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Classification Model for Discriminating Trunk Fatigue During Running

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Abstract—

Purpose: **Fatigue is often associated with increased injury risk. Many studies have focused on fatigue in the lower extremity muscles brought on by running, yet few have examined the relationship between fatigue of the core musculature and associated changes in running gait. To investigate the relationship between trunk fatigue and running dynamics, this study had two goals: (1) to use machine learning to determine which gait parameters are most associated with trunk fatigue; and (2) to develop a machine learning algorithm that uses those parameters to classify individuals with trunk fatigue. We hypothesized that we could effectively differentiate between the non-fatigued and fatigued states using machine learning models derived from running gait parameters.**

Methods: **Seventy-two individuals performed a trunk fatigue protocol. Lower extremity running biomechanics were collected pre- and post- the trunk fatigue protocol using an instrumented treadmill and 10-camera motion capture system.The fatiguing protocol involved executing a series of trunk fatiguing exercises until established fatigue criteria were reached. Gait variables extracted from the non-fatigued and fatigued states served as model inputs to aid in the development of the machine learning model that would distinguish between non-fatigued and fatigued running.**

Results: **The machine learning protocol determined three variables – stance time, maximum propulsive GRF and maximum braking GRF - to be the best discriminators between non-fatigued and fatigued running. The SVM with Bagging was the best performing model that discriminated between non-fatigued and fatigued running with an accuracy of 82%, precision of 77%, recall of 90%, and area under the receiver operating curve of 0.91.**

Conclusion: **The machine learning model was effective in classifying between non-fatigued and fatigued running using three gait parameters extracted from GRF waveforms. The ability to classify fatigue using these easy to measure GRF derived parameters enhances the ability for the model to be integrated into wearable technology and the clinical setting to aid in the detection of fatigue and potentially injury, as fatigue is often a precursor to injury.**

***Clinical Relevance*— This model has the potential to be implemented in a clinical setting to determine the onset of trunk fatigue through basic gait analysis, involving only the ground reaction forces. This model would be aimed toward injury prevention since fatigue is linked to increased risk of injury.**

I. Introduction

Muscle fatigue is a recurrent topic in relation to gait analysis, due to the impact is has on physical performance and the established link between fatigue and increased risk of injury. When discussing the effects of fatigue on gait, the common focus is on muscles in the lower extremity. However, more recent studies have shifted focus to examine the relationship between fatigue in the core musculature of the trunk and the resulting mechanical changes in the lower extremity. Olson (2009) examined this relationship by applying trunk extensor fatigue and analyzing changes in walking gait. The study showed that the applied fatigue had a significant effect on the muscle activation patterns but little to no effect on measured gait parameters [1]. This same line of thought, connecting trunk fatigue to changes in gait, has somehow not been well explored in running gait, which has more reliance on trunk motion compared to walking. However, other types of fatigue have been analyzed with running gait, showing significant changes in trunk flexion and anterior-posterior ground reaction force between normal and fatigued running [2-4].

The next step is to examine the difference between normal and trunk induced fatigue running to observe any significant changes in running gait brought on by this type of fatigue. This observation can help determine if there are gait parameter changes that are indicative of trunk fatigue. Researchers are constantly struggling to find objective measures to define fatigue, given the wide range in types of fatigue and the complexity of its onset. Traditionally participants rate their own exertion on a scale, but those scales are subjective measures of perceived exertion. However, if we can associate perceived exertion with physical changes in gait parameters, we can generate a quantitative model that is indicative of fatigue. Thus, this premise provided the foundation for this study in which fatigue was modeled using parameters extracted from changes in running dynamics measured before and after a trunk fatiguing protocol.

Previous studies have followed the same premise of relating changes in gait parameters to the perceived onset of fatigue during running and walking in the hopes of classifying fatigue [5-9]. Most of these studies [4-8] used inertial

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measurement units (IMUs) to collect data wirelessly and measured gait parameters as participants fatigued over time. One study decided to focus on the muscles themselves when quantifying fatigue, so they used surface electromyography measurements as their raw data for machine learning [9]. These studies all benefitted from previous works that describe the changes in gait from lower extremity running fatigue. Our current study differs in that there are not well documented changes in gait that have been associated with trunk fatigue.

