

Index of Physical activity and Fall Efficacy scale classification through biomechanical signals and Machine Learning.

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ABSTRACT

The rapid increase in the elderly population and chronic diseases has increased disability worldwide. This has led researchers and engineers to create tools and technologies that allow health caregivers, physical trainers, and health policymakers to understand, measure, and treat people with disabilities. In addition, artificial intelligence techniques have been used to improve the performance of these technologies. This article presents the development of a novel classifier that utilizes machine learning (ML) algorithms and biomechanical signals to predict a subject's International Physical Activity Questionnaire (IPAQ) and Fall Efficacy Scale (FES) scores. Three ML algorithms were applied: K-nearest neighbors (KNN), decision tree, and support vector machine (SVM). The results showed classification accuracies of over 95%, 99%, and 89%, respectively, and validated the correlation between qualitative scales and biomechanical responses in balance training. This classifier is an innovative tool that helps professionals adjust and improve their physical training programs.

Keywords: Postural Sway; Physical Activity; Support Vector Machine; K-Nearest Neighbors; Decision Tree.

INTRODUCTION

According to the World Health Organization (WHO), more than one billion people worldwide have some type of disability. This is a growing figure, attributed to the aging of the population and the increase in chronic diseases (“OMS | Discapacidad y rehabilitación,” n.d.). Balance and postural control are among the main skills affected by aging, neuromotor diseases, and trauma at the motor level.

However, diagnosis, training, and balance rehabilitation processes use evaluation methodologies that are usually based on qualitative tests. Tests such as the Berg Balance Scale (Brouwer, Kal, van der Kamp, & Houdijk, 2019), IPAQ (Craig et al., 2003), and FES (Hauer et al., 2010) are applied by specialized personnel. Nonetheless, the results tend to be subjective and depend on the evaluators' experience.

Novel training programs have been developed to obtain more efficient and reliable processes (Betker, Szturm, & Moussavi, 2005; Fitzgerald, Trakarnratanakul, Dunne, Smyth, & Caulfield, 2008; Van Diest, Lamoth, Stegenga, Verkerke, & Postema, 2013), including assistive robotics technologies (Kharboutly et al., 2015; Patané & Cappa, 2011; Rastegarpanah, Saadat, Borboni, & Stolkin, 2017; Schouten, Boonstra, Nieuwenhuis, Campfens, & Van Der Kooij, 2011). However, the benefits, advantages, and disadvantages of these tools for physical training and rehabilitation procedures are not yet clear (Gui, Tan, Liu, & Zhang, 2020; Jakob et al., 2018; Zhang et al., 2017). Due to this, (Agarwal & Deshpande, 2019; Franceschini et al., 2020; Rodgers et al., 2019; Stinear, Lang, Zeiler, & Byblow, 2020; Yozbatiran & Francisco, 2019) support the idea of the need for better procedures and protocols, which helps to clarify the impact that robotics brings to this type of task and mitigates the problem of subjectivity in these procedures.

In recent years, various artificial intelligence and machine learning techniques have been implemented in topics related to the classification of levels of physical activity and activities of daily living (Pires, Garcia, Pombo, Flórez-Revuelta, & Spinsante, 2017), detection of falls (Sun, Hsieh, & Sosnoff, 2019; Yang & Gao, 2020), autonomous training, execution of tasks without the supervision of an expert (Jiao, Wu, Bie, Umek, & Kos, 2018), detection of emotions when executing physical exercises (Rincon, Costa, Carrascosa, Novais, & Julian, 2019), and methodologies of assisted training with haptic feedback (Bao, Klatt, Whitney, Sienko, & Wiens, 2019a). Recently, these applications have used direct measurements such as electrocardiogram (ECG) signals (Allam, Samantray, & Ari, 2020; Patro, Jaya Prakash, Jayamanmadha Rao, & Rajesh Kumar, 2020; Prakash & Ari, 2019b, 2019a), electroencephalograms (EEG) (Venkata Phanikrishna, Jaya Prakash, & Suchismitha, 2021), and COP to classify, monitor, and assist training and rehabilitation programs to improve user performance.

Based on the state-of-the-art and current trends in intelligence and machine learning algorithms, this article presents the development of an automatic classification system for the IPAQ and FES that utilizes postural sway signals from an existing database (Santos & Duarte, 2016) and machine learning. The hypothesis proposes that it is possible to determine the level of IPAQ and FES and even detect the characteristics of the surface on which the training is carried out (stable and unstable surfaces) through the quantitative analysis of signals typical of the COP of a user and anthropometric measurements.

