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Classification Model for Differentiating Post-ACLR Individuals Using Loading Rate Variation

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Abstract*— In post-ACLR individuals, gait variability often represents the presence of altered motor control. Quantifying variable limb loading is challenging, yet nonlinear analyses have been successful in detecting changes in gait variability due to altered motor control. Here, nonlinear metrics were derived and used to train multiple machine learning models to classify between healthy controls and post-ACLR individuals. The metrics were extracted from individuals' vertical ground reaction force data during a fast-walking trial as variable limb loading is exacerbated when the system is stressed and being challenged. It was hypothesized that effective differentiation between healthy control and post-ACLR individuals would be achieved using machine learning models derived from limb loading rate variability measures. Seventeen healthy control and fourteen post-ACLR participants with measured between-limb loading rate asymmetries completed the walking protocol. Ground reaction force data was collected on an instrumented treadmill where they performed walking trials at 1.5 m/s. Nonlinear limb loading rate measures extracted from the healthy controls and post-ACLR participants' data served as inputs to the models in order to train them to distinguish between the two states. A Decision Tree Classifier that utilized a bagging strategy was the best model for distinguishing between healthy control and post-ACLR participants. The model was successful in classifying participants, reporting an accuracy score of 73%, precision score of 100%, and an AUC score of 0.77, despite the smaller dataset. The ability to detect and classify post-ACLR loading rate variation has significant clinical implications, as these methods could be implemented in clinical settings to diagnose pathological limb loading dynamics and/or altered motor control.

***Clinical Relevance*— This classification model can be easily integrated into the clinic to help diagnose pathological limb loading based solely on vertical ground reaction forces and can aid clinicians in providing data-driven metrics to help inform rehabilitation decisions.**

I. Introduction

Gait variability as emerged as a strong indicator of pathological movement. In post anterior cruciate ligament reconstruction (ACLR) individuals, gait variability often represents altered motor control [1], [2]. Altered motor control is problematic as it can contribute to detrimental limb loading and the initiation and progression of knee osteoarthritis [3]–[5]. Therefore, accurately characterizing loading rate variability is important. Research has shown that increased gait variability signifies a disruption of ordered movement, a loss in gait complexity, and an inability to adopt and store new movement patterns in response to changing conditions [2], [5], [6]. Thus, this study sought to develop a model using nonlinear and linear metrics that can characterize changes in gait variability to classify between healthy controls and post-ACLR individuals.

Post-ACLR individuals often suffer from impaired proprioception, which is a consequence of reduced motor control [1], [7], [8]. Therefore, increased loading rate variability is likely to be found in the post-ACLR population, however, quantifying and accurately representing this variability can be difficult due to their unique compensatory gait dynamics. For instance, it has been found that both post-ACLR individuals' reconstructed and non-reconstructed limbs produce increased limb loading during walking, suggesting that impaired motor control does not exclusively affect the reconstructed limb [8]. Thus, post-ACLR individuals' limbs can be classified as overloaded or underloaded based on loading rate patterns found during baseline or pre-screening walking trials. By using this approach to identify the overloaded limb, it will increase the likelihood of grouping limbs with similar motor control and aid in investigating the relationship between limb loading rate variability and motor control.

Quantifying gait variability is challenging due to the complexity of gait. Yet, nonlinear analyses are well suited for capturing gait complexity [6]. Poincaré analysis, approximate entropy, the Lyapunov exponent, and sample entropy are all nonlinear analyses that have demonstrated the ability to evaluate the underlying regularity, predictability, and complexity within repetitive motion [5], [6], [9]–[11]. Here the nonlinear based metrics will serve as inputs into the machine learning algorithms to create a model to classify between healthy and pathological limb loading during fast walking. This model is significant because it not only identifies pathological gait but will highlight how their impaired motor control disrupts their limb's ability to adopt and sustain healthy gait mechanics when placed under greater physical demand.

