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Wireless inertial measurement unit (IMU)-based posturography

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Abstract

Background Classical posturography techniques have been recently enhanced by the use of different motion tracking devices, but for technical reasons they are not used to track directly the body spatial position of a subject.

Objective To describe and clinically evaluate a wireless inertial measurement unit-based mobile system to track body position changes.

Methods The developed system used a calculus transformation method using the acceleration data corrected by Kalman and Butterworth filters to output position data. A prospective non-randomized clinical study involving 15 healthy subjects was performed to evaluate the agreement between the confidence ellipse areas synchronously measured by the new developed system and a classical posturography system while performing a modified clinical test of sensory interaction in balance.

Results The overall intra-class correlation index was 0.93 (CI 0.89, 0.96). Grouped by conditions, under conditions 1–4, Pearson's correlation was 0.604, 0.78, 0.882, and 0.81, respectively.

Conclusion The developed wireless inertial measurement unit-based posturography system was valid for tracking the sway variances in normal subjects under habitual clinical testing conditions. Further studies are needed to validate this system on patients and also under other posture conditions.

Keywords IMU · Posturography · CEA · Accelerometer · Body position tracking

Introduction

Balance has been defined as the ability to maintain the center of gravity of a body on its base of support [1]. To achieve this, a subject must maintain the center of pressure, which is a good indicator of the projection of the center of gravity during slow movements under certain limits of stability [2]. The contributions of vestibular, visual, and somatosensory systems and their integration by the central nervous system are essential for the correct functioning of the above-mentioned process [3, 4]. The set of methods used to evaluate and quantify the balance capability of a subject is known as posturography [5]. In the last decades, an exponential growth in the balance testing methodology has contributed to complement and expand [4] the first models of computerized posturography developed during the twentieth century [6]. Computer posturography methods can be classified into two main types: static and dynamic posturography. The principle of static computerized posturography is the detection of the center of pressure in an upright stance on a force platform [5, 7]. In contrast, in dynamic computerized posturography, the platform and visual surrounding are repositioned by the computer during the test, usually in reference to a sway. Thus, it allows the detection of stances and dynamic movement along with the ability to estimate the information inputs and their central integration [8]. However, force platforms are relatively expensive and time consuming in terms of the performance of the tests and careful installation

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of the related software [9]. Therefore, the development of a tool that is both user-friendly and inexpensive is an objective of increasing interest to researchers as it is needed for facilitating efficient balance assessment in clinical settings [3].

Technological advances have made it possible to develop new measurement techniques that have improved and expanded the evaluation and diagnosis of patients with balance disorders. One of the most relevant and innovative advances in this field is the use of body-mounted motion sensors, such as gyroscopes and accelerometers. A demonstrated prototype example of this emerging technology is the Sway Star system (Balance International Innovations GMBH, Switzerland) developed by Allum [10]. This system is based on the direct measurement of the angular deviations of a trunk near the center of mass (having previously firmly attached a device composed of two sensors near the back of a subject at L3–L5 levels). In comparison to force platforms, which indirectly estimate sway angles using complex mathematical methods, the above sensor technology has led to the direct estimation of sway parameters [11]. It also allows the analysis of the balance control in two directions: in the pitch (anterior to posterior) and roll (side to side) planes [12]. However, these motion sensor devices are not sufficiently accurate to determine real body displacements and typically reference the dynamic changes in the acceleration, velocity, and orientation angles. We hypothesized that inertial measurement unit (IMU) devices, having been commercially developed and used to track real positions of many electronic devices when compass-based or satellite positioning systems are not adequate or possible, could be effective technologies for balance quantification. This could be achieved by directing the mobility advantages of the classical motion sensors toward the ability of computer posturography to quantify real spatial displacements.

The objective of the present study was to present in detail the development process and validate the measurements of a wireless IMU device system to objectively quantify the sway area of healthy subjects, directly calculated using real displacement (position) data.

