Published in final edited form as:

IEEE Trans Neural Syst Rehabil Eng. 2019 February ; 27(2): 275–282. doi:10.1109/TNSRE.

2019 2891525

Feasibility of Incorporating Test-Retest Reliability and Model Diversity in Identification of Key Neuromuscular Pathways during Head Position Tracking

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Abstract

To study complex neuromuscular control pathways in human movement, biomechanical parametric models and system identification methods are employed. Although test-retest reliability is widely used to validate outcomes of motor control tasks, it was not incorporated in system identification methods. This study investigates the feasibility of incorporating test-retest reliability in our previously published method of selecting sensitive parameters. We consider the selected parameters via this novel approach to be the key neuromuscular parameters because they meet three criteria: reduced variability, improved goodness of fit, and excellent reliability. These criteria ensure that parameter variability is below a user-defined value, the number of these parameters is maximized to enhance goodness of fit, and their test-retest reliability is above a user-defined value. We measured variability, goodness of fit, and reliability using Fisher information matrix, variance accounted for, and intraclass correlation, respectively. We also incorporated model diversity as a fourth optional criterion to narrow down the solution space of key parameters. We applied this approach to head position tracking in axial rotation and flexion/extension. Forty healthy subjects performed the tasks during two visits. With variability and reliability measures 0.35 and 0.75 respectively, we selected three key parameters out of twelve with goodness of fit >69%. The key

parameters were associated with at least two neuromuscular pathways out of four modeled pathways (visual, proprioceptive, vestibular, and intrinsic), which is a measure of model diversity. Therefore, it is feasible to incorporate reliability and diversity in system identification of key neuromuscular pathways in our application.

Keywords

Head Position Tracking; Neuromuscular pathways; Parameter estimation; System Identification; Test-retest reliability

I. Introduction

IDENTIFICATION techniques for parametric models are needed to investigate the neuromuscular control pathways involved in human movement. Unfortunately, we do not have direct access to individual pathways, but instead rely on gross measures such as movement kinematics and electromyography [1]. Therefore, neuromuscular parametric models have been used to estimate the relative contribution of various neuromuscular control pathways [2]–[5]. These parametric models typically have multiple independent neuromuscular control signal pathways. Because the neurophysiology is complex with many pathways, these models also tend to be complex with a large number of parameters to be estimated [4], [6], [7]. For a fixed amount of information (measurement), increased parameterization results in increased parameter variability [4], [8]–[10], which subsequently decreases reliability.

Reliability is usually assessed for nonparametric measures such as root mean square error and mean velocity [11]–[14]. Reliability is rarely assessed for estimated model parameters (we are aware of a single study that reported reliability of parameter estimates [15]). No study, to our knowledge, considered incorporating reliability as a selection criterion in system identification for estimating model parameters. Excellent parameter reliability is important for system identification methods to be useful in biomechanical and clinical applications [16]–[18]. Therefore, reliability should be incorporated in existing system identification methods for estimating model parameters.

We previously developed a system identification method that estimates only sensitive model parameters while fixing the remaining ones to preliminary values [19]. It allows selection across all possible parameter subsets, which makes it exhaustive. Because no parameter is eliminated (parameters are either estimated or fixed), all neuromuscular pathways are present in the final model. Sensitive parameters were selected based on parameter variability (measured by Fisher information matrix (FIM)) and goodness of fit.

The main purpose of this study was to investigate the feasibility of incorporating test-retest parameter reliability in our existing FIM method of selecting sensitive parameters. We used a neuromuscular model of the head-neck system for position-tracking in axial rotation (Yaw) and flexion/extension (Pitch). We hypothesized that it is feasible to select sensitive parameter subsets with excellent reliability. We consider these parameters to be the key model parameters substantially affecting head-neck control.

II. Methods

A. Subjects

Forty healthy subjects were recruited for this study (TABLE I). They did not have neck pain lasting more than three days in the last year nor neurological or balance disorders. The Michigan State University's Biomedical and Health Institutional Review Board approved the experiment protocol. All subjects signed an informed consent before participation.

