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Validation of a Grip Force Scheduled LPV Model of Time-Varying Neuromuscular Admittance

Rik Palings, Daan M. Pool, Marinus M. van Paassen and Max Mulder

Abstract—Haptic Shared Control (HSC) systems offer a means to support human drivers in the transition to fully-automated driving. Matching HSC systems settings with drivers' time-varying neuromuscular system (NMS) dynamics requires real-time HSC adaptations. This paper presents an experimental validation of a previously proposed method for predicting drivers' time-varying neuromuscular admittance using an 'average' grip force scheduled linear parameter varying (LPV) model. The quality of LPV model predictions is compared to that of Recursive Least Squares (RLS) fits of an admittance model on the same data. Ten participants performed steering wheel manipulation tasks with steering wheel perturbations that needed to be kept within a certain displacement boundary by adapting their grip force. Time-invariant (TI) and time-varying (TV) boundary levels were used to, respectively, construct and validate the LPV model. Results show that the average relation between admittance and grip force that underlies the current LPV method varies too much between TV and TI tasks, hampering accurate admittance predictions. Compared to the quality-of-fit of 80-90% obtained with RLS on the TV data, the LPV model's predictions are insufficiently accurate and do not exceed 55% on average. An approach that enables individual instead of average LPV models to be constructed directly from TV experiment data needs to be pursued for HSC implementations.

I. INTRODUCTION

To reduce driver workload, decrease fatigue, and minimize traffic accidents Haptic Shared Control (HSC) systems are introduced [1]. HSC systems support the driver by providing force feedback on the control device, while keeping the driver engaged and, in fact, in control. To ensure an agreeable match between human and HSC, generated feedback forces need to be matched with driver's Neuromuscular System (NMS) admittance [2], as the HSC and driver will effectively control the vehicle together. Given that human drivers are known to change their admittance frequently and rapidly in response to changes in the driving task, environment, fatigue, etc. [3]–[5], it is crucial that HSC systems are designed to account for this variability as well [1], [2].

Multiple techniques exist for obtaining, potentially real-time, estimates of the time-varying NMS admittance, such as those based on time-sliding windows [6], [7], wavelets [3] or recursive regression methods in both the time [8], [9] or frequency domain [10]. Another promising concept are Linear Parameter Varying (LPV) models. In LPV models, time-varying dynamics are implemented to vary based on a pre-defined Scheduling Variable (SV). Compared to other methods, LPV models have two key advantages: 1) when an LPV model is available, real-time predictions only require

a real-time measurement of the SV to predict driver admittance, without the need for further system perturbation, and 2) changes in admittance can be predicted without the latency that is often inherent to recursive or windowed estimation methods [6], [9]. Past research successfully exploited the direct relation between grip force and NMS admittance [11] to develop a grip force scheduled LPV admittance model for driver steering [12], [13].

This paper focuses on further validating the grip force scheduled LPV model proposed in [12], [13]. Due to fundamental differences in the time-invariant steering wheel manipulation tasks (SWMTs) used for obtaining the LPV model in [13] and its application to a time-varying driving task, potential effects of cognitive steering behavior prevented a 1-to-1 model validation. This paper presents a follow-up human-in-the-loop experiment performed to further validate the grip force scheduled LPV model presented by [13]. LPV admittance model predictions are directly compared to time-varying admittance estimates obtained through recursive-least squares (RLS) [8], [9].

In the experiment, ten drivers performed SWMTs that required them to actively adapt their neuromuscular properties and grip strength to ensure the externally perturbed steering wheel did not displace beyond a certain boundary limit that was varied; matching the experiments of [12], [13]. Time-invariant (TI) SWMTs with five different constant boundary limit settings that induced a range of admittance dynamics representative of driving [14], [15] were performed to construct a global LPV model from five local admittance measurements. As validation data, the same participants performed four different time-varying (TV) SWMT where the steering wheel displacement boundaries were varied as a function of time, forcing the drivers to adapt their neuromuscular admittance. As explained in more detail in [16], a key difference with the experiment of [12], [13] was the use of a different steering wheel perturbation signal, to facilitate the use of RLS for admittance estimation [9].