Materials and methods

IMU-based posturography system design

While acceleration is the main measurement output of digital accelerometers, in the neurotology field, most clinical devices for studying posture are based on the body position data. To overcome this measurement mismatch between the acceleration and position data from a theoretical perspective, the position data can be obtained from the acceleration data by the double integration of the latter [13]. However, when we apply this calculus-based method to real acceleration data, we must use a mathematical approach to calculate the double integral data. The most common mathematical approach to integrate the acceleration is the cumulative trapezoidal graphical integration method [14]. The above mathematical approach requires that the data obtained from each interval must be cumulatively added to the data of the previous intervals. This implies that for each interval, we also add the error measurement inherent in the accelerometer device to the "true" position data. In most common accelerometer devices, there are two main measurement errors. The first is the variability in the measurement of the device, as determined by the hardware, and the second is the gravity acceleration, which is typically present in the environment of the earth and also measured by accelerometers. These two errors are introduced in each measurement made by an accelerometer; however, only for one acceleration measurement, the error is easy to correct and the accuracy of the accelerometer is not significantly affected. When we add these errors to the cumulative trapezoidal sum, the result is a velocity- and position-infinite tendency deviation (Fig. 1). This "integration drift" is a well-known artifact, which affects the position calculation using accelerometers [15].

To avoid this integration drift, two solutions are usually considered. The first is minimization of the integration drift using only the angular orientation or velocity data as indirect estimators of the spatial position. The above method ensures a good approximation for tracking the posture [16], but is limited because the position data are unknown. The second method is to use corrective algorithms in the accelerometer measurement to minimize the integration drift problem. In fact, the best results are obtained with techniques that use two sources for the acceleration data (accelerometer and gyroscope or accelerometer and magnetometer). In most cases, the accelerometer data are corrected using a gyroscope/magnetometer system and (Bayesian) Kalman filter [15, 17]. An example of the effect of this method can be observed in Fig. 1. The digital devices that use the abovementioned correction method are known as IMUs.

We considered that only the second method, i.e., the method based on the accelerometer measurement correction, was sufficiently unique and adequate for building a posturography system based on the position data obtained from the acceleration data.

For this research, we used a Meta Motion C (MBIENTLAB INC, San Francisco, CA, USA) device, a wireless IMU device using a low-energy Bluetooth connection with a nominal sampling frequency of 100 Hz, when the accelerometer and gyroscope fusion measuring method was used.

The IMU device was connected to a mobile phone device. Consecutively, an application was developed using the XCode 10.0 (Apple INC, Cupertino, CA, USA) development environment and Swift 4.0 (http://www.swift.org) as the default computer development language. To

