Classification of Spatiotemporal Features of Time Series in Post-Fatigue Gait

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Abstract— **Muscle fatigue affects gait to the point of causing changes in your patterns. People with muscle training have more endurance and better recovery time from muscle fatigue than people without training. The study compared three classification algorithms in the analysis of gait data under normal conditions and different levels of muscle fatigue. Spatio-temporal data from a group of people who do and do not do weight training were analyzed. The result showed that the classification accuracy of the k-nearest neighbor algorithm had the best result with 86.78% accuracy. The results indicated by the classification algorithms show a difference in the muscle fatigue recovery process between the groups, similar to the clinical results discussed in the literature.**

Keywords— **Muscle Fatigue, Classification, kNN, Random Forest, SVM**

I. INTRODUCTION

Muscle fatigue can be explained by the loss of contractile capacity of the muscle as a result of muscle activity and the decrease in the ability to produce force as a result of continuous or repeated activation or intense work [1]. Severe muscle fatigue can contribute to the increase in the occurrence of falls accidents [2], interruption of the afferent feedback system, alteration of joint awareness [3], alteration of reflexes and changes in the pattern of muscle activation [4].

According to [5], gait adjustment as a consequence of muscle fatigue seems to be influenced: by the muscles involved in fatigue; by the type and duration of the exercise; by the pre-existing physical condition and by physiological differences between the sexes. The calf muscles, in particular, play an important role in postural control and locomotion, and muscle fatigue in this region can significantly influence gait behavior.

Other studies also seek to observe the impacts that muscle fatigue causes on postural control and gait [6], [7].

Also, it is known that subjects without physical conditioning, referring to activities related to muscle condition, can reach the degree of muscle fatigue more quickly than active subjects. Weight training has been widely adopted by people with the aim of increasing muscular endurance and also in rehabilitation protocols.

The objective of this study is to assess the classification performance of different machine learning algorithms by verifying gait data from groups of people who practice weight training and non-practitioners, under normal conditions and at different levels of muscle fatigue. Although statistical methods can also be used to establish a classification of groups, the use of machine learning allows a computational gain after training the model. This advantage is most evident in large databases. Furthermore, a set of characteristics can be analyzed with the trained model, while in statistics there would be a need for a re-analysis.

Our hypothesis is that the effects of fatigue and the level of muscle recovery can affect the spatio-temporal characteristics to the point of allowing the classification between a trained and untrained person. This study may contribute to the construction of intelligent applications that seek to help health and physical education professionals, making it possible to identify the levels of fatigue between people with and without experience during muscle physical training, allowing strategic decision-making during training.

II. METHODS

A. Subjects

Forty-one young women, 20 weight training practitioners (TG) (22.00 ± 3.27 years; 1.60 ± 0.04 m; 57.10 ± 6.35 kg) and 21 non-practitioners (UTG) (21.76 ± 3.01 years; 1.62 ± 0.05 m; 62.35 ± 8.50 kg) participated in this study. The TG group was composed of women who had performed weight training for less than 12 months. The inclusion criteria for the participants were: (i) age between 18 and 27 years; (ii) not present functional impairment, pain or orthopedic pathology in the last six months; (iii) not present any cardiovascular, pulmonary or neurological disease. Participants were instructed not to perform strenuous physical activity within 48 hours of data collection and not to consume stimulants.

The study was conducted in accordance with the Declaration of Helsinki after local approval by the Ethics Committee. All subjects signed a consent form before the experiment.

B. Procedures

Each participant walked 4 min on the treadmill for ambiance. Their preferred walking speed (PWS) on the treadmill was assessed according to the protocol [8] followed by 4 min of rest. The participant walked for 4 min at PWS speed before the fatigue protocol (PreF). Afterwards, a isometric maximum voluntary contraction (MVC) test was performed, followed by the fatigue protocol and a second MVC test. Then, the participant performed three walks (0-PostF; 6-PostF; and 12-PostF) of 4 min at PWS speed with 2 min of rest between them. Finally, the participant performed another MVC test.

