An extended statically equivalent serial chain-Identification of whole body center of mass with dynamic motion

Alejandro González, Philippe Fraisse, Mitsuhiro Hayashibe

An Extended Statically Equivalent Serial Chain - Identification of Whole Body Center of Mass with Dynamic Motion

A. González[a,*], P. Fraisse[b], M. Hayashibe[a]

[a]DEMAR-LIRMM, INRIA, Montpellier 34090, France
[b]DEMAR-LIRMM, University of Montpellier, Montpellier 34090, France

Abstract

Background: Tracking the whole body center of mass (CoM) trajectory of balance-impaired individuals with a personalized model is useful in the development of customized fall prevention strategies. A personalized CoM estimate can be obtained using the statically equivalent serial chain (SESC) method, but the subject has to perform an identification procedure to determine the set of subject-specific SESC parameters. During this identification, the subject must hold a series of static poses, some of which are unsuitable for balanced-impaired individuals.

Research question: Can non-static poses be used to replace the static poses during SESC parameter identification?

Methods: A new method that extends the range of postures used to determine SESC parameters is presented. It takes advantage of CoM dynamics and can be executed by predominantly using dynamic motions with a few static frames. Furthermore, it is implemented using a Kalman filter to allow automatic switching between the dynamic and static models. The proposed method was tested with motion data obtained from seven healthy adults using a Vicon

*Corresponding author
Email addresses: alejandro.gonzalez@uaslp.mx (A. González), fraisse@lirmm.fr (P. Fraisse), hayashibe@lirmm.fr (M. Hayashibe)
[1]A. González is currently at CONACYT-Universidad Autónoma de San Luis Potosí, San Luis Potosí 78215, Mexico. M. Hayashibe is currently at Tohoku University, Sendai, 980-8579, Japan.

motion capture system and an AMTI force platform.

Results: We found that dynamic motions could be used to estimate the SESC parameter and even reproduce ground reaction forces; however a small number of static poses are still required to determine the subject's CoM position. The SESC-based CoM estimate obtained with this new approach was similar to that obtained using conventional full-static identification, except that the subject did not have to assume and maintain static poses.

Significance: Our proposed extension of the conventional SESC method would facilitate its application in the field of neuro-rehabilitation, especially in patients who need balance training. This personalized CoM method could be applicable for patients who are not able to maintain a static posture. In addition, this method helps minimize the total identification time by increasing the number of usable recorded frames.

Keywords: center of mass, center of pressure, parameter identification, personalized model, ground reaction forces

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1. Introduction

Tracking the whole body center of mass (CoM) position of a human subject can help improve the clinical balance assessment of the elderly and other categories of balance-impaired individuals. Indeed, the CoM trajectory can be used to evaluate improvements in balance and posture coordination during physiotherapeutic training, thus enabling caregivers to better determine the risk of falls [1]. This idea is present in applications, such as those developed by Stone and Skubic [2], who estimated the trajectory of the subject's centroid and other gait performance indexes to detect falls. In order to evaluate balance and its relationship with movement, Herr and Popovic [3] used the CoM position, the ground reaction force and the foot placement to study walking stability as a function of the angular momentum around the CoM. The accuracy of these methods can be further improved by including a subject-specific CoM model. The CoM position can be estimated by kinematic methods that use values found in anthropometric tables [4–6] and must be adjusted before a subject-specific estimate can be obtained. Usually, table adjustments only take the subject's sex, height and body mass into consideration, but not his/her mass distribution. Unadjusted anthropometric values may potentially lead to incorrect CoM estimates, especially when the subject does not match the characteristics of the population for which the table was created [7–9]. These incorrect estimates could be ascribed to a number of medical reasons, such as amputation, sarcopenia, stroke, and other motor-impairments leading to muscle atrophy. Alternatively, other conditions that lead to an abnormal mass distribution might be the cause.

Pataky *et al.* [10] computed a set of subject-specific parameters by obtaining a series of *in-vivo* measurements using a reaction board. This method can be used to determine the CoM position of a body segment or its mass when the other quantity is known. The procedure requires careful manual measurements of the orientation of each body segment and can be time-consuming when developing a full three-dimensional model. Similarly, a set of reflective markers and a force platform can be used to obtain a set of subject-specific parameters that can help to determine the CoM position via the statically equivalent serial chain (SESC) method introduced by Cotton *et al.* [11]. To estimate these parameters, the subject must perform a series of postures where the body's CoM acceleration is negligible; these postures are referred to in previous works as *static*. When a complete dynamic model is required, the same measurement tools can be used for dynamic identification [12, 13]. In this process the subject performs a series of rapid movements, wherein each body segment is subject to a range of accelerations that excites the segment's dynamics. Both of these methods require measurement of ground reaction forces and moments only during the parameter identification phase. Once the subject specific parameters have been determined, they can then be used to compute the CoM position from kinematic data. Unfortunately, it is difficult to apply these methods safely to balance-impaired individuals because of the purely dynamic or exclusively static approach used in their parameter identification procedure. That is, some of the static postures or dynamic movements required may be unsafe to perform.

