CS230

Fast Brain Strain Evaluation in Head Impact

Xianghao Zhan
Department of Bioengineering
Stanford University
xzhan96@stanford.edu

Yiheng Li
Department of Biomedical Informatics
Stanford University
yhli@stanford.edu

Abstract

Risk of repetitive injury and post concussive symptoms increases if time elapses before diagnosis, calling for fast monitoring of brain strain after head impacts for early warning. Conventional methods typically involve Finite Element Analysis (FEA), which are both time-consuming and difficult to model efficiently. In this work, a novel method to evaluate brain strain in the head impact with deep learning is proposed. To train the model, we use kinematics given by the instrumented mouthguard in contact sports with DNN and LSTM. To model the brain as an entity, our model gives comparable results to previous publications. To show the element-wise brain strain, our models show similar results to those of FEA but with a significant speed increase (on the order of 3,500× faster). This project has the potential to help those engaging in contact sports better detect brain injury.

1 Introduction

While moderate and severe traumatic brain injury (TBI) has been widely studied[1, 2], mild traumatic brain injuries (mTBI), such as those common in repetitive head impacts in contact-sport, influences over 500,000 adolescents but usually goes subclinical and latent, lwhich leads to accumulative brain damage and may cause neurodegenerative diseases[3, 4]. An accurate and real-time visualization of brain deformation in head impact is much in need for doctors and managers in sport teams to better understand potential damage at specific brain region and how serious it is. Conventional Finite Element Analysis (FEA) is time-consuming (about 30 mins to visualize an impact), resource-consuming and difficult to model efficiently. A faster method which is easily accessible to players and medical professionals is required for more practical applications. Instead, deep learning provides a promising solution but there is no previous work in applying deep learning to tackle such problem. We are going to compare the deep learning results with the results from KTH model, a commonly-used FEA human head model in the study of traumatic brain injury [5, 6] and test the applicability of deep learning in a novel approach for the fast brain deformation visualization.

2 Related work

In the field of mild traumatic brain injury, Shaoju Wu et al.[7] has innovatively applied convolutional neural network(CNN) to estimate the maximum principal strain(MPS) of the whole brain, the corpus callosum and fiber strain of the corpus callosum. Although they did not present the distributional profiles and maps of brain deformation, this group of researchers creatively transformed the head rotational velocity profiles into images for input of the CNN and used convolutional neural network to reach an accurate and instant estimation of max principal strain and fiber strain, which is inspiring for this work. Able to model offline and predict online, machine learning approaches enable faster real-time evaluation of brain impact and brain deformation. With the current technology, i.e. Stanford

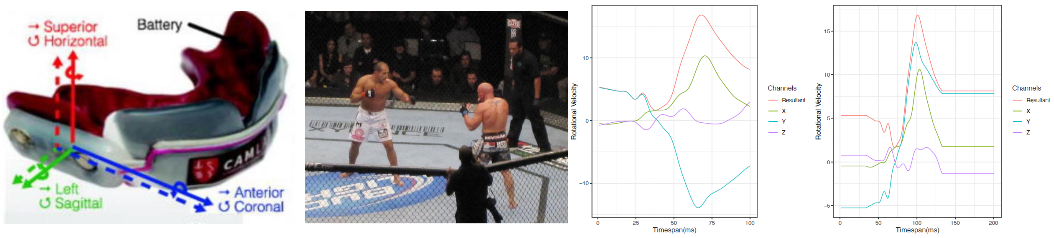

Figure 1: The Stanford MouthGuard [9] applied in mixed martial art [10] for data acquisition. Example raw signals and padded signals are also shown.

Instrumented Mouthguard, we could monitor the head impact in real-time. But the simulation of brain deformation with FEA takes hours to characterize the impacts one player suffers. The effect of head impact could not be known to the players and doctors in a real-time manner. With machine learning, the characterization can be fastened to give out real-time information about brain deformation in the form of distribution maps for better prevention of potential mild traumatic brain injury.

3 Data Source and Data Processing

3.1 Data Source

Our data set includes 79 mixed-martial-art(MMA) impacts and 517 American football impacts. The kinematic data of 79 MMA impacts and 518 American football impacts were recorded with Stanford Instrumented Mouthguard during regular matches. To protect the privacy of subjects, the Human Subject Protocol was approved by the Stanford, Trinity College and Institute of Technology Tallaght Panel. The data acquisition process was conducted according to the institutional review boards' guidelines and regulations.

The Stanford Instrumented Mouthguard measured head impact kinematic data from 6 degrees of freedoms, i.e. linear acceleration and angular velocity in three dimensions respectively, with a triaxial accelerometer and triaxial gyroscope. The sensing board was sealed with 3 layers of ethylene vinyl acetate (EVA) and the data were gathered using Bluetooth. More details could be found in related publications [5, 8]. Figure1 shows an example of kinematic data after preprocessing. Due to different time ranges of different sports, the timesteps for are 80ms in MMA and 100ms in American football.