II. METHODS

A. Steering admittance model

Fig. 1 shows a schematic neuromuscular representation of a driver controlling a steering wheel, whose dynamics are described by H_{sw} [13]. This is a simplified model where the main neuromuscular system (NMS) feedback contributions are represented by H_{int} , which models the *intrinsic dynamics* of the driver's lower arms, and H_{cont} , which describes the *contact dynamics* between the driver's hands and the steering wheel. Changes to these dynamics

Control & Simulation, Faculty of Aerospace Engineering, TU Delft, The Netherlands. Email: {d.m.pool, m.m.vanpaassen, m.mulder}@tudelft.nl

are induced by co-contracting the lower arm muscles [13]. Furthermore, the noise input (N) accounts for non-linearities of the driver. Fig. 1 shows that the driver torque (T_d) and a perturbation torque (T_{dist}) may act on the steering wheel to induce a steering wheel displacement angle (θ_{sw}). This paper focuses on NMS adaptations *without* considering (cognitive) steering behavior; hence the CNS reference torque $T_{ref} = 0$. Furthermore, a multi-sine perturbation torque signal T_{dist} is considered to enable admittance identification [17].

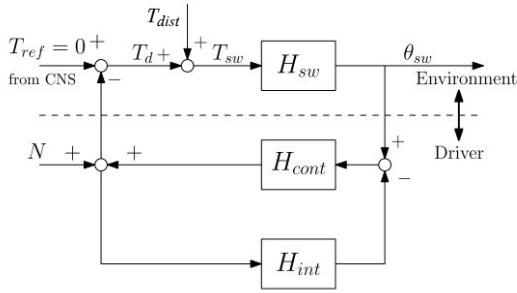


Fig. 1. Driver neuromuscular steering wheel control loop [13].

The contact dynamics shown in Fig. 1 can be modeled as $H_{cont}(s) = b_c s + k_c$, with b_c and k_c the contact damping and contact stiffness. Similarly, the intrinsic arm dynamics can be modeled as $H_{int}(s) = 1/(I_i s^2 + b_i s + k_i)$, with I_i , b_i , and k_i representing the intrinsic inertia, intrinsic damping and intrinsic stiffness of the driver's arms. The admittance dynamics resulting from H_{cont} and H_{int} are given by:

$$H_{adm}(s) = H_{int}^{-1}(s) + H_{cont}(s) = \frac{I_i s^2 + (b_c + b_i)s + k_c + k_i}{b_c I_i s^3 + (I_i k_c + b_c b_i)s^2 + (k_c b_i + b_c k_i)s + k_c k_i} \quad (1)$$

B. LPV admittance model

The linear-parameter varying (LPV) model considered in this paper implements the admittance dynamics as given by (1) with parameter values that may vary with a *scheduling variable* μ , here chosen to be the exerted grip force. The same two-step approach to construct the LPV model as considered in [13] is used: first *local* linear time-invariant (LTI) models are identified at specific operating points (μ values), where in the second step interpolation is used to obtain the *global* LPV model. As the model of (1) has three poles and two zeros, the LPV model is implemented as a series connection of interpolated LTI model gains (γ_i), first-order (F_i), and second-order (S_i) subsystems:

$$H_{adm}^{LPV}(s, \mu) = \gamma_i(\mu) \cdot F_i(s, \mu) \cdot S_i(s, \mu) \quad (2)$$

For a more detailed description of the grip force scheduled LPV model and the used interpolation, see [13], [18].

C. RLS admittance estimation

To validate the LPV model using a different, independent method to estimate time-varying admittance, a recursive least squares (RLS) algorithm as described in [9] is applied.

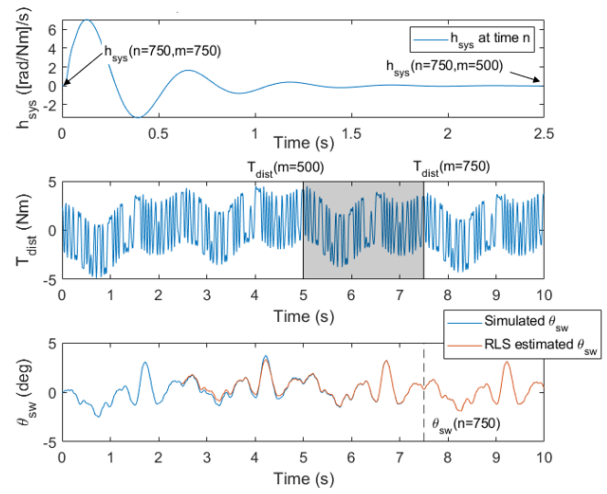


Fig. 2. Example RLS impulse response estimate for $n = 750$ (7.5 s).

