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Standing Balance Assessment by Measurement of Body Center of Gravity Using Smartphones

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ABSTRACT Assessment of balance by means of posturographic analysis is frequently used in the clinical practice for evaluating the risk of falls or as an indicator of balance-related disorders. The development of automatic, affordable and accurate systems for gauging balance capabilities in the elderly is deemed a crucial step towards the adoption of prevention strategies and the reduction of associated social costs, especially in a context of growing average age of population.

In this article we propose to exploit signals that can be collected from sensors on board of common consumer-grade smartphones for posturographic analysis. To this aim, we introduce several processing algorithms for extracting useful information from the acceleration data streams, and we also present an assessment framework based on the comparison of the trajectory of the body center of gravity, estimated from embedded triaxial accelerometers, with a homologous counterpart, estimated from the reference plate force, thus adding to the consistency of the whole process.

Experimental results confirm the effectiveness of the proposed system in terms of its capability of achieving signals and posturographic features which agree with those obtained by means of balance board platforms, potentially opening the way to novel research studies and applications of mobile technology in this field.

INDEX TERMS Mobile Application, Postural Balance, Smartphone Sensors

I. INTRODUCTION

Unstable balancing and falls are serious health problems that affect a major percentage of the population [1]. Problems with mobility, balance, and loss of muscle strength contribute to the likelihood of falling [2]. Most cases of falls impact older adults over the age of 65: as a matter of fact, based on study by Rubenstein [1], 40% of this portion of population is affected by at least one fall-related injury each year. While most falls are not followed by seeking medical care [3], one fortieth of injuries require hospitalization and often are followed by serious complications with possible long-term negative effects in respect of physical and psychological well-being. These factors are often also linked to a decrease in life quality and reduced life expectancy [4]. Moreover, high incidence in the elderly population explain why unintentional falls represent one of the most frequent causes of death [1].

Over the next decades, thanks to the rising average age

of population, the number of yearly injuries caused by falls are projected to increase significantly potentially resulting into a considerable burden, in terms of medical costs for the public health [5]. Previous research has indicated that falls and related injuries are predictable and can be prevented by targeting specific risk factors (such as exercises, home safety improvements, and reducing medications) [6]. As such, well-developed preventive strategies that target subjects at risk could indeed lead to a considerable reduction in medical costs [2].

Clinical balance assessment through posturographic analysis has been shown to be an indicator of fall risk that can be used to determine underlying reasons for balance disorders [7], [8]. Despite the clear tie between falls and balancing impairment, current medical practice often depends on unreliable subjective measures (like self-reports based on patient recollections).

Effective and accessible tools for balance assessment, which enable unskilled users to perform inexpensive and quick tests, are required to facilitate the adoption of pervasive fall-prevention programs [9]. Given the ubiquitous nature of smartphones in older adults and the presence of several on-board motion sensors, smartphones have the opportunity of serving as a portable balance screening tool for both controlled and unsupervised settings [10].

In this article we propose to exploit the embedded accelerometers usually mounted on board of smartphones for the evaluation of standing balance. While the idea of using smartphones as a support for human posture assessment is not novel, lots of scientific issues (from the design of well-grounded algorithms to the development of consistent validation protocols) remain to be addressed in order to build reliable, accurate, and automatic systems to support diagnostic practice. The main contributions of this work in this direction can be summarized as follows:

- we propose a cascade of signal processing algorithms, implemented into a consistent tool flow, aimed at processing the data streams gathered from accelerometers on board of a smartphones for estimating the trajectory of the center of mass and, subsequently, the standing balance;
- we put forward to transform the center of pressure sway, obtained from a reference force plate, in order to compute an estimate of the subject's center of gravity, that can be suitably used to evaluate smartphone-based system performance with respect to stabilometric platforms usually adopted in clinical settings.

This is the structure of the remainder of the article: in Section II we outline the main scientific literature related to our study; in Section III we describe the background concepts of posturographic analysis; in Section IV we illustrate the methods and key features of the proposed approach; in Section V we report the results of validation experiments; in Section VI we set forth the main findings of our investigation.

II. RELATED WORK

Most **fall risk assessment** methods rely on retrospective fall histories by patients (which may be unreliable due to the patient's poor recollection) or other clinical assessments tools. Even though they are widely used as standard methods, these tools still do not achieve 100% diagnostic accuracy. Several other methods make use of inertial sensors located on one (or more) of the patient's anatomical areas (such as the lower back, lower limbs, head, shoulders, elbows, knees, etc.) tracking steady state walking, standing balance, or standard movements (such as "timed up and go" or "five time sit to stand") [9]. While these approaches provide interesting clues on the effectiveness of using inertial sensors for assessing human balance, our research is focused on the development of a portable, cheap and easy-to-use system based on smartphones. Indeed, despite the ubiquitous nature and potential of these devices, their adoption in the context of fall prevention is

relatively novel. Further research, focusing on solution validity and usability, is needed [10].

A number of mobile applications for human body balance assessment are available on major mobile platforms (Android and iOS). These "mobile health" apps are generally designed to be used by end-users to perform simple self-assessments. While many of these apps support a variety of tests (including sitting balance, knee balance, or sway), they supply results in the form of an overall score or as simplified graphs, which make them less useful for clinical usage [11]. Also, only a small percentage of apps are backed by scientific publications providing validation of their results [12]. The aim of our study is to present a set of techniques for processing inertial sensor data streams and estimating the trajectory of the center of mass in a sound way; moreover we also define a consistent methodology to enable the comparison between the *COG* and the corresponding quantity estimated from the reference plate force.

