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ESTIMATION OF 6 DEGREE OF FREEDOM ACCELERATIONS FROM HEAD IMPACT TELEMETRY SYSTEM OUTPUTS FOR COMPUTATIONAL MODELING

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Abstract: *Head impact exposure in contact sports has been extensively studied; however, the biomechanical basis of subconcussive head impacts is not well-understood. Finite element (FE) modeling may be used to further study this. FE simulation of head motion requires 6 degree of freedom (6DOF) curves defining the boundary conditions, which is not available from the Head Impact Telemetry (HIT) System, a common head impact sensor. The goal of this study was to develop a transformation algorithm to determine 6DOF acceleration curves based on the corresponding HITS output data. The transformation algorithm was developed from a dataset of 14,767 head impacts collected with the HIT System. HITS output is limited to peak XYZ linear acceleration values, peak XY rotational acceleration values, a 40 ms linear resultant time trace, and azimuth and elevation of each impact. For this set of impacts, Simbex (Lebanon, NH) provided the 6DOF information. The 6DOF data was used to calculate characteristic curves corresponding to impact location and polarity of XYZ accelerations peaks. First, the impacts were sorted into 1 of 192 impact regions defined by approximately equal divisions of azimuth and elevation, then classified by polarity of peak accelerations. Polarity was described by a 1x6 vector of positive or negative ones corresponding to the polarity of XYZ linear and rotational acceleration. Then, characteristic curves for each unique polarity combination were calculated by averaging aligned normalized acceleration curves. The algorithm was validated against 50 random impacts by comparing predicted and true acceleration curves. CORA, an objective curve comparison metric, was used to quantify error. CORA scores were calculated for all 6 acceleration curves and averaged to get a single rating for each tested impact. The mean, minimum, and maximum CORA scores of the 50 validation impacts were 0.497, 0.267, and 0.733, respectively. These results demonstrate the algorithm accurately estimates 6DOF motion characteristics from 5DOF inputs.*

1 INTRODUCTION

There are approximately 5 million athletes playing organized football in the United States; 2,000 professional players, 100,000 college players, 1.3 million high school players, and 3.5 million youth players [1–3]. Sports-related traumatic brain injury (TBI) is an important public health concern due to number of people affected and some unknown and potentially serious resulting conditions. Although football has a high rate of concussion, exposure to repetitive subconcussive head impacts, which occur as part of normal participation in the sport, and associated changes in the brain related to neurodegenerative diseases is of increasing concern [6–10]. Although head impact exposure in football has been extensively studied, the biomechanical basis of subconcussive head impacts is not well-understood [11–15]. To better understand the effects of repetitive subconcussive impacts, biomechanical factors of head impact, such as impact location and direction, should be well-characterized and understood.

To characterize brain response to head impact exposure, finite element studies quantify the strain response of the brain to conditions representative of typical football impacts. In 2014, Ji et al. used the Dartmouth Head Injury Model (DHIM) and the Simulated Injury Monitor (SIMon) to investigate brain-strain related responses in a range of loading conditions representative football impacts experienced at the youth, high school and collegiate levels [16]. Brain deformation was measured using deformation metrics proposed to have a correlation to brain injury, such as maximum principal strain (MPS) and Von Mises stress [17,18]. This study also investigated the relative contributions of linear and angular acceleration to the strain response and found that isolated linear acceleration generates negligible strain. A similar study used the DHIM, SIMon, and Wayne State University Brain Injury Model (WSUBIM) models to study regional brain response in the cerebrum, cerebellum, brainstem, and whole brain [19]. Smith et al. (2015) used the UCDBTM to evaluate strain response for indirect, direct, and combined loading scenarios [20]. Darling et al. (2016) used the head model from the Global Human Body Models Consortium (GHBMC) full body model to evaluate the strain response to two typical loading conditions experienced in football – frontal impact and crown impact [21]. Various studies have attempted to establish an injury threshold derived from FE modeling, as noted above, but there is some variance between studies and a larger dataset of simulated impacts would be very valuable in identifying such a threshold, if one exists.

FE simulation of head motion requires 6 degree of freedom (6DOF) curves defining the boundary conditions, which is not available from the Head Impact Telemetry (HIT) System, a common head impact sensor. HITS output is limited to peak XYZ linear acceleration values, peak XY rotational acceleration values, a 40 ms linear resultant time trace, and azimuth and elevation of each impact. Therefore, the objective of this study was to develop a transformation algorithm to determine 6DOF acceleration curves based on the corresponding HITS output data. This study used an existing dataset of real impacts collected with the HIT System. For this set of impacts, Simbex (Lebanon, NH) also provided the 6DOF information as part of an existing study. The developed algorithm was validated against 50 random impacts by comparing predicted and true acceleration curves.

