Medical Engineering & Physics 21 (1999) 235–240
Medical Engineering & Physics
www.elsevier.com/locate/medengphy

Inter- and intra-individual variability of ground reaction forces during sit-to-stand with principal component analysis

Gianluca Borzelli [a,*], Aurolio Cappizzo [b], Elisabetta Papa [b]

[a] *Telespazio S.p.A., Rome, Italy*
[b] *Istituto di Fisiologia Umana, Università degli Studi di Roma, La Sapienza, Italy*

Received 5 October 1998; received in revised form 17 June 1999; accepted 24 June 1999

Abstract

Variable reduction is an important issue in biomechanics, because the definition of a non-redundant set of variables necessary for a complete description of a given motor act provides information about the motor strategy. A systematic tool for dealing with variable reduction problems is Principal Component Analysis. In this paper, as an example of an application of this technique, the set of Ground Reaction Forces (GRFs) provided by a six-component force plate, gained during standing up in a heterogeneous population of 82 normal individuals, was reduced to a set of fewer variables. Each subject was required to stand up from a chair five times at different, randomly self selected, speeds, obtaining a data set of 410 trials. Principal Components (PCs) of GRFs were computed for each trial. On average, over the ensemble of trials, first and second PCs (PC1 and PC2) explained together 90% of the data set variance, indicating that, during standing up, movement of the human body may be reliably described by using two PCs. Inter- and intra-individual repeatability of the first two PCs was investigated by examining the correlation coefficient between PC waveforms obtained from the whole set of trials and within the set of trials performed by the same subject, respectively. While the PC1 exhibited repeatable patterns, the second one, although repeatable within the group of trials performed by the same subject, displayed marked inter-individual variability. Therefore, PC1 was related to intrinsic aspects of the motor task and PC2 to inter-subject features. © 1999 IPEM. Published by Elsevier Science Ltd. All rights reserved.

Keywords: Principal components; Ground reaction forces; Sit to stand

1. Introduction

Description of human movement occurs by measuring variables that describe the dynamics and/or the kinematics of the body during the execution of a motor act. In these situations, because no a priori information is generally available on the dynamic of a motor act, the human body is considered an unconstrained rigid body with six degrees of freedom and, the description of movement, is accomplished by assigning a set of six kinematic and/or dynamic variables (generally joint trajectories and/or forces). However, coordination produces symmetries that decrease the degrees of freedom the subject can manage to accomplish the required motor task, rendering the set of six variables used to describe motion of the human body over dimensioned with respect to the actual needs of the analysis. Coordination arises from the necessity of adjusting internal and external forces in such a way to allow the execution of a motor act, and the motor strategy is the result of tuning mechanisms between these forces. Therefore, the identification of a non-redundant set of variables necessary for describing a given motor act provides important information about the motor strategy. An analysis of Ground Reaction Forces (GRFs) provided by a six channel force plate during Sit-To-Stand (STS) experiments is presented in this paper.

There are two reasons for concentrating on STS: first, STS is considered an important task for evaluating differences in individual motor ability [1,2 pp. 109–116,3–5]. Second, although inter-individual differences in accomplishing this motor task constraints and symmetries during its execution led researchers to identify common strategies between different subjects in rising from a chair [6,7]. In particular, Roberts and McCollum [7] hypothesized that constraints related to the final

* Tel: +3906-40793684; fax: +3906-40793628.
E-mail address: gianluca@biolab.med.unisi.it (G. Borzelli)

1350-4533/99/$ - see front matter. © 1999 IPEM. Published by Elsevier Science Ltd. All rights reserved.
PII: S1350-4533(99)00050-8

achievement of this motor task, could induce symmetries that allowed to model the human body during STS as a mechanical system with only two degrees of freedom.

Principal Component (PC) analysis [8] is a classical approach for dealing with variable reduction problems. This technique is based on the identification of a linear transformation of variables that diagonalyzes the data covariance matrix. Therefore, PCs represent transformed, uncorrelated variables responsible for given fractions of the overall data set variance. Furthermore, the number of significant variables necessary for a faithful description of the phenomena investigated is accomplished by analyzing only those PCs that explain high fractions of the entire data set variance.

