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A method for estimating subject-specific body segment inertial parameters in human movement analysis

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ABSTRACT

An optimization-based, non-invasive, radiation-free method was developed for estimating subject-specific body segment inertial properties (BSIPs) using a motion capture system and two forceplates. The method works with accurate descriptions of the geometry of the body segments, subject-specific center of pressure (COP) and kinematic data captured during stationary standing, and an optimization procedure. Twelve healthy subjects performed stationary standing in different postures, level walking and squatting while kinematic and forceplate data were measured. The performance of the current method was compared to three commonly used predictive methods in terms of the errors of the calculated ground reaction force, COP and joint moments using the corresponding predicted BSIPs. The current method was found to be capable of producing estimates of subject-specific BSIPs that predicted accurately the important variables in human motion analysis during static and dynamic activities. With the differences in the BSIPs from the current method, the mean COP errors were less than 5 mm during stationary standing postures, while those from the existing comparative methods ranged from 11 to 25 mm. During dynamic activities, the existing methods gave COP errors three times as large as the proposed method, with up to 2.5 times RMSE in joint moments during walking. Being non-invasive and using standard motion laboratory equipment, the current method will be useful for routine clinical gait analysis and relevant clinical applications, particularly in patient populations that are not targeted by the existing predictive methods.

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1. Introduction

In human movement analysis, mechanical variables such as joint forces, moments and energy are calculated by using mathematical models with experimental measurements [1]. Body segment inertial parameters (BSIPs), along with other anthropometric data, are essential for model customization to individual subjects. Errors in BSIPs have been shown to have significant effects on the mechanical variables calculated by a model [2–4]. Therefore, accurate estimation of BSIPs helps to reduce errors of the calculated results [5].

Several methods for estimating subject-specific BSIPs have been proposed, including cadaver-based prediction equations [6–8], medical imaging methods [3,9–14] and mathematical modeling methods [15–17]. Cadaver-based prediction equations have been derived mostly from a limited number of older adults, allowing for the calculation of subject-specific BSIPs from measurable anthropometric data such as the subject's body weight and segment lengths. However, errors of the estimated BSIPs may become significant when applying these models to subjects outside the sample population, such as to young adults, children, obese individuals and non-Caucasians [17,18]. Another limitation is that body symmetry is assumed. Therefore, the accuracy may be limited in pathological conditions in which body asymmetry is commonplace.

Medical imaging methods, such as three-dimensional (3D) scanning [11,13], MR imaging [9,12,19], gamma-ray scanning [14] and dual energy X-ray absorptiometry (DEXA) [3,10,20], can be used to obtain subject-specific data. However, some of these methods are expensive [9,12,19]; some are subject to radiation exposure [14,21] and others are too complex and time-consuming for routine clinical motion analysis [22]. Generally, 3D scanning and MR imaging involve reconstructing the segment shapes and assigning density values from the literature to each tissue type. Often, the calculated sum of the segment masses is different from the directly measured body mass [9,12]. Both gamma-ray scanning and DEXA provide only mass distribution information in the frontal

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plane [20]. Despite these limitations, data obtained from these imaging methods have been used to develop predictive equations for specific populations [9,14].

Mathematical modeling approaches provide an important alternative to experimental methods [11,15,17,23,24]. However, all these models require input of tissue densities from previous cadaver studies. Therefore, errors may exist if tissue densities of the subject are different from those found in the literature. A proper adaptation of the tissue densities to individual subjects may help resolve the problem.

Other models use a combined modeling and experimental approach. Kingma et al. [24] obtained BSIPs from the literature [25] and then refined the center of mass (COM) position of the trunk using measured center of pressure (COP) data [24]. Pataky et al. [17] estimated subject-specific masses of the limbs using forceplate data with segment COM taken from the literature. However, both methods were limited to two-dimensional estimations.

Only a limited number of studies evaluated their performance against experimental measurements [3,24]. Kingma et al. [24] validated the estimated trunk COM position by comparing the external moment measured by forceplate against the rate of change of the body's angular momentum. Ganley and Powers [3] verified the accuracy of the BSIPs by comparing the joint moments calculated by using DEXA and cadaver-based estimates of BSIPs. However, no study has compared experimentally the performances of their proposed methods against the commonly used predictive methods in three-dimensions.