We used the well-known KTH model to simulate the reference labels. This model was developed by the KTH Royal Institute of Technology [11]. In this model, brain, skull, scalp meninges, cerebrospinal fluid (CSF) and 11 pairs of bridging veins are included and modeled. This model has been widely used in the researches of head impact modeling [5, 6]. The simulations were performed on LS-DYNA for modeling each of the recorded impacts. The label MPS ranged from 0.0007 to 1.2303.

3.2 Data Processing

The dataset includes 79 MMA impacts and 517 American football impacts recorded by mouthguard. For each sample of the data, there are 6 channels of kinetics signals and a record timespan (80 milliseconds for MMA, and 100 milliseconds for American football). Although 6 channels of kinetics data are recorded, including 3 channels of linear accelerations (anatomic X, Y, Z axis) and 3 channels of rotational velocities (anatomic X, Y, Z axis), we only included 3 rotational velocity channels to train our model, because linear accelerations are known to have little impact on our target, brain strains. So the whole data set are of the format (1)MMA: [N, timespan, channels] = [79,81,3]; (2)American football: [N, timespan, channels] = [517,100,3].

3.2.1 Padding and Shifting

Due to the fact that the impact records from American football were not auto-triggered and the time span was cut-off manually by reviewing match videos, the start and end of each impact is likely to vary; the peak rotational velocity is an important indicator for brain strains; and that MMA data and American football data have different timespan, we shifted each of the sample series so that the resultant peak rotational velocity is synchronized. As shown in Figure1, This synchronization is done by creating a 200 millisecond time series for each sample, fix the resultant peak rotational velocity at 100ms time point, and then pad the rest of the time series assuming 0 acceleration (no outside impact). By padding and shifting, we want to mimic the situation that each impact took place after 100ms of record, thus reduces the variance across data. Similar data processing procedure of this problem has been tested to be beneficial to model learning, and unifies data timespan. Mechanical information was used to remove the linear acceleration because of their negligible effect on MPS.

3.2.2 Dimensionality Reduction

From KTH model, we get brain maximum principle strains (MPS) for the whole brain, with totally 4124 elements, denoting different regions in the brain. However, the strains from adjacent elements of the brain is highly correlated. So we used dimensionality reduction method principle component analysis (PCA), extracting 10 major components from the training set that explained over 90% percent of 4124 dimension data variance, to optimize the model structure and training by reducing the output label of the models to be 10. In training set, the original data (shape=[M,4124]) were standardized and principle component analysis were performed to gain 10 principle components (shape=[N, 10]), and batch normalization were performed during training. When testing, standardized principle components are predicted, the original 4124 elements were reconstructed using training set mean and standard deviation, along with reverse transformation of PCA.

3.2.3 Feature Engineering

Though multiple methods and efforts were meant to generalize model acceptable data format while keeping consistency across data, the amount of inconsistency reduced is unknown to us. Also, while we were inputing one value for every milliseconds of each channel, it is often considered that only several important time points and features from input data have considerable impact on the model output, while most other inputs are noises. So, instead of simply taking the whole time series as input, according to previous publications [12, 13] in machine learning biomedical signal processing and the intuitive ideas based on the measured kinematic signals, we extracted the following 6 types of features for each of these 6 time-signals $a_x, a_y, a_z, \omega_x, \omega_y, \omega_z$, as was denoted as $f(t)$ in the following definitions: 1) Maximum value: $max[f(t)]$; 2) Minimum value: $min[f(t)]$; 3) Integral of the time-signal: $\int f(t)dt$; 4) Integral of the absolute value of time-signal: $\int |f(t)|dt$; 5-6) Exponential Moving Average of Signal Derivative: $E_a = [min(y(t)), max(y(t))]$

The discrete sampling exponential moving average was given by the following definition:

$$y(t) = (1-a)y(t-1) + a(f(t) - f(t-1)) \tag{1}$$

The smoothing coefficient, a was calculated by $a = \frac{1}{SR}$. Such that, $y(1) = af(1)$. $SR = 1000$ was set as the sampling frequency. E_a contained the minimum and maximum values of the exponential averages of each of the 6 time-signals. Feature engineering was done on MATLAB® R2019b. Then, an engineered feature matrix was constructed with 596 impacts and 36 variables.

4 Model Architecture and Optimization

Besides feature extraction, the data processing is based on Keras in Python. Evaluation metrics include: R^2, mean absolute error(MAE), root mean squared error(RMSE).