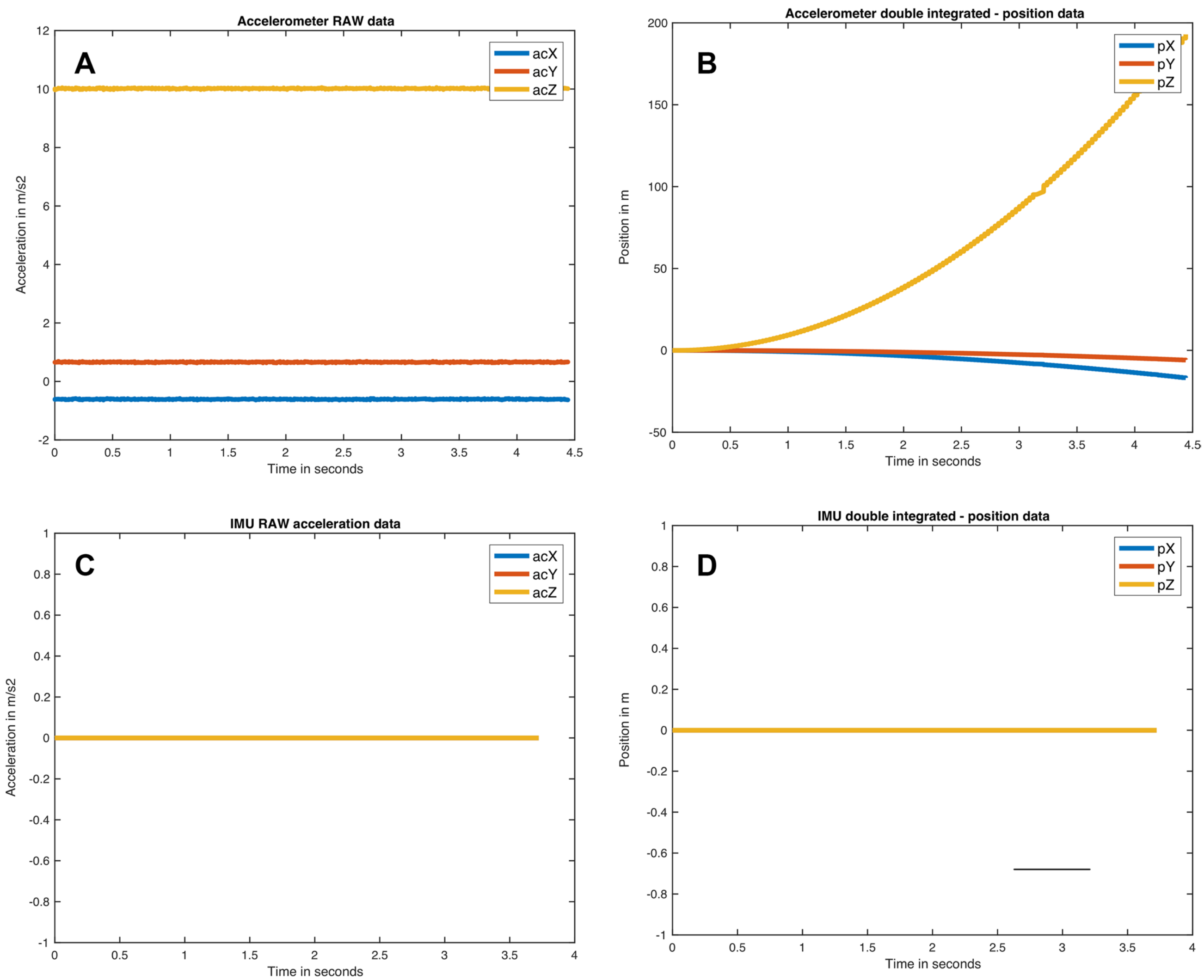

Fig. 1 Integration drift. In **a**, the raw acceleration data obtained from the accelerometer in static position (recorded at 100 Hz) are plotted. Because of the spatial orientation of the accelerometer that determines the gravity field effect on the measurement unit, the *x* and *y* axes (blue and red lines) are slightly shifted from the 0 m/s^2 line, and the *z* axis (yellow line) is significantly shifted from the 0 m/s^2 line; this enhanced shift is due to the fact that the accelerometer *z* axis is almost parallel and under the (acceleration) effect of the earth gravity field. In **b**, the effect on the position of the static accelerometer due to the cumulative acceleration shift addition mathematical procedure is displayed. The position plot tends to exhibit an exponential position deviation higher on the *z* axis. In **c**, results are shown for the same accelerometer set as IMU with a Kalman filter, using the gyroscope data as the correction reference (recorded at 100 Hz). The shifts observed in **a** are now corrected and, consequently, **d** A static plot calculated by the double integration method. In **c**, **d** because of the IMU correction, *X* and *Y* lines are plotted (as can be observed on the plot's legends) but they are hidden because now they are aligned with the *Z* position and acceleration lines. Plots are obtained using the IMU device of this research; these measurements were obtained from a dummy body on fixed position

manage the IMU connection, IMU fabricant development libraries for XCode were used. The IMU device was configured using live Bluetooth low-energy data streaming at a sampling rate of 100 Hz in the integrated accelerometer and gyroscope operation mode. The data were stored in real time and plotted on a mobile phone application to be further exported.

Despite the good results obtained in the static measurements (Fig. 1), some drift is still observed when the IMU device is applied to real body position data. Thus, the IMU-recorded data are post-processed using MATLAB 2016b (64-bit version, by The MathWorks Inc., Natick, MA, USA).

The recorded data are filtered using two second-order Butterworth filters for the acceleration data (Fig. 2a):

A single high-pass filter is configured for a sampling rate of 100 Hz and normalized cutoff frequency of 0.0095 Hz.
A single low-pass filter is configured for a sampling rate of 100 Hz and normalized cutoff frequency of 0.02 Hz.