The purpose of the study was to develop an optimization-based, non-invasive, radiation-free method for estimating subject-specific BSIPs, using a motion capture system and two forceplates. The performance of the current method was evaluated by comparing the predicted ground reaction force (GRF) and COP to those directly measured for static postures, squatting and level walking. Joint moments calculated using predicted forceplate data were also compared to those calculated using measured forceplate data for level walking. For comparison, three commonly used predictive methods were also evaluated, namely methods by Dempster [8] (DM), Zatsiorsky and Seluyanov [14] (ZM), and Cheng et al. [9] (CM).

2. Materials and methods

2.1. Subjects

Twelve adults (24 ± 2 years; 69 ± 8 kg; 178 ± 5 cm) without any neuromusculoskeletal pathology participated in the study with written informed consent. Each subject wore 54 retroreflective markers placed by a well-trained physical therapist at positions used by Huang et al. [26], and at the mandibular condylar processes, sternal notch, C7, radial styloid processes, and the second and fifth metacarpal heads. The proximal and distal circumference lengths for each segment were measured with a measuring tape.

2.2. Test activities

In a gait laboratory, the subject stood on a forceplate (AMTI, USA) in 10 different static postures each for 5 s, including abduction and flexion of the shoulder; flexion, extension and abduction of the hip; flexion of the knee; flexion and extension of the trunk; and their combinations. These postures displaced the relevant body segments horizontally as far as possible from their anatomical positions, while being stabilized by a metal frame fixed to a second forceplate with two height-adjustable plates to support vertically the extremities. The subjects also performed evaluation activities, namely walking, arm-swing squatting and three standing postures with 30° trunk flexion, 45° hip flexion, and 90° shoulder abduction, respectively. During all activities, kinematic data were measured by a 7-camera motion analysis system (VICON 512, Oxford Metrics, UK) while the GRF was measured by two forceplates.

2.3. The new optimization-based method (OM)

A 3D, 16-rigid-segment model of the body was developed, with the head modeled as a spheroid, the neck, upper arms, forearms, thighs and shanks as frustums, and the trunk, pelvis, hands and feet as ellipsoids. Marker and circumference length data were used to customize the model to individual subjects.

Given a set of segmental densities (d^i, i = 1–16), the method (OM) calculated the mass, COM and second moment of inertia (MOI) for each segment. The COM of each segment was taken as the geometric center except for the 16th segment (trunk) whose COM position (d^{17}, d^{18} and d^{19}) was allowed to move within its boundary because the trunk was inhomogeneous [24]. For accurate estimation of the inertial parameters, the optimum segmental densities and trunk COM position, i.e. the design variables (d^i, i = 1–19), were obtained by minimizing the sum of the squared distances between the calculated and measured COP in the 10 static postures as follows.

$$\min f\left(d^1, d^2, \ldots, d^{19}\right) = \sum_{j=1}^{10} (\vec{q}_j\,'(d^1, d^2, \ldots, d^{19}) - \vec{p}_j)^T (\vec{q}_j\,'(d^1, d^2, \ldots, d^{19}) - \vec{p}_j) \tag{1}$$

$$\vec{q}_j = \frac{\sum_{i=1}^{15} d^i V^i \vec{q}_j^{\,i} + d^{16} V^{16} \vec{q}_j^{\,16}(d^{17}, d^{18}, d^{19})}{M} \tag{2}$$

where $\vec{p}_j$ was the measured COP that was closest to the mean COP during the jth posture; $\vec{q}_j$ was the position vector of the model body's COM for the jth posture, the vertical projection of which gave the calculated COP $\vec{q}_j\,'$; $\vec{q}_j^{\,i}$ was the position vector of the COM of the ith segment for the jth posture; V^i was the volume of the ith segment, and M was the measured body mass. All vectors are column vectors and T denotes the transposition of a vector. The following constraints were also imposed.

$$\sum_{i=1}^{16} d^i V^i = M \tag{3}$$

$$d_l^i \le d^i \le d_u^i \quad i = 1\text{–}19 \tag{4}$$

$$std(d^i) \le S \quad i = 1\text{–}16 \tag{5}$$

Eq. (3) required that the model body mass was equal to the measured. Eq. (4) defined the bounds of the design variables. Since the densities of the tissues of the body lie between 0.563 g/cm^3 in the lung [27] and 1.892 g/cm^3 in the cortical bone [7], the lower and upper bounds of the densities were taken as 0.5 and 1.9 g/cm^3, respectively. The bounds for d^{17}, d^{18} and d^{19} were taken as −0.2 and 0.2 m. Eq. (5) required that the standard deviation of the densities remain less than a constant S that was empirically determined to be 0.05. The optimization problem (Eqs. (1)–(5)) was solved by using a sequential quadratic programming algorithm.