In a recent study by Mayagoitia et al., a smartphone placed at the approximate height of the patient's center of mass was used to track accelerations and mapping them to sway distance on the floor. Results extracted from the movement of the user's projected center of gravity (*COG*) and center of pressure (*COP*)—as measured with a force platform—were found not to be directly comparable but nonetheless having a similar behavior [13]. In this article, we propose to convert the *COP* (as given by a force plate) into the *COG* in order to make possible a comparison with the *COG* computed by a smartphone. Furthermore, several features commonly used in posturography are extracted from the *COG* signal and their suitability and consistency are investigated with respect to their usage in this context.

A more recent study by Hsieh et al., including 30 healthy participants, compared sensor readings from a smartphone (held medially against the chest along the sternum) with data from a force platform. In this case, acceleration values were directly compared to *COP* movement, focusing on the 95% confidence ellipse and the velocity in the anteroposterior (*AP*) and mediolateral (*ML*) directions, which were considered reliable indicators of fall risk in older adults. Each participant completed a physiological profile assessment (*PPA*), which measures fall risk based on vision, reaction time, and balance, and was classified as having a 'high' or 'low' risk of falling. Results have shown that it is possible to discriminate between these risk classes using smartphone sensor data [7]. However, while in [7] the acceleration signals are straightly correlated to the *COP*, we bring forward the comparison of homogeneous quantities (namely, the *COG*) by means of suitable pre-processing.

III. BACKGROUND ON POSTUROGRAPHIC ANALYSIS

In this section we briefly review some basic concepts of posturographic analysis, in particular the biomechanical model of the single inverted pendulum and the parameterization techniques used to extract meaningful information from sway movement trajectories.

Despite the huge amount of research studies that have been carried on during the last decades, the analysis of posturographic data can still be considered a complex activity, which entails tackling several challenges, from the design of adequate processing algorithms to the modeling of balance and postural control system. Posturographic analysis methods are usually classified into *static* or *dynamic*. Static analysis entails experimental protocols where the sway movements are collected from subjects which are asked to stand on a flat, horizontal surface (with eyes open and/or closed) without any kind of perturbation. Typically, sway movements are gathered by means of force plates capable of recording the trajectory of the *COP*. It represents the resulting vector of all the pressures over the surface area in contact with the ground. In particular, when a force platform is used to record the *COP* trajectory, its two orthogonal components (in the anteroposterior and in the mediolateral directions) are sampled by means of several load cells. The *COP* trajectory is subsequently parameterized for information extraction. In dynamic settings, postural balance is perturbed in an unpredictable manner (from the subject point of view) in order to gain some insights (e.g. the contribution of given sensory channels) on the capability of recovering the initial posture. The aim of this article is to investigate the use of smartphone for static posturography analysis which is, in general, a more affordable method for the clinical practice (with respect to dynamic protocols), while it also allows to achieve specific knowledge regarding the activity performed by the posture control system, namely the stabilization of the *inverted pendulum* of the body [14].

A. THE SINGLE INVERTED PENDULUM MODEL

Indeed, the main modeling assumption of state-of-the-art scientific literature relies on the representation of human body in standing balance as an inverted pendulum system [14], [15].

Figure 1 illustrates the main quantities used to derive the model, taking into consideration, for the sake of simplicity, only the anteroposterior direction of a person standing still. The system composed by the ankle joint, feet and rest of the body is modeled by the single inverted pendulum pivoted around the ankle; in this framework, sway movements represent the back and forth oscillations of the pendulum as the effect of two opposite forces: *i*) the gravity force, destabilizing the system; *ii*) the stabilizing effect of ankle muscles. Particularly, the motor torque τ_m due the muscles acting around the ankle counterbalances the momentum of the ground reaction force F , which is applied at the *COP*.

According to classical Newton-Euler mechanics equations, the dynamics of the system can be described by means of the following equation [15]:

$$\frac{d^2 COG_v}{dt^2} \approx \frac{mgh}{I} (COG_v - COP) \quad (1)$$

where COG_v is the projection of the center of gravity, COP the center of pressure, h is the distance between the ankle and the barycenter and I is the moment of inertia of the body around the ankle joint.

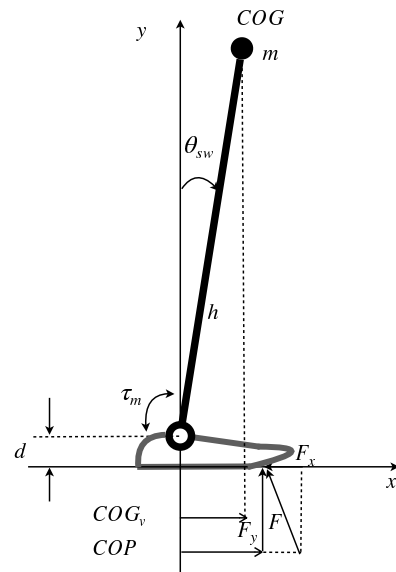


FIGURE 1: The single inverted pendulum model. COG : center of gravity; COG_v : projection of COG w.r.t. the ankle joint; COP : center of pressure; m : body mass; g : acceleration of gravity; θ_{sw} : sway angle; τ_m : ankle torque; F : ground reaction force; F_x, F_y : horizontal and vertical components of the ground reaction force; d height of the ankle joint w.r.t. the ground; h : distance between COG w.r.t. and ankle joint.