2 METHODS

The transformation algorithm was developed from an existing dataset of head impacts collected with the HIT System. First, the impacts were sorted into impact regions defined by approximately equal divisions of azimuth and elevation. Twelve impact levels representing

15° in elevation angles were defined (Figure 1B), numbered from the top of the head (1) to the bottom (12). Starting at the impact level with the largest surface area (level 6), regions were divided into 15° azimuth regions. Then, for impact levels 5 through 1, regions were defined using azimuth angles that resulted in the surface area of impact regions closest to the surface area for impact regions from impact level 6. This resulted in between 4 and 24 regions defined per level to define ensure approximately equal impact regions surface area. This process resulted in a total of 192 impact regions (Figure 1C).

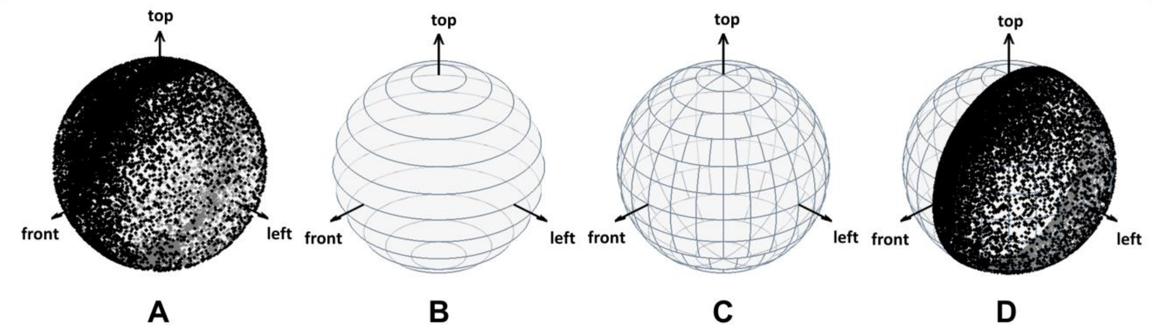

Figure 1. All impacts plotted on a sphere representing the head (A), impact levels (B), impact regions (C), and all impacts reflected to left side (D).

Next, assuming symmetry, impacts that occurred on the right side of the head were reflected to the left side so all impacts occurred on the left hemisphere (Figure 1D). To reflect an impact, the azimuth angle was inverted, as well as the following acceleration components: linear Y, rotational X, and rotational Z. An ‘unfolded’ view of the numbering scheme for impact regions is shown in Figure 2.

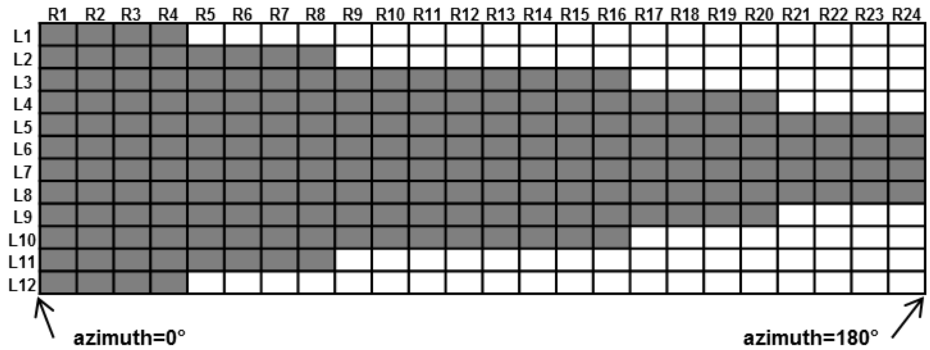

Figure 2. Numbering scheme for impact regions.

Impacts were then classified by polarity of peak accelerations with a 1x6 vector of positive or negative ones corresponding to the polarity of XYZ linear and rotational acceleration. For example, the polarity characterization corresponding to the impact shown in Figure 3 is [-1 -1 -1 +1 -1 -1]. Impacts corresponding to each region were then grouped by unique polarity combinations. For example, there were 17 unique polarity combinations corresponding to the 318 impacts in impact Level 2, Region 2 (Table 1).

