A Wearable and Modular Inertial Unit for Measuring Limb Movements and Balance Control Abilities

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Abstract— **Measuring human movement has many useful applications ranging from fall risk assessment, to quantifying sports exercise, studying people habits and monitoring the elderly. Here we present a versatile, wearable device based on a 9-degrees-of-freedom inertial measurement unit conceived for providing objective measurements of trunk or limb movements for the assessment of motor and balance control abilities. The proposed device measures linear accelerations, angular velocities and heading and can be configured to either wirelessly transmit the raw or preprocessed data to a computer for online use, e.g. visualization or further processing, or to store the acquired data locally for long term monitoring during free movement. Further, the device can work in either single sensor or multiple sensors configuration, to simultaneously record several body parts for monitoring full body kinematics. Here, we compare body sway and trunk kinematic data computed based on our sensor with those based on data from a force platform and a marker-based motion tracker, respectively, during the evaluation of both static and dynamic exercises drawn from clinical balance scales. Results from these experiments on two populations of healthy subjects are encouraging and suggest that the proposed device can be effectively used for measuring limb movements and to assess balance control abilities.**

I. Introduction

FROM THE standpoint of balance control the human body can be modeled as an inverted pendulum, i.e. a pendulum with its center of mass above the pivot joint, which is an inherently unstable system. The control of balance during quiet standing, movements and locomotion is therefore a complex task involving several sensory systems, i.e. vestibular, proprioceptive and visual, as well as the motor system, which is needed to counteract the natural tendency to loose the unstable equilibrium point of the system. Postural and balance control abilities gradually decline with age, so that one third of the population aged over 65 fall at least once per year. Those affected with balance disorders typically suffer from multiple impairments, e.g. multi-sensory loss, weakness, orthopedic constraints and cognitive impairments [1]-[3]. Clinically, balance control abilities are typically assessed using clinical balance scales. The clinician oversees the execution of a set of simple, everyday-life movements, or items, and scores each one of them on a predefined scale. The scores of each item are added up and compared to predefined thresholds, providing a diagnosis of balance control abilities or of fall risk. The most common clinical scales are: the Tinetti test [4], [5], the Berg balance scale [6], and the BEST test [7]. In all these scenarios the physiatrist or the physiotherapist commonly evaluates the subject's performance by observing the execution of each exercise. Such evaluation process is therefore affected by subjective factors causing possible inter- and even intra-evaluator variability of judgment, so that a more objective approach to the evaluation of balance is called for. On the other hand, technological advances continue to reduce the size, weight, and cost of MEMS inertial sensors, so that they are increasingly used for monitoring human movement through body-worn devices [8]-[17]. In particular, custom-made systems based on a single three-axes accelerometers are used in [9,10,11,12,14]. Wireless IMUs are presented in [15] and [17], but one integrates only a 3-axes accelerometer and a 2-axes magnetometer, whereas the other one integrates a 3-axes accelerometer and a 3-axes gyroscope. A few commercially available nine-degrees-of-freedom wireless IMUs have been used for research projects [8,13,16] and some considerations and a comparison with our system will be presented later on in the text.

Based on our previous experience with the development of an instrumented insole for measuring comfort and movement parameters [18], we have recently designed and built a novel, portable, low-cost 9-degrees-of-freedom inertial measurement unit embedding a three axial accelerometer, a three axial gyroscope, and a three axial magnetometer, aimed at providing objective measurements of limb movements for the assessment of motor and balance control abilities (Fig. 1(a)). While a preliminary overview of the system has been reported in [19], hereinafter we provide a detailed description of the device, highlighting the features that differentiate it from similar commercial devices and presenting new experimental results for validating its measurements.

