Experimental Scheduling Functions for Global LPV Human Controller Modeling

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Abstract: In this paper, the Linear Parameter Varying (LPV) model identification framework is applied to estimating time-varying human controller (HC) dynamics in a single-loop tracking task. Given the inherently unknown time changes in HC behavior, a global LPV approach with experimentally determined Scheduling Functions (SFs) is needed for this application. In this paper, a methodology based on the Predictor-Based Subspace Identification (PBSID) algorithm is tested. Using Monte Carlo simulation data matching a recent experimental study, two experimental SFs derived from measured HC control inputs are tested for their LPV model identification performance. The results are compared with LPV models obtained using the true (analytical) SFs used for generating the simulation data. An experimental SF obtained from the double derivative of HCs’ control inputs using zero-phase low-pass filtering was found to yield time-varying HC model estimates of equivalent accuracy as obtained with the analytical SFs; a promising result for future application of this methodology to measured HC behavior.

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1. INTRODUCTION

Much of the available knowledge on human controllers’ (HC) dynamics is restricted to time-invariant control tasks, where the HC is considered as a time-invariant controller (McRuer and Jex, 1967; Mulder et al., 2016). In reality, however, it is the adaptive nature of humans, and how they respond to changes in the environment, that is actually of interest and still largely unknown (Young, 1969; Mulder et al., 2016). A key example is a situation where a sudden change in the controlled system dynamics occurs (e.g., failure) (Hess, 2016; Zaal, 2016). For quantitative analysis of time-varying HC behavior, novel and explicitly time-varying methods for modeling and identifying HC dynamics are needed (Mulder et al., 2016).

While numerous time-varying identification techniques – such as wavelets (Thompson et al., 2001), Kalman filters (Boer and Kenyon, 1998), recursive least-squares (Olivari et al., 2014), and time-domain maximum likelihood estimation with set parameter variation functions (Zaal, 2016) – have so far been applied to identifying time-varying human controller dynamics, most obtained results were not fully satisfactory and easily generalizable. Given the quasi-linearity of HC behavior (McRuer and Jex, 1967), a promising approach to time-varying HC identification is the Linear Parameter-Varying (LPV) framework, which has been developed for the identification of industrial systems (Chiuso, 2007; van Wingerden and Verhaegen, 2009; Tóth et al., 2012). In an LPV model, the change in the system’s dynamics over time is tied to the instantaneous values of selected external variables, called Scheduling Variables (SVs). LPV models may be constructed from local identification results obtained for different constant SV values, or identified in one (global) step from time-varying data directly. The local model approach has, for instance, been applied with some success to identifying time-varying human neuromuscular admittance dynamics (Pronker et al., 2017). Identifying the inherently unknown, inconsistent, and highly transient time variations in HC behavior, however, requires a global LPV identification approach, such as Predictor-Based Subspace Identification (PBSID) (van Wingerden and Verhaegen, 2009), for which a software toolbox is available (DCSC, 2015). Critical to the success of such an approach is the selection of an appropriate Scheduling Function (SF), describing the SV variation over time. In our application of time-varying human controller behavior, we need an SF that avoids any a priori assumptions on the nature of the time variation.

The goal of this paper is to compare the effectiveness of various SFs for LPV modeling of HC behavior. A distinction is made between analytical (a priori assumed time variation) and experimental (derived from measured signals) SFs. Offline HC model simulation data for the control task with time-varying controlled element (CE) dynamics tested experimentally by Zaal (2016) is used for this evaluation. Two simulation cases are considered: one where the variation in HC parameters matches that of the induced change in the CE exactly, and a second where a perturbation is added in the transient region of the time-variation. The different cases and SFs are then compared for the resulting quality-of-fit of the LPV models, as well as the accuracy of estimated time-varying HC parameters.
2. LPV IDENTIFICATION PROBLEM

2.1 Time-Varying Manual Control Task

The manual control scenario considered in this paper is a single-axis compensatory tracking task based on the human-in-the-loop experiment of Zaal (2016). A block diagram representation of this task is shown in Fig. 1.