B. Data Collection

The experimental setup of head position tracking (Fig. 1) used a helmet, secured on the subject's head, with two string potentiometers (SP2-50, Celesco, Chatsworth, CA) attached to measure head angle [14]. The reference marker $r(t)$ along with the head position marker $y(t)$ were displayed on a monitor (SyncMaster SA650, Samsung; 27 cm $\times$ 47.5 cm) fixed 1 meter away from the subject. Subjects were instructed to track the reference marker as fast and accurate as possible. The reference signal was a pseudorandom sequence with random step durations (0.3-0.9 seconds) and amplitudes such that the maximum amplitude was $\pm 4^\circ$ centered around 0° (the upright head position) [14]. Subjects completed each task (Yaw and Pitch) on two visits separated by an average of 6.7 (range 1-21) days. Each task consisted of two 15-second practice trials and three 30-second trials during each visit. Data was sampled at 50 Hz and collected with a data acquisition card (cDAQ-9172, National Instruments, Austin, TX).

C. Data Analysis

1) The Parametric Model—The parametric models of the tasks (Fig. 2) used previously published physiological subsystems [6], [20], [21], but the output was modified from head acceleration to head position. This modification does not alter the model behavior, nor the physiological parameter interpretation given in those studies. The physiological parameters (TABLE II) were divided into parameters that may be estimated (candidate key parameters)

$$\Theta := [K_{\text{vis}}, K_{\text{ver}}, K_{\text{cer}}, \tau, \tau_{1A}, \tau_{\text{CNS1}}, \tau_c, \tau_{\text{CNS2}}, \tau_{\text{MS1}}, \tau_{\text{MS2}}, B, K]^T, \quad (1)$$

and fixed parameters $\Theta_{\text{fixed}} := [J \ T_c \ m \ h]^T$ (fixed value across subjects). The physiological descriptions of the parameters are listed in TABLE II. They are the model parameters of visual, vestibular, proprioceptive, and intrinsic pathways, torque converter, and the head-neck plant (Fig. 2).

2) Parameter Estimation—Estimated model parameters identify the physiological contributions of neuromuscular control pathways. Because the parameters had different magnitudes (TABLE II), which may cause numerical issues in optimization, the parameters were normalized. For the i^{th} parameter Θ_i , its normalized counterpart is $\Phi_i \in [-1, 1]$. Any subset $\phi \subseteq \Phi$ is estimated in the same way as Φ , therefore, we use ϕ for generalization. Parameters were estimated by nonlinear least squares

$$\hat{\phi} = \underset{\phi}{\operatorname{argmin}} \left\| y(t) - \hat{y}(t; \phi) \right\|_2^2, \quad (2)$$

where y is the concatenated head position measurement of three trials, $\hat{y}$ is the simulated model output, and $\|\cdot\|_2$ is the 2-norm of a vector. We used MATLAB's function 'lsqnonlin' to solve (2). Preliminary estimates of Θ were obtained per subject per visit (nominal values, TABLE III and TABLE IV) based on which we defined the parameters' bounds (TABLE II). For a given subset ϕ , its parameters were estimated (per subject per visit) while fixing the remaining parameters to the mean (across subjects and visits) of the nominal values. Because the Pitch model has a gravity component while the Yaw model does not (Fig. 2), each model was fitted for its task separately.

3) The Existing FIM Method—FIM is a square matrix computed at the normalized true model parameters ϕ_0 and denoted by $\mathbb{I}(\phi_0)$. Because the subjects' true parameters are unknown, we used the nominal values (TABLE III and TABLE IV). The diagonal elements of FIM inverse ($\mathbb{I}^{-1}$) are parameter estimation error variance (represent parameter variability).

The FIM method [19], [22] for a single dataset (single subject, single visit) selects sensitive parameter subsets (Θ or ϕ). The method formulated as

$$\left. \begin{aligned} \phi &= \arg \max_{\substack{\phi \subseteq \Phi \\ n_{\phi} = \text{length}(\phi)}} n_{\phi}, \\ \text{subject to: } \text{rcond}(\mathbb{I}(\phi_0)) &\geq \varepsilon, \\ d_{\max}(\mathbb{I}^{-1}(\phi_0)) &\leq \sigma_{\text{allowable}}^2, \end{aligned} \right\} \quad (3)$$

searches all possible parameter subsets to maximize the number of sensitive parameters per subset (n_{ϕ}) while bounding parameter variability below a user-defined value [19].