The proposed device was designed in order to fulfill different kinds of monitoring needs: long term monitoring for balance hazards detection during real life activities, real-time balance monitoring for fall prevention or balance research

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studies, or even the need for simultaneously monitoring the activity of more than one limb in kinematics analyses of gait or other gestures. The developed instrument has therefore been conceived as a modular device (Fig. 1(b)) which can be used in different scenarios: 1) single unit wirelessly connected to a PC or handheld device (laboratory experiments, short-term monitoring); 2) single unit capable of storing the acquired data on a local memory (patient/subject's home, long-term monitoring); 3) body network, i.e. multiple units deployed on the subject's body and wired to a gateway unit which can have a local memory or a wireless connection to a PC or handheld device (full body monitoring of exercises, several scenarios). Although a number of wearable IMU devices that can be used for monitoring posture and movements are available on the market, we preferred to build our own IMU "platform" to grant us maximum flexibility for adding custom features. This is hardly possible with commercial devices, as they generally come with their own software and, in particular, their firmware cannot be modified as needed. Among them, Lumoback (Lumo BodyTech, Inc., CA, USA) seems a very interesting system, but can only be connected to an Apple device with a proprietary application. Table I shows a list of other wireless IMUs available on the market that have been used for research purposes. Only six out of the nine listed devices can be used either as data loggers or as wireless sensors networks (WSNs). Most (eight out of nine) come with software development kits that allow the user to build his/her own applications. Nevertheless, only one of them (SHIMMER3 by Shimmer, Ireland) offers the user the capability of reprogramming its firmware (e.g. adding an onboard custom processing).

Besides having both data logger and WSN features, our system is provided with LabVIEW and Python libraries for software application development. Moreover, the microcontroller's firmware can be reprogrammed via a USB connection by means of an integrated development environment (IDE) with a C/C++ compiler and debugger (free versions for up to 64KB of code can be easily found on the Internet). C-code libraries for communicating with the accelerometer, gyroscope and magnetometer are already available; in the future we will develop ad-hoc libraries to be used in fall detection and activity recognition applications. With respect to the above mentioned SHIMMER3, which is based on a 24 MHz 16-bit CPU (MSP430 microcontroller by Texas Instruments, USA) our system is based on a 72 MHz 32-bit CPU (STM32F303VC by ST Microelectronics, Switzerland) which grants higher computing power allowing for more complex processing features. A number of digital and analog inputs and outputs are also made available on the printed circuit board of the device. In particular, synchronous and asynchronous serial connections and IN/OUT digital ports can be used for sharing data and to manage external devices (e.g. electro stimulators).

II. System Description

The device described in the present work is an autonomous system aimed at monitoring the movements of the subject wearing it. The circuit layout was designed to minimize the size of the final device and the battery was selected to minimize its weight, in order to obtain a wearable system well suited for acquiring inertial signals generated by the activity of the wearer without impeding his/her movement. Sensor components were also chosen among those having a linearity range and a sensitivity allowing to properly carry out measurements of human movements. Our instrument is based on a STM32F303VC microcontroller (by ST Microelectronics) embedding a high performance ARM Cortex M4 32-bit RISC core operating at a frequency of up to 72 MHz. Although in the initial experimental trials such as those reported in section IV of this paper our IMU has been used to collect raw data that have been processed off-board, the device was conceived as an inertial platform that can perform online processing, i.e. filtering or parameter extraction, of the acquired data. Moreover, in a body network scenario, the gateway unit processes the data coming from its sensors and from the other connected units. For these reasons, we decided to select a high performance microcontroller nonetheless allowing the design of low-power consumption applications. The STM32F303VC is able to interact with external devices through an extensive range of peripherals, while maintaining relatively small dimensions (7 mm × 7 mm × 1.6 mm). The same package hosts also a 256 Kbytes flash memory, for permanent data storage, and 40 Kbytes of SRAM for temporary data storage.

