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Performance evaluation of a pre-computed brain response atlas in dummy head impacts

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Abstract

A pre-computed brain response atlas (pcBRA) may have the potential to accelerate the investigation of the biomechanical mechanisms of traumatic brain injury on a large-scale. In this study, we further enhance the technique and evaluate its performance using angular velocity profiles from dummy head impacts. Using the pcBRA to simplify profiles into acceleration-only shapes, sufficiently accurate strain estimates were obtained for impacts with a major dominating velocity peak. However, they were largely under-estimated when substantial deceleration occurred that reversed the direction of angular velocity. For these impacts, estimation accuracy was substantially improved with a biphasic profile simplification (average correlation coefficient and linear regression slope of 0.92 ± 0.03 and 0.95 ± 0.07 for biphasic shapes, respectively, vs. 0.80 ± 0.06 and 0.80 ± 0.08 for acceleration-only shapes). Peak maximum principal strain (ϵ_p) and cumulative strain damage measure (CSDM) from the estimated strains consistently correlated stronger than kinematic metrics with respect to the baseline ϵ_p and CSDM from the directly simulated responses, regardless of the brain region (e.g., correlation of 0.93 vs. 0.75 compared to Brain Injury Criterion (BrIC) for ϵ_p in the whole-brain, and 0.91 vs. 0.47 compared to BrIC for CSDM in the corpus callosum). These findings further support the pre-computation technique for accurate, real-time strain estimation, which could be important to accelerate the pace of model-based brain injury studies in the future.

Keywords

Traumatic brain injury; concussion; contact sports; pre-computation; finite element model; Worcester Head Injury Model

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Disclosure

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Introduction

Mild traumatic brain injury (mTBI) including sports-related concussion is a major public health problem in the world ¹¹. Reliable diagnosis of concussion is important to mitigate this prevailing neurological disorder. However, current diagnostic practices are challenging because they depend solely on neurological examinations and symptomatic measures ³¹. Studies have found a high rate of unreported concussions in high-school football players ³⁵ or premature “return-to-learn” after a diagnosed concussion ¹⁰. This places players at increased risk of cumulative or catastrophic effects from recurrent injury ³⁵. The heightened public awareness of sports-related concussion, especially in youth ^{12,49}, has led to recommendations to immediately address the biomechanical determinants of injury risk and to identify effective concussion diagnostic metrics and biomarkers, among others ¹.

Developing a reliable biomechanical injury metric for traumatic brain injury (TBI), including mTBI, is a constant process. Historically, such efforts have been focused on empirical metrics derived from impact kinematics; in part, because they can provide instantaneous feedback on the risk of injury. Numerous kinematic variants have been developed that are either based on linear or rotational accelerations, or their combinations (e.g. the rotational injury criterion (RIC), power rotational head injury criterion (PRHIC) ²⁷, brain injury criterion (BrIC) ⁴⁰, and rotational velocity change index (RVCI) ⁴²).

While kinematic metrics offer important insight into the biomechanical basis of TBI, they cannot be directly related to micro-scale injury tolerances. There is general consensus that finite element (FE) models of the human head serve as a unique and important vehicle to transform external head impact kinematics into tissue mechanical responses (e.g. strain and strain rate) thought to cause injury ²⁸. Commonly used tissue response injury metrics to predict the occurrence of injury include peak maximum principal strain and cumulative strain damage measure (CSDM) of the brain. More recently, white matter fiber stretch ^{17,24,39,45} is also being explored as a potential improvement, as they better match with neuroimaging findings than isotropic maximum principal strain ²⁴. Indeed, recent studies have shown that tissue response-based metrics outperform kinematics in injury prediction ^{17,19,27,33}. This has led to the use of model-simulated brain strains to benchmark injury prediction performances of other kinematic metrics ^{15,27,40}. For example, BrIC and RVCI were identified to correlate the best overall among 15 kinematic metrics with directly simulated brain strains in diverse automotive impact conditions ¹⁵.

Unfortunately, FE models of the human head incur a substantial computational cost to simulate even a single head impact. Although model-estimated, response-based injury metrics are desirable and already exist ^{14,41}, they remain infeasible for large-scale, real-world applications (e.g., directly on the sports field). To address the challenge, a pre-computed brain response atlas (pcBRA) was recently established to enable real-time strain estimation ²³. Conceptually, this approach treats a head model as a non-linear mathematical mapping function to enable interpolation of strains based on a large pre-computed “lookup” table. The technique simplifies real-world head impact rotational kinematics into triangulated rotational acceleration profiles. As it regularly samples the input-output response hypersurface, parametric investigations of important kinematic variables become

straightforward as their relationships are directly embedded in an implicit functional form⁴⁶.

This superior computational efficiency comes at the cost of simplifying impact kinematic profiles into idealized shapes. Initially, the pcBRA strain estimation accuracy was validated using two sagittal, resultant rotational impulses²³. The close match relative to the directly simulated counterparts suggested potential of this technique for accurate, real-time strain estimation. However, the prior study was limited to uniaxial, one degree-of-freedom (1-DOF), acceleration-only rotations that were not representative of most field conditions.

In this study, we evaluate the pcBRA performance more systematically. This was facilitated by using impact kinematics from anthropomorphic test device (ATD) drop tests³² as model inputs, as they simulate real-world injury scenarios with multiple drop locations common in TBI. In addition, we identified angular velocity profile shapes that required further improvement in profile simplification. Similarly to previous studies^{23,48}, estimated brain strains from simplified profiles were compared with the directly simulated counterparts in both pattern and magnitude. Further, we investigated the correlations between injury metrics from estimated strains and baselines generated by directly simulating the actual profiles. These results do not inform how the pcBRA performs for real-world impacts or whether it indeed improves injury prediction performance over state-of-the-art kinematic injury metrics. This requires further investigation using real-world injury and non-injury cases. Nevertheless, they are important for further technique development and performance assessment using controlled dummy head impacts before its potential real-world applications in the future.