In this study, PC analysis is used to reduce the set of six Ground Reaction Forces (GRFs) gained during STS experiments to a set constituted by fewer significant variables. Then, inter- and intra-individual repeatability of reduced variables is investigated by using standard tests of correlation analysis.

2. Material and methods

2.1. Data acquisition and processing

A sample of 24 healthy young adults (14 males and 10 females, age 22–34, body mass 48–84 kg, body height 1.58–1.78 m) and 58 healthy elderly (22 males and 36 females, age 58–82, body mass 52–101 kg, body height 1.42–1.71 m) was analyzed, after informed consent had been obtained. The experimental apparatus consisted of: (1) a chair modular seat without backrest of adjustable height; (2) a six-component *BERTEC* force plate (0.4×0.6 m), positioned under both the subject's feet and the chair, (3) software tools for data acquisition and processing, purposely developed using National Instruments LabView® and MatLab®. In order to make the subject feel comfortable, the support base provided by the force plate was enlarged by means of a wooden platform (0.6×0.9×0.02 m). Nevertheless, during the experiments the center of pressure remained within the area defined by the four force transducers.

Subjects were asked to sit in a standardized posture (chair height adjusted at 80% of knee height from the ground, arms folded across the chest, vertical trunk). Removable markers were located on the platform and the chair, to make the subject assume the same initial posture prior to all trials. Subjects were instructed to rise from the seat at an operator command, not move the feet during the task and remain still once the upright position was reached until a further operator's command was imparted. Five STS trials, at randomly self-selected speeds, were recorded for each subject. During each trial, the force plate readings were acquired for 5 s with sampling frequency of 100 sample/s.

The result of the experimental data set was a set of 410 trials, consisting of six waveforms (three force and three moments), for each different act. For each trial, the epoch identifying the execution of the act was automatically isolated and extracted from the corresponding file. The commencement of movement was defined as the intersection of the line connecting 20 to 80% of the maximal value of the antero–posterior GRF component with the time axis. The start of the "stabilization" phase [9] was defined as the intersection of the line connecting 80 to 20% of the minimal value of the GRF vertical component with the body weight level.

We have already seen that PCs obtained from data represent independent patterns responsible for given fractions of the entire data set variance. The effect of random noise generated by the amplifier of the force plate may induce variability in the data, that modifies the level of variance explained by the different PCs. Therefore, to minimize the effect of random noise, before performing PC analysis, experimental GRFs were filtered using a digital, low pass, second order, Butterworth filter. In order to prevent non-linear phase shifting and attain linear phase response in the filtered data, filtering was performed by adopting a cascade forward–backward technique [10]. Filtering cut-off frequencies were selected for each waveform by using residual analysis and residuals between experimental and filtered signals were quantified using the following strategy. First, Fourier Transform (FT) of experimental waveforms was estimated by using standard routines of the MatLab® package [10]. Then, the signal was rebuilt by considering fewer harmonic constituents than those contained in the entire spectrum. Increasing the number of harmonic constituents, the residual between experimental and filtered signal decreases and the correlation coefficient between these waveforms varies, as a function of the number of harmonic constituents, as shown in Fig. 1. Correlation coefficients plots display two regions where the correlation coefficient varies roughly linearly but with different slope. The interception between these lines provides cut-off frequencies. To identify the couple of lines that best represent the variation of correlation coefficients, data shown in Fig. 1 were padded in two windows. By varying the window size and, fitting data in the two windows separately with a straight line, different couples of lines that fit data were obtained. The couple of lines that best represent data were chosen by maximizing the correlation coefficient between data and their representation in terms of couples of lines (Fig. 1). This procedure was applied separately for each GRF component of every trial, obtaining a set of six different cut-off frequencies for each trial.