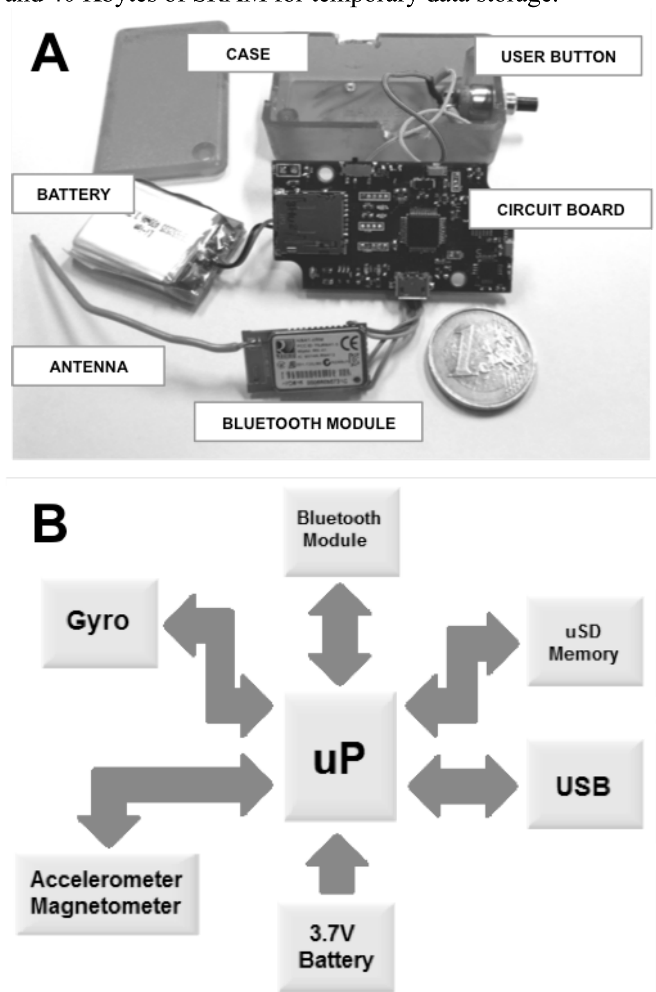

Fig. 1 (a) The assembled device and casing. (b) System architecture.

