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Shoe midsole hardness, sex and age effects on lower extremity kinematics during running

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ABSTRACT

Previous studies investigating the effects of shoe midsole hardness on running kinematics have often used male subjects from within a narrow age range. It is unknown whether shoe midsole hardness has the same kinematic effect on male and female runners as well as runners from different age categories. As sex and age have an effect on running kinematics, it is important to understand if shoe midsole hardness affects the kinematics of these groups in a similar fashion. However, current literature on the effects of sex and age on running kinematics are also limited to a narrow age range distribution in their study population. Therefore, this study tested the influence of three different midsole hardness conditions, sex and age on the lower extremity kinematics during heel-toe running. A comprehensive analysis approach was used to analyze the lower-extremity kinematic gait variables for 93 runners (male and female) aged 16–75 years. Participants ran at 3.33 ± 0.15 m/s on a 30 m-long runway with soft, medium and hard midsoles. A principal component analysis combined with a support vector machine showed that running kinematics based on shoe midsole hardness, sex, and age were separable and classifiable. Shoe midsole hardness demonstrated a subject-independent effect on the kinematics of running. Additionally, it was found that age differences affected the more dominant movement components of running compared to differences due to the sex of a runner.

1. Introduction

Midsole hardness is assumed to influence kinematics, performance, comfort and injuries (Clements et al., 2001; Frederick et al., 1984; Frederick, 1986; Hamill et al., 1983; Hardin et al., 2004). Current literature investigating the effects of shoe midsole hardness on running kinematics have often been limited in the number of participants and focused on male participants of a certain age range (Hardin et al., 2004; Morio et al., 2009). However, certain groups of individuals demonstrate group-specific movement patterns during over-ground running. For example, sex-related anatomical differences are known to affect lower extremity kinematics such as hip adduction, hip internal rotation and knee abduction during running with female runners showing typically a larger range of movement in the frontal and transverse planes than their male counterparts (Chumanov et al., 2008; Ferber et al., 2003). It is also known that ankle and knee joint kinematics are affected as the musculoskeletal system becomes stiffer with aging (Fukuchi and Duarte, 2008; Karamanidis and Arampatzis, 2007; Kerrigan et al., 1998; Silder et al., 2008). As these groups demonstrate different lower extremity kinematics, it is unknown whether a certain intervention such as a shoe will affect the kinematics of these groups in a similar manner. Answering this question requires the systematic testing of age and sex sub-groups using the same methodology within the same study.

To our knowledge, the biomechanical testing of a large sample of recreational runners of both sexes from a wide age range has never been completed. Additionally, most kinematic evaluations of the effects of footwear, sex, and age have focused on biomechanical variables evaluated at discrete time points (Butler et al., 2006; Fukuchi and Duarte, 2008; Hardin et al., 2004; Keenan et al., 2011). This approach depends on the investigator selecting the appropriate variables for the question of interest and leaves a large portion of the kinematic data unanalyzed where interesting results may appear. A more comprehensive analysis approach should be taken in order to take advantage of the full data set rather than choosing discrete kinematic variables.

An analysis approach that has gained more interest in biomechanical research is the use of vector-based pattern recognition methods such as principal component analysis (PCA) (Daffertshofer et al., 2004; Epifanio et al., 2008; Maurer et al., 2012; Moore et al., 2011; Troje, 2002) and support vector machine (SVM) (Begg and Kamruzzaman, 2005; Vapnik, 1995; Weston, 1999). The kinematic marker data from an entire stance phase can then be used in one

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analysis step to determine lower-extremity differences for certain groups. The principal component analysis method allows for the dominant movements of a certain activity to be identified, such as the control movements used in bicycle riding at different speeds (Moore et al., 2011). The most dominant movements arise in the lower number principal component vectors while the less dominant movements arise in the higher number principal components vectors. In the case of running, principal component analysis has the potential to identify dominant movements that explain the overall running movement. It is then possible to determine which movements of the running motion are affected by certain conditions (age, sex, shoe midsole hardness). The separation and classification rate between age, sex, and shoe midsole hardness can then be determined using mathematical approaches such as a leave-one-out support vector machine (SVM) (Begg and Kamruzzaman, 2005; Vapnik, 1995; Weston, 1999).