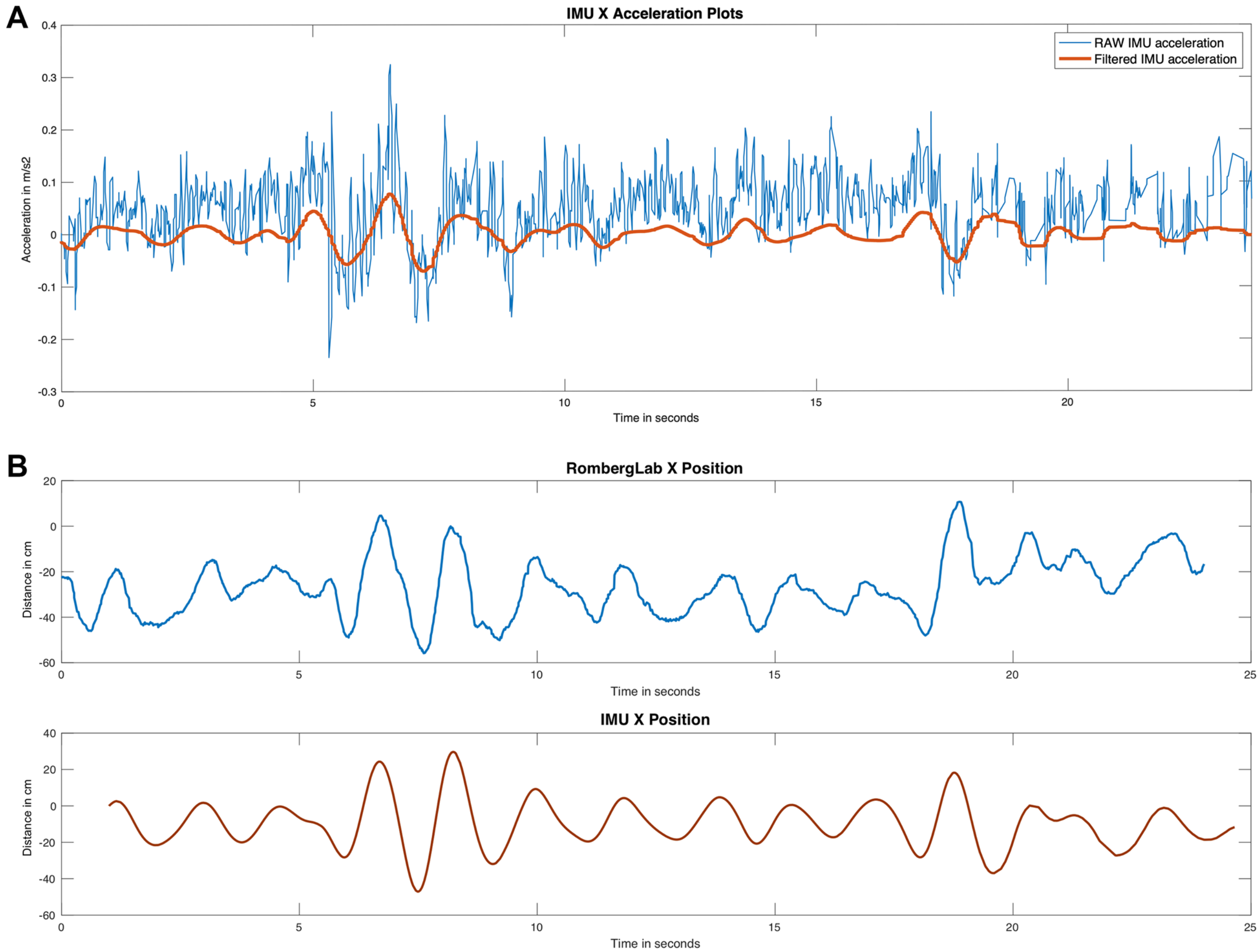

Fig. 2 Filtering and scaling. In **a**, the acceleration plots obtained with the IMU device (blue line) when significant noise and deviation are observed are plotted; the red line plots the post-processed signal. The acceleration data are processed with a single high-pass second-order Butterworth filter (normalized cutoff frequency: 0.0095 Hz) and a second low-pass second-order Butterworth filter (normalized cutoff frequency: 0.02 Hz). In **b**, the synchronously real recorded data obtained from a sample subject using the static posturography system (RombergLab) are displayed in the upper plot (blue position line) and post-processed wireless IMU data are displayed in the bottom plot (red line). Both measurements are recorded at a 100 Hz sampling frequency. Note that on **b**, despite oscillation movements are well detected by the IMU, there is a little difference in reference to the "real" *X* position plot obtained with RombergLab. As can be observed, this initial position is about 0 cm in the IMU plot while in the RombergLab plot it is around − 20 cm. This difference in initial position is because at 0 time it is not possible to know the original position using an IMU-based method, because pre-recording acceleration values that determine the initial position are unknown. For the posturography method, the initial position in relation to the dynamometric platform reference system is always known. **a**, **b** are recordings from (two) different participants

In addition, the velocity data are filtered using a single second-order Butterworth filter, configured for a sampling rate of 100 Hz and normalized cutoff frequency of 0.0075 Hz.

These filter parameters were calibrated by synchronously collecting the IMU acceleration data and posturograph position data from the data of three healthy subjects. These data were evaluated by a MATLAB algorithm that iterated between all the numeric combinations of the following three unknown variables: low-pass acceleration cutoff frequency, high-pass acceleration cutoff frequency, and low-pass velocity cutoff frequency. The Pearson correlation between the target posturographic data and double-integrated acceleration data for each iteration was used by the calibration algorithm. In this regard, 8×10^7 iterations were evaluated by this algorithm.

