Gait & Posture 36 (2012) 40–45

Contents lists available at SciVerse ScienceDirect

Gait & Posture

journal homepage: www.elsevier.com/locate/gaitpost

Discrimination of gender-, speed-, and shoe-dependent movement patterns in runners using full-body kinematics

Christian Maurer *, Peter Federolf, Vinzenz von Tscharner, Lisa Stirling, Benno M. Nigg

Human Performance Laboratory, Faculty of Kinesiology, University of Calgary, Calgary, Alberta, Canada

ARTICLE INFO

Article history:
Received 31 October 2011
Received in revised form 8 December 2011
Accepted 19 December 2011

Keywords:
Gait analysis
Principal component analysis
Support vector machine
Principal movement patterns
Full-body marker setup

ABSTRACT

Changes in gait kinematics have often been analyzed using pattern recognition methods such as principal component analysis (PCA). It is usually just the first few principal components that are analyzed, because they describe the main variability within a dataset and thus represent the main movement patterns. However, while subtle changes in gait pattern (for instance, due to different footwear) may not change main movement patterns, they may affect movements represented by higher principal components.

This study was designed to test two hypotheses: (1) speed and gender differences can be observed in the first principal components, and (2) small interventions such as changing footwear change the gait characteristics of higher principal components.

Kinematic changes due to different running conditions (speed – 3.1 m/s and 4.9 m/s, gender, and footwear – control shoe and adidas MicroBounce shoe) were investigated by applying PCA and support vector machine (SVM) to a full-body reflective marker setup.

Differences in speed changed the basic movement pattern, as was reflected by a change in the time-dependent coefficient derived from the first principal. Gender was differentiated by using the time-dependent coefficient derived from intermediate principal components. (Intermediate principal components are characterized by limb rotations of the thigh and shank.) Different shoe conditions were identified in higher principal components.

This study showed that different interventions can be analyzed using a full-body kinematic approach. Within the well-defined vector space spanned by the data of all subjects, higher principal components should also be considered because these components show the differences that result from small interventions such as footwear changes.

1. Introduction

The characteristics of human locomotion may change for different boundary conditions such as running speed [1], footwear [2], and running surface [3]. In addition, locomotion characteristics may differ for groups of subjects that differ in terms of gender [4] or age, and/or groups with different anthropometrical characteristics. In studying the adaptation of gait characteristics to changes in boundary conditions (e.g. changes in footwear), one is faced with the problem that subject-specific differences (e.g. gender, anatomical differences) or test conditions (e.g. running speed, environment) may have a larger effect on gait characteristics than the typically small changes due to footwear [5]. However, the identification of changes due to footwear is important for the development of rehabilitative footwear.

In trying to identify the adaptations of gait characteristics to changes in footwear, two different approaches have been applied: (a) the quantifying of discrete variables and (b) the full-body kinematic approach.

Discrete variable analysis has often been used to monitor the effects of changing boundary conditions [6,7]. This approach uses a prior, often intuitive, selection of variables that "most likely" contain the desired information. It does not use a large portion of the data collected during a movement task, and it may not automatically select the most sensitive variables.

The full-body kinematic approach uses all of the information that is recorded within a specific set of data and mathematical tools are used to separate the information that has changed due to an intervention from changes that have occurred due to the nature of the task (e.g. [8–10]).

Pattern recognition methods [11] have been developed that can be used in a full-body kinematic approach. Of these, principal

* Corresponding author at: Human Performance Laboratory, Faculty of Kinesiology, University of Calgary, 2500 University Drive NW, Calgary, Alberta, Canada T2N 1N4. Tel.: +1 403 220 2170; fax: +1 403 282 7637.
E-mail address: christian.maurer.cm@gmail.com (C. Maurer).

0966-6362/$ – see front matter.
doi:10.1016/j.gaitpost.2011.12.023

component analysis (PCA) is one of the most frequently applied basic tools. It analyzes the data according to their variance. The interpretation of a PCA result depends on the generation of an input matrix. Different approaches for generating an input matrix are discussed below. Two result characteristics are the same for all PCAs. The first is a set of principal component vectors. Each principal component vector combines variables that are correlated in time. Principal component vectors can, therefore, be interpreted as principal movements (PMs). The first PM points in the direction of the largest variability within the data set. The second characteristic is a set of principal component coefficients. Principal component coefficients are projections of the input data onto the PMs, and are called principal values (PV) throughout this paper. Principal values represent movement changes in time and are, in general, time dependent.

