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Vertical displacement of the approximated body center of mass during typical daily activities: A transition-based complementary filter method using barometric and inertial data

Alessandra Audisio [*,1], Daniele Fortunato [1], Paolo Tasca, Marco Caruso, Andrea Cereatti

Politecnico di Torino, Department of Electronics and Telecommunications, Corso Duca degli Abruzzi, 24 10129 Torino, Italy

A R T I C L E I N F O

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A B S T R A C T

By monitoring the movement of the body's centre of mass during daily-living activities, it is possible to gather information on an individual's functional capacity and quantify key abilities such as lower limb strength, postural control and dynamic stability. To this end, a wearable inertial measurement unit attached to the lower back can offer a practical solution for analysing CoM movement in real-world conditions. However, accelerometer-based measurements are prone to drift, limiting their suitability for long-term monitoring. To mitigate these effects, miniaturized high-resolution barometers can be integrated to provide stable direct height measurements. In this study, we developed and validated a method for the reconstruction of the vertical displacement of the centre of mass during daily activities (Transition-Based Complementary Filter). The method consisted of two steps: first, the transition intervals within which vertical displacements of the centre of mass occur are identified, then, within these intervals, the complementary filter is applied to estimate the vertical displacement. Validation was carried out on twenty healthy subjects wearing an inertial unit and a barometer on the lower back, while a marker-based stereophotogrammetry system served as reference. Participants performed a series of motor tasks replicating typical home-based activities, including standing, sitting, lying, squatting, and stair climbing. The method demonstrated high accuracy, achieving a median root mean square error of 0.02 m and a median concordance correlation coefficient of 98 %. These findings underscore its robustness and clinical utility, paving the way for improved rehabilitation strategies and enhanced patient outcomes.

1. Introduction

The vertical displacement of the body Center of Mass (CoM) is fundamental for biomechanical analysis, offering crucial insights into energy expenditure (Voleno et al., 2010), and functional mobility (Nguyen et al., 2017). Older adults and individuals with motor impairments may encounter difficulties in performing daily activities that require the elevation or lowering of the CoM against gravity. In particular, the analysis of transitional movements—such as sitting down, standing up, squatting, getting out of bed, and stair climbing—can quantitatively describe an individual's functional capacity (Masse et al., 2016), reflecting key abilities such as lower-limb strength, postural control, and dynamic stability, useful for monitoring disease progression and rehabilitation outcomes (Janssen et al., 2010).

Recent advancements in wearable technology have enabled movement analysis in both laboratory settings and real-world conditions (Salis et al., 2023). In this context, an approximated description of the CoM movement during various daily activities can be obtained by attaching a single inertial measurement unit (IMU) to the lower back (Germanotta et al., 2021; Pavei et al., 2019; Mancini et al., 2012; Kerrigan et al., 1997). However, IMU-based methods for trajectory estimation suffer from signal drift, caused by stochastic and deterministic errors in accelerometer and gyroscope readings (Caruso et al., 2024).

To enhance long-term accuracy, some authors have proposed to fuse IMU data with other complementary sensors such as a barometer, which provides a direct measurement of the vertical motion variations based on pressure changes (Manivannan et al., 2022). Although barometric readings are influenced by environmental factors such as airflow and

* Corresponding author.
E-mail addresses: alessandra.audisio@polito.it (A. Audisio), daniele.fortunato@polito.it (D. Fortunato).

[1] We would like to note that Alessandra Audisio and Daniele Fortunato contributed equally to this work and share first authorship. Alessandra Audisio will serve as the corresponding author.

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temperature variations, recent studies suggested that integrating a MEMS barometer with an IMU (IMU-Baro) can lead to improvements in CoM tracking during daily-life activities (Manivannan et al., 2022). In the literature, IMU-Baro systems have been proposed for human activity recognition including walking, stair climbing, cycling, and elevator use (Sagawa et al., 1998). Furthermore, IMU-Baro systems have been applied to extract relevant features for energy expenditure estimation (Ohtaki et al., 2005; Voleno et al., 2010), as well as to assess fall risk or identify fall events (Bianchi et al., 2010).

However, relatively few studies have focused on the estimation of CoM vertical displacement. Tanigawa et al. (Tanigawa et al., 2008) tested the accuracy of an IMU-Baro system (Xsens MTi-G) by manually moving it up and down (displacement amplitudes: 0.5–2 m; duration about 30 s) reporting an absolute errors of ~0.2 m. Experiments on a single subject while climbing the stairs with an IMU-Baro attached to the chest were also performed, but no errors assessment was reported. In another study, Sabatini and Genovese (Sabatini and Genovese, 2014) proposed a method for the estimation of the vertical CoM trajectory based on a complementary filter. The measurement system consisted of an IMU integrated with a Bosch BMP085 barometer. The IMU-Baro was attached to the upper trunk of a participant executing a single squat, and the CoM vertical trajectory was reconstructed with errors of approximately 0.5 m. In another study (Lee, 2016), a hybrid two-step Kalman/complementary filter framework was presented. The IMU-Baro system included a Bosch BMP180 barometer, and experiments consisted in manually moving the system up-and-down at different heights (displacement amplitudes: 1–3.5 m) and velocities. The accuracy was assessed by comparing the IMU-Baro reconstructed trajectories against the one measured using an optical motion capture system, reporting root mean square errors of about 0.2 m.