These methods could be adapted to use a quasi-static approach at the expense of not estimating the complete dynamic body segment parameters [14]. Other CoM identification approaches, such as the double integral methods, successfully reconstruct the CoM trajectory based on CoM dynamics are better suited for offline analysis, but do not show the relationship between posture and CoM position. Additionally, the double integral methods require constant measurement of ground reaction forces, thereby constraining the subject to walk/stand on a force platform or move using force sensing shoes. A few examples of these methods are presented by Zatsiorsky *et al.* [15] and Schepers *et al.* [16].

SESC is a simple and fast method suitable for performing *in-vivo* measurements and can be implemented using portable tools [17]. Unlike the methods developed by Pataky *et al.* [10] it does not assume an approximate knowledge of the body segment lengths or masses. The SESC method is based on the concept that the CoM of any linked chain (be it serial or branched [18]) can be expressed linearly, as the product of a matrix containing the orientation of the chain segments and a set of parameters that are dependent on the geometry and mass distribution of the segments. The SESC parameters are defined as constants when the chain is described using only spherical or pin joints, as is the case for several full-body human models [4, 19, 20]. Cotton *et al.* [11] and Bonnet *et al.* [21] used the SESC method to find subject-specific parameters for healthy, elderly and young subjects. They carried out this process by measuring both the subject's center of pressure (CoP) and his/her body segment orientation simultaneously during a series of static postures that needed to be maintained for at least five seconds.

Until now, SESC parameters have been identified by approximating the projection of the CoM ($\boldsymbol{c}$) onto the ground plane by the measured CoP ($\boldsymbol{c}_p$) from static postures or frames. However, this strategy is only acceptable when the CoM experiences a small acceleration. The lower the CoM acceleration, the smaller will be the difference between $\boldsymbol{c}$ and $\boldsymbol{c}_p$ [22]. In practice, this means that only static poses should be considered for the identification of SESC parameters, and subjects are required to hold each pose to ensure that static frames are obtained by averaging out the $\boldsymbol{c}_p$ of several neighboring low velocity frames. Effectively, this limits the application of the SESC as achieving these static postures is often difficult and demanding for balance-impaired individuals who may be following a physical rehabilitation program.

[Figure 1 about here.]

In this regard, we sought to determine if the static constraint for SESC parameter identification could be relaxed or if, on the contrary, static poses alone were required for correct parameter identification. We propose a new identification procedure that *combines both a static and a dynamic CoM model* and, when appropriate, uses measured forces instead of the CoP position to determine the subject specific SESC parameters from dynamic motions. Please note that we use the term *dynamic* here simply to denote the non-static characteristic of the motion: we make no assumptions about the magnitude of the velocity of the acceleration of the CoM. The mixed model can be supplied with an identification dataset having different static to dynamic frame ratios in order to evaluate the need for static poses. The subject-specific parameters obtained in this way are evaluated using a cross-validation dataset. The identification procedure is implemented using recursive Kalman filter identification, which is suitable for real-time applications [23] and is capable of switching between static and dynamic models to reflect the nature of the measured data.

2. Methods

2.1. Protocol and Data Collection

Informed consent was obtained from seven healthy adults (six males and one female, age: 30±3 years, height: 1.75±0.07 m, body mass: 78.6±18.3 kg). Before the experiment, 37 reflective markers were placed on the subjects' bony landmarks according to the Plug-in-Gait (PiG) marker set [24, 25]. The subjects were instructed to stand on top of a force platform and perform a series of postures that required a large range of motion; a representative subset of these postures is shown in Fig. 2. Each subject was asked to carry out this step twice. The first time while moving in a continuous fashion and without pauses between each posture. Each subject did this at a self-determined slow pace. In the second time, the subject was asked to perform and hold a pose for at least 10 seconds following the standard SESC parameter identification procedure. A higher number of static frames were thus recovered in the second recording. These recordings were used as the *identification* and *cross-validation* datasets respectively.

The subject's CoP, as well as ground reaction forces and moments for both the identification and cross-validation datasets were recorded using an AMTI-OR6 (Advanced Mechanical Technology, Inc.) six axis force platform sampled at 1 kHz. The position and orientation of the body segments defined by the PiG model were obtained using a Vicon system (Oxford Metrics Group) composed of eight cameras recording at 100 Hz.

[Figure 2 about here.]

2.2. Extended identification of the Statically Equivalent Serial Chain Parameters

The subject's movements are modeled using a nine segment model composed of the trunk, arms, and legs [6] shown in Fig. 1. A SESC model describing the CoM motion of such a structure may required up to 27 parameters [21]. The number of parameters can be reduced under certain assumptions. For example, it can be assumed that, a link's CoM falls on the line connecting consecutive joints. Additionally, we can assume that the human body has bilateral symmetry; that is, the masses and inertial properties of the left-side's arms/legs match those on the right side. In this manner, the subject's CoM motion can be described with as little as seven non-zero parameters (three parameters for the head-and-trunk and four parameters for the limbs). Both the subjects and the measurement set-up comply with these assumptions. For the work presented here, we will use this simplified seven parameter model. Additionally, this will allow us to better compare or results to our previous work [17, 23]. However, please note that the SESC method has been defined in a way as to easily account for differences in the body's mass distribution by increasing the number of estimated parameters [11]. The SESC method is summarized in the following section.