Thus, the purpose of this study was to determine the influence of three different midsole hardness conditions, sex and age on the lower extremity kinematics during heel-toe running using a principal component analysis approach.

It was hypothesized that:

H(1). Age, sex, and shoe midsole effects on kinematics are separable and classifiable using a principal component analysis approach.

H(2). Subject-independent changes due to shoe midsole hardness exist.

Table 1
Number of subjects in each age and sex subgroup.

Gender	Age Group	Number of Subjects	Age (years)		Height (cm)		Mass (kg)	
			Average	SEM	Average	SEM	Average	SEM
Male	16–20	13	17.9	0.5	178.0	1.6	69.6	2.5
	21–35	13	25.5	1.1	179.7	2.0	74.0	2.0
	36–60	11	48.5	1.8	175.3	1.3	77.5	2.0
	61–75	10	66.9	1.5	174.5	1.8	74.6	3.0
Female	16–20	12	18.1	0.4	162.9	2.0	55.4	1.7
	21–35	12	26.2	0.9	166.8	2.4	62.5	2.1
	36–60	11	49.6	1.5	165.2	1.4	64.5	2.6
	61–75	11	65.5	1.5	162.0	1.6	55.6	1.5

2. Methods

2.1. Subjects

Ninety-three recreational runners (47 male, 46 female) who ran at least 30 min per week participated in this study (Table 1). Approval for research using human subjects was obtained from the University of Calgary's Conjoint Health Research Ethics Board and all participants provided written informed consent. All subjects were free from injury or pain at the time of testing. Four age groups were defined as follows: Group 1 (G1)—Age 16–20, Group 2 (G2)—Age 21–35, Group 3 (G3)—Age 36–60, and Group 4 (G4)—Age 61–75.

2.2. Experimental setup

Three different shoe conditions provided by Decathlon (now Oxylane Group, France) that differed only in their midsole hardness were investigated: Asker C-40 (Soft), Asker C-52 (Medium) and Asker C-65 (Hard). Kinematic data were collected using 12 retro-reflective markers mounted on the pelvis and right lower extremity to measure three-dimensional movements of each segment (Fig. 1) with an eight-camera, 240 Hz motion capture system (Motion Analysis, CA). Data were filtered with a low pass fourth order Butterworth filter with a cutoff frequency of 12 Hz.

Subjects performed heel-toe running trials on a 30 m lane in the Human Performance Laboratory at the University of Calgary. A force plate embedded in the floor of the running lane was used to determine heel contact and toe off. Five running trials (3.33 ± 0.16 m/s) for each of the three different shoe conditions were collected. The order in which the shoes were tested was randomly selected for each subject. Subjects were allotted familiarization time prior to data collection for each of the shoe conditions.

2.3. Data analysis

Markers were identified and tracked using EVaRT Real Time (Version 5.0.4, Motion Analysis, CA). All variables were clipped for the stance phase of the step with the right foot on the force plate. Heel contact and toe-off were determined using a 15 N threshold in the vertical ground reaction force.

A position matrix was formed using the marker position data for all 93 subjects. As a first step, all marker positions were expressed as distances to the pelvis center and normalized to the static height of each subject. The motion data for the x, y, and z coordinates of each of the 12 markers were normalized to 100% of the stance phase (101 time points $\times$ 3 directions $\times$ 12 markers) and combined into a 3636-dimensional column vector. All vectors for each subject, shoe, and trial combination (93 subjects $\times$ 3 shoe conditions $\times$ 5 trials) were used to form a position vector matrix. Hence, the position matrix had the dimensions 1395×3636 (Fig. 1) and formed the input for the PCA.

The position matrix was further refined depending on the goal of the analysis. To analyze shoe effects, subject-specific differences were reduced. This was done with a whitening approach, where the mean of each subject's position vectors was subtracted from each trial for that subject (Fukunaga, 1990; Theodoridis and Koutroumbas, 2006). Each trial with the subject mean subtracted was then divided by the standard deviation of that subject's position vectors. The reduction of subject specific differences increased the prominence of the shoe differences.

