Classification of head impacts based on the spectral density of measurable kinematics.

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Abstract
Traumatic brain injury can be caused by head impacts, but many brain injury risk estimation models are less accurate across the variety of impacts that patients may undergo. We investigated the spectral characteristics of different head impact types with kinematics classification. Data was analyzed from 3,262 head impacts from lab reconstruction, American football, mixed martial arts, and publicly available car crash data. A random forest classifier with spectral densities of linear acceleration and angular velocity was built to classify head impact types (e.g., football), reaching a median accuracy of 96% over 1,000 random partitions of training and test sets. To test the classifier on data from different measurement devices, another 271 lab-reconstructed impacts were obtained from 5 other instrumented mouthguards with the classifier reaching over 96% accuracy. The most important features in the classification included both low-frequency and high-frequency features, both linear acceleration features and angular velocity features. Different head impact types had different distributions of spectral densities in low-frequency and high-frequency ranges (e.g., the spectral densities of MMA impacts were higher in high-frequency range than in the low-frequency range). Finally, with the classifier, type-specific, nearest-neighbor regression models were built for 95th percentile maximum principal strain, 95th percentile maximum principal strain in corpus callosum, and cumulative strain damage (15th percentile). This showed a generally higher $R^2$-value than baseline models. The classifier enables a better understanding of the impact kinematics in different sports, and it can be applied to evaluate the quality of impact-simulation systems and on-field data augmentation.

Key words: traumatic brain injury, head impacts, classification, impact kinematics

Introduction
Traumatic brain injury (TBI) is a growing public health hazard with high mortality and morbidity, as well as a socio-economic issue causing enormous diagnosis and treatment expenses¹. This is particularly urgent for mild TBI (mTBI), given that mTBI is notoriously underreported, difficult to diagnose, and pose a potential predisposing factor to long-term neurodegenerative processes². TBI/mTBI can be caused by various types of head impacts such as accidental falls, bike accidents, car crashes, American football impacts, mixed martial arts (MMA) impacts, water polo and car crashes³-⁵.

Considering the consequences and prevalence of TBI/mTBI, various biomechanical studies have focused on the estimation of brain injury risk⁶-¹⁰. Recent study¹¹ found that different head impact types tend to have variable biomechanical characteristics, and the impact types should not be ignored when estimating the risk of TBI/mTBI. However, the brain injury criteria (BIC) were developed based on certain types of head impacts⁵,¹², and should not be used across head impact types as the different kinematic features these BIC use can weigh differently across impact types¹³,¹⁴. To better develop risk evaluation models adaptable to various head impact types for detection and monitoring of TBI/mTBI, it is worthwhile to investigate the difference in the kinematics of various types of head impacts. Sports-specific monitoring and protection strategies can be developed if we understand the difference among types of head impacts.

To study the difference across head impact types, we used the kinematics of 3,262 head impacts from head model simulations, American football, MMA, automobile crashworthiness tests and car racing. We extracted the spectral density of linear acceleration and angular velocity, classified these impacts, and then analyzed the most important features for classification. Finally, we used the classification model to
build type-specific regression models of 95% maximum principal strain (MPS95), 95% maximum principal strain in corpus callosum (MPSCC95) and cumulative strain damage (CSDM, 15%, indicating the volume fraction of brain with MPS exceeding the threshold of 0.15), and compared with a baseline model developed with a mixture of different types of head impacts.

Materials and Methods

1. Data description

To study a broad range of head impact types, we collected kinematics from a total of 3,262 head impacts from various sources: 2,130 laboratory head impacts (HM: head model) simulated from a validated finite element (FE) model of the Hybrid III anthropomorphic test dummy headform, 302 college football (CF) head impacts measured by the Stanford instrumented mouthguard, 457 MMA head impacts (MMA) measured by the Stanford instrumented mouthguard, 53 reconstructed head impacts with helmet from the National Football League (NFL), 48 head impacts in automobile crashworthiness tests from NHTSA (NHTSA), and 272 reconstructed head impacts from National Association for Stock Car Auto Racing (NASCAR).

2. Feature Extraction

To classify different types of head impacts, we extracted the spectral density features of the impacts because we believe different head impact types have different spectral characteristics. The features were extracted from the linear acceleration and angular velocity (four channels: three spatial components and the magnitude; x: posterior-to-anterior, y: left-to-right, z: superior-to-inferior), because they are directly measured by accelerometers. (Example impacts were shown in Fig. S1.)

