Journal of Exercise and Health Science, Vol 1, No 2, Spring 2021, page 75-86

Original Article

Selection of Biomechanical Features for Pattern Recognition in Postural Stability Analysis

Maedeh Najafi-Ashtiani[1], Mohammadreza Asghari Oskoei[2]

1. Allameh Tabataba'i University (Corresponding Author)
2. Allameh Tabataba'i University

Received: 2020/12/26 **Accepted: 2021/01/31**

Abstract

Balance maintenance is provided through using different joint strategies considering the perturbation conditions. The kinematic-based features of the joint strategies are calculated to assess the performance of them. The aim of this study was to identify the most effective stability features of the dominant role-playing strategy while standing on an unstable platform. Sixteen healthy young men participated in perturbed standing tests on an unstable platform supported via low and high stiffness springs. To measure the joints angular rotations, the motion capture analysis was used in the sagittal plane. Path length of angular velocity and displacement, standard deviation, total mean velocity, , root mean square and fractal dimension features were extracted to analyze the quantitative stability. Then, the K-nearest neighbor (KNN), support vector machine (SVM) and multilayer perceptron neural network (MLP) classifiers in the Wrapper feature selection technique were used to classify the high and low stiffness supports of the platform. At first, the results suggested that the ankle was dominant strategy in keeping the balance. All three classifiers revealed acceptable performance for data classification, but by applying the Wrapper method and selected velocity-based features finally, the support vector classification with 93.75% accuracy had the highest accuracy and efficiency. This study could provide an early diagnosis of balance problems as well as standing and joint mechanisms to prevent falls by evaluating the classifiers.

Keywords: Postural, Stability, Perturbation, Wrapper, Support Vector Machine

---

1. Email: maedeh.najafi72@gmail.com
2. Email: oskoei@atu.ac.ir

Introduction

Normally, standing is the first task of the body's neuromuscular system so that other daily activities depend on it [1]. The postural instability happens when the body cannot overcome any external or even internal perturbation to return to the initial equilibrium position [2]. In comparison with quiet and unperturbed standing, applying any disturbance to the musculoskeletal system of a human requires more efforts to keep the balance. These efforts can be possible with changing the joint kinematics called postural adjustment using joint strategies [3,4]. The aim of the application of the perturbations, in general, was to represent a real physiological condition that may interfere with the control of the posture. However, quiet standing in static positions, for instance, may rely on the knee strategy [5]. Nevertheless, standing on an unstable platform as a form of difficult external physical disturbance may make the body instable [6-10]. Quantitatively to analyze the joint mechanisms, the previous studies have used some linear or non-linear metrics [5]. The musculoskeletal behavior of a certain group of participants in response to different test conditions can be obtained from calculating these metrics. Since the posture adjustment is accomplished through the learned patterns of muscle synergies controlled by the human central nervous system (CNS), it is hypothesized that the joint behaviors are limited to certain classes. Machine learning (ML) methods can be utilized to diagnose diseases and examine the differences between states in experiments via data analysis [11]. A study in pattern recognition by classifying movement data of young and old adults achieved 81.7% accuracy while walking on a treadmill through SVM classification [12]. In addition, 92.3% accuracy was obtained by extracting features such as step time, length and width in walking to find the risk of falling in the elderly via multilayer perceptron neural network [13]. Dynamic pattern of healthy individuals and Parkinson's patients achieved 94.7% accuracy by using the SVM classification [14]. In another study, the diagnosis of foot drop between healthy and individuals was classified by random forest (RF) classifier with an accuracy of 93.18% during walking on a stable surface [15]. Classification accuracy of an artificial neural network classifier was 89% for two groups with or without stepping after utilizing external perturbation on healthy young people [16].