2.2.1. Static Model

The CoM position of a human body composed of a head-and-trunk (HT), left and right thigh (LTH, RTH), left and right shank and foot (LSK, RSK), left and right upper arm (LUA, RUA), and left and right forearm and hand (LFA, RFA) segments can be expressed as:

$$\begin{aligned} \boldsymbol{c} = \boldsymbol{p}_{fb} + \frac{1}{M} (& \mathbf{A}_{HT}\boldsymbol{r}_{HT} + \mathbf{A}_{LTH}\boldsymbol{r}_{LTH} \dots \\ & \dots + \mathbf{A}_{LSK}\boldsymbol{r}_{LSK} + \mathbf{A}_{RTH}\boldsymbol{r}_{RTH} + \mathbf{A}_{RSK}\boldsymbol{r}_{RSK} + \dots \\ & \dots + \mathbf{A}_{LUA}\boldsymbol{r}_{LUA} + \mathbf{A}_{LFA}\boldsymbol{r}_{LFA} + \mathbf{A}_{RUA}\boldsymbol{r}_{RUA} + \dots \\ & \dots + \mathbf{A}_{RFA}\boldsymbol{r}_{RFA}) \end{aligned} \tag{1}$$

where $\boldsymbol{c}$ is the position of the CoM, $\boldsymbol{p}_{fb}$ is the position of the model's root segment (usually body landmark that can be measured directly), M is the total body mass, $\mathbf{A}$ is a 3-by-3 rotation matrix that expresses the orientation of each body segment, and $\boldsymbol{r}$ is the segment's SESC parameter. The value of this parameter is dependent on the subject's mass distribution and limb size. For example, $\boldsymbol{r}_{LSK} = \boldsymbol{c}_{LSK} m_{LSK}$, where $\boldsymbol{c}_{LSK}$ is the position of the segment's CoM with respect to the knee and m_{LSK} is its mass. The complete set of equations for all SESC parameters can be found in [17]. Under the assumption of bilateral symmetry, we obtain the following relationships: $\boldsymbol{r}_{LSK} = \boldsymbol{r}_{RSK}$, $\boldsymbol{r}_{LTH} = \boldsymbol{r}_{RTH}$, $\boldsymbol{r}_{LUA} = \boldsymbol{r}_{RUA}$ and $\boldsymbol{r}_{LFA} = \boldsymbol{r}_{RFA}$. By having $\boldsymbol{r}_1 = \frac{1}{M}\boldsymbol{r}_{HT}$, $\boldsymbol{r}_2 = \frac{1}{M}\boldsymbol{r}_{LTH}$, $\boldsymbol{r}_3 = \frac{1}{M}\boldsymbol{r}_{LSK}$, $\boldsymbol{r}_4 = \frac{1}{M}\boldsymbol{r}_{LUA}$, $\boldsymbol{r}_5 = \frac{1}{M}\boldsymbol{r}_{LFA}$, $\mathbf{A}_1 = \mathbf{A}_{HT}$, $\mathbf{A}_2 = \mathbf{A}_{LTH} + \mathbf{A}_{RTH}$, $\mathbf{A}_3 = \mathbf{A}_{LSK} + \mathbf{A}_{RSK}$, $\mathbf{A}_4 = \mathbf{A}_{LUA} + \mathbf{A}_{RUA}$, $\mathbf{A}_5 = \mathbf{A}_{LFA} + \mathbf{A}_{RFA}$, equation

(1) can be rewritten in matrix form as:

$$\boldsymbol{c} - \boldsymbol{p}_{fb} = \begin{bmatrix} \mathbf{A}_1 & \dots & \mathbf{A}_5 \end{bmatrix} \begin{bmatrix} \boldsymbol{r}_1 \\ \vdots \\ \boldsymbol{r}_5 \end{bmatrix} = \mathbf{B}\boldsymbol{r} \tag{2}$$

where $\mathbf{B}$ is a matrix encoding the orientation of every segment in the SESC chain, and $\boldsymbol{r}$ is the set of constant and subject-specific SESC parameters. Please note, when assuming that a link's CoM falls on the line connecting consecutive joints parameters $\boldsymbol{r}_{2\dots5}$ contain only four non-zero parameters. Interested readers may find an in-depth discussion of these assumptions in [17, 23].

The constant parameter vector ($\boldsymbol{r}$) can be determined from measured data once enough data from a number of different postures are obtained. This may be completed online using a recursive identification method such as the Kalman filter [23]. However, as the CoM ground projection cannot be directly measured, it is usually replaced by the measured CoP for postures that are considered static [11, 21].