Both PMs and PVs depend on an input matrix. Different sets of kinematic data can be used to generate an input matrix. Recently, position data for limbs [9,10,12,13] or joint angles have been used [14–17]. Principal component analysis can be applied per condition [12–14,16], per subject [9,14,16,17], or across subjects [10,12,15–17]. In interpreting the data, one can use the variability explained by individual PMs [12–17]. It is possible to examine the change in PM for different conditions [9,10,12–14,17], or to interpret the change in PVs for different conditions [9,10,15,16,18]. The PMs and PVs for different conditions can be differentiated using classification methods such as support vector machine (SVM) or spherical classification [19,20].

In this paper, the position data for all conditions and subjects are included within one input matrix. Therefore the PMs are the same for all conditions and subjects, and a direct comparison between conditions and subjects can be made using the time-dependent PVs. In using this approach with data from running, the first five PMs often explain more than 95% of the variability and, therefore, represent the basic movements of the task [9,10,12,13]. Higher-order PMs are often neglected, as they explain only a small fraction of the variability and are considered to represent random noise. If sufficient input data is available, however, higher-order PMs may contain information pertaining to small changes and thus become relevant. In this paper all PMs are analyzed. Variables such as speed and gender are assumed to change basic movement patterns. Smaller interventions may not change basic movements, but they may lead to significant changes in the PV of higher PMs.

This study was designed to test two hypotheses: (1) speed and gender differences are typically observed in the first principal components, and (2) interventions such as changing footwear change the gait characteristics of higher principal components.

2. Methods

Twenty healthy, physically active, recreational athletes participated in this study. Subjects were recruited with flyers. Based on a literature review the sample size was chosen to include ten female subjects (age 32 ± 9 years, mass 61.3 ± 6.1 kg, mean and SD) and ten male subjects (age 25.4 ± 5.4 years, mass 75.8 ± 11.3 kg). Subject grouping was a matter of convenience in order to keep the time commitment on an acceptable level. All subjects gave their written informed consent in accordance with the University of Calgary's policy on research using human subjects. The study protocol was approved by the Conjoint Heath Research Ethics Board at the University of Calgary.

2.1. Experimental protocol

The effects of shoes were studied using the females in the test group. The female participants performed two runs of one hour each on a treadmill, four weeks apart. Both runs were performed at approximately 95% of their maximal aerobic speed (MAS). (MAS was determined at a separate session). For this study, 30 s of data were collected at 10 min into each of the two test runs. We used two groups to test the