In a study, the classification of different states of physical difficulty (two levels of spring stiffness below an unstable plate: the first type spring with 3375 stiffness (higher spring) and second type spring with 1680 stiffness (lower spring) Newton per meter) was investigated by some biomechanical features of the most important joint when standing on an unstable plate. The general aim of selecting the feature of algorithms is to choose the most relevant properties of data classes and to increase the classification performance [17]. As a result, the aim of this study was to extract the most outstanding strategy among the joints by evaluating the joint mechanisms when standing on an unstable support and selecting features of human lower limb joints leading to the increase of classification accuracy in postural control. The results of this investigation could present a preliminary diagnostic framework to assess the possible but hidden problems in the postural control of individuals only by applying classification techniques on balance test outcomes. Moreover, the stability characteristics, givingthe most precision in detection can be determined.

Methods

The statistical and biomechanical analysis, feature selection and classification were conducted according to the methodology illustrated in figure 1. In the following, each step is described in detail.

Participants

Totally, 16 healthy young men (age = 25.8 ± 4.4 years, weight = 72.5 ± 9.4 kg, height = 176 ± 4.2 cm) participated in this study. All participants who signed the consent form had normal eyesight with no history of muscle disorders, fractures and surgery on their lower limbs and spine. The ethical issues of this study were approved by the University's Ethical Committee (code: IR.ATU.REC.1398.007).

Procedure

Two standing conditions were existed based on two different stiffnesses of springs under an unstable platform. The higher and lower springs were 3400 N/m and 1700 N/m, respectively. The unstable platform was a rocker board of 35 cm width and 45 cm length, mounted on three half-ellipses with a small diameter of 13 cm to rotate only in the sagittal plane. In all conditions, the volunteers stood barefooted and their arms crossed over the chests as well as they were asked to demonstrate the least fluctuation in standing posture. The first step in figure 1 illustrates the details of standing conditions. Each test was repeated in three trials for 30 s. To prevent fatigue, a minimum of one-minute interval was considered between the trials. The choice of the stiffness level of the unstable platform was random. Proper safety conditions were provided to prevent people from falling.

Data Acquisition

The knee, ankle and hip joints kinematics were recorded using motion capture method. Five active markers were attached to the fifth metatarsal, lateral malleolus, lateral femoral condyle, greater trochanter and acromion process in order to measure the movement of the markers. The body motions were captured using 120 frames/s recording speed (Casio EXZR20, Tokyo, Japan) for two seconds after perturbation, and then an image processing code was extracted from the kinematic data (Fig. 1).

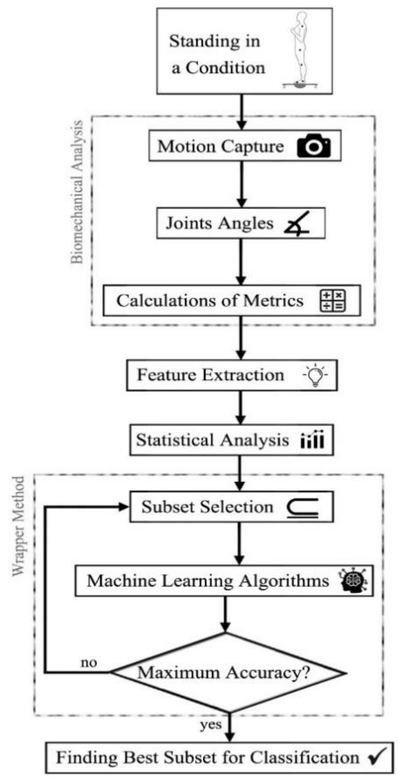

Fig 1- Methodology flowchart

Feature Extraction

Six features (five linear and one nonlinear) were extracted to analyze the participants' motor behavior. Table 1 provides the mathematical definitions of these features. The dataset was as follows: 16 × (5 + 1) × 3 × 2 = 574, indicating 16=number of volunteers, 5+1=number of linear and non-linear features, 3=number of joints and 2=number of classes.