2.2.2. Proposed Dynamic Model

By considering the CoM dynamics, we developed a new identification procedure that overcomes the static constraint discussed in the previous section. The relationship between the acceleration of a body's CoM and the forces acting upon it is given by the linear function:

$$M\ddot{\boldsymbol{c}} = M\boldsymbol{g} + \boldsymbol{f} \tag{3}$$

where $\boldsymbol{g}$ is the gravity vector, $\boldsymbol{f}$ is the sum of all external forces acting on the body, and M is its total mass [26]. After obtaining the double derivative of (2) and substituting the value of $\ddot{\boldsymbol{c}}$ from (3) we derive the dynamic SESC model as follows:

$$\left(\boldsymbol{g} + \frac{\boldsymbol{f}}{M} - \ddot{\boldsymbol{p}}_{fb}\right) = \ddot{\mathbf{B}}\boldsymbol{r} \tag{4}$$

The SESC parameters can be obtained by measuring the angular velocities and accelerations of the PiG model as well as via measurements of the ground reaction forces.

2.3. Signal Processing

All measured data were down-sampled to 30 Hz. The data values were filtered using a Savitzky-Golay (SG) smoothing filter [27] because of its real-time capabilities. Smoothing filters operate on the data points inside a sliding window and find the best polynomial fit for them, effectively acting as a low-pass filter with null phase-shift. Moreover, using such filters, the time derivative of the output signal is easily obtained. To obtain the results shown here, we selected a third order SG filter with a seven frame window size. This filter was chosen due to its satisfactory performance in previous work [28] and similar performance to those applied in SESC literature [29]. Carpentier *et al.* [30] present an in-depth study of the observability of the CoM position using different sensors and discuss the spectral distribution of their estimation noise and shows that CoM estimation based on force plate measurements is well suited for low frequency ranges.

2.4. Data Analysis

We estimated the subject-specific SESC parameters using a recursive approach based on a Kalman filter. The filter's initial SESC parameter estimate was set to zero. Additional details on the application of the Kalman filter to the SESC identification problem can be found in [23].

To study the effect of using a combination of static and dynamic frames on the identified SESC vector, we developed an application that is capable of switching between static (2) and dynamic (4) SESC models appropiately. The proposed extended SESC identification method is outlined in Fig. 3. To switch between the static and dynamic models, the postural data at a given time instant was tested and labeled as belonging to either a static or dynamic frame. If the total sum of joint velocities (computed as the sum of the magnitudes of angular velocities around each joint) was greater than 0.06 rad/s or if the magnitude of the CoP velocity exceeded 0.04 m/s, that frame was labeled as dynamic.These thresholds were set heuristically and could be refined in future studies as a function of the measurement system. We obtained a personalized SESC parameter vector for each subject. These vectors were calculated using a different ratio of static to dynamic data frames than that used in the identification dataset. Each SESC vector was initially estimated using an n_{static} number of static postures ($n_{static} \in N = \{0, 5, 10\}$), following which step, the estimate was improved by adding up to 300 dynamic frames ($n_{dynamic} \in N = \{0, 1, \ldots, 300\}$).

Both the static and dynamic frames used for the parameter estimation procedure were chosen randomly from the *identification* set. In order to improve the performance of the estimated parameters, special care was taken to avoid using more than one frame per pose. This was achieved by ensuring that all frames were separated by, at least, one second from each other. In this way, we simulate a parameter estimation session in which static poses are difficult to find.

The performance of each SESC vector was evaluated using the cross-validation set containing data not used during the parameter identification. In this manner, the model performance of the model when it has to deal with unknown poses can be observed. We computed the difference between the estimated CoM ground projection and the measured CoP for static frames in the dataset and reported its root mean square error ($rmse$). Additionally, we obtained the difference between the estimated and the measured ground reaction forces for the full dataset and reported the percentage errors in magnitude (M), in phase (P), and a comprehensive error factor (C) [31].

Metrics M, P, and C highlight the similarity between two time signals, *i.e.* the smaller their value, the more similar are both the signals. The error in magnitude (M) is insensitive to phase discrepancies, while the error in phase (P) is insensitive to magnitude differences. The comprehensive error factor (C) is computed as the root of the squares of M and P; it is meant to represent a combination of both the phase and magnitude metrics and is a useful global indicator. They were proposed by Sprague and Geers [31] to evaluate identified dynamic systems, and used by Hansen *et al.* [32] to compare estimated and measured ground reaction forces.

[Figure 3 about here.]

3. Results

Fig. 4 gives the cross-validation results for a single subject, with respect to the difference between the measured CoP and the estimated ground projection of the CoM for that single subject for a series of static poses. The horizontal lines display the estimation error when only static frames were considered during the SESC parameter identification, while the colored lines show the evolution of the error when dynamic frames were presented to the Kalman filter. The addition of either static or dynamic frames improved the results by decreasing the estimated *rmse*. This was observed for all seven subjects. In addition, we noted that the smallest *rmse* was obtained when the SESC parameter vector was identified using a mix of static and dynamic frames.

[Figure 4 about here.]

Fig. 5 shows the estimated ground reaction forces, for the same subject, obtained for the cross-validation dataset. Unlike the subject's CoM position, ground reaction forces are measurable, and have been presented by Hansen et al. as a way to validate the estimated parameters [32].

[Figure 5 about here.]