Therefore, this study had two objectives: (1) to use machine learning techniques to narrow down which gait parameters are most representative of trunk fatigue in running gait; and (2) to develop and test a machine learning model that can classify participants as rested or fatigued using running gait parameters. We hypothesized that we could effectively differentiate between fatigued and non-fatigued states using machine learning models derived from running gait parameters.

II. Methods

A. Experimental Protocol

Seventy-two healthy controls; age: 25.5 ± 5.2 yrs; height: 1.8 ± 0.1 m; mass: 73.2 ± 14.9 kg; running speed: 2.7 ± 0.5 m/s performed a running protocol on an instrumented treadmill collecting at 1200 Hz (Bertec Corporation, Columbus, Ohio). A fifty-six retro-reflective marker set and a 10-camera motion capture system (Motion analysis Corporation, Santa Rosa, CA) were used to collect marker trajectories during the running protocol at a frame rate of 200Hz. Markers were placed following the same protocol as Noehren et al. (2013) [10]. Ground reaction force (GRF) data was simultaneously collected with the marker trajectory data during running.

Each participant performed two trials: one pre- and on post- trunk fatigue protocol. First, each participant ran at a self-selected speed until they verbally reported a perceived score of 14 on the 20-point Borg scale. Next, the participants performed the trunk fatigue protocol where they completed 20 mountain climbs while in a plank position followed by a core rotation exercise. The core rotation exercise required that the participants hold a 4.54 kg weight and then rotate their trunk to one side, flex their trunk, rotate to the other side, extend their trunk and then return to the middle. The exercises were repeated until the participants met two of the following three fatigue criteria which were 1) reaching 17 on the Borg scale; 2) display an inability to control their trunk during the rotation exercise; or 3) a 25% increase in the time to perform the 20 mountain climbers. Once the participants were fatigued, they immediately performed the post fatigue running protocol where they ran at the same pre-fatigue self-selected speed for 2 minutes.

B. Machine Learning Protocol

A total of 334 pre- and post- fatigue gait related variables were obtained from the experimental running trials for the 72 participants. The datasets were split into training and testing sets where 60% of the data was used for training and 40% for testing. The 60-40 split is often used for smaller datasets. The gait parameters were all standardized in the training and test sets before developing the classification algorithm. The standardization process involved adjusting each variable to have a mean of zero and standard deviation of one.

Data reduction was conducted by performing a grid search using a Random Forest classifier and assessing the area under the receiver operating curve (ROC). The resulting feature importance ratings helped reduce the dataset to three gait parameters that were used to differentiate between the pre- and post- fatigued conditions. The accuracy, precision, recall, and ROC area under the curve were considered at each stage to determine if there was a significant loss in performance with the reduction in the number of variables. A K-Folds cross validation strategy was used on the training dataset (k = 5) to make sure the algorithm was not overfitting the training set. Overfitting was evaluated by comparing the evaluated accuracy of the training set to the average accuracy for the K-Folds cross validation and measuring the standard deviation of K-Folds cross validation accuracy scores.

The Random Forest, SVM with a bagging strategy, K Nearest Neighbors (KNN), and a boosted decision tree were used to develop the models. The Random Forest had the benefit of rating feature importance, the KNN algorithm is simple and commonly used, and the Boosted Decision Tree and Bagging SVM are both commonly used to handle some of the limitations associated with small datasets. Each algorithm was run through a grid search to determine the variables that produced the best area under the ROC curve. Following the grid search, these algorithms were checked for overfitting using a Leave-One-Out cross validation strategy, evaluated by comparing the accuracy on the training set and the average accuracy of the cross validation. The resulting best models were then evaluated on the test data.