Regarding acceptable errors for CoM vertical displacement estimation, it should be noted that the vertical displacement of the CoM during many common movement daily activities ranges between 0.15 m and 1 m (step ~ 0.15 m; sit-to stand ~ 0.4 m, lying down ~ 1 m) that is the same order of magnitude of the CoM errors reported in the abovementioned studies. This circumstance strongly limits the applicability of the previous methods in the context of human movement analysis. Furthermore, when proposing a method for the estimation of the CoM vertical displacement for biomechanical applications, it is essential to test its validity against reference data under experimental conditions similar to those observed in the end-use applications.

This study aims to address the abovementioned issues by proposing and validating an accurate method to estimate the CoM displacement exclusively along the vertical axis during common daily movements. Experimental data were collected on twenty healthy subjects equipped with an IMU-Baro system attached to the lower back while performing various daily activities, using an optical motion capture system as reference.

2. Methods

2.1. Imu-baro system description

A high-resolution digital barometer (BMP390, Bosch, Gerlingen, Germany) was integrated into an IMU (MITCH, 221e srl, Abano Terme, Italy) at the hardware, firmware, and software levels and enclosed in a custom-designed case (Fig. 1A). The IMU-Baro system enabled synchronized data acquisition and was further configured for hardware synchronization with the stereophotogrammetric system, employed as the gold-standard reference.

Both the IMU and the Barometer were characterized in terms of noise level in accordance with IEEE 2700–2017 standard for sensor performance parameter definitions (IEEE 2017). Additional details on sensor specifications are provided in the Appendix as suggested by the International Society of Biomechanics recommendations for IMU-based studies (Cereatti et al., 2024).

2.2. Data Collection

Twenty healthy young adults (9 females, 11 males; age 26 ± 4 years) were involved in the study, each providing written informed consent in accordance with the research ethics committee of the Politecnico di Torino (protocol number 27213). The sample size was determined based on an expected intra-class correlation coefficient (ICC > 0.94), a minimally acceptable ICC of 0.7, the number of repeated measurements per subject, a significance level ($\alpha = 0.05$), and a statistical power of 95 % (Walter, Eliasziw, and Donner, 1998).

Participants wore IMU-Baro securely positioned on the lower back using a Velcro strap above the trouser waistband (Fig. 1B). This positioning is commonly adopted in biomechanical studies as a practical approximation of the CoM (Kerrigan et al., 1997). A reflective marker, attached to the barometer, was tracked by a 14-cameras stereophotogrammetric system (Vicon Vero, Oxford metrics) and used as reference for vertical displacement reconstruction. Stereophotogrammetric and IMU data were recorded at 100 Hz, while the barometer was sampled at 25 Hz (synchronization error within ±1 sample).

Each participant was asked to complete two different trials based on two different experimental set-up (Experimental Set-up Mattress and Experimental Set-up Stair, Fig. 2). Each trial included a repetition of different motor-tasks replicating typical home-based activities involving vertical CoM displacement and lasted approximately 5–7 min. Recorded motor-task included sit-to-stand or stand-to-sit movements (*StS*) from a chair at a self-selected comfortable and slower (*Slow StS*) speed, movements involving lying down and rising from a mattress (*lying*), squatting (*squat*), ascending or descending a single step (*single step*), and stairs climbing involving multiple steps (*stair climbing*). The selected motor tasks allowed to test CoM vertical displacement in the range of 0.14–0.8 m with duration from 1 to 3 s, and CoM maximum velocity from 0.22 to 0.84 m/s.

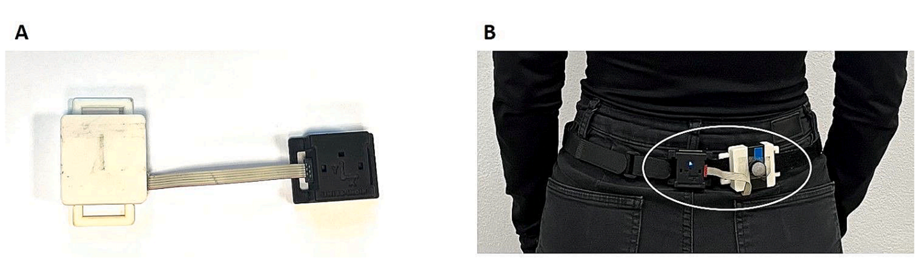

Fig. 1. A) Top view of the IMU–Baro system, showing the IMU on the right and the barometer on the left, both enclosed in 3D-printed housings. **B)** Posterior view of the IMU–Baro system positioned on the lower back, featuring a passive marker for the stereophotogrammetric system.