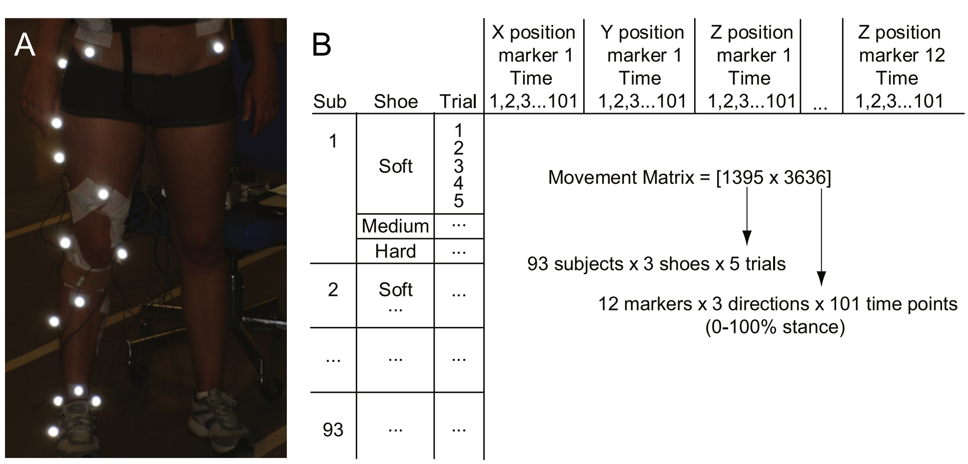

Fig. 1. (A) Frontal view of retro-reflective marker placement on the shoe, shank, thigh and pelvis and (B) Position matrix for the principal component analysis. Marker positions in the x, y, and z direction normalized to stance (101 time points) formed the columns of the input matrix while subject, shoe, and trial combinations formed the rows.

For the sex and age analysis, the whitening process was not used. Therefore, the mean of all subject position vectors was subtracted from each trial for the analysis of sex and age effects. As a result of these steps, a different input matrix was used for the shoe analysis than for the age and sex analysis.

Following the normalization procedures, a principal component analysis (PCA) was used on each respective input movement matrix (Daffertshofer et al., 2004). A support vector machine (SVM) was used to determine if the shoe, sex, and age conditions were separable and classifiable based on the first principal components that explained at least 95% of the variance in the data (Duda et al., 2001). A leave-one-out method was applied to determine the classification rate for a new subject (Fukunaga, 1990). A binomial distribution was also completed to determine significance for classification rates. The CRITBINOM function of Microsoft Office Excel was used to determine the number of correctly classified subjects needed to reach a 95% level of confidence.

For the functional interpretation of the data, principal component projections with a large Cohen's d effect size ($d>0.8$) between sex, age groups and shoe conditions were determined (Cohen, 1969). Principal components showing significant differences with respect to a group or condition were linearly combined. The combination indicates common differences in the movement between two groups or conditions. For these principal component vectors, the direction of change in the marker position between conditions was determined and plotted on stick figure diagrams of the right lower extremity and pelvis. Mean marker positions were indicated with black circles while the direction of change of the marker movement was indicated with blue arrows. The length of the arrows indicates the contribution of the movement of individual markers to the overall condition-dependent movement changes. The projection of the movement onto this vector gives the change of the markers averaged over all marker positions.

3. Results

3.1. Shoe midsole

Using a leave-one-out method with the first 35 principal components which explained 95.6% of the variance in the data, a classification rate of 99.5% (SD 2.3) was found between the hard and the soft midsole while a classification rate of 95.6% (SD 8.8) was found between the hard and the medium midsole and a classification rate of 86.0% (SD 14.4) was found between the soft and the medium midsole. All of these classification rates were significant. Principal component vectors 3, 5, 6, and 19 showed a large effect size for the projection difference between the shoe midsole conditions (Fig. 2). Plotting the projection for each trial onto principal component 3 and 5 demonstrated a clustering of the soft, medium and hard midsole trials (Fig. 2). An investigation of the movements described by these principal components indicated less range of motion for hip flexion and knee flexion and more range of motion for ankle dorsiflexion with the soft midsole as compared to the hard midsole. The direction of change in marker position in the combined principal component vector (PC 3, 5, 6, 19) for the hard shoe compared to the soft shoe was plotted on a stick figure diagram of the right lower limb and pelvis (Fig. 3). The average displacement from the mean of all 12 markers during the stance phase for principal component vectors 3, 5, 6, and 19 was 3.7 mm. Support vector machine separation and leave-one-out classification rates for midsole stiffness can be seen in Table 2.

