Function-on-Scalar Regression of Female and Male Volunteer Head Angular Velocities in Frontal Impacts

Corina Espelien, Mary Gallaher, Jason Forman, Pavel Chernyavskiy

I. INTRODUCTION

Head kinematic validation data are critical for injury prediction tools, such as crash test dummies and human body computational models. Understanding how the head moves in a controlled laboratory setting can help identify factors that contribute to variability of responses, which in turn could assist in explaining observed differences in head injury risk from field data [1]. These driving factors can be specific to the individual, like sex, age and anthropometry, or to the collision scenario, like the impact pulse. The aim of this study was to assess the effect of input factors on a time-history head kinematic from volunteers in a frontal impact test condition.

II. METHODS

Data used in this analysis were available via the Biodynamics Data Bank (BIODYN), which is a publicly available dataset of volunteer testing performed by the U.S. Airforce [2]. One study, the 199503 study, was selected for evaluation, which tested three conditions of 6.5 g (29 km/h), 8.0 g (34 km/h) and 10.0 g (44 km/h). This study used a reverse acceleration sled to simulate impacts on female (n = 12) and male (n = 15) volunteers wearing helmets in an upright seat with a harness restraint. Each subject was typically tested at more than one impact severity, resulting in 65 test runs. Head kinematics were collected via an instrumented bite block. For this analysis, only the angular velocity in the sagittal plane was analysed.

To assess sources of variation in the resulting data, functional data analysis (FDA) was used to model head angular velocity. FDA techniques admit data from the entire curve or function, rather than a scalar representative value (e.g. peak kinematics), or a numerical summary (e.g. mean velocity). In this analysis, function-on-scalar regression was performed, meaning the predictor variables were scalars and the response variable was a function (i.e. a parameterised form of a curve from discrete data points). The fda [3] and refund [4] packages in R were used. A naïve model was generated that included no predictors for the response, generating an average kinematic profile of angular velocity. Three subsequent types of model with scalar predictor variables were examined, described in Equations (1)–(3). Subject-specific functional random intercepts were added to account for within-subject correlation and to correctly quantify estimation uncertainty for this test series where individuals were typically tested more than once [5].

$$y_{ij}(t) = \mu_{ij}(t) + b_{i0}(t) + \varepsilon_{ijt} \quad (1)$$

$$y_{ij}(t) = \mu_{ij}(t) + b_{i0}(t) + \beta_g(t)x_g + \varepsilon_{ijt} \quad (2)$$

$$y_{ij}(t) = \mu_{ij}(t) + b_{i0}(t) + \beta_s x_s + \varepsilon_{ijt} \quad (3)$$

In these equations, $y_{ij}(t)$ is the response for the i^{th} subject in the j^{th} condition at time t, $\mu_{ij}(t)$ is the mean kinematic response, $b_{i0}(t)$ is the subject-specific functional random intercept, ε_{ijt} is the error term, $\beta_g(t)$ and x_g are the coefficient and predictor variable, respectively, for the nominal input peak acceleration, and β_s and x_s are the coefficient and predictor variable, respectively, for a single subject characteristic (e.g. age).

III. INITIAL FINDINGS

The angular velocity in the sagittal plane from the 199503 study for the three test conditions, coloured according to subject sex, can be found in Fig. 1. For the different statistical models examined, the R-squared values (R-sq.) were used as a measure of additional variable contributions above what is represented by the mean kinematic response. A naïve (functional intercept only) model with no covariates provided an R-sq. of

C. Espelien (e-mail: cme2kd@virgina.edu; tel: +1-434-297-8050) is a PhD student, M. Gallaher is an undergraduate researcher and J. Forman is a Principal Scientist at the Center for Applied Biomechanics at University of Virginia, USA. P. Chernyavskiy is an Assistant Professor of Biostatistics at University of Virginia, USA.

0.788. The Eq. (1) model (functional subject-specific random intercepts) provided an R-sq. of 0.876 (0.088 improvement from naïve). The Eq. (2) model (time-varying effect of nominal peak acceleration), and Eq. (3) models (time-fixed effects of subject sex, age, height or weight examined separately), provided R-sq. of 0.914 (0.126 improvement from naïve) and 0.876 (0.088 improvement from naïve, for all models), respectively. Of the subject-focused models examined with the Eq. (3) model, sex, age, height and weight were each significant on their respective models (Table I).