This method estimates the impulse response $h_{sys}(n)$ of the complete closed-loop system dynamics shown in Fig. 1 – i.e., the combined dynamics of H_{sw} , H_{cont} and H_{int} – at all discrete time instances n . An example of an impulse response estimate obtained with this method, for $n = 750$ (7.5 seconds), is shown in Fig. 2. For the analysis in this paper, the impulse response length was set to 2.5 seconds as in [9], while all data were sampled at 100 Hz. The RLS forgetting factor λ was set at 0.99, which was found the optimal balance between noise susceptibility and convergence speed in [9].

From the RLS impulse response estimates, the overall system's Frequency Response Function (FRF) at time n (i.e., $H_{sys}(j\omega, n)$) can be found by calculating the Fast Fourier Transform (FFT) of $h_{sys}(n)$. Then, the following relation, which can be derived directly from Fig. 1, enables retrieving the corresponding time-varying admittance estimate:

$$H_{adm}^{RLS}(j\omega, n) = \frac{H_{sw}(j\omega)H_{sys}(j\omega, n)}{H_{sw}(j\omega) - H_{sys}(j\omega, n)} \quad (3)$$

In (3), H_{sw} is the (known) frequency response of the steering wheel and ω indicates the frequency vector (in rad/s) that contains all sines included in the multi-sine disturbance torque signal T_{dist} . For further details on the RLS implementation, the reader is referred to Refs. [9], [16].

III. EXPERIMENT

A. Apparatus

The human-subject experiment was performed in the driving simulator setup of the HMI-Lab at the Faculty of Aerospace Engineering of TU Delft, see Fig. 3(a). The electrical actuator on the steering wheel was used to generate perturbation torques for measuring the admittance. The steering wheel's dynamic properties were set to match a second-order mass-spring-damper system with $I_{sw} = 0.3 \text{ Nms}^2/\text{rad}$, $b_{sw} = 2 \text{ Nms}/\text{rad}$, and $k_{sw} = 4.2 \text{ Nm}/\text{rad}$:

$$H_{sw}(s) = \frac{1}{I_{sw}s^2 + b_{sw}s + k_{sw}} \quad (4)$$

Grip force was measured using Tekscan 4256E pressure sensors, see Fig. 3(b). The sensitivity of the individual sensors was in the range of 6.9 to 206.8 kPa [13]. Only the total measured grip force across all sensors at each sampling time n was used in the current analysis.

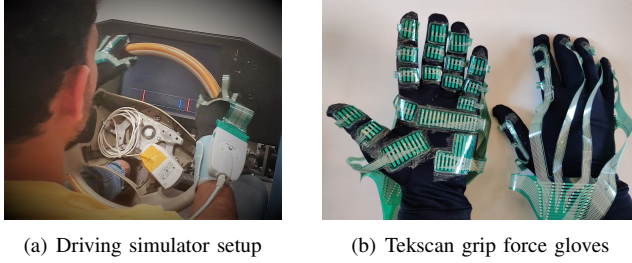


Fig. 3. The HMI-Lab driving simulator setup with a participant performing the 18-deg boundary condition (a) and the Tekscan grip force sensors (b).

B. Participants

Ten participants (8M/2F, average age $25.3 \text{ years} \pm 1.9$ years standard deviation) volunteered for the experiment. All were students at TU Delft and in possession of a drivers license for on average 6.6 ± 3.2 years. The participants' average height and weight were $185 \pm 12 \text{ cm}$ and $81.9 \pm 12 \text{ kg}$, respectively.

C. Control tasks

Participants first performed a time-invariant (TI) steering wheel manipulation task (SWMT), for which they were instructed to always hold the steering wheel in a ten-to-two position, as shown in Fig. 3(a). The steering wheel displacement was shown with a blue vertical bar on the dashboard display. Participants were instructed to keep the blue indicator within the indicated red boundaries without actively counter-steering, but by applying the required constant level of grip force to the steering wheel. The size of the boundaries was varied across five different TI experiment conditions matching [13] and participants were instructed to use different grip (and hence admittance) levels based on the boundary width, but to not aim to keep the steering wheel displacements at zero. The tested boundary levels (BL) were equal to 0, 5, 8, 12, and 18 degrees [13], where a lower BL (i.e., allowed steering wheel displacement) would require higher grip forces and reduced admittance to perform the SWMT. Trials lasted for 45 seconds, of which the first 5 seconds were available for participants to attain the required grip force level and not used for the analysis.