This study primarily focuses on the development of a classifier system. The features extracted from stabilometric signals and anthropometric measurements were selected and processed. Continuing with the design and choice of optimal parameters of the classifiers commonly used in balance evaluation tasks, KNN (Ahmed, Mehmood, Nadeem, Mehmood, & Rizwan, 2017; Liang, Liu, Li, & Zhao, 2019), decision trees (Leu, Ko, Lin, Susanto, & Yu, 2017), and SVM (Bao et al., 2019a) using concurrent algorithms. The selected algorithms present several advantages. For instance, SVM is effective in high-dimensional space tasks, even in cases where the number of dimensions is greater than the number of samples. KNN is a non-parametric method that is helpful in tasks where decision boundaries are not regular, and decision trees are perfect for handling multi-output problems (Pedregosa et al., 2011). Finally, the precision, F1-score, and recall results of the three techniques are presented.

MATERIALS AND METHODS

For the design of the physical activity classifier, the database described by (Santos & Duarte, 2016), which consisted of information from 1,930 tests performed by 163 subjects, was used. For data capture, the participants maintained a stationary standing position for 60 s in four different situations: eyes open or closed, while standing on a stable or unstable surface. Each condition was tested in triplicates. The experimental setup is illustrated in Fig. 1.

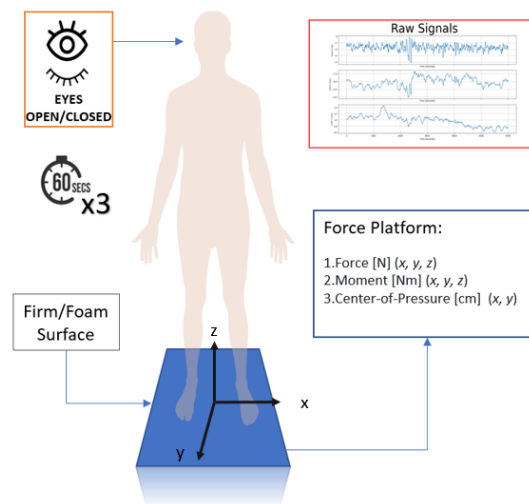


Figure 1. Experimental Setup

Eight different signals were captured through a force platform:

1. Force [N] (x, y, z)
2. Moment [Nm] (x, y, z)
3. Center-of-Pressure [cm] (x,y)

The database includes the results of qualitative evaluations of physical activity indices and participant balance.

- Short Falls Efficacy Scale International
- International Physical Activity
- Trail Making Test
- Mini Balance Evaluation Systems Tests

The classifier only included information corresponding to healthy subjects who did not report any type of disability or disease according to the information provided by the researchers.

Signal processing and filtering

The signals were filtered and processed before the extraction and selection of relevant features. A fifth-order Butterworth type low pass filter was applied with a cutoff frequency equal to 5 Hz according to (Doyle, Hsiao-Weckler, Ragan, & Rosengren, 2007; Paillard & Noé, 2015). Because it is not known whether the acquisition instruments have a constant calibration for each test, the mean signal level of each sample was eliminated by subtracting a polynomial of degree six, which models the behavior of each signal. Fig. 2 shows the process described above using data from the force on the Y-axis.