3.2. Sex effects

The first 20 principal components explained 95.9% of the variance in the data and allowed a classification rate of 86.6% (SD 27.2) between the male and female subjects. This classification rate was significant. Principal component vectors 8, 9, and 19 showed a large effect size for the projection difference between the male and female subjects. Plotting the projection of each trial onto principal components 8 and 9 demonstrated a clustering of the male and female subjects (Fig. 4). An investigation of the movements described by these principal components indicated greater movements in the frontal plane including greater range of motion for hip adduction and knee abduction for the female subjects compared to the male subjects. There also appears to be greater pelvis tilt for the female subjects compared to the male subjects. The direction of change in marker position in the combined principal component vector (PC 8, 9, 19) for male vs.

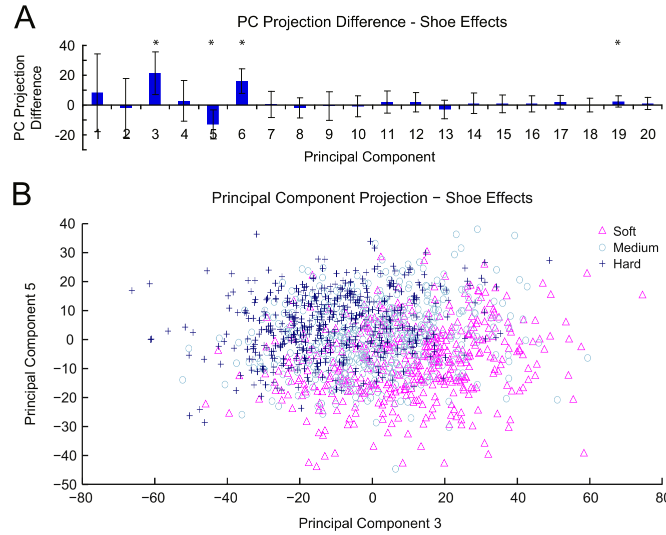

Fig. 2. (A) Average principal component projection difference due to shoe midsole hardness for the first 20 principal component vectors. Principal component vectors with a significant effect size are marked with an asterisk. (B) Principal component projections (3,5) for the soft (pink, △), medium (green, ○) and hard (blue, +) midsole conditions. A clustering of the three conditions is already visible even with only two principal component vectors. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

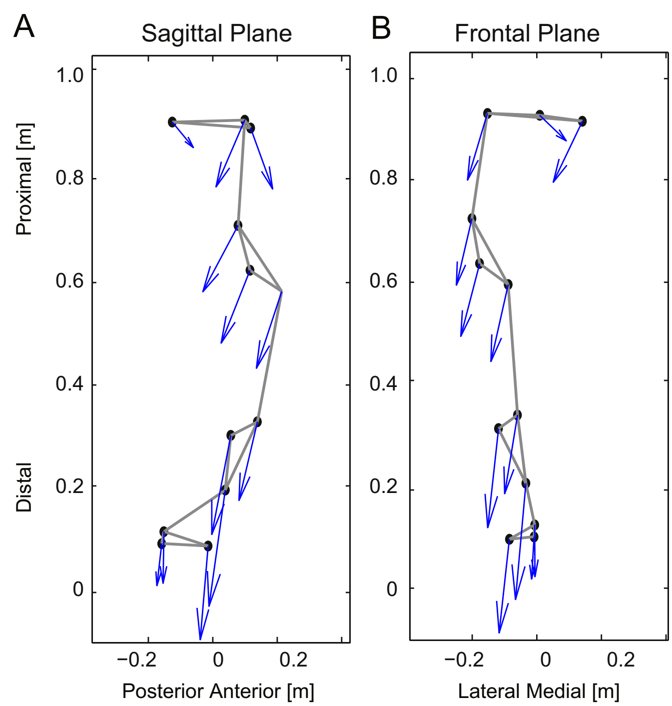

Fig. 3. Visualization of the linear combination of principal components 3, 5, 6, and 19 at mid-stance in the sagittal plane (A) and the frontal plane (B). The blue arrows indicate direction of marker movement changes from the hard midsole to the soft midsole. The length of the arrows indicates the contribution of the movement of individual markers to the overall condition-dependent movement changes. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 2
Support vector machine classification rates and separation rates (average, standard deviation, and significance level) for shoe effects using a leave-one-out method on the first 35 principal components. Significant classification rates are marked with a *.