Maximizing the number of estimated parameters indirectly improves goodness of fit. The first constraint on the reciprocal condition number $\text{rcond}(\cdot)$ to be larger than the machine epsilon guarantees the inverse matrix operation ($\mathbb{I}^{-1}$) is well-conditioned. $d_{\max}(\cdot)$ returns the maximum diagonal element, and $\sigma_{\text{allowable}}^2$ is the maximum allowable parameter variability (a user-defined value). This constraint eliminates any parameter subset that has a parameter variability larger than $\sigma_{\text{allowable}}^2$. As the user decreases $\sigma_{\text{allowable}}^2$, the selection becomes more conservative (selects less variable parameter subsets).

To be conservative, this constraint was modulated to bound $d_{\max}$ across all subjects and visits below $\sigma_{\text{allowable}}^2$. That is.

$$\max_{i \in \{1, \dots, 40\}, j \in \{1, 2\}} \left(d_{\max} \left(\mathbb{I}^{-1}(\phi_{0,(i,j)}) \right) \right) \leq \sigma_{\text{allowable}}^2 \quad (4)$$

where i is the subject index, j is the visit index, and $\phi_{0,(i,j)}$ is the normalized nominal parameters of the i^{th} subject in the j^{th} visit. Therefore, sensitive subsets were selected only if their maximum variability was $\sigma_{\text{allowable}}^2$ for all subjects and visits. For a concise notion, we define the variability of a subset by

$$\text{Variability}(\phi) = \max_{i \in \{1, \dots, 40\}, j \in \{1, 2\}} \left(d_{\max} \left(\mathbb{I}^{-1}(\phi_{0,(i,j)}) \right) \right). \quad (5)$$

We used 10 equally-spaced values ($k = 1:10$) of $\sigma_{\text{allowable}}^2$ from 0.05 to 0.95 to select the sensitive parameter subsets. At $\sigma_{\text{allowable}}^2(k)$, the number of selected subsets is $N_{\text{candidate}}(k)$.

4) Reliability of a Parameter Subset—Between-visit reliability is important in our application. Between-visit comparison of parameters can detect the effect of an intervention introduced between two visits, which is a long-term goal of our work. Therefore, between-visit reliability of the normalized sensitive parameter estimates was computed using intraclass correlation coefficient for absolute agreement ICC(A, k) with 95% confidence interval (CI) [23]. The reliability of a normalized parameter subset (ϕ) was considered the smallest ICC of its parameters. That is

$$\text{Reliability}(\phi) = \min_{i \in \{1, \dots, n_{\phi}^*\}} \left(\text{ICC}(\phi_i) \right), \quad (6)$$

where n_{ϕ}^* is the number of sensitive parameters in the subset ϕ . The ICCs were classified as poor (<0.40), fair (0.40-0.59), good (0.60-0.74), or excellent (0.75-1.00) [24].

5) The Proposed Method—To investigate the feasibility of incorporating reliability in the FIM method, we used three criteria to select key model parameters for estimation. They are parameter variability, goodness of fit, and parameter reliability. The first two were adjusted from the existing FIM method. The variability criterion selects the subsets whose variability does not exceed a user-defined upper bound σ_{max}^2 , i.e., $\text{Variability}(\phi) \leq \sigma_{\text{max}}^2$. The goodness of fit criterion selects the subsets that have the largest number of parameters. The reliability criterion selects the subsets whose reliability is greater than or equal to a user-defined lower bound ICC_{min} , i.e., $\text{Reliability}(\phi) \geq \text{ICC}_{\text{min}}$. If there is more than one feasible solution (two or more parameter subsets) after applying the three criteria, a fourth optional criterion reflecting model diversity was applied to reduce the solution space. Our proposed system identification method is summarized in TABLE V.

Diversity in our model may be postulated as the presence of independent neuromuscular pathway signals in the model. Therefore, selecting parameters in as many pathways as possible yields a "diverse" parametric model. In our model (Fig. 2), we have four pathways: visual, vestibular, proprioceptive, and intrinsic. A diversity index is how many pathways are represented by the selected parameters.