![Block diagram of a compensatory tracking task with time-varying CE dynamics.](image)

Fig. 1. Block diagram of a compensatory tracking task with time-varying CE dynamics.

Fig. 1 shows an HC in control of a system with dynamics $H_C$. The HC’s objective is to make the output of the CE ($y$) follow the target signal (a multisine, see Section 3.2) as closely as possible. In this compensatory task, the HC only receives feedback of the tracking error $e$. Time-varying HC control dynamics ($H_p(s, t)$) are induced with a time variation in the CE dynamics ($H_c(s, t)$), as given by:

$$H_c(s, t) = \frac{K_c(t)}{s + \omega_c(t)}$$  

(1)

Eq. (1) is a low-order approximation valid for a wide range of typical vehicle dynamics (McRuer and Jex, 1967), i.e., a system that transitions from first order ($1/s$) to second order ($1/s^2$) at the break frequency $\omega_c$. Both the CE gain $K_c$ and break frequency $\omega_c$ are varied over time. For both CE parameter variations for two simulation cases.

2.2 Time-Varying HC Dynamics

For stationary tracking tasks with CE according to Eq. (1), HC’s adopt time-invariant control dynamics of the form (McRuer and Jex, 1967):

$$H_p(s) = K_p [T_L s + 1] e^{-s\tau_p} H_{nm}(s)$$  

(3)

Here, $K_p$ represents the HC control gain and $\tau_p$ is the HC delay. For CEs as given by Eq. (1), HC’s perform lead equalization if $\omega_c$ is not significantly higher than the crossover frequency (McRuer and Jex, 1967), which is modeled with the lead term and lead time constant $T_L$ in Eq. (3). Finally, the dynamics of the neuromuscular system are modeled as a second-order mass-spring damper system (McRuer and Jex, 1967), with the natural frequency $\omega_{nm}$ and damping ratio $\zeta_{nm}$ as parameters:

$$H_{nm}(s) = \frac{s^2}{s^2 + 2\zeta_{nm}\omega_{nm}s + \omega_{nm}^2}$$  

(4)

For modeling the time-varying HC dynamics in response to the time-varying CE dynamics $H_c(s, t)$, a logical choice would be to keep the dynamic form of the HC dynamics of Eq. (3), but with all parameters free to vary over time. However, as Zaal (2016) found no evidence for strong time variations in $\tau_p, \omega_{nm}$ and $\zeta_{nm}$, here these parameters will be considered constant over the duration of the measurement. Furthermore, as separate identification of the coupled $K_p$ and $T_L$ parameters is known to be problematic for cases when $T_L$ is high — i.e., when $\omega_c$ is low and a lot of HC lead is required — a different parametrization of the HC equalization term is adopted. This gives the following form for the time-varying HC dynamics that we aim to identify in this paper:

$$H_p(s, t) = [K_c(t)s + K_c(t)] e^{-s\tau_p} H_{nm}(s)$$  

(5)

In Eq. (5), the gain-leading term of Eq. (3) is replaced by separate error $K_c = K_p$ and error rate $K_c = K_p T_L$ response gains to facilitate improved identification, especially after the CE transitions ($\omega_c = 0.2 \text{ rad/s}$).

2.3 LPV Model Structure

The time-varying HC model of Eq. (5) can, except for the HC delay $\tau_p$, be directly converted to the discrete state-space form estimated with PBSID (van Wingerden and Verhaegen, 2009). With the time variation in the dynamics only in the HC control gains ($K_c, K_e$), the following LPV model structure is appropriate:

$$x_{k+1} = Ax_k + (B + B_{\mu} \mu_k) u_k$$  

(6)

$$y_k = Cx_k + Du_k$$  

(7)

Eq. (6) shows a standard linear state transition equation, where the time-varying dynamics, linked to a Scheduling Function $\mu$, are for our application only present in the input contribution through $B_{\mu}$. The $A, B, C,$ and $D$ matrices describe the dynamics of the system when $\mu = 0$, and hence also include all time-invariant system parameters.
2.4 LPV Identification Approach

Fig. 3 shows the flow chart of our approach to identify time-varying HC dynamics using an LPV model structure and PBSID. All steps are discussed below.

