

Estimating Brain Strain Metrics using Measured Kinematics from a Wearable Helmet Impact Sensor: Preliminary Findings from a Laboratory Study using the Hybrid III Head

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I. INTRODUCTION

In the last decade, wearable sensors have been developed to measure directional kinematics of the head in living humans during an impact. Some of these sensors monitor helmet kinematics [1-3] and have been shown to systematically overestimate head kinematics, although several data reduction methods have been proposed to remove these systematic errors [1-2]. If these methods are successful, then helmet-based sensors could play a central role in studying impact induced brain injury in athletes. One way to examine brain injury mechanics is to use finite-element (FE) models of the human skull and brain. These models use skull kinematics as inputs and provide estimates of brain tissue stress and strain as outputs. The input kinematics can be estimated from laboratory impacts using test dummies, but wearable sensors have the potential to quantify actual injury-related kinematics that then can be compiled to estimate tolerance levels for brain injury. To date, there has been little research quantifying how systematic errors in kinematic measurements affect the stress/strain estimates of brain models. Thus, the objective of this work was to quantify determinants of measured kinematics that predict strain error, which we define as the difference in strains predicted by Hybrid-III-measured kinematics and wearable-sensor-measured kinematics for the same impact.

II. METHODS

We performed laboratory impacts to generate kinematic data from both reference sensors and a helmet-mounted wearable sensor. We then estimated maximum principal strain (MPS) in the brain tissue using the Simulated Injury Monitor (SIMon) [4] brain FE model from both kinematic data sets.

Experimental Testing

A helmeted Hybrid III head and neck installed on a drop tower [3] were used to perform impacts at speeds up to 6 m/s using certified hockey helmets (Bauer 4500, Medium). The helmets were fit directly over the bare vinyl nitrile skin of the Hybrid III head with the front rim of the helmet positioned 25mm above the brow. The helmet chin strap tension was not measured. The impact surface was an ASTM compliant modular elastic programmer. The Hybrid III had a 3-2-2-2 array of linear accelerometers with 100 kHz acquisition rate (64C-2000-260, Measurement Specialties Inc., Hampton, VA, USA), post-processed to yield linear and rotational kinematics about the head centre of mass. Linear acceleration (acquired at 3 kHz, low-pass filtered at 300 Hz) and angular velocity (800 Hz, low pass filtered at 100 Hz) were also measured using a GForceTracker© (GFT; Richmond Hill, ON, Canada) impact sensor installed in the helmet after calibration, as per manufacturer guidelines. All Hybrid III measures were post processed per SAE J211 using channel frequency class 1000. The impacts were nominally centroidal and most impacts generated head rotation predominantly about the horizontal axis. The distribution of the impacts and impact sites are given in Table 1.

TABLE 1
HOCKEY HELMET IMPACT LOCATIONS AND NUMBER OF IMPACTS.

<i>Impact location</i>	Front	Rear	Front-Boss	Rear Boss	Side	Total
<i>Number of impacts</i>	26	22	13	24	24	109

Computational Modelling

Our modelling work consisted of three parts: a) a parametric exploration of the effect of rotational velocity changes about the three principal axes, b) a parametric exploration of how a misalignment of the coordinate axes alone affects MPS, and c) a pairwise comparison of the MPS for the reference and wearable sensors. For the first part, angular velocities ranging over 6 to 40 rad/s about each of the head x, y, and z-axes were simulated. For the second part, a single reference data-set (rear impact, peak $\omega_x = -22.5$, $\omega_y = -32.7$, $\omega_z = 7.3$ rad/s) from the hockey helmet tests was selected. The kinematic data were then rotated in 15° increments about each of the three principal axes to simulate misalignment between the reference data (original data) and simulated wearable sensor data (rotated data), and MPS error (in percent) was then computed. For the third part, we simulated and compared the MPS using the kinematics of both the reference and wearable sensors from 109 hockey helmet impacts. The axis misalignment between the two sensors was adjusted theoretically before data comparison. Errors in angular velocity ($\Delta\omega$) and maximum principal strain (ΔMPS) between GFT and Hybrid III for each impact were computed.

III. INITIAL FINDINGS

We focused our analysis on rotational head velocity because it correlated best with MPS [3]. MPS values were largest for rotations about the vertical z-axis, followed by the Medio lateral y-axis, and then the anteroposterior x-axis (Figure 1). Misalignments created by our imposed rotations about the y-axis generated the largest errors for the selected impact (Figure 2). Angular velocity comparisons of the Hybrid III and GFT data for the 109 impacts showed x-axis kinematics correlated best ($R^2=0.67$, Figure 3). MPS errors correlated better with the resultant kinematic errors than with the component kinematic errors (Figure 4).

