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Estimating driver time-varying neuromuscular admittance through LPV model and grip force

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Abstract: Humans can rapidly change their low-frequency arm dynamics (i.e., stiffness) to resist forces or give way to them. Quantifying driver's time-varying arm dynamics is important for the development of steer-by-wire systems and haptic driver support systems. Conventional LTI identification, and even time-varying techniques such as wavelets, fail to capture rapidly-varying low-frequency dynamics. In this study, we propose to estimate driver admittance in real-time, using grip force measurement of the hands on the steering wheel and linear parameter-varying (LPV) modeling techniques. We hypothesized that grip force is strongly correlated to neuromuscular admittance, and can serve as an appropriate scheduling variable for an LPV model. We performed an experiment in which 18 subjects performed a boundary tracking task, and applied torque perturbations to the steering wheel to perform a baseline LTI identification. Six different boundary widths were used to evoke changes in admittance, while their grip force was measured with pressure gloves. A global LPV model is identified by linear interpolation between the local LTI models identified for each boundary width. The estimated stiffness and damping parameters varied proportionally with the grip force. Although small between-subject variations in grip force levels are found, we conclude that grip force can indeed serve as an appropriate scheduling variable for a global LPV model, which is capable of tracking fast-changing admittance changes. Future work focuses on using the LPV model in realistic driving tasks, permitting admittance estimates to be obtained without the need to apply external disturbance torques on the steering wheel.

Keywords: Human-machine systems, admittance, driver models, parameter identification

1. INTRODUCTION

Haptic shared control systems support drivers with force feedback on for example the steering wheel to improve human-vehicle interaction (Abbink et al., 2012). When designing these systems it is important to take the effect of neuromuscular (NMS) admittance of the driver on the feedback forces into account, because this influences the system's effectiveness (Abbink et al., 2011). The admittance describes the dynamic relation between a force input and position output of a limb: a large admittance corresponds to lower resistance to external perturbations, a small admittance to higher resistance, commonly as a result of stronger reflex activity and co-contraction.

Estimation of neuromuscular admittance of drivers has drawn significant interest in recent years, primarily using linear time-invariant (LTI) models. For example, admittance of the ankle-foot complex has been identified during car following tasks through frequency domain analysis (Abbink et al., 2011). Humans are capable, however, of changing their admittance based on, among others, the environment they are interacting with and the task they perform (de Vlugt et al., 2002). In order to develop *adaptive* haptic support systems, which consider individual and changing driving behavior (Van der Wiel et al., 2015), it is necessary to use time-varying modeling and identification techniques (Verhaegen and Yu, 1995).

Several approaches have been explored to estimate time-varying admittance. A wavelet transformation was applied to estimate time-varying driver behavior (Mulder et al., 2011); time-sliding windows, assuming LTI behavior, were used to estimate the time-varying admittance of a driver's arm (Katzourakis et al., 2014); recursive least squares were used to estimate the lower arm admittance when controlling a side-stick (Olivari et al., 2015). However, all these methods are not capable of providing reliable, fast converging, estimates over the complete frequency range when admittance is changing fast. Hence, this paper takes a different approach, which is to estimate the time-varying admittance through identifying a linear parameter varying (LPV) model. LPV models are a class of non-linear models with a model structure which varies linearly in a parameter as a function of a time-dependent scheduling signal (Tehrani et al., 2013). When LPV models are identified accurately, and proper scheduling variables are chosen, they are better capable of tracking fast changing dynamics, and also without the need of introducing additional perturbations into the system, which would be extremely valuable in real-life driving applications.

This paper considers modeling time-varying admittance of a driver's arm, through a global LPV model based on local LTI models (Paijmans et al., 2008). Previous studies reported an inverse relation between grip force and admittance (Nakamura et al., 2011), (Kuchenbecker et al., 2003), which makes grip force a possible candidate to act as scheduling variable. To obtain the global LPV model, we performed an experiment to

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obtain a range of LTI identification models, while measuring grip force at the steering wheel with pressure gloves. The experiment involved a boundary-tracking steering wheel manipulation task (SWMTs), with six different boundary widths to evoke different admittance levels. For each level, a parametric admittance model was fit to analyze the relation between measured grip force and estimated intrinsic and contact dynamics parameters. The local LTI models were then 'connected' through polynomial interpolation, yielding a global LPV model (de Caigny et al., 2009). Future work involves a more realistic driving task to analyze the variation of grip force and admittance changes when driving along wide and narrow roads. Results will be compared to the SWMT findings, to assess the validity of the identified LPV model for real driving tasks.