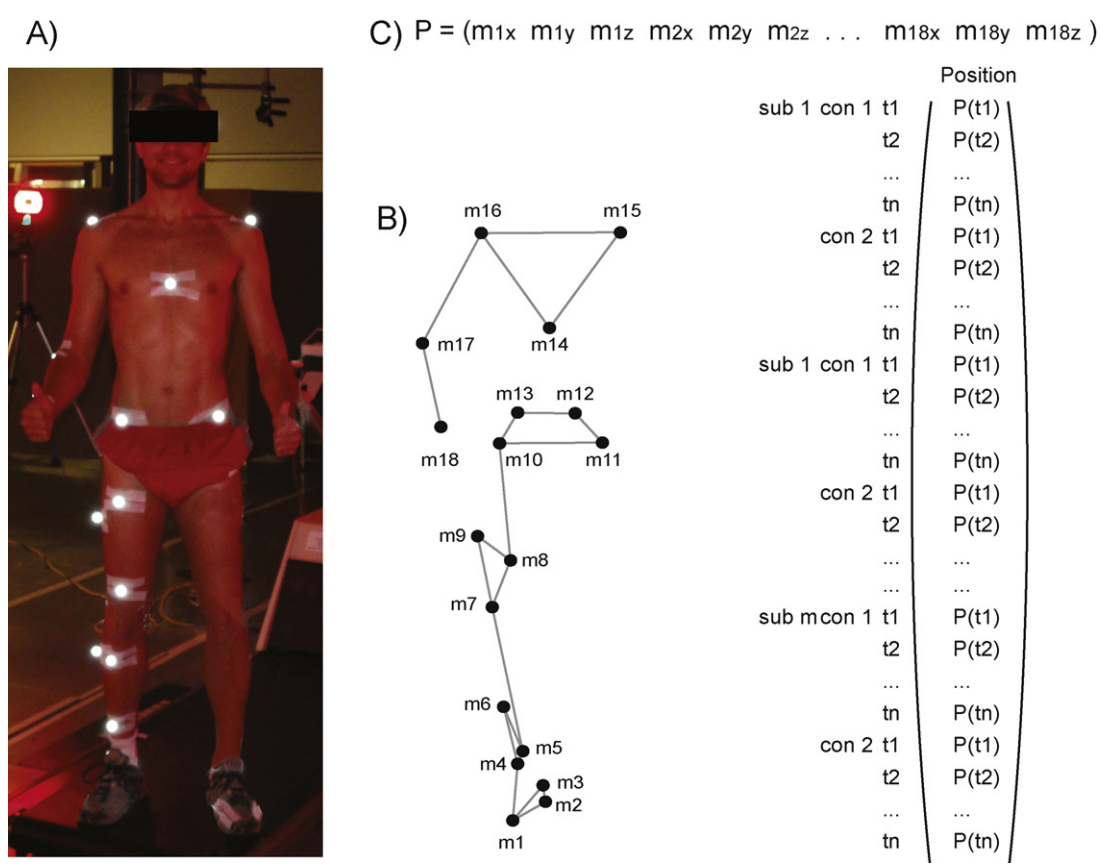

Fig. 1. Marker setup and matrix definition. Eighteen markers were placed on landmarks of the right leg and arm (A and B). The *x*, *y*, and *z* coordinates of the marker define the posture vector (C). Time-dependent position vectors subtracted from the subject mean for all conditions and markers generates the input matrix for the covariance calculation.

effects of changing shoes. Group A ($n = 3$) wore the same shoes for both tests, and group B ($n = 7$) wore their own shoes for the first run, and adidas MicroBounce [21] shoes for the second run. Group size was chosen in order to address day to day variability with group A and differences in shoe conditions with group B.

The male participants performed two short, consecutive runs on a treadmill at different running speeds (3.1 m/s and 4.9 m/s) on the same day wearing their own shoes. After warming up for 10 min, the subjects ran for 40 s at each speed. The data used in this study were recorded during the last 30 s at each speed.

Kinematic data for the right leg, right arm, hip, and both shoulders were recorded at 240 Hz using a standard motion analysis system with eight cameras (Eagle Eye, Motion Analysis Corporation, USA). Eighteen infrared reflective markers (diameter 1 cm) were attached to the lower and upper body of each runner (Fig. 1).

2.2. Conditions

Differences in *speed* were compared within the male subgroup ($n = 10$). *Gender* differences were analyzed for a speed of 3.1 m/s for the males and 3.0(0.3) m/s for the females, with all subjects running in their own footwear ($n = 20$). *Shoe* differences were evaluated in the subgroup of female runners ($n = 7$) who wore their own shoes for the first run and the adidas MicroBounce shoes for the second run.

2.3. Data processing

2.3.1. Principal component analysis

The data were tracked with Cortex® (Motion Analysis Corporation, USA), and then analyzed with Matlab® (Mathworks 2008b) using custom-made programs. The kinematic data were analyzed using a PCA [9,10]. A position vector matrix for one subject was constructed as follows: All marker coordinates (x, y, and z) divided by the height of the subject were placed in columns, one for each sample during a 30-s period, yielding a matrix dimension of 7200×54 (rows $\times$ columns). A second matrix with position vectors for the second condition (speed or shoe) was appended to the rows of the first matrix (Fig. 1). The subject's means of all position vectors was subtracted from each position.

The position vector matrices of all subjects were appended row-wise to one another to form the input matrix, P, for the PCA (Fig. 1). Thus, P contained normalized position vectors (individual means subtracted) for all time points, for all subjects, with two conditions per subject (speed for males and shoe for females). P had a dimension of $288{,}000 \times 54$.

The PCA of the matrix P yielded 54 PMs (eigenvectors of the covariance matrix of P) and 54 eigenvalues. The eigenvectors are an orthonormal base of the vector space. The variability explained by each PM vector was expressed as fraction of the total variability. The principal values, PV, were the projections of the position vectors in P onto the PMs. The PVs for each gait cycle were computed and normalized in time (heel strike to heel strike of the same foot) for all trials and subjects. The normalization in time was achieved by down-sampling the frames of the gait cycle (144 ± 10 frames) to 101 time points. We called the resultant PV time series "PV waveforms," and used all 54 PV waveforms for each condition and subject in further analysis. The basic movement was defined with the first PMs representing 99% of the movement variance.