Gait kinematic data were collected using a motion capture system, with 10 infrared cameras operating at 100 Hz (Vicon Nexus, Oxford Metrics, Oxford, UK). Thirteen reflexive markers were placed on the lateral malleoli, heels, heads of the second and fifth metatarsals (bilaterally), the right and left anterior superior iliac spine, the right and left posterior superior iliac spine, and the spinous processes of the first thoracic vertebrae (T1).

The MVC test and the fatigue protocol were conducted according to [5]. The fatigue protocol adopted ensured that all participants had the same level of muscle fatigue during the *N*-PostF collections.

C. Data analysis

Kinematic data were filtered using a fourth order low pass band, zero lag Butterworth filter with 10 Hz cutoff frequency. All collections were calculated for intermediate 150 strides, discarding the initial and final steps. The steps were detected from the zero-cross velocity of the heel marker [9]. Data analysis was performed using MatLab (R2020A, MathWorks, Natick, MA).

D. Classification

The spatio-temporal variables of the kinematic data were used as a set of input characteristics for training and testing the classification algorithms. The output variable consists of determining two types of classes: TG or UTG. Characteristics related to spatio-temporal variables were chosen due to the diversity of equipment that can collect these types of data. Nowadays it is possible to obtain spatio-temporal data through cameras, accelerometer, smartphone, among others. This facility can contribute to the development of future commercial applications.

In this study, three learning machine methods were used to classify the proposed dataset: k-nearest neighbors (kNN); random forest (RF); and support vectors machine (SVM). kNN is an instance-based learning algorithm that classifies unlabeled observations assigning a class based on the characteristics of the nearest neighbors. The nearest neighbors are determined calculating the distance between them and the term k indicates the number of neighbors used to determine the class of the observed object [10]. Based on ensemble learning, the RF algorithm aims to build several decision trees where each one is considered a classifier, the majority of votes determine the final classification prediction [11]. SVM is a supervised learning method that seeks to minimize classification errors and maximize the geometric margin between classes expanding the dimensional space by building a hyperplane that can separate the dataset [12].

E. Steps for data processing

Before applying the classification algorithms, some procedures were performed to prepare the data and define the best fit parameters for the construction of the learning models. First, the spatio-temporal data were submitted to feature selection methods, considering: the correlation coefficient; the degree of importance of the feature; and the low importance of the feature. After choosing the most relevant characteristics for the classification task, the data passed a characteristic standardization through a scaling of the mean and standard deviation. Tests were performed to define the best parameters for the three algorithms through GridSearch.

The training and prediction of the algorithms were executed $n=30$ times. In each round, a cross-validation with 10-Fold was used [13]. The accuracy of the algorithms is the result of the averages of cross-validation and executions.

Dataset accuracy was analyzed in all gait conditions (PreF; 0-PostF; 6-PostF; and 12-PostF) and separately in each group.

III. Results and Discussion

A. Feature Selection

The initial dataset of this study consisted of eight characteristics: Step Time (STEP_TIME); Step Frequency (STEP_FREQ); Cadence (CADENCE); Step Length (STEP_LENG); Stride Width (STRIDE_WIDTH); Support Phase Duration (SUPPORT_PD); Swing Phase Duration (SWING_PD); and Double Support Phase Duration (DOUBLES_PD). There are also two columns that identify the gait condition (0 – PreF; 1 – 0-PostF; 2 – 6-PostF; 3 – 12-PostF) and the group (0 – UTG; and 1 – TG).

The Fig. 1 presents the graph of the autocorrelation between the spatio-temporal characteristics. It is possible to notice a very strong correlation of the variable STEP_TIME with SUPPORT_PD, SWING_PD since the duration of the gait phases are essential components to determine the step time. The variables STEP_LENG and STRIDE_WDTH are related to step frequency, while STEP_FREQ and CADENCE are strongly correlated.

The most relevant characteristics for the classification task were also analyzed, Fig. 2. The three best features evaluated were: STRIDE_WDTH; STEP_LENG; and DOUBLE_PD.