	Leave-one-out Classification [%]			Support Vector Machine Separation [%]
	Average	SD	Significance	
Hard vs. Soft	99.5	2.3	*Binomial(93)=93($p<0.05$)	99.6
Soft vs. Medium	86.0	14.4	*Binomial(93)=62($p<0.05$)	85.1
Hard vs. Medium	95.6	8.8	*Binomial(93)=81($p<0.05$)	95.9

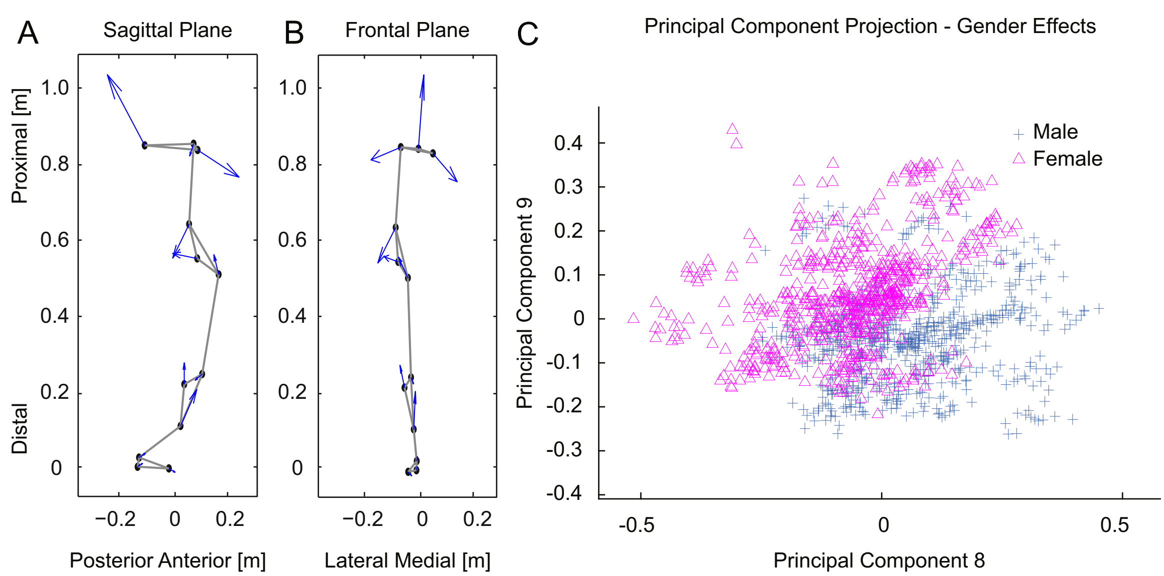

Fig. 4. Visualization of the linear combination of principal components 8, 9 and 19 at mid-stance in the sagittal plane (A) and the frontal plane (B). The blue arrows indicate direction of marker movement changes from male to female subjects. The length of the arrows indicates the contribution of the movement of individual markers to the overall condition-dependent movement changes. (C) Principal component projections (8,9) for the male (blue, +) and female (pink, △) subjects. A clustering of the male and female subjects is already visible even with two principal component vectors. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 3
Support vector machine classification rate and separation rate (average, standard deviation, and significance level) for sex effects using a leave-one-out method on the first 20 principal components.

	Leave-One-Out Classification [%]			Support Vector Machine Separation [%]
	Average	SD	Significance	
Male vs. Female	86.6	27.2	*Binomial(93)=78($p<0.05$)	90.8

female subjects can be seen in Fig. 4. The average displacement from the mean of all 12 markers during the stance phase for principal component vectors 8, 9, and 19 was 4.4 mm. Support vector machine separation and leave-one-out classification rates for sex are listed in Table 3.

3.3. Age effects

Using the first 20 principal components, the largest classification rate was found between Group 1 (youngest) and Group 4 (oldest) with a rate of 79.4% (SD 30.3). Significant classification rates were found between all age groups except for Group 2 and 3 and Group 3 and 4. Leave-one-out classification rates and support vector machine separation rates can be seen in Table 4 with significant rates marked with an asterisk. Principal component vector 1 showed a large effect size for the projection difference for multiple age groups. Plotting the projection for each trial onto principal component 1 and 2 demonstrated a clustering of the age groups (Fig. 5). An investigation of the movements described by the first principal component indicated greater movements in the sagittal plane including increased range of motion for knee flexion and ankle dorsiflexion and greater vertical displacement of the pelvis for the younger groups compared to the older groups (Fig. 5). The average displacement from the mean of all 12 markers during the stance phase for principal component vectors 1 and 2 was 9.2 mm.