Further, our focus here in strain accuracy comparison does not directly address the critical question of how a sophisticated model can be used to bridge the gap between external head impacts and neurological assessment of TBI. Again, this requires accurate kinematic input as well as reliable clinical evaluation of injury (e.g., via quantitative electroencephalography (qEEG)³⁸, diffusion tensor imaging (DTI)^{3,34}, and functional magnetic resonance imaging (fMRI)²¹) of a sizeable population to train the model, without which, the practical value of a computational model is rather limited. Nevertheless, if sufficiently accurate strains can be estimated in real-time, the pcBRA may accelerate the process of identifying the causal or correlative relationships between measured external head impacts, estimated tissue mechanical responses, observed neuroimaging and cognitive alterations, and diagnosed concussions in the real world. Ultimately, these efforts may widen the deployment of sophisticated head models for practical clinical applications in the future.

Materials and Methods

Worcester Head Injury Model (WHIM)

The Worcester Head Injury Model (WHIM; Fig. 1; previously known as the Dartmouth Head Injury Model (DHIM)) was used for impact simulation. Details of the WHIM mesh development, material property and boundary condition assignment, as well as validation performances were reported previously^{24,25}. Most recently, this model has also incorporated whole-brain tractography for injury analysis^{44,45}. Importantly, the WHIM validation against

relative brain–skull displacement and intracranial pressures from cadaveric impacts, as well as strain responses in a live human volunteer has achieved an overall “good” to “excellent” rating in terms of correlation scores based on Normalized Integral Square Error, as reported before^{24,25}.

Pre-computed brain response atlas (pcBRA)

The pcBRA is analogous to a non-linear mapping function between head impact kinematic parameters and brain strain responses. By simplifying impact kinematics and pre-computing the end-to-end mapping relationship, brain strains can be efficiently interpolated based on existing atlas solutions. The atlas was initially established by sampling four controlling parameters required to generate triangulated rotational acceleration impulses: peak acceleration magnitude (a_{rot}^p), impulse duration (t), and azimuth (θ) and elevation (α) angles of the rotational axis²³. The sampling ranges of a_{rot}^p and t were determined by on-field measurements (1500–7500 rad/s² and 4–16 ms, respectively), while their sampling densities were determined empirically (750 rad/s² and 3 ms, respectively).

However, the pcBRA required an explicit impulse duration for interpolation, which may be challenging to determine in practice. Fortunately, for the sampled rotational impulse conditions corresponding to contact sports, varying the duration while maintaining an identical peak angular velocity did not significantly alter the strain magnitude for most part of the brain⁴⁶, as similarly and independently observed before²⁹. Therefore, we used a fixed impulse duration of 10 ms (average value in high school football head impacts⁶) to sub-sample the 4D impact-strain response hypersurface into 3D using three independent parameters: peak angular velocity (v_{rot}^p), and θ and α angles, with 1521 (9×13×13) unique solutions (Table 1).

Head angular velocity profiles—Head impact kinematics from helmeted head drop tests were used to simulate American football impacts³². A 50th percentile male head ATD was oriented in a net to induce free falls onto an aluminum plate at six locations (vertex, frontal, oblique, parietal, occipital, and facemask) and three heights (10 cm, 60 cm, and 100 cm, respectively). Each test configuration was performed three times, resulting in 54 six degree-of-freedom (6-DOF) linear acceleration and angular velocity (v_{rot}) profiles recorded in a body-fixed coordinate system. The profiles were transformed into a ground-fixed frame to isolate rotational kinematics for model input. As brain strains due to linear acceleration are negligible for the majority of the brain^{25,43}, only the transformed 3-DOFs v_{rot} profiles were used.

The current pcBRA strategically samples angular accelerations/velocities most relevant to concussive and sub-concussive head impacts in contact sports to maximize its potential utility²³. However, the recorded dummy head impacts captured v_{rot}^p ranging 2.6–36.0 rad/s, of which nearly half of the impacts (26 out of 54) were below the pcBRA sampling range (Table 1). While the pcBRA sampling range could be easily expanded, these “real-world” impacts were only collected at a few discrete locations and heights. Therefore, to avoid “extrapolation” and to simulate “arbitrary” head rotations, we chose to randomly scale the impact data to be within the sampling range. Specifically, all components of each 3-DOF v_{rot}

profile were scaled by a same random number so that the peak resultant magnitude was within the pcBRA sampling range. The resulting profile was further rotated about a random axis passing through the head center of gravity with a random magnitude (within 0° – 90°). This was performed twice for each profile, leading to 108 v_{rot} profiles (60 ms in duration). Their corresponding angular acceleration profiles were generated using a 5-point stencil approach (Fig. 2).

Strain estimation using the pcBRA—Three key parameters were necessary to interpolate strain using the sub-sampled pcBRA: peak magnitude of resultant angular velocity, v_{rot}^p , and θ and α angles. First, the largest peak of the resultant angular acceleration was identified²³. The corresponding peak magnitude of resultant angular velocity, v_{rot}^p , was then determined. At its time of occurrence, the three corresponding orthogonal velocity components (v_x , v_y , and v_z , respectively) were used to define an instantaneous rotational axis, $\vec{aX}$, of which θ and α angles were readily determined using four-quadrant inverse tangent (*atan2d.m* in Matlab):

$$\theta = \arctan\left(\frac{v_y}{v_x}\right), \quad (1)$$

$$\alpha = \arctan\left(\frac{v_z}{\sqrt{v_x^2 + v_y^2}}\right), \quad (2)$$

This process is illustrated in Fig. 2. The largest acceleration peak was used to aid the determination of v_{rot}^p because for some profiles, the maximum resultant angular velocity (ω_m) during the entire impact may not correspond to v_{rot}^p (see Fig. 2 for impact to the oblique region). Element-wise strains were then interpolated using a technique established before²³.

Strain estimation using biphasic simplified angular velocity profiles—The key to the potential success of the pcBRA technique is to identify unique patterns of head motion kinematic profiles and simplify them into idealized shapes to generate a large lookup table^{23,48}. Our previous effort focused on angular acceleration peaks²³, as they have been typically reported in the literature. However, angular velocity is more predictive of rotation-induced brain strains^{25,29,40,43,48}. Therefore, an important limitation of the current pcBRA, because of the reported impact kinematic profiles available, was that it captured angular acceleration only but not deceleration that would always present in real-world impacts²³. Therefore, when substantial deceleration occurred, e.g., when v_{rot} reversed its directionality, the pcBRA may not yield sufficiently accurate estimate.