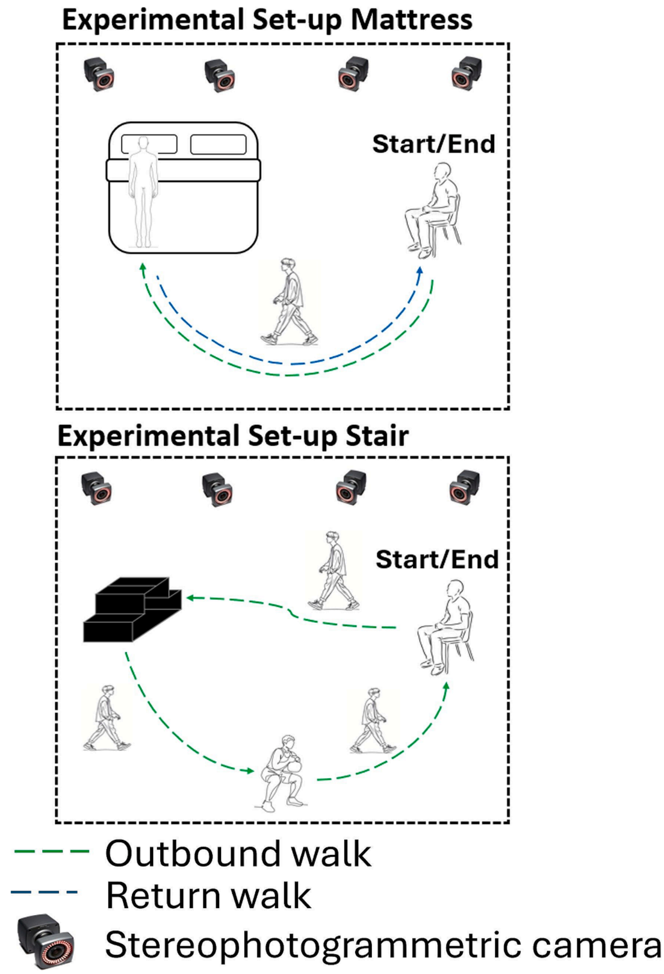

Fig. 2. Experimental Set-up Mattress: The participant performed a sit-to-stand transition from the chair (transition 1), walked, lay down on the mattress (transition 2), stood up from the mattress (transition 3), walked, and sat on the chair (transition 4). This sequence was repeated four times during the same trial, resulting in a total of 16 vertical transitions. During the third and fourth repetitions, the participant performed sit-to-stand transitions at a slower speed. **Experimental Set-up Stair:** The participant performed a sit-to-stand transition from the chair (transition 1), walked, climbed the stairs (transition 2), walked, performed a squat (transition 3), walked, and sat on the chair (transition 4). Next, the participant repeated a sit-to-stand transition (transition 5), walked, executed four single-step transitions (transitions 6–9) with brief pauses in between, walked, performed a squat (transition 10), walked, and finally sat on the chair (transition 11). This sequence was repeated twice during the same trial, yielding a total of 22 vertical transitions.

2.3. Data processing

The barometric signal P(t) was recorded by the barometer in ultra-high-resolution mode (x16 pressure oversampling, x2 temperature oversampling, without IIR filter), and was converted to altitude, resulting in the CoM vertical displacement z_b (Bolanakis, 2017):

$$z_b = \mathrm{H}^* \ln\left(\frac{\mathrm{P}_0}{\mathrm{P(z)}}\right) \tag{1}$$

where $H = \frac{k \cdot T}{m \cdot g}$, is the pressure scale height; k is Boltzmann's constant; T is the temperature in Kelvin; m is the average atomic mass ($4.76 * 10^{-26}$ kg); g is the gravity acceleration (9.81 m/s^2). Using P_0, the reference pressure (Pa), as the pressure at the start of each trial, the resulting altitude provided the height in meters relative to the initial position (Fig. 3).

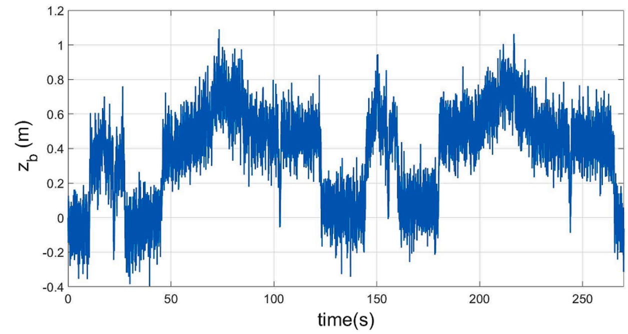

Fig. 3. Example of raw barometric signal, converted to altitude, recorded during one of the experimental sessions.

Additionally, the altitude z_b was detrended with a quadratic polynomial (detrend function in MATLAB), to remove the low-frequency drift observed in barometric measurements. The orientation of the IMU positioned on the pelvis was estimated using a complementary filter (Madgwick, Harrison, and Vaidyanathan, 2011) initialized with an algebraic quaternion to ensure fast convergence (Caruso et al., 2021) (Valenti et al., 2015), thereby removing the gravitational component from the proper acceleration measured by the accelerometer (for further details see Appendix).

2.4. Transition-Based complementary filter method

Since the integration of inertial signals for vertical trajectory estimation is affected by drift, an original "transition detection step" was introduced. This operation aimed at identifying and isolating the time intervals within which the vertical displacement of the CoM occurs (transitions), thus reducing the duration of the integration intervals. Within these intervals, a "vertical displacement reconstruction step" was then applied using a complementary filter (Sabatini and Genovese, 2014; Higgins 1975) to estimate the CoM's vertical displacement (Fig. 4). The method was referred to as Transition-Based Complementary Filter (TRA-COF).