Three acceleration and velocity filters and the cumulative trapezoidal algorithms were exported to XCode as C language files to be implemented in the IMU control application to develop an "all-in-one" measurement software.

As a main posturographic parameter, we used the 95% confidence ellipse area (CEA) algorithm developed by Rey-Martinez and Perez [4], which was implemented in both the XCode (https://github.com/bendermh/RombergLab) and MATLAB environments.

Owing to the smoothing produced by the three filters, the data were scaled by a factor of 2431.5.

An example of the results of this signal post-processing using a real data process can be seen in Fig. 2b.

Clinical validation study

A prospective non-randomized clinical study was conducted to evaluate the statistical agreement between the IMU sway area measurement and static computerized posturography.

Subjects Fifteen healthy individuals were selected in the age range from 20 to 65 years between September 2018 and November 2018. The inclusion criteria were as follows: absence of known pathology affecting the balance, absence of clinical signs of vestibular pathology or neurological disorders, no use of medication affecting the central nervous system or coordination and balance, and absence of psychological disorders. It was also mandatory to have normal vision (or vision corrected with glasses) and understand and agree with the clinical study procedures. Written informed consent was obtained from all the participants. Clinical and demographic data and a physical examination, measuring the height and weight, were also collected for every patient.

Clinical protocol Each participant was tested by performing a modified clinical test of sensory interaction in balance (mCTSIB) [18]. This test consisted of four conditions for evaluating the static postural stability: eyes open on a firm surface, eyes closed on a firm surface, eyes open on a foam surface, and eyes closed on a foam surface. For the foam conditions, we used a 50 × 40 × 14 cm (width × length × thickness) foam with 40 kg/m^3 density, particularly manufactured by a specialized company (https://www.espumaamedida.com—Terrassa, Spain). This test was simultaneously recorded for each patient by a posturography platform and with the IMU device firmly attached to the back of the participants at L3–L5 levels. The mCTSIB test was performed after ensuring that the IMU device was set at its correct position and online on a mobile phone device. Subsequently, each patient was requested to remain on the posturography platform and follow the instructions that had been previously explained by the instructor. The four mCTSIB conditions were achieved by the subjects for 20s. Consequently, the patients stood on the platform in the Romberg position, with footwear and with their feet slightly apart (no more than the breadth of the shoulders). To synchronously record the static posturography data, we used the RombergLab system, an experimental-purpose open-source posturography method designed to be used with low-cost dynamometric platforms. The RombergLab system is validated and normalized as a static posturography mCTSIB testing method [4, 19] and was used according to the instructions published by its developers.

This study was designed and performed in accordance with the ethical guidelines of the 1975 Declaration of Helsinki.

Because non-medical, non-invasive CE-marked measurement devices were used on humans for this study, a local government ethics committee (CEIC-Donostia) was required and formed for this study.

Statistical analysis

The study used the R 3.5.2 statistical computation language (R Core Team (2018). R: A language and environment for statistical computing, R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/) with standard comprehensive R archive network libraries for the statistical assessments.

A Kolmogorov–Smirnov with Lilliefors correction test was used to explore the normality of the quantitative variables. Because the Romberg Lab area units were not in cm^2, to evaluate the correlation between the IMU and Posturograph data, Pearson's correlation and linear regression were used. The clinical agreements between the IMU and posturograph measurements were evaluated by an intra-class correlation coefficient (ICC) with two-way random effects, absolute agreement, and multiple raters method (ICC 2, k) based on the Shorout and Fleiss 1979 convention [20, 21]. According to Koo and Li, an ICC value of > 0.90, between 0.75 and 0.9, between 0.5 and 0.75, and < 0.5 implies excellent concordance, good concordance, moderate concordance, and poor concordance, respectively [21]. For this study, the ICC parameter was established as the main parameter to validate the IMU measurements and as an adequate method to analyze the position changes. In addition, the Bland–Altman plot [22] was used as a graphical concordance assessment method. For these concordance tests, the RombergLab area measurements were converted to m^2 using a statistical correction factor described by the RombergLab developers [4].

The statistical significance level was set as 0.05.

Results

Fifteen subjects were included in the validation study. Nine were female and six were male. The mean age was 30.06 years with a standard deviation (SD) of 13.53 years; the minimum age was 23 years and the maximum age was 62 years. The mean height was 167.2 cm (SD 9.634 cm), minimum height was 150 cm, and maximum height was 182. The mean weight was 67.53 kg (SD 19.93 kg), minimum weight was 45 kg, and maximum weight was 130 kg.