For these impacts, a more sophisticated shape simplification was also implemented. First, the dominant v_{rot} component along the three major axes was identified, whose magnitude was the largest at the time when v_{rot}^p was reached. The directionality of v_{rot} was said to have

reversed if the dominant component crossed zero in magnitude. This occurred in 36 of the 108 head impacts, most of which (89%) were impacts to the frontal and vertex regions. These profiles were further idealized into a biphasic v_{rot} shape, according to the following pseudo-algorithm (see Fig. 2 “frontal” for illustration):

Step 1. Identify v_{rot}^p of the first v_{rot} peak, v_{rot}^{p1} as well as the rotational axis, $\vec{ax}$, using the same previous approach (Eqns. 1 and 2).

Step 2. Generate a full-stop v_{rot} profile with a peak magnitude of v_{rot}^{p1} by integrating a triangulated acceleration-deceleration profile with a fixed 10 ms duration in each phase (total of 20 ms).

Step 3. Immediately following the idealized v_{rot} profile, create a secondary full-stop v_{rot} profile with a peak magnitude of that of the actual v_{rot} profile, v_{rot}^{p2} , with a rotational axis of $-\vec{ax}$, i.e., reversing the velocity directionality of the first idealized v_{rot} profile.

Effectively, this process generated a 40 ms biphasic v_{rot} profile (20 ms in each of the two v_{rot} shapes) rotating about the same axis but in opposite directions. Four independent parameters were necessary to characterize the idealized profile: v_{rot}^{p1} , v_{rot}^{p2} , as well as θ and α angles. These simplified v_{rot} profiles were then used as inputs for model simulations.

The directly simulated brain strains (ϵ_{actual}) using the actual 3-DOF v_{rot} profiles were used to benchmark the accuracy of the estimated counterparts (ϵ_{est}). For profiles with v_{rot} reversal in directionality, ϵ_{est} obtained from simulating idealized biphasic v_{rot} profiles were also used. Pearson correlations were conducted between element-wise ϵ_{est} and ϵ_{actual} to compare their spatial distributions. A fitting slope from linear regression was also used to indicate an overall over- or under-estimation in magnitude (slope above or below 1.0, respectively, with a zero-intercept).

Performance evaluation in injury metrics—Characterizing the performance of ϵ_{est} -based injury metrics was important to assess its potential for real-world applications. Two commonly used, strain-based injury metrics were derived from ϵ_{est} and ϵ_{actual} , respectively: peak maximum principal strain (ϵ_p) and CSDM¹⁵. The comparison was conducted in four ROIs (cerebrum, cerebellum, brainstem, and the corpus callosum) and the whole brain. To avoid potential numerical issues, ϵ_p was determined as the element-wise 95th percentile peak response¹⁵. For CSDM, a range of strain thresholds were enumerated (0.05 to 0.25, with a step size of 0.05). For each injury metric, linear regression across all of the simulated impacts was conducted between the ϵ_{est} - and ϵ_{actual} -derived metrics with a zero-intercept constraint, from which a coefficient of determination (R^2) was obtained. Result for the CSDM was only reported at the threshold of 0.1, as its R^2 was the highest.

The ϵ_{est} -based injury metrics were further compared with two other commonly used kinematic metrics: maximum magnitude of resultant angular velocity (ω_m) and acceleration (a_m), as well as a recent metric, BrIC⁴⁰. BrIC was selected because it was one of the 15 kinematic metrics that correlated the strongest with the directly simulated brain strains in diverse automotive impact conditions¹⁵. BrIC is formulated using the maximum magnitudes

of three orthogonal head angular velocity components, ω_x , ω_y , and ω_z in a body-fix coordinate system, regardless of their time of occurrence:

$$BrIC = \sqrt{\left(\frac{\omega_x}{\omega_{xc}}\right)^2 + \left(\frac{\omega_y}{\omega_{yc}}\right)^2 + \left(\frac{\omega_z}{\omega_{zc}}\right)^2} \quad (3)$$

where ω_{xc} , ω_{yc} , and ω_{zc} are critical velocity values corresponding to a 50% injury probability along the three major axes. The critical values depend on the FE model employed and the injury dataset utilized. The original critical values were derived from simulating kinematics data scaled from 67 animal brain injury experiments using SIMon to characterize the probability of AIS 4+ injuries in humans⁴⁰. As the pcBRA was established to characterize the likelihood of concussion (corresponding to an injury level of AIS 2+⁴⁰) or sub-concussive injury in contact sports, these critical values were not applicable here.

Instead, we adopted the following approach to determine the critical values based on the reconstructed NFL injury dataset³⁷, as employed with the KTH model recently¹⁷. Briefly, the WHIM was used to simulate 58 reconstructed head impacts (25 concussions and 33 non-injury cases)⁴⁸. The resulting 95th percentile peak maximum principal strains (i.e., ϵ_p) were used to fit a logistic regression against the corresponding binary concussion statuses. This led to an ϵ_p threshold of 0.29 for a 50% probability of concussion (comparable to 0.26 found in the gray matter in another study³⁰). Full-stop idealized v_{rot} profiles adopted in the original BrIC study⁴⁰ with varying magnitudes (18–37.5 rad/s, based on the pcBRA sampling range) were used to simulate sagittal, coronal and axial rotations. For each direction, the critical velocity value was obtained when ϵ_p reached the threshold previously identified. They were 30.4 rad/s, 35.6 rad/s, and 23.5 rad/s for ω_{xc} , ω_{yc} , and ω_{zc} , respectively.

Data analysis

For each impact, the Pearson correlation coefficient (r) as well as the slope and coefficient of determination (k and R^2 , respectively) from e_{est} - e_{actual} linear regression were reported (both k and R^2 were reported, as the regressions were constrained). The two strains were also compared by linearly regressing their corresponding ϵ_p and CSDM_{0.1}. The resulting R^2 was further compared with that obtained by linearly regressing kinematic injury metrics and the baselines from e_{actual} . Statistical significance was reached when $p < 0.05$.

Simulating a 60 ms impact using Abaqus/Explicit (Version 2016; Dassault Systèmes, France) typically required 30 min on a 12-CPU Linux cluster (Intel Xeon E5-2680v2, 2.80 GHz, 128 GB memory). Strains were reported at a temporal resolution of 1 ms, which required an additional 9 min to generate element-wise cumulative strains (single threaded). In contrast, strain interpolation was real-time (<0.01 sec) with GPU acceleration (NVIDIA Quadro K620, 384 cores, 2 GB memory). All data analyses were conducted in MATLAB (R2016b; Mathworks, Natick, MA).