TABLE I. COMPARISON OF VARIOUS WIRELESS IMUS AVAILABLE ON THE MARKET AND ALREADY USED FOR RESEARCH PURPOSES

Device	Dimensions / Weight	Sensors	Battery life	Wireless connectivity	Sensor network?	Data logging?	Software library?
MotionNode Bus Motion Workshop, Seattle, USA [20]	Sensor: 35 mm × 35 mm × 15 mm / 10 g Controller: 80 mm × 40 mm × 20 mm / 80 g Battery: 180 g	3-axes accelerometer; 3-axes gyroscope; 3-axes magnetometer	5 sensors: 7.00 h 10 sensors: 5.50 h 15 sensors: 4.75 h	802.11g	Yes Up to 20 sensors wired to host unit providing wireless PC connection	Yes 4 GB internal flash memory	Yes open source SDK in C++, C#, Java, and Python
Opal APDM™, Inc., Portland, USA [21]	48.4 mm × 36.1 mm × 13.4 mm / 22 g (with battery)	3-axes accelerometer; 3-axes gyroscope; 3-axes magnetometer	Wireless Streaming: 8 h Synchronous Logging: 12 h Asynchronous Logging: 16 h	Low-power wireless communication protocol	Yes A wireless network of up to 24 devices is possible	Yes 8 GB internal flash memory	Yes SDK includes support for MATLAB, Java, Python, and C
MTw Development Kit Xsens Technologies B.V., Enschede, The Netherlands [8],[22]	34.5 mm × 57.8 mm × 14.5 mm / 27g	3-axes accelerometer; 3-axes gyroscope; 3-axes magnetometer; static pressure sensor	Continuous use (typical): ~3.5 h Stand-by: 90.0 h	Awinda radio protocol	Up to 32 MTw's in a configurable wireless-area network	No (only data buffering)	Yes Examples code for C, C++ and Matlab
Memsense W2 IMU Memsense, Rapid City, USA [23]	40.1 mm × 33.5 mm × 15.2 mm / not specified	3-axes accelerometer; 3-axes gyroscope; 3-axes magnetometer; temperature and atmospheric pressure sensor	5 h	Bluetooth	No	No	No (proprietary software)
STT-IBS STT Engineering and systems, San Sebastian, France [24]	36.0 mm × 15.0 mm 46.5 mm / 30 g	3-axes accelerometer; 3-axes gyroscope; 3-axes magnetometer	Not specified	WiFi, Bluetooth	No (multiple sensors need appropriate software application)	Yes (memory capacity not specified)	Yes SDK that can be integrated in .NET and C++ environments
Colibri Wireless TRIVISIO Prototyping GmbH, Trier, Germany. [25]	56 mm × 42 mm × 17 mm / 41 g (with battery)	3-axes accelerometer; 3-axes gyroscope; 3-axes magnetometer; temperature sensor	16 h	Wireless 2.4 GHz band operation	Yes Up to 10 trackers synchronized in the wireless network	No (1 KB non-volatile memory for user data)	Yes API for implementing extended Kalman filter for tracking orientation
I2M Motion SXT NexGen Ergonomics Inc., Pointe Claire, Canada. [26]	48.5 mm × 36.0 mm × 12.0 mm / 22 g	3-axes accelerometer; 3-axes gyroscope; 3-axes magnetometer	Wireless streaming: > 8 h Logging: > 16 h	Proprietary low-power wireless communications protocol.	Yes Up to 24 STXs (wireless mode)/ up to 18 SXTs (logging mode)	Yes 8 GB internal flash memory	Yes Support for MATLAB™, Java, Python, and C
SHIMMER3 Shimmer, Dublin, Ireland [13]	51 mm × 34 mm × 14 mm / not specified	3-axes accelerometer; 3-axes gyroscope; 3-axes magnetometer; altimeter	Not specified	Bluetooth	Yes (max number of nodes not specified)	Yes (memory capacity not specified)	Yes LabVIEW, Matlab, Java/Android, C# drivers
Physilog Gait Up SA, Avenue d'Ouchy, Switzerland [16]	50.0 mm × 37.0 mm × 9.2 mm / 19 g	3-axes accelerometer; 3-axes gyroscope; 3-axes magnetometer; barometric pressure sensor	< 21 h depending on model and programming	Bluetooth	Yes (max number of nodes not specified)	Yes 4 GB internal memory	Yes Ready to use code in MATLAB, C/C++, or Python
Proposed device University of Pavia, Italy	60 mm × 35 mm × 20 mm / 36 g	3-axes accelerometer; 3-axes gyroscope; 3-axes magnetometer	Wireless streaming: ~ 6 h Logging: > 16 h	Bluetooth	Yes Up to 10 nodes	Yes Extractible Micro Secure Digital card	Yes LabVIEW and Python libraries for software development; reprogrammable firmware

Body movements are measured using three inertial sensors: an accelerometer; a magnetometer and a gyroscope. We chose to use ST Microelectronics sensors mostly for our extended experience with them, so that we had access to their reference designs and to existing libraries.

The LSM303DLHC (ST Microelectronics) provides measurements of the three-dimensional accelerations as well as those related to the magnetic field; it is a system-in-package featuring a 3D digital linear acceleration sensor and a 3D digital magnetic sensor. Magnetic and accelerometer sensors can be enabled or put into power-down mode separately, thereby allowing to reduce the power consumption when one of these features is not required.

The three dimensional angular rate is instead provided by the L3G4200D (ST Microelectronics), a digital low-power three-axes angular rate sensor. The full-scale values of the sensors can be modified by means of specific commands sent by the microcontroller [27][28]. In the experiments presented in this paper, we used the following configuration: +/-2g for the accelerometer; +/-8.1 G for the magnetometer; +/-250 °/s for the gyroscope.