**Step 1: HC delay estimation and compensation:** As including a delay in the discrete LPV model of Eq. (6) would require a high model order, which is inefficient and requires significant computational effort, the HC delay was estimated before performing the time-varying LPV identification. This was done by iteratively estimating low-order \((N = 2)\) LPV models with increasing input delay values \((0 \leq \tau_p \leq 0.4)\), from which the delay estimate that yielded the best quality-of-fit (highest VAF) was selected as the final estimate \(\hat{\tau}_p\). For Step 3, the HC input signal \(e\) was shifted with the estimated delay.

**Step 2: Experimental SF calculation:** For fitting an LPV model, the scheduling function(s) \(\mu\) need to be defined \textit{a priori}. In this paper, we compare different experimentally obtained SFs, with “analytical” SFs matching the time-variation applied to the CE. The details of our experimental SFs will be provided in Section 3.4.

**Step 3: LPV HC identification (PBSID):** With pre-processed input-output data \((e(t - \tau_p)\) and \(u(t)\), a chosen scheduling function \(\mu\) and the settings for the model order \((N = 2)\), past window size \((p = 120)\), and future window size \((F = 2)\), in this step the matrices \(A, B, B_u, C, D\) are estimated using the PBSID algorithm.

**Step 4: Parameter retrieval:** With the estimated model matrices and the known scheduling function \(\mu\), a discrete time-invariant state-space model can be obtained at each discrete time \(k\). To retrieve the variations in the parameters of the HC model of Eq. (5), these local models were converted to continuous transfer function form, i.e.:

\[
\hat{H}_p(k) = \frac{\hat{b}_0 + \hat{b}_1 s}{\hat{a}_0 + \hat{a}_1 s + s^2} e^{-\hat{\tau}_p s}
\]

Comparing Eq. (8) with Eq. (5), it is clear that this allows for straightforward retrieval of \(\hat{K}_e, \hat{K}_c, \hat{\omega}_{nm_k}\), and \(\hat{\zeta}_{nm_k}\) from the local transfer function model coefficients.

3. METHODS

3.1 HC Parameter Settings

To verify the effectiveness of different scheduling functions for LPV modeling of HC behavior, two different cases for an assumed time-variation of \(H_p(s, t)\) were tested. Both cases changed \(K_e\) and \(K_c\) to adapt to the initial and final CE dynamics \(H_e(s, t)\), see Table 1. These settings are based on the experiment data of Zaal (2016).

| State | \(K_e\) | \(K_c\) | \(\tau_p\) | \(\omega_{nm}\), rad/s | \(\zeta_{nm}\) |
|-------|-------|-------|-------|----------------|-------|
| 1: \(t = 0\) s | 0.09 | 0.036 | 0.28 | 11.25 | 0.35 |
| 2: \(t = 100\) s | 0.07 | 0.084 | |

The listed values of \(K_e\) and \(K_c\) imply a change in the visual lead time constant from \(T_L = 0.4\) s to \(T_L = 1.2\) s consistent with the much stronger lead equalization required for the CE after the transition.

The two cases for the time-variation in \(H_p(s, t)\), for which Fig. 4 shows the \(K_e\) and \(K_c\) time traces, are:

- **Case S:** The time-variation of \(K_e\) and \(K_c\) matches the time-variation of \(H_e(s, t)\) perfectly, i.e., according to a sigmoid with \(M = 50\) s and \(G = 0.5\) s\(^{-1}\).
- **Case S:** The time-variation of \(K_e\) and \(K_c\) follows the same sigmoid function as for \(S\), but with a deterministic perturbation defined by a Gaussian function \((\mu_p = 50\) s, \(\sigma_p = 8\) s, \(K_p = 0.6)\) superimposed. This models a case where, e.g., through surprise, the time variation in \(H_p(s, t)\) cannot be directly linked to the applied change in \(H_e(s, t)\).