Table 1 shows the average and standard deviation (*std*) values for the *rmse*, M, P, and C that were obtained for all seven subjects. This table shows the results obtained using only a few static frames (left side) and those obtained using a combination of static and dynamic frames (right side). Please note that the metrics shown for CoP correspond to only static frames while those regarding ground reaction forces were computed over the entire cross-validation set and included both static and dynamic frames. We found that the errors decreased when more frames were used regardless of whether they were considered static or dynamic. Table 1 also shows the identification results when no static frames were used to identify the subject's SESC parameters. Finally, it also depicts the identification errors when the subject's CoM position was estimated using anthropometric values obtained from de Leva [6] (AT).

[Table 1 about here.]

4. Discussion

We found that it was possible to estimate a set of subject-specific SESC parameters capable of reproducing both ground reaction forces and CoP displacement for a series of postures.

This was achieved by extending the current identification procedure to use a combination of static and dynamic frames. The SESC model implemented here can be described using seven parameters that can ideally be obtained using as few as four static frames. While a larger amount of static frames are preferred in order to decrease the identification error, Table 1 and Fig. 4 indicate that dynamic frames could be used to extend the conventional SESC identification method whenever static frames are difficult to obtain. However, a few static frames are required for an accurate CoM identification. This can be seen in both Table 1 and Fig. 4 where the performance of the SESC parameters obtained using a few static postures ($n_{static} = 5, n_{dynamic} = 295$) is better than that obtained using only dynamic postures ($n_{static} = 0, n_{dynamic} = 300$). This is also true fort the double integral methods used for estimating the CoM position. The double integral methods still require some knowledge of the CoM's initial position and velocity. For example, Zatsiorsky and King [15] monitored the horizontal components of the ground reaction forces and used frames where they were equal to zero to correct their estimation (effectively removing integration drift). This was done after observing that CoP was an accurate representation of CoM at these times as a result of a negligible change in angular momentum.

This is similar to the implementation we propose here where measurements are labeled, during run-time, as a static frame owing to their low CoP displacement and joint angle velocities.

Please note that the choice of static frames will have a large impact on the estimation results. In theory, and with ideal measurements, only four static poses are required to invert (2) and find the SESC parameters (as each measurement contributes two equations to the linear system). However, these poses should be distinct enough such that $\mathbf{B}$ is full-rank and invertible. This would not be the case if, for example, the same pose was used twice. For this reason, it is important to measure a wide range of postures which make it possible to find a solution in the Least Squares sense. That is, the quality of the estimated SESC parameters depends greatly on the variety of exiting data used to determine the model. This work shows that is it possible to estimate the SESC parameters not using only static poses, but that relevant exiting data can be obtained also from dynamic poses. By randomly selecting both static and dynamic poses and limiting the number of static posed to be used, we show that a SESC model, capable of reproducing CoP trajectory and ground reaction forces can be obtained. We also show that the estimation error is reduced by using several dynamic frames, whenever static frames are not available. We hope this will allow the estimation method to be used even when the subject is incapable of holding a fully static pose, as the overall error will be reduced by having enough dynamic data.

When compared to a full dynamic identification such as the ones presented in [12–14, 32] the SESC method may offer one advantage: ease of implementation. The full dynamic identification model, as stated in the introduction, requires large accelerations of the body segments in order to obtain a suitable excitation of the relevant parameters. When these high exciting trajectories are not achieved, some parameters may not be correctly identified. For these cases, the identification model can be reduced eventually resulting in the estimation of the SESC parameters as they have been described here. However, the computation of the required regressor matrix is not trivial and its components are nonlinear relations of joint angles and their velocity and acceleration.

The extended identification method presented here is capable of automatically detecting dynamic frames, while still using the static frames to improve the SESC parameter vector, by automatically switching between both models. Furthermore, the estimation results obtained with this new method are equivalent to those presented earlier using an equivalent human model, when only the static frames were considered [17, 23]. However, the SESC method is capable of obtaining smaller errors (with respect to CoP-CoM position error in static frames) [21] when a larger SESC parameter vector is considered and a greater number of static frames are obtained. Our research was aimed at exploring the use of dynamic data to supplement a small number of static frames. The results seem to support the validity of our approach.

Finally, the dynamic model presented here could be used to estimate, in real-time, the ground reaction forces for slow full body movement. This can be achieved by computing the CoM acceleration. In this way some balance evaluation techniques, such as those based on the rate of change of angular momentum [33] could be easily personalized and implemented whenever the subject's kinematics are measured.

5. Conclusion

The SESC parameter identification procedure could be extended to include information from dynamic motions, rather than only from static frames. To test this, we implemented an application capable of determining whether the nature of the measured frame was static or dynamic. Based on this determination, our application is automatically able to apply the corresponding SESC model. In this manner, more information can be processed and a subject-specific SESC parameter vector can be obtained even when an insufficient number of static frames are recorded. This could happen with subjects that suffer from balance impairment, and for whom the previous static identification procedure would not be recommended. Furthermore, this can be carried out with no loss of accuracy of the estimated CoM position as compared to the previous identification method.

Once the SESC parameters are obtained, they can be used to determine the position the subject's CoM without requiring a force platform, as long as the orientation of the body segments can be measured. Finally, personalized CoM position estimates may be used to assess balance [3, 28] and fall risk [34] or, potentially, even to quantify a patient's improvement during physical rehabilitation.