2.4.1. Transition detection step

Transition interval of first approximation based on the barometric signals

The CoM vertical displacement, z_b, was low-pass filtered with a cutoff frequency of 0.5 Hz to reduce noise, resulting in a smoothed signal, $\tilde{z_b}$. The first derivative of $\tilde{z_b}$, denoted $\tilde{z_b}'$, was computed to highlight changes in CoM vertical velocity.

To identify the different types of transitions that can be encountered during daily life activities, two different algorithms were implemented. Algorithm A was designed to analyse transitions that are temporally distant from each other by exploiting the CoM vertical velocity $\tilde{z_b}'$, whereas algorithm B for the analysis of two transitions occurring in close succession based on the CoM vertical displacement $\tilde{z_b}$ (Fig. 5). Transition intervals as detected by the two algorithms were then combined to enhance overall performance. In cases where transition intervals detected by the two algorithms partially overlapped, priority was given to those identified by algorithm B.

In particular, algorithm A identified the instant of time corresponding to the peak of the norm of the CoM vertical velocity $\tilde{z_b}'$. For each detected peak, the transition was then determined as the time interval between the first zero-crossing instants to the left and right of the peak, under the assumption that the vertical velocity at the start and end of each transition is zero (Fig. 5A). Instead, algorithm B leveraged a peak detection directly to $\tilde{z_b}$ and the start and end transition instants were determined in correspondence of the nearest local maxima to the left and right of each detected peak. To avoid detecting false transition due to spurious CoM oscillations, a minimum threshold (0.10 m) on the vertical displacement between adjacent peaks was imposed (Fig. 5B).

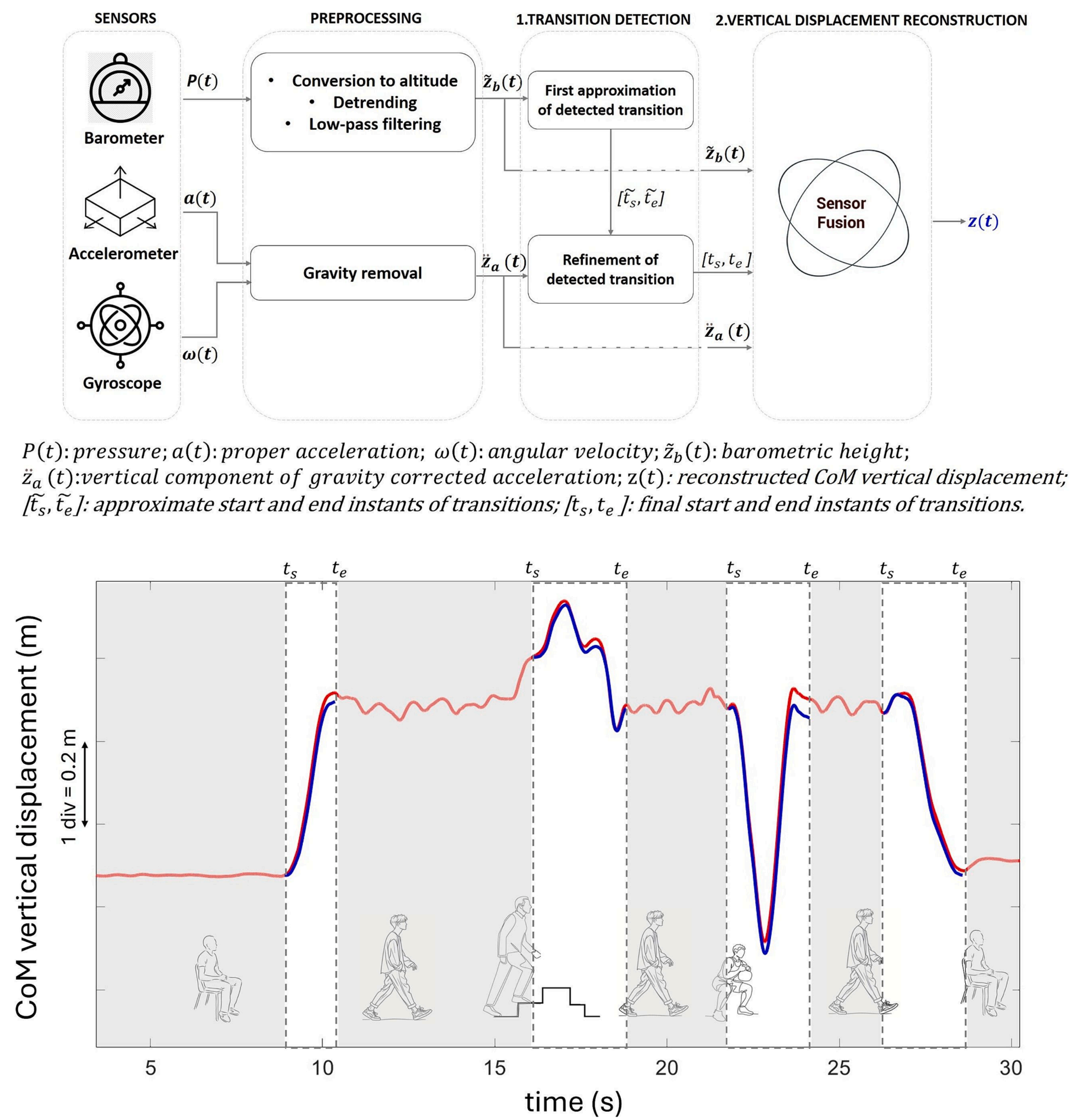

Fig. 4. Block diagram of the proposed method. The figure below shows the reference altitude acquired with the stereophotogrammetric system (red) and the motor tasks performed by the subject. The proposed TRA-COF method identified the transitions (dashed vertical lines), defined as intervals where vertical displacement of the CoM occurred, and reconstructed the vertical displacement (blue) of CoM during these intervals with respect to the initial position in each interval using a complementary filter. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Each transition interval of first approximation was identified by the start instant ($\tilde{t}_s$) and end instant ($\tilde{t}_e$).