2.4. Performance Evaluation

The BSIPs determined using OM were compared to those estimated using DM, ZM and CM. For this purpose, segment definitions from Dempster [8] were used. The differences in the BSIPs between OM and each of the other methods were expressed as percentages of BSIP values of OM.

For each method, the predicted BSIPs were used to calculate the GRF and COP during the evaluation activities. The distances between the calculated and measured COP (COP errors) were then obtained for the standing postures, and the root mean squared error (RMSE) between the calculated and measured vertical GRF and COP was determined for dynamic activities. These errors provided a measure of the performance of the method. During walking, effects of these errors on the calculated joint moments were also expressed as the RMSE between the "calculated moments" obtained using the calculated forceplate data and the "measured moments" obtained using the measured forceplate data.

2.5. Statistical analysis

The means and standard deviations for each of the BSIPs were calculated across all subjects, segment mass being normalized to body mass, COM position to segment length, and MOI in terms of radius of curvature normalized to segment length. The BSIPs of the right and left side by OM were compared using a paired t-test and were used to calculate symmetry indices (SI), i.e., 2(right − left)/(right + left) [28], to indicate the bilateral symmetry of each BSIP for each subject. The differences in segmental mass, COM position and MOI between OM and each of the other methods were also calculated for all subjects. These differences between the three methods were then compared using one-way ANOVA. Pair-wise comparisons were performed using a paired *t*-test if a method effect was found. One-way ANOVA was also used to compare the four methods for the COP errors in the standing postures, the RMSE of the COP and vertical GRF during dynamic activities, and RMSE of the joint moments during walking. If a significant method effect was found, *post hoc* tests were conducted using a paired *t*-test to evaluate the differences between OM and the other methods, with a Bonferroni corrected significance level of 0.017 (0.05/3). All statistical analyses were performed using SPSS (SPSS Inc., Chicago, IL).

Table 1
The means (standard deviations) of the segmental masses as a percentage of the body mass (%BM). Note that standard deviations were not available using Dempster's and Zatsiorsky's studies. Data for OM were averaged values for both sides.

	OM	CM	DM	ZM	|OM − CM|/OM (%)	|OM − DM|/OM (%)	|OM − ZM|/OM (%)	Method effect	SI $2(R-L)/(R+L)$
Head and neck	7.13(0.59)	7.25(0.6)	8.10	7.35	6.17(5.84)	15.03(7.90)	8.71(5.61)	$p=0.001^{+}$	–
Trunk and pelvis	46.49(1.61)	43.5(3.5)	49.70	42.55	6.35(3.62)	7.05(4.23)	8.35(4.18)	$p=0.580$	–
Trunk	35.32(1.72)		35.5						–
Pelvis	11.17(0.94)		14.2						–
Upper arm	3.73(0.28)	3.77(0.5)	2.80	2.67	5.44(3.20)	24.61(4.71)	28.04(4.31)	$p=0.001^{+,*,\#}$	−0.005(0.083)
Forearm	1.33(0.09)	1.41(0.3)	1.60	1.61	6.94(4.80)	20.69(6.36)	21.71(5.80)	$p=0.001^{+,*}$	−0.005(0.089)
Hand	0.57(0.06)	0.62(0.32)	0.60	0.65	10.17(8.25)	8.24(6.78)	13.37(8.27)	$p=0.006^{*}$	0.008(0.060)
Thigh	11.41(1.04)	12.8(1.8)	10.00	14.31	14.21(4.30)	11.91(6.13)	26.04(8.15)	$p=0.004^{*,\#}$	0.008(0.081)
Shank	4.48(0.37)	4.14(0.3)	4.65	4.44	8.82(4.88)	6.39(6.60)	6.02(5.09)	$p=0.334$	0.008(0.085)
Foot	1.66(0.16)	1.88(0.2)	1.45	1.46	14.12(9.76)	12.18(7.83)	11.92(5.84)	$p=0.688$	0.008(0.090)

R: The value of the right side. L: the value of the left side.
$^{+}$ Significant difference between the differences of the CM and DM.
* Significant difference between the differences of the CM and ZM.
$^{\#}$ Significant difference between the differences of the DM and ZM.