2. BACKGROUND

2.1 Parametric model

Fig. 1 shows a model of a driver controlling a steering wheel (SW). T_p is the torque perturbation, T_d the driver torque, N the remnant signal which accounts for non-linearities, θ_{sw} is the SW angle and T_{ref} is the torque reference input from the central nervous system.

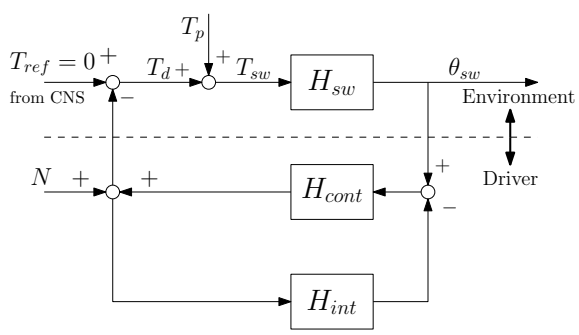


Fig. 1. Parametric admittance model (adapted from (van der Helm et al., 2002))

The arm NMS admittance is modeled by a mass spring damper system with contact dynamics. The mechanical properties of the arm muscles, which depend on the level of co-contraction, are described by the intrinsic dynamics:

$$H_{int}(s) = 1/(I_i s^2 + b_i s + k_i), \tag{1}$$

with I_i the inertia, b_i the damping and k_i the intrinsic stiffness. The contact dynamics represent the visco-elasticity of the driver's arm contact with the SW and can be modeled as a spring-damper system:

$$H_{cont}(s) = b_c s + k_c, \tag{2}$$

with b_c and k_c the damping and stiffness, respectively. The NMS admittance, the frequency response from T_d to θ_{sw}, excluding remnant noise, is then derived as:

$$H^{par}_{adm}(s) = H^{-1}_{cont}(s) + H_{int}(s) \tag{3}$$

2.2 Spectral Analysis

When assuming LTI behavior, the driver's arm admittance can be estimated using spectral analysis. The cross-spectral densities between the disturbance signal T_p and measured steering wheel angle θ_{sw}, and between the disturbance signal T_p and driver torque T_d, are used to estimate the driver's admittance:

$$\hat{H}_{adm}(f) = \hat{S}_{T_p\theta sw}(f)/\hat{S}_{T_pT_d}(f) \tag{4}$$

To evaluate the estimation, the coherence can be calculated. This is a measure of the linearity between input and output signal and varies between 0 and 1:

$$\Gamma_{T_p\theta_{sw}} = \sqrt{\frac{|\hat{S}_{T_p\theta_{sw}}(f)|^2}{\hat{S}_{T_pT_p}(f)\hat{S}_{\theta_{sw}\theta_{sw}}(f)}} \tag{5}$$

2.3 Parameter estimation

To estimate the neuromuscular parameters ($\underline{p} = \{I_i, b_i, k_i, b_c, k_c\}$) of the intrinsic and contact dynamics, the transfer function of the admittance model is fitted to the estimated frequency response by minimizing the least-square-errors. The frequency response is weighed by the coherence, to emphasize reliable estimates, and by $1/f$, to compensate for the logarithmic frequency distribution. The intrinsic inertia was assumed to be constant. To evaluate the accuracy of the estimated parameters we use the Cramèr-Rao lower bound, the inverse of the Fisher information matrix. The standard errors of the mean (SEM) equal the matrix diagonal elements. The admittance model can be simulated using the measured T_d as input, yielding the predicted SW angle. The variance accounted for (VAF) is a measure of how well the model explains the measurements:

$$VAF = 100 \cdot \left(1 - \frac{\sum_{k=1}^{N}(\theta^{meas}_{sw}(k) - \theta^{par}_{sw}(k))^2}{\sum_{k=1}^{N}(\theta^{meas}_{sw}(k))^2}\right) \tag{6}$$

2.4 LPV identification by interpolating local LTI models

To construct a global LPV admittance model with grip force as scheduling function, first local LTI models are identified. A polynomial interpolation method is then used to construct a numerically well-conditioned LPV model (de Caigny et al., 2009). The following steps are taken:

(1) Identify local LTI transfer functions at each operating point (OP);
(2) Decompose each local LTI model in a series connection of a gain multiplied with first and second order sub-models;
(3) Transform each local sub-model to observable form state space format;
(4) Interpolate state space coefficients of sub-models between local OPs, and interpolate local LTI gains;
(5) Recompose the sub-models and gain to construct a global LPV model using the estimated polynomials.