It is also possible to notice that the CADENCE variable does not appear on the chart since it had zero importance. The degree of importance was calculated based on the missing values, on the characteristics that have only unique values, on the correlation between the characteristics, on the zero and low importance methods.

The feature selection showed that only the variables: STEP_TIME; STEP_LENG; and STRIDE_WIDTH are required to perform the classification task. Therefore the other features were removed from the dataset.

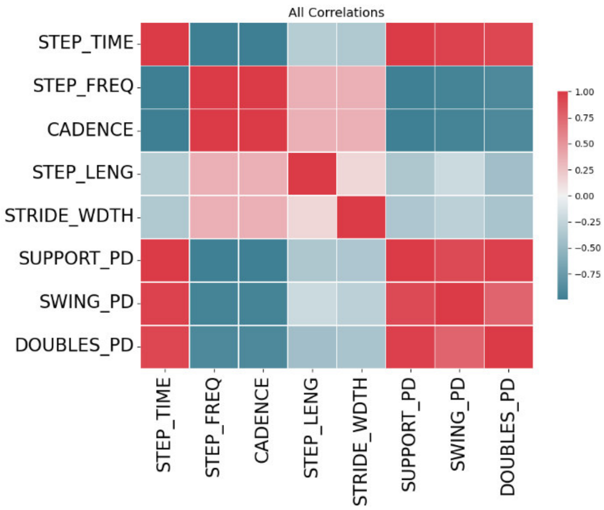

Fig. 1 Plot of autocorrelation between characteristic variables

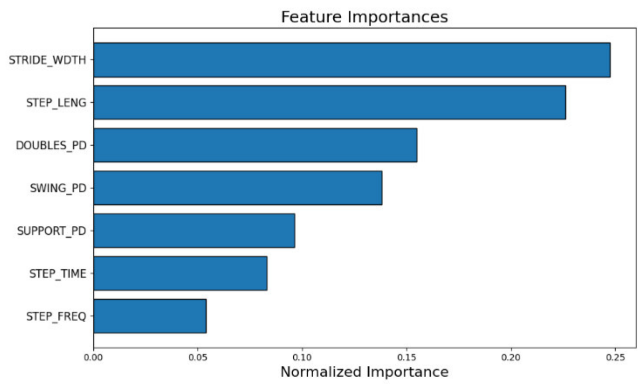

Fig. 2 Rank chart of the most important characteristics for classification task

Fig. 3 presents the pair plot of the characteristics used in the classification algorithms. The graph presents the data separated by group. It is possible to notice a greater separation of the data by group when the variable STRIDE_WDTH is compared with the others.

B. Classification

The hyper-parameters were defined through the grid search. For the kNN algorithm, the number of neighbors and different types of metric were analyzed to calculate the distance. In the RF algorithm, the tree separation criteria, the number of trees generated, the minimum quantity of necessary samples generated and the minimum quantity of samples necessary to form a node were analyzed. In the SVM algorithm, the tolerance criterion, the regularization parameter and different types of kernel were analyzed.

In this first test, classification algorithms were applied to estimate the accuracy in predicting which group a given set of spatio-temporal data belongs to. In this dataset all conditions were considered. Fig. 4 presents the results of the three algorithms. Considering the mean and the highest value of the thirty executions, for this dataset, the kNN was the one that obtained the highest accuracy in the classification prediction, with 86.78% and 90.88%, respectively.