Table 2
The means (standard deviations) of the segmental COM position as a percentage of segment length relative to the proximal end. Note that standard deviations were not available in Dempster's and Zatsiorsky's studies. Data for OM were averaged values for both sides.

	OM	CM	DM	ZM	|OM − CM|/OM (%)	|OM − DM|/OM (%)	|OM − ZM|/OM (%)	Method effect	SI $2(R-L)/(R+L)$
Head and neck	87.42(2.40)	49.60(1.8)	100	91.99	43.22(1.60)	14.47(3.23)	5.31(3.11)	$p=0.001^{+,*,\#}$	–
Trunk and pelvis	57.11(0.70)	60.20(2.4)	50.00	62.27	5.43(1.29)	12.44(1.07)	9.05(3.36)	$p=0.001^{+,*,\#}$	–
Trunk	69.31(5.02)		63.00						–
Pelvis	49.00(0.68)		10.50						–
Upper arm	43.80(0.90)	43.40(5.6)	43.60	41.13	1.77(1.17)	1.63(1.13)	6.05(3.37)	$p=0.001^{*,\#}$	−0.003(0.010)
Forearm	42.95(0.71)	47.30(7.0)	43.00	54.39	2.61(1.98)	7.62(2.65)	16.79(3.38)	$p=0.001^{+,*,\#}$	0.004(0.006)
Hand	49.67(0.60)	42.00(9.6)	50.60	65.81	15.44(0.77)	1.87(0.93)	32.51(4.88)	$p=0.001^{+,*,\#}$	−0.008(0.016)
Thigh	43.79(0.76)	44.70(3.5)	43.30	47.88	3.34(2.10)	3.43(2.79)	8.74(7.59)	$p=0.021^{*,\#}$	0.002(0.005)
Shank	43.25(0.78)	44.20(1.2)	43.30	45.16	1.75(1.07)	1.86(1.64)	4.37(2.93)	$p=0.009^{*,\#}$	−0.000(0.005)
Foot	48.55(0.42)	54.00(3.8)	50.00	62.28	11.64(1.54)	3.37(1.45)	27.82(4.63)	$p=0.001^{+,*,\#}$	−0.008(0.009)

R: The value of the right side. L: the value of the left side.
$^{+}$ Significant difference between the differences of the CM and DM.
* Significant difference between the differences of the CM and ZM.
$^{\#}$ Significant difference between the differences of the DM and ZM.

3. Results

Since BSIPs by OM were not significantly different between sides with very small SI values (Tables 1–3) ($p > 0.1$ for all BSIPs), the data from both sides were averaged for subsequent comparisons with other methods. The results by CM were found to be significantly closer to those by OM than either the results by DM or ZM, or sometimes both, in the predicted masses of the head and neck, upper arm, forearm, hand and thigh (Table 1). For the COM positions, both CM and DM were significantly closer to OM than ZM was for all segments except for the head and neck (Table 2). For segmental MOI, the smallest difference values among the three methods varied across all segments (Table 3).

During static postures, mean COP errors of OM (5 mm) were significantly smaller than those of the other methods (11–25 mm, Table 4). Errors from CM were also significantly smaller than those

Table 3
The means (standard deviations) of the square root of the segmental moments of inertia divided by segment mass and the square of segment length. Note that standard deviations were not available in Cheng's, Dempster's and Zatsiorsky's studies. Data for OM were averaged values for both sides.

	OM	CM	DM	ZM	|OM − CM|/OM (%)	|OM − DM|/OM (%)	|OM − ZM|/OM (%)	Method effect	SI $2(R-L)/(R+L)$
Head and neck	0.32(0.004)	0.27	0.50	0.36	14.39(7.39)	56.55(1.67)	14.87(4.42)	$p=0.001^{+,\#}$	–
Trunk and pelvis	0.28(0.004)	0.32	–	0.35	16.67(8.69)	–	24.84(1.74)	$p=0.001^{+,*,\#}$	–
Trunk	0.34(0.009)								–
Pelvis	0.32(0.004)								–
Upper arm	0.30(0.008)	0.31	0.32	0.25	7.92(5.99)	8.16(0.64)	17.03(2.95)	$p=0.001^{*,\#}$	0.002(0.035)
Forearm	0.30(0.007)	0.32	0.30	0.18	11.99(5.56)	4.83(0.51)	37.60(1.35)	$p=0.001^{+,*,\#}$	−0.000(0.035)
Hand	0.32(0.005)	0.32	0.30	0.36	8.22(6.76)	1.36(0.71)	20.93(3.61)	$p=0.001^{+,*,\#}$	0.002(0.028)
Thigh	0.30(0.008)	0.26	0.32	0.28	12.48(6.35)	9.05(1.05)	6.67(3.79)	$p=0.010^{*}$	0.001(0.034)
Shank	0.30(0.009)	0.37	0.30	0.27	26.93(10.74)	4.36(0.43)	7.07(3.01)	$p=0.001^{+,*,\#}$	−0.007(0.038)
Foot	0.33(0.010)	0.34	0.48	0.36	6.96(4.23)	42.86(4.13)	7.21(3.83)	$p=0.001^{+,\#}$	−0.008(0.027)