2.3.2. Condition-dependent separation of waveforms

An SVM was used to test whether the PV waveforms could be used to distinguish between two conditions or two subject groups [22,23]. The SVM was used to find a discriminant that optimally separated the waveforms of known conditions. A classification rate was calculated using the leave-one-out cross-validation method. A Matlab®-compatible software package [24] was used with a linear kernel.

2.3.3. Recombination of waveforms

By recombining waveforms that are significantly condition-dependent with those that show no differences, a movement can be split into a condition-dependent movement and a condition-independent movement. We combined PMs where the PV waveforms showed a significant classification, thus yielding the movement with the greatest change due to a condition. This was done by multiplying the eigenvalues with the corresponding PM and summing over all vector components. The direction of the changes was plotted in stick figure diagrams (Figs. 3–5), in

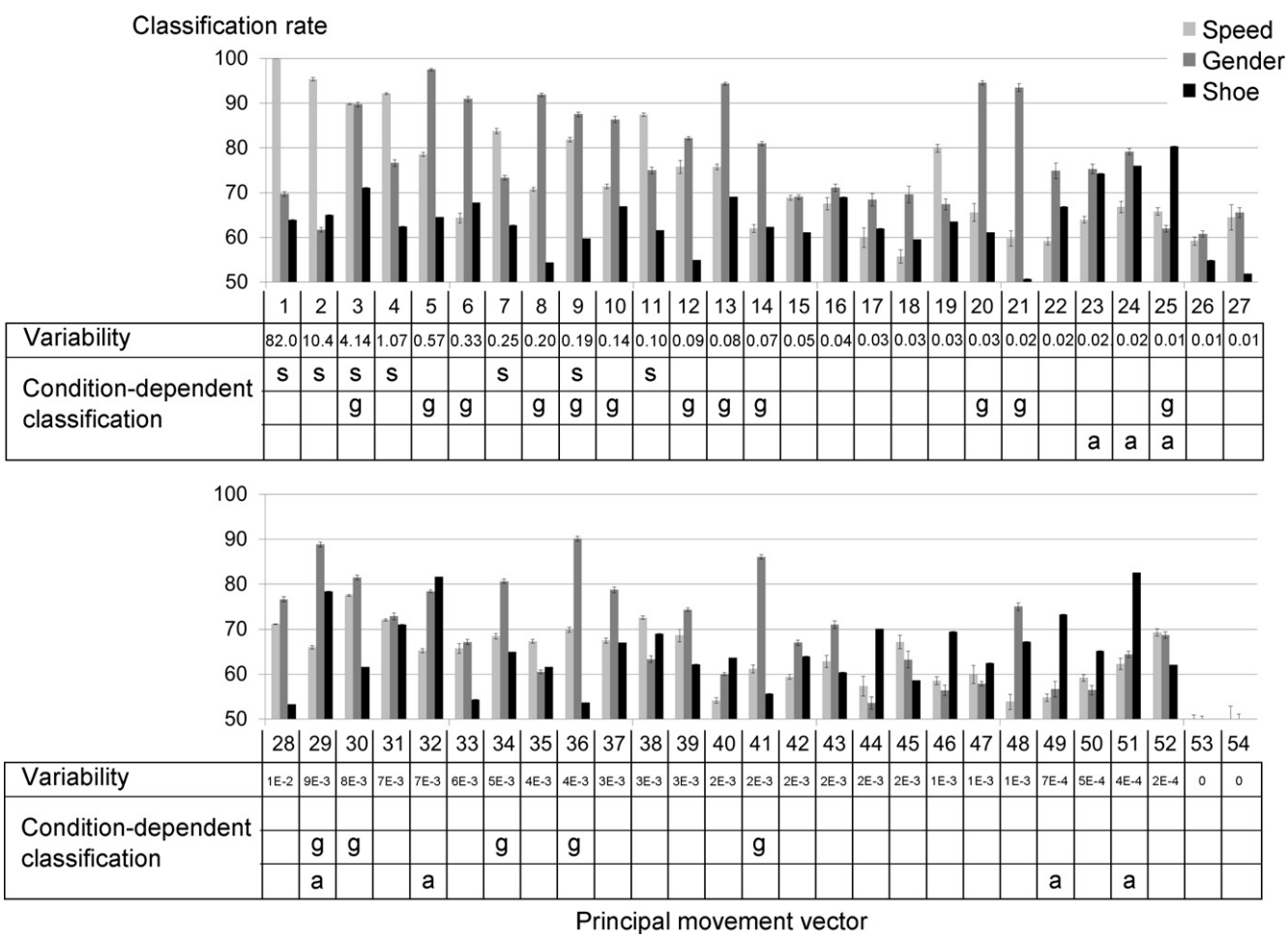

Fig. 2. Classification rate with support vector machine for different conditions. Conditions: speed (s – light gray), gender (g – middle gray), shoe condition (a – black). Classification rates for speed and gender above 90% are significant on a significance level of $\alpha = 0.99\%$ ($n = 20$). Classification rates for shoe conditions above 71.4% are significant on a significance level of $\alpha = 0.95\%$ ($n = 14$). Variability is the movement explained by the individual PMs.