This study sought to develop a model using machine learning algorithms to classify healthy and pathological limb loading rate variability during gait in healthy controls and post-ACLR individuals. Successful classifications would lead to better understanding of motor control changes in pathological populations and would suggest that post-ACLR individuals' limbs continue to suffer from impaired motor control. It is hypothesized that effective differentiation between healthy control and post-ACLR individual's limb loading will be achieved when using machine learning algorithms derived from nonlinear and linear variability metrics. This work will provide further insight into post-ACLR individuals' motor control that could identify potential injury risks and long-term gait and joint health.

II. Methods

A. Experimental Protocol

Seventeen healthy control participants (mean ± standard deviation; age: 20.6 ± 2.0 years; height: 1.7 ± 0.10 m; mass:

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74.9 ± 14.4 kg; 7 females and 10 males) and fourteen post-ACLR participants (mean ± standard deviation; age: 21.6 ± 3.0 years; height: 1.7 ± 0.11 m; mass: 73.3 ± 16.8 kg; time since reconstruction 43.5 ± 29 months; 8 females and 6 males; graft type: 7 hamstring, 6 patellar tendon, 1 quadricep, 1 gracilis) with measured between-limb loading rate asymmetries completed the walking protocol. Each participant provided written consent to participate in the study in accordance with the University of Connecticut institutional review board.

The participants performed the walking protocol during a single session, on a Bertec split-belt instrumented treadmill (Bertec Corporation, Columbus, Ohio). Ground reaction force data was collected at 1200 Hz. An initial 5-minute warm-up walking trial was conducted to allow participants to become accustomed to the equipment. After the participants were acclimated to the instrumented treadmill, they each performed one 5-minute walking trial at 1.5 m/s. Vertical ground reaction forces were extracted from the overloaded limb of post-ACLR individuals and the right limb of the controls, and loading rates were then calculated for each stride.

B. *Metrics to Detect Limb Loading Rate Variability*

Considering the complexity of gait, an assortment of nonlinear variability metrics were used in conjunction with one linear metric, standard deviation. The nonlinear variability measures utilized were short-term and long-term variability metrics derived from Poincaré analysis, approximate entropy, the Lyapunov exponent, and sample entropy. The short- and long-term variability measures reflect stride-to-stride and overall task variability, respectively, and are calculated using the standard deviation of the entire data set and the standard deviation of the differences between data points [12]. Approximate entropy was used to measure the regularity and predictability of the data [5]. Lyapunov exponent was computed to quantify the underlying structure of variability during periodic movement [6]. Sample entropy is derived from approximate entropy and similarly reflects predictability and complexity, although it is not as influenced by length of the data series [11]. All metrics were calculated using a custom MATLAB code (MATLAB R2019a, The MathWorks, Inc., Natick Massachusetts, USA).

C. *Machine Learning Protocol*

The walking trials yielded 20 gait variability metrics for each of the 31 participants. The data was split into training and testing subsets, where the training subset accounted for 65% of the data and the testing subset accounted for 35%. This 65-35 split was used because the dataset is small, and similar splits are often used for small datasets. The variability metrics in each of the training and testing subsets were standardized, such that each metric had a mean of zero and a standard deviation of one, before utilizing them in the classification modalities.

The classification models utilized included a Decision Tree Classifier (DTC), a Support Vector Machine (SVM), a K-Nearest Neighbors (KNN) model, and a K-Means (KM) model. Each algorithm was performed with a bagging strategy to overcome the limitation of a smaller dataset. Furthermore, the DTC and SVM models with bagging were chosen because of their ability to deliver high accuracy scores, and the KNN and KM were used because of their simplicity and computational efficiency. Each model was passed through a grid search that evaluated the model's performance based on optimized area under the receiver operating curve (ROC). Lastly, a Leave-One-Out cross validation strategy was implemented for each of the classification models to ensure overfitting of the training set was not occurring. Evaluation of overfitting was performed by comparing the accuracy found on the training set to the average accuracy found at each fold of the cross validation and computing the standard deviation of the accuracy scores from the cross validation.

The metrics used to assess each classification method's performance on testing data were accuracy, precision, recall, and F1 scores, as well as area under the ROC (AUC). These evaluations were chosen as accuracy reflects overall performance on testing data, precision represents the percentage of true positive results to total positive results, recall reflects the percentage of predicted positive outcomes to the total number of actual positive outcomes, and F1 sums precision and recall to a more direct method of comparison. Furthermore, the AUC score reflects the model's success in discerning between classes, which here are "healthy" and "ACL".