All the patients performed the posturography test, measuring the position changes with the posturography and IMU devices simultaneously without any reported damage or injury. No errors or difficulties were found using the IMU device or in the connection, storage, and exportation processes using the specifically developed mobile phone application.

No significant differences were found for any of the quantitative variables obtained by the Kolmogorov–Smirnov normality test. The main CEA measurements obtained for each participant are presented in Table 1.

Pearson's correlation for the unconverted posturography data and IMU position data was 0.875 in the 95% confidence interval (CI) between 0.798 and 0.923 with a $p < 0.0001$. Grouping by conditions, condition 1 correlation was 0.604 (CI 0.134, 0.852) $p = 0.01$, condition 2 correlation was 0.787 (CI 0.461, 0.926) $p = 0.004$, condition 3 correlation was 0.882 (CI 0.674, 0.96) $p < 0.0001$, and condition 4 correlation was 0.81 (CI 0.525, 0.937) $p = 0.0001$. Linear regression lines by condition are plotted in Fig. 3.

The intra-class correlation coefficient (ICC 2, *k*) was 0.93 (CI 0.89, 0.96), $p < 0.0001$ when all the conditions were considered. The Bland and Altman plot can be observed in Fig. 4 and it shows that most of data pairs are inside the ± 2 standard deviation area.

Table 1 Results of the sway area obtained for simultaneously recorded static posturography and IMU-based posturography of each participant and condition

N	Cond.	Area RL	Area RL (m^2)	Area IMU (m^2)	*N*	Cond.	Area RL	Area RL (m^2)	Area IMU (m^2)
1	1	45.76	0.00054	0.00068	8	1	11.48	0.00013	0.00021
1	2	52.21	0.00062	0.00049	8	2	18.06	0.00021	0.00013
1	3	40.66	0.00048	0.00074	8	3	27.35	0.00032	0.00038
1	4	277.43	0.00332	0.00431	8	4	56.34	0.00067	0.00068
2	1	5.81	0.00006	0.00016	9	1	28.27	0.00033	0.00018
2	2	9.24	0.00011	0.00023	9	2	91.11	0.00109	0.00097
2	3	36.49	0.00043	0.00070	9	3	176.71	0.00212	0.00148
2	4	118.94	0.00142	0.00102	9	4	145.21	0.00174	0.00144
3	1	4.39	0.00005	0.00004	10	1	36.55	0.00043	0.00041
3	2	4.48	0.00005	0.00006	10	2	50.93	0.00061	0.00036
3	3	31.3	0.0003	0.00039	10	3	77.93	0.00093	0.00141
3	4	27.03	0.00032	0.00089	10	4	376.47	0.00451	0.00349
4	1	2.48	0.00002	0.00010	11	1	11.13	0.00013	0.00008
4	2	3.31	0.00003	0.00006	11	2	12.38	0.00014	0.00064
4	3	10.34	0.00012	0.00037	11	3	42.9	0.00051	0.00074
4	4	25.97	0.00031	0.00076	11	4	111.21	0.00133	0.00109
5	1	9.23	0.00011	0.00024	12	1	5.7	0.00006	0.00006
5	2	12.62	0.00015	0.00034	12	2	8.93	0.00010	0.00026
5	3	76.38	0.00091	0.00092	12	3	10.46	0.00012	0.00024
5	4	101.73	0.00122	0.00068	12	4	48.62	0.00058	0.00096
6	1	21.64	0.00025	0.00037	13	1	21.77	0.00026	0.00107
6	2	8.19	0.00009	0.00014	13	2	16.27	0.00019	0.00012
6	3	20.76	0.00024	0.00020	13	3	66.07	0.00079	0.00073
6	4	34.53	0.00041	0.00033	13	4	141.98	0.00170	0.00075
7	1	5.25	0.00006	0.00028	14	1	48.2	0.00057	0.00036
7	2	4.54	0.00005	0.00014	14	2	54.2	0.00065	0.00043
7	3	12.27	0.00014	0.00016	14	3	45.36	0.00054	0.00085
7	4	41.32	0.00049	0.00065	14	4	140.39	0.00168	0.00115
					15	1	80.93	0.00097	0.00071
					15	2	21.1	0.00025	0.00044
					15	3	134.87	0.00161	0.00210
					15	4	139.35	0.00167	0.00335