From Equation 1, the transfer function of the dynamical system with input COP and output COG_v can be written as:

$$\frac{COG_v(\omega)}{COP(\omega)} = \frac{\omega_0^2}{\omega^2 + \omega_0^2} \quad (2)$$

In Equation 2, ω represents the angular frequency and $\omega_0 = \sqrt{\frac{mgh}{I}}$ the natural angular frequency of the inverted pendulum; it also follows that, as frequency grows, the output of the system progressively decreases, with a typical low-pass filter behavior. Hence, in the frequency domain, the projection of the center of gravity can be considered a filtered version of the center of pressure, with values of the cutoff frequency around 0.4 Hz for a *typical* subject.

The raw data gathered for posturographic analysis usually consists of the trajectory of the COP in two dimensions, namely AP and ML . In this article we propose to process and analyze data gathered from accelerometers embedded on smartphones, through which we aim at directly estimating the sway of the center of gravity COG (i.e. its trajectory along the AP and ML axis). While the two types of curves appear to be similar, they differ in the frequency content, especially for frequencies higher than 1 Hz. This can be explained by the fact that they represent different physical quantities. Several studies show that the COP signal (a.k.a. *statokinesigram*) represents a force, while the COG signal is related to the sway of the inverted pendulum and, as such, it represents a movement [14]–[17]. Hence, the COP trajectory is a time series directly representing the forces generated by muscles in the activity of stabilizing the body; the COG can be instead

seen as a variable controlled by the COP . The low-pass filter behavior resulting from modeling the human body balance as an inverted pendulum, clearly explains the relationship between these two quantities, where the frequency bandwidth of the COP signal is much higher than that of the COG signal, which oscillates with the majority of its components below 1 Hz.

Interestingly, Equation 2 also enables the derivation of COG_v from COP ; in particular, given the natural angular frequency of the pendulum, the time series of the COG_v can be estimated by computing the inverse discrete Fourier transform of the product between the transfer function and the Fourier transform of the COP . Since we propose to compare the statokinesigrams obtained by means of a force plate (e.g. a balance board) with those collected by means of a smartphone, we can therefore use this method to estimate the center of gravity once we have recorded the center of pressure, and compare it with the center of gravity resulting from the measurements taken by the smartphone on-board accelerometers.

It is worthwhile to mention that mathematical modeling of the posture control system is far to be considered a solved question, especially for what regards its coordination, control principles and related motor commands. Attempts to improve the model accuracy and explanatory capabilities encompass the Double Inverted Pendulum, which involves the coordinated control of ankle and hip joints, and the association of a Virtual Inverted Pendulum to the double pendulum. The virtual inverted pendulum is an inverted pendulum that doesn't exist physically but can be thought as an ideal connection between the ankle joint and the center of mass of the body, also enabling the stabilization of the system with mechanisms similar to those studied for the single inverted pendulum [18].

B. PARAMETERIZATION METHODS

A commonly accepted categorization of parameterization methods classify them into *global* and *structural* posturographic parameters. The former class belongs to methods whose aim is to estimate the overall size of the sway patterns, while the latter are based on the decomposition of sway trajectories into sub-units that can potentially be related by their role w.r.t. the underlying motor control processes. The most widely used type of structural parameters are the so called *sway density plots* essentially obtained by counting the number of consecutive trajectory samples that fall within a circle of a given radius.

In order to provide a thorough validation of our proposed approach we opted for selecting a non-redundant, yet possibly significant, set of features, namely:

- 1) *Sway-Path (SP)*: the length of the trajectory of the COG divided by the measurement time. It provides an indication of the size of the statokinesigram. Measurement unit: $[mm/s]$.
- 2) *FB-AP, FB-ML*: the frequency bands that contain a fraction (equal to 0.8) of the area of the amplitude spectrum of the posturograms, in the *AP* or *ML* direc-

tion. It represents a synthetic index that summarizes the spectrum of the posturography-related activity, sensitive to its transients. Measurement unit: $[Hz]$.

- 3) *Mean Distance*: the mean distance from center of COG trajectory. Measurement unit: $[mm]$
- 4) *Displacement STD*: the standard deviation of COG total displacement. Measurement unit: $[mm]$.
- 5) *Range*: the range of COG displacement (difference between max and min values of the COP displacement). Measurement unit: $[mm]$.

It is worth noticing that, among the above listed parameters, *SP* and *FB* are two of the four parameters that were selected (out of an initial set of 39 quantities) by Baratto and co-authors according to their reliability and discriminative capability of distinguishing between pathological conditions, within a framework of biomechanical modeling of postural stabilization system [14]. Indeed, the mean distance, standard deviation and the range of the displacement are other parameters that have been frequently adopted for analyzing posturographic data, in particular for what regards the analysis of acceleration data [19]. All chosen measures belong to the class of global parameters, a choice dictated by our approach based on comparing $COGs$ rather than $COPs$ for which, the adoption of structural quantities doesn't represent a suitable option. For each of the selected parameters, lower values indicate a better standing balance. In fact, intuitively, *Sway-Path*, *Mean Distance*, *Displacement STD* and *Range* increase with lower capabilities of keeping the inverted pendulum stable. Regarding the frequency domain, greater values correspond to higher postural variability which can be related to increased difficulty in posture control.

Overall, the selected parameters provide a well-grounded set of features adopted and validated in a wide range of research and clinical applications which can be used for assessing novel methodologies and systems.

IV. METHODS AND EXPERIMENTS

In this section we report the proposed method used to validate a smartphone as a stabilometric analysis tool. In particular, during a classical stabilometric test, the signals collected by the triaxial accelerometer of a smartphone, approximately placed at the height of the whole body center of mass of a subject, are compared with the signals collected simultaneously by a force platform.