Results

Representative strain-encoded coronal images from ϵ_{est} were compared with directly simulated ϵ_{actual} at selected time points (Figs. 3–6). Fig. 3 shows results for the case with the highest element-wise correlation, r (achieved at the end of the impact; corresponding to an impact to the facemask). ϵ_{actual} continued to evolve after reaching v_{rot}^p , especially in the central region (Fig. 3ef). Despite deceleration (Fig. 3c) that led to decrease in v_{rot} magnitude (Fig. 3b), ϵ_{est} closely matched with ϵ_{actual} in both pattern (r of 0.99) and magnitude (k of 1.06). For the case with the largest over-estimation (k and R^2 of 1.30 and 0.85, respectively; also corresponding to an impact to the facemask; Fig. 4), the two strains had a similar pattern (r of 0.91; Fig. 4h). Although a single major peak was apparent in the v_{rot} profile (Fig. 4b), two major positive acceleration peaks occurred consecutively (Fig. 4c). The observed strain over-estimation was similar to that found in NFL impact simulations⁴⁸.

For the case with the lowest element-wise correlation that also had the greatest under-estimation at the end of impact based on the pcBRA (corresponding to an impact to the vertex; Fig. 5), it was intriguing to observe that ϵ_{est} closely matched with ϵ_{actual} immediately after reaching v_{rot}^p (13.8 ms after onset; r , k and R^2 of 0.96, 1.02 and 0.93, respectively). The secondary peak reversed the v_{rot} directionality (Fig. 5b) and significantly amplified strains, which substantially degraded the ϵ_{est} - ϵ_{actual} match at the end of impact (r , k , and R^2 reduced to 0.71, 0.65, and 0.56, respectively). However, when using a biphasic v_{rot} shape to better approximate the profile, the resulting ϵ_{est} - ϵ_{actual} match substantially improved (r , k , and R^2 improved to 0.92, 0.86, and 0.85, respectively; Fig. 6).

The estimated strain, ϵ_{est} , was considered sufficiently accurate when r between element-wise strains was above 0.9 while k was between 0.9 and 1.1. Pooling together results from all impacts (Fig. 7), 57 out of the 108 or 53% cases were sufficiently accurate using ϵ_{est} from the pcBRA. For cases considered to have a single major v_{rot} peak without reversal in directionality (72 cases), nearly all of them (70 or 97%) had an r value greater than 0.9. However, poor accuracy was also evident for the other 36 impacts that had a reversal in v_{rot} directionality (average r , k and R^2 of 0.80 ± 0.06 , 0.80 ± 0.08 , and 0.68 ± 0.06 , respectively, with ranges of 0.71–0.90, 0.65–0.95, and 0.56–0.80, respectively). Nevertheless, with a biphasic v_{rot} simplification, the estimation accuracy for these cases was significantly improved, as half of these cases (50%) were now considered sufficiently accurate (Fig. 6; average r , k and R^2 of 0.92 ± 0.03 , 0.95 ± 0.07 , and 0.85 ± 0.05 , respectively, with ranges of 0.84–0.96, 0.86–1.06, and 0.74–0.92, respectively). Taken together, ϵ_{est} was found to be sufficiently accurate for 74 out of the 108 or 69% cases, when a subset of cases utilized a biphasic v_{rot} simplification scheme.

With acceleration-only profile simplification, ϵ_{est} -derived ϵ_p and CSDM_{0.1} correlated with those from ϵ_{actual} stronger than those between kinematic metrics and the baselines, for the whole-brain and cerebrum (Fig. 8). The biphasic profile simplification further improved the correlations for ϵ_{est} -derived metrics, especially in the corpus callosum. They were stronger than all kinematic metrics, regardless of the ROI (R^2 ranged 0.77–0.94 and 0.75–0.95, respectively, for ϵ_p and CSDM_{0.1}, vs. 0.46–0.77 and 0.28–0.71 for the kinematic metrics, respectively).

Discussion

Developing and deploying an effective, tissue response-based injury metric as opposed to solely relying on impact kinematics may have a profound implication for the detection, diagnosis, and prevention of brain injury. Although strain-based metrics already exist, they remain infeasible for large-scale, real-world applications because of the substantial computational cost involved in model simulations. A pre-computed brain response atlas (pcBRA) may have the potential to resolve this well-known sophistication-vs.-efficiency dilemma¹⁸, particularly for those in contact sports due to their similar kinematic characteristics within the participants^{7,9}. In this study, we significantly extended an earlier evaluation on its accuracy in more realistic, full 6-DOF head impacts from dummy head drop tests.

Based on results from 108 impact simulations, we found that estimates from pcBRA (ϵ_{est}) could be sufficiently accurate compared to the directly simulated (ϵ_{actual}) in both distribution pattern and magnitude when a single v_{rot} peak dominated (Fig. 3). Most of these cases (97% or 70 out of 72) had a correlation coefficient greater than 0.9, suggesting an excellent ϵ_{est} - ϵ_{actual} match in distribution pattern. Impacts to the facemask appeared to present some unique kinematic characteristics, inducing considerable over-estimation (i.e., $k > 1.1$) for some profiles (but not all, see cases in Figs. 3 and 4). In contrast, significant under-estimation occurred for impacts with v_{rot} reversal in directionality (most of which were impacts to the frontal and vertex regions; Fig. 5). With a biphasic v_{rot} profile simplification, however, the estimation accuracy was substantially improved in both distribution pattern and magnitude (Fig. 6), for all of the cases identified (Fig. 7).

With the augmented v_{rot} profile simplification strategy (i.e., with a subset of impacts parameterized into a biphasic v_{rot} shape), both of the ϵ_{est} -derived metrics, ϵ_p and CSDM_{0.1}, correlated with the ϵ_{actual} -derived baselines stronger than BrIC, maximum magnitude of resultant angular velocity (ω_m) and acceleration (a_m), regardless of the ROI, and by a large margin (Fig. 8). For example, R^2 for ϵ_p and CSDM_{0.1} in the whole-brain were 0.93 and 0.94 using ϵ_{est} -derived metrics, and they were 0.75 and 0.65 for BrIC. The superior performance was also evident for the corpus callosum (ϵ_p : 0.90 vs. 0.64 for BrIC; CSDM_{0.1}: 0.91 vs. 0.47 for BrIC).