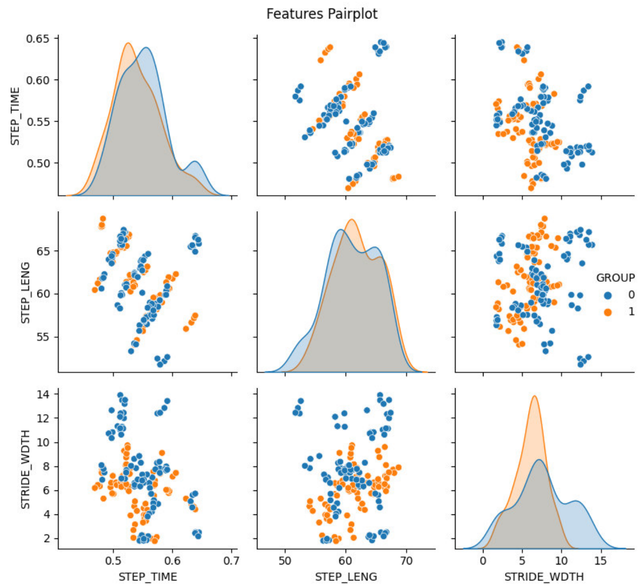

Fig. 3 Pair plot of selected features

From these results, it is possible to state that the strategy of counting the nearest neighbor classes for this data distribution, Fig. 3, was more advantageous than seeking the separation of groups with the creation of a new hyperplane or