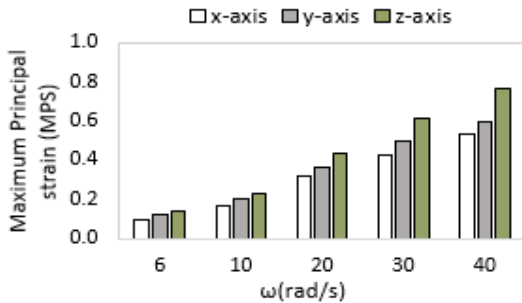


Fig. 1. Predicted MPS stratified by rotation axis and peak angular speed (rad/s).

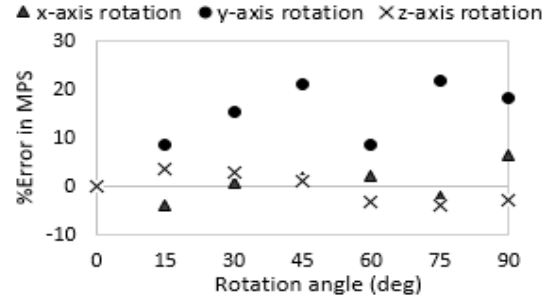


Fig. 2. Percentage error in predicted MPS for head coordinate system misalignment (deg)

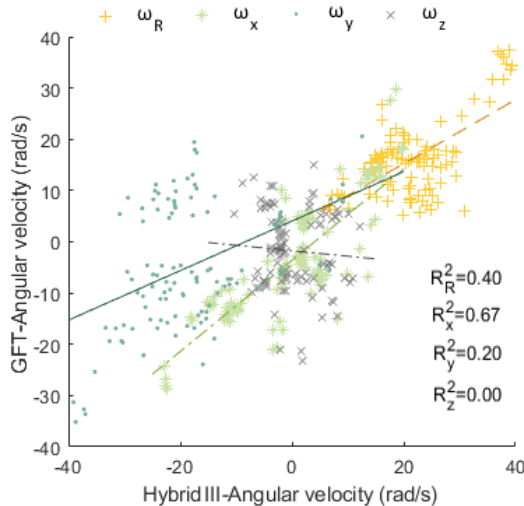


Fig. 3. Angular velocity of the Hybrid III vs. GFT sensors. Coefficients of determination for regressions are noted.

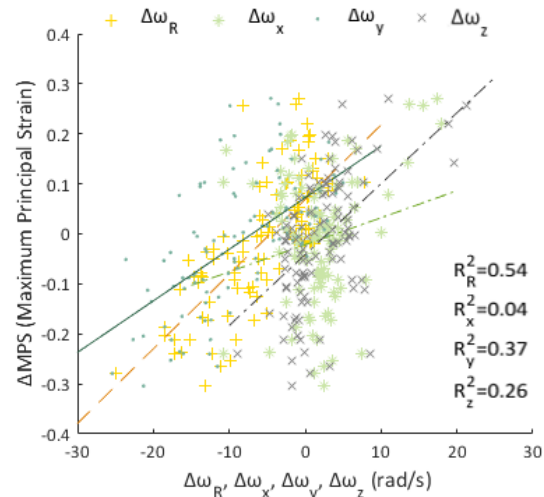


Fig. 4. ΔMPS plotted against Δω. Coefficients of determination from regressions are noted.

IV. DISCUSSION

Our preliminary work shows that misalignment between the coordinate systems of a wearable sensor and the head can cause differences in the component kinematics that manifest as differences in MPS. In our study, misalignment is pre-impact differences between wearable and reference co-ordinate systems. Notable in Figure 4 is that ΔMPS correlated best with Δω_R. Although this result suggests resultant kinematic error is the best predictor of ΔMPS, resultant kinematic error cannot be determined without reference sensors, and therefore further work is needed to understand how sensor errors in magnitude and direction interact to generate errors in strain. Further work is also needed to examine a wider range of component kinematics and helmets. Our preliminary work suggests that if wearable kinematics are used as inputs to brain models, then researchers will need to transition away from validation and calibration procedures that focus on resultant kinematics and perform more onerous validation and calibrations that consider all component axes.

V. REFERENCES

[1] Allison, MA et al, Ann Biomed Eng., 2015
 [2] Siegmund, GP et al, Ann Biomed. Eng., 2016
 [3] Knowles, BM et al, J Appl. Biomech, 2017
 [4] Takhounts, EG et al, Stapp Car Crash J., 2008.