Fast Fourier Transform (FFT) was applied to each channel of the kinematics, and the spectrum was split into windows, each with a width of 50Hz. We kept the first four windows because the four windows show high classification accuracy. In each window, the mean, maximum and median of the spectral density were extracted as the features. A total of 96 features (2 kinematics, 4 channels, 4 spectrum windows, 3 statistics) were extracted for each impact. (Feature heatmap was shown in Fig. S1.)

3. Classification Algorithm and Evaluation

We applied the random forest as the classification algorithm. It is a tree-based ensemble learning algorithm that builds multiple decision trees to classify the samples into different leaves via the minimization of Gini index or entropy. Random forest builds trees with sub-samples of the dataset, adopts bootstrap aggregating (bagging), and performs a majority vote on the output of the trees. The reason to use random forest was that it does not suffer from overfitting based on bagging. It can also show the feature importance while not suffering from feature collinearity, which otherwise makes other interpretable classifiers (e.g., logistic regression) harder to interpret feature importance. The random forest was implemented with scikit-learn package (version 0.24.1).

To validate the feasibility of classifying different types of head impacts, we randomly partitioned the entire dataset of 3,262 impacts into 80% training set and 20% test set with stratified sampling over 1,000 repeats. The hyperparameters of the classifier (the number of decision trees and the maximum depth of each tree) were tuned in a five-fold cross validation on the training set by optimizing the classification accuracy.

To assess the classification performance, and to assess whether the classifier biased towards certain classes, the accuracy (percentage of correct predictions in all test samples) and three binary classification metrics: the mean precision, the mean recall, and the mean area under the receiver operating characteristic curve (AUROC) on the 20% test impacts were calculated. As the precision (e.g., correct MMA predictions divided by all predicted MMA impacts), recall (e.g., correct MMA predictions divided by all MMA impacts)
and AUROC are binary classification metrics, we averaged the three metrics after calculating them on the respective classification of each type of head impact (e.g., MMA vs. non-MMA, CF vs. non-CF).

4. Important Feature Analysis
As previous studies found significantly different performance of brain injury risk estimation models across head impact types, with the classification model, we can interpret the most important features for kinematics classification to find the different spectral characteristics intrinsic to different types of head impact kinematics. The importance of a feature is calculated by the normalized total reduction of the classification criterion (Gini index or entropy) brought by a feature\textsuperscript{21,22}. To ensure the result robustness, we recorded the normalized feature importance in the modeling of random forest classifiers over the 1,000 repeats. In each repeat, the feature importance was calculated on the 80% training data. Finally, the mean feature importance was calculated and ranked. Finally, we did an additional validation of the features by picking up the top 5, 10 and 20 important features and modeling the random forest classifiers, with the same four metrics calculated.

5. Brain strain regression with classification
Upon verifying the feasibility of kinematics classification, we built type-specific brain injury risk evaluation models with the classifier, rather than the mixture of all different types, to address the hardship of estimating brain injury risks across different head impacts types observed by researchers\textsuperscript{9,13}.

We used the four major datasets (HM, CF, MMA, NASCAR) with the most impacts, and performed a k-nearest neighbor (KNN) regression of 95% maximum principal strain (MPS95), 95% maximum principal strain on corpus callosum (MPSCC95) and cumulative strain damage (CSDM) on the kinematics after partitioning the dataset into 80% training data and 20% test data. We used these three metrics because strained-based metrics that directly summarize the brain deformation have shown superior injury predictability\textsuperscript{6,7,9,10,13}. KNN was used as it did not require strong distribution and model assumptions. In the regression, the k nearest training impacts of a test impact were found based on Euclidean distance. Then, the MPS95/MPSCC95/CSDM prediction for the test impact is the averaged MPS95/MPSCC95/CSDM of the k nearest training impacts. The hyperparameter k was tuned via a five-fold cross-validation on the 80% training data while optimizing the root mean squared error. Here, besides the spectral densities, we included the time-peaks of the linear acceleration and angular velocity (four channels for each). For one thing, we would select the kinematics which are directly measurable by sensors. For another, the time-peaks of the angular velocity have been shown to correlate well with MPS95 and are incorporated in the designs of many BIC\textsuperscript{25,26}. The ground-truth MPS95/MPSCC95/CSDM values were given by the KTH model, which is a validated FE model\textsuperscript{27}.