6) Assessing Goodness of Fit—To assess goodness of fit for the selected parameters, we used variance accounted for (VAF) [4], [25]

$$\text{VAF} = \left[1 - \frac{\|y(t) - \hat{y}(t; \phi)\|_2^2}{\|y(t)\|_2^2} \right] \times 100 \% . \quad (7)$$

As VAF approaches 100%, the simulated data better fits the experimental data.

III. Results

A. Illustrative Example

A simulation example is provided in the supplementary material. It uses a simple model with over-parametrization. It provides a step-by-step deployment of our proposed method. Our method could eliminate over-parameterization of the model hence restore identifiability. Moreover, our method could improve the reliability of the selected parameters compared to the reliability of the nominal parameters.

B. Experimental Results

Sensitive parameter subsets were selected using the FIM method. The maximum number of sensitive parameters per subset n_θ^* ranged from 2 to 3, and from 2 to 4 for Yaw and Pitch, respectively (Fig. 3). For the interval $(0, \sigma_{\text{allowable}}^2]$ in the inequality (4), the number of sensitive subsets is $N_{\text{candidate}}$ (Fig. 3). The sensitive subsets (TABLE VI) are listed for the intermediate intervals such as (0.05,0.15].

The ICCs of the sensitive parameters were greater (more reliable) than those of all 12 model parameters (TABLE VI). The reliability of a sensitive subset was considered the smallest ICC of its parameters. Therefore, the reliability of the sensitive subsets ranged from 0.07 to 0.85 and from 0.30 to 0.91 for Yaw and Pitch, respectively.

Key model parameters for estimation were selected using the four criteria defined earlier. First, for the variability criterion, we selected an upper bound $\sigma_{\text{max}}^2 = 0.35$, which eliminated all subsets below the 4th row in TABLE VI. Second, the maximum number of sensitive parameters per subset (in the remaining rows) is $n_\theta^* = 3$. Therefore, we eliminated the upper three rows in Yaw and the 1st row in Pitch. Third, for excellent reliability, we selected $\text{ICC}_{\text{min}} = 0.75$. This led to one feasible solution in Yaw $\{K_{\text{vis}}, K_{\text{ccr}}, \tau\}$ (diversity index=2), and three feasible solutions in Pitch $\{\{K_{\text{ccr}}, \tau, \tau_{\text{CNS1}}\}, \{K_{\text{vis}}, \tau, \tau_{\text{CNS1}}\}, \{K_{\text{vcr}}, \tau, \tau_{\text{CNS1}}\}\}$ (diversity indices = 3, 2, and 2, respectively). Fourth, by maximizing the diversity index, the

selected key parameters for Yaw and Pitch were $\{K_{vis}, K_{ccr}, \tau\}$, and $\{K_{ccr}, \tau, \tau_{CNS1}\}$, respectively.

The key parameters were estimated while fixing the remaining ones to their nominal values (TABLE III and TABLE IV). In Yaw, the 95% CI of ICCs ranged from 0.55 to 0.93. In Pitch, the 95% CI of ICCs ranged from 0.69 to 0.96.

IV. Discussion

We hypothesized that it is feasible to incorporate parameter reliability in our FIM method to select key model parameters that substantially affect head-neck control. In our application, the reliability of the sensitive parameters ranged from very poor to excellent, however, they were still more reliable than all model parameters (TABLE VI). This indicates that the FIM method of selecting sensitive parameters improves reliability, but it does not guarantee excellent reliability. Hendershot *et al.* found a similar wide range of parameter reliability (from 0.19 to 0.72) [15]; however, they did not select sensitive parameters as in our case. Out of the sensitive parameter subsets (TABLE VI), there was more than one subset with excellent reliability (ICC = 0.75). Therefore, it is feasible to incorporate parameter reliability in our FIM method.

Incorporating reliability as a selection criterion in system identification is transformative. Estimating all model parameters, in our case, yielded some negative ICCs (TABLE VI). Although negative ICCs are possible given the mathematical formula [23], they may suggest that the model is not appropriate for modeling the data. Given our results that we could extract parameter subsets with excellent reliability, we provide a remedy for system identification with lack of identifiability and reliability.