Table 1- Mathematical definitions of extracted features

Feature	Abbreviated Symbol	Formula
Path length	PL	$\sum_t \lvert x_{t+1} - x_t \rvert$
Root mean square	RMS	$\sqrt{\sum_i \frac{x_i^2}{n}}$
Path length of velocity	PLV	$\sum_t \lvert v_{t+1} - v_t \rvert$
Fractal dimension	FD	$\frac{d\, log\,(pl(k))}{d\, log(k)}$
Total mean velocity	TMV	$\frac{1}{T}\sum_1^T \lvert x_{t+1} - x_t \rvert$
Standard deviation	SD	$\sqrt{\frac{1}{N}\sum_i (x_i - \mu)^2}$

Statistical Analysis

For statistical analysis, a mixed model of analysis of variance (ANOVA) was used in SPSS 16. The independent variable was unstable plate, and the dependent variables were linear and nonlinear features calculated from the angles of the lower limb.

Feature Selection and Classification of Data

The selection of appropriate features was carried out to improve the performance of time and accuracy of classification. In the current study, the space of features was reduced to smaller dimensions in order to delineate more prominent features of the stability during detection and to achieve better results in classification. Then, the classification was done in a new dimension. The Wrapper method was applied to select the appropriate feature in the present study. In this method, all possible subsets of features were examined, and its effect on the accuracy of the final classification was delineated with the help of ML algorithms (Fig. 1). The K-nearest neighbor algorithm with K=3 was done between two experimental conditions. In the algorithm for the support vector machine (SVM), the linear kernel was applied with the safe margin=0.8 because the class data were separable using the linear margin. For multilayer perceptron network training, the learning coefficient was set to 0.1, and the maximum iteration was set 300 times. The neural network used in the ongoing study after selecting the appropriate feature had two inputs, four neurons in the hidden layer and two neurons in the output layer. To ensure the maximum coverage of the data in terms of testing and training, the cross-validation technique was utilized. In this approach, the dataset was divided into 4 non-overlapping groups. During each run, one set was reserved for testing (25%), and the other three sets were used for training (75%) the ML algorithm. This process was repeated four times with different testing sets so that every dataset was applied once for testing and three times for training. The final result was the average of four runs for each algorithm.

Results

Statistical comparison in terms of p-values between the features of joint pairs in two high stiffness (HS) and low stiffness (LS) spring conditions presented in table 2 displays that the ankle plays a prominent role in postural control during different support conditions.

Table 2- Statistical comparison in terms of *p*-values between the features of joint pairs in two spring conditions.

	PLV		PL		SD		RMS		FD		TMV	
	HS	LS	HS	LS	HS	LS	HS	LS	HS	LS	HS	LS
Ank vs. Kne	**0.025**	**0.030**	0.470	**0.029**	1.000	0.237	**0.023**	**0.014**	1.000	1.000	0.133	**0.016**
Ank vs. Hip	**0.010**	**0.022**	0.461	**0.019**	0.809	0.429	1.000	1.000	1.000	1.000	0.083	**0.014**
Kne vs. Hip	1.000	1.000	1.000	1.000	1.000	1.000	**0.032**	**0.018**	1.000	1.000	1.000	1.000

The ankle's linear and non-linear metrics of stability were mainly different from the knee and hip features significantly. Therefore, it could be concluded that the ankle mechanism revealed the main kinematic response of movement to maintain the balance. Bold-faced values were significant ($p < 0.05$). Hence, based on more prominent role of the ankle, the dataset was considered as follows: $16 \times (5 + 1) \times 1 \times 2 = 192$, in which 16 was the number of volunteers, 5+1 was the number of linear and non-linear features, 1 was the only ankle joint and 2 was the number of classes. Since the ankle as the first kinematic response always tried to maintain equilibrium, the features related to this joint were used in the data classification. The accuracy of different combinations of features in various dimensions was calculated for these three classifications and displayed as a box plot (Figure 2).