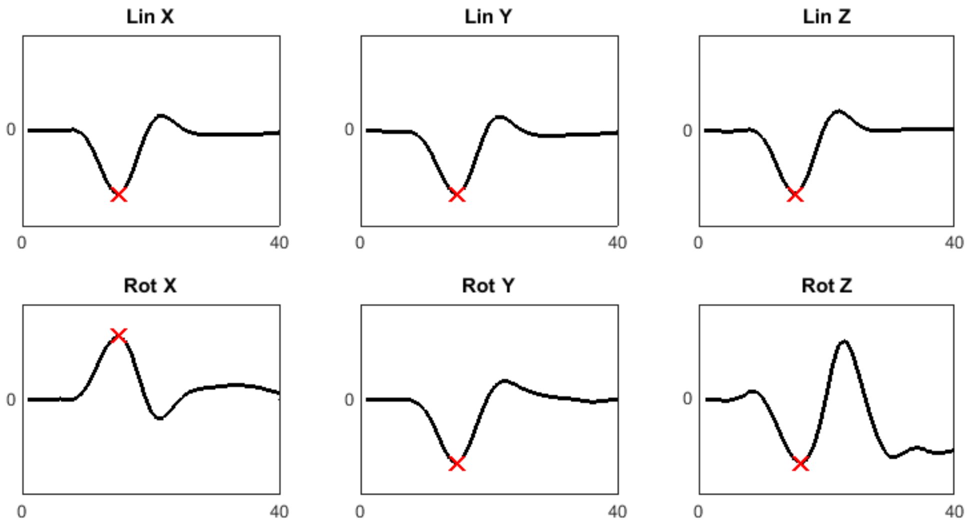

Figure 3. Example impact demonstrating polarity characterization.

Table 1: Unique Polarity Combinations for Level 2, Region 2.

Lin X	Lin Y	Lin Z	Rot X	Rot Y	Rot Z	# Impacts
-1	-1	-1	+1	-1	-1	123
-1	-1	-1	+1	+1	-1	87
-1	-1	-1	+1	-1	+1	70
+1	-1	-1	+1	+1	-1	9
-1	-1	-1	+1	+1	+1	7
+1	-1	-1	+1	+1	+1	4
+1	+1	+1	-1	+1	+1	4
+1	-1	-1	+1	-1	-1	3
+1	-1	-1	+1	-1	+1	3
-1	-1	-1	-1	-1	-1	1
-1	+1	-1	-1	-1	+1	1
-1	+1	-1	+1	+1	+1	1
-1	+1	+1	-1	+1	-1	1
+1	-1	-1	-1	+1	-1	1
+1	+1	-1	-1	+1	+1	1
+1	+1	+1	-1	-1	+1	1
+1	+1	+1	-1	+1	-1	1

To use the algorithm to estimate 6DOF curves for a given HITS impact, characteristic curves corresponding to the appropriate impact region and polarity are determined and then scaled to the peak values output by the HIT System.

To validate the algorithm, 50 random impacts from the dataset were selected and the true and predicted acceleration curves were compared. CORA, an objective comparison metric, was used to quantify error between the true and predicted curves [22]. CORA is an objective rating method that combines two independent sub-methods, a corridor rating and a cross-correlation rating. These two ratings range from 0 to 1 and are averaged to determine the CORA rating (1 indicates a perfect match). The corridor method computes a rating based on where the simulation curve falls in relation to corridors around the experimental curve. The cross-correlation method is based on ratings for the phase shift, size and shape of time-shifted curves. In addition to incorporating both point-by-point and peak value comparisons for assessing model performance, CORA is also able to evaluate the cross-correlation of two curves. CORA scores were calculated for all 6 acceleration curves and averaged to get a single rating for each tested impact.

3 RESULTS

The dataset consisted of 14,767 impacts which were sorted into 192 impact regions. The number of impacts associated with an individual impact region ranged from 9 to 710. A total of 8,060 (54.6%) impacts were reflected from the right hemisphere to the left. The number of unique polarities per impact region ranged from 4 to 44 combinations.

Characteristic curves for each unique polarity combination were calculated by averaging aligned normalized acceleration curves. The characteristic curves for the impact Level 4, Region 2 (Figure 4) are shown in Figure 5. 6DOF curves were generated for each impact by scaling the characteristic curves to the peak values output by the HIT System given the impact region and polarity.

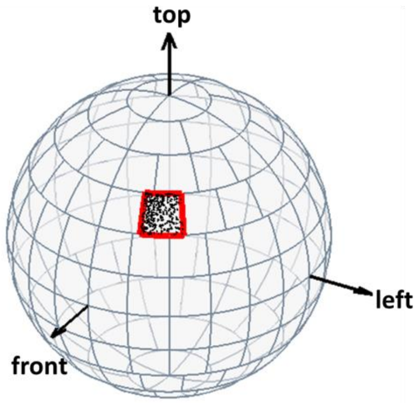

Figure 4. Impacts associated with impact Level 4, Region 2.