Since our method provides a unique solution of the estimated parameters, it can be useful for a clinical comparison test (of an intervention), where subjects with and without an intervention need to be compared. Our result (the selected key parameters) can be also utilized for a single visit because in general clinicians are busy to take repeated measurements in multiple visits.

Reducing the solution space of the FIM method is an advantage of adding the third reliability criterion. For example, in Pitch, the solution space was reduced from 6 sensitive parameter subsets to 3. This helps modelers reach a better decision by eliminating less-reliable sensitive parameter subsets. To reduce the solution space further, we proposed selecting subsets with the most diverse parameters, i.e., parameters from different feedback pathways (visual, vestibular, proprioceptive, and intrinsic). Using the variability, goodness of fit, reliability, and diversity criteria on data of forty subjects, we selected one subset of key model parameters in Yaw and Pitch. However, the modeler might have a specific preference that can replace this diversity criterion. For example, if a modeler expects major differences to be present in the vestibular pathway before and after an intervention, then selecting subsets with more parameters from the vestibular pathway is a better choice.

Some physiological parameters and feedback pathways are relatively more important than others in head position tracking tasks. In Yaw, the visual, proprioceptive, vestibular, and

intrinsic parameters were in 7, 6, 5, and 0 sensitive subsets out of 9, respectively (TABLE VI). In Pitch, these parameters were in 14, 9, 13, and 0 sensitive subsets out of 16, respectively. This suggests that the visual pathway is the most important feedback in head position tracking tasks. This finding validates the previously published simplified models that considered only the visual feedback for tracking tasks [21], [26]. The results also suggest that the vestibular pathway is more important for Pitch than for Yaw. It might be due to the effect of gravity in Pitch. By investigating the visual parameters further, the visual delay τ was in 6 out of 9 and 14 out of 16 sensitive subsets in Yaw and Pitch, respectively. On the other hand, the visual gain K_{vis} was in 3 and 4 subsets in Yaw and Pitch, respectively. This may suggest that the visual delay is the most important parameter in the most important pathway contributing to head position tracking performance in Yaw and Pitch.

Some limitations of our study are worth noting. First, the physiological parameter bounds affect the selected sensitive parameter subsets because FIM is computed at the normalized nominal parameters. For example, if the bounds of a parameter are expanded, its normalized variability $\mathbb{I}^{-1}(\phi_i)$ shrinks, i.e., this parameter becomes more sensitive than it really is.

Therefore, reasonable parameter bounds must be used. Second, the key parameter estimates might be biased (offset from the true values), but they are more precise (with less variability) than the estimates of all model parameters [19]. This bias cannot be measured because the true subject parameters are unknown. However, for a given study, such as detecting the effect of an intervention introduced between two visits, using between-visit comparison of parameters, the bias effect is relatively constant, while the estimates are more precise.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Acknowledgments

This work has been supported in part by grant number U19AT006057 from the National Center for Complementary and Integrative Health (NCCIH) at the National Institutes of Health. Its contents are solely the responsibility of the authors and do not necessarily represent the official views of NCCIH. The work of Jongeun Choi is funded in part by the Mid-career Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Science and ICT (NRF-2018R1A2B6008063).

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Fig. 1. The experimental setup of head position tracking tasks in (a) axial rotation (Yaw), and (b) flexion-extension (Pitch).

Fig. 2.

The block diagram of neuromuscular control for the head position tracking tasks. The contributing neurophysiological pathways are visual, vestibular, proprioceptive, and intrinsic.

* the gravity effect ($-mgh$) was used for Pitch only.

(a)

(b)

Fig. 3.

The solution space (the sensitive parameter subsets) of the FIM method for (a) Yaw, and (b) Pitch. The solution space was discretized at 10 values of $\sigma_{\text{allowable}}^2$. n_{θ}^* is the maximum number of sensitive parameters per subset. $N_{\text{candidate}}$ is the number of sensitive subsets with n_{θ}^* parameters and parameter variability $\sigma_{\text{allowable}}^2$.

TABLE I

Demographic characteristics of the subjects given as (mean $\pm$ standard deviation).