The baseline regression accuracy was given by using the 80% training data to build the model and the 20% test data to assess the model coefficient of determination ($R^2$). Different from the baseline model, the classification-regression model first built a classifier on the 80% training data and built KNN models for each type of head impact. In the testing stage, the impacts were classified into one of the types of head impacts in the training set and then the MPS95/MPSCC95/CSDM associated with the test impact was calculated by the type-specific KNN model. Because most impacts were from the dataset HM, directly calculating the RMSE and $R^2$ would have led to biased estimates of regression accuracy. Therefore, on the test impacts, we calculated the RMSE and $R^2$ based on the ground-truth types of head impacts (HM/CF/MMA/NASCAR) and took an average over the four types to avoid the influence exerted by the majority dataset HM. Finally, Wilcoxon signed-rank tests were done to test statistical significance on $R^2$.

6. Validation of the classifier on different measurement devices
To estimate the influence of measurement devices on the classifier, we applied the classifier to 271 head impacts collected by five different mouthguards in the lab: Stanford Instrumented Customized/Boiling-and-Bite, Prevent Customized/Boiling-and-Bite, SWA Customized. 54 impacts were analyzed for each mouthguard except 55 for SWA Customized mouthguards. The data was collected with a hybrid III headform and a pneumatic impactor which could deliver football-like impact.

**Results**

Firstly, we performed kinematics classification based on the 96 features with random forest. Over 1,000 repeats of random partitions of 80% training set and 20% test set, the accuracy, mean precision, mean recall, and mean AUROC were shown in Fig. 1 A-D. The medians of 1) classification accuracy, 2) mean precision, 3) mean recall, and 4) mean AUROC were above 0.95, 0.93, 0.85, 0.92, respectively, which demonstrates the feasibility of classifying different types of head impacts. (Example confusion matrices were visualized in Fig. S2.)

Based on the classifier, according to the Method Section 4, the top 20/10/5 most important features were extracted over the 1,000 repeats of random dataset partitions. The features and their definitions are listed in Table 1. The most important features included both angular velocity features and linear acceleration features. The different frequency ranges were also found to be important in the classification: there were 6 features in the low-frequency range (0-50Hz) among the top 10 most important features, including the mean and median spectral density of the resultant angular velocity, the Y-axis angular velocity and the resultant linear acceleration. Among the other top-10 important features, there were 3 features in the frequency range of 150-200Hz from the Y-axis and Z-axis linear acceleration. Additionally, among the top 20 features, there were 9 angular velocity features (7 from the magnitude and 2 from the spatial components) and 11 linear acceleration features (2 from the magnitude and 9 from the spatial components), which showed that both measured kinematics and both the magnitudes and the kinematic components in the classification were informative.

The distribution of the six datasets on the top 5 features are shown in Fig. 2. It was shown that on these five features from the low-frequency range (0-50Hz), the MMA impacts had the lowest spectral densities, while NHTSA/HM/NFL impacts had higher spectral densities in this range, and the CF/NASCAR impacts generally had spectral densities higher than MMA impacts and lower than NHTSA/HM/NFL impacts. On the contrary, in the high-frequency range (100-200Hz) shown in Fig. S3, the MMA impacts had higher spectral densities while NHTSA/HM impacts had lower spectral densities.

The classification performance on the 20/10/5 most important features was shown in Fig. 1 A-D: there was a general performance decline as the feature number decreased while the classifiers based on top 10 features still showed high classification performance with medians of 1) classification accuracy, 2) mean precision, 3) mean recall and 4) mean AUROC above 0.94, 0.88, 0.80, 0.90, respectively. These results demonstrated the feasibility of the kinematics classification with the subsets of most important features.

Furthermore, to further validate the classifier’s performance did not rely heavily on the measurement device and overfit the types of head impacts we collected, we performed the classification of 271 lab impacts collected by different mouthguards and the results were shown in Fig. 1 E. All the impacts were classified into football-like types, and most of them were HM/NFL impacts, which used the same methodology to generate head impacts as these 271 impacts.

Finally, to test whether classification could improve brain injury risk estimation, we built the KNN regression models of MPS95/MPSCC95/CSDM with/without classification and showed the test $R^2$ averaged over four datasets in Fig. 1 F-H. It was shown that the regression models with classification were significantly more accurate in MPSCC95 and CSDM regression (p<0.05) while similarly accurate in
MPS95 regression (p>0.1). The results demonstrated the application of the classification and type-specific models for better estimation of brain injury risk.

**Discussion**

In this study, we demonstrated that the spectral densities of the head impact kinematics enable high classification performances. With the classification, more accurate brain strain regression based on impact kinematics can be achieved. In this study, the MMA and college football impacts were measured by the Stanford instrumented mouthguard, while the head model simulated impacts and NHTSA impacts were both simulated with the Hybrid III anthropomorphic test dummy headform. Our additional validation on 271 lab-reconstructed impacts measured by 5 other mouthguards also showed most predictions were HM/NFL impacts which were also football-like impacts simulated/reconstructed with dummy heads. It was clear from the results on these two pairs and the validation experiment that the model generally successfully classified different types of head impacts. For the football-like impacts, the measurement devices generally do not have an influence on the classification performance.