In order to obtain sets of waveforms gained from different trials formed by the same number of points, extracted epochs were interpolated. To avoid high frequency variability related to the interpolation scheme

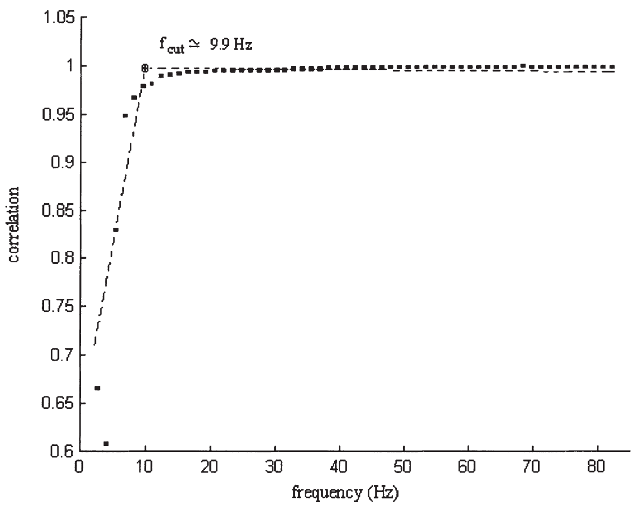

Fig. 1. Illustration of the method used to assess cut-off frequency for filtering GRFs waveforms. Application to the medio–lateral waveform gained from one trial. Points represent correlation values between original waveform and its representation in terms of fewer harmonics than those contained in the whole spectrum. Two regions, identified by the intersection of the two regression lines (dashed line), are visible.

rather that to the signal, resampling was accomplished by using a polyphase algorithm, that applies to original data an anti-aliasing, lowpass, FIR filter with Kaiser window [11]. For each different act, the resampling rate was chosen so as to guarantee signals gained during the fastest trial, not to be resampled with frequency higher than the acquisition frequency. Duration of the fastest trial was approximately 1.2 s, so that associated signals were resampled by requiring the whole duration of the act to be covered with 128 samples.

2.2. Principal components analysis

PC analysis is a method widely used for statistical reduction of experimental data [8] and it is useful for reducing sets of time-varying correlated variables into novel sets of time varying uncorrelated (orthogonal) variables, termed PCs or patterns of residual variance. To each PC is associated a fraction of the entire data set variance. The fraction of variance associated with each PC determines the importance of the features described by that PC in determining the entire data set variability.

The PCs of one trial data set were determined as follows. Let the data matrix **D** be

$$\mathbf{D}=[x_{ij}],\ i=1...M,\ j=1...N \quad (1)$$

where x_{ij} is the ith sample of the jth component of the GRFs vector, M=128, N=6. The covariance matrix is defined from the data matrix as

$$\mathbf{C}=\frac{\mathbf{D}'^{\mathrm{T}}\cdot\mathbf{D}'}{M} \quad (2)$$

where $\mathbf{D}'=[x_{ij}-\bar{x}_j]$, and $\bar{x}_j$ is the mean value of the jth column of matrix **D**. **C** is a real, symmetric and square ($N\times N$) matrix, that can be reduced to diagonal form with eigenvalues $\lambda_j\geq 0$ (j=1...N). This was done using Singular Value Decomposition [12]. Termed $\mathbf{U}=[u_{ij}]$ the matrix whose columns are the eigenvectors of **C**, the columns of the $M\times N$ matrix $\mathbf{P}=\mathbf{D}'\cdot\mathbf{U}$ are, by definition, the PCs of the data set [1]. By computing the matrix elements of the product $\mathbf{U}^{\mathrm{T}}\cdot\mathbf{U}$, using the fact that eigenvectors of **C** are orthogonal, it can be shown that **U** is unitary. Using this property, from the definition of PCs, the relationship between the ith sample of the jth component of GRFs vector is

$$x_{ij}-\bar{x}_j=\sum_{n=1}^{N}p_{in}u_{jn} \quad (3)$$

where p_{in} is the ith element of the nth PC.

It can be shown that PCs are orthogonal functions [8] and, thus, they are uncorrelated [13]. Furthermore, to each PC is associated a fraction of the overall data set variance [8]. The cumulative variance associated with a group of PCs determines how well, through Eq. (3), data may be represented limiting the sum (3) to that group of PCs. When PCs are ordered according to the value of the corresponding eigenvalue, and the cumulative variance associated with the firsts N_0 ($\leq N$) PCs is retained satisfactory for a faithful description of the data set, data are represented truncating (3) to N_0. For these reasons PCs identify a set of independent variables, deduced with a linear transformation of the original set of GRFs.