Next to the TI SWMTs, participants also performed different time-varying (TV) conditions for LPV model validation. The TV trials all lasted 80 seconds, of which again the first 5 seconds were used as initialization. In the TV trials, the SWMT's boundaries changed instantly at times 25 s and 50 s, see Fig. 4. Four different TV conditions were tested: "Outerlimits" (0 deg to 18 deg to 0 deg), "Operating points" (5 deg to 12 deg to 5 deg), "Intermediate points" (3 deg to 10 deg to 3 deg), and "Driving" (5.5 deg to 7.5 deg to 5.5 deg, matching the realistic driving data of [13]).

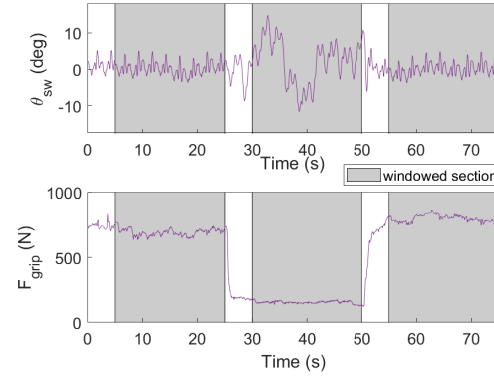


Fig. 4. Example time-varying (TV) experiment data for the "Operating Points" condition, with the grey 20-second sections indicating the data windows that can be used for time-invariant admittance identification.

D. Perturbation signal

The reduced power method [17] was used to define a multi-sine steering wheel perturbation, i.e., $T_{dist}(t) = \sum_{i=1}^{N_f} A_i \sin(\omega_i t + \phi_i)$, for a measurement window of 20 s. The perturbation had $N_f = 52$ excited frequencies, where full-power was applied at the frequencies up until 0.8 Hz and reduced power was applied from 0.8 to 20 Hz, see Fig. 5. To avoid sudden peaks, the phase sets ϕ_i were chosen to achieve a minimum crest factor. To prevent participants from anticipating the perturbation, four different ϕ_i sets were used. The overall magnitude of $T_{dist}(t)$ was set to achieve a signal standard deviation of 2.26 Nm, matching [13], see Fig. 5. Please refer to [16] for the full details on the used T_{dist} .

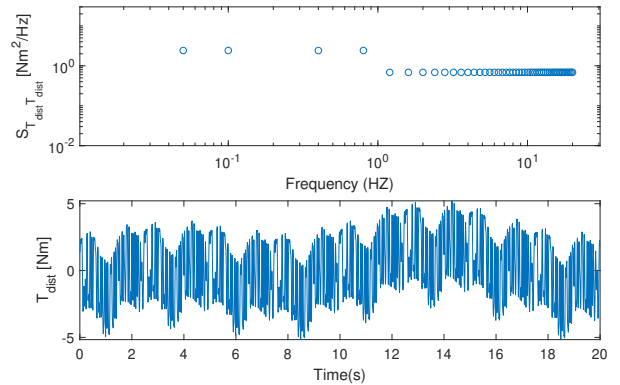


Fig. 5. Example spectrum and time trace of the multi-sine steering wheel perturbation signal.

E. Procedure

To familiarize participants with the SWMT, four TI training trials with constant boundaries were performed prior to collecting the measurements: two trials with a narrow boundary (4 degrees) and two with a wide boundary (15 degrees). After this familiarization, all participants repeated every experiment condition four times: the first trial to familiarize themselves with the condition, the other three for

our data analysis. In-between the TI and TV runs, two further training runs were performed for familiarization with the TV boundaries. The order in which the different SWMTs were performed was balanced (Latin square) across participants to prevent order effects. The study was approved by TU Delft's Human Research Ethics Committee (application #1750).