As for the research contributions, firstly, the analysis of the most important features in the classification enables better understanding of the differences among head impact types. For instance, the NHTSA impacts have higher spectral densities in low-frequencies and lower spectral densities in high-frequencies, while the MMA impacts have lower spectral densities in low-frequencies and higher spectral densities in high-frequencies. Via the classification algorithm, we can investigate the key features that may determine the impact types and the sports and visualize the distribution of the spectral densities.

Secondly, we built classifiers for different types of head impacts and made the model trained on the entire dataset publicly available. As the previous study have shown the issues of generalizability of brain strain estimation models across different head impact types, we have shown that the classifiers can benefit the development of type-specific brain injury risk estimation models, which shows higher accuracy in brain strain regression in this study. As the classification is based on noisy patterns defined by humans (i.e., sports), this categorization may not capture the intrinsic types of sports. However, this noisy categorization of patterns works in the improvement of risk estimation accuracy. For example, for a new impact needing to be evaluated, even though it is measured from American football event, it may be classified into NASCAR considering its spectral density fingerprint and the overall performance of the classification-regression leads to an improvement in the accuracy.

Thirdly, as data from laboratory impacts are relatively easier to obtain than on-field data, such as MMA impacts, researchers can conduct domain adaptation in the future to generate more simulated on-field impacts with model deep learning techniques, such as generative adversarial network (GAN) for data augmentation. This classifier with high performance can be useful as the discriminator for the evaluation of the simulated impacts.

Furthermore, as is shown in our validation experiments across different mouthguards, the classifier successfully distinguished the lab-reconstructed football-like impacts from on-field college football impacts, which indicates that the football-like impacts generated on the dummy head with pneumatic impactor still cannot fully capture on-field college football characteristics. Therefore, this classifier can be applied to evaluate the quality of dummy head impact reconstruction/simulation systems.

As for the study limitations, first, to test our classifier does not rely heavily on measurement devices, we only used football-like impacts measured by five mouthguards. In the future, more MMA impacts, NHTSA impacts measured by different devices can be collected and used to test the model’s sensitivity to measurement devices on impacts other than football impacts. Second, to enable the classifier to be more accurate and broader in applications, more data from diverse types of head impacts should be collected and
modeled. Additionally, we used the KTH model as the validated model to calculate brain strain. It is limited when compared to the recently developed state-of-the-art finite element head models (FEHM)\textsuperscript{29,30}. For example, the KTH model does not model the gyri or sulci which have been shown to have significant influences on the FEHM behavior. In the future, more recently developed FEHMs can be applied to validate the results on the brain strain.

**Conclusion**

In this study we performed the classification of different types of head impacts and demonstrated the feasibility of classification with high accuracy based on the spectral density of measurable head kinematics (i.e., linear acceleration and angular velocity). The important features for head impact classification included both low-frequency and high-frequency ranges, both linear acceleration and angular velocity. The classifier was also validated on 5 other instrumented mouthguards to rule out the possibility of heavy reliance on the specific model of instrumented mouthguard devices. Finally, this study exhibited higher accuracy in the regression of MPS95, MPSCC95, and CSDM with classification of different types of head impacts, rather than a mixture of all types of impacts together. The classification also reveals the difference of different types of head impacts in the frequency domain. The classifiers are publicly available for researchers to build better type-specific estimation models for brain injury risk.

**Code and data availability**

The classification model, feature extraction code, example kinematics file and a user introduction are posted at: [https://github.com/xzhan96-stf/kinematics_classifier](https://github.com/xzhan96-stf/kinematics_classifier).