An issue of practical importance when PCs are performed from experimental data relates to physical dimensions of the data matrix columns. Indeed, if waveforms that form the columns of the data matrix are expressed in different units, the corresponding PCs computation may be affected by artifacts due to variabilities related to different units rather than changes of the dynamical state of the system. To avoid such artifacts, original waveforms were transformed, before performing PC analysis, according to the equation

$$\tilde{x}_l(t)=\frac{x_l(t)-x_l^{(0)}}{x_e^{(1)}-x_e^{(0)}} \quad (4)$$

where $x_l^{(1)}$ and $x_l^{(0)}$ are maximum and minimum of the lth waveform, respectively.

For each trial, waveforms, obtained by applying Eq. (4) to resampled force plate readings, were arranged as columns of the data matrix and, then, PC analysis was performed by diagonalyzing the data covariance matrix using a standard Singular Value Decomposition algorithm [12]. Finally, correlation coefficients between different PC waveforms and between PC waveforms and GRFs were computed by using standard routines of the MatLab® package [11].

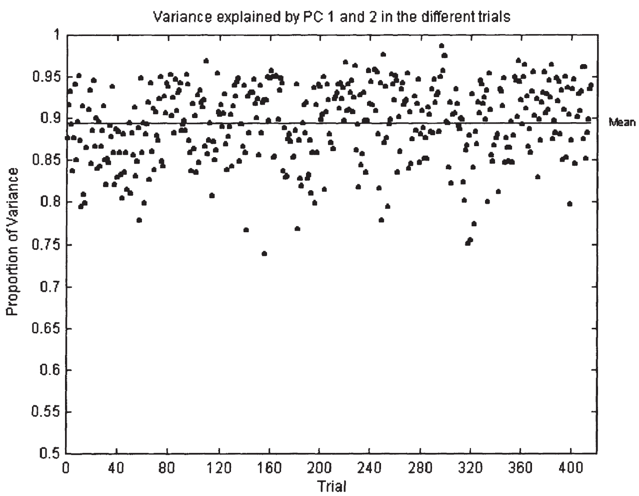

Fig. 2. Cumulative variance explained by PC1 and PC2.

3. Results

In Fig. 2 cumulative variances associated with the first PCs (PC1) and the second PCs (PC2) for every trial are shown. Except in a few cases, PC1 and PC2 explained cumulatively more than 80% of the total variance with mean value of approximately 89%. PC1 and PC2 explained on average 62.6 and 26.8% of total variance, respectively, whilst, in every trial, negligible fractions of variance were associated to succeeding PCs (see Table 1, for reference).

In Fig. 3, PC1 for all trials are shown. The analysis of Fig. 3 indicates that first PCs gained from different trials exhibit similar temporal variability with mean correlation coefficient on the order of 0.84. This indicates that, although inter-individual differences occur during raising from a chair, PC1 of GRFs is a recurrent feature of the act.

In Fig. 4, the mean waveform of the medio–lateral moment, averaged over the entire ensemble of trials, is shown. Dashed lines, in the same figure, represent standard deviations of the corresponding waveform, performed over the same population of trials. Comparing Figs. 3 and 4, similarities between PC1 and medio–lateral moment waveforms are evident. The mean correlation