IV. RESULTS

A. Time-invariant (TI) data

To derive the grip force-scheduled LPV admittance model, the median measured grip force for each BL setting of the time-invariant (TI) experiments (see Fig. 6) was linked to the corresponding average local admittance dynamics (see Figs. 7 and 8), matching the approach of [13]. In-between the extreme values of the scheduling variable μ – i.e., in between grip forces for BL=0 and 18 deg – linear interpolation is used in the global LPV model. For grip forces higher than 557 N (BL=0 deg) or lower than 92 N (BL=18 deg), the global LPV model is restricted to the corresponding extreme operating point, i.e., no extrapolation is performed.

The average variation in grip force with boundary width as measured in the TI experiment is shown in Fig. 6. The decreasing grip force when wider boundaries are available is fully consistent with the earlier experiment of [13]. While a continuously decreasing grip force level with increasing BL is observed on average, statistical analysis (paired t-tests) reveals that no significant differences in grip force occur for the wider boundaries (BL = 8, 12, and 18 deg). As also reported by [13], this continuously decreasing grip force level was not always present in the underlying individual participant data. For example, Subjects 2, 7 and 9 showed higher grip forces for the 12-deg BL case than for the 8-deg and 18-deg boundaries. As this leads to interpolation problems when creating individual-specific LPV models [13], we focus only on the performance of an 'average' LPV admittance model, for which the median grip force for each condition (i.e., 557 N, 262 N, 151 N, 112 N, and 92 N, respectively) is used to schedule the global LPV model, i.e., μ in (2).

The corresponding average LTI admittance FRF estimates and fitted models obtained from the TI experiments are shown in Fig. 7. Consistent with [13], smaller boundaries are seen to lead to lower levels of admittance. The corresponding admittance model parameters are shown in Fig. 8, where the blue markers indicate the average parameter values used for the local LPV models for each BL. Overall, the contact damping b_c was found to remain approximately constant across all BL cases. The contact stiffness k_c is seen to reduce with increasing boundary width, which causes the difference in underdamped peaking as seen between 2.5 and 3.5 Hz for the 0 and 5 deg BL cases in Fig. 7. The strongest variation with BL is observed for the intrinsic stiffness parameter k_i , which defines the low-frequency magnitude of the admittance dynamics. It should be noted that the intrinsic inertia I_i , a physical property not expected to vary with BL, was kept constant across all conditions for each participant and is hence not shown in Fig. 8. For the LPV model, the average inertia was estimated at 0.1686 Nms²/rad.

B. Time-varying (TV) data

Fig. 9 shows that the grip force was found to be consistently higher in the time-varying experiments (TV) than in the corresponding time-invariant (TI) experiments, for all BL. The TV results were obtained from the "Outerlimits" and "Operating Points" experiment conditions, see Section III-C. For the four BL settings tested in both the TI and TV experiments (BL = 0, 5, 12, and 18 deg), the grip force increases by 10%, 23%, 43% and 52%, respectively, on average. While none of these measured differences are statistically significant for the current dataset ($p = 0.68, 0.42, 0.43$ and 0.16 , respectively), Fig. 9 shows that the increased grip force levels will directly impact the scheduling of the LPV admittance model. Especially for BL = 12 and 18 deg, the TV grip forces are closer to the LPV-scheduled level (horizontal colored lines) for a lower BL value than actually tested.

Fig. 10 shows the average estimated admittance FRFs for both the TI and TV experiments corresponding to the same BL cases shown in Fig. 9. For the TV data, the FRFs were estimated from the constant sections of the ("Outerlimits" and "Operating Points") TV trials, see Fig. 4. Fig. 10 shows that the admittance FRFs are equivalent for the TI and TV data. While this confirms that the TV SWMTs, with their varying boundary width, effectively induce different admittance levels, the consistently higher grip force in the TV experiments introduces a fundamental bias in the scheduling by the LPV model.

This issue with the LPV model approach is further confirmed from Fig. 11, which compares the quality-of-fit – expressed in terms of the Variance Accounted For (VAF) – for the RLS_{self}, RLS, and LPV admittance models. The RLS estimates have consistently higher VAFs (between 80 and 90%) than the LPV model (between 45 and 55%) for all TV conditions. The fact that no differences between the LPV model VAFs for the "Operating Points" and "Intermediate Points" conditions are found indicates that the interpolation of the LPV model does not add further inaccuracies.