Previously, in [17] we studied portable sensors such as the Kinect (Microsoft®, Redmont, WA, USA) and the Wii balance board (WBB by Nintendo® Co., Ltd., Kyoto, Japan) as tools for the identification of subject-specific SESC parameters. The procedure presented here can also be applied to data from such sensors, thus facilitating clinical use of the extended parameter identification process.

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Conflict of interest statement

The authors declare that there is no conflict of interest.

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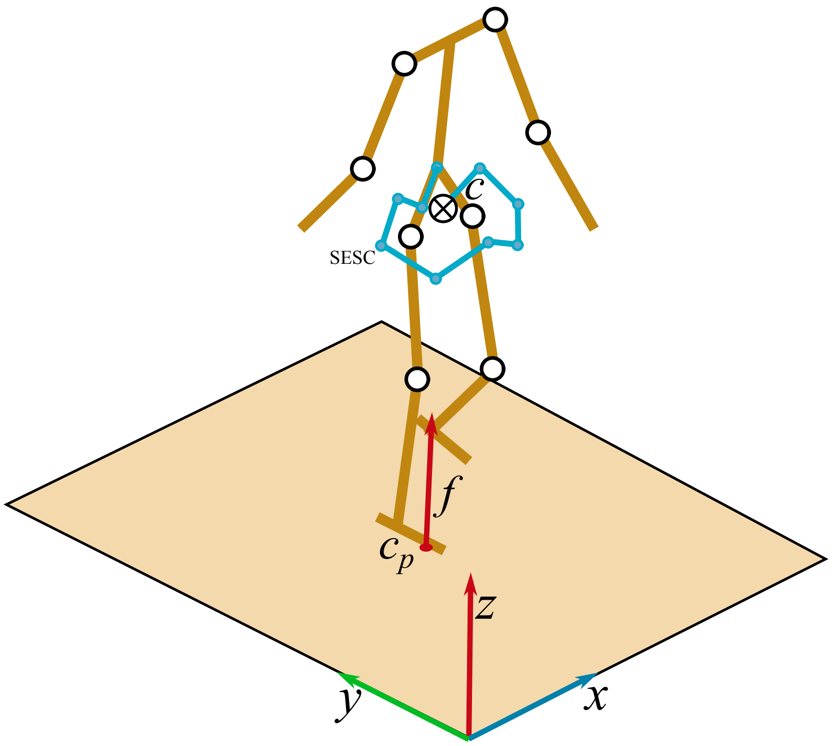

Figure 1: The whole body CoM position for different postures is associated with the corresponding CoP and ground reaction forces. Their relationship can be represented through the CoM dynamic model. The position of the CoM can be estimated by methods such as the SESC, while the CoP and ground reaction forces are measured using force platforms.

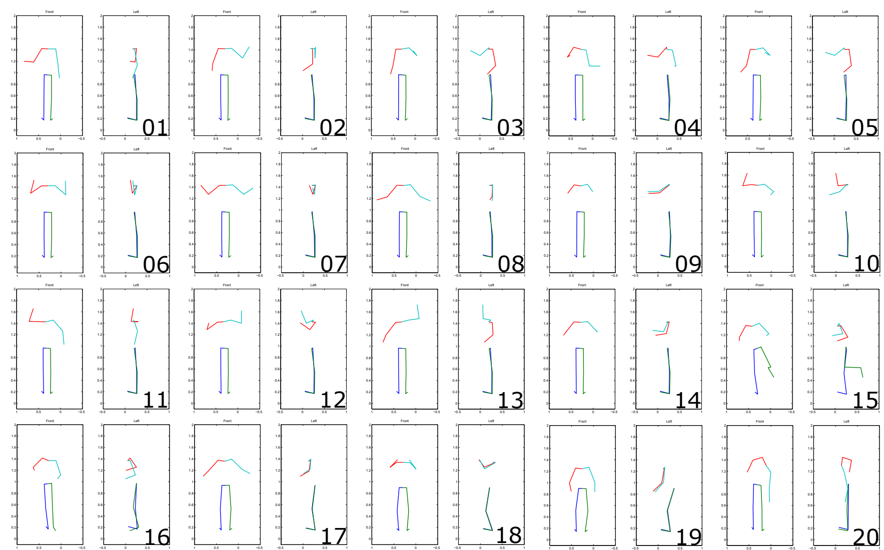

Figure 2: The subject was asked to assume and maintain a series of postures, some of which can be seen here. The poses present the subject's body segment in different orientations. They also require the subject to move the position of her/his CoM.