which the mean position delineated by the markers is indicated by blue circles, and the direction of the changes (change vector) is indicated by red arrows. The length of the arrows indicates the contribution of the individual markers to the condition-dependent changes. The magnitude of the changes between conditions can be seen in the plotted marker displacement. The actual marker movement with the highest difference was plotted for both conditions.

The PM for which the PV waveforms show no significant classification represents the orthogonal complement and the combination of these PMs yield the movement that is independent of the condition.

The mean movement of the groups that shows a difference between two conditions and the one that shows no difference were created (Movies 1–3). The sum of these two movements recreates the original movement.

The stick figure diagrams and movies were used to visually determine where in the body the largest condition-dependent changes occurred.

3. Results

The first nine PMs represented 99% of the movement, and are considered to be the *basic movement* (Fig. 2). For the speed condition, six PV waveforms within the basic movement (PM 1 to 4, 7, 9) and one in a higher PM (11) showed changes (significance level alpha = 0.01). PMs that are changed by speed represent 98% of the movement. Gender differences could be found in five PMs (3, 5, 6, 8, 9) of the basic movement and in 11 higher PMs (10, 12 to 14, 20, 21, 29, 30, 34, 36, and 41) (significance level alpha = 0.01). Shoe differences were found only in higher PMs (23 to 25, 29 32, 49, and 51), representing 0.067% of the movement (significance level alpha = 0.05).

Speed mainly changed the movement of the leg kinematics in the sagittal plane (Fig. 3A and B and Movie 1). The combination of PMs with a highly significant classification rate led to a cyclic rotation of the lower body kinematics in the sagittal plane. Leg displacement was greater at higher speeds, with the most displacement occurring in the foot, followed by the shank, followed by the thigh. At faster speeds, the first minima and maxima for the heel marker (m_3) were reached earlier in the gait cycle (Fig. 3C). With higher speed, stride length increases, as does the range of motion of the legs.

Gender differences were mainly evident in the shank and thigh movements indicating an internal/external rotation of these segments (Fig. 4A and B). At heel strike, the women had a higher external rotation in the hip joint and a higher internal rotation in the knee joint compared to the men (Movie 2). The waveforms for marker m_6 (proximal tibia) showed clear differences between female and male runners. The external rotation in the hip joint during the stance phase (35% of gait cycle) was higher for females than for males $t(18) = 5.86$ ($p < 0.05$).

Shoe-specific characteristics were observed in higher PMs. The classification rate also increased with higher PMs. The vectors for changes were highest in the foot and indicated a change in knee flexion when wearing the different shoes. The extremes of the adidas MicroBounce shoes are closer together than those of the control shoes (Fig. 5C and Movie 3).

4. Discussion

The purpose of this project was to identify the principal movements that change when a boundary condition such as running speed, gender, or footwear changes. It was hypothesized that speed and gender would affect lower-order principal movements, while