4.1 95% MPS for Entire Brain

Initially, to be comparable to existing literature, a model of 95% MPS as a single prediction of brain deformation characterization was constructed. This used the ninety fifth percentile value of the KTH element values for MPS. This approach regarded the whole brain as a single object and output one generally recognized metric to characterize the overall brain deformation. We split the data into train:test = 4:1 and among the training samples, train:validation was 9:1. Training set was data augmented by adding noises abiding by normal distribution with zero mean and standard deviations of 0.01, 0.02, 0.05 times of feature standard deviation.

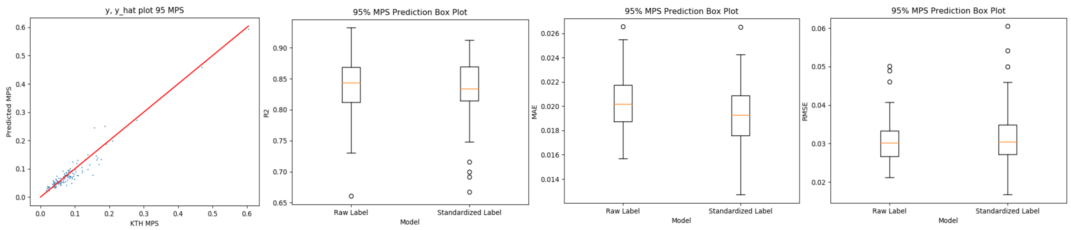

Figure 2: Results of whole brain strain evaluation(95 percentile MPS): An example prediction-truth relationship; R^2, MAE, $RMSE$ of the model predictions over 50 repeats with random initialization and random data set splits.

We built a fully-connected neural network for this task based on engineered features. To make comparison, we tested the cases when the training labels were z-normalized and not. With recursive tests on validation set, the best model structure and hyperparameters were: nodes in layers: Input 36, Layer 1: 60, Layer 2: 30, Dropout: 0.5, Output: 1; Initialization: random normal with std 0.05; L2 regularization: 0.006 for 2 hidden layers; Activation: ReLu; Learning rate: 0.0003, decay: 1e-7; Loss function: mean squared error. Epoch: 600; Optimizer: Adam. We repeated the model training and evaluation for 50 times with different random train/val/test splits and random initialization. The results were shown in Fig.2. According to the results, label standardization does not play an important role in whole brain strain metric prediction. We compared our results with previous publication [7], which showed that our model reached higher accuracy than most of the models and comparable to the reported best model (R^2 ranged from 0.6 to 0.9, $RMSE$ ranged from 0.03 to 0.06). We also tested LSTM and DNN models that directly used padded signals as input, but the results were much worse with R^2 close to zero. A potential reason may be that the data were not of enough quality for the LSTM to capture the features automatically. To predict the whole brain strain metric based on a small and noisy dataset, aggregating the temporal information may be a wiser choice to generalize the signals with reduced dimensionality.

4.2 MPS for All Brain Elements

In this task, we built 4 models: DNN with engineered features, DNN with padded signals as input and with/without PCA, LSTM with padded signals as input and with PCA. The model details and results are shown below.

1. DNN with Engineered Features: The details of this model were: Input: 36 features. Output: 4124 MPS values. Labels were z-normalized based on training set mean and std. Architecture: Input 36, Layer 1:120, Layer 2: 480, Dropout 1: 0.5, Layer 3: 1000, Dropout 2: 0.5, Output Layer: 4124. Initialization: random normal with 0.05 std. Regularization: L2, default(0.01). Learning rate: 0.0007 with decay 1e-7. Optimizer: Adam. Activation: ReLu. Batch size: 128. Loss Function: Mean squared error.

2. DNN with Padded Signals: The details of this model were: Input: 603 (flattened signals from 3 channels). Output: 4124 MPS values. Labels were z-normalized based on training set mean and std. Architecture: Input 603, Layer 1:200, Layer 2: 50, Output Layer: 4124. Initialization: Xavier. Learning rate: 0.0001. Optimizer: Adam. Epoch:100 Activation: ReLu. Batch size: 64. Loss Function: Mean squared logarithmic error.

3. DNN with Padded Signals and PCA: The details of this model were: Input: 603 (flattened signals from 3 channels). Output: 10 PCs. Labels were z-normalized based on training set mean and std before PCA. Architecture: Input 603, Layer 1: 100, Layer 2: 30, Output Layer: 10. Initialization: Xavier. Learning rate: 0.00003. Optimizer: Adam. Epoch:200 Activation: ReLu. Batch size: 64. Loss Function: Mean squared logarithmic error.