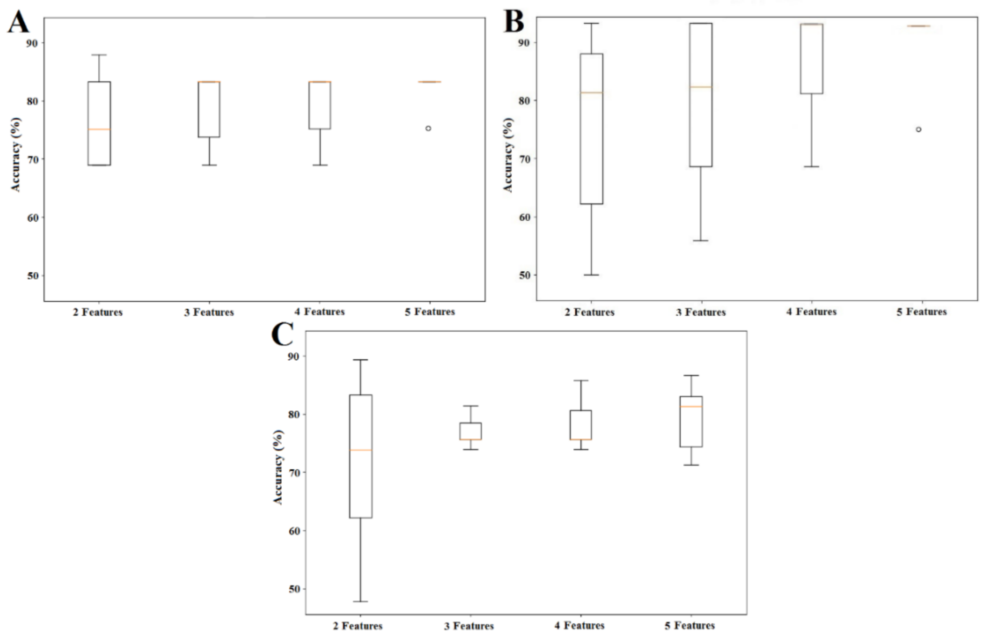

Fig 2- Box plots of the accuracy (%) of three classifications in selecting different combinations of features for performance of (a) KNN, (b) SVM, (c) MLP

The average accuracy of each classifier applied to different combinations of features is reported in table 3. In spite of the similarity between the input and output samples used in classifier training, the SVM classifier performed better than the other two classifiers.

Table 3- Average accuracy (%) of three classification algorithms for subsets with 2, 3, 4, 5 and 6 (all) features.

Algorithm	2 features	3 features	4 features	5 features	6 features
KNN	76.6	76.8	78.3	80.2	81.3
SVM	75.4	81.1	86.6	90.6	93.8
MLP	71.8	72.9	76.8	76.7	89.6

Optimal feature selection was conducted to compare the performance of the classifiers using the Wrapper method. The results of the accuracy of the classifiers including optimal features from the feature set are represented in table 4. Although the highest accuracy of all three classifications was gained through selecting two features from the feature set, the SVM classifier had higher accuracy than the other classifications. This value of the accuracy was obtained by choosing the top two features of the path length of velocity (PLV) and total mean velocity (TMV) by the Wrapper feature selection algorithm.

Table 4- The comparison the accuracy (%) of three classifiers using the wrapper method.

Algorithm	Top two features	Top three features	Top four features	Top five features
KNN	87.5	81.3	81.3	81.3
SVM	93.8	93.8	93.8	93.8
MLP	89.6	83.4	85.4	87.5

Discussion

The aim of this study was to identify the best stability features of the most important joint in two conditions on an unstable support platform in order to achieve the best accuracy in classifying experiment classes. Standing on an unstable plate is inherently difficult even for healthy individuals [6]. For the center of mass was continuously moving, and its rate was dependent on body deflection; thus, it was more difficult to control the posture requiring more muscle activity [18]. Therefore, evaluation of the joint mechanisms suggested the overall neuro-musculoskeletal system, keeping the balance in such a difficult physical condition on the unstable plate. Simulations of states close to a variety of equilibrium diseases were done to investigate the effect of perturbations such as physical perturbations on equilibrium.