The metrics used for assessment included accuracy, precision, recall, F1 score, and area under the ROC curve (AUC). Accuracy represents how well the trained model performed on test data overall. The precision represents the proportion of true positive results over total positive results, where the positive result in this case is the fatigued case. The recall represents the proportion of predicted positive outcomes over the total number of actual positive outcomes. The F1 score is an aggregate of the precision and recall, giving a single result to compare the models. The area under the ROC curve shows how successful the model is at distinguishing between the classes, in this case normal and fatigued.

III. Results

Three parameters – stance time, maximum propulsive GRF, and maximum braking GRF - were extracted from the running dataset and served as the input features to the machine learning models. The Leave-One-Out cross validation strategy showed that none of the optimized models were overfitting the training data, all having a difference in training accuracy and mean cross validation accuracy of ≤ 8% (Table 1).

Table 1. The training data cross-validation results for each algorithm. Shows the accuracy for the algorithm to predict the training data and the mean accuracy from the Leave-One-Out cross validation.

Algorithm	Training Accuracy	Leave-One-Out Mean Accuracy
Boosted Decision Tree	84%	76%
K-Nearest Neighbors	77%	73%
Random Forest	76%	74%
SVM with Bagging	76%	74%

The SVM with Bagging algorithm outperformed the three other models across the board as it reported the highest accuracy, precision, recall, F1 score, and area under the ROC curve (Table 2). It was able to correctly classify nearly 82% of the test data and had a recall of almost 90%, showing that it correctly predicted fatigue in 90% of the participants that went through the fatiguing protocol. The precision was lower, at about 77%, but this was still the highest recall among the models. The high area under the ROC curve of 0.91 represents the algorithm's greater ability to distinguish between the two classes. The ROC curve for the top performing SVM model is shown in Figure 1.

Table 2. Comparison of the performance of the machine learning algorithms in classifying between the pre- and post- fatigue states.

Algorithm	Accuracy	Precision	Recall	F1	AUC
Boosted Decision Tree	80.0%	75.8%	86.2%	80.6%	0.85
K-Nearest Neighbors	78.3%	72.2%	89.7%	80.0%	0.88
Random Forest	78.3%	75.0%	82.8%	78.7%	0.88
SVM with Bagging	81.7%	76.5%	89.7%	82.5%	0.91

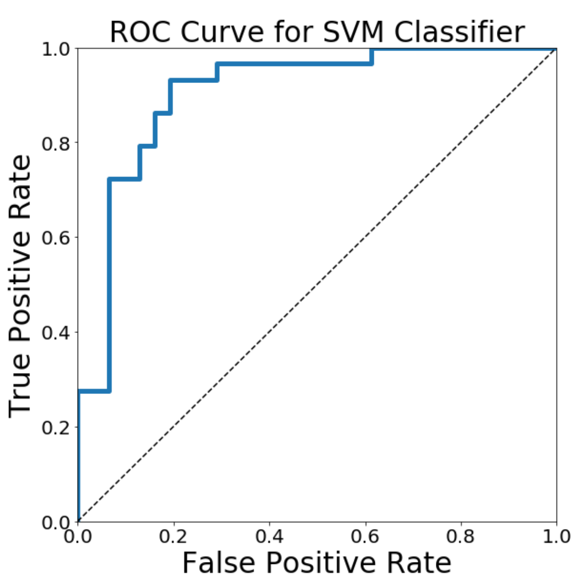

Figure 1. The ROC curve for the SVM Classifier with bagging , which showed the best result on the test data.

IV. Discussion

The objectives of this study were to determine the running gait parameters that are most representative of trunk fatigue and to develop a machine learning model that can classify trunk fatigue. The results supported the hypothesis as stance time, maximum propulsive GRF and maximum braking GRF were determined to effectively differentiate between the fatigued and non-fatigued states with an accuracy of 82% and recall of 90%. These three parameters were deemed to be highly representative of trunk fatigue despite not being direct measures of trunk motion. Their ability to classify trunk fatigue can be linked to their ability to measure changes in center of mass that are connected to trunk flexion. The implementation of machine learning made it possible to identify the link between these GRF based measures and trunk fatigue that resulted in the development of a quantitative model of fatigue. Overall, this model is a step forward in classifying this type of fatigue quantitatively and by analyzing the parameters involved it could provide a better understanding of the physiological effects of fatigue on running biomechanics.