	Males (n=19)	Females (n=21)
Height (cm)	178.9 $\pm$ 6.1	162.9 $\pm$ 5.6
Weight (kg)	86.8 $\pm$ 10.7	62.0 $\pm$ 6.7
Age (years)	43.2 $\pm$ 14.5	40.5 $\pm$ 15.1

TABLE II

Physiological parameters used in the neck motor control model (Fig. 2) and their bounds. Bounds were based on preliminary estimates (TABLE III). Θ has model parameters that may be estimated (candidate key parameters), while Θ_{fixed} has fixed parameters.

Parameters		Max	Min	Description
Θ	$K_{\text{vis}} \left[\frac{Nm}{rad} \right]$	10^3	50	visual gain [21]
	$K_{\text{vcr}} \left[\frac{Nms^2}{rad} \right]$	10^4	500	vestibular gain [6]
	$K_{\text{ccr}} \left[\frac{Nm}{rad} \right]$	300	1	proprioceptive gain [6]
	$\tau[s]$	0.4	0.1	visual delay [21]
	$\tau_{IA}[s]$	0.2	0.01	lead time constant of the irregular vestibular afferent neurons [6]
	$\tau_{\text{CNS1}}[s]$	1	0.05	lead time constant of the central nervous system [6]
	$\tau_c[s]$	5	0.1	lag time constant of the irregular vestibular afferent neurons [6]
	$\tau_{\text{CNS2}}[s]$	60	5	lag time constant of the central nervous system [6]
	$\tau_{\text{MS1}}[s]$	1	0.01	first lead time constant of the neck muscle spindle [6]
	$\tau_{\text{MS2}}[s]$	1	0.01	second lead time constant of the neck muscle spindle [6]
	$B \left[\frac{Nms}{rad} \right]$	5	0.1	intrinsic neck damping [6]
	$K \left[\frac{Nm}{rad} \right]$	5	0.1	intrinsic neck stiffness [6]
Θ_{fixed}	$J[kgm^2]$	0.0148/0.106	0.0148/0.106	head-neck inertia in Yaw/Pitch about the center of mass
	$T_c[s]$	0.1	0.1	torque converter time constant
	$m[kg]$	4.909	4.909	head-neck mass
	$h[m]$	0.126	0.126	distance from C6-C7 to head-neck center of mass

TABLE III

The estimates of preliminary (Nominal) and selected key model parameters with the corresponding variance accounted for (VAF) in Yaw. Values are given as mean $\pm$ standard deviation across subjects (and visits for Nominal). Between-visit reliability was measured by ICC(A, k) with 95% confidence interval (CI).

Yaw Parameters	Nominal	Selected Key Parameters		
		Visit 1	Visit 2	ICC, 95% CI
$K_{\text{vis}} \left[\frac{Nm}{rad} \right]$	357 $\pm$ 159	226 $\pm$ 52	220 $\pm$ 44	0.76, [0.55,0.87]
$K_{\text{vcr}} \left[\frac{Nms^2}{rad} \right]$	5285 $\pm$ 2248	–	–	–
$K_{\text{ccr}} \left[\frac{Nm}{rad} \right]$	59.7 $\pm$ 49.1	32.5 $\pm$ 34.0	25.9 $\pm$ 28.2	0.87, [0.75,0.93]
$\tau[s]$	0.302 $\pm$ 0.040	0.289 $\pm$ 0.033	0.277 $\pm$ 0.029	0.85, [0.63,0.93]
$\tau_{1A}[s]$	0.089 $\pm$ 0.060	–	–	–
$\tau_{\text{CNS1}}[s]$	0.687 $\pm$ 0.225	–	–	–
$\tau_c[s]$	1.962 $\pm$ 0.999	–	–	–
$\tau_{\text{CNS2}}[s]$	26.7 $\pm$ 16.2	–	–	–
$\tau_{\text{MS1}}[s]$	0.540 $\pm$ 0.342	–	–	–
$\tau_{\text{MS2}}[s]$	0.440 $\pm$ 0.362	–	–	–
$B \left[\frac{Nms}{rad} \right]$	1.728 $\pm$ 1.351	–	–	–
$K \left[\frac{Nm}{rad} \right]$	2.579 $\pm$ 1.634	–	–	–
VAF(%)	72.2 $\pm$ 8.7	69.5 $\pm$ 8.1	73.1 $\pm$ 8.8	–

TABLE IV

The estimates of preliminary (Nominal) and selected key model parameters with the corresponding variance accounted for (VAF) in Pitch. Values are given as mean $\pm$ standard deviation across subjects (and visits for Nominal). Between-visit reliability was measured by ICC(A, k) with 95% confidence interval (CI).