4. LSTM with Padded Signals and PCA: The details of this model were: Input: (201,3). Output: 10 PCs. Labels were z-normalized based on training set mean and std before PCA. Architecture: Input (201,3), LSTM Layer: 100, FC Layer 1: 50, Output Layer: 10. Initialization: random normal with 0.05 std. Learning rate: 0.001. Optimizer: Adam. Epoch:200 Activation: ReLu. Batch size: 64.

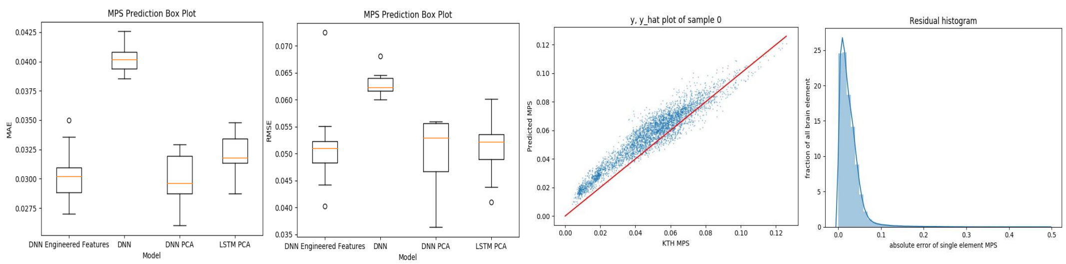

Figure 3: Box plots evaluation of the mean absolute error and root mean squared error of 4 types of models in MPS prediction of all brain elements. Example prediction of the first test sample and error histogram of the best model.

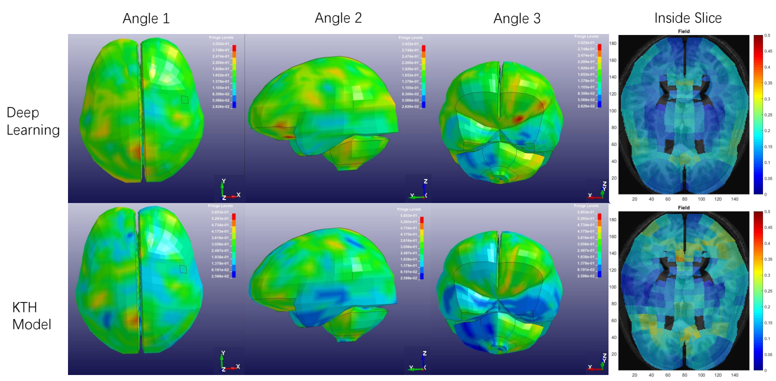

Figure 4: An example 3-D visualized result of brain impact from 3 angles based on LS-prepost.

We designed a customized loss function that based on mean squared error but with weighted mean that emphasize on the more important components of PCA, in order to let PCA-predicting models to yield more accurate prediction. the loss function is defined as follows:

$$L(Y_{PCA}, f(X)) = Var \times ESS \times (Y_{PCA} - f(X))^2$$

Where ESS is the explained variance by each principle component, Var is the variance of each principle component. We repeated the process for 10 times for each model based on different random initialization and random data set splits. The comparison results were shown in Fig.3. An example 3D impact visualization result was also shown in Fig.4.

One of the vulnerabilities is its incapability of dealing with time series shift. For each lstm node, the trained model fixed the parameters whether each gate should be remember or forget. However, as our data's data input's important time points may vary, even after shifting and padding, the model may has difficulty to decide which time point is important pass on the information

5 Conclusion and Future Work

This project proposes a deep learning method to characterize brain strain in head impact with head kinematics. Our single-metric for whole brain model gave results comparable to existing literature [7]. Additionally, we built MPS predictors for all brain elements and gave similar results to that from KTH model. The deep learning models were able to give the brain strain for every element in real-time within 0.5 seconds, with a speed increase of over 3500$\times$ when compared with the finite element analysis that usually takes 30 minutes to calculate. The current accuracy is still not very good. In future work, more data will be generated by directly simulating impact kinematics to generate data with higher quality. Meanwhile, CNN and DNN with FFT preprocessed signals could be used as new input to test for potential improvement.

6 Contributions

Xianghao Zhan conceived the project, acquired data, did literature review and simulation to get labels, engineered features and did the entire brain MPS(95% MPS) modeling, optimization and evaluation, final visualization. Yiheng Li did the majority of fundamental coding and built pipelines for data preprocessing, model fitting, model evaluation and visualization, padded and shifted the signals, did the majority of element-wise prediction modeling and optimization including DNN, DNN/PCA and LSTM/PCA and designed customized loss function based on this problem. The preliminary models were built by Xianghao and Yiheng together.

7 Code

`https://github.com/xzhan96-stf/Fast-Brain-Strain-Evaluation-in-Head-Impact.git`

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