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Application of principal component analysis in vertical ground reaction force to discriminate normal and abnormal gait

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ABSTRACT

Discrete parameters from ground reaction force (GRF) are been considered in gait analysis studies. However, principal component analysis (PCA) may provide additional insight into gait analysis for considering the complete pattern of GRF. This study aimed at testing the application of PCA to discriminate the vertical GRF pattern between control group (CG) and patients with lower limb fractures (FG), as well as proposing a score to quantify the abnormality of gait. Thirty-eight healthy subjects participated of CG and 13 subjects in FG, five subjects from FG were also evaluated after physiotherapeutic treatment (FGA). The GRF was measured by an instrumented treadmill. Principal component coefficients (PCCs) were obtained by singular value decomposition using GRF of complete stride. Two, four and six PCCs were used to obtain the standard distance (*D*). The classification between groups was mainly given by the first PC, which indicated higher loading factors during push off of affected side and heel strike of unaffected side. The classification performance achieved 92.2% accuracy with two PCCs, 94.1% with four PCCs and 96.1% with six PCCs. Four subjects reached normal boundary after treatment, with all FGA subjects presenting decreased *D*. This study demonstrates that PCA is an adequate method for discriminating normal and abnormal gait and *D* allows an objective evaluation of the progress and effectiveness of rehabilitation treatment.

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1. Introduction

Gait analysis is acknowledged for quantifying gait disorders and clinical evaluation of patients [1–2]. In routine gait analysis, ground reaction force (GRF) is recorded by force platforms and changes in its morphology are related to pathological gait [3]. The GRF can be applied to discriminate normal and pathological gait, as well as pre- and post-treatment conditions [4]. Analyzing gait data is challenging due to its high-dimensionality, temporal-dependence, high variability and correlated nature [5]. As a result, to analyze normal and pathologic gait, some authors have used parameterization techniques. Such techniques extract instantaneous values of amplitude from GRF curve, and the pattern of movement is ignored [6]. Therefore, examining the whole GRF data is expected to be more effective for identifying specific locomotion characteristics [4,7]. Although many statistical techniques are available to reduce data and extract useful information, there is still a lack of effective and robust techniques applied in clinical gait analysis [5]. While the description of the walking patterns promotes an overall impression of lower limb movements, in absence of an adequate statistical analysis, gait interpretation becomes more subjective [8].

Recently, principal component analysis (PCA) has become a common method of reducing dimensionality and analyzing waveforms in gait analysis. This method provides a reduced set of uncorrelated variables, which retaining maximally the variances from the original data [9,10]. Such variables can then be used to differentiate between groups [11–15]. PCA are also used to develop a measure of how closely an individual gait pattern approaches normal. Romei et al. [1] and Schutte et al. [2] addressed this issue by considering only discrete variables in searching for a normalcy gait index. Additionally, Tingle et al. [16] and Chester and Wrigley [6] consider multiple curves simultaneously in the creation of such score. However, none of these studies address to analyze the GRF to objectively quantify the patient's gait and to measure the improvement following an intervention.

The present study aimed at testing the application of PCA to discriminate the vertical component of GRF pattern between normal subjects and patients with lower limb fractures and also

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applying the principal components coefficients to obtain a standard distance as a score to classify as normal and abnormal GRF. Additionally, this method is used for the assessment of a physiotherapeutic treatment.

2. Material and methods

Thirteen subjects with unilateral lower limb fracture (FG) (Table 1) and 38 normal subjects (CG) (18 men and 20 women), average ages 23.09 ± 3.77 years, average body mass 67.04 ± 13.66 kg and average height 171.75 ± 7.99 m, without physical lesions, neurological or skeletal muscle disorders participated in the study. Five subjects in FG underwent physiotherapeutic treatment three times a week for about 4 months. Those patients were also assessed after having received treatment (FGA). Each treatment session lasted one hour, consisting of stretching exercises followed by: treadmill walking, muscle strengthening, balance training, proprioceptive training and floor walking. A local ethics committee approved the experimental protocol and all subjects signed a free informed consent.

2.1. Gait analysis and signal processing

Subjects walked on an instrumented treadmill Gaitway® (Kistler Winterthur, Switzerland), at a controlled speed (4 km/h) with their regular walking shoes. After 10-min adaptation period walking in his/her self-selected comfortable speed, the vertical component of the GRF was collected with sampling frequency of 300 Hz during 10 s. This time corresponded to approximately 10 consecutive cycles of gait from one trial, which were used to obtain the average GRF (aGRF) for each limb. The use of the aGRF is recommended to reduce mechanical noise from treadmill [17]. This also takes into account the advantage of treadmill analysis of acquiring larger datasets and thus obtaining a representative gait pattern [18]. The aGRF was normalized by the subject's body weight.

All signal processing and statistical analysis procedures were implemented with the software Matlab 6.5 (The Mathworks, USA). To minimize the effect of random noise, aGRF data were filtered using a low pass, second order Butterworth filter, with cut-off frequency at 30 Hz [8]. To prevent phase drifting, the filter was applied in forward and backward directions. The signals were interpolated and resampled with 100 points according to the stance phase period of each foot. Thus, the 200 samples of the aGRF for a complete stride (right and left side in CG and affected and unaffected limb in FG) were used for analysis.

