Data Analytics of Mild Traumatic Brain Injury Kinematic and Clinical Analysis

Abstract:
The relationship between specific closed- head injury kinematics ï such as peak angular velocity, minimum angular acceleration, and positive acceleration duration ï and outcomes after mTBI is currently unknown. During the first round of Doherty funding, we explored the relationship between injury kinematics, acute recovery times, and neuropathology after a mTBI in swine. In addition, we completed a retrospective analysis of archived data that were generated with a porcine model of closed-head diffuse rotational acceleration mTBI. After that, machine learning and data analytics techniques were applied to determine the most significant acute recovery parameters in animals experiencing a mTBI, so an injury kinematics model was developed to relate injury kinematics to the standing time, extubation time, recovery time, and apnea time parameters

Research Objectives:
In the first part of the study, we applied several machine learning and data analytics techniques to determine the most significant acute recovery parameters in animals experiencing a mTBI. In addition, we analyzed how injury kinematics affected the acute recovery parameters.
During SURE 2024, we will continue this study in order to utilize the developed injury kinematics model in a clinical setting as we believe that individual kinematics could be instrumental in developing translational diagnostics for clinical mTBI. Therefore, the ultimate goal is to analyze and discover certain patterns and trends related to the pathological and functional parameters observed in clinical mTBI.
Next, we will time augment the mTBI image data (MRI and X-ray images) with genetics and blood data as this will help in diagnosis and medications prescribed by neurologists, MDs, and other healthcare professionals.

Approach/Methodology
Scientific Approach and Impacts:
Sensitivity Analysis
The connection between each of the kinematic features and the injury target features (standing time, extubation time, recovery time, and apnea time), hereafter referred to as target features, was examined using self-organizing maps (SOMs). During training, SOMs learn to cluster data based on similarities in one or more dimensions. Figure 1 shows the clusters formed when a SOM is trained on the experimental data from an mTBI dataset (Wofford et al., 2021). The clustering was done using the MeanShift algorithm in the scikit-learn python package. Negative controls were excluded from this analysis because the separation between positive and negative samples was too great and led to trivial results where all points were clustered based on whether they were positive or negative controls. Altering the dataset by removing or duplicating certain features and then observing the effects on the resulting clusters can indicate which features are most important to the clustering tendency of the dataset. If the clusters have significantly different values of the target features, this can suggest that the kinematic feature in question may be connected to the target feature.

Figure 1. SOM clustering of kinematic features without manipulation. After training a SOM on the

the right where the clusters are no longer present. The clusters in the left side plot could be used to differentiate two animal groups with significantly different standing times. Since the removed feature also removed the SOM's ability to cluster the two different groups of animals, the kinematic features were likely important in making this distinction.

Figure 2. Example of subtractive SOM analysis method. Kinematic features are removed one at a time, and the SOM model is retrained on the dataset. Changes in clustering are observed with loss of significant clustering, indicating a kinematic feature is important to the clustering tendency of the dataset.

Standing time

Each of the target features was observed independently. The shape of the clusters is always the same regardless of the target feature because the target feature is not an input to the SOM training, only the kinematic features. However, significant differences between the clusters may vary depending on the target feature. For the standing time analysis, once all the features were removed one by one from the dataset using the subtractive method described above, the four features in Figure 3 were found to have the most profound effect on the clustering tendency of the dataset. Because of this, they were given a higher importance score in Table 1.

Figure 3. SOM plots resulting from the removal of important kinematic features for discriminating standing times. Each subplot is titled with the kinematic feature removed from the dataset before retraining the SOM. Each cluster is labeled with the average standing time of the cluster. These plots show a significant reduction in clustering when compared to the original plot in Fifg w t TJETQq0.0sds7.2 0 612 792 reW

input data was also enhanced using a cluster labeling method. This cluster labeling method consisted of training a SOM on the input features and using the MeanShift algorithm to label the point according to their cluster. These cluster labels were then included as inputs into the regression model during training. In some cases, all of the kinematic features were used as inputs, whereas other models were trained only using the 13 most important features from SOM sensitivity analysis. Some models were trained using the features found to be most important in the original study that generated this dataset (Wofford et al., 2021).

TABLE 1. Evaluation of regression models trained on kinematic features.

Features included in analysis	Cluster labels	Target	Model Type	RMSE	R2
Important clustering features	Yes	Factor from included features			

mTBI. This helps both the student and faculty mentor to align a novel research agenda that has not been explored *a priori*

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Description of other funding you will be using related to your proposed research (Doherty Grant, Lasallian Research Grant, External Research Grant, Caterpillar Grant, etc.) and how 12;

- Mock Presentation Supervisor (Practice for Symposium)
- Other: 1) Principles of Scientific Communication
  2) Informational Interviewing Skills