The present study was fulfilled with the help of classifications on standing variables and factors affecting equilibrium, which finally by evaluating the classifiers could provide an early diagnosis of balance problems, standing and joint mechanisms to prevent falls. Classifying different standing conditions and maintaining balance by practical tests helped to better understand the factors affecting standing. Classification and recognition of the healthy and young individuals' data were inherently more complex than those of the healthy and patient or young and elder population as studied in previous works. One of the factors that influenced the classification was the extraction of more precise features from the pre-processed motion data i.e. the features that represented the maximum separation between classes and increased the classification rate [14, 19-21]. Linear and non-linear stability indices were used to investigate this type of physical perturbation on stability. Five linear features such as path length, PLV, TMV, standard deviation and root mean square as well as one non-linear fractal dimension feature were calculated. Then, the Wrapper method was utilized to select the appropriate features to achieve the best separation. According to the table 4, the best results for classification can be achieved only by having two features of TMV and PLV. Among the three classifications, the SVM classification always has the highest accuracy. In addition, the results shown in table 4, like those of Domingo's research emphasize that more features are not always useful. In fact, when the maximum accuracy was obtained, adding further features that are not good representatives of the separation of two classes could have a detrimental effect on the classification performance [22]. Among the biomechanical features, the TMV and PLV were based on the velocity of the ankle. Besides, the time derivatives can be utilized as the most important features of classification in perturbation-induced stepping strategy [16]. The stability concept was, in general, relied on the velocity of the parameter of interest. The velocity-induced parameters in addition to the position indicated the controllability of the joint mechanism. The amounts of high positive and negative velocity revealed rapid and unstable states of the body probably due to the lower muscle synergies. A proper neuro-muscular effort routinely recruited adequate co-contractions to provide smoother joint movements leading to higher levels of postural stability. Therefore, higher values of these velocity-induced parameters demonstrated more changes in movement direction and lower stability level.

Conclusions

The results of the present study suggested that the stability was intermittently caused by ankle in a closed-loop control. Focusing on the mechanism of this joint leads to a better classification among the test states. Furthermore, among the calculated features, two ankle features such as PLV and TMV are as the most appropriate features in creating two-dimensional space for applying the appropriate classification for these two test states. Classification accuracy of KNN and MLP were 87.5 and 89.6%, respectively. Finally, among the three classifications used, the SVM with the simplicity and speed of achieving a unique answer with 93.75% accuracy was recognized as the best classifier in the present study.

References

1. Mazaheri, M., Coenen, P., Parnianpour, M., Kiers, H. and van Dieën, J.H. Low back pain and postural sway during quiet standing with and without sensory manipulation: a systematic review. *Gait & posture*; 37:12-22. https://doi.org/10.1016/j.gaitpost.2012.06.013 (2013).
2. Wagner, H. & Blickhan, R. Stabilizing function of skeletal muscles: an analytical investigation. *Journal of theoretical biology*; 199:163-179. https://doi.org/10.1006/jtbi.1999.0949 (1999).