These correlation comparisons were particularly encouraging, even though ϵ_{est} was considered sufficiently accurate for only 69% (74 of the 108) of the cases (Fig. 7). This was, in part, because we have adopted a more conservative and stringent accuracy criterion that considered both element-wise strain distribution and magnitude. In contrast, scalar metrics, such as ϵ_p and CSDM, do not consider strain distribution or pattern.

Regardless, the biphasic v_{rot} simplification scheme employed a fixed duration for both idealized peaks and assumed the head to rotate about the same rotational axis in opposite directions, which may not be true in real-world impacts. However, this was a calculated tradeoff between technique simplicity/feasibility and response accuracy (i.e., less vs. more characterizing parameters). The simplification scheme only required identification of the two peak angular velocities, which appeared straightforward. Likely, this would simplify the

idealization of real-world impact profiles, as some of the parameters may be difficult to determine without ambiguity (e.g., duration⁴⁸). The different idealized profile shapes (an acceleration-only peak²³, a single full-stop v_{rot} peak as in⁴⁰, or biphasic peaks in this study) may serve as the basic building blocks to approximate real-world impact kinematics for an expanded pcBRA in the future.

Certainly, further study is necessary to determine how best to simplify real-world impact profiles into these half-, single-, or biphasic profiles, which likely will also depend on the specific impact data available (e.g., whether or not head deceleration is captured in the first place). In extreme cases when such profile idealization becomes infeasible for truly arbitrary head rotations with no apparent pattern (e.g., potentially, for head impacts in automotive crashes), a pcBRA may still be constructed, by using angular velocity profiles to sample the maximum change in angular velocity in the three orthogonal directions. This is conceptually analogous to BrIC⁴⁰ or RVC⁴², but with an added benefit of directly using an actual model to pre-compute brain responses, rather than relying on an empirical formula to indirectly infer the strain level. It awaits further investigation how, even this degenerated pcBRA, would compare with other state-of-the-art kinematic injury metrics in real-world applications.

Nevertheless, systematically probing the response “perturbation” may also improve accuracy and lead to a “second-order” approximation via compensation⁴⁸. However, this will likely require a large number of temporally accurate real-world impact profiles for training. Inevitably, this places burden on head impact sensors that, at present, only focus on the accuracy of peak magnitude in resultant angular acceleration or velocity, but not yet on its temporal accuracy^{2,4}.

Kinematic injury metrics

For both ϵ_p and CSDM_{0.1}, ω_m correlated with the baseline strain injury metrics better than a_m , regardless of the ROI (with an exception of CSDM in the cerebellum; Fig. 8b). This confirmed that angular velocity may be more predictive of brain strains than angular acceleration^{29,48} for the impacts we used. In addition, we found that ω_m and BrIC largely had a comparable correlation performance with respect to the baseline strain injury metrics for the whole brain or cerebrum. For BrIC and ω_m , the R^2 values for the whole brain were largely comparable to those obtained in diverse automotive impacts¹⁵, ranging approximately 0.6–0.8. However, R^2 values for a_m here were somewhat lower (e.g., ~0.5 vs. ~0.5–0.7 in the latter study). Potential contributors to the observed discrepancies included head model differences, different strain threshold for CSDM (0.1 here vs. 0.25), possibly different impact kinematic characteristics between ATD drop tests and those in diverse automotive head impacts, and the filtering and differentiation methods used to generate angular acceleration.

Biomechanics of rotation-induced brain strains

Linear acceleration alone generates little strain for the majority of the brain²⁵. A poor correlation is expected between linear acceleration or its derivatives and brain strain-based metrics¹⁵. Therefore, we chose to isolate head rotational kinematics for model input and

subsequent strain analysis. However, it must be recognized that linear and rotational kinematics, when typically prescribed in a body-fixed coordinate system²⁶, are co-dependent rather than independent to each other. Therefore, it was necessary to transform impact kinematics into a ground-fixed frame first before isolating the two kinematic components for model input^{20,47}, especially for long-duration impacts to avoid accumulated error.

It was intriguing to observe that the cumulative strains continued to evolve especially in the central region even after the resultant angular velocity already reached its peak (subfigures (e) and (f) in Figs. 3 and 5). This was because of the time delay for the shear deformation emanating from the rotating rigid-body skull to reach the central brain. While angular velocity was the main driver for brain strains, angular acceleration that was directly related to v_{rot} profile “shapes”, did induce perturbation to brain strain as well. This was consistent with recent findings on the significance of v_{rot} profile shapes on brain strain uncertainty⁴⁸.

Head injury models for real-world clinical applications—The ultimate goal of a computational head injury model is to facilitate clinical evaluation of the risk and severity of brain injury. Most biomechanical studies have so far focused on identifying the “best” injury predictor to assess the probability of the occurrence of a binary injury^{8,15,17,19,27,28,30,33,40,44}. There is a large gap of knowledge on how external head impacts, through induced brain responses at the time of impact, are related to subsequent, specific neurological disorder and injury severity often observed at a later time in the clinic. The symptoms are presumably a result of aggregated injury to specific brain ROIs, functionally important neural tracts, and/or the underlying structural and functional networks of the brain⁵.

Establishing the causal or correlative relationships between the various aspects of TBI requires a systems approach^{5,24}. Unfortunately, most biomechanical head injury models incorporate generic regions of the brain but not yet targeted ROIs or the structural basis for brain function that is available from advanced neuroimaging (except, perhaps, for limited work incorporating whole-brain tractography^{16,44,45}). Existing response-based injury metrics such as ϵ_p and CSDM do not consider the spatial distribution of impact-induced strains. This is a limitation as they do not inform specific brain regions or their network connections that are potentially injured, while such information is likely important for the observed neurological dysfunction. Conversely, a binary “concussion” or “injury” status for the whole-brain may not accurately characterize the specific neurological disorder either, which adds to the mismatch.

Further, for contact sports where accumulated head impacts are thought important, they are not yet incorporated into tissue response-based injury metrics either. Kinematics-based, cumulative metrics do exist (e.g., Risk Weighted cumulative Exposure, RWE¹³, and Cumulative Head Impact Index, CHII³⁶); however, like other empirically derived kinematic metrics, they do not inform how tissue deforms. Further, they do not consider time interval between head impacts that are considered important as well. These observations highlight current limitations in TBI biomechanics studies.