Refinement of the transition intervals based on accelerometric signals

Under ideal conditions, the transition intervals identified from barometric signals and those identified from accelerometric signals would coincide. However, due to differences in the transfer functions and noise characteristics between these types of sensors, the velocity signal (v_{baro}), obtained from the barometer through differentiation of the altitude signal, and the velocity signal (v_{acc}), obtained through integration of the acceleration signal are different and, in particular, v_{acc} vary depending on the chosen integration interval.

To minimize the differences between velocities signals—and, consequently, in the corresponding vertical displacement estimates—the transition intervals of first approximation were refined by maximizing the similarity between the v_{baro} and v_{acc} in terms of cross-correlation (for further details see Appendix). As a result, the final start (t_s) and end (t_e) instants of the transition intervals were obtained.

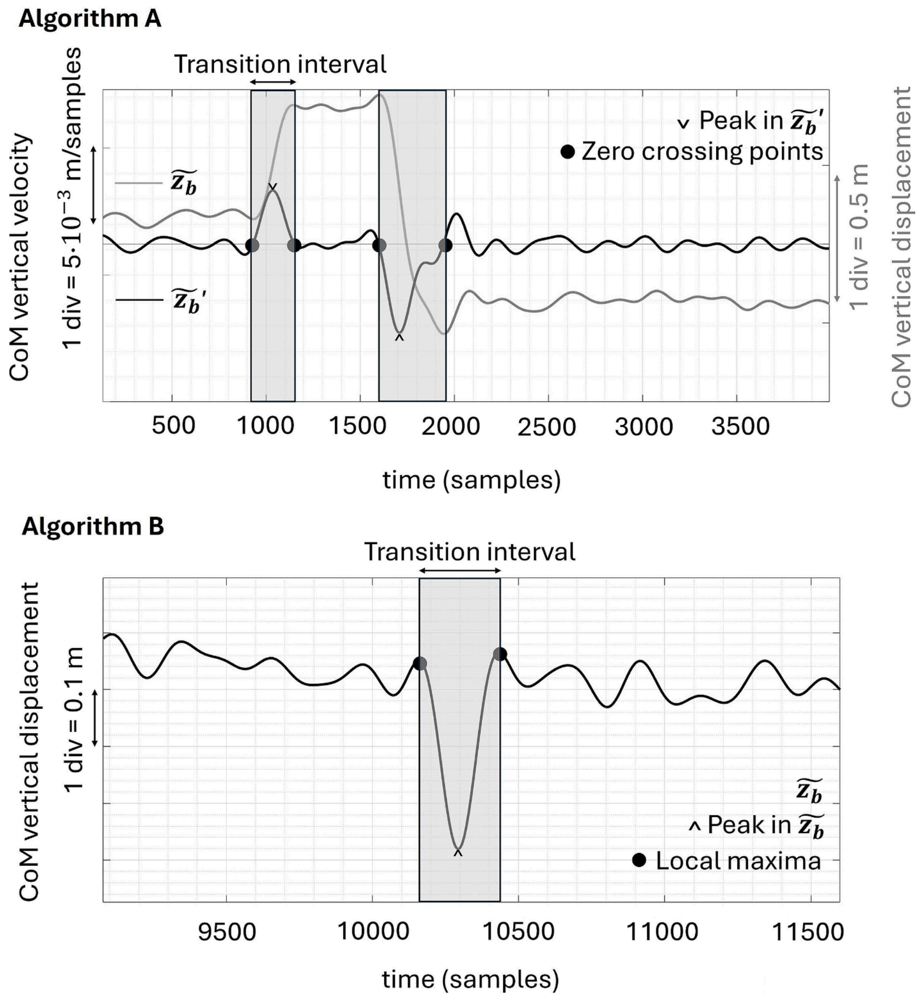

Fig. 5. Algorithm A) The filtered height ($\widetilde{z_b}$, solid grey) obtained from the barometric sensor, and its relative first derivative ($\widetilde{z_b}'$, solid black), are shown during Sit-to-Stand and Lying transitions, occurring at approximately 1000th and 1700th sample, respectively. The positive and negative peaks in $\widetilde{z_b}'$ identified the transitions in $\widetilde{z_b}$. Around the peaks, the zero-crossing points in $\widetilde{z_b}'$ identified the start and end instants of transitions. **Algorithm B)** Example of a squat transition in $\widetilde{z_b}$. The transition is identified by detecting peaks in $\widetilde{z_b}$, with the start and end instants of transition marked by the local maxima to the left and right of each peak.

2.4.2. *Vertical displacement reconstruction step*

To reconstruct the CoM vertical displacement during the transition intervals, a complementary filtering algorithm was used to fuse the barometric and accelerometer measurements (Sabatini and Genovese, 2014).