3. Lamontagne, A., Richards, C.L. & Malouin, F. Coactivation during gait as an adaptive behavior after stroke. *Journal of Electromyography and Kinesiology*; 10:407-415. https://doi.org/10.1016/S1050-6411 (00)00028-6 (2000).
4. Ashtiani, M.N. & Azghani, M.R. Effects of visual and cognitive interference on joint contributions in perturbed standing: a temporal and spectral analysis. *Australasian physical & engineering sciences in medicine*; 41(1):21-30. https://doi.org/10.1007/s13246-017-0606-7 (2018).
5. Ashtiani, M.N. & Azghani, M.R. Open-and closed-loop responses of joint mechanisms in perturbed stance under visual and cognitive interference. *Biomedical Signal Processing and Control*; 42:1-8. https://doi.org/10.1016/j.bspc.2018.01.005 (2018).
6. Ivanenko, Y.P., Levik, Y.S., Talis, V.L. & Gurfinkel, V.S. Human equilibrium on unstable support: the importance of feet-support interaction. *Neuroscience Letters*; 235:109-112. https://doi.org/10.1016/S0304-3940 (97)00721-0 (1997).
7. Hausbeck, C.J., Strong, M.J., Tamkei, L.S., Leonard, W.A. & Ustinova, K.I. The effect of additional hand contact on postural stability perturbed by a moving environment. *Gait & posture*; 29:509-513. https://doi.org/10.1016/j.gaitpost.2008.11.014 (2009).
8. Strang, A.J., Haworth, J., Hieronymus, M., Walsh, M. & Smart, L.J. Structural changes in postural sway lend insight into effects of balance training, vision, and support surface on postural control in a healthy population. *European journal of applied physiology*; 111:1485-1495. https://doi.org/10.1007/s00421-010-1770-6 (2011).
9. Amori, V., Petrarca, M., Patané, F., Castell, E. & Cappa, P. Upper body balance control strategy during continuous 3D postural perturbation in young adults. *Gait & posture*; 41: 19-25. https://doi.org/10.1016/j.gaitpost.2014.08.003 (2015).
10. Oliaei, S., Ashtiani, M.N., Azma, K., Saidi, S. & Azghani, M.R. Effects of postural and cognitive difficulty levels on the standing of healthy young males on an unstable platform. *Acta Neurobiol Exp*; 78:60-68. 10.21307/ane-2018-006 (2018).
11. Mirzaei, S. et al. Two-stage feature selection of voice parameters for early Alzheimer's disease prediction. *IRBM*; 39(6): 430-435. https://doi.org/10.1016/j.irbm.2018.10.016 (2018).
12. Begg, R.K., Palaniswami, M. & Owen, B. Support vector machines for automated gait classification. *IEEE transactions on Biomedical Engineering*; 52:828-838. 10.1109/TBME.2005.845241 (2005).
13. Commandeur, D. et al. Difference scores between single-task and dual-task gait measures are better than clinical measures for detection of fall-risk in community-dwelling older adults. *Gait & posture*; 66:155-159. https://doi.org/10.1016/j.gaitpost.2018.08.020 (2018).
14. Altilio. R., Paoloni, M. & Panella, M. Selection of clinical features for pattern recognition applied to gait analysis. *Medical & biological engineering & computing*; 55:685-695. https://doi.org/10.1007/s11517-016-1546-1 (2017).
15. Bidabadi, S.S., Murray, I., Lee. G.Y.F., Morris, S. & Tan, T. Classification of foot drop gait characteristic due to lumbar radiculopathy using machine learning

algorithms. *Gait & posture*; 71:234-240. https://doi.org/10.1016/j.gaitpost.2019.05.010 (2019).
16. Emmens, A.R., Asseldonk, E.H van, Prinsen, V. & Kooij, H van der. Predicting reactive stepping in response to perturbations by using a classification approach. *Journal of neuroengineering and rehabilitation*; 17:1-15. https://doi.org/10.1186/s12984-020-00709-y (2020).
17. Uçar, M.K. Classification Performance-Based Feature Selection Algorithm for Machine Learning: P-Score. *IRBM*; 1: 1–11. https://doi.org/10.1016/j.irbm.2020.01.006 (2020).
18. Shumway-Cook, A. & Woollacott, M. Assessment and treatment of the patient with mobility disorders. *Motor control theory and practical application, Maryland: Williams & Wilkins*; 315-54 (1995).
19. Semwal, V.B., Singha, J., Sharma, P.K., Chauhan, A. & Behera, B. An optimized feature selection technique based on incremental feature analysis for bio-metric gait data classification. *Multimedia tools and applications*; 76:24457-24475. https://doi.org/10.1007/s11042-016-4110-y (2017).
20. Sun, B., Zhang, Z., Liu, X., Hu, B. & Zhu, T. Self-esteem recognition based on gait pattern using Kinect. *Gait & posture*; 58:428-432. https://doi.org/10.1016/j.gaitpost.2017.09.001 (2017).
21. Bardhan, S. & Bhowmik, M.K. 2-Stage classification of knee joint thermograms for rheumatoid arthritis prediction in subclinical inflammation. *Australasian physical & engineering sciences in medicine*; 42(1):259-277. https://doi.org/10.1007/s13246-019-00726-9 (2019).
22. Domingos, P. A few useful things to know about machine learning. *Communications of the ACM*; 55:78-87. 10.1145/2347736.2347755 (2012).