While our current work does not address how TBI biomechanics correlates to clinical observations of real-world injury, the high-throughput strain estimation pipeline it attempts to establish may be important to enable future studies to explore such relationships more efficiently. This may be especially useful for contact sports that involve repetitive head impacts for each player (hundreds or more) and when studying a large athletic population. Head models will likely continue to evolve with more advanced features and sophistication¹⁸ to meet the challenges of answering the important clinical questions. However, this will also likely degrade the model simulation efficiency, significantly⁴⁵. In such a scenario, the pcBRA real-time model simulation framework may become even more important and valuable to facilitate future TBI studies.

Limitations—First, the accuracy of the estimation scheme reported in this study, albeit encouraging, were for helmeted dummy head impacts in the context of simulated American football³². Further investigation especially for its application in real-world impact cases merits further exploration. Nevertheless, our current study was an important stepping-stone towards accelerating the process of assessing the effectiveness of tissue response-based injury metrics for improved injury prediction in large-scale, real-world applications in the future.

Second, we have only selected a few rotation-based kinematic injury metrics for comparison (3 here vs. 15 metrics in¹⁵). This was because a poor correlation was expected between brain strains and metrics derived from linear acceleration. However, we did not compare with other rotation-based metrics such as RIC, PRHIC²⁷ and RVC⁴², which were found to be slightly inferior or comparable to BrIC¹⁵. Regardless, these kinematic injury metrics have been typically tuned for binary injury prediction for the whole brain. As the pcBRA could perform well in both magnitude and distribution (Fig. 3), this technique may have the potential to enable developing metrics in more targeted regions (e.g., corpus callosum; Fig. 8) to assess the risk and severity of brain injury, when there is such a need in the future.

Finally, the ability to augment the profile simplification scheme was only demonstrated in limited impact conditions relevant to contact sports. Future studies are necessary to assess the capability of scaling the pcBRA in expanded impact conditions such as automotive crashes.

Conclusion

Our study demonstrated that the previously established pre-computed brain response atlas (pcBRA) based on simplified acceleration-only profiles could achieve sufficient estimation accuracy relative to the directly simulated counterpart, especially when a single major angular velocity peak dominated. For impacts with substantial deceleration that reversed velocity directionality, a biphasic simplification strategy was also implemented to improve estimation accuracy. Injury metrics based on estimated strains correlated with the baselines from directly simulated responses stronger than all other kinematic injury metrics considered, regardless of the brain region, for dummy head impacts. These findings further support the feasibility of the pcBRA technique for accurate strain estimation and in real

time. The idealized profile shapes may serve as the basic building blocks for an expanded pcBRA in the future.

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References

1. (NRC), I. of M. (IOM) and N. R. C. Sports-related concussions in youth: improving the science, changing the culture. Washington, DC: 2014. at <<http://www.ncbi.nlm.nih.gov/books/n/nap18377/pdf/>>
2. Allison, Ma, Kang, YS., Bolte, JH., Maltese, MR., Arbogast, KB. Validation of a helmet-based system to measure head impact biomechanics in ice hockey. *Med Sci Sports Exerc.* 2014; 46:115–23. [PubMed: 23846161]
3. Bazarian JJ, Zhu T, Blyth B, Borrino A, Zhong J. Subject-specific changes in brain white matter on diffusion tensor imaging after sports-related concussion. *Magn Reson Imaging.* 2012; 30:171–80. [PubMed: 22079073]
4. Beckwith JG, Greenwald RM, Chu JJ. Measuring head kinematics in football: correlation between the head impact telemetry system and Hybrid III headform. *Ann Biomed Eng.* 2012; 40:237–48. [PubMed: 21994068]
5. Bigler ED. Systems Biology, Neuroimaging, Neuropsychology, Neuroconnectivity and Traumatic Brain Injury. *Front Syst Neurosci.* 2016; 10:1–23. [PubMed: 26834579]
6. Broglio SP, Schnebel B, Sosnoff JJ, Shin S, Fend X, He X, Zimmerman J. Biomechanical properties of concussions in high school football. *Med Sci Sports Exerc.* 2010; 42:2064–71. [PubMed: 20351593]
7. Broglio SP, Sosnoff JJ, Shin S, He X, Alcaraz C, Zimmerman J. Head impacts during high school football: a biomechanical assessment. *J Athl Train.* 2009; 44:342–9. [PubMed: 19593415]
8. Cai Y, Zhao W, Li Z, Ji S. Concussion classification via deep learning using whole-brain white matter fiber strains. 2017
9. Camarillo DB, Shull PB, Mattson J, Shultz R, Garza D. An instrumented mouthguard for measuring linear and angular head impact kinematics in American football. *Ann Biomed Eng.* 2013; 41:1939–49. [PubMed: 23604848]
10. Carson JD, Lawrence DW Md, Kraft SA Md, Garel A, Snow CL, Chatterjee A Md, Libfeld P, MacKenzie HM Md, Thornton JS PhD, Moineddin R PhD, Frerhont P Md PhD. Premature return to play and return to learn after a sport-related concussion: Physician's chart review. *Can Fam Physician.* 2014; 60:310–315. [PubMed: 24733314]
11. CDC. Report to Congress on Traumatic Brain Injury in the United States: Epidemiology and Rehabilitation. 2015; doi: 10.1161/HYPERTENSIONAHA.111.186106
12. Chrisman S, Schiff M, Chung S, Herring S, Rivara F. Implementation of concussion legislation and extent of concussion education for athletes, parents, and coaches in Washington state. *Am J Sports Med.* 2014; 42:1190–96. [PubMed: 24510067]
13. Davenport EM, Whitlow CT, Urban JE, Espeland MA, Jung Y, Rosenbaum DA, Gioia GA, Powers AK, Stitzel JD, Maldjian JA. Abnormal white matter integrity related to head impact exposure in a season of high school varsity football. *J Neurotrauma.* 2014
14. Franklyn M, Fildes B, Zhang L, Yang K, Sparke L. Analysis of finite element models for head injury investigation: reconstruction of four real-world impacts. *Stapp Car Crash J.* 2005; 49:1–32. [PubMed: 17096266]
15. Gabler LF, Crandall JR, Panzer MB. Assessment of Kinematic Brain Injury Metrics for Predicting Strain Responses in Diverse Automotive Impact Conditions. *Ann Biomed Eng.* 2016; doi: 10.1007/s10439-016-1697-0
16. Garimella HT, Kraft RH, Carimella HT, Kraft RH. Modeling the mechanics of axonal fiber tracts using the embedded finite element method. *Int j numer method biomed eng.* 2016; 2823:26–35.