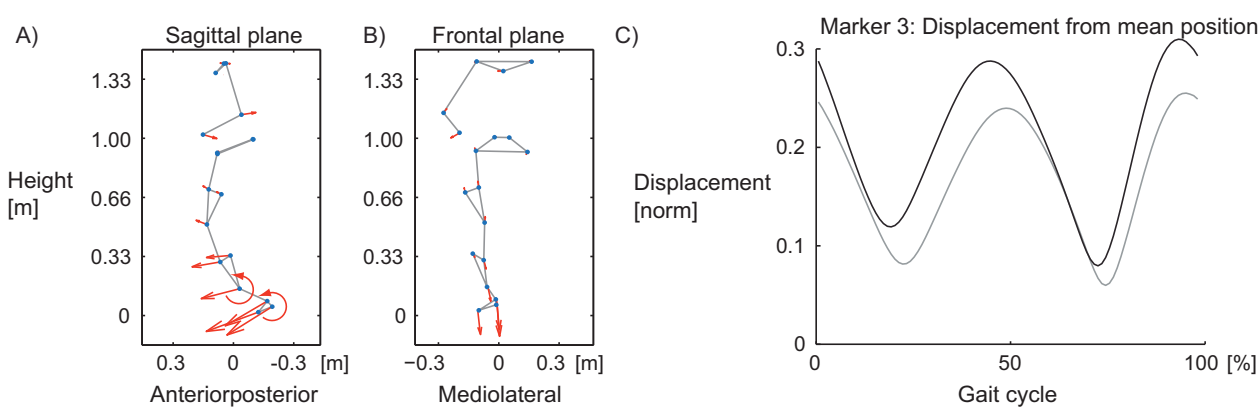

Fig. 3. Combination of speed-dependent PMs. (A and B) Straight red arrows represent the direction of changes due to speed. Within a gait cycle, these changes rotate 360° in the sagittal plane (curved red arrows). (C) Displacement of the upper heel marker (SD = 2×10^{-4}, not shown); black 4.9 m/s; gray 3.1 m/s. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

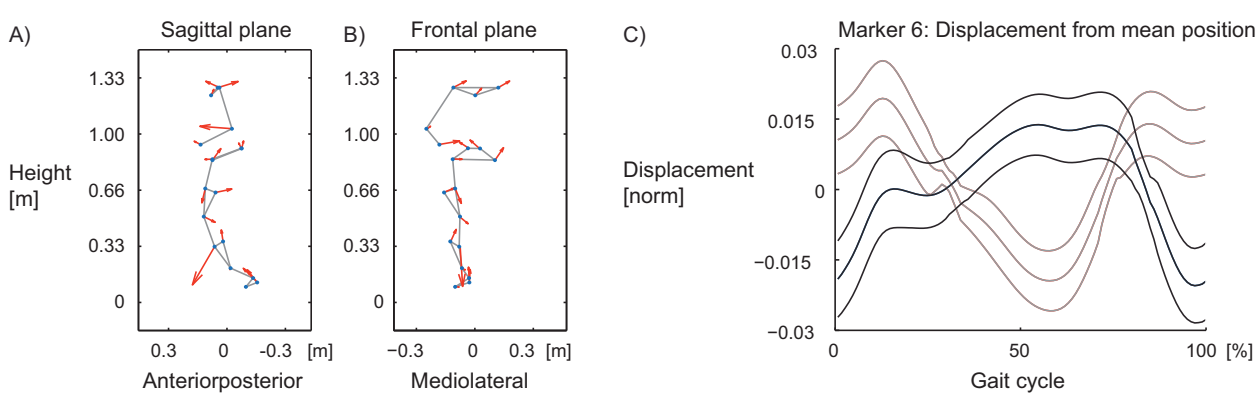

Fig. 4. Gender-specific differences in gait pattern. (A and B) Direction and relative magnitude of the changes. (C) Movement of marker 6 (proximal end of tibia); black – male; gray – female; both at 3.1 m/s. Mean (thick line) and SD (thin line) for all 20 subjects.