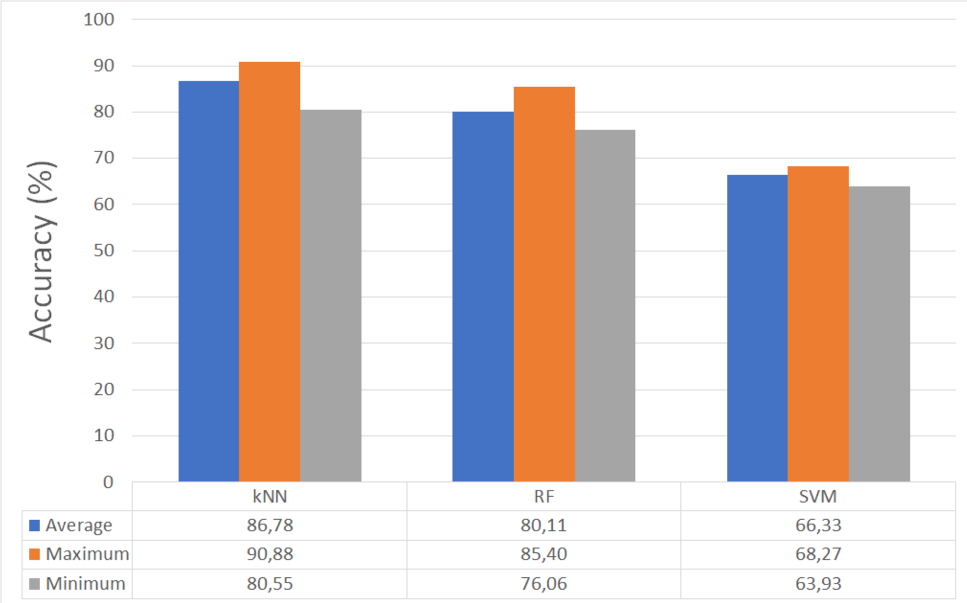

Fig. 4 Accuracy of classification algorithms under all conditions

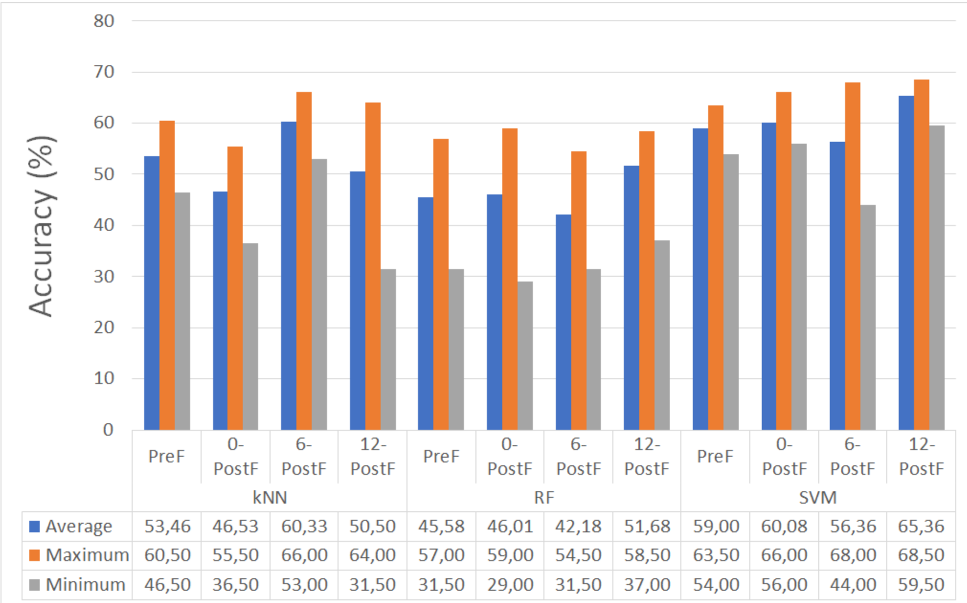

Fig. 5 Accuracy of condition classification algorithms

creating a set of decision trees that seek the best path regarding classification prediction. We believe that the STRIDE_WIDTH variable contributed to the best result of the kNN strategy to stand out in relation to the other algorithms.

C. Classification by Condition

The classification algorithms were also submitted to the dataset under the conditions separately. The accuracy of each algorithm in classifying the four conditions (PreF; 0-PostF; 6-PostF; and 12-PostF) can be observed in Fig. 5. The best results of accuracy in the prediction can be observed in the 12-PostF condition. In this condition, the SVM was the algorithm that presented the best accuracy (65.36%).

Overall, all algorithms reduced their ability to predict this dataset. To verify if the dimensionality reduction in this case could be compromising the classification process, we ran the algorithms again with the complete dataset. However, there was no progress.

The fact that the RF and SVM algorithms obtain greater accuracy in the 12-PostF condition means a greater spacing of the analyzed characteristics (STRIDE_WDTH, STEP_LENG, STEP_TIME) between the groups.

From a biomechanical point of view, this difference may mean that a given group has a greater capacity to recover from muscle fatigue than the other, causing the distance in spatio-temporal features between the groups, facilitating the classification task. Through a clinical analysis, [5] it was found that the TG group presented better conditions for the execution of the fatigue protocol and better recovery of the MVC. Also in Lehnen, [5], it is possible to notice a lower stability in the TG group in relation to the UTG and in the 12-PostF condition for both groups.

D. Limitations

Dataset size may have been a limiting factor in the analysis under separate conditions. The lack of more strongly correlated attributes and the sparse distribution shown in Fig. 3 may also have been an aggravating factor. Another cross-validation method indicated for small databases, Leave-One-Out Cross-Validation (LOOCV) was tested, there was an improvement in the results, but we believe that this improvement was due to overfitting. Also, the researchers in [5] report that the analyzed data did not show statistical differences between the groups.

IV. Conclusion

In this study, groups of women practitioners and non-practitioners of weight training walked on a treadmill before and after the application of a fatigue protocol. After the fatigue protocol, data were collected at different rest times to verify the muscle recovery process. The kNN algorithm was able to produce the best classification result in relation to RF and SVM for all gait conditions.

The results show that the use of classification algorithms in these cases can help in the development of an autonomous diagnostic system for muscle fatigue discrimination based on spatio-temporal characteristics of the gait. This study has potential applicability in physical therapy and weight training, classifying and understanding the level of muscle fatigue can contribute to more efficient and concentrated training. Also, the classification of these spatio-temporal variables during muscle fatigue can help in the diagnosis of diseases related to muscle weakness and neuromuscular disorders. Clinical studies are of fundamental importance to understand the object of study and the results generated by the classification algorithms. Although the results are promising, the research can be improved by parameterizing these algorithms in larger databases.

For future work, it is suggested to parameterize the models with larger databases. Test other combinations and cross-validation methods. Use other sets of features such as fractal properties, maximum Lyapunov exponent, linear gait variability and stability margin.

Conflict of Interest

The authors declare that they have no conflict of interest.

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