The embedded triaxial accelerometer of the smartphone is used to measure the displacement of the COG_v . In fact, if a smartphone, is rigidly anchored at the level of the center of mass of the subject, the accelerometer is capable to record its accelerations along the three axes x , y , and z . During the experiment, the measured acceleration along each axis is the sum of an inertial acceleration component, due to an active movement, and of the gravitational acceleration component due to terrestrial gravity field. Dedicated biaxial and triaxial accelerometers have been widely used to investigate the human balance control during quiet standing. The main studied approach isolates the inertial acceleration by

removing the gravitational component from recorded signals and then applies a double integration to calculate COG_v displacement [19]–[22].

The goal of this study is to calculate the COG_v by sampling over the time the direction of the gravitational force, in the body center of mass, instead of using horizontal acceleration. Figures 2 (a) and (b) show two kinematics diagrams of a subject, described with the inverted pendulum model, during quiet standing. Figure 2.(a) represents a generic moment during the maintenance of the erect balance position in which the COG is not in axis with the COP . The evolution in the position of the COG over the time describe the projection of the COG (COG_v) on the floor. The COG_v can be divided into two orthogonal components along the antero-posterior and medio-lateral orientations which are respectively COG_{vAP} and COG_{vML} . In a hypothetical static condition, without any horizontal accelerations, a triaxial accelerometer like that of current smartphones, positioned in the COG , would measure the g_x , g_y , and g_z components of the gravitation according to the x, y, z reference systems plotted in green. Notice that assuming the smartphone vertically aligned with the vertical axis of the body and positioned with the screen facing forward, the z axis of the accelerometer corresponds to the AP direction while the x axis correspond to the ML direction. The line labeled with d represent the distance between the COG and the floor and it does not change during a quiet standing experiment. Starting from g_x , g_y , and g_z , measured by the accelerometer, calculating the AP and ML components of the COG_v is a simple trigonometric problem. Figure 2.(b) shows a simplified kinematic diagram reporting only a displacement of the COG along the AP axis. In this condition the gravitational acceleration (g) is made only by two not-null components which are g_z and g_y . These two components describe two right triangles, namely A and B , which can be shown to contain the same angles so that we can write:

$$\theta_1 = \theta_2 = \theta \quad (3)$$

For the right triangles theorem we have:

$$\sin \theta = \frac{g_z}{g} \quad (4)$$

and:

$$COG_{vAP} = \sin \theta \cdot d \quad (5)$$

From Equations 4 and 5 we obtain:

$$COG_{vAP} = \frac{g_z}{g} \cdot d \quad (6)$$

Following the same approach we can derive the Equation 7 for the ML component of the COG_v :

$$COG_{vML} = \frac{g_x}{g} \cdot d \quad (7)$$

Obviously, in presence of horizontal accelerations the measured g_z and g_y also contain acceleration components not related to the gravitational force which can impair the COG_v calculation. The most widespread approach, when an accelerometer is used as an inclinometer, is to remove the horizontal accelerations from the signal by means of low-pass filtering [23], [24]. Several authors validate this solution under the assumption that the horizontal acceleration is sufficiently small in comparison to the gravity [25], [26]. In fact, in a quiet standing experiments, such as in those for human balance evaluation, the horizontal acceleration is always lower than the gravitational acceleration. To confirm this assumption we elaborated some COG_v traces and we quantified the horizontal acceleration during quiet standing. Our results show that the horizontal acceleration is two orders of magnitude lower in respect to the gravitational acceleration so that it can be safely ignored.

To the best of our knowledge, only Mayagoitia et al. in 2002 proposed a preliminary study which made use of the gravitational acceleration extracted from a dedicated triaxial accelerometer to evaluate standing balance [13]. Despite the authors adopt an approach similar to that proposed in this work, they do not consider the influence of the horizontal accelerations and they do not carry out a punctual and systematic comparison with the traces extracted from the force platform. In fact, Mayagoitia et al. try to compare the projection of the COG , calculated from the accelerometer, with the COP extracted from a force platform. As already explained in Section III-A, it has been shown that the position of the COP does not coincide with the projection of the COG on the floor.

The method we proposed in the present study tries to overcome these limitations by comparing the COG_v , estimated from the smartphone accelerometer, with the COG_v obtained by applying the algorithm proposed by Duarte et al. on the COP sampled by a force platform [15]. In particular, this algorithm, based on the inverted pendulum model, contains a low-pass filter built around the moment of inertia of the human body which defines the natural frequency of the pendulum. For instance, a person with 70 kg of mass and 1.70 m of height exhibits a natural frequency of about $3rad/s$, and a filter with this parameter is similar to a low-pass filter with a cutoff frequency in the range of 0.4–0.5 Hz [15]. Once the two signals representing both the trajectory of the COG_v are obtained (one from the smartphone and one from the force platform), it is possible to define several similarity metrics to implement a direct comparison of the dynamic of the COG collected by the two different devices. Furthermore, it is still possible to extract from the two signals the global metrics, in the time and frequency domain, which are traditionally used in literature to make an indirect comparison.