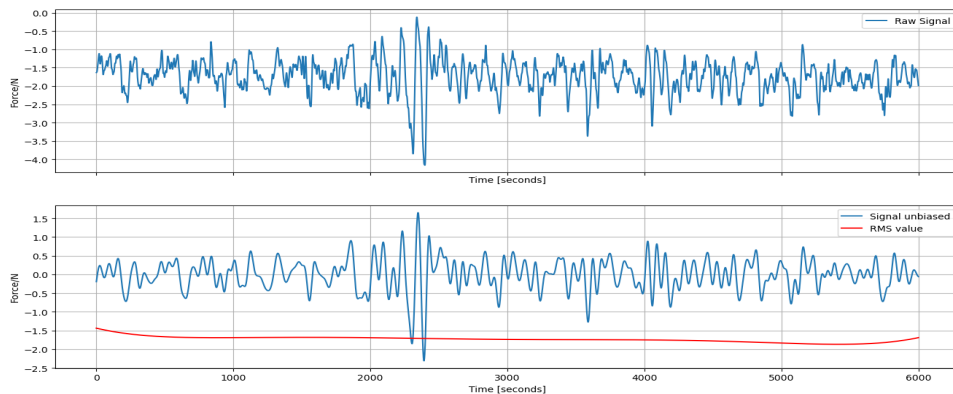


Figure 2. Signal processing

Feature selection

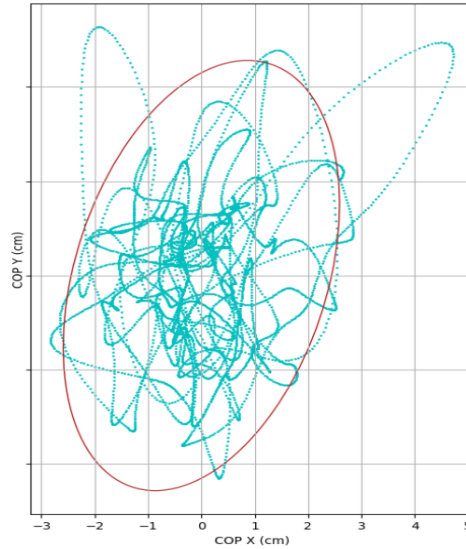
The features extracted from the signals were obtained from the categories listed in Table 1. These are some of the most common methods for analyzing the COP behavior of individuals (Brouwer et al., 2019; Doyle et al., 2007; Yamamoto et al., 2015). Kinematic and statistical estimators of each of the database signals and anthropometric measurements of the test subjects were applied.

A total of 85 features, usually determined using postural control and stabilometry analyzers (Paillard & Noé, 2015; Yamamoto et al., 2015), were extracted by combining the categories listed in Table 1. The measurements included the maximum displacement, maximum frequency, mean amplitude, area of the COP, maximum length in each axis of excursion, maximum force in each axis, root mean square in each axis of displacement, and mean displacement angle. Anthropometric variables directly involved in the various balance mechanisms of the human body were incorporated: body mass index, weight, foot length, and height.

Table 1. Feature extraction categories

Kinematic Estimator	Statistical estimator	Anthropometric measures
1. 95% confidence ellipse 2. Length of total displacement 3. Root mean square of the COP 4. Frequency 5. Velocity gradient COP 6. Maximum displacement per-axis 7. Angle	8. Mean 9. Median 10. Fashion 11. Standard deviation 12. Maximum 13. Minimum 14. Variance	15. Body Mass Index (BMI) 16. Height 17. Weight 18. Foot length

Figure 3. 95% confidence ellipse area



Values within the 95% confidence ellipse area were used to eliminate abnormal disturbance values during data capture. This estimator was calculated as described (Doyle et al., 2007); and the time, angles and maximum amplitudes corresponding to the area described by the subject's movement were extracted (Fig. 3).

Physical activity index classifier

To determine the IPAQ, FES, and surface of the experiment, the data were filtered, scaled, and normalized using only healthy subjects (without any reported disease). In total, 648 observations with 85 features were used. Eighty% of the data was used for the training process, and the remaining 20% was used for algorithm validation. Data from the participants were used either in the training or testing sets.

The techniques selected to design the classifier were KNN, decision trees, and SVM. These algorithms are supervised classification techniques that are typically used for state or outcome prediction problems based on known and correlated data or features.

Classification techniques were implemented in Python using the scikit-learn tool (Li & Phung, 2014). For their validation and evaluation, the F1-score, precision, and recall of each algorithm (Bao, Klatt, Whitney, Sienko, & Wiens, 2019b) were evaluated.

$$F1\text{-Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \quad (1)$$

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \quad (2)$$

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative} \quad (3)$$

Statistical analyses using ANOVA, F-values, and p-values were performed to select the most relevant features for each algorithm. These show the statistical significance of independent versus dependent variables and are commonly used in problems where the input data are numeric and the output variable is categorical.

Classification algorithms

The classification algorithms selected to determine the desired outputs were the KNN, decision trees, and SVM. The operating parameters are listed in Table 2.