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Tables

Table 1. The ranking and definitions of the top 20 most important features in kinematics classification and the mean normalized importance values over 1,000 random dataset partitions.

| Ranking | Meaning                          | Mean Normalized Importance |
|---------|----------------------------------|----------------------------|
| 1       | $|\omega|$: median spectral density in [0,50Hz] | 0.094                      |
| 2       | $\omega_y$: median spectral density in [0,50Hz] | 0.062                      |
| 3       | $|\omega|$: mean spectral density in [0,50Hz] | 0.056                      |
| 4       | $|\alpha|$: median spectral density in [0,50Hz] | 0.036                      |
| 5       | $\alpha_y$: mean spectral density in [0,50Hz] | 0.031                      |
| 6       | $a_z$: max spectral density in [150, 200Hz] | 0.023                      |
| 7       | $a_z$: max spectral density in [100, 150Hz] | 0.022                      |
| 8       | $|\alpha|$: mean spectral density in [0,50Hz] | 0.021                      |
| 9       | $a_y$: max spectral density in [150, 200Hz] | 0.020                      |
| 10      | $a_z$: mean spectral density in [150, 200Hz] | 0.019                      |
| 11      | $|\omega|$: max spectral density in [0,50Hz] | 0.019                      |
| 12      | $|\omega|$: median spectral density in [150,200Hz] | 0.019                      |
| 13      | $|\omega|$: median spectral density in [50,100Hz] | 0.019                      |
| 14      | $|\omega|$: mean spectral density in [50,100Hz] | 0.017                      |
| 15      | $a_x$: mean spectral density in [0, 50Hz] | 0.016                      |
| 16      | $a_z$: max spectral density in [150, 200Hz] | 0.016                      |
| 17      | $|\omega|$: max spectral density in [50, 100Hz] | 0.015                      |
| 18      | $a_z$: mean spectral density in [100, 150Hz] | 0.015                      |
| 19      | $a_z$: max spectral density in [100, 150Hz] | 0.015                      |
| 20      | $a_x$: median spectral density in [0, 50Hz] | 0.015                      |
Figures

Figure 1. Classification performance metrics of the random forest classifier and the MPS95/MPSCC95/CSDM regression accuracy with/without kinematics classification. The accuracy (A), mean precision (B), mean recall (C) and mean AUROC (D) of the classification based on different number of features over 1,000 random dataset partitions. The prediction results of 271 lab-reconstructed football-like impacts measured by 5 different instrumented mouthguards (E). The mean regression R² of MPS95 (A), MPSCC95 (B) and, CSDM (C). 1000 random train-test partitions were done in the regression. (*p<0.05, Wilcoxon signed-rank test)

Figure 2. Distribution of the six datasets on the top 5 most important features for classification. The data distribution in the median spectral density in [0,50Hz] of the resultant angular velocity (A), the median spectral density in [0,50Hz] of the Y-axis angular velocity (B), the mean spectral density in [0,50Hz] of the resultant angular velocity (C), the median spectral density in [0,50Hz] of the resultant linear acceleration (D), and the mean spectral density in [0,50Hz] of the Y-axis angular velocity (E). HM: head model simulated impacts without helmet, CF: on-field college football impacts, MMA: on-field MMA impacts, NFL: lab-reconstructed NFL impacts with helmet, NHTSA: NHTSA car crash impacts, NASCAR: NASCAR car crash impacts.
Supplementary Materials

Supplementary Figures

Figure S1. Example kinematics of the six types of head impacts and the visualization of the six datasets used in this study with heatmap. (A) The magnitude of linear acceleration at the brain center of gravity. (B) The magnitude of angular velocity. (C) The heatmap of features of all samples. 0-HM: head model simulated impacts without helmet, 1-CF: on-field college football impacts, 2-MMA: on-field MMA impacts, 3-NFL: lab-reconstructed NFL impacts with helmet, 4-NHTSA: NHTSA car crash impacts, 5-NASCAR: NASCAR car crash impacts.

Figure S2. The example confusion matrices of the classification based on four different numbers of features. The confusion matrices for (A) all 96 features, (B) top 20 features, (C) top 10 features, and (D) top 5 features. 0-HM: head model simulated impacts without helmet, 1-CF: on-field college football impacts, 2-MMA: on-field MMA impacts, 3-NFL: lab-reconstructed NFL impacts with helmet, 4-NHTSA: NHTSA car crash impacts, 5-NASCAR: NASCAR car crash impacts.

Figure S3. The distribution of six datasets on the sixth-to-tenth most important features for classification. The data distribution in the max spectral density in [150, 200Hz] of the Z-axis linear acceleration (A), the max spectral density in [100, 150Hz] of the Z-axis linear acceleration (B), the mean spectral density in [0,50Hz] of the resultant linear acceleration (C), the max spectral density in [150, 200Hz] of the Y-axis linear acceleration (D), the mean spectral density in [150, 200Hz] of the Z-axis linear acceleration (E). HM: head model simulated impacts without helmet, CF: on-field college football impacts, MMA: on-field MMA impacts, NFL: lab-reconstructed NFL impacts with helmet, NHTSA: NHTSA car crash impacts, NASCAR: NASCAR car crash impacts.