R: The value of the right side. L: the value of the left side.
$^{+}$ Significant difference between the differences of the CM and DM.
* Significant difference between the differences of the CM and ZM.
$^{\#}$ Significant difference between the differences of the DM and ZM.

Table 4
Means (standard deviations) and *p*-values of COP errors during standard static postures and the RMSE of the COP errors and vertical GRF during squatting and walking, calculated using BSIPs obtained from the current method, DM, CM and ZM.

	OM	CM	DM	ZM	Method effect
COP error (mm)					
Static standing with					
30° trunk flexion	2.72(1.23)	17.62* (7.39)	19.62* (5.58)	25.43* (11.99)	$p < 0.001$
45° hip flexion	4.68(1.52)	15.30* (5.31)	15.04* (5.78)	21.50* (6.76)	$p = 0.001$
90° shoulder abduction	3.3(1.44)	11.05* (4.04)	14.65* (7.12)	21.26* (7.90)	$p < 0.001$
Arm-swing squatting	9.4(2.95)	20.6* (5.31)	27.9* (13.37)	30.3* (20.30)	$p < 0.001$
Walking	12.8(2.08)	22.9* (6.76)	31.6* (11.10)	35.9* (20.27)	$p < 0.001$
Vertical GRF (%BW)					
Arm-swing squatting	3.1(0.75)	3.2(0.78)	3.2(0.78)	3.3(0.80)	$p = 0.987$
Walking	4.8(1.10)	4.8(1.05)	4.7(1.09)	4.67(1.00)	$p = 0.889$

* Significant difference from OM.