Table 2. Classification parameters

Algorithm	Parameters	Output
KNN	<ul style="list-style-type: none"> • K=1 • Search algorithm ='kd_tree' • distance =Manhattan distance 	IPAQ
	<ul style="list-style-type: none"> • K=3 • Search algorithm ='kd_tree' • distance=Manhattan distance 	FES/ Surface
Decision trees	<ul style="list-style-type: none"> • Search criteria =entropy • Max Depth=30 • Random state=32 	IPAQ/ FES/ Surface
SVM	<ul style="list-style-type: none"> • Penalty parameters (C=110.1) • Kernel='rbf' • Decision function shape=one vs one 	IPAQ/ FES/ Surface

The parameter K of the KNN estimator was evaluated by studying the resulting precision according to the variation of K during 100 epochs. Fig. 4, green margin represents the standard deviation of the accuracy for a certain number of neighbors (K). The Manhattan distance parameter showed better results compared to the traditional Euclidean distance parameter because this measure works best with larger data.

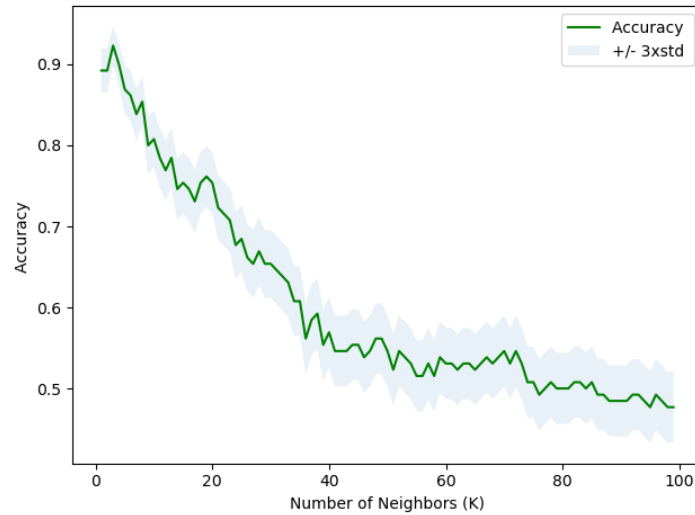


Figure 4. Best K for KNN and standard deviation accuracy

The search criterion for the decision tree was entropy as it aimed to eliminate the heterogeneity of the elements located in each section of the tree. A search depth of 30 was used because of the large number of extracted features.

Similar to the KNN algorithm, the SVM estimator is constructed as a multiclass estimator, evaluating various combinations of parameters by employing a random search with the RandomizedSearchCV library (Li & Phung, 2014). The penalty parameters (C), kernel, and weight of the characteristics were found through random optimization according to (“3.2. Tuning the hyper-parameters of an estimator — scikit-learn 0.24.1 documentation,” n.d.).

RESULTS AND DISCUSSION

The following results were obtained by applying different ML techniques to the test set. The designed classifier was first evaluated by considering 85 extracted features. Using (2), the results obtained are shown in Table 3. To improve the results, the search for the main features using ANOVA was implemented according to the dependent variable studied, IPAQ (High, Low, and Moderate) and FES (High Concern, Medium Concern, and Low Concern).

Table 3. Precision Before Choosing Main Features

Algorithm	Precision Before Feature Importance		
	IPAQ	FES	Surface
KNN	0.87	0.84	0.98
Decision Tree	1.00	0.97	0.99
SVM	0.77	0.73	0.97

The biomechanical variables reflected by the COP showed acceptable statistical significance when evaluating the IPAQ and type of surface; however, in the evaluation of the FES, the anthropometric features of the individual showed greater significance than the biomechanical variables. This validates the initial hypothesis regarding the possibility of classifying individuals according to quantitative variables. The Main 5 features of each outcome are listed in Table 4.

Table 4. Statistical significance of biomechanical features

Outcome	Number of Feature importance	Main 5 Biomechanical Features	p-value
IPAQ	53	Variance of Moment in Z	0.000427
		Variance of Moment in X	0.00105
		RMS of Moment in Z	0.00164
		Standard deviation of Moment in Z	0.001648
		Standard deviation of Moment in X	0.00204
FES	34	Maximum Frequency in Z	0.044
		Average Force in X	0.05735
		X-Force Mode	0.06471
		Maximum frequency in X	0.06472
		Variance of Force in X	0.069
Surface	48	COP displacement in Y	6.91e-156
		COP length in Y	6.53e-146
		Standard deviation COP in Y	2.611e-145
		RMS COP in Y	2.611e-145
		COP length in X	1.742e-144

Once the most relevant features were identified for each outcome, the precision of the classifier was re-evaluated for each technique. Table 5 lists the precision after the feature-importance procedure.