The state vector at the k^{th} sample, $\mathbf{z}_k$, comprised two components: the displacement (z_k) and velocity ($\dot{z}_k$) of the CoM along the vertical axis, each updated iteratively at discrete time intervals $t_k = kT_S$, where T_S denotes the sampling period.

The evolution of the system's state is represented as:

$$\mathbf{z}_k = \begin{bmatrix} z_k \\ \dot{z}_k \end{bmatrix} = \begin{bmatrix} 1 & T_S \\ 0 & 1 \end{bmatrix} \mathbf{z}_{k-1} + \begin{bmatrix} 1 & T_S/2 \\ 0 & 1 \end{bmatrix} K_C \bullet T_S \Delta z_{k-1} + \begin{bmatrix} T_S/2 \\ 1 \end{bmatrix} \Delta v_{k-1} \tag{2}$$

Here:

- $\Delta z_k = z_k - z_{bk}$ represents the difference between the estimated vertical position (z_k) and the barometric altitude measurement (z_{bk}), which was detrended and low pass filtered.
- $\Delta v_k = T_S \ddot{z}_{ak}$ is the velocity increment derived from the vertical linear acceleration ($\ddot{z}_{ak}$), corrected from gravitational bias.

The complementary filter gain, K_C, was calculated as:

$$K_C = -\begin{bmatrix} \sqrt{2\sigma_w/\sigma_v} \\ \sigma_w/\sigma_v \end{bmatrix} \tag{3}$$

where σ_w and σ_v represent the standard deviations of the noise in the accelerometer-based vertical acceleration ($\ddot{z}_{ak}$) and the barometric altitude (z_{bk}), respectively.

For the initialization of the computation in Eq. (2), it was assumed that at the start of the transition interval $\mathbf{z}_0 = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$, and $\Delta v_0 = T_S \ddot{z}_{a\,0}$.

2.5. *Statistical data analysis*

2.5.1. *Transitions detection performance assessment*

Detected transitions were classified as true positives (TP), false negatives (FN) and false positives (FP) based on the transitions visually identified and labelled from the marker trajectories measured by the stereophotogrammetric system as reference. Then, for each subject and recording, Positive Predictive Value (PPV), sensitivity and F1-score were derived:

$$PPV = \frac{TP}{TP + FP} \tag{4}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{5}$$

$$F1 - score = \frac{2 \bullet PPV \bullet Sensitivity}{PPV + Sensitivity} \tag{6}$$

For each metric, the median values and coefficients of variation were computed.

2.5.2. Vertical displacement reconstruction performance assessment

The validity of the vertical CoM displacement estimated by the proposed method was assessed for the TP transitions in terms of RMSE, $RMSE_{\%}$ and Concordance Correlation Coefficient (CCC). For each *i-th* TP transition, the reconstructed vertical displacement (z_k) was compared with the reference vertical displacement measured by the stereo-photogrammetric reference system (z_{SPk}), assuming the initial COM vertical position to coincide at the start of the interval:

$$RMSE_i = \sqrt{\frac{1}{N}\sum_{k=1}^{N}(z_{SPk} - z_k)^2} k = 1, \cdots, N \tag{7}$$

$$RMSE_{\%i} = \frac{\sqrt{\frac{1}{N}\sum_{k=1}^{N}(z_{SPk} - z_k)^2}}{|\max(z_{SPk}) - \min(z_{SPk})|} k = 1, \cdots, N \tag{8}$$

$$CCC_i = \frac{2\rho\sigma_{z_{SPk}}\sigma_{z_k}}{\sigma_{z_{SPk}}{}^2 + \sigma_{z_k}{}^2 + (\mu_{z_k} - \mu_{z_{SPk}})^2} \bullet 100 \tag{9}$$

where N is the number of samples in the transition, ρ is the Pearson correlation coefficient between z_k and z_{SPk}, σ is the standard deviation, and μ is the mean of each variable.

Transitions were grouped by motor task type across subjects and recordings, and the median, 25th, and 75th percentiles of $RMSE_i$, $RMSE_{\%i}$, and CCC_i distributions were calculated. Additionally, metrics distribution across different motor tasks and subjects were evaluated.

The total vertical CoM displacement performed by each subject was calculated by summing the cumulative displacement across all detected transitions in the two trials. The difference between the reconstructed (Cum_z) and reference ($Cum_{z_{SP}}$) cumulative displacements was computed for each subject, across two trials, in terms of:

$$e_{cum}\% = \left|\frac{Cum_{z_{SP}} - Cum_z}{Cum_{z_{SP}}}\right| \bullet 100 \tag{10}$$

where

$$Cum_{z_{SP}} = \sum_{i=1}^{nTP}\sum_{k=1}^{N-1}|z_{SPk+1} - z_{SPk}| \tag{11}$$

$$Cum_z = \sum_{i=1}^{nTP}\sum_{k=1}^{N-1}|z_{k+1} - z_k| \tag{12}$$

here *nTP* represents the number of TP transitions, N represents the number of samples in the *i-th* TP transition.