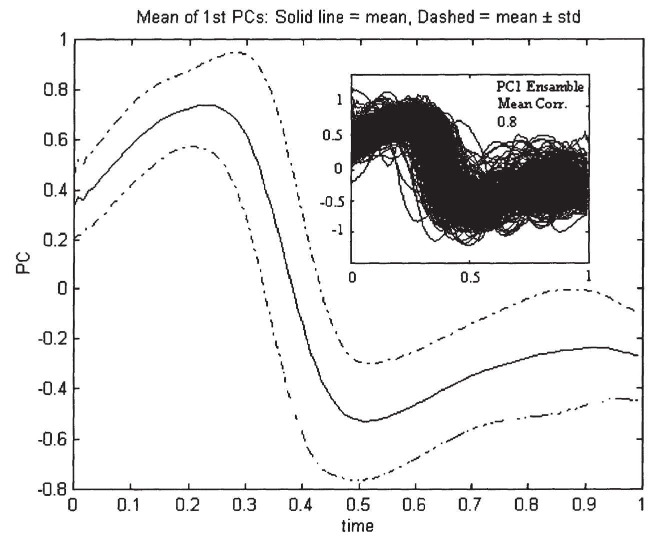

Fig. 3. PC1s of GRFs gained from the different trials. In the main frame the mean PC1, averaged over the ensemble of 410 PC1s is shown (solid line). Dashed line represents the standard deviation about the mean. In the small frame the entire ensemble of PC1s is shown. Note that PC1s are vectors made up of 128 elements and, thus, the mean PC1, along with the standard deviation, is a vector of length 128.

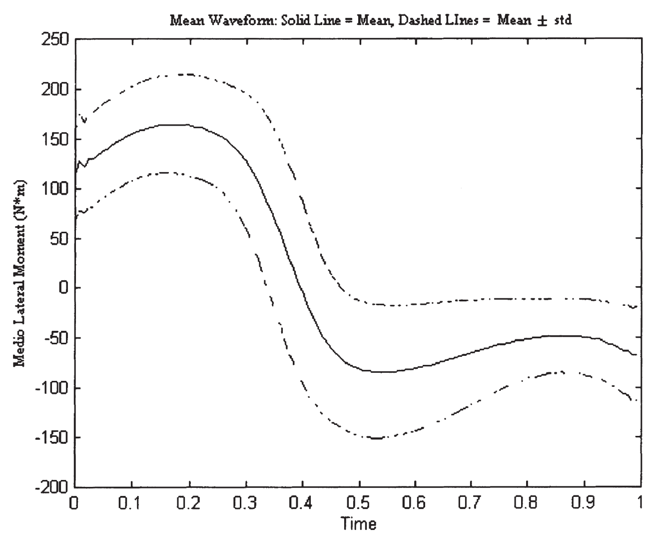

Fig. 4. Solid lines represent mean medio–lateral moment, averaged over the whole ensemble of trials. Dashed lines represent standard deviations about the mean.

Table 1
Summary of the results of Principal Component Analysis

	PC1	PC2	PC3	PC4	PC5	PC6
Mean significance ± $\sigma/2$	0.6262±0.0361	0.2683±0.0328	0.0789±0.0205	0.0191±0.0044	0.0062±0.0019	0.0013±0.0009
Mean correlation coefficient between different trails (inter-individual repeatability)	0.8437	0.4306	0.2813	0.3436	0.2288	0.2782
Mean correlation coefficient between different trails of the same subject (intra-individual repeatability)	0.8813	0.8632	0.3012	0.2812	0.3971	0.2964

coefficient between medio–lateral moment and PC1 is 0.88.

Levels of correlation between second PC2 gained from different trials have been estimated to assess the level of inter-subject repeatability of patterns displayed by these PCs. The mean correlation coefficient between second PC2 waveforms, averaged over the entire ensemble of trials, is 0.43, indicating that features displayed by PC2 cannot be related to intrinsic aspects of STS. However, in Fig. 5(a–b), two sets of five PC2, gained from the five trials performed by two different subjects, are shown. In these exemplar cases, it is visible that, although there are inter-subject differences, PC2 is well reproduced across different trials of the same subject. The mean correlation coefficient, averaged over the entire subject population, between waveforms gained from different trials of the same subject is 0.86, indicating that this aspect of the execution of STS is common to the different trials performed by the same subject.

4. Discussion and conclusion

In the execution of STS, mechanical constrains are imposed on the subject, which limit the degrees of freedom he/she can manage. Such constraints are responsible for the redundancy of the information associated with the six components of the GRFs demonstrated in this paper. In fact, unless fractions of variance are in the order of 10%, which may be related to noise, the analysis of variance explained by PCs indicated that the number of variables necessary for describing standing up is 2. Generally speaking, constraints may be ascribed to the nature of the movement required, which imposes a progressive elevation of the body center of mass, accompanied by a well-tuned forward progression, necessary to gain a stable upright posture.