Pitch Parameters	Nominal	Selected Key Parameters		
		Visit 1	Visit 2	ICC, 95% CI
$K_{\text{vis}} \left[\frac{Nm}{rad} \right]$	365 $\pm$ 172	–	–	–
$K_{\text{vcr}} \left[\frac{Nms^2}{rad} \right]$	6212 $\pm$ 2404	–	–	–
$K_{\text{ccr}} \left[\frac{Nm}{rad} \right]$	63.5 $\pm$ 55.3	84.2 $\pm$ 59.3	77.7 $\pm$ 50.8	0.85, [0.73,0.92]
$\tau[s]$	0.318 $\pm$ 0.030	0.282 $\pm$ 0.042	0.278 $\pm$ 0.043	0.93, [0.87,0.96]
$\tau_{1A}[s]$	0.050 $\pm$ 0.035	–	–	–
$\tau_{\text{CNS1}}[s]$	0.587 $\pm$ 0.326	0.810 $\pm$ 0.223	0.856 $\pm$ 0.194	0.84, [0.69,0.91]
$\tau_c[s]$	1.472 $\pm$ 1.219	–	–	–
$\tau_{\text{CNS2}}[s]$	29.7 $\pm$ 12.8	–	–	–
$\tau_{\text{MS1}}[s]$	0.377 $\pm$ 0.306	–	–	–
$\tau_{\text{MS2}}[s]$	0.428 $\pm$ 0.298	–	–	–
$B \left[\frac{Nms}{rad} \right]$	2.400 $\pm$ 1.324	–	–	–
$K \left[\frac{Nm}{rad} \right]$	2.198 $\pm$ 1.505	–	–	–
VAF (%)	74.7 $\pm$ 11.9	71.0 $\pm$ 11.6	75.6 $\pm$ 12.4	–

TABLE V

An algorithm of our proposed method for incorporating parameter reliability and model diversity in selecting key model parameters.

Input:	1) FIMs $\mathbb{I}(\phi_0, (i, j))$ of nominal parameters ϕ_0 for each subject $(i \in \{1, \dots, 40\})$ and each visit $(J \in \{1, 2\})$. 2) Variability upper bound $\sigma_{\max}^2$. 3) Reliability lower bound $\text{ICC}_{\min}$
Output:	1) The key parameter subsets.
1	Grid $\sigma_{\text{allowable}}^2$ using 10 equally-spaced values ($k = 1:10$) from 0.05 to 0.95.
2	Use the FIM method in (3) to select sensitive parameter subsets at each grid point $k = 1:10$ (the FIM solution space).
3	The variability criterion: a. Select (from the FIM solution space in step 2) the subsets whose variability does not exceed the variability upper bound, i.e., $\text{Variability}(\phi) \leq \sigma_{\max}^2$. b. if no subsets are selected then increase $\sigma_{\max}^2$ and goto step 3a.
4	The goodness of fit criterion: Select (from the remaining subsets after step 3) the subsets that have the largest number of parameters.
5	The reliability criterion: a. Select (from the remaining subsets after step 4) the subsets whose reliability is greater than or equal to the reliability lower bound, i.e., $\text{Reliability}(\phi) \geq \text{ICC}_{\min}$. b. if no subsets are selected then i. if smaller $\text{ICC}_{\min}$ is acceptable then decrease $\text{ICC}_{\min}$ and goto step 5a. ii. else increase $\sigma_{\max}^2$ and goto step 3a.
6	The diversity criterion: if more than one subset is feasible (after step 5) and less number of subsets are required then select (from the remaining subsets after step 5) the subset(s) with the maximum diversity index.

TABLE VI.