3.2 Forcing Function

The target forcing function \(f_1\) (see Fig. 1) from Zaal (2016) was implemented for our HC model simulations. It is the sum of ten sinusoids:

\[
f_1(t) = \sum_{i=1}^{10} A_i \sin(\omega_i t + \phi_i(t))
\]

The sinusoid amplitudes \((A_i)\), frequencies \((\omega_i)\) and phases \((\phi_i)\) are listed in Table 2. The signal was periodic over its measurement period of \(T_m = 81.92\) s. The sampling frequency of the simulations was 100 Hz.

Fig. 4. \(K_e\) and \(K_c\) time variations for two simulation cases.
Table 2. Forcing function parameters.

| $t_i$ | $\omega_i$, rad/s | $A_{2i}$, deg | $\phi_i$, rad |
|-------|-------------------|--------------|--------------|
| 1     | 0.230             | 1.186        | -0.753       |
| 2     | 0.384             | 1.121        | 1.564        |
| 3     | 0.614             | 0.991        | 0.588        |
| 4     | 0.997             | 0.756        | -0.546       |
| 5     | 1.687             | 0.447        | 0.674        |
| 6     | 2.608             | 0.245        | -1.724       |
| 7     | 4.065             | 0.123        | -1.963       |
| 8     | 6.596             | 0.061        | -2.189       |
| 9     | 10.661            | 0.036        | 0.875        |
| 10    | 17.564            | 0.025        | 0.604        |

3.3 Monte Carlo Simulations

For testing the identification approach of Fig. 3, Monte Carlo simulations of the compensatory task with 100 different remnant noise realizations were performed. Matching Zaal (2016), remnant noise was generated by passing white noise through a low-pass remnant filter $H_n(s) = K_n/(0.2s + 1)$. The gain $K_n$ was chosen such that the remnant power for the initial $H_C(s,t)$ and $H_p(s,t)$ combination was a desired percentage of the HC control signal power: $P_n = \sigma_n^2/\sigma^2$. Three different levels of remnant, representative for HC data with weak to strong remnant contributions, were considered: $P_n = 0.05, 0.15, 0.25$.

Example time traces for a single realization of a Case S simulation are shown in Fig. 5. Note that both before and after the transition in $H_c(s,t)$, the target signal $f_t$ is tracked with the accuracy expected for an HC. Also note from Fig. 5(c) that the control inputs generated after the transition are larger and more high-frequent, as expected due to the increased $K_c$. Fig. 5(d) shows the time trace of the double derivative of the control signal ($\ddot{u}$), whose magnitude corresponds well with the shape of $\mu_A$.

3.4 Scheduling Functions

In the LPV framework, the Scheduling Function is critical, as it directly drives the time variation of the modeled dynamics (van Wingerden and Verhaegen, 2009). While the use of multiple SFs is possible and required for certain applications, in this paper only the use of a single SF for modeling time-varying HC behavior is considered. Key to this approach is the selection of a suitable and preferably measurable SF, to ensure that the SF that captures the a priori unknown time-variation of the HC.

To compare the effectiveness of different SFs, four SFs are used here: two “analytical” SFs, derived from a priori knowledge of the change in $H_p(s,t)$, and two “experimental” SFs, derived from the measured double derivative of the HC control signal, $\ddot{u}$, see Fig. 5(d). The tested SFs are all shown in Fig. 6 and are defined as:

- **Analytical SF** $\mu_{A1}$, see Fig. 6(a), is the normalized sigmoid function with $M = 50$ s and $G = 0.5$ s$^{-1}$, that exactly matches the time-variation of the CE: $\mu_{A1}(t) = 1/(1 + e^{-G(t-M)})$
- **Analytical SF** $\mu_{A2}$, see Fig. 6(b), is the summation of $\mu_{A1}$ and the (normalized) Gaussian perturbation centered on $t = 50$ s (see Section 3.1).
- **Experimental SF** $\mu_{E1}$, see Figs. 6(a) and 6(b), is obtained by smoothing the measured $\ddot{u}$ signal through 20 successive calculations of windowed root mean square (rms) values over 10 past samples. This repeated rms calculation is necessary to attain acceptable smoothness of the $\mu_{E1}$ signal. To obtain an SF of equivalent magnitude to $\mu_{A1}$ and $\mu_{A2}$, the rms-filtered signal is normalized by first subtracting its mean over the first 40 seconds (before transition) and then dividing by the mean over the last 60 seconds (after transition). While this smoothing can also be applied in real-time (i.e., not only during post-processing), it has the clear drawback of adding phase lag to the signal, see Fig. 6(b).
- **Experimental SF** $\mu_{E2}$, see Figs. 6(a) and 6(b), is obtained by passing $[\ddot{u}]$ through a zero-phase second-order Butterworth filter ($\omega_{3DB} = 0.1$ rad/s) in both forward and reverse directions (Oppenheim et al., 1999). After filtering, the obtained signal is normalized as done for $\mu_{E1}$.

Note that with the above four SFs, it is evident that $\mu_{A1}$ would be expected to be the optimal SF for Case S, while $\mu_{A2}$ should be optimal for Case S.

3.5 PBSID Settings

As indicated in Fig. 3, the PBSID approach requires setting three characteristics of the fitted discrete state-space model structure: the model order $N$, the past window size $p$, and the future window size $F$. The system order and future window size were set to equal values, as this decreases the computational effort in finding optimal PBSID settings without much effect on the outcome quality (van Wingerden, 2008). To match the known time-varying HC dynamics given by Eqs. (4) and (5) that are of second-order, both were set to $N = F = 2$. This choice greatly
simplifies the extraction of the HC model parameters (Step 4 in Fig. 3). After initial testing, the past window size was set to $p = 120$, which gave the best compromise between suppression of truncation errors in the PBSID state predictions (van Wingerden, 2008) and limitation of the required computational time, which increases with $p$ (van Wingerden and Verhaegen, 2009).

4. RESULTS

Following the procedure outlined in Fig. 3, LPV models were fitted to the Monte Carlo simulation data generated for Cases $S$ and $\hat{S}$ using all four considered SFs, two analytical ($\mu_{A_1}$ and $\mu_{A_2}$) and two experimental ($\mu_{E_1}$ and $\mu_{E_2}$). Fig. 7 shows the attained VAF values for all fitted models obtained with these different SFs. Boxplots indicate the VAF distributions over the 100 Monte Carlo simulation runs. Fig. 7(a) presents VAFs calculated over the complete measurement window, while the VAFs for the transition region only (see Fig. 2) are shown in Fig. 7(b).

Fig. 7 shows that, as expected, increased remnant levels (higher $P_n$) result in lower VAF values. Furthermore, the maximum difference in attained VAF with the four different SFs on the same dataset is around 5%, with slightly larger effects noted for the transition region data in Fig. 7(b). This indicates that even with an assumed (e.g., $\mu_{A_1}$ for Case $S$) or experimentally retrieved SF (e.g., $\mu_{E_1}$) that do not perfectly match the true time-variation in $H_p$ in the transition region, a high-quality model fit is obtained. Overall, still the highest VAFs are obtained with the analytical SFs that were used for the data generation, i.e., $\mu_{A_1}$ for Case $S$ and $\mu_{A_2}$ for Case $\hat{S}$, respectively. Experimental SF $\mu_{E_1}$, with notable lag in the transition phase, is seen to always result in the worst model fits. Fig. 7 shows that for $\mu_{E_2}$, the model quality is equivalent to the results for the analytical SFs.

This is further confirmed in Figs. 8 and 9, which show the estimated changes in $K_e$ and $K_{\hat{e}}$ for Case $S$ and $\hat{S}$, respectively, for the 100 Monte Carlo simulation runs. For both Cases, the reference analytical SF results – i.e., $\mu_{A_1}$ for $S$ in Fig. 8 and $\mu_{A_2}$ for $\hat{S}$ in Fig. 9 – are compared with those for $\mu_{E_2}$. In gray, all figures show the true variations in $K_e$ and $K_{\hat{e}}$ used for generating the HC data.