The high correlation between PC1 values gained from different trials and different subjects, indicates that, although subject specific standing up strategies, the whole population accomplished the motor task by adjusting GRFs in such a way as to produce the same PC1. This result suggests to relate features displayed by PC1 to intrinsic aspects of the motor task. In this context, it is worth noticing the heterogeneous nature of the sample population investigated in terms of age and anthropometric features.

The high correlation between the medio–lateral moment (moment about the transverse axis) and PC1 indicates that the latter is essentially determined by the product between the vertical force and the antero–posterior component of the center of the pressure trajectory, consistent with the considerations of the mechanical constraints reported above. Furthermore, PC1 depends neither on the lateral displacements of the center of pressure nor on the lateral component of force. Indeed, Hesse et al. [5], analyzing standing up in a population of healthy subjects, found substantial differences in lateral drifts of the center of pressure across subjects. Therefore, it is possible to conclude that lateral displacements of the center of pressure characterize the subject, but not STS.

The fact that PC1 explains the greatest portion of the entire data set variance, shows that individual standing up strategies are strongly influenced by mechanical constraints, which are the same for different healthy subjects. This consideration provides the key for interpreting difficulties in classifying GRF waveforms gained from different individuals during standing up. Indeed, the analysis presented here shows that most important standing up patterns are common to a heterogeneous population of subjects and, thus, although providing important information on intrinsic aspects of the act, are not useful for handling classification problems.

Individual differences are evident in PC2 that exhibits intra-individual repeatable patterns, but shows marked differences across different subjects. Relationships between the PC2 and original GRF waveforms have been analyzed, but, in contrast to PC1, no clear evidences for relationships of this component with a given GRF or a linear combination of them has been observed.

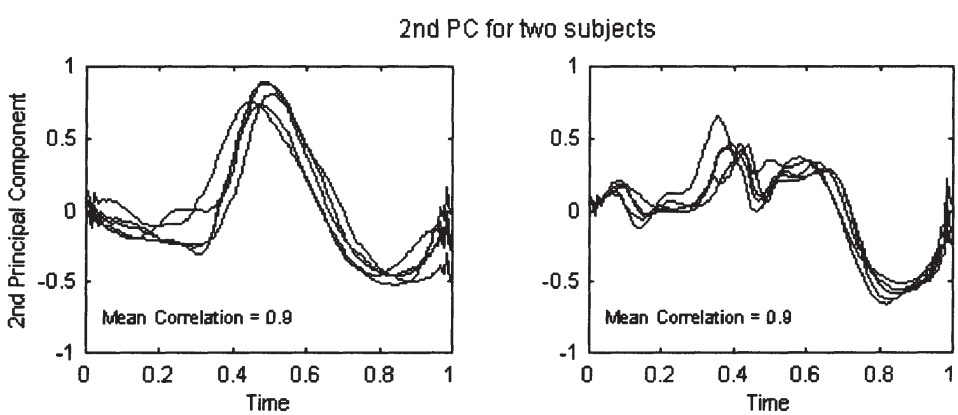

Fig. 5. PC2s of GRFs gained from five trials of two distinct individuals. Note that this PC is not repeatable between the subjects.

In fact, although the linear combination of GRFs determining PC2 remained unchanged within the group of trials gained from the same subject, marked differences were observed across subjects. Thus, PC2 arises from different ways individuals accommodate both the actions of internal and external forces to achieve the motor task.