A list of the sensitive subsets (solution space) of the FIM method (Fig. 3). The parameters' intraclass correlation coefficients (ICCs) are given in parentheses. A sensitive subset reliability (equation (6)) is given in brackets. The selected key model parameters for estimation are highlighted in green.

$\sigma^2_{\text{allowable interval}}$	Yaw	Pitch
(0,0.05]	$\{K_{vis}(0.83), \pi(0.83)\} [0.83],$ $\{K_{cvt}(0.81), \pi(0.77)\} [0.77],$ $\{K_{vet}(0.85), \pi(0.85)\} [0.85].$	$\{K_{vis}(0.91), \pi(0.95)\} [0.91],$ $\{K_{cvt}(0.90), \pi(0.93)\} [0.90],$ $\pi(0.96), \tau_{CNS1}(0.87)\} [0.87].$
(0.05,0.15]	$\{K_{vis}(0.43), K_{cvt}(0.47)\} [0.43].$	$\{K_{cvt}(0.85), \pi(0.93), \tau_{CNS1}(0.84)\} [0.84],$ $\{K_{vis}(0.85), \pi(0.94), \tau_{CNS1}(0.87)\} [0.85],$ $\{K_{cvt}(0.77), \pi(0.93), \tau_c(0.30)\} [0.30],$ $\{K_{vis}(0.41), K_{cvt}(0.61), \pi(0.91)\} [0.41].$
(0.15,0.25]	$\{K_{vet}(0.65), K_{cvt}(0.75)\} [0.65],$ $\{K_{cvt}(0.74), \tau_{CNS1}(0.16)\} [0.16],$ $\{\pi(0.76), \tau_{CNS1}(0.83)\} [0.76].$	$\{K_{vet}(0.82), \pi(0.94), \tau_{CNS1}(0.86)\} [0.82].$
(0.25,0.35]	$\{K_{vis}(0.76), K_{cvt}(0.87), \pi(0.85)\} [0.76].$	$\{K_{cvt}(0.83), \pi(0.93), \tau_{CNS2}(0.41)\} [0.41].$
(0.35,0.45]	–	$\{K_{vis}(0.63), \pi(0.94), \tau_d(0.61)\} [0.61],$ $\{\pi(0.92), \tau_{CNS1}(0.89), \tau_{CNS2}(0.87)\} [0.87].$
(0.45,0.55]	–	$\{K_{cvt}(0.48), K_{cvt}(0.86), \pi(0.91)\} [0.48],$ $\{K_{vet}(0.73), K_{cvt}(0.85), \tau_{CNS1}(0.83)\} [0.73].$
(0.55,0.65]	–	$\{K_{cvt}(0.93), \tau_c(0.91), \tau_{CNS2}(0.89)\} [0.89].$
(0.65,0.75]	$\{K_{vet}(0.07), K_{cvt}(0.78), \pi(0.58)\} [0.07].$	$\{\pi(0.90), \tau_d(0.84), \tau_{CNS2}(0.65)\} [0.65].$
(0.75,0.85]	–	$\{K_{vet}(0.75), K_{cvt}(0.76), \pi(0.90), \tau_{CNS1}(0.90)\} [0.75].$
(0.85, ∞) [§]	$\{K_{vis}(-0.40),$ $K_{vet}(0.04),$ $K_{cvt}(-0.39),$ $\pi(-0.06),$ $\tau_{IA}(0.08),$ $\tau_{CNS1}(0.09),$ $\tau_c(-0.22),$ $\tau_{CNS2}(-0.57),$ $\tau_{MS1}(0.27),$ $\tau_{MS2}(0.50),$ $B(-0.17),$ $K(0.23)\} [-0.57].$	$\{K_{vis}(0.28),$ $K_{vet}(0.46),$ $K_{cvt}(-0.20),$ $\pi(0.47),$ $\tau_{IA}(0.25),$ $\tau_{CNS1}(0.48),$ $\tau_c(0.52),$ $\tau_{CNS2}(0.31),$ $\tau_{MS1}(0.56),$ $\tau_{MS2}(0.46),$ $B(0.14),$ $K(-0.23)\} [-0.20].$

[§]For the interval (0.85, ∞), only the case of estimating all 12 model parameters is shown.