Each local LTI model is expressed as the product of gain (γ) and first (F) and second (S) order subsystems:

$$H_i(\mu) = \gamma_i(\mu)\prod_{k=1}^{n_f} F_i^k(\mu)\prod_{l=1}^{n_s} S_i^l(\mu), \tag{7}$$

with μ the (time-varying) scheduling variable, and n_f and n_s the number of first and second order subsystems. It is assumed that all local LTI models have the same number of first and second order subsystems; these are transformed to the observable form. For instance, for a second order subsystem with two poles and two zeros, we obtain:

$$S_i^l = \left[\begin{array}{cc|c} 0 & a_{i,1}^l & b_{i,1}^l \\ 1 & a_{i,2}^l & b_{i,2}^l \\ \hline 0 & 1 & 1 \end{array}\right] \tag{8}$$

The entries of the state space matrices can be derived from the zero and pole locations of the sub-model. Next, the entries of each subsystem are interpolated between the local OPs to obtain global subsystems. Again taking the second order subsystem as an example, the global subsystem is derived as:

$$S^l = \left[\begin{array}{cc|c} 0 & \sum_{p=0}^{N_p} \alpha_{1,p}^l \mu(t)^p & \sum_{p=0}^{N_p} \beta_{1,p}^l \mu(t)^p \\ 1 & \sum_{p=0}^{N_p} \alpha_{2,p}^l \mu(t)^p & \sum_{p=0}^{N_p} \beta_{2,p}^l \mu(t)^p \\ \hline 0 & 1 & 1 \end{array}\right], \tag{9}$$

where $\mu(t)$ is the scheduling variable, N_p is the polynomial order and α and β are polynomial coefficients. The gains of the local LTI models are also interpolated polynomially:

$$\gamma(\mu) = \sum_{p=0}^{N_p} g_p \mu(t)^p, \tag{10}$$

where g_p are the polynomial coefficients. To calculate the polynomial coefficients of the global subsystems, we minimize the least-square errors between the polynomials and state space entries of the local subsystems. The global LPV model is then constructed by re-composing the global polynomial gain and subsystems in a series connection.

In this paper we propose measured grip force as the scheduling variable $\mu(t)$ of our LPV model, as previous work showed that grip forces varies systematically with changes in admittance (Nakamura et al., 2011). Hence, to derive a *global* LPV model from the local (OP) LTI models, it is assumed that each LTI admittance model corresponds to a fixed level of grip force, which will need to be experimentally obtained.

3. METHOD

3.1 SW Manipulation Tasks

Previous research showed that humans can, when instructed to vary their grip, maintain multiple levels of grip force, while changes in admittance are small (Nakamura et al., 2011). Here, to obtain a set of different endpoint admittance that span the complete ramge, we used a task in which participants held the SW in the presence of a torque disturbance, and varied the range over which the wheel was allowed to move, by indicating this with boundary lines on the display.

Subjects were asked to hold the SW in a "10-to-2" hand position and keep an upright posture. The aim was to evoke six different levels of admittance. Torque perturbations were introduced into the SW and the SW angle was shown on the dashboard. Two classical control tasks, position task (PT) and relax task (RT), were used to determine the lower and upper levels of the admittance, respectively. To measure the intermediate admittance levels, the novel boundary task (BT) was used. During these tasks, subjects were instructed to be "as compliant as possible, while still keeping the SW angle within the boundary shown on the display" (Fig. 2). Four boundary tasks were performed, with fixed boundary widths of 18, 12, 8 and 5 degrees. Note that the RT can be interpreted as an BT with infinite boundaries, the PT is an BT with a zero-width boundary.