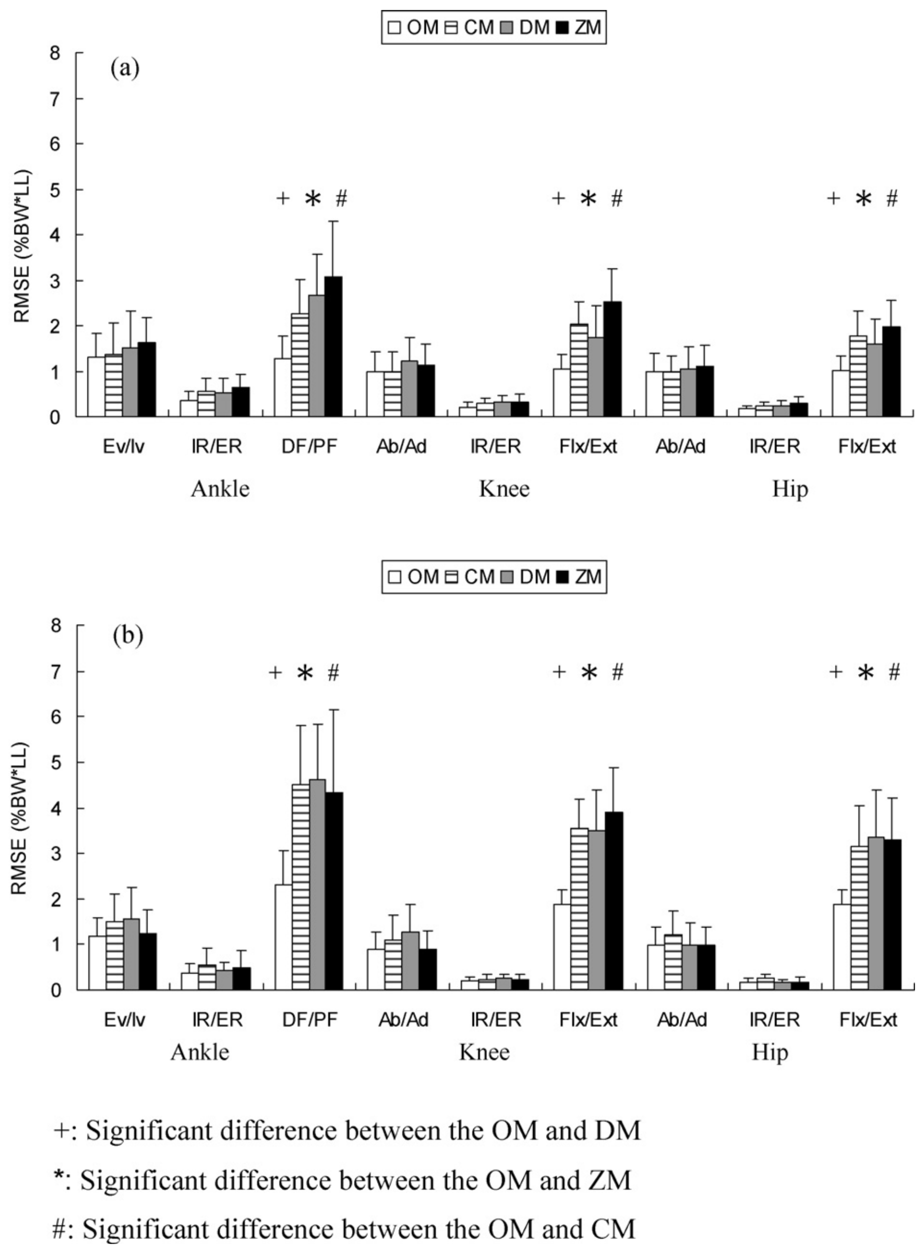

Fig. 1. Mean RMSE of joint moments for the stance (a) and swing (b) limbs across all subjects as a percentage of the body weight (BW) and leg length (LL). The error bar indicates the corresponding standard deviation. An asterisk indicates significance in the results between the current method and the other three methods. (Ev/Iv: evertor/invertor; IR/ER: internal/external rotator; DF/PF: dorsiflexor/plantarflexor; Ab/Ad: abductor/adductor; Flx/Ext: flexor/extensor).

from DM and ZM in two standing postures. During dynamic tasks, the RMSE of the COP from OM were significantly smaller than those from the other methods while no significant method effects were found for the vertical GRF errors (Table 4).

During walking, the RMSEs of the joint moments in the stance limb were generally smaller than those in the swing limb, Fig. 1. The RMSEs of the sagittal joint moments from OM were significantly smaller than those from the other methods for all joints of the stance limb ($p < 0.015$ for all three methods) and for the swing limb ($p < 0.001$ for all three methods), Fig. 1. There was no significant method effect in the RMSEs of the moments for any joint in the other two planes ($p > 0.05$ for all ANOVA).

4. Discussion

The current aim was to develop a non-invasive, radiation-free, optimization-based method (OM) for the estimation of subject-specific BSIPs, using standard equipment in a gait laboratory. With simple geometrical models of the segments, and subject-specific COP and kinematic data acquired during stationary standing, the OM was found to produce subject-specific BSIPs that led to more accurate estimation of GRF, COP and lower limb joint moments when compared to the other methods.

The performance of the three existing methods seemed to be affected by subject population as previously suggested [21]. These methods accounted for body stature using body mass and segment length as regressors in the prediction equations, except for ZM which uses both body mass and height as regressors for COM estimation. The OM used measured COP and kinematic data during static postures to fine-tune the densities of the segments and the COM position of the trunk. With similar body heights and weights between the current and the Cheng and Zatsiorsky studies [9,14], the consistently more distal COM position in most of the segments found for ZM suggests that the intra-segment mass distributions in their subject database were different from those of the current group (Table 2). Compared to the other methods, the smaller differences in segment messes between OM and CM suggest that the inter-segment mass distributions described by these two methods were more similar. The subject groups in Cheng and the current study were both from a young adult Chinese population with similar intra-segment and inter-segment mass distributions. This may be the reason why the COP errors of the evaluation standing postures from CM were also smaller than from DM and ZM. All three existing methods produced significantly different segmental MOI data compared to OM (Table 3), which may be the result of differences in subject populations and measurement methods used [29].