Table 5. Precision of classifiers after choice of main features

Algorithm	Precision After feature Importance		
	IPAQ	FES	Surface
KNN	0.97	0.92	0.98
Decision Tree	1.00	1.00	0.97
SVM	0.85	0.84	0.99

The results obtained suggest that the procedure of choice and optimization of parameters for each estimator improved the average precision of the KNN classifiers from 89.6% to 95.6% and that of the SVM from 83.3% to 89.3%, considering their performance in estimating the IPAQ, FES, and Surface.

The decision tree registered an increase in FES prediction; however, it registered a slight decrease when predicting the surface of the experiment. This suggests that the algorithm requires all 85 extracted features to achieve the highest precision.

Finally, (2) and (3) were replaced in (1) to evaluate the F1-Score. The performance results of the classifier are listed in Table 6, and the average performance of the classifiers throughout the different validations of the IPAQ, FES, and Surface are listed in Table 7.

Table 6. Results of F1 score and Recall of each classifier.

Algorithm	F1 Score and Recall After feature Importance					
	IPAQ		FES		Surface	
	F1 score	recall	F1 score	recall	F1 score	recall
KNN	0.97	0.97	0.91	0.90	0.98	0.98
Decision Tree	1.00	1.00	1.00	1.00	0.97	0.97
SVM	0.84	0.83	0.81	0.81	0.99	0.99

Table 7. Average performance of classifiers

Average Performance (IPAQ, FES, Surface)	KNN	Decision Tree	SVM
Precision	95.6%	99%	89.3%
F1-score	95.3%	99%	88%
Recall	95%	99%	87.6%

The average results support the use of COP as a direct measure of physical activity status. In addition, these results (over 95 %) are comparable to those of other studies that applied direct measures of human beings, such as ECG (Allam et al., 2020; Prakash & Ari, 2019b) and EEG (Venkata Phanikrishna et al., 2021), and applied similar ML techniques with similar average results. Although the tests did not present greater complexity to the participants, and the extracted signals did not show easily identifiable patterns of behavior, the classification algorithms achieved a high average performance when classifying the various states of the IPAQ and FES.

Of note, these results are comparable with those of Liao et al. (Liao, Wu, Wei, Chou, & Chang, 2021), who used the same database selected for this article to analyze COP signals using a decision tree and empirical mode decomposition to predict falls among older adults. This supports the use of ML and COP measures for classifying physical activity conditions.

Finally, the biomechanical variables extracted from the COP were directly correlated with the type of surface on which the standing experiments were performed. Although this was a predictable result, it corroborated the design of the classifiers and highlighted the ability of these techniques to identify correlations in features that are difficult to observe with the naked eye, even by highly trained personnel (therapists, physiatrists, trainers, etc.).

The main limitation of the proposed classifier is related to the database. Although data recollection was stated in the study protocol (Santos & Duarte, 2016), there may be biases and confounders that affect the generalizability of the data to other populations.

CONCLUSION

The designed classifier uses the COP to classify the IPAQ and FES of subjects with a high accuracy of over 95.6%. In addition, a correlation between the qualitative assessment scales (IPAQ and FES) and the features of the biomechanical behavior of the human body was found using the feature importance process. Thus, the high F1 score, recall, and precision of the designed algorithms validated the application of these techniques to predict the IPAQ, FES, and Surface. Moreover, this classifier is an innovative tool to support diagnosis, assessment, and physical training processes through a direct measure of the COP.

This system shows the possibility of using similar solutions to support the diagnosis and evaluation of physical activity by specialized personnel. The integration of this classifier with the assistive robotics system for balance training presented by (Rivera, Abril, Niño-Suarez, Avilés, & Castillo-Castañeda, 2021), is intended to mitigate the problem of subjectivity present in balance evaluation systems, allowing them to adjust the assistance parameters of the robotic platform according to the user's performance.

In future studies we intend to compile a database of healthy subjects during the execution of dynamic exercises (e.g., limits of stability and reaching exercises) to determine the correlation between the variables extracted by the classifier and the performance of the user in certain balance training. This will help evaluators adjust or validate procedures in clinical settings.

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