V. CONCLUSIONS AND OUTLOOK

This paper aimed to validate a previously proposed approach for predicting time-varying driver admittance using a grip force scheduled linear parameter varying (LPV) model. For this, a human-in-the-loop experiment was performed where ten participants performed steering wheel manipulation tasks that required them to restrict steering wheel displacements to remain within a certain boundary range by changing the exerted grip force. Next to time-invariant (TI) tasks used for extracting the global LPV admittance model, the experiment also collected time-varying (TV) validation data, where the allowed steering wheel displacement boundaries were varied as a function of time. For validating the LPV model's effectiveness at predicting time-varying driver admittance, the true variations in admittance were estimated with an independent Recursive Least Squares (RLS) method. The admittance variations with boundary level were found to match very well between the TI and TV steering wheel manipulation tasks. However, the average applied grip force

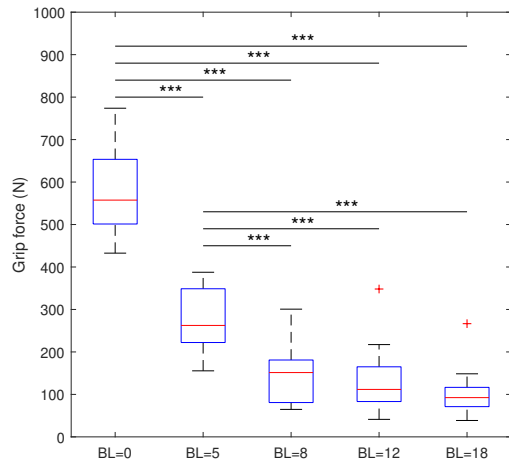


Fig. 6. Measured average grip force during the time-invariant experiments across all subjects ($N = 10$, paired t-test, *** indicates $p < 0.001$).

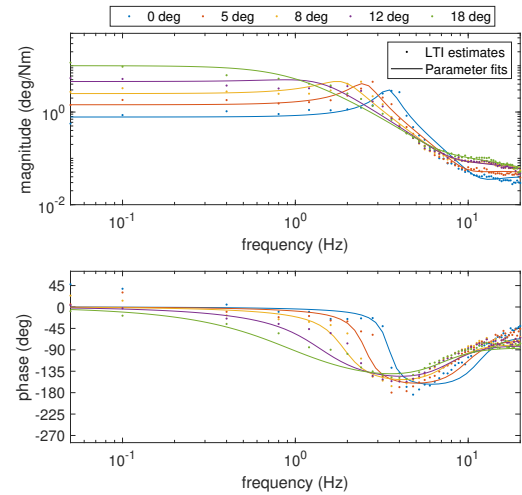


Fig. 7. Average admittance FRF estimates for each condition (markers) and fitted local LTI models (lines).

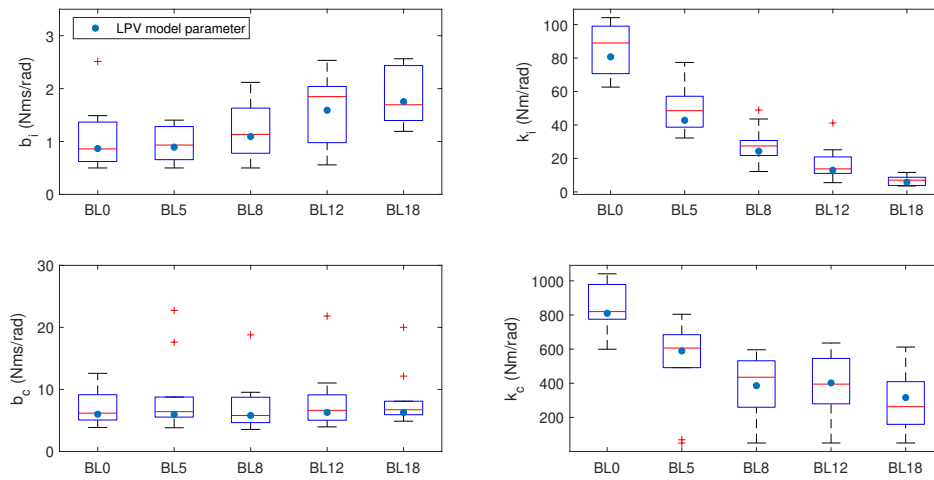


Fig. 8. Estimated LTI admittance model parameters. Blue markers indicate the estimated parameters corresponding to the local LPV models.

level was between 10 and 52% higher in the TV tasks, causing a persistent mismatch in the LPV model's admittance predictions. While the time-varying driver admittance was accurately estimated using the applied RLS algorithm (average Variance Accounted For (VAF) values between 80 and 90%), the LPV model's predictions only achieved VAF values between 45 and 55%, on average.