During ground movement, the COP of the GRF is a collected result of the masses, MOI and COM positions of all body segments apart from the movement itself. Errors in the COP significantly affected the calculated joint moments [30]. Therefore, given the same measured kinematic data, the differences between the calculated and measured COP positions provide a quantitative measure of the performance of the methods in estimating the BSIPs. In static postures, the COP errors are solely a result of errors of segmental masses and COM positions. The three evaluation standing postures enabled the effects of the errors in mass and COM of the trunk, lower limbs and upper limbs on the measured COP to be examined separately. The much greater COP errors of the static postures in the existing methods (Table 4) showed that OM performed better in estimating segmental masses and COM positions, with better representation of the intra-segment and inter-segment mass distributions. For the three existing methods, a comparison of the COP errors between the three evaluation standing postures showed that the errors in the mass and COM position of the trunk were the main contributors to COP errors (Table 4). The lower limb appeared to be the second major contributing factor to the COP errors observed in the existing methods, the COP error from ZM in the 45° hip flexion posture being the greatest. The masses and COM positions of the lower limb segments predicted by ZM also had the greatest differences compared to OM (Tables 2 and 3). While the predicted masses and COM of the upper limb segments gave the smallest errors of COP compared to the trunk and lower limbs, the COP error was still three times greater than that of OM, while that of ZM was also the largest. For all segments, OM significantly decreased the COP error by fine-tuning the segment densities and allowing the COM position of the trunk to move within its boundary under the control of the optimization procedure. Therefore, the segmental masses and COM positions estimated by OM can be considered to be better estimates than those predicted by the other methods.

Analysis of the COP errors during dynamic activities enable the effects of the error in the MOI to be considered, given the basic data of the effects of segmental masses and COM positions during static postures. With the differences in the BSIPs from OM (Tables 1–3), the existing methods gave COP errors three times as large as OM during dynamic activities, resulting in up to 2.5 times RMSE in joint moments during walking (Table 4 and Fig. 1). Note that these moment errors were a direct result of the COP errors and should not be confused with those estimated using correct BSIPs with measured forceplate data. Among the three existing methods, CM produced the best results in the COP and joint moments for both static postures and dynamic activities. This is most likely because the subjects in the current and Cheng's studies were both from a normal young Chinese population. Nonetheless, individual variations not accounted for by CM still gave at least three times greater COP errors during static postures and 1.8 times greater COP errors than OM during walking (Table 4), with RMSEs of up to 4.5 (%BW $\times$ LL) in joint moments (Fig. 1). The results on dynamic activities further show that the BSIPs by OM can be considered to be better estimates than those predicted by the other tested methods, giving more accurate estimates of GRF, COP and lower limb joint moments.

The current choice of the design variables for OM was a compromise between accuracy and computational efficiency. Apart from the COM position of the trunk, those of other body segments may be included. Optimization based on gait data may also help refine the MOI determined by the geometric model. Further study is needed to identify principle variables that produce the best performance of the method with acceptable computational efforts. For patients who have difficulty in maintaining static standing postures, other postures such as sitting or lying may be used. While measures were taken to reduce the variability in model definitions (e.g., joint center positions from markers) and in the performance of the static postures, further study is needed for a complete assessment of the repeatability of the estimated BSIPs using OM when subject to the above-mentioned variability.

In conclusion, the OM is capable of producing subject-specific BSIPs with better accuracy than the three predictive methods in the estimates of the GRF, COP and lower limb joint moments during the evaluation static and dynamic activities. Being non-invasive and using standard equipment found in standard motion laboratories, the OM will be useful for clinical gait analysis and relevant applications, particularly in patient populations that are not targeted by the current predictive methods.

Conflicts of interest

There are no conflicts of interest.

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References

[1] Elftman H. Forces and energy changes in the leg during walking. Am J Physiol 1939;125(2):339–56.

[2] Cappozzo A, Berme N. Subject specific segment inertial parameter determination - a survey of current methods. Washington, OH: Bertec; 1990.

[3] Ganley KJ, Powers C. M. Determination of lower extremity anthropometric parameters using dual energy X-ray absorptiometry: the influence on net joint moments during gait. Clin Biomech (Bristol Avon) 2004;19(1):50–6.

[4] Pearsall DJ, Costigan P. A. The effect of segment parameter error on gait analysis results. Gait Posture 1999;9(3):173–83.

[5] Kingma I, Toussaint HM, De Looze MP, Van Dieen JH. Segment inertial parameter evaluation in two anthropometric models by application of a dynamic linked segment model. J Biomech 1996;29(5):693–704.