A. DATA PROCESSING

Data preparation and analysis were performed using Matlab®. Figures 3 (a) and (b) show, respectively, the flowcharts of the data processing applied to smartphone data and to

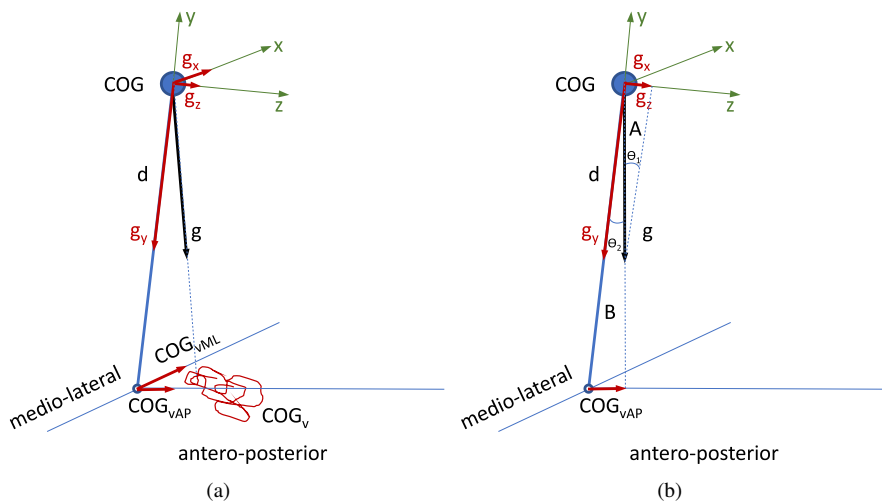


FIGURE 2: Kinematics diagrams of the human balance during quiet standing according to the inverted pendulum model. (a) represents a generic moment in which the COG is not in axis with the COP while (b) shows a simplified version to highlight the relation between gravitational components and COG_v

force platform data to obtain comparable signals. Both for smartphone and force platform data, two seconds in the beginning of the record are subtracted as a pre-settling time. Then smartphone data are filtered with a 4th order Butterworth low-pass filter with a cutoff frequency of 1.0 Hz to isolate gravitational acceleration as proposed by Van Hess et al. [24]. After that a tilt axis correction to the gravitational components is applied by rotating the accelerometer reference axes of the smartphone until the average value of each gravitational component, namely g_x , g_y , and g_z , matches the perfect vertical positioning (see Figure 2.(a)). In other words, a rotation in respect to the origin of the reference axes is applied to maximize the average value of the gravitational components along the vertical axis, namely y . The tilt axes correction is needed to cope with a possible wrong positioning of the smartphone with respect to the body axes.

This correction is necessary, because of the use to which this application could be dedicated. In fact, in self-diagnosis applications, the user may not have the skills necessary to correctly orientate the smartphone, possibly compromising the result of the analysis.

The next processing step entails the downsampling to 50 Hz of the recorded data in order to match the typical working conditions of a stabilometric analysis. At this time the smartphone collected data are ready to be processed by applying Equations 6 and 7 to calculate COG_{vAP} and COG_{vML} . The last steps remove any possible base line drifts by subtracting the average values from the AP and ML components and then calculate the time and frequency domain features as described in literature [14], [19]

Data recorded by the force platform are processed as described by the flowchart shown in Figure 3.(b). Notice that a force platform directly records the COP components along

the AP and ML axes. After removing the pre-settling time (2 seconds) these two components are filtered with a 2th order Butterworth low-pass filter with a cutoff frequency of 12.0 Hz and downsampled at a frequency of 50 Hz. Then the inverted pendulum model is applied to the COP in order to estimate the COG_v trajectory. Also in this case, any possible base line drifts are removed by subtracting the average values and then the time and frequency domain features are calculated.

B. DIRECT COMPARISON OF THE COG_v

In order to validate the use of a smartphone in the standing balance assessment, the trajectory of the COG_v collected by means of the smartphone, during each experiment, has been directly compared with that collected by means of the force platform. To carry out a direct comparison, a procedure for calculating the similarity between the trajectories has been defined. In particular, three similarity metrics have been investigated based on the following measures: i) Euclidean distance; ii) Dynamic Time Warping (DTW) distance; iii) Cross-correlation. The Euclidean distance between two trajectories has been calculated by summing the the distance between each corresponding points of the two trajectories while, the Dynamic Time Warping distance and the Cross-correlation have been separately calculated on the AP and ML components and then averaged. All three metrics have been obtained by taking the best value between the smartphone COG_v and a shifted copy of the force platform COG_v as a function of a shift parameter, to remove any desynchronization problem between the two sampling devices. Notice that the maximum value of the applicable shift, expressed in time, has been fixed to 1 second. Moreover, while directly compare two COG_v trajectories any misalignment between the AP and ML axes of the sampling devices could impair the similarity calculation.

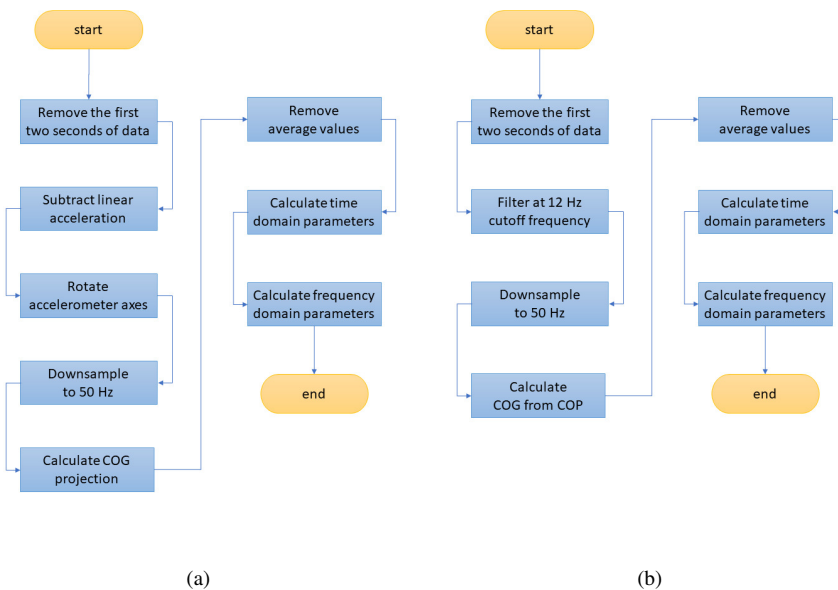


FIGURE 3: Flowcharts of the data processing applied to smartphone data (a) and to force platform data (b) to obtain comparable signals.