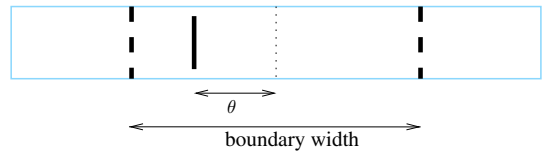


Fig. 2. Dashboard display, θ steering wheel angle deviation

3.2 Apparatus

Driving simulator The experiment was conducted in the fixed-base driving simulator of TU Delft, with an electrically-actuated steering wheel. Its second order dynamics' parameters were fixed during the experiment, see Table 1. The SW diameter was 38 cm; the grip diameter was 3.2 cm. The dashboard display was used to give visual feedback on the SW angle.

Table 1. Steering Wheel Dynamic Parameters

I_{sw} $[Nm/rad]$	b_{sw} $[Nms/rad]$	k_{sw} $[Nm/rad]$	$f_{n_{sw}}$ $[Hz]$	β_{sw} [-]
0.3	2	4.2	0.60	0.89

Grip force measurements Grip force applied to the SW was measured using gloves with pressure sensors (TekScan Grip sensor 4256E). The sensor consists of 349 individual pressure sensing locations (sensils) and can detect pressures in the range of 6.9 - 206.8 kPa. Here we consider only the *total* grip force applied to the SW (held with both hands), i.e., the summation of the forces applied to each individual pressure sensil.

3.3 Perturbation design

A multi-sine perturbation signal with variable phase was designed according the Reduced Power Method (Mugge et al., 2007). This method was used to identify full bandwidth dynamics while evoking low bandwidth behavior. Double frequency bands allowed frequency-averaging to improve identification accuracy. Full power was applied up to 0.7 Hz, reduced power from 0.7 to 20 Hz. A 45 seconds perturbation signal with 31 double bands was used, with SD 2.26 Nm.

3.4 Participants

Eighteen subjects (4 females, 14 males) participated, all TU Delft students (aged 23.2 years; SD 2.1 yrs). Participation was voluntary; no financial compensation was offered.

3.5 Experimental procedure and statistical analyses

Subjects performed the six SWMTs (RT, BT18, BT12, BT8, BT5 and PT), in a repeated-measures design. A Latin square counter-balanced potential effects of fatigue and learning. Before each task, subjects did one familiarization trial. Then two repetitions were performed, to allow for Welch-averaging of the spectral estimates.

A repeated-measures ANOVA was used to evaluate within-subject effects between the six SWMT conditions; Bonferroni corrections were applied to pairwise comparisons.

3.6 LPV verification

LTI models are fit to the average Fourier coefficient estimates of the admittance over 18 subjects. A global LPV model is identified using these LTI models, with the average grip force of all subjects for each condition as OP. To assess the accuracy of the identified LPV model, the identification process is verified at multiple steps. To verify that the Fourier coefficients are estimated accurately, we calculated the coherence, Eq. (5). To verify that the LTI transfer functions models are fitted accurately to the frequency response data at each OP, the fit percentage is calculated in the frequency domain:

$$FIT_{perc} = 100 \cdot \left(1 - \frac{\sum_{k=1}^{N} \frac{1}{f} |\hat{H}_{adm}(f) - H_{adm}^{par}(f)|^2}{\sum_{k=1}^{N} \frac{1}{f} |H_{adm}^{par}(f)|^2}\right) \quad (11)$$

To evaluate the LPV model, we use an intermediate OP that is *not* included when deriving the global model; we repeat this step for each of the intermediate OPs.

3.7 Hypotheses

We hypothesized that grip force increases when admittance is lower. It will be verified that a global LPV model can be constructed that accurately represents the steering wheel manipulation data for all conditions.

4. RESULTS

Fig. 3 illustrates measured signals of a single subject. SW angle deviations θ_{sw} due to force perturbations increase, and grip forces decrease, for larger boundary widths. Variations in driver torque T_d increase slightly for smaller boundaries; also larger torques are applied here.

