area. In the detection
graphs, blue data are the “raw” detections that represent
all instances when the parameter trace goes outside of the
reference band, while the green data indicates the
“final” result, i.e., the first detection that has a length
longer than ∆T. For reference, the subjective detection
(button press) is indicated in red. The results presented
here were obtained for an initial heuristic tuning of the
hyperparameters for both algorithms, based on inspection
of the nature and variability of the identified pilot param-
eter traces across our dataset.

Figs. 6 and 7 show that adaptation detection based on
Kc is more troublesome, as inherent parameter variations
unrelated to the CE change seem to be comparatively
larger than for Kε. Fig. 7 even shows a clear FP, as only
a very early detection well before the actual CE change is
triggered for the MA method. For error detection based
on Kε, the raw detection data show that both methods
are also clearly triggered due to local, short-duration,
varying adaptations in the neuromuscular parameters are
observed.

Table 1. Error detection confusion matrix for both methods. Hyperparameters: δKc = 0.06, δKε = 0.02, ∆T = 3 s, ns = 1500.

| Condition | Method | Parameter | TP | FP | TN | FN |
|-----------|--------|-----------|----|----|----|----|
| TV12F     | TICA   | Kc        | 12 | 33 | 0  | 27 |
|           | MA     | Kc        | 0  | 15 | 0  | 57 |
| TV12S     | TICA   | Kc        | 6  | 30 | 0  | 35 |
|           | MA     | Kc        | 2  | 10 | 0  | 59 |
4.3 Comparison with Subjective Detection Times

To verify the latency of the adaptation detection, the detection lags for all FP detections were compared with the recorded subjective detection lags (button presses). For the subjective data, statistical analysis with a two-way repeated-measures ANOVA – with G and the added run-in time as factors – showed no difference due to different run-in times, $F(2,14) = 1.92, p > 0.05$. Hence, in the further analysis of detection times, the results of all run-in times were combined. A significant difference was, however, found between TV12F and TV12S, $F(1,7) = 15.76, p < 0.05$, with the sudden change (TV12F) being noted 5 s earlier on average, see Fig. 8.

Fig. 8. Lags of true positive detections with MA and TICA compared to subjective detection times (SUBJ.).

Fig. 8 shows the distribution of detection lags, for all TP cases, for the subjective detections (“SUBJ.”) and the two tested detection methods (“TICA” and “MA”) applied to the identified $K_e$ data. For TV12F, the detection lags for TICA and MA are found to be equivalent and not significantly different – i.e., $t(103.1) = -1.62, p > 0.05$ and $t(66.7) = -0.63, p > 0.05$, respectively – from the subjective data. For the more gradual change in the TV12S condition, all detection lags increase by around 5 s, but still the identification detection lags are equivalent to the subjective data, especially for TICA ($t(97.0) = 1.42, p > 0.05$). For MA, the 11 FP detections are found to occur a bit earlier on average than the subjective detections, a significant effect $t(35.0) = 5.13, p < 0.05$.

5. CONCLUSION

This paper tested and compared two methods for the detection of time-varying pilot adaptation from pilot response gain traces estimated online with a recursive ARX identification technique. The methodology was tested on experimental tracking data and identification detection times were explicitly compared to the participants’ subjective indication of when they noticed the induced change in the vehicle dynamics. Overall, it was found that identified values of pilot error response gain $K_e$ showed the most consistent variations due to degraded vehicle stability and hence the most accurate adaptation detection results. The TICA detection method, which checks for differences with a priori measured non-adapted pilot behavior, was found to be the most reliable, with a detection accuracy of 57%. The tested MA method, which uses a moving average of the past identified $K_e$ parameter trace itself as a reference, is more practical for online implementations, but had a lower detection accuracy, which can be improved with better hyperparameter tuning. On average, for offline data processing, the adaptation detection times of both methods were found to be equivalent to the recorded subjective detection lags. Overall, these results indicate that an approach as tested in this paper has the potential to enable accurate and timely detection of pilot adaptations to time-varying adaptations in the controlled vehicle dynamics.

REFERENCES

Boer, E.R. and Kenyon, R.V. (1998). Estimation of Time-Varying Delay Time in Nonstationary Linear Systems: An Approach to Monitor Human Operator Adaptation in Manual Tracking Tasks. *IEEE Trans. on Systems, Man, and Cybernetics – Part A*, 28(1), 89–99.

Duarte, R.F.M., Pool, D.M., van Paassen, M.M., and Mulder, M. (2017). Experimental Scheduling Functions for Global LPV Human Controller Modeling. In *Proc. of the 20th IFAC World Congress*, Toulouse, 15853–58.

Farjadian, A.B., Annaswamy, A.M., and Woods, D.D. (2016). Towards A Resilient Control Architecture: A Demonstration of Bumpless Re-Engagement Following an Anomaly in Flight Control. In *Proc. of the International Symposium on Sustainable Systems and Technologies*, Phoenix (AZ).

Hess, R.A. (2009). Modeling Pilot Control Behavior with Sudden Changes in Vehicle Dynamics. *Journal of Aircraft*, 46(5), 1584–1592.

Hess, R.A. (2016). Modeling Human Pilot Adaptation to Flight Control Anomalies and Changing Task Demands. *J. of Guidance, Control, and Dynamics*, 39(3), 655–666.

Ljung, L. (1999). *System Identification – Theory for the User*. Prentice Hall, Inc., second edition.

McRuer, D.T. and Jex, H.R. (1967). A Review of Quasi-Linear Pilot Models. *IEEE Trans. on Human Factors in Electronics*, HFE-8(3), 231–249.

Mulder, M., Pool, D.M., Abbink, D.A., Boer, E.R., Zaal, P.M.T., Drop, F.M., van der El, K., and van Paassen, M.M. (2018). Manual Control Cybernetics: State-of-the-Art and Current Trends. *IEEE Trans. on Human-Machine Systems*, 48(5), 468–485.

Popovici, A., Zaal, P.M.T., and Pool, D.M. (2017). Dual Extended Kalman Filter for the Identification of Time-Varying Human Manual Control Behavior. In *Proc. of the AIAA Modeling and Simulation Technologies Conference*, Denver (CO), AIAA-2017-3666.

Schiess, J.R. and Roland, V.R. (1975). Kalman Filter Estimation of Human Pilot-Model Parameters. Technical Report NASA-TN-D-8024, NASA Langley Research Center, Hampton (VA).

Thompson, P.M., Klyde, D.H., and Brenner, M.J. (2001). Wavelet-Based Time-Varying Human Operator Models. In *Proc. of the AIAA Atmospheric Flight Mechanics Conference*, Montreal (CA), AIAA-2001-4009.

van Grootheest, A., Pool, D.M., van Paassen, M.M., and Mulder, M. (2018). Identification of Time-Varying Manual Control Adaptations with Recursive ARX Models. In *Proc. of the AIAA Modeling and Simulation Technologies Conference*, Kissimmee (FL), AIAA-2018-0118.

Young, L.R. (1969). On Adaptive Manual Control. *Ergonomics*, 12(4), 635–674.

Zaal, P.M.T. (2016). Manual Control Adaptation to Changing Vehicle Dynamics in Roll-Pitch Control Tasks. *Journal of Guidance, Control, and Dynamics*, 39(5), 1046–1058.