After extracting the ensemble mean, the aGRF data were organized in a matrix $\mathbf{E}$ (51×200), to calculate the corresponding covariance matrix $\mathbf{S}$ (200×200), with elements $s_{j,k}$ given by [9]:

$$s_{j,k} = \frac{1}{N-1}\sum_{i=1}^{N}(x_{ij} - \bar{x}_j)(x_{ik} - \bar{x}_k) \quad (1)$$

where $N = 51$, and $\bar{x}_j$ and $\bar{x}_k$ are the values of the ensemble mean of the corresponding samples j and k.

The principal components (PCs) were obtained by the solutions of the linear system given by:

$$\mathbf{S}\,\mathbf{x}_p = \lambda_p \mathbf{x}_p. \quad (2)$$

where λ are the 200 eigenvalues ranked in decreasing order and $\mathbf{x}$ are the corresponding normalized eigenvectors. The eigenvector with the highest eigenvalue is the first PC. The second PC corresponds to the second highest and so on. The SCREE Test using the logarithmic scale for the eigenvalues [9] and Broken Stick test [9,19–21] criteria were used for choosing the relevant PCs for the analysis.

Each column of $\mathbf{Z}_p$ matrix of principal component coefficients (PCCs) $\mathbf{Z}$ ($N \times P$) was obtained by

$$\mathbf{Z}_p = \mathbf{E}\,\mathbf{x}_p. \quad (3)$$

Thus, matrix $\mathbf{Z}$ was composed by coefficients that measure the contribution of the PCs to each individual waveform [14].

2.2. Normalcy index

The standard distance (D) proposed by Flury and Riedwyl [22] was calculated to measure how far each subject's gait was from CG dataset, using as a reference the mean value of PCCs of CG. This parameter corresponds to the square root of the Mahalanobis distance, representing the distance between each observation (o_i) and the mean of the PCC values of CG ($\bar{m}$), normalized by the variance of each PCC, as follows:

$$D_i = [(o_i - \bar{m})' S^{-1} (o_i - \bar{m})]^{1/2} \quad (4)$$

where S^{-1} is the inverse of covariance matrix from CG, and $(o_i - \bar{m})'$ is the inverse of the vector $(o_i - \bar{m})$. This parameter emphasizes the distance between two observations in the direction of the low-variance PCs and down weights distances in the direction of high-variances PCs. The D was calculated for each subject of the CG, FG and FGA. For classifying normal or abnormal GRF pattern, the cut-off point between D values from CG and FG was obtained by logistic regression [23].

The classifier performance was assessed by leave-one-out cross-validation technique, which provides a good indication of reliability in classification of small datasets [24]. In N observations one was removed and further compared with the cut-off point given by the remaining ($N - 1$). Afterward, the data point was replaced and another observation removed from dataset. This process was repeated up to all observation had been left out in turn. The results of each comparison were used to assess the performance of the classifier, by computing overall accuracy, sensitivity (correct classification of FG) and specificity (correct classification of CG).

2.3. Elliptical boundary

Only two PCCs were considered to delimit CG in an elliptical boundary of constant probability [9]. The two axes of the ellipse were obtained by PCA as proposed by Oliveira et al. [25]. The ellipsoids gave contours of equal cut-off point D calculated with two PCCs. This approach was used to allow visual interpretation.

2.4. Statistical analysis

The Wilcoxon Rank Sum test was used to compare differences between PCCs from CG and FG. The non-parametric test was chosen because the small sample size of FG. The significance level used was $\alpha = 0.05$.

3. Results

The qualitative inspection of averaging aGRF from CG allows observing a typical bimodal pattern (Fig. 1a), with reduced dispersion around the peaks and good symmetry between sides. In contrast, FG presented asymmetric pattern between affected and unaffected limbs (Fig. 1b). In the affected limb, both push-off force appears reduced when visually compared to GC and unaffected limb. Increased loading rate in the heel strike was observed in an unaffected limb.

Table 1
Fracture group characteristic

Subject	Age (years)	Body mass (kg)	Height (m)	Gender	Localization of the fracture
1	24	102	180	Male	Tibial and fibula
2	29	69	171	Male	Calcaneus
3	28	61.5	176	Male	Tibia and fibula
4	16	99.5	194	Male	Tibia and fibula
5	40	110	177	Female	Calcaneus
6	34	89	183	Male	Calcaneus
7	32	65.6	165	Female	Femur
8	21	61.8	168	Male	Femur
9	33	77.2	171	Male	Calcaneus
10	28	81.8	180	Male	Tibia
11	58	76.5	159	Female	Femur
12	43	91.9	170	Male	Calcaneus
13	28	89.2	172	Male	Tibia
Average (±S.D.)	31.85 (±10.66)	92.50 (±17.9)	174.31 (±8.87)		

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