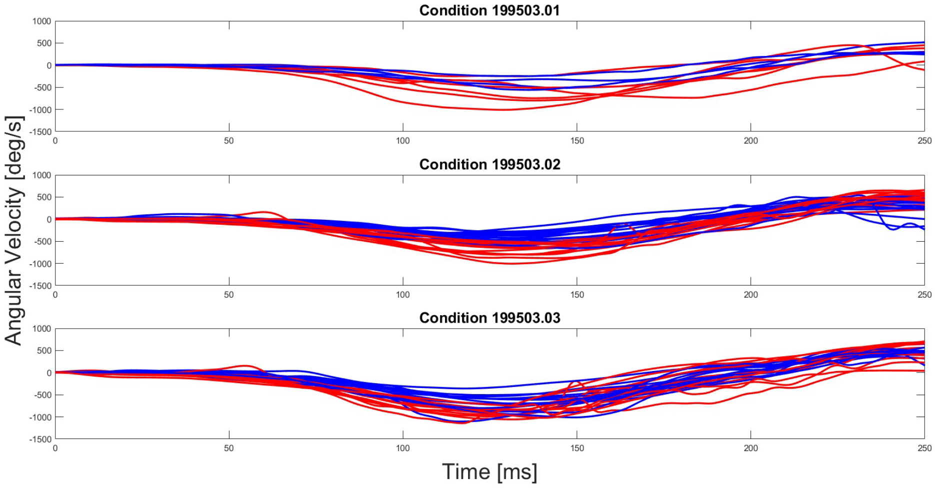

Fig. 1. Individual subject head angular velocity in the sagittal plane at 6.5 g (top), 8.0 g (middle) and 10.0g (bottom) impact levels with females in red and males in blue.

TABLE I

Eq. (3) Covariate	Covariate effect estimate (95% CI)	t-value
Sex	72.80 (38.62, 106.98)	4.18
Age	-19.14 (-24.00, -14.28)	7.72
Height	2.97 (0.63, 5.30)	2.49
Weight	-2.77 (-4.13, -1.40)	3.98

IV. DISCUSSION

In this analysis, models in Eq. (1) and Eq (3) have equivalent R-sq., but each subject-focused covariates in the Eq. (3) form were statistically significant in its respective model (Table I). The t-values in Table I, which are statistics adjusted for uncertainty and different units of the covariate effect estimates, indicate that age has the most important effect (largest t-value) on head angular velocity. Like other subject-focused covariates, sex was significant in the model in Eq. (3) but was not analysed by impact level. The interaction of subject covariates and impact level are of interest because at higher pulses, the severity of the impact may dominate, while at lower severities differences in subjects may have a larger relative contribution to the response (e.g. qualitative separation of female and male responses at 6.5 g or 8.0 g, but not 10.0 g impacts in Fig. 1). Interaction terms and effects were not explored in this preliminary application of FDA, but will be investigated in future works.

FDA provides a promising exploratory and confirmatory family of methods for biomechanics kinematic research because it allows for the evaluation of the entire temporal or spatial response curve, rather than requiring a simplification of a curve to a scalar value, like a peak or mean. This can assist in the understanding of underlying causes of variability of entire kinematic traces from sources like subject or boundary condition differences. Because predictor variables are included in the analysis, data from multiple studies can be assessed together. For instance, an analysis of head kinematics from volunteers and post-mortem human subjects (PMHS) could be performed, with the subject type included as a covariate. This can assist biomechanists in leveraging volunteer and PMHS data to estimate the effect of muscle contraction during an impact.

V. REFERENCES

[1] Forman, J., *et al.*, *TIP,* 2019.
[2] Cheng, H., *et al.*, *DTIC,* 2004.
[3] Ramsay, J., *et al.*, 2022.
[4] Goldsmith, J., *et al.*, 2023.
[5] Scheipl, F., *et al.*, *J Comput Graph Stat,* 2015.