To avoid this problem, the procedure to calculate the similarity describe above has been iterated by rotating counter-clockwise one COG_v , with respect to the other, by one degree at a time to take the best value. The maximum rotation range applicable has been fixed to 90 degrees which correspond to the switch between the AP and ML axes.¹

Notice that, before to calculate the Euclidean and DTW distances the COG_v have been normalized by means of a classical min-max normalization, for Euclidean distance, and by means of a Z-score normalization in the DTW case.

C. EXPERIMENTAL PROTOCOL

The experimental protocol conceived to effectively compare the data collected by a force platform with those obtained by a smartphone is based on a set of experiments widely used to validate posturographic force platforms [27]. In particular, posturographic data were collected from two healthy persons (the age was 34 and 35 years) according to four configurations: i) standing on two legs with open eyes (*TLOE*), ii) standing on two legs with closed eyes (*TLCE*), iii) standing on one leg with open eyes (*OLOE*), and iv) standing on one leg with closed eyes (*OLCE*).

Each configuration has been tested 20 times for each subject, who was asked to remain still standing without shoes on a force platform, for 30 seconds in the *TLOE* and *TLCE* configurations (i.e., standing on two legs) and for 10 seconds in the *OLOE* and *OLCE* configurations (i.e.,

¹The average value of the shift resulting during the comparison experiments was about 0.24 seconds while the average value of the rotation angle was about 5.48 degrees.

standing on one leg). The subjects were instructed to stand in a comfortable position and to keep looking straight ahead at a fixed point (except in configurations that required the subjects to close their eyes). The subjects kept their arms comfortably at their sides while standing on two legs or stretched them out to the side in order to maintain their balance while standing on one leg.

D. DATA COLLECTION

Each subject was wearing an elastic belt with a smartphone attached to it following the orientation of Figure 2 and placed approximately at the height of the whole center of mass. The smartphone used was a Motorola Moto G4 running Android 6.0 ‘Marshmallow’ with an embedded triaxial accelerometer capable to collect up to 100 samples per second. An Android application has been developed ad-hoc to sample the accelerometer and to save data to the SD card. The application announces the start of the recording by means of a countdown marked by a sound then it starts to sample data. In order to avoid any file-system related delay, each sample is stored in an array pre-allocated in RAM and, only at the end of the test, the whole array is written back to the SD card.

The smartphone was calibrated once at the start of the study by placing it on a stable surface and the accelerometer measurements were recorded for 30 seconds. The purpose of the calibration was to remove any static bias of the accelerometer during data post processing.

A Nintendo Wii balance board has been used as force platform to collect *COP* trajectories. This inexpensive and portable device has been recently compared against standard

Task	Euclidean	DTW	Correlation
<i>TLOE</i>	0.64 ± 0.11	0.85 ± 0.08	0.86 ± 0.16
<i>TLCE</i>	0.60 ± 0.13	0.80 ± 0.06	0.81 ± 0.12
<i>OLOE</i>	0.63 ± 0.10	0.78 ± 0.12	0.82 ± 0.11
<i>OLCE</i>	0.63 ± 0.08	0.73 ± 0.19	0.81 ± 0.12

TABLE 1: Comparison between COG_v trajectories using different similarity metrics.

force platforms and it has been found to be a reliable assessment device [27], [28]. The balance board has been connected to a laptop equipped with Bluetooth running a software developed ad-hoc starting from the WiimoteLib library developed by Brian Peek. WiimoteLib is a .NET library for interfacing Nintendo Wii Remotes such as Wiimote and balance board. Data was exchanged between the balance board and the laptop using the built-in Bluetooth interface at a sample frequency of about 100 Hz.

V. RESULTS AND DISCUSSIONS

In this section we report the results of the posturometric experiments and we discuss the validity of the proposed approach. For a better comprehension, the results of the direct and of the indirect comparison are treated separately.

A. DIRECT COMPARISON

Direct comparison has been carried out as described in Subsection IV-B. In particular, each of the 160 trajectories obtained via smartphone has been compared with the corresponding one obtained using the force platform. Figure 4 graphically reports one of these comparison in which the two COG_v have been aligned with the correlation metrics. Figure 4.(a) shows the two trajectories of the COG_v on the plane where the dotted line represents the signal sampled by the smartphone while the solid line is the signal sampled by the force platform. Figure 4.(b) and Figure 4.(c) plots respectively the anteroposterior and the mediolateral components. The comparison between the trajectories, but above all the comparison between the *AP* and *ML* components, show a strong similarity between the two signals, both in the temporal dynamics and in the quantitative spatial extension. Notice that, the results reported in this figure are related to a *TLOE* test conducted by one of the subjects, which, as expected is a strongly stable test that does not involve large COG displacements.