4. Discussion

The purpose of this study was to identify the influence of three different midsole hardness conditions, sex and age on the lower extremity kinematics during heel-toe running. A principal component analysis approach with a support vector machine was used to identify the movements of running that are most strongly influenced by each of these conditions. The results of this study supported the hypothesis that movement effects due to midsole hardness, sex, and age are separable and classifiable using such a

Table 4
Support vector machine classification rates (average, standard deviation, and significance level) for age effects using a leave-one-out method on the first 20 principal component vectors. Significant classification rates are marked with a *.

	Leave-One-Out Classification [%]			Support Vector Machine Separation [%]
	Average	SD	Significance	
G1–G2	68.0	42.7	*binomial(50)=33($p<0.05$)	89.3
G1–G3	75.4	39.0	*Binomial(47)=33($p<0.05$)	92.1
G1–G4	79.4	30.3	*Binomial(46)=35($p<0.05$)	94.2
G2–G3	65.0	42.4	Binomial(47)=27($p=0.12$)	84.7
G2–G4	77.3	36.1	*Binomial(46)=36($p<0.05$)	93.3
G3–G4	54.3	42.4	Binomial(43)=20($p=0.62$)	81.1

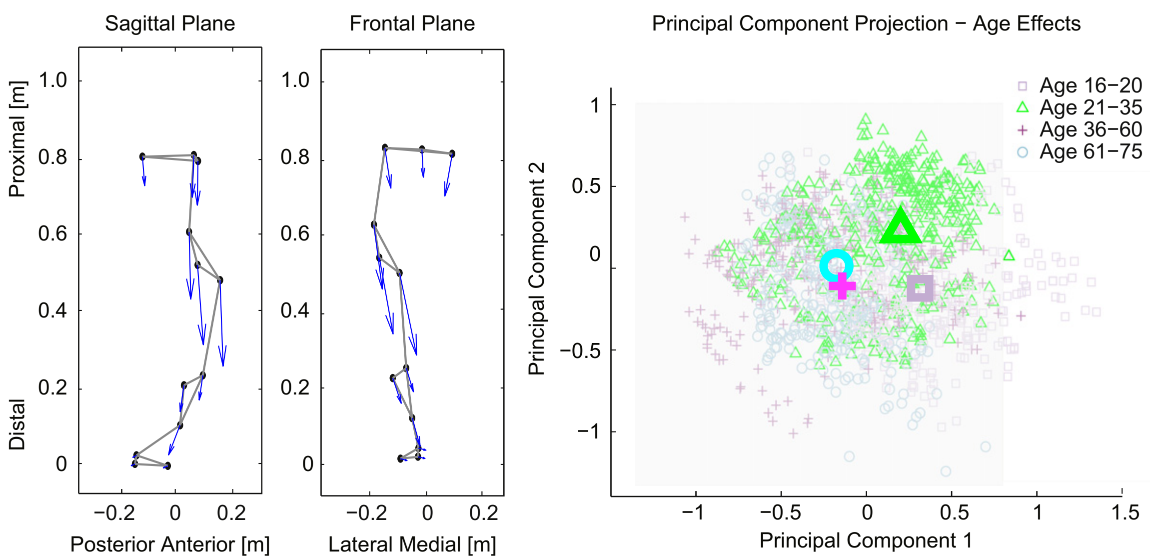

Fig. 5. Visualization of the linear combination of principal components 1 and 2 at mid-stance in the sagittal plane (A) and the frontal plane (B). The blue arrows indicate direction of marker movement changes from the oldest age group to the youngest age group. The length of the arrows indicates the contribution of the movement of individual markers to the overall condition-dependent movement changes. (C) Principal component projections (1,2) for the various age groups (Group 1—purple (□), Group 2—green (△), Group 3—pink (+), Group 4—blue(○)). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

statistical approach. The second hypothesis was also supported as subject-independent shoe midsole hardness effects were seen regardless of sex and age.