III. RESULTS

The performance of each of the classification algorithms revealed that each model has acceptable potential to appropriately discern healthy controls and post-ACLR individuals based upon their limb loading rate variability metrics. Both the Decision Tree Classifier and K-Nearest Neighbors models had high training accuracy, but much lower cross validation accuracy (Table I). Based on the Leave-One-Out cross validation results, it is possible that overfitting may have been occurring.

TABLE I. THE TRAINING AND CROSS-VALIDATION RESULTS FOR EACH CLASSIFICATION MODEL, ALL OF WHICH IMPLEMENTED A BAGGING STRATEGY. SHOWN IS 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
Decision Tree	80%	50%
SVM	55%	55%
K-Nearest Neighbors	90%	70%

The Decision Tree Classifier (DTC) with bagging outperformed the other two models, reporting higher accuracy, precision, F1, and AUC scores compared to the SVM and K-Nearest Neighbors models (Table II). It recorded an accuracy score of nearly 73% on the testing data, as well as a precision score of 100%, highlighting the model's ability to correctly discern post-ACLR individuals despite the incredibly small dataset. Furthermore, the relatively high AUC score of 0.77 reported for the DTC, derived from the ROC curve (Fig. I), represents the model's greater ability to distinguish between classes.

TABLE II. COMPARISON OF THE PERFORMANCE OF THE MACHINE LEARNING ALGORITHMS, ALL OF WHICH UTILIZED A BAGGING STRATEGY, IN CLASSIFYING BETWEEN THE HEALTHY AND ACL STATUSES.

Algorithm	Accuracy	Precision	Recall	F1	AUC
Decision Tree	72.7%	100%	40.0%	57.1%	0.77
SVM	54.5%	27.2%	50.0%	35.3%	0.53
K-Nearest Neighbors	54.5%	53.6%	53.3%	53.0%	0.53

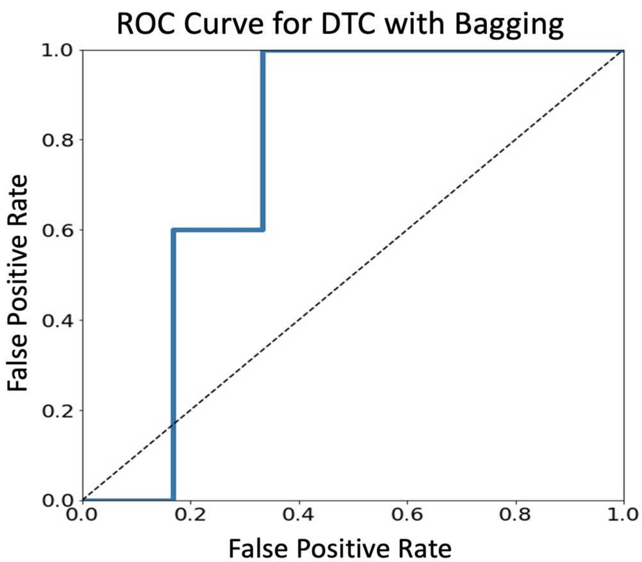

Figure 1. The ROC curve for the Decision Tree Classifier with bagging, which showed the best performance on testing data.

IV. DISCUSSION

This study successfully implemented classification models to differentiate between healthy control and post-ACLR participants using limb loading rate variability metrics. Consistent with the hypothesis, a model was derived that was effectively able to classify healthy control and post-ACLR individuals, despite the small number of participants. The findings demonstrate that post-ACLR individuals' overloaded limbs exhibit significantly different limb loading rate variability compared to healthy controls at the 1.5 m/s walking speed, indicated by the models' ability to distinguish between participants. This also illustrates that post-ACLR individuals struggle to consistently load their limbs and suggests that the overloaded limb likely continues to suffer from altered motor control uncovered at faster walking speeds. The ability to distinguish and discern between healthy control and post-ACLR participants based on limb loading rate variability indicates that machine learning methods could potentially serve as a valuable tool to identify altered motor control in pathological populations.