The changes in propulsive and braking GRF can be directly related to the change in center of mass associated with increased trunk range of motion, which has been routinely observed in previous fatigue studies [2-4]. The change in center of mass, caused by the change in the leaning of the trunk, leads to a shift in the angle of the net GRF, leading to a greater force in the anterior-posterior direction as the trunk flexion increases [11-13]. This change in running strategy has also been shown to have influence on the knee and ankle, helping to decrease loading at the knee without increasing the activity of the ankle plantarflexors [14,15]. Given that trunk flexion was not measured in this study, the propulsive and braking GRFs served as surrogate measures for trunk flexion. While future adaptations of the model could include trunk flexion as a model parameter, an advantage of the current model parameters is that they can be measured from GRF waveforms alone. Stance time and maximum propulsive and braking GRFs can all be easily measured using wearable pressure insoles, which eliminates the need for expensive motion capture equipment. Furthermore, embedding this model into wearable sensors enhances the model's utility as a diagnostic tool as it can not only be used to detect fatigue but could potentially be used for injury detection and/or prevention as fatigue often precedes injury.

Stance time was found to be indicative of fatigue. Given that individuals were running at the same self-selected speed both pre- and post- fatigue, it is evident that individuals were adopting an alternate running strategy during the fatigued state. Once fatigued, the participants spent significantly less time with their feet on the ground suggesting that individuals adapted to the fatigue by increasing their stride frequency. This gait adaptation adopted in response to trunk fatigue differed from other fatigued induced running gait adaptations. Previous studies that investigated changes in gait biomechanics due to fatigue after running for long distances or at high rates of speeds found that stance time either stays the same or increases post fatigue [4, 16]. In this case, since the trunk muscles were fatigued and unable to help with the attenuation of loading effects, the participants may have adapted their running biomechanics by limiting their time on the ground, which has shown promise in decreasing impact loading [15]. These findings are significant because it indicates that different gait strategies are adopted in response to different types of fatigue and that our model possesses the sensitivity to detect trunk fatigue.

A limitation of the study was not including a trunk flexion measure. Given that the objective of the study was to generate a quantitative model to detect trunk fatigue, it is likely that trunk flexion would be impacted and thus potentially serve as a strong classifier. However, the measures included in the study were sensitive to changes in trunk position and produced a strong, accurate model. Moreover, the fact that the resulting metrics were extracted from the GRF waveforms was advantageous because it meant that the model could be easily integrated into wearable technology to aid in the clinical and diagnostic capabilities of the model.

V. Conclusion

This study produced a machine learning model that can effectively delineate between exerted and normal running patterns after implementation of a trunk fatigue protocol. The model showed an accuracy of 82%, and a recall of 90%. The model accomplishes this using only three gait parameters that can all be derived from GRF data, including maximum propulsive GRF, maximum braking GRF, and stance time. The use of only GRF data makes this model well suited for clinical applications since it does not require data from a motion capture system for classification. The strength of the model shows that the model parameters are highly correlated with the presence of fatigue. The maximum propulsive and braking GRF parameters are linked with increased trunk flexion, which is a common result observed during fatigued running. In most cases increased trunk flexion can be a compensatory strategy to help alleviate forces on the knee and ankle through the shift in center of mass, but in this study, adaptive changes in response to the trunk fatiguing protocol were observed as an increase in stance time and the associated step rate. These findings highlight the effectiveness of this work in both its ability to classify fatigued running and the critical insight the model parameters provide regarding the changes that individuals adopt in response to trunk fatigue that will aid in the clinical implementation and utility of this model.

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