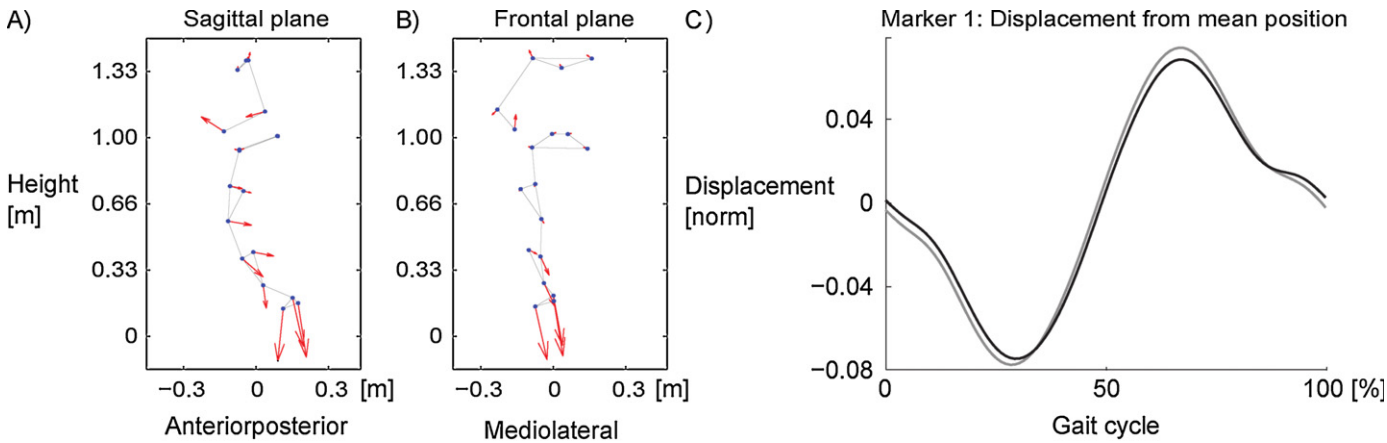

Fig. 5. Shoe-dependent differences. (A and B) Direction and magnitude of changes. (C) Movement of the lateral forefoot marker (m1); gray – control; black – adidas MicroBounce shoes.

shoes would affect higher-order principal movements. The results of the study support the stated hypotheses.

Locomotion studies addressing the kinematics at changes in running speeds [25,26] and for different genders have shown variations in discrete kinematic variables [4,27], which suggests that these changes are in the lower-order principal movements. However, studies analysing kinematic variations for different running shoes have typically reported that no significant group differences were found in discrete marker coordinates or joint angles [5,28,29].

Subject-specific changes due to different shoe conditions have been reported [5]. Changes can be seen at different joints for different subjects. With the whole-body approach presented in this paper, one combines the different joints that are influenced by a specific condition. By combining several principal movements, subject-independent movement changes can be identified. These changes are consistent throughout different subjects, however the changes in footwear are small compared to the changes within the movement and the importance of these changes has to be further analyzed. For future research projects, this approach might lead to a functional interpretation for even small interventions like a change in footwear or inserts.

A paradigm recently introduced into biomechanics is the "preferred movement path" [5,30]. This paradigm claims that for small interventions such as different shoes, changes in running surface, or fatigue, human movement stays relatively constant. Only when the movement task itself is altered does the preferred movement path change. This change is evident when comparing tasks like running and walking, or when running speed is increased.

In this study, the combined movement of the first nine PMs explained more than 99% of the locomotion pattern. The preferred movement path might, therefore, be thought of as the movements described within the first nine PMs. The preferred movement path is changed when speed is altered. The gender-specific movement patterns might also be interpreted as two different preferred movement paths, as five of the PMs that showed a difference between genders are within the first nine PMs. Small interventions like footwear changes caused changes in PMs greater than the 23rd PM. This result suggests that small interventions like footwear changes do not alter the preferred movement path.

5. Conclusion

The combination of PCA and SVM allows complex movements to be decomposed into movements that stay constant and movements that show changes with respect to a specific condition. In this study full-body kinematic was dissected into principal movements using PCA. Then, using a classification method (SVM), the principal movements that showed significant differences were identified. A gait pattern can, therefore, be separated into two movements. The first movement is in the direction where changes occurred. A second movement, orthogonal to the first, describes the portion of the gait pattern that does not change systematically in response to a condition, although subject specific-changes may still occur.

Furthermore, this method allows the identification of group-specific changes, even for conditions that affect the movement pattern only slightly compared to the variability of the movement. This paper showed the application for different speeds, gender, and shoe conditions. Conditions that change the principal movement path can be found in the first or lower PMs. Small boundary conditions (e.g. footwear) influence only parts of the movement, and can be mainly found in the higher PMs. Those PMs that show a significant difference due to a condition can be combined into one vector that is indicative of the changes, and this combination allows us to determine the location of the greatest changes within a movement pattern.

Acknowledgments

This research was supported by the Da Vinci Foundation and by Biomechanigg Research Inc.

Conflict of interest

We wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome. We confirm that the manuscript has been read and approved by all named authors and that there are no other persons who satisfied the criteria for authorship but are not listed. We further confirm that the order of authors listed in the manuscript has been approved by all of us.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at doi:10.1016/j.gaitpost.2011.12.023.

References

[1] Cavanagh PR, Kram R. Stride length in distance running—velocity, body dimensions, and added mass effects. Medicine and Science in Sports and Exercise 1989;21(4):467–79.