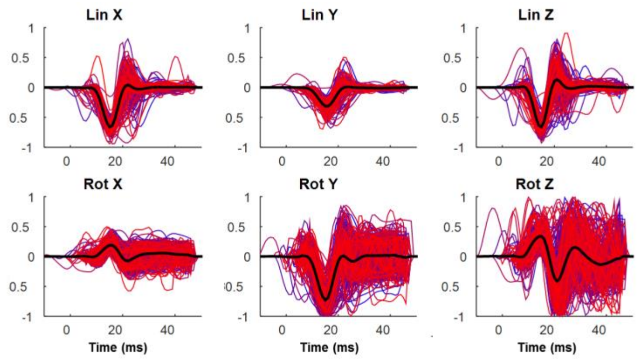

Figure 5. Characteristic curves for impact region shown in Figure 4.

To validate the characteristic curves produced by the 5DOF to 6DOF algorithm, 50 random impacts were selected and the curves predicted by the algorithm were compared to the true acceleration curves for that impact. CORA scores were calculated for all 6 acceleration curves and averaged to compute a single rating for each tested impact. The mean, minimum, and maximum CORA scores of the 50 validation impacts were 0.497, 0.267, and 0.733, respectively. Comparison of true and predicted curves for an example sampled impact is shown in Figure 6, which had an average CORA score of 0.675.

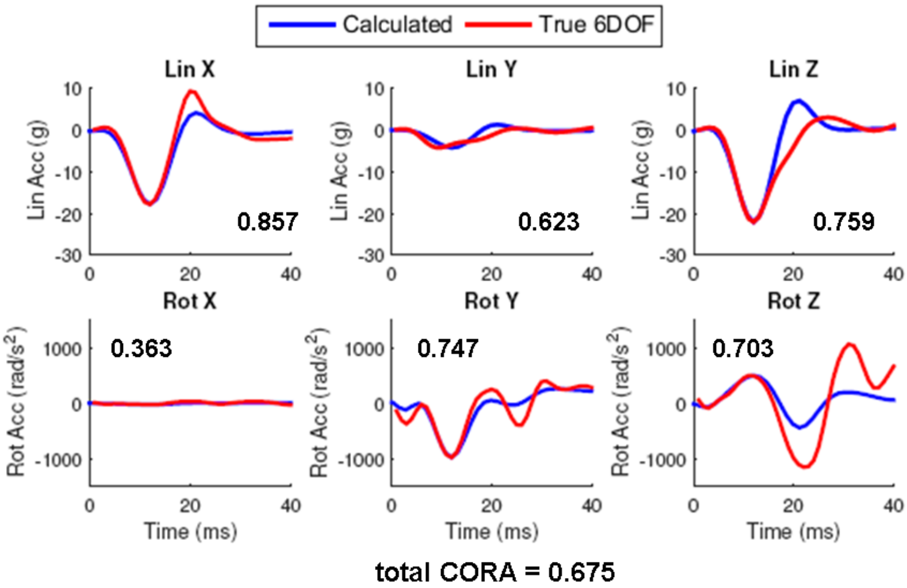

Figure 6. Validation of an example sampled impact.

4 DISCUSSION

The algorithm presented in this study utilizes calculated characteristic curves associated with specific polarities at each impact region to compute 6DOF data from 5DOF HITS data. In this approach, the impact region and polarity combination is calculated to determine the associated characteristic curves. The curves are then scaled to the peak values of the acceleration components determined from the HITS output. These results demonstrate the algorithm accurately estimates 6DOF motion characteristics from 5DOF inputs. This algorithm allows the leveraging of thousands of head impacts collected using the HITS system over years of research to be further studied using FE brain models. This ability will contribute to the goal of identifying concussion injury thresholds and mechanisms.

A limitation of this approach is that we are using estimated inputs to the algorithm (FE boundary conditions) to predict strain and other metrics correlated with injury. While the algorithm provides promising results and demonstrates the ability to closely predict acceleration curves, small differences may still result in differences in the FE output.

5 CONCLUSION

The goal of this study was to develop a transformation algorithm to determine 6DOF acceleration curves based on the corresponding HITS output data. An algorithm consisting of a set of characteristic curves was calculated which can be used with HITS output to estimate 6DOF acceleration curves. This algorithm was validated against 50 random impacts and resulted in mean, minimum, and maximum CORA scores of the 50 validation impacts were 0.497, 0.267, and 0.733, respectively. These results demonstrate the algorithm accurately estimates 6DOF motion characteristics from 5DOF inputs.

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