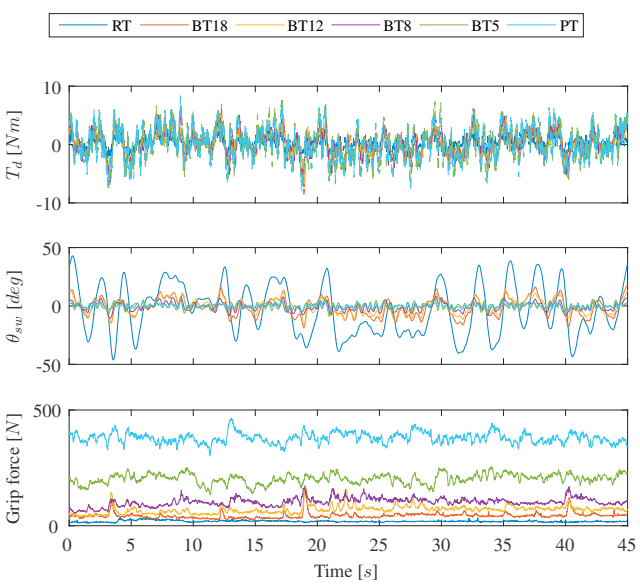


Fig. 3. Measured time domain signals (Subject 12)

Grip force Fig. 4 shows boxplots of the average and standard deviation of the grip force (18 subjects). Grip force increases for smaller boundary widths. Between-subject variations in grip force are considerable, especially when the boundary width decreases. The grip force STD increases for smaller boundaries.

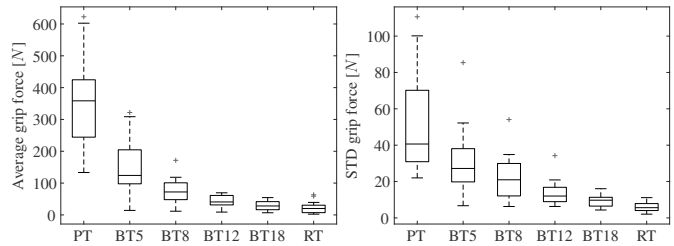


Fig. 4. Grip force SWMTs (18 subjects)

Hence, average grip force and variation in grip force are coupled, which can be explained from motor noise in the muscles.

The average grip force is significantly different between all conditions (p <0.01) except between the RT and BT18. Pairwise comparisons of the grip force STD reveal that the differences are not always significant between two adjacent boundary widths: Effects of boundary width on grip force variations are smaller than on average grip force.

Spectral analysis For each subject, admittance is estimated and the coherence calculated. For each Fourier coefficient, a 95% confidence interval is calculated (18 subjects), see Fig. 5. The goal of the SWMTs, to evoke multiple levels of admittance, has been successful: smaller boundary widths yield lower admittance levels. High coherences over the whole frequency range indicate good signal-to-noise ratios (SNR). Coherence drops at very low frequencies, however; here the linearity between the perturbation torque and SW angle is lower.

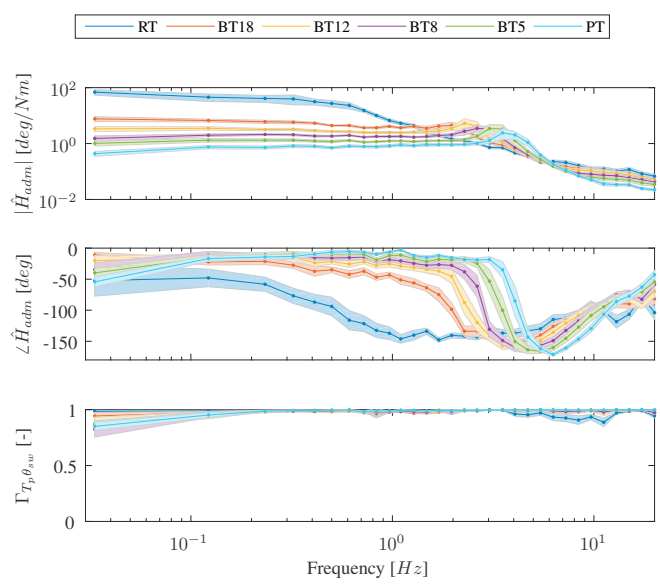


Fig. 5. Estimated admittance during the SWMTs

Parameter estimation Parameters were estimated, using the spectral estimates of each individual subject as well as for the Welch-averaged admittance spectrum (18 subjects). Fig. 6 shows boxplots of the estimated parameters. Note that the intrinsic inertia I_i was kept constant. Accurate parameter estimates with a low SEM could be achieved when the two lowest frequencies (corresponding with the lower coherence) were omitted. Damping parameters have a higher SEM than the stiffness parameters: the former contribute less to the frequency fit accuracy. Covariance of the estimated parameters was low: they are not correlated and could be estimated correctly.