To examine the influence of motor task type on the method's performance, statistical analysis of the $RMSE_{\%}$ distributions was conducted for the six motor tasks: StS, StS slow, Lying, Single-step, Stair climbing, Squat. Normality was assessed using Shapiro-Wilk test, which indicated that all the distributions were not normal (p-value < 0.001). Homogeneity of the distributions' variance was assessed by Levene's test, resulting in all the distributions having different variances (p-value < 0.001). Finally, differences between the distributions grouped by movement type were evaluated with Kruskal-Wallis test, with post-hoc adjustments performed using the Bonferroni correction to account for multiple comparisons (Bender and Lange, 2001). All tests assumed a 5 % level of significance.

Finally, to ensure a fair comparison between our method and the method proposed by Sabatini and Genovese, we also tested their complementary filtering algorithm on the data collected in this study. The complementary filter was applied throughout the entire duration of the trials, and the RMSE of the displacement was evaluated during the transitions identified by our method.

All data processing and statistical analyses were performed using MATLAB (R2023a, The MathWorks Inc., Natick, MA, USA). The data utilized in this work are openly accessible at: https://doi.org/10.5281/zenodo.15046577.

3. Results

3.1. Transition detection

The transition detection step was evaluated in terms of the number of correctly recognized transitions, achieving a median PPV of 97 %, a sensitivity of 92 % and an F1-score of 95 %, across subjects and trials (Table 1).

3.2. Vertical displacement reconstruction

The method reconstructed the vertical CoM trajectory with an RMSE of 0.02 m, an RMSE% of 7 %, and a CCC of 98 % across the 694 true positive transitions automatically detected (Table 2). In comparison, applying the method proposed by Sabatini and Genovese to the same transitions intervals resulted in a RMSE of 0.13 ± 0.08 m.

An example of reconstructed vertical CoM displacement for a subject during the different motor tasks included in the experimental protocol is shown in Fig. 6.

For each subject, the CoM vertical displacement during the two trials was overall about 17 m, with mean e_{cum}% across subjects equal to 2 ± 1 %.

4. Discussion

In this study, we presented an innovative method specifically designed to reconstruct the vertical displacement of the CoM exclusively during transition intervals commonly performed in daily life. The key innovation lies in the identification of vertical CoM transitions. This ensures that reconstruction is applied exclusively to biomechanically relevant movements, like StS, rather than over the entire trial. By integrating an acceleration-based refinement step for transition detection, the method enables optimal identification of these intervals while minimizing drift-related errors in inertial signals.

The method was validated on twenty subjects performing a set of motor tasks, including sitting, standing, squatting, and stair climbing. To the best of the authors' knowledge, this is the first method capable of accurately tracking the vertical displacement of the CoM during daily-life movements and transfers, validated on a substantial number of participants.

A two-step approach was implemented, first the recorded data were segmented to detect CoM vertical transitions and then the vertical displacement was reconstructed exclusively within each transition interval. The transition detection step achieved excellent performance, with median PPV, sensitivity, and F1-score values of 97 %, 92 %, and 95

Table 1
Median values and Coefficient of variation of Positive predictive value, sensitivity and F1-score.

Metrics	Median value (%)	Coefficient of Variation (%)
PPV	97	5
Sensitivity	92	4
F1-score	95	3

Table 2
Results in terms of RMSE, $RMSE_{\%}$ and CCC for the reconstruction of CoM vertical displacement are reported as median [25th, 75th percentile], for the detected transitions.

Motor tasks	# detected transition	Displacement range (m)	RMSE (m)	$RMSE_{\%}$ (%)	CCC (%)
StS (normal)	236	0.34 ± 0.07	0.03 [0.02 0.04]	8 [4 12]	97 [94 99]
Lying	153	0.80 ± 0.11	0.04 [0.02 0.05]	4 [3 7]*	99 [98 100]
Stair climbing	38	0.28 ± 0.03	0.02 [0.02 0.04]	8 [6 13]	96 [91 98]
StS (slow)	71	0.30 ± 0.10	0.02 [0.02 0.04]	8 [5 14]	97 [91 99]
Single step	119	0.14 ± 0.02	0.01 [0.01 0.02]	8 [5 15]	98 [93 99]
Squat	77	0.42 ± 0.13	0.03 [0.01 0.05]	7 [4 11]	98 [96 99]
Total	694	0.14–0.8	**0.02** [0.01 0.04]	**7** [4 12]	**98** [95 99]

* Indicates statistically significant difference (p-value) < 0.05).