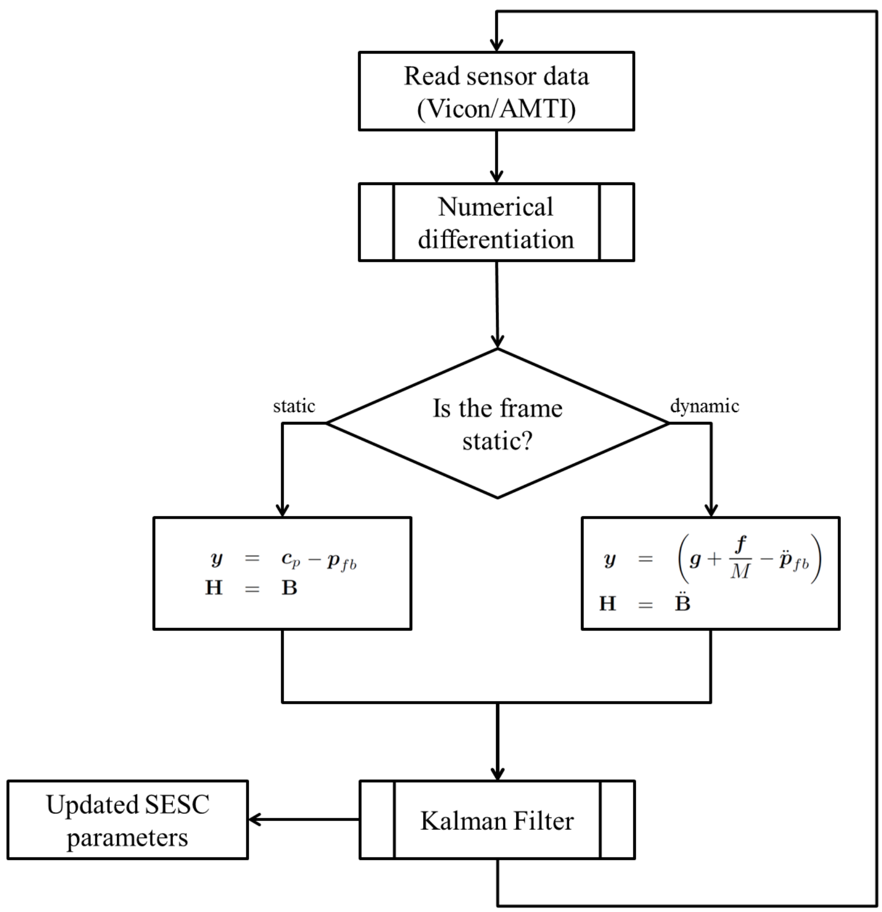

Figure 3: Proposed extended SESC identification procedure based on a Kalman filter. We developed an application that can, in real time, switch between a static and a dynamic SESC model depending on the characteristics of the measured frames.

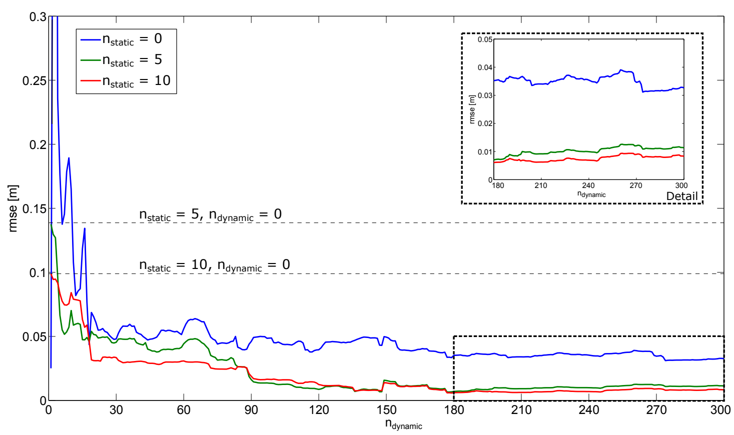

Figure 4: Estimated *rmse* for the CoM position using SESC parameters with different static to dynamic frames ratios. The information provided by the dynamic frames improved theSESC model performance. The horizontal lines show the expected *rmse* when only a few static frames were used to identify the subject's SESC parameters.

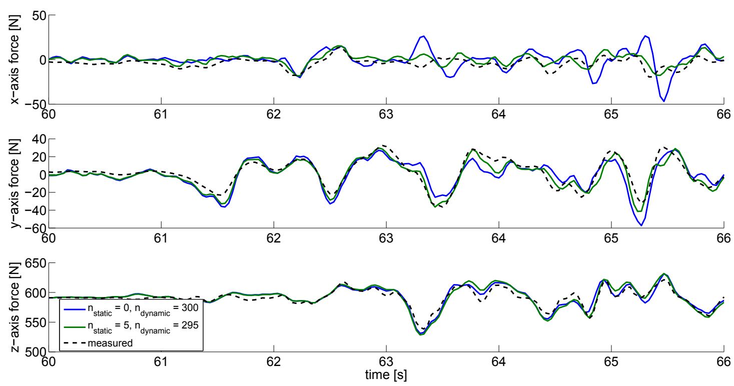

Figure 5: Estimated ground reaction forces for a cross-validation data set. Ground reaction forces can be used to validate the performance of the identified SESC parameters for dynamic postures.