For all parameters (except intrinsic inertia) the within-subject effects of boundary width were found to be statistically significant. Post-hoc analyses showed that the intrinsic stiffness is the only parameter which varies over all conditions within subjects and is thus definitely related to boundary width. When analyzing the estimated parameters based on the Welch-averaged frequency response, it was found that both b_c and k_c increase for smaller boundary widths; no significant relation between intrinsic damping and boundary width is found.

Model predictions are accurate, except for the RT which has a significantly lower VAF. Here the subjects' NMS was very compliant, and the SW angle could easily drift away from the reference, causing many prediction inaccuracies.

LPV model identification An LPV model is derived based on the Welch-averaged admittance estimate of 18 subjects (Fig. 5). The identified models at the OPs are used as local LTI models: all are third order models with two zeros and three poles. The medians of 18 subjects of the average grip force at each condition are the corresponding local OPs of the scheduling variable (Fig. 4). Table 2 shows the fit accuracy at each local OP.

Table 2. Fitting accuracy at OPs, FIT_{perc} [%]

OP	PT	BT5	BT8	BT12	BT18	RT
LTI	94.1	96.7	99.0	98.0	96.6	91.5
LPV	91.5	94.9	97.7	95.2	95.1	-

The local LTI models were each decomposed in a series connection of a gain, a first order subsystem with one zero and a second order subsystem with one zero. A polynomial order of two was chosen for the interpolation between the local subsystems; higher model orders led to over-fitting. It was not possible to achieve accurate polynomial fits when including the RT OP. Since no significant difference in grip force was found between the RT and BT18, and the RT LTI models had significantly lower VAFs, it was decided to omit this local OP when deriving the LPV model. As drivers are unlikely to be as compliant during real driving as during an RT, this is a reasonable step.

The LPV model fits at the local OPs are shown in Fig. 7(b). Only a small decrease in VAFs is observed between the LPV fit and the LTI fit (Table 2).

LPV model verification To verify the interpolation method, the LPV model is constructed while excluding an intermediate local OP. Then the frequency response at this 'verification OP' is estimated using the derived LPV model. The interpolation accuracy is high, with VAFs $> 80\%$, when excluding the OPs BT12 and BT8. However, the LPV model cannot accurately estimate the admittance at the higher grip force OP, BT5 (VAF $= 0\%$), when this point is not included.

5. DISCUSSION

We showed that the novel boundary tracking (BT) task can evoke multiple levels of admittance. A caveat of the BT tasks is that they require a large perturbation amplitude. This is because a clear distinction between the boundary widths is necessary such that subjects are capable of performing the tracking task at different admittance levels. This makes it more complex to later compare the results to the driving task results.

When considering the grip force during the SWMTs, a large difference is found between the PT and the other conditions where subjects were asked to be more compliant. During the PT, subjects used a strategy of maximally co-contracting, which resulted in a very high grip force. Applying a higher grip force resulted in better performance (smaller SW angle variations), but performance saturated for grip forces higher than $\pm 200N$. Hence, the LPV grip force OP for the PT is higher than realistic, since higher grip forces do not lead to changes in admittance.

For the parametric model it was chosen to include intrinsic and contact dynamics. Whereas intrinsic dynamics represent the muscles' mechanical properties, the contact dynamics are relevant when investigating grip force. More extensive parametric admittance models are possible, but these higher order models are likely to be more difficult to validate experimentally.

Between subjects, the variation in estimated admittance for each condition was small. Therefore, it is possible to identify the parametric LTI models for the LPV model based on the subject averaged admittance estimate. Between-subject variation in grip force is higher and the median grip force level at each condition was taken as OP. This implies that the identified LPV model is more accurate for subjects with grip forces closer to the subject median.

The LPV identification method is not based on the estimated physical parameters, but uses the admittance state space model coefficients for interpolation. The physical parameters could be derived from the LPV model for the entire scheduling range after interpolation. It was found that it was very important that the individual local models are similar in terms of pole and zero locations, despite the fact that the method should be capable of coping with transitions of a complex conjugate pole (or zero) pair to a pair of real poles (or zeroes) (de Caigny et al., 2009). Because of this, the RT OP could not be included in the LPV identification even though a high FIT_{perc} was achieved for the LTI model. For this particular application it is therefore recommended to identify an LPV model based on interpolation of individual parameter estimates.