17. Giordano C, Kleiven S. Evaluation of Axonal Strain as a Predictor for Mild Traumatic Brain Injuries Using Finite Element Modeling. *Stapp Car Crash J.* 2014; 58:29–61. [PubMed: 26192949]
18. Goriely A, Geers MGD, Holzapfel GA, Jayamohan J, Jérusalem A, Sivaloganathan S, Squier W, Van Dommelen JAW, Waters S, Kuhl E. Mechanics of the brain: perspectives, challenges, and opportunities. *Biomech Model Mechanobiol.* 2015; doi: 10.1007/s10237-015-0662-4
19. Hernandez F, Wu LC, Yip MC, Hoffman AR, Lopez J, Grant G, Kleiven S, Camarillo DB. Six Degree of Freedom Measurements of Human Mild Traumatic Brain Injury. *Ann Biomed Eng.* 2014; 43:1918–1934. [PubMed: 25533767]
20. Hernandez F, Wu LC, Yip MC, Laksari K, Hoffman AR, Lopez JR, Grant GA, Kleiven S, Camarillo DB. Erratum to: Six Degree-of-Freedom Measurements of Human Mild Traumatic Brain Injury (*Annals of Biomedical Engineering* Vol., (43:8), 2015, (1918–1934), 10.1007/s10439-014-1212-4). *Ann Biomed Eng.* 2016; 44:828–829. [PubMed: 26518413]
21. Iraj A, Benson RR, Welch RD, Neil BJO, Woodard JL, Ayaz I, Kulek A, Medado P, Soltanian-zadeh H, Liu T, Haacke M, Kou Z. Resting State Functional Connectivity in Mild Traumatic Brain Injury at the Acute Stage: Independent Component and Seed Based Analyses. *J Neurotrauma.* 2014
22. Ji S, Margulies S. Brainstem Motion within the Skull: Measurement of the Pons Displacement In Vivo. *J Biomech.* 2007; 40:92–99. [PubMed: 16387309]
23. Ji S, Zhao W. A pre-computed brain response atlas for instantaneous strain estimation in contact sports. *Ann Biomed Eng.* 2015; 43:1877–1895. [PubMed: 25449149]
24. Ji S, Zhao W, Ford JC, Beckwith JG, Bolander RP, Greenwald RM, Flashman LA, Paulsen KD, McAllister TW. Group-wise evaluation and comparison of white matter fiber strain and maximum principal strain in sports-related concussion. *J Neurotrauma.* 2015; 32:441–454. [PubMed: 24735430]
25. Ji S, Zhao W, Li Z, McAllister TW. Head impact accelerations for brain strain-related responses in contact sports: a model-based investigation. *Biomech Model Mechanobiol.* 2014; 13:1121–36. [PubMed: 24610384]
26. Kang Y-S, Moorhouse K, Bolte JH. Measurement of Six Degrees of Freedom Head Kinematics in Impact Conditions Employing Six Accelerometers and Three Angular Rate Sensors (6a ω Configuration). *J Biomech Eng.* 2011; 133:111007. [PubMed: 22168739]
27. Kimpara H, Iwamoto M. Mild traumatic brain injury predictors based on angular accelerations during impacts. *Ann Biomed Eng.* 2012; 40:114–26. [PubMed: 21994065]
28. King AI, Yang KH, Zhang L, Hardy W, Viano DC. Is head injury caused by linear or angular acceleration?. 2003
29. Kleiven S. Evaluation of head injury criteria using a finite element model validated against experiments on localized brain motion, intracerebral acceleration, and intracranial pressure. *Int J Crashworthiness.* 2006; 11:65–79.
30. Kleiven S. Predictors for Traumatic Brain Injuries Evaluated through Accident Reconstructions. *Stapp Car Crash J.* 2007; 51:81–114. [PubMed: 18278592]
31. Kroshus E, Kubzansky L, Goldman R, Austin S. Norms, Athletic Identity, and Concussion Symptom Under-Reporting Among Male Collegiate Ice Hockey Players: A Prospective Cohort Study. *Ann Behav Med.* 2014; 49:95–103.
32. Kuo C, Wu LC, Hammor BT, Luck JF, Cutcliffe HC, Lynall RC, Kait JR, Campbell KR, Mihalik JP, Bass CR, Camarillo DB. Effect of the mandible on mouthguard measurements of head kinematics. *J Biomech.* 2016; 49:1845–1853. [PubMed: 27155744]
33. Marjoux D, Baumgartner D, Deck C, Willinger R. Head injury prediction capability of the HIC, HIP, SIMon and ULP criteria. *Accid Anal Prev.* 2008; 40:1135–1148. [PubMed: 18460382]
34. McAllister TW, Ford JC, Ji S, Beckwith JG, Flashman La, Paulsen K, Greenwald RM. Maximum principal strain and strain rate associated with concussion diagnosis correlates with changes in corpus callosum white matter indices. *Ann Biomed Eng.* 2012; 40:127–40. [PubMed: 21994062]
35. McCrea M, Hammeke T, Olsen G, Leo P, Guskiewicz K. Unreported concussion in high school football players: implications for prevention. *Clin J Sport Med.* 2004; 14:13–7. [PubMed: 14712161]