List of Tables

	SESC model established with only static frames				SESC model established with combined static and dynamic frames			
	$n_{static}=5$; $n_{dynamic}=0$				$n_{static}=5$; $n_{dynamic}=295$			
	rmse	M	P	C	*rmse*	M	P	C
$\boldsymbol{c}_{p_x}$	48.8 ± 27.0 mm	-0.0669 ± 0.0727	0.0627 ± 0.0345	0.1063 ± 0.0558	20.9 ± 8.0 mm	-0.0442 ± 0.0288	0.0265 ± 0.0103	0.0540 ± 0.0251
$\boldsymbol{c}_{p_y}$	35.2 ± 35.0 mm	-0.0088 ± 0.0430	0.0338 ± 0.0327	0.0469 ± 0.0421	14.1 ± 6.0 mm	0.0073 ± 0.0122	0.0141 ± 0.0065	0.0191 ± 0.0077
$\boldsymbol{f}_x$	12.2 ± 11.2 N	-0.2936 ± 0.3323	0.3489 ± 0.0488	0.5266 ± 0.1783	7.4 ± 4.0 N	-0.0670 ± 0.2693	0.3020 ± 0.0442	0.3894 ± 0.0957
$\boldsymbol{f}_y$	11.6 ± 12.1 N	-0.1920 ± 0.2395	0.2518 ± 0.0720	0.3366 ± 0.2177	6.8 ± 5.4 N	-0.0266 ± 0.1257	0.1863 ± 0.0566	0.2203 ± 0.0607
$\boldsymbol{f}_z$	44.8 ± 23.4 N	-0.0042 ± 0.0033	0.0186 ± 0.0086	0.0192 ± 0.0089	34.0 ± 18.1 N	-0.0029 ± 0.0024	0.0136 ± 0.0034	0.0141 ± 0.0035
	$n_{static}=10$; $n_{dynamic}=0$				$n_{static}=10$; $n_{dynamic}=290$			
$\boldsymbol{c}_{p_x}$	24.7 ± 18.4 mm	-0.0472 ± 0.0474	0.0308 ± 0.0221	0.0613 ± 0.0454	17.9 ± 8.6 mm	-0.0358 ± 0.0219	0.0234 ± 0.0126	0.0444 ± 0.0218
$\boldsymbol{c}_{p_y}$	20.6 ± 20.3 mm	-0.0003 ± 0.0219	0.0207 ± 0.0202	0.0260 ± 0.0244	13.2 ± 6.4 mm	0.0034 ± 0.0115	0.0134 ± 0.0068	0.0164 ± 0.0093
$\boldsymbol{f}_x$	8.1 ± 4.4 N	-0.1701 ± 0.2897	0.3162 ± 0.0559	0.4302 ± 0.1469	7.4 ± 4.0 N	-0.0888 ± 0.2635	0.3012 ± 0.0413	0.3876 ± 0.1046
$\boldsymbol{f}_y$	8.7 ± 5.5 N	-0.1425 ± 0.2104	0.2290 ± 0.0649	0.3008 ± 0.1667	6.8 ± 5.4 N	-0.0509 ± 0.1287	0.1887 ± 0.0570	0.2239 ± 0.0770
$\boldsymbol{f}_z$	43.3 ± 23.2 N	-0.0040 ± 0.0031	0.0180 ± 0.0087	0.0186 ± 0.0089	34.0 ± 18.1 N	-0.0029 ± 0.0024	0.0137 ± 0.0034	0.0141 ± 0.0035

	de Leva				$n_{static}=0$; $n_{dynamic}=300$			
	rmse	M	P	C	*rmse*	M	P	C
$\boldsymbol{c}_{p_x}$	10.1 ± 2.6 mm	0.0211 ± 0.0169	0.0133 ± 0.0042	0.0282 ± 0.0101	37.7 ± 22.6 mm	-0.0827 ± 0.0995	0.0367 ± 0.0211	0.1048 ± 0.0841
$\boldsymbol{c}_{p_y}$	15.6 ± 4.9 mm	-0.0354 ± 0.0142	0.0106 ± 0.0035	0.0371 ± 0.0142	35.3 ± 22.7 mm	-0.0497 ± 0.0695	0.0227 ± 0.0169	0.0713 ± 0.0518
$\boldsymbol{f}_x$	5.8 ± 2.2 N	0.0722 ± 0.2381	0.2872 ± 0.0416	0.3528 ± 0.1244	7.5 ± 4.0 N	-0.1251 ± 0.2721	0.3051 ± 0.0536	0.3964 ± 0.1430
$\boldsymbol{f}_y$	5.2 ± 3.0 N	0.0320 ± 0.0935	0.1714 ± 0.0504	0.1971 ± 0.0381	7.7 ± 5.0 N	-0.0594 ± 0.1751	0.2177 ± 0.0449	0.2646 ± 0.1020
$\boldsymbol{f}_z$	34.0 ± 17.9 N	-0.0028 ± 0.0024	0.0136 ± 0.0034	0.0141 ± 0.0035	42.6 ± 23.7 N	-0.0040 ± 0.0030	0.0177 ± 0.0088	0.0183 ± 0.0090

Table 1: Summary of the identification results during a cross-validation. Note that as it is not possible to know the position of the subject's CoM, this table summarizes the differences in estimated CoM position and measured CoP for the static postures; however, errors corresponding to ground reaction forces were computed considering both the static and dynamic frames. It also summarizes the difference between the estimated and measured ground reaction forces while using anthropometric table data (de Leva).