[2] Razeghi M, Batt ME. Biomechanical analysis of the effect of orthotic shoe inserts—a review of the literature. Sports Medicine 2000;29(6):425–38.
[3] Marco S. Review of motor control mechanisms underlying impact absorption from falls. Gait and Posture 2005;21(1):85–94.
[4] Ferber R, McClay Davis I, Williams III DS. Gender differences in lower extremity mechanics during running. Clinical Biomechanics 2003;18(4):350–7.
[5] Nigg BM. Biomechanics of sport shoes. Topline Printing; 2010.
[6] Higginson BK. Methods of running gait analysis. Current Sports Medicine Reports 2009;8(3):136–41.
[7] Novacheck TF. The biomechanics of running. Gait and Posture 1998;7(1): 77–95.
[8] Begg R, Kamruzzaman J. A machine learning approach for automated recognition of movement patterns using basic, kinetic and kinematic gait data. Journal of Biomechanics 2005;38(3):401–8.
[9] Daffertshofer A, Lamoth CJC, Meijer OG, Beek PJ. PCA in studying coordination and variability: a tutorial. Clinical Biomechanics 2004;19(4):415–28.
[10] Troje NF. Decomposing biological motion: a framework for analysis and synthesis of human gait patterns. Journal of Vision 2002;2(5).
[11] Fukunaga K. Introduction to statistical pattern recognition, 2nd ed., San Diego, CA, USA: Academic Press Professional, Inc.; 1990.
[12] Lamoth CJC, Daffertshofer A, Huys R, Beek PJ. Steady and transient coordination structures of walking and running. Human Movement Science 2009; 28(3):371–86.
[13] Verrel J, Lovden M, Lindenberger U. Motor-equivalent covariation stabilizes step parameters and center of mass position during treadmill walking. Experimental Brain Research 2010;207(1–2):13–26.
[14] Bockemuhl T, Troje NF, Durr V. Inter-joint coupling and joint angle synergies of human catching movements. Human Movement Science 2010;29(1):73–93.
[15] Epifanio I, Ávila C, Page A, Atienza C. Analysis of multiple waveforms by means of functional principal component analysis: normal versus pathological patterns in sit-to-stand movement. Medical and Biological Engineering and Computing 2008;46(6):551–61.
[16] Forner-Cordero A, Levin O, Li Y, Swinnen SP. Principal component analysis of complex multijoint coordinative movements. Biological Cybernetics 2005; 93(1):63–78.
[17] Vallery H, Buss M. Complementary limb motion estimation based on interjoint coordination using principal components analysis. In: Proceedings of the 2006 IEEE international conference on control applications, vol. 1–4; 2006. p. 529–34.
[18] Moore JK, Hubbard M, Schwab A, Kooijman J, Peterson DL. Statistics of bicycle rider motion. Procedia Engineering 2010;2(2):2937–42.
[19] Déniz O, Castrillón M, Hernández M. Face recognition using independent component analysis and support vector machines. Pattern Recognition Letters 2003;24(13):2153–7.
[20] vonTscharner V, Valderrabano V. Classification of multi muscle activation patterns of osteoarthritis patients during level walking. Journal of Electromyography and Kinesiology 2010;20(4):676–83.
[21] Dickson MJ, Fuss FK. Optimization of directional energy transfer in adidas bounce tubes. Procedia Engineering 2010;2(2):2795–800.
[22] Abe S. Support vector machines for pattern classification. Advances in pattern recognition. Springer; 2010.
[23] Cristianini N, Shawe-Taylor J. An introduction to support vector machines and other kernel-based learning methods. Cambridge University Press; 2004.
[24] Chang CC, Lin CJ. LIBSVM: a library for support vector machines, Software available at <http://www.csie.ntu.edu.tw/~cjlin/libsvm>; 2001.
[25] Dufek JS, Mercer JA, Griffin JR. The effects of speed and surface compliance on shock attenuation characteristics for male and female runners. Journal of Applied Biomechanics 2009;25(3):219–28.
[26] Saibene F, Minetti A. Biomechanical physiological aspects of legged locomotion in humans. European Journal of Applied Physiology 2003;88(4):297–316.
[27] Kerrigan DC, Todd MK, Croce UD. Gender differences in joint biomechanics during walking: normative study in young adults. American Journal of Physical Medicine and Rehabilitation 1998;77(1):2–7.
[28] Nawoczenski DA, Cook TM, Saltzman CL. The effect of foot orthotics on three-dimensional kinematics of the leg and rearfoot during running. The Journal of Orthopaedic and Sports Physical Therapy 1995;21(6):317–27.
[29] Stacoff A, Nigg BM, Reinschmidt C, van denBogert AJ, Lundberg A. Tibiocalcaneal kinematics of barefoot versus shod running. Journal of Biomechanics 2000;33(11):1387–95.
[30] Nigg BM. The role of impact forces and foot pronation: a new paradigm. Clinical Journal of Sport Medicine 2001;11(1):2–9.