36. Montenegro PH, Alosco ML, Martin B, Daneshvar DH, Mez J, Chaisson C, Nowinski CJ, Au R, McKee AC, Cantu RC, McClean MD, Stern RA, Tripodis Y. Cumulative Head Impact Exposure Predicts Later-Life Depression, Apathy, Executive Dysfunction, and Cognitive Impairment in Former High School and College Football Players. *J Neurotrauma*. 2016; 13:0–55.
37. Pellman EJ, Viano DC, Tucker AM, Casson IR, Waeckerle JF. Concussion in professional football: reconstruction of game impacts and injuries. *Neurosurgery*. 2003; 53:799–814. [PubMed: 14519212]
38. Rapp PE, Keyser DO, Albano A, Hernandez R, Gibson DB, Zambon RA, Hairston WD, Hughes JD, Krystal A, Nichols AS. Traumatic Brain Injury Detection Using Electrophysiological Methods. *Front Hum Neurosci*. 2015; 9:11. [PubMed: 25698950]
39. Sullivan S, Eucker Sa, Gabrieli D, Bradfield C, Coats B, Maltese MR, Lee J, Smith C, Margulies SS. White matter tract-oriented deformation predicts traumatic axonal brain injury and reveals rotational direction-specific vulnerabilities. *Biomech Model Mechanobiol*. 2014; doi: 10.1007/s10237-014-0643-z
40. Takhounts EG, Craig MJ, Moorhouse K, McFadden J, Hasija V. Development of Brain Injury Criteria (BrIC). *Stapp Car Crash J*. 2013; 57:243–66. [PubMed: 24435734]
41. Ward C, Chan M, Nahum a. Intracranial Pressure-A Brain Injury Criterion. 1980; doi: 10.4271/801304
42. Yanaoka T, Dokko Y, Takahashi Y. Investigation on an Injury Criterion Related to Traumatic Brain Injury Primarily Induced by Head Rotation. 2015; doi: 10.4271/2015-01-1439.Copyright
43. Zhang J, Yoganandan N, Pintar Fa, Gennarelli Ta. Role of translational and rotational accelerations on brain strain in lateral head impact. *Biomed Sci Instrum*. 2006; 42:501–6. [PubMed: 16817658]
44. Zhao W, Cai Y, Li Z, Ji S. Injury prediction and vulnerability assessment using strain and susceptibility measures of the deep white matter. *Biomech Model Mechanobiol*. 2017; in press. doi: 10.1007/s10237-017-0915-5
45. Zhao W, Ford JC, Flashman LA, McAllister TW, Ji S. White Matter Injury Susceptibility via Fiber Strain Evaluation using Whole-Brain Tractography. *J Neurotrauma*. 2016; 33:1834–1847. [PubMed: 26782139]
46. Zhao, W., Ji, S. Parametric investigation of regional brain strain responses via a precomputed atlas. 2015.
47. Zhao W, Ji S. Feasibility of a pressure response superposition scheme in blunt head impact. 2015
48. Zhao W, Ji S. Brain strain uncertainty due to shape variation in and simplification of head angular velocity profiles. *Biomech Model Mechanobiol*. 2017; 16:449–461. [PubMed: 27644441]
49. Zonfrillo M, Kim K, KBA. Emergency department visits and head computed tomography utilization for concussion patients from 2006 to 2011. *Acad Emerg Med*. 2015; 22

Fig. 1.

The WHIM showing color-coded head exterior (a) and intracranial components (b). The model includes part of the spinal cord with an elastic membrane at the end to improve biofidelity in the inferior²⁴, as it allows the spinal cord to move through the foramen magnum as observed in a live human study²². The x -, y -, and z -axes of the model coordinate system correspond to the posterior–anterior, right–left, and inferior–superior direction, respectively.

Fig. 2.

Representative angular velocity (top) and acceleration (bottom) profiles corresponding to impacts to the oblique (left), occipital (middle), and frontal (right) regions. The peak angular velocity (v_{rot}^p) corresponding to the major acceleration peak was first identified. Its orthogonal components, v_x , v_y , and v_z , were determined (crosses on dashed vertical lines passing through v_{rot}^p), which may or may not be the same as the maximum magnitudes of the angular velocity components, ω_x , ω_y , and ω_z (circles). The profile was simplified into triangulated acceleration (only shown as integrated velocity profiles for clarity; dark lines). When v_{rot} reversed its direction, a biphasic v_{rot} shape was also used (right; also see Fig. 6 in Results).

Fig. 3.

Comparison between ϵ_{est} (a) and ϵ_{actual} at four selected time points (e–h; i.e., peak strains from onset of impact up to the current time point), as identified in the angular velocity (b) and acceleration (c) profiles. The largest angular acceleration peak identified to determine the corresponding v_{rot}^p (c). Linear correlation between the pcBRA-estimated element-wise strains and those directly simulated using the actual profile is shown in (d). This case yielded the highest element-wise correlation between the two strains (sufficiently after the end of impact).

Fig. 4. Same illustration for the case with the largest over-estimation. See Fig. 3 for caption. Note that the largest angular acceleration peaks corresponded to the same angular velocity peak.

Fig. 5.

Same comparison for the case with the lowest element-wise correlation that also had the greatest under-estimation. See Fig. 3 for caption. Note that ε_{actual} immediately after the first angular velocity peak before reversing its direction (f; boxed) matched well with ε_{est} (r , k and R^2 of 0.96, 1.02 and 0.93, respectively). However, the match degraded significantly (g and h) due to the secondary peak in v_{rot} (arrow) that reversed the directionality.

Fig. 6.

When using a biphasic v_{rot} shape for profile simplification (a; solid dark curve), the match between ϵ_{est} (b) and ϵ_{actual} (c) substantially improved, as shown in (d), compared to Fig. 5.

Fig. 7.

Summary of Pearson correlation coefficient and slope from constrained linear regression between element-wise ϵ_{est} and ϵ_{actual} for the 108 impacts. Cases 1, 2, and 3 are those with the highest r (Fig. 3), the greatest over-estimation (Fig. 4), and the lowest r that also had the greatest under-estimation (Fig. 5), respectively. Most cases with a reversal in v_{rot} directionality yielded a poor accuracy using the pcBRA, but were significantly improved with a biphasic v_{rot} simplification (“*” moved to “+”), as illustrated by the pair labeled “3” with circles. In total, ϵ_{est} (directly from pcBRA or estimated from a biphasic simplification for cases with v_{rot} reversal in directionality) was considered sufficiently accurate for 74 out of the 108 (69%) cases.

Fig. 8.

Correlations (R^2) between ϵ_{est} -derived injury metrics (using either pcBRA based on acceleration-only profile simplification, or with further augmentation by a biphasic simplification for a subset of impacts), ϵ_p (a) and CSDM (b), and the baselines from ϵ_{actual} for all impacts simulated, along with correlations between selected kinematic injury metrics and the baselines.

Summary of the pcBRA kinematic variables. Impact duration, t_i was fixed to 10 ms. Consequently, v_{rot}^p and a_{rot}^p uniquely corresponded to each other for triangulated acceleration impulses.

Table 1

Variable	v_{rot}^p (rad/s)	a_{rot}^p (rad ² /s)	t (ms)	θ (°)	α (°)
Range	[7.5, 37.5]	[1500, 7500]	10	[-90, 90]	[-90, 90]
Step size	3.75	750	N/A	15	15
# of samples	9	9	1	13	13