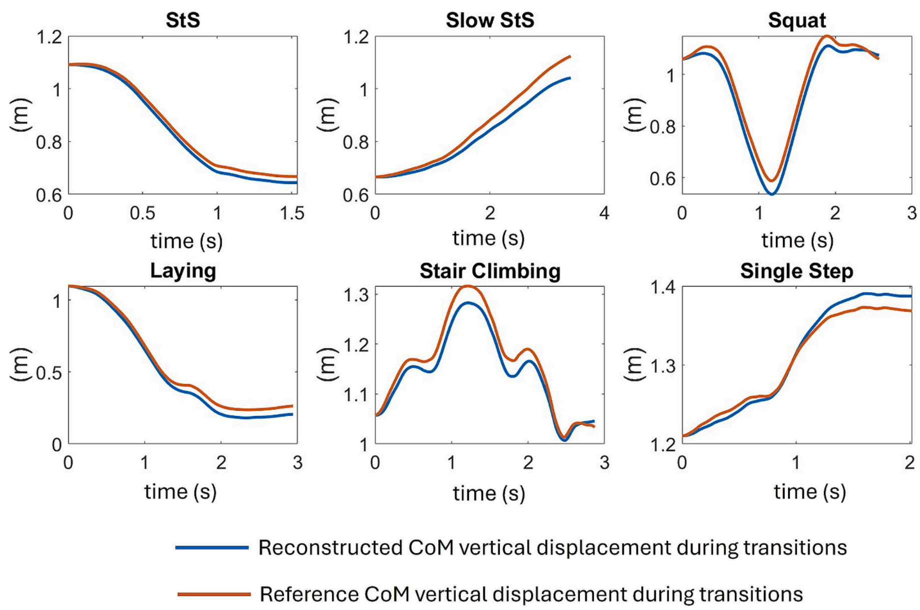

Fig. 6. Examples of reconstructed (blue) and reference (red) signals of the centre of mass during transitions grouped by movement type and automatically detected with the proposed transition detection step. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

%, respectively. These values underscored the robustness of the method in detecting vertical transitions with minimal false positives or missed detections, ensuring reliability for subsequent trajectory reconstruction. Vertical CoM displacement was reconstructed with high accuracy, achieving an overall RMSE median value of approximately 0.02 m and a median CCC of 98 %. These results highlighted the effectiveness of the complementary filter in addressing sensors-specific limitations, optimally leveraging the barometric altimeter's low-frequency stability and the accelerometer's high-frequency responsiveness.

The cumulative percentage error in the CoM vertical displacement was about 2 %, and considering that, on average, the total CoM vertical displacement over the two trials was about 17 m, it implied an uncertainty in the true vertical CoM displacement of about 0.35 m. These results indicated that the proposed method is effective to provide an overall description of the CoM displacement during the execution of different motor tasks, suggesting its applicability for energy expenditure assessment.

The proposed method performed equally well across different motor tasks, with median RMSE values ranging from 0.01 to 0.04 m and median CCC values between 96 % and 99 %. When analyzing the effect of specific motor tasks on the reconstruction of vertical CoM displacement, it was found that $RMSE_{\%}$ values for the lying task were smaller and statistically different compared to the other tasks. This result was expected, as the lying task involved a larger displacement, while the RMSE errors remained relatively contained compared to the other tasks.

When comparing with the results reported in previous studies, the proposed method improved the CoM vertical displacement of about an order of magnitude (RMSE = 0.20 m for Lee, 2016; RMSE = 0.50 m for Sabatini and Genovese, 2014; RMSE = 0.02 m for the proposed method).

Additionally, the application of the method proposed by Sabatini and Genovese to the detected transition of our dataset showed an improvement in performance compared to their original study, with the RMSE decreasing from 0.50 ± 0.11 m to 0.13 ± 0.08 m.

It should be acknowledged that the barometer used in the present study has probably better performances with respect to those employed in previous studies. Technological advancements in sensor development can also play an important role for explaining different performances among studies. Nonetheless, the proposed TRA-COF method achieved superior performance (RMSE = 0.02 m) because it focused exclusively on reconstructing vertical displacement during relevant CoM movements as identified by transition detection step. Unlike previous methods that continuously integrate inertial and barometric signals over the entire acquisition, our approach selectively applies reconstruction only within transition intervals, minimizing drift accumulation and optimizing vertical velocity updates.

The results of this study should be interpreted considering certain limitations. First, we acknowledged that the use of an IMU-Baro system attached to the lower trunk can only provide an approximation of the true CoM movement, but such information can be still useful for several applications. Second, it is important to emphasize that the proposed method did not provide the absolute vertical position of the CoM, but only the vertical displacement with respect to the vertical position at the beginning of each CoM transition. While it is recognized that for some applications the continuous description of the absolute or relative vertical position of the CoM may be of interest, this was beyond the scope of this study. Another limitation is that the method was tested during paradigmatic motor task characterized by a vertical CoM displacement between 0.14 m for the "single step" task and 0.8 m for the "lying" task, and any vertical CoM oscillation smaller than 0.1 m was automatically disregarded. This implied that CoM physiological oscillations occurring during walking would not be detected.

Finally, although the acquisitions in this study lasted around 5–7 min, the proposed method is suited for long-term recordings, as the initial CoM height is always reset at the beginning of each transition. This ensures robustness over extended monitoring periods.

Nevertheless, despite the analysed conditions were designed to closely simulate daily activities, the experiments were conducted in a controlled laboratory setting. Extending the proposed method to real-world applications remains a future direction, alongside further testing in ecological and home-based environments.

Future testing of the proposed method in real-world conditions can open new perspective in the field of digital mobility based on wearable systems by complementing traditional key digital mobility outcomes pertaining to the gait with a biomechanical description of the CoM movements during other paradigmatic motor tasks (Salis et al., 2023).

CRediT authorship contribution statement

Alessandra Audisio: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation. **Daniele Fortunato:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation. **Paolo Tasca:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation. **Marco Caruso:** Writing – review & editing, Visualization, Supervision, Software, Methodology, Formal analysis. **Andrea Cereatti:** Writing – review & editing, Visualization, Supervision, Resources, Project administration, Methodology, Funding acquisition, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jbiomech.2025.112711.

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