The microcontroller can manage the external sensors through two different kinds of synchronous serial communication interfaces: an Inter Integrated Circuit (I2C) and a Serial Peripheral Interface (SPI). The I2C exploits only two digital lines and allows the interaction with the LSM303DLHC module, whereas the SPI is a communication based on 3 digital lines and is used to send commands and receive data from the L3G4200D gyroscope. The SPI interface is also used to store data as ASCII files on a micro Secure Digital (μSD) card, which can then be extracted and read on different devices such as a PC or smartphone for data visualization and processing. Alternatively, the acquired data can also be wirelessly sent to a remote device (such as notebook, tablet or smartphone) using a RN-41 class 1 Bluetooth® radio module (by Microchip Technology Inc., USA). This small (13.4 mm × 25.8 mm × 2.0 mm), low power (30 mA connected, < 10 mA sniff mode) module exchanges data with the microcontroller through a Universal Asynchronous Receiver/Transmitter (UART) interface, and delivers a data rate of up to 3 Mb/s for distances up to 100 meters. A custom designed 4 layers, 55 mm × 30 mm × 2 mm, printed circuit board hosts the above listed components and provides the wiring for data transmission.

The circuit is powered by a very small (5 mm × 25 mm × 35 mm), extremely lightweight (9 g) 3.7 V Polymer Lithium Ion battery with a nominal capacity of 400 mAh, including a built-in protection against over voltage, over current, and minimum voltage. Battery charging is simplified by providing a USB plug on the main circuit board. The power consumption pie chart for the working device is presented in Fig. 2. The system is currently capable of continuously acquiring and transmitting data to a PC for about 6 hours, but we are implementing power saving techniques in order to further extend the battery life. These include putting the system into sleep-mode when no movements are detected, or decreasing the sampling frequency when the subject's activity is low. The capability of LSM303DLHC to generate interrupt signals based on acceleration thresholds as well as on the orientation of the device itself is extremely helpful for this purpose.

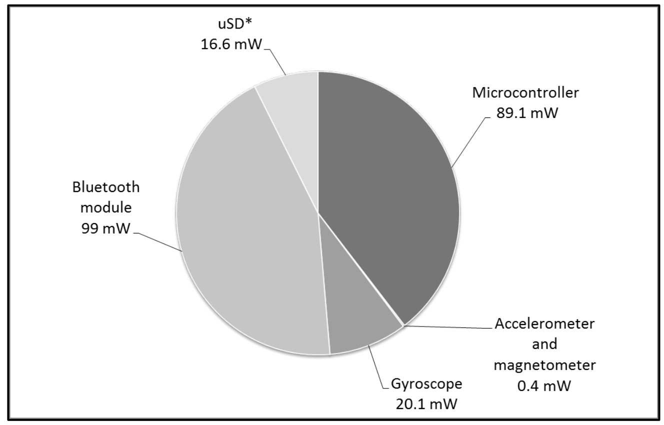

Fig. 2 Device power consumption. *The reported value of μSD power consumption refers to the case when all data coming from the 3 sensors, acquired at 100 Hz, are stored in the μSD. This results in 28 pages of 256 bytes written every second.

The entire device, including the circuit board, the Bluetooth module and the battery, are enclosed in a 60 mm × 35 mm × 20 mm box, which is made of translucent plastic, allowing to easily see the working LED indicators available on the board. The developed prototype is lightweight (36 g) and unobtrusive, and its small packaging allows to easily wear it on any limb or portion of the trunk using elastic Velcro straps or a similar support. The wearable device has currently been used for measuring data on trunk and thigh movements in over 100 clinical trials without inducing any complaint on freedom of movement or on discomfort.

III. System Application

As mentioned, the device was conceived with three kinds of scenarios [19] in mind.

In the first scenario, a single unit is attached to the limb of interest, or to the trunk, and wirelessly connected via Bluetooth® to a PC or other device for on-line processing of the acquired signals while the subject performs some predefined movements (e.g. exercises drawn from a clinical balance scale).

In the second scenario, the single unit is used for long-term monitoring, such as while the patient/subject is at home or freely moving in everyday life. In this case the Bluetooth® module is not necessary and therefore, once the presence of a μSD card with an appropriate configuration file is verified, it is simply switched off. The configuration file is a text file on the local μSD memory card specifying the sensors axes to be enabled, the sensors ranges, the sampling frequency, the size and the name of the log files. The acquisition starts when the user button (Fig. 1(a)) is pressed, thereby activating data logging to the local µSD memory card where the collected data samples are arranged in text spreadsheet files until the user button is pressed again. A blinking led (visible through the transparent case) informs the user that the acquisition is in progress. When the device is returned back to the laboratory/clinic, the µSD is extracted and the files can be downloaded to a PC for further processing. In this setting the device is capable of continuously acquiring and storing data for more than 11 hours (at the maximum sampling rate). Power saving techniques (i.e. reducing the sampling rate or going into sleep mode when the subject is not moving) allow for longer acquisition times.

In the third, and most complex scenario several basic units are simultaneously worn by the subject, e.g. one at the level of L3, two on the thighs, two on the wrists or arms and one on the head, for detailed monitoring of full body kinematics. One of these devices, typically the one on L3 for wiring ease, acts as a gateway and relay node that it is wired to all the other devices and collects their data. It may then process the data and extract parameters of interest, if needed, and either store data and computed figures on the µSD card or transmit them wirelessly to a PC. The peripheral units are connected to the gateway unit using a multiprocessor serial communication protocol, implementing a single master – multiple slaves architecture. The system allows for a body network with up to ten (9 slave and 1 master) units, with 9 signals (3 accelerations, 3 angular velocities, 3 magnetic field signals) provided by each unit, sampled at up to 400 Hz per channel.

IV. EXPERIMENTAL TRIALS

In order to test the system's performance in measuring movements and balance control abilities, we carried out two experiments in which selected items drawn from common clinical balance scales were simultaneously recorded using both our sensor in single-unit wireless mode (1st scenario) and a reference instrument for comparison.

In the first experiment we evaluated postural control abilities during quiet standing using the accelerometer as an inclinometer on low-pass filtered data, thereby neglecting inertial accelerations, to obtain trunk inclination with respect to the gravity vertical. In the second experiment, we evaluated postural control abilities in dynamic conditions, i.e. when inertial acceleration is not negligible, and the sensor's motion was computed by integrating accelerometer and gyroscope signals during specific movements.

In the first experiment we asked a group of 10 healthy subjects to perform four static exercises, each one lasting 40s: 1) standing with eyes open (SEO), 2) standing with eyes closed (SEC), 3) standing with eyes open on a soft foam cushion (SEO_F), 4) standing with eyes closed on a soft foam cushion (SEC_F). The first two items were selected from the Tinetti Test [5], whereas the last two were drawn from the BESTest [7].

We recorded each subject's Centre of Pressure (CoP) at a frequency of 30 Hz by means of a Wii Balance Board (WBB) (Nintendo, Kyoto, Japan). The WBB is a force platform, the typical gold standard for CoP measurements, which has proven to be a valid and reliable tool for assessing CoP displacements [29], in spite of its affordability. We estimated the subjects' Centre of Mass (CoM) displacements on the horizontal plane (X, Y) by applying a 0.4 Hz low pass filter to CoP displacements recorded by the WBB, as suggested in [30].

The accelerometer data from the IMU worn using an elastic belt at the level of L3-L4, i.e. at the approximate CoM height,were acquired on a laptop via Bluetooth. Pitch and roll inclinations of the trunk, with respect to gravity, were calculated based on IMU data, using the accelerometer as an inclinometer after low pass filtering its data at 0.4 Hz. Assuming an inverted pendulum model of the body, CoM displacements on the horizontal plane (X, Y) were thus estimated as the projection of the sensor location on the ground using pitch and roll angles [31] and considering the height of the sensor on the subject's body as the pendulum length.

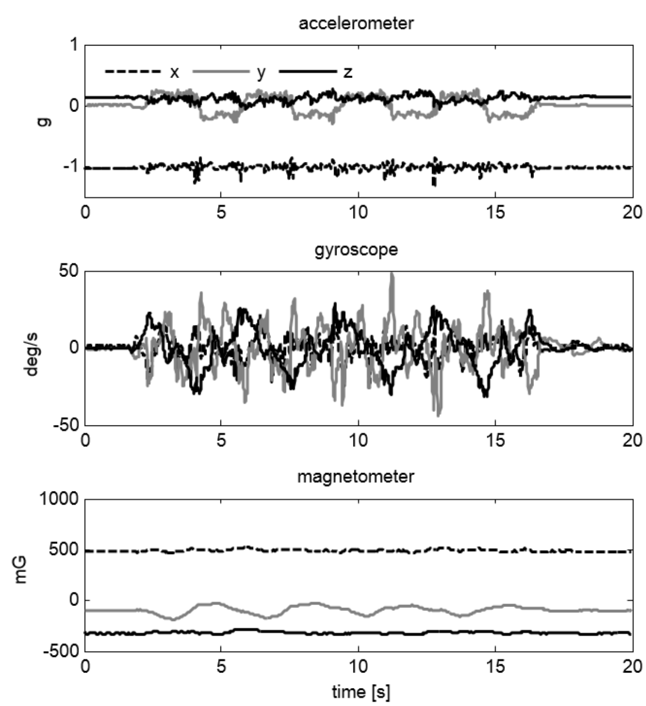

Fig. 3 Accelerometer (a), gyroscope (b) and magnetometer (c) raw signals acquired while a subject places each foot alternately on a stool during standing unsupported (SOS, 8 steps for 20 seconds of recording). The sensor was worn at the level of L3-L4 on the back of the subject. Accelerometer and gyroscope signals were used to reconstruct roll trunk inclination during the exercise, providing the results shown in Fig. 4(f).

Comparisons of a representative subject's X and Y CoM displacements, estimated based on the WBB and on our device during SEO and SEC_F, are shown in Fig. 4 (a)-(d). The median value of Pearson's linear correlation coefficients and confidence intervals are shown (lower bound has been computed as difference between the median, i.e. the 2nd quartile, and the 1st quartile, whereas the upper bound as the difference between the 3rd quartile and the median value). For all static exercises (SEO, SEC, SEO_F, SEC_F), linear correlation coefficients were computed directly on WBB and IMU estimated CoM displacement signal.

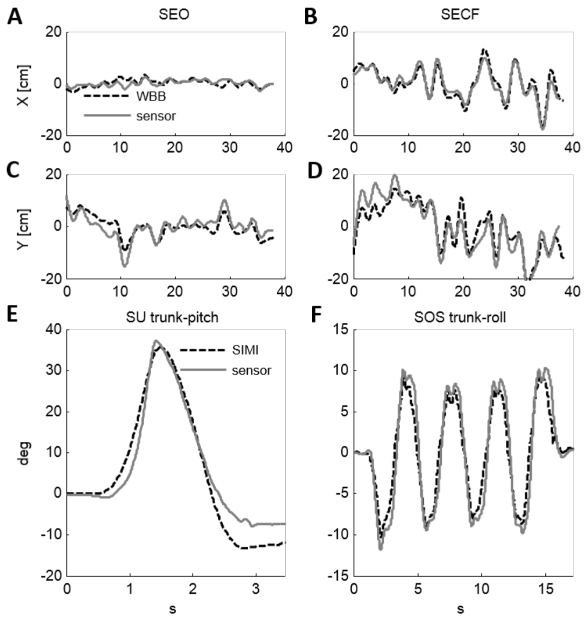

Fig. 4 Top two rows. Comparison of X and Y CoM displacements estimated based on IMU data (gray solid line) and WBB (black dashed line) data, recorded during the SEO (panel (a), (c), small oscillations) and SECF (panel (b), (d), large oscillations). Bottom row. Comparison of trunk inclination angles estimated based on IMU (gray line) and SIMI Motion (black dashed line) data recorded during the SU (panel (e), pitch angle) and SOS (panel (f), roll angle) exercises performed by a representative subject. Data in panel (f, gray line) are calculated from signals shown in Fig, 3(a, b).

To further assess the reliability of our tool, we considered three features that are typically used in the evaluation of upright stance in static balance exercises and compared their values obtained using the estimated CoM displacements based on IMU data with those obtained using the CoP data