In the treatment presented here, some criticism could be directed at experimental protocols. It could be argued that the initial sitting height (80% of knee height) and data windowing based on a force threshold (20 and 80% of maximum horizontal force) are arbitrary. In this context, it should be emphasized that, despite the particular application, the proposed methodology is expected to be efficiently applicable as a tool for variables reduction in many different movement studies as, for instance, gait analysis. Of course results depend on the motor task chosen and the experimental protocols adopted, but, as far as STS is accomplished within the protocols stated above, the identification of a non-redundant set of variables provided valuable information about the way different individuals accommodate external and internal forces during the execution of this motor task. Changing experimental protocols quantitative results are expected to change too. Nevertheless, qualitative information is expected to remain unchanged. For instance, by decreasing the sit height, more knee torque and, thus, more moment about the medio–lateral axis, is required for standing up [14]. Since PC1 is related to the medio–lateral moment, by decreasing the seat height, PC1 is expected to explain a greater portion of variance as compared to that explained adopting the protocol presented here. However, inter- and intra-individual repeatability of the PC1 and PC2, respectively, are expected to remain unchanged.

STS has been chosen for two main reasons: first, it is related to strength and, thus, it is recognized as an important task for evaluating human motor task performance [14]; second, it necessitates considerable postural control and requirements to balance are expected to be similar for different individuals. Therefore, aspects common to different subjects are expected to play an important role in accomplishing this motor task, rendering Principal Component Analysis a powerful tool for analyzing STS. With similar considerations Principal Component Analysis is expected to be useful for analyzing other motor acts, like, for instance gait sequences, where postural control accompanied by a considerable muscle strength is required.

Although PCs have been related to intrinsic and subject-specific aspects of standing up, no attempts of classification have been carried out. In this context it cognitive rather than the methodological nature of the study presented here, should be emphasized. The heterogeneity of the sample analyzed, in terms of anthropometry and the non-strict standardization imposed on the initial posture, guarantee a generality of results but do not contain definite classes to which different subjects may be assigned. Future research should focus on classification problems. In particular, an intriguing hypothesis would be testing whether or not the ways different subjects accommodate their GRFs to produce their own PC2 is related to their anthropometric features and, thus, assign different subjects to different classes assessed on the basis of these features. Unfortunately the sample presented here do not allow such an investigation. To this end, much work, based on ad hoc experimental campaigns, has still to be carried out.

Acknowledgements

Professors F. Eusebi and P. Barbini are greatly acknowledged for critical discussion of the data and precious suggestions. Acknowledgements are due to two anonymous referees, whose comments and constructive criticism contributed to improve the original manuscript.

References

[1] Jones FP, Hanson FP. Time–space pattern in a gross body movement. Percept Motor Skills 1961;12:35–41.
[2] Bobath B. Adult hemiplegia: evaluation and treatment. London: William Heinemann Medical Books Ltd, 1978.
[3] Burdett RG, Habasevic R, Pisciotta J, Simon SR. Biomechanical comparison of rising from two types of chairs. Phys Ther 1985;65:1177–83.
[4] Jones FP, Hansen JA, Miller JF, Bossom J. Quantitative analysis of abnormal movement: the sit-to-stand pattern. Am J Phys Med 1963;42:208–18.
[5] Hesse S, Shauer M, Jahnke MT. Standing up in healthy subjects: symmetry of weight distribution and lateral displacement of the centre of mass as related to limb dominance. Gait Postu 1996;4:287–92.
[6] Schenkman ML, Berger RA, Riley PO, Mann PW, Hodge WA. Whole body movements during rising from sitting to standing. Phys Ther 1990;70:638–51.
[7] Roberts PD, McCollum G. Dynamics of the sit-to-stand movement. Biol Cyber 1996;74:147–57.
[8] Joliffe IT. Principal component analysis. New York: Wiley, 1986.
[9] Karlj A, Jaeger RJ, Munit M. Analysis of standing up and sitting down in humans: definitions and normative data presentation. J Biomech 1990;23:1123–8.
[10] MatLab 5 language reference manual. MathWorks, 1996.
[11] Parks TW, Burrus CS. Digital filter design. New York: Wiley, 1987.
[12] Press WH, Flannery BP, Teukolsky SA, Vetterling WT. Numerical recipes. Cambridge: Cambridge University Press, 1987.
[13] Paopulis A. Signal analysis. New York: McGraw-Hill, 1977.
[14] Alexander NB, Shultz AB, Ashton-Miller JA, Gross MM, Giordani B. Muscle strength and rising from a chair in older adults. Muscle Nerve 1997;Suppl 5:S56–9.