A Method to Characterize Impactor Displacement Time History Based on Experimental Parameters via Principal Component Analysis

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I. INTRODUCTION

High-rate non-penetrating blunt impacts (NPBI) generate back face deformation (BFD) of personal protective equipment (PPE) as energy from a high-velocity projectile is transferred to the body [1]. Though PPE is effective at preventing penetration, there is still risk of injury due to the BFD and energy transmitted to the underlying tissue [1]. This risk of injury in the high-rate NPBI environment has been investigated with *in vivo* animal models [2–4]. One study completed ovine experiments using an impactor (modified captive bolt gun, Schermer KC Stunner) simulating BFD to the thoracic region [3][5]. This study reported impactor displacement-time traces for a subset of impacts and for others, only three key parameters (max depth, impact velocity, and duration). A finite element ovine thorax model (FE-OTM) was developed from the same ovine population to simulate these experimental impacts [6]. To accurately simulate the experimental impact, boundary prescribed motion is applied to the impactor head requiring the input of a full displacement-time trace (not just the parameters above). Therefore, simulations have previously been limited to impacts in which the full displacement-time history traces were reported. To overcome this limitation and model the remaining experimental impacts, principal component analysis (PCA) is utilised to convert impact parameters into displacement-time traces. PCA is a common multivariate statistical technique used across various scientific disciplines for forecasting [7–9]. The goal of this study is to reproduce complete displacement-time traces based on only three parameters and validate PCA representative outputs for the use in the FE model.

II. METHODS

A previous experimental study conducted *in vivo* high-rate NPBI experiments on ovine subjects utilising an impactor where the head of the impactor was representative of BFD [3]. These experiments covered a range of impact parameters, including two nominal impact velocities (40 and 70 m/s), maximum depths from 17 mm to 59 mm, impact angles 0° to 25° from perpendicular to the spine, and two different impactor head shapes (flat and hemispherical) [3]. The experimental impacts were subdivided into two groups based on impact velocities (40 and 70 m/s). Separate PCA models were developed for each group using n = 21 for 40 m/s and n = 17 for 70 m/s, where 15 traces were used to train the 40 m/s, and 12 traces were used to train the 70 m/s model. The key parameters of interest (max depth, duration, and impact velocity) from the ovine experimental model were used to define a feature matrix (F) for the training data, where duration is the time from impact to peak displacement/depth. Each training data trace was sampled to 1000 data points, and a matrix of the displacement values (Y) was built with each trace in its own row. Equations 1 – 5 define the linear algebra steps that make up the PCA; where Y_n is the normalised Y data, Y_c is the centered Y data, VA is the vector of column averages, v is the eigenvector of the covariance of Y_c, S is the PCA score (the five largest values were used), C is the coefficient matrix, T is the vector of target features (duration, max depth, initial velocity), and Y_p is the predicted Y values. The PCA models were validated using the remaining experimental data as T to generate new curves, where n = 6 curves at 40 m/s and n = 5 at 70 m/s. The generated curves were compared to the experimental curves using the area under the curve (AUC). The AUC was calculated for both the experimental and generated curves, these areas were then compared using difference (Δ) between the original and generated curves. Additionally, the Δ between the peak displacement (depth) and velocity were compared to better display the difference between the experimental and generated representative curves.

(1) $$\boldsymbol{Y_n} = \frac{\boldsymbol{Y_{i,:}}}{\mathbf{max}_j \, \boldsymbol{Y_{i,j}}}$$

(2) $$Y_c = Y_n - VA$$

(3) $$S = Y_c * v'$$

(4) $$\boldsymbol{C} = \boldsymbol{S}^{[1:5]} * (\boldsymbol{F}')^{+}$$

(5) $$Y_p = \left(VA + v^{[1:5]} * (C * T)\right) * T^{[2]}$$

Where A′ is the transpose and
A⁺ is the Moore-Penrose inverse

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III. INITIAL FINDINGS

Table 1 A (left) and B (right) summarises the target features and resulting outputs for each of the generated traces and their Δ for each target metric. There is little variation in depth and duration (Δ = 0 for all generated traces), while the velocity and Δ AUC vary slightly but are still both below 0.51 m/s and 0.31 respectively. The PCA predicted curve closely matches the experimental training data (Fig. 1 A and B) for both impact velocities.

Table 1. Feature matrix and Δ AUC for the (A). 40 m/s and (B). 70 m/s predictive traces

40 m/s						70 m/s					
Trace	depth (mm)	Δ depth (mm)	velocity (m/s)	Δ velocity (m/s)	Δ AUC	Trace	depth (mm)	Δ depth (mm)	velocity (m/s)	Δ velocity (m/s)	Δ AUC
1	26.09	-0.03	41.76	-0.80	-0.15	1	26.22	-0.02	75.13	6.10	0.27
2	29.90	-0.03	40.53	-0.77	-0.01	2	42.55	-0.03	74.47	-1.83	0.14
3	19.87	-0.02	42.02	1.03	-0.18	3	32.03	-0.02	42.60	-3.60	0.10
4	30.58	-0.03	43.97	0.76	0.22	4	19.10	-0.01	64.07	-9.33	-0.05
5	19.38	-0.02	45.55	3.53	0.18	5	30.70	-0.02	70.45	-4.02	-0.31
6	32.60	-0.03	45.53	3.18	0.51						

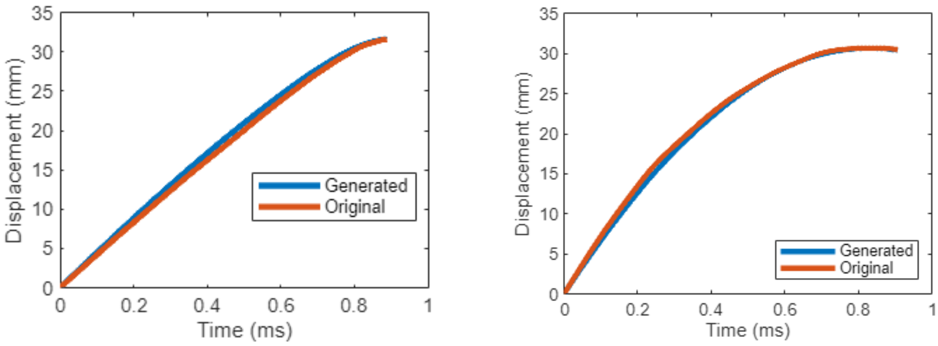

Fig. 1 (A). 40 m/s (B). 70 m/s example plots for predictive data from PCA compared to experimental traces

IV. DISCUSSION

PCA was successfully implemented to recreate displacement-time traces of impactor motion for a specific experimental setup. This technique leverages limited experimental data to estimate full time histories for use as inputs into an FE model. One strength of this specific set up was the accuracy of the predicted curve despite the limited number of parameters and experimental training traces. This technique allows for the use of subject outcome or injury data from experiments that otherwise may not be able to be compared or correlated to the FE models. In other words, this approach can make more legacy data available for model development and validation. A limitation is that the data was split between nominal velocities of the impacts (40 vs 70 m/s), so to predict impacts between these nominal velocities the data sets should be combined. This analysis pipeline will be a valuable tool both for validation and pre-test prediction studies.

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VI. REFERENCES

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