Table 1 reports for each task the average values, together with its standard deviations, of the similarities between the COG_v calculated using the three metrics described in section IV-B. For each task, the reported value is obtained by averaging 40 different experiments conducted by the two subjects. The metric based on the Euclidean distance shows lower results, in terms of similarity, even if it always remains above 60%. It is interesting to note that the value does not change appreciably in the different tasks. The DTW and the Correlation metrics, on the contrary, both produce greater similarity values in the comparison of tasks conducted standing on two legs (*TLOE* and *TLCE*) with respect to

these where the subjects were standing on one legs (*OLOE* and *OLCE*). Moreover, the similarity values are greater in the task where the eyes were kept open (*TLOE* and *OLOE*) with respect to the same task but with the eyes kept closed (*TLCE* and *OLCE*). This indicates that in tests where body balance is more stable (i.e. the dynamics are slower and movements are less marked), the signals sampled by the smartphone and those sampled by the force platform are more similar than in more unstable experiments. Probably this is due to the fact that the smartphone (because of its high position with respect to the floor and/or for a greater sensitivity) tends to amplify the movements of the COG with respect to those obtained starting from the COP sampled by the force platform. To confirm this, we calculated the average speed of the displacements of the COG_v and we found values appreciably higher when it has been sampled with the smartphone compared to the one sampled with the force platform during tasks characterized by a more unstable equilibrium. In fact, the average values calculated when the subject was standing on two legs with open eyes (*TLOE*) were 2.67 mm/s and 3.37 mm/s respectively for the force platform and for the smartphone while, when the subject was standing with one leg with closed eyes (*OLCE*), they were respectively 22.15 mm/s and 25.49 mm/s. Despite this tendency to amplify, found in the smartphone, a correlation always greater than 80% and a similarity between 73% and 85% obtained with the DTW metric allow us to assert that the smartphone succeeds in faithfully sampling the movements of the COG_v during a normal postural balance test.

B. FEATURES COMPARISON

The indirect comparison has been carried out by extracting the parameters introduced in Section III-B both from the smartphone and from the balance board COG_v .

Figure 5 shows the histograms obtained by plotting the value of the features calculated for the tasks of the experimental protocol (namely *TLOE*, *TLCE*, *OLOE*, and *OLCE*). For the time domain features (i.e., *Sway-Path* (a), *Mean Distance* (b), *Displacement STD* (c) and *Range* (d)) the more unstable the task, the higher the measured value. Indeed, the minimum value of all features was recorded in the more stable task, that is while the subject was standing on two legs with open eyes (*TLOE*). On the contrary, the configuration with one leg with closed eyes, which is the most unstable, shows the highest recorded values. Subject stability also affects the repeatability of the experiment, as demonstrated by the higher error bars obtained in *OLOE* and *OLCE* configurations. Also in this case, as already discussed in Section V-A, the smartphone tends to amplify the displacement of the COG with the result of providing appreciably higher values of the features in situations where the balance is more unstable.

In the frequency domain, the *FB_80* features, reported in Figures 5.e and 5.f, both on the *AP* and *ML* axes, show significantly higher values in experiments conducted with only one leg compared to those on two legs. It should be recalled that *FB_80* is defined as the frequency interval that includes

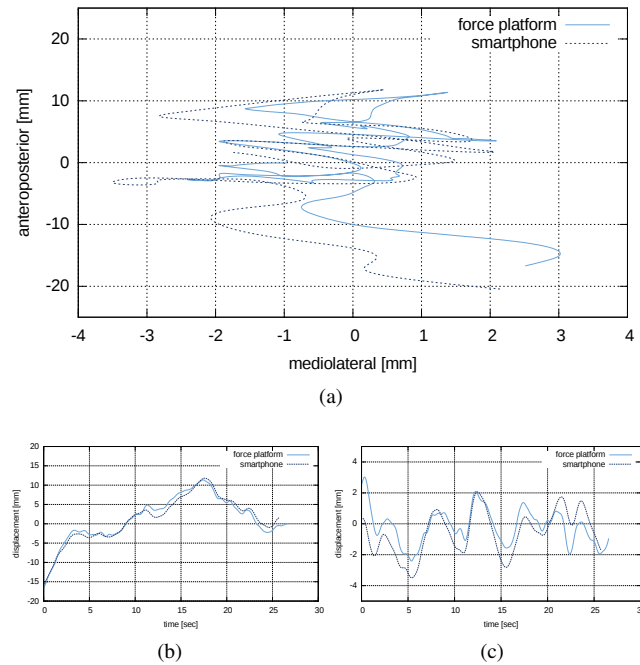


FIGURE 4: Comparison between the COG_v recorded using the Wii balance board (solid line) and using a smartphone (dotted line) during a *TLOE* test conducted by the subject 1. (a) shows the COG_v trajectory while (b) and (c) are, respectively, the anteroposterior and the mediolateral components.

the 80% of the area under the amplitude spectrum: a higher value entails higher frequencies of the COG movements, which are a characteristic of unstable postures [14]. On the other hand, openness of eyes does not seem to appreciably influence the value of this feature.

The agreement between the value obtained with the smartphone and those recorded with the force platform always remains high, in each type of experiment and for each feature. Obtained results confirm the effectiveness of the proposed system in terms of its capability of registering posturographic signals.