Cond. testing condition of modified CTSIB test, *N* participant reference number, *Area RL* RombergLab (static posturography) sway area in both custom and m^2 area units, *Area IMU* IMU-based posturography sway area

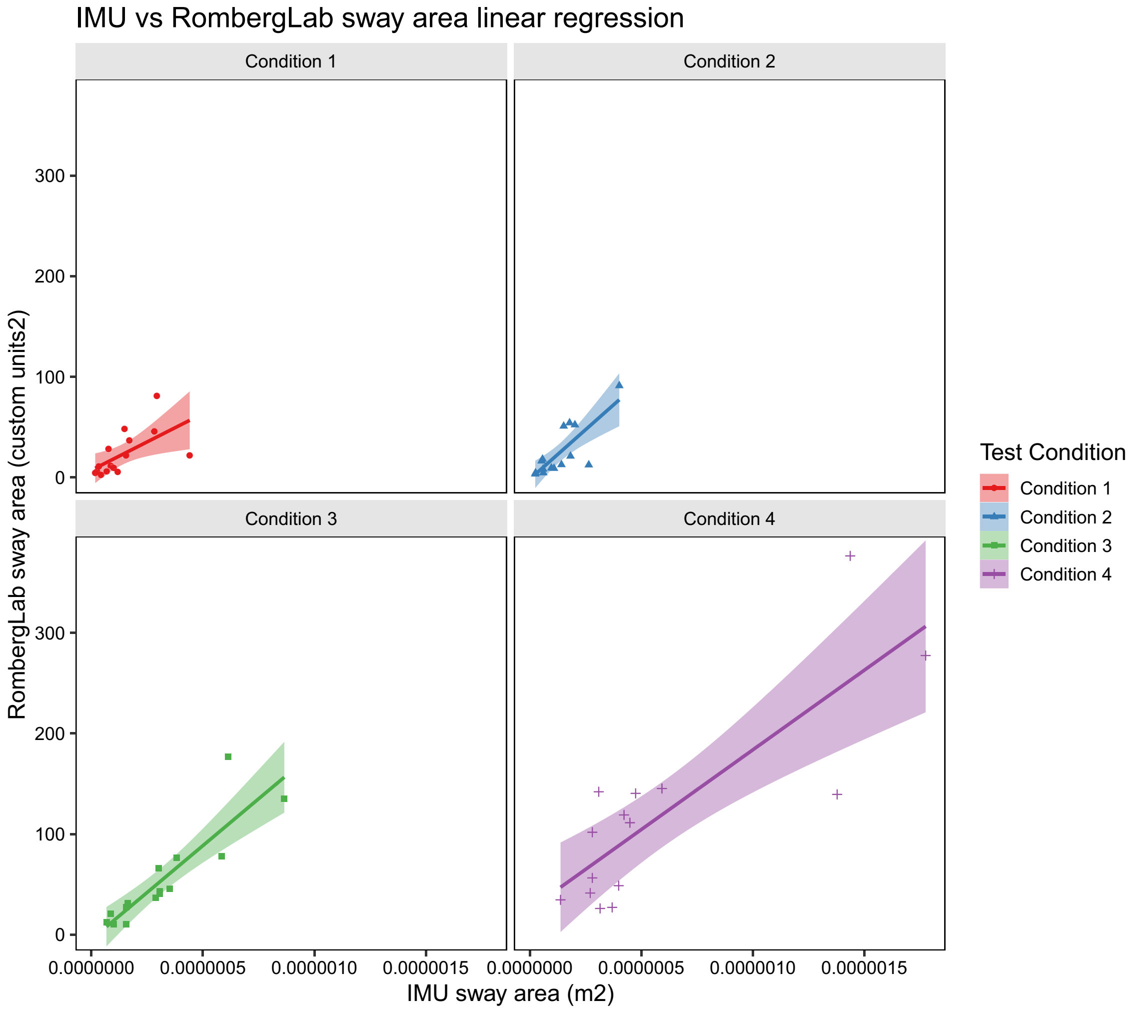

Fig. 3 Regression lines for each test condition. Linear regression obtained for 95% CEA values from wireless IMU and static posturography. Data are plotted separately for each mCTSIB test condition. The colored continuous line plots the linear regression line, and the color shadow area around the regression line plots the 95% confidence interval of the regression line. Most of the IMU–static posturography data peer points in all the conditions are near the regression line and inside the 95% confidence interval regression area

Discussion

The main objective of this study is to validate the proposed IMU for the spatial position sway assessment using the CEA parameter. This is achieved based on the ICC (ICC 2, *k*) concordance value of 0.93 obtained when statistically evaluating the synchronously recorded IMU and static posturography CEA data.