Increased gait variability is a result of reduced motor control [2], [5], [6]. The altered loading rate variability found in post-ACLR individuals' overloaded limbs represents changes in motor control and gait performance, which impact the limbs' ability to adopt and maintain healthy limb loading dynamics. Furthermore, these differences in loading rate variability are likely indicative of lingering neuromuscular impairments that contribute to the altered motor control and inhibit consistent, healthy limb loading. Inconsistent limb loading is concerning because it leads to uneven loading across the knee, which contributes to the initiation of cartilage degeneration [7], [8], [13]. The ability to distinguish between healthy and pathological states using machine learning methods that used nonlinear variability metrics to quantify and detect alterations in motor control highlights the utility of machine learning as a gait assessment, rehabilitation, and diagnostic tool.

The success of the classification model's ability to differentiate between healthy control and post-ACLR participants emphasizes how machine learning can be used to contribute to post-ACLR treatment and rehabilitation. It is well documented that gait deficits and biomechanical compensation strategies can be present in post-ACLR individuals throughout rehabilitation. For instance, diminished quadriceps function, impaired rate of torque development, and the adoption of rigid, "cautious" gait are all a consequence of unresolved neuromuscular dysfunction that contribute to altered limb loading variability [14]–[17]. In this study, the average time since ACL reconstruction surgery in the post-ACLR individuals was approximately 4 years and the model detected pathological limb loading throughout the post-ACLR participants. This is concerning as it indicates that long-term post-ACLR individuals are still demonstrating altered gait and are at an increased risk of further injury.

However, the integration of classification models into rehabilitation protocols could be beneficial as they can help to identify underlying motor control deficits which can aid clinicians in making well informed rehabilitation strategies and decisions. Specifically, the implementation of this classification algorithm into diagnostic and rehabilitative environments can aid clinicians in identifying subtle gait abnormalities or deficits, like pathological loading rate variability, that otherwise would remain undetected. Furthermore, with the rising advancement and use of wearable inertial measurement units (IMUs), and considering that few clinics have split-belt treadmills with embedded force plates, the algorithm could be adapted for classification based on ground reaction force outputs from wearable force sensors and IMUs.

This study did have limitations. A limitation of this study is the small dataset and number of participants. With only 17 healthy participants and 14 post-ACLR participants, accurately and appropriately training machine learning models for classification is challenging. However, with the high accuracy and AUC scores reported for the Decision Tree Classifier that applied a bagging strategy, the results are promising, and the addition of more subjects would aid in decreasing the discrepancy found between training and cross-validation accuracies. Another limitation of the study is that the participants performed the walking protocol on an instrumented treadmill rather than overground. Considering the treadmill controls for gait speed, variables associated with gait speed could vary between walking on the treadmill and walking overground. However, prior research has shown that biomechanical metrics can be generalized to overground walking, and since all the participants walked on the same treadmill, the comparison of gait dynamics across limbs is also appropriate [12], [18], [19].

V. Conclusion

This study successfully produced a classification model that could differentiate and classify healthy control and post-ACLR participants according to their gait variability during fast walking. The model reported an accuracy score of 73% and an area under the ROC curve score of 0.77, which are promising scores considering the smaller dataset. Furthermore, the model was successful in using only a handful of nonlinear variability metrics calculated from ground reaction force data alone. Thus, this model is well suited for clinical applications, as it can be used diagnostically and does not require additional data, such as from a motion capture system. The model's success in differentiating between healthy control and post-ACLR participants' limbs reveals that post-ACLR individuals are adopting altered motor control strategies at faster walking speeds. This indicates that the altered gait variability, or their decreased ability to maintain consistent limb loading, is masked during slower speeds and is exposed when the individual's neuromuscular system is challenged by the faster walking pace. The findings of this study emphasize the utility of this machine learning to both classify between healthy and pathological gait dynamics and provide critical insight into the gait adaption and motor control strategies that post-ACLR individuals employ during fast walking.

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