[6] Chandler RF, Clauser CE, McConville JP. Investigation of the inertial properties of the human body. Ohio: Aerospace Medical Research Laboratories; 1975.

[7] Clauser CE, McConville JP, Young JW. Weight, volume and center of mass of segments of the human body. Ohio: Aerospace Medical Research Laboratories; 1969.

[8] Dempster WT. Space requirement of the seated operator. Ohio: Aerospace Medical Research Laboratories; 1955.

[9] Cheng CK, Chen HH, Chen CS, Chen CL, Chen CY. Segment inertial properties of Chinese adults determined from magnetic resonance imaging. Clin Biomech (Bristol Avon) 2000;15(8):559–66.

[10] Durkin JL, Dowling JJ, Andrews DM. The measurement of body segment inertial parameters using dual energy X-ray absorptiometry. J Biomech 2002; 35(12):1575–80.

[11] Jensen RK. Estimation of the biomechanical properties of three body types using a photogrammetric method. J Biomech 1978;11(8–9):349–58.

[12] Mungiole M, Martin PE. Estimating segment inertial properties: comparison of magnetic resonance imaging with existing methods. J Biomech 1990;23(10): 1039–46.

[13] Norton J, Donaldson N, Dekker L. 3D whole body scanning to determine mass properties of legs. J Biomech 2002;35(1):81–6.

[14] Zatsiorsky VM, Seluyanov VN. The mass and inertia characteristics of the main segments of the human body. IL: IL: Human Kinetics Publishers Champaign; 1983.

[15] Davidson PL, Wilson SJ, Wilson BD, Chalmers DJ. Estimating subject-specific body segment parameters using a 3-dimensional modeller program. J Biomech 2008;41(16):3506–10.

[16] Hatze H. A new method for the simultaneous measurement of the movement of inertia, the damping coefficient and the location of the centre of mass of a body segment in situ. Eur J Appl Physiol Occup Physiol 1975;34(4):217–26.

[17] Pataky TC, Zatsiorsky VM, Challis JH. A simple method to determine body segment masses in vivo: reliability, accuracy and sensitivity analysis. Clin Biomech (Bristol Avon) 2003;18(4):364–8.

[18] Hinrichs RN. Regression equations to predict segmental moments of inertia from anthropometric measurements: an extension of the data of Chandler et al. (1975). J Biomech 1985;18(8):621–4.

[19] Pearsall DJ, Reid JG, Ross R. Inertial properties of the human trunk of males determined from magnetic resonance imaging. Ann Biomed Eng 1994;22(6): 692–706.

[20] Wicke J, Dumas GA. Estimating segment inertial parameters using fan-beam DXA. J Appl Biomech 2008;24(2):180–4.

[21] Durkin JL, Dowling JJ. Analysis of body segment parameter differences between four human populations and the estimation errors of four popular mathematical models. J Biomech Eng 2003;125(4):515–22.

[22] Martin PE, Mungiole M, Marzke MW, Longhill JM. The use of magnetic resonance imaging for measuring segment inertial properties. J Biomech 1989;22(4):367–76.

[23] Hatze H. A mathematical model for the computational determination of parameter values of anthropomorphic segments. J Biomech 1980;13(10): 833–43.

[24] Kingma I, Toussaint HM, Commissaris DA, Hoozemans MJ, Ober MJ. Optimizing the determination of the body center of mass. J Biomech 1995;28(9):1137–42.

[25] Plagenhoef S. Anatomical data for analyzing human motion. Res Q Exerc Sport 1983;54(2):169–78.

[26] Huang SC, Lu TW, Chen HL, Wang TM, Chou LS. Age and height effects on the center of mass and center of pressure inclination angles during obstacle-crossing. Med Eng Phys 2008;30(8):968–75.

[27] Erdmann WS, Gos T. Density of trunk tissues of young and medium age people. J Biomech 1990;23(9):945–7.

[28] Lu TW, Lin HC, Hsu HC. Influence of functional bracing on the kinetics of anterior cruciate ligament-injured knees during level walking. Clin Biomech (Bristol Avon) 2006;21(5):517–24.

[29] Damavandi M, Barbier F, Leboucher J, Farahpour N, Allard P. Effect of the calculation methods on body moment of inertia estimations in individuals of different morphology. Med Eng Phys 2009;31(7):880–6.

[30] Cappozzo A, Leo T, Pedotti A. A general computing method for the analysis of human locomotion. J Biomech 1975;8(5):307–20.