Future work will focus on developing more accurate *personalised* LPV models by avoiding the current issues with the local 'average' TI model method and directly obtaining a global model from individual TV grip and admittance measurements, e.g., by using explicit 'global' LPV methods as previously used in [19]. This has the added benefit of eliminating the differences in the admittance-grip force relation between TI and TV tasks observed in the current experiment. Alternatively, measuring the TI grip force variations at a higher resolution than obtained from the five tested boundary widths in the current experiment, and increasing the number

of repeated trials, may enable obtaining a robust continuously decreasing grip force variation with increasing BL for all individuals and, hence, facilitate the retrieval of personalised LPV models with the approach used in this paper. Finally, future experiments will investigate the effectiveness of these personalised adaptive admittance models for real-time optimization of haptic shared control systems.

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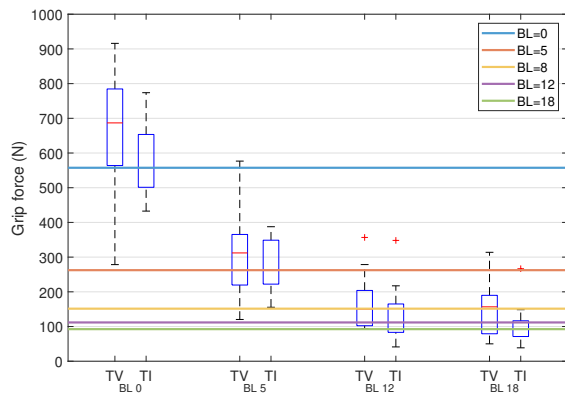


Fig. 9. Comparison of average grip force in the time-invariant and time-varying experiments for all boundary levels.

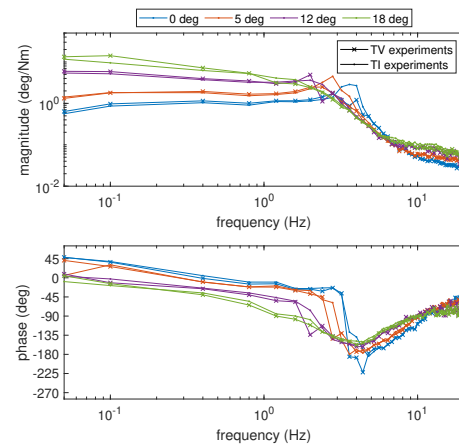


Fig. 10. Comparison of average admittance FRFs in the time-invariant (dots) and time-varying (crosses) experiments for all boundary levels.

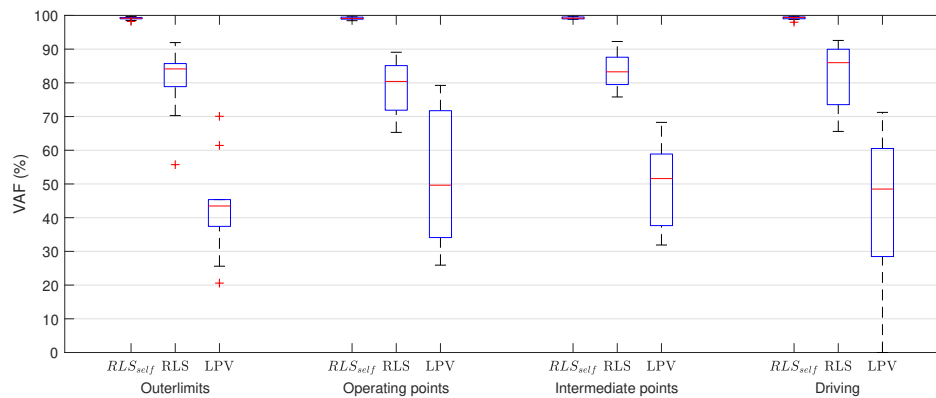


Fig. 11. Steering wheel angle quality-of-fit (VAF) for RLS and LPV admittance models for all 10 participants and all four TV conditions.

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