VI. CONCLUSIONS

Mobility and balance problems represent a significant issue in the elderly population. Posturographic analysis is commonly performed at a clinical level for obtaining diagnostic markers of possible diseases and estimating the risk of falls. However, current standing balance assessment methods often rely on expensive instruments—for instance force plates—hampering a wide-scale diffusion of standardized monitoring protocols and motivating, on the other hand, the search for inexpensive, automatic, and easy-to-use systems. The availability of low-cost sensing capabilities (e.g., accelerometers, gyroscopes, etc.) on board of typical smartphones, associated with their increasing diffusion, makes this technology particularly interesting for designing novel mobile health applications.

In this article we pursued this line of research by investigating the use of smartphone embedded accelerometers for the assessment of standing balance. In order to accomplish this

goal, several scientific challenges have to be faced, ranging from the design of novel algorithmic solutions to the adoption of sound validation protocols. To this aim, we presented a set of signal processing algorithms aimed at distilling meaningful information from the data obtained from the devices used during standing balance evaluations. Moreover, to validate our approach, we also advocated a shift from the commonly assumed paradigm that directly correlates the trajectory of the center of pressure obtained by means of force plates and the trajectory achieved by means of wearable/mobile devices. Indeed, we proposed to compare the trajectory of *COP* detected from a force plate (suitably transformed to obtain an estimate of the sway of the center of mass) with that of the *COG*, as computed from the acceleration data streams.

Experimental results provide evidence of satisfying performance of the proposed system, measured in terms of: *i*) similarity levels (according to different metrics) between the posturographic trajectories achieved by our approach and those obtained from a commercial balance board platform taken as a reference; *ii*) agreement between the features extracted by our processing flow and those from the force platform.

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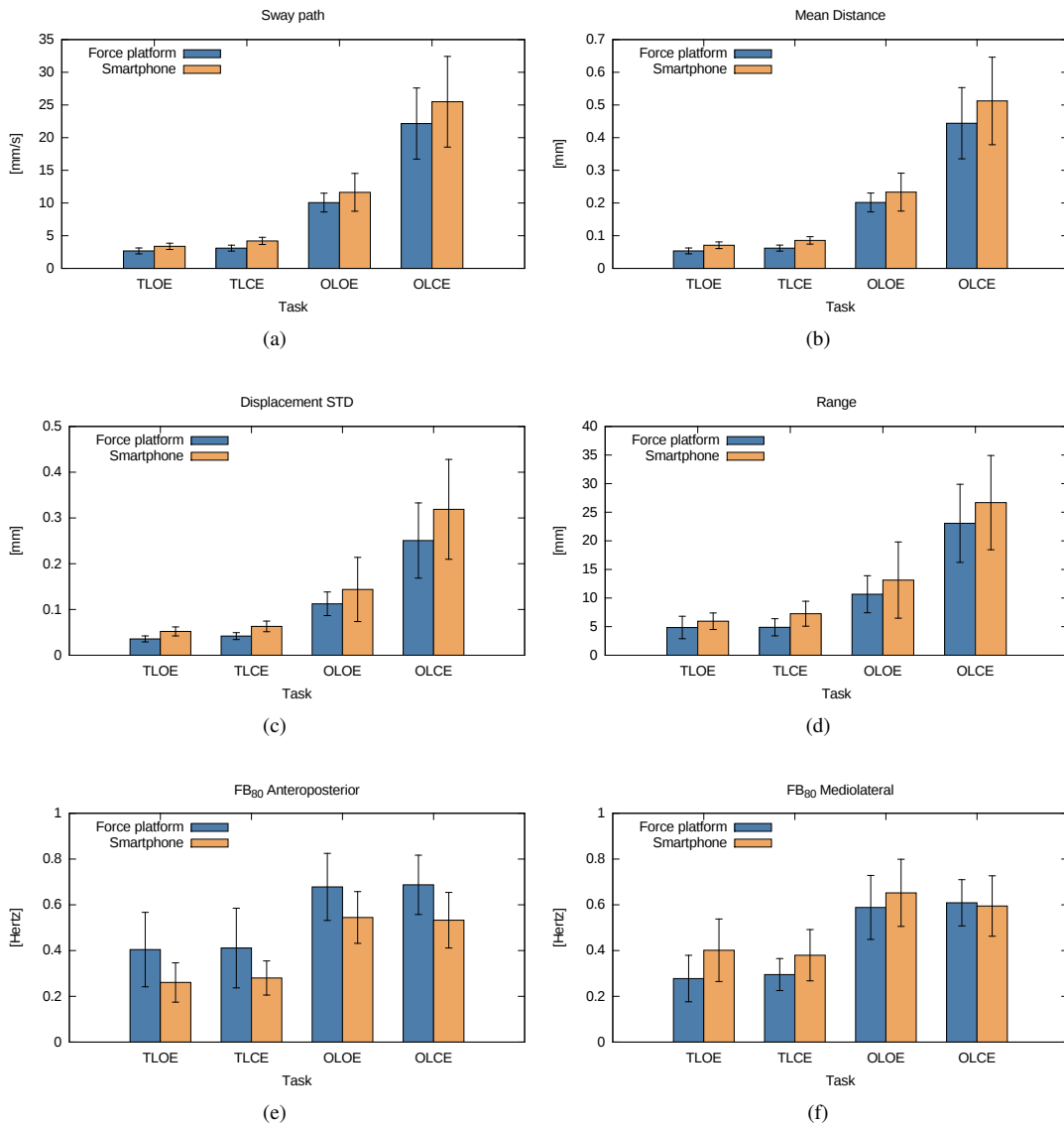


FIGURE 5: Features comparison in time domain (figures from *a* to *d*) and in frequency domain (figures *e* and *f*).

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