It has been reported in the literature that female runners demonstrate a larger range of movement in the frontal plane during running, specifically increased magnitudes of hip adduction and knee abduction compared to male runners (Chumanov et al., 2008; Ferber et al., 2003). The results of this study support these previous findings and demonstrate that these movement patterns between men and women are classifiable. The effects of age on the kinematics of running have also been investigated with older individuals demonstrating less knee flexion (Fukuchi and Duarte, 2008). The results of this study also support these findings and demonstrate that movement patterns between age groups are often classifiable. However, this separation is more prominent with increasing age differences between individuals.

Using a principal component analysis approach in biomechanics allows for a certain motion to be broken down into its dominant movement components. It can then be determined if certain interventions affect the more dominant movements of a motion or the less dominant movements. The results from this study suggest that age affects the more dominant movements of over-ground heel-toe running as age differences were seen in the lower principal component vectors (principal component vectors 1 and 2). An individual's sex, on the other hand, affected the less dominant movements of running as differences were not seen until the higher principal component vectors (principal component vector 8 and 9). This would indicate that age affects the more dominant movements of running compared to an individual's sex.

What was most interesting in this study was that subject-independent effects of shoe midsole hardness on running kinematics could be identified. This indicates that regardless of an individual's sex or age category, shoe midsole hardness affects certain movement components of running similarly for all individuals. Previous research using a discrete approach found no effects of shoe midsole hardness on the muscle activity of the lower extremity (Nigg and Gerin-Lajoie, 2011). The application of a principal component analysis to these data may provide more information regarding the effects of shoe midsole hardness on muscle activity and if this can be used to explain the differences seen in the kinematics.

The movements of running that were affected by the shoe midsole hardness were seen more dominantly in the sagittal plane. As the shoe midsole hardness did not appear to affect movements in the frontal plane at the knee and hip as strongly as sagittal movements at the knee and ankle, midsole hardness may not be the shoe characteristic to customize for female runners compared to male runners. The mean displacement of all markers from the mean for the shoe differences was in the same order of magnitude as that for the age differences. This may indicate that shoe midsole hardness could affect the sagittal movements for a runner enough to compensate for the sagittal movement effects due to age.

This study also demonstrated the benefit of using a statistical comprehensive approach for the analysis of running kinematics. Using this statistical approach, a more general interpretation of the effects of shoe midsole hardness, sex, and age on the modes of heel-toe running can be visualized. These results may be functionally difficult to interpret, however, and should be interpreted with caution. Additionally, while this approach added the benefit of analyzing the entire stance phase, information may also be found in the analysis of the full stride cycle (stance and swing phase).

5. Concluding remarks

The use of a principal component analysis allows for the analysis of the complete marker set data collected during running. This ensures that the entire data set is analyzed and avoids the risk of poor discrete variable selection that may miss important information within the data set. The combination of this approach with a leave-one-out support vector machine demonstrated that the kinematic effects of shoe midsole hardness, sex, and age were separable and classifiable. While age affected the more dominant movements of running, sex influenced the less dominant movements. It was found that subject-independent effects on the running movement due to shoe midsole hardness exist. These effects are more prominent at the ankle and in the sagital plane and, therefore, shoe midsole hardness may be more customizable for age groups as opposed to sex, where differences are seen more in the transverse and frontal planes at the hip and knee.

Conflict of interest statement

There were no conflicts of interest with this study.

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References

Begg, R., Kamruzzaman, J., 2005. A machine learning approach for automated recognition of movement patterns using basic, kinetic and kinematic gait data. Journal of Biomechanics 38, 401–408.

Butler, R.J., Davis, I.S., Hamill, J., 2006. Interaction of arch type and footwear on running mechanics. American Journal of Sports Medicine 34, 1998–2005.

Chumanov, E.S., Wall-Scheffler, C., Heiderscheit, B.C., 2008. Sex differences in walking and running on level and inclined surfaces. Clinical Biomechanics 23, 1260–1268.

Clements, K.M., Bee, Z.C., Crossingham, G.V., Adams, M.A., Sharif, M., 2001. How severe must repetitive loading be to kill chondrocytes in articular cartilage? Osteoarthritis and Cartilage 9, 499–507.

Cohen, J., 1969. Statistical Power Analysis for the Behavioral Sciences, 1st Edition Lawrence Erlbaum Associates, Hillsdale (2nd Edition, 1988).