Despite the reduced smoothness of the parameter traces obtained with the experimental SF $\mu_{E_2}$, Figs. 8 and 9 show that overall the retrieved time variations in $K_e$ and $K_{\hat{e}}$ are equivalent to the analytical SF results, and show similar spread over the 100 realizations. This confirms that the use of experimental SFs, derived from the measured control signal $u$, is feasible for global LPV modeling of HC’s behavior. It should, however, be noted that the true parameter variations are not perfectly estimated from the simulation data with any of the tested SFs. As highlighted with the gray areas in Figs. 8 and 9, the $K_e$ and $K_{\hat{e}}$ estimates are only reliable in the part of the time data where these gains are dominant: the pre-transition phase for $K_e$ and the post-transition phase for $K_{\hat{e}}$.

5. DISCUSSION

This paper investigated the effectiveness of global LPV modeling of time-varying HC behavior, focusing on the scheduling function that drives the time variation in LPV models. Using a developed time-varying identification approach centered on the PBSID algorithm (van Wingerden and Verhaegen, 2009), data from Monte Carlo simulations of a time-varying control task based on (Zaal, 2016) were identified using four different candidate SFs.

In our proposed approach, the HC delay $\tau_p$ is not included in the fitted LPV model, and thus assumed to be constant over time. Unfortunately, the PBSID algorithm does not allow for estimation of a time-varying system delay, without greatly increasing the LPV model order $N$. For the current human control scenario with time-varying CE dynamics, Zaal (2016) also concludes that HCs’ delays do not vary over time and this limitation would thus not be problematic. However, for other applications it may be in fact the variations in $\tau_p$ that are of interest (Boer and Kenyon, 1998), which would thus require a different time-varying identification approach.

Given the unknown nature of time-varying adaptations in HC behavior, an experimental SF is needed for LPV modeling for our application. Our comparison of two analytical (a priori assumed, matching the applied CE time variation) and two experimental SFs showed clear potential for deriving experimental SFs from measured control loop signals, such as the double derivative of the control input signal ($\ddot{u}$). As shown for our experimental SF $\mu_{E_1}$, extreme care should be taken in the processing performed in calculating the SF time trace, e.g., to avoid inducing any phase lag through filtering. Still, our results show that LPV models estimated with an experimental SF obtained from zero-phase low-pass filtering of $\ddot{u}$ ($\mu_{E_2}$) yields VAF values and estimated HC parameters equivalent to those obtained with the true, simulated, SFs.

From the work presented in this paper, a number of future research steps for our application of LPV models may
be identified. First, future work will verify the results presented in this paper by applying the same methodology to collected experimental HC data. Furthermore, we tested one method for identifying a global LPV model from time-varying measurement data (PBSID, (van Wingerden and Verhaegen, 2009)). It should be tested if other recently developed LPV methods – e.g., those based on orthonormal basis functions (Tóth et al., 2012) – yield improved results. Finally, as the crucial property of all LPV models is the SF definition, future work on LPV modeling of HC behavior should focus on the retrieval of experimental SFs from measured control task data or other external measurements (Pronker et al., 2017), as well as verifying the use of multiple SFs to more independently drive the time-variations in different HC parameters.

6. CONCLUSION

This paper assessed the viability of using a global LPV modeling framework, based on the PBSID algorithm, for modeling time-varying human controller dynamics. The main focus was on finding a suitable experimental scheduling function for this application. Representative time-varying HC data were generated with Monte Carlo simulations ($n = 100$) and fitted with four different LPV models, each having a different (analytical or experimental) scheduling function. Two experimental SFs were tested, both smoothed signals obtained from the double derivative of HCs’ control inputs. A comparison of the obtained quality-of-fit (VAF) and retrieval of time variations in the HC parameters showed that with a zero-phase filtered experimental SF, equivalent results were obtained as with the true, simulated, SF. This shows promise for using a similar approach with experimental SFs for modeling experimental time-varying HC data.

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