6. CONCLUSION

This study established a quantified relationship between grip force and admittance, using different boundary tracking tasks to evoke a complete range of possible endpoint admittance of driver's arms on a steering wheel. A global LPV model was derived, based on local LTI models representing six NMS admittance levels. A smooth second order interpolation to the frequency responses at the operating points was obtained, with a high goodness-of-fit ($> 90\%$). The interpolation method was robust to exclusion of intermediate operating points. It is concluded that grip force is a good candidate to act as scheduling variable when estimating time-varying admittance of a driver's arm. The resulting LPV model allows a fast, reliable and on-line estimate of driver admittance, without the need to apply force perturbations on the steering wheel. Future work includes a more realistic driving experiment where drivers will naturally adjust their admittance to external factors, to validate the use of grip force as a scheduling variable for our global LPV model. Effects of vehicle speed, road friction and steering resisting moment – which all affect the driver's steering torque – may need to be included in the LPV model structure.

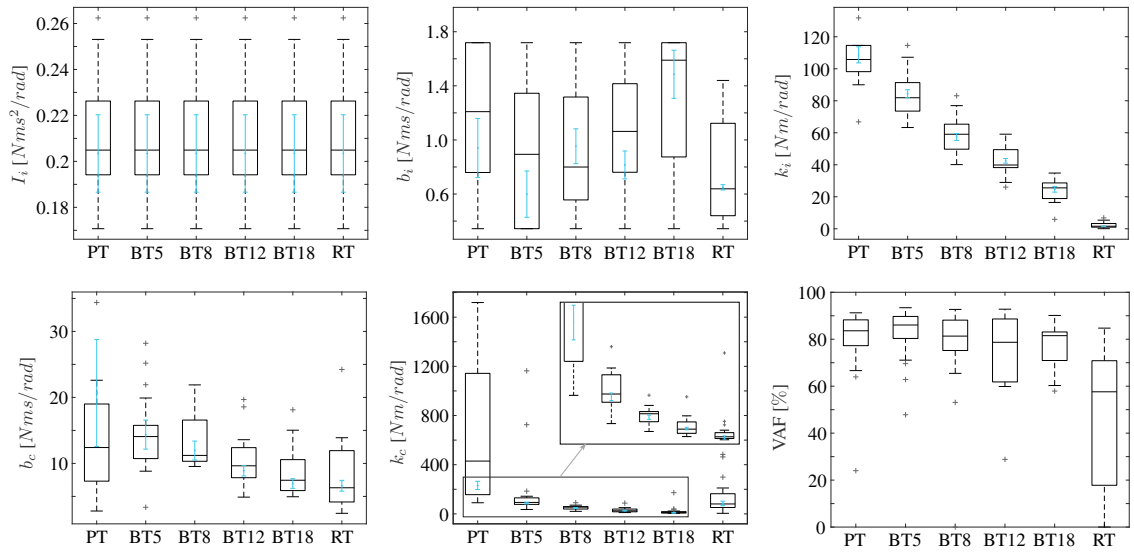
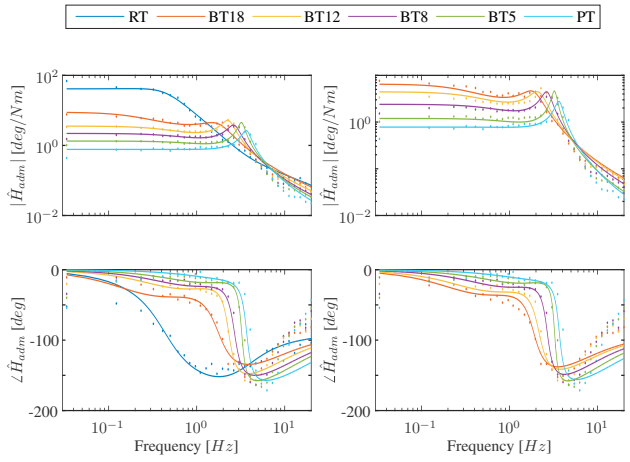


Fig. 6. Boxplots show individual parameter estimation results of SWMTs (18 subjects); In blue: estimated parameters with SEMs on Welch-averaged frequency response



(a) LTI fits (b) LPV fits

Fig. 7. Verification of LTI fits and LPV interpolation

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