However, we believe that some considerations need to be made for adequate interpretation. Despite the good concordance obtained, the probable main concern regarding our methodology is the IMU acceleration data post-processing. As it is described in "Materials and methods", the original data streamed by IMU are mathematically corrected in the IMU hardware by a Kalman filter. These original data are then post-processed with three second-order Butterworth filters and a data scale to counteract the data smoothing of the data caused by the consecutive filters (Fig. 2).

It is obvious that for normal subjects, the developed post-process method appears to be valid for evaluating the sway area. However, with patients having altered postures of vestibular and neurologic origin, whose sway frequencies are different from those of a normal subject [23, 24], the developed method can be inadequate. Thus, despite obtaining good evidence that using IMU devices is valid for evaluating the sway changes in normal subjects and a priori, we cannot extrapolate this validation to other populations with different sway patterns. Further studies will be needed to evaluate the IMU device-developed methodology on patients with specific sway alterations.

Another caveat is that only one attempt is made for each condition. For example, in the sensory organization test,

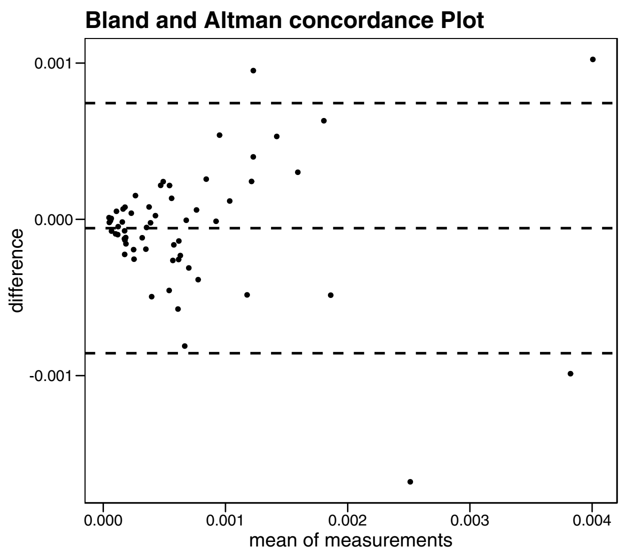

Fig. 4 Bland–Altman graphical IMU versus static posturography (RombergLab) concordance plot. Most of the paired IMU and posturography data are centered around the mean difference line (central discontinuous horizontal line) and inside the ± 2 standard deviation lines (upper and lower discontinued lines). It can be observed that data scattering is increased for the high sway results. Only 4 out of the 60 data points were outside the ± 2 standard deviation lines, probably because of the effect of the IMU scaling process

the patient performs thrice under each condition. Previous studies concluded that using only a single tracing was not very reliable [25] and so further studies should clarify the number of attempts needed to achieve optimal assessment with IMU-based posturography.

There are also some interesting capabilities of IMU devices that should be considered in further posturography studies to best understand the role of these devices. Currently, there are different types of posturography available for assessing balance in humans. Static and dynamic posturography can now be extended with mobile posturography, which allows assessment of conditions with a subject in motion (which are more attuned to real life) or in many different environments or physical activities.

Dynamic computerized posturography has been defined by the American Academy of Neurology as the "gold standard" for the evaluation of the instability of patients with balance disorders [26]. However, it has some limitations:

- Its cost, which has impeded its dissemination and generalization.
- The learning effect has to be considered when we perform the assessment [27].
- Its environment is artificial and differs significantly from the sensory situations in which patients find themselves in their daily lives.

Concurrently, mobile posturography assesses the dynamic tasks in which falls usually occur and it correlates better with the balance impairments in our patients [24]. Despite the potential utility of these mobile posturography systems, they should be tested in specific clinical research.

From this study, we conclude based on the obtained results that the developed wireless IMU-based posturography mobile system is valid for tracking sway variances in normal subjects under habitual clinical testing conditions. Further studies are needed to extend this validation for the use of wireless IMU devices on patients with postural impairment and also to test normal subjects in non-classical (clinical) environments.

Funding No funding was received for this research.

Compliance with ethical standards

Conflict of interest The authors declare no conflict of interest.

Ethical approval Because not medical device CE mark measurement non-invasive devices were used on humans for this study, local government ethic committee (CEIC-Donostia) was required and obtained for this study.

Statement of human rights This clinical study was designed and performed in accordance with the ethical guidelines of the 1975 Declaration of Helsinki.

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