Daffertshofer, A., Lamoth, C.J.C., Meijer, O.G., Beek, P.J., 2004. PCA in studying coordination and variability: A tutorial. Clinical Biomechanics 19, 415–428.

Duda, R.O., Hart, P.E., Stork, D.G., 2001. Pattern Classification. John Wiley & Sons, New York, New York.

Epifanio, I., Avila, C., Page, A., 2008. Analysis of multiple waveforms by means of functional principal component analysis: normal versus pathological patterns in sit-to-stand movement. Medical & Biological Engineering & Computing 46, 551–561.

Ferber, R., McClay Davis, I., Williams III, D.S., 2003. Sex differences in lower extremity mechanics during running. Clinical Biomechanics 18, 350–357.

Frederick, E.C., Clarke, T.E., Hamill, C.L., 1984. The effect of running shoe design on shock attenuation. In: Frederick, E.C. (Ed.), Sport Shoes and Playing Surfaces. Champaign, IL, Human Kinetics, pp. 190–198.

Frederick, E.C., 1986. Kinematically mediated effects of sport shoe design: a review. Journal of Sports Sciences 4, 169–184.

Fukuchi, R.K., Duarte, M., 2008. Comparison of three-dimensional lower extremity running kinematics of young adult and elderly runner. Journal of Sports Sciences 26, 1447–1454.

Fukunaga, K., 1990. Introduction to Statistical Pattern Recognition. Academic Press, San Diego.

Hardin, E.C., van den Bogert, A.J., Hamill, J., 2004. Kinematic adaptations during running: effects of footwear, surface, and duration. Medicine & Science in Sports & Exercise 36, 838–844.

Hamill, J., Bates, B.T., Knutzen, K.M., Sawhill, J.A., 1983. Variations in ground reaction force parameters at different running speeds. Human Movement Science 2, 47–56.

Karamanidis, K., Arampatzis, A., 2007. Aging and running experiences affects the gearing in the musculoskeletal system of the lower extremities while walking. Gait and Posture 25, 590–596.

Keenan, G.S., Franz, J.R., Dicharry, J., Della Croce, U., Kerrigan, C., 2011. Lower limb joint kinetics in walking: the role of industry recommended footwear. Gait & Posture 33, 350–355.

Kerrigan, C.D., Todd, M.K., Della Croce, U., Lipsitz, L.A., Collins, J.J., 1998. Biomechanical gait alternations independent of speed in the healthy elderly: evidence for specific limiting impairments. American Congress of Rehabilitation Medicine and the American Academy of Physical Medicine and Rehabilitation 79, 317–322.

Maurer, C., Federolf, P., von Tscharner, V., Stirling, L., Nigg, B.M., 2012. Discrimination of gender-, speed-, and shoe-dependent movement patterns in runners using full-body kinematics. Gait & Posture http://dx.doi.org/10.1016/j.gaitpost.2011.12.023.

Moore, J.K., Kooijman, J.D.G., Schwab, A.L., Hubbard, M., 2011. Rider motion identification during normal bicycling by means of principal component analysis. Multibody System Dynamics 25, 225–244.

Morio, C., Lake, M.J., Gueguen, N., Rao, G., Baly, L., 2009. The influence of footwear on foot motion during walking and running. Journal of Biomechanics 42, 2081–2088.

Nigg, B.M., Gerin-Lajoie, M., 2011. Gender, age, and midsole hardness effects on lower extremity muscle activity during running. Footwear Science 3, 3–12.

Silder, A., Heiderscheit, B., Whittington, B., Thelen, D.G., 2008. Active and passive contributions to joint kinetics during walking in older adults. Journal of Biomechanics 41, 1520–1527.

Theodoridis, S., Koutroumbas, K., 2006. Pattern Recognition. Elsevier, San Diego.

Troje, N.F., 2002. Decomposing biological motion: A framework for analysis and synthesis of human gait patterns. Journal of Vision 2, 371–387.

Vapnik, V., 1995. The Nature of Statistical Learning Theory. Springer-Verlag, New York.

Weston, J., 1999. Leave-one-out support vector machines. In: Proceedings of the Sixteenth International Joint Conference on Artificial Intelligence, IJCAI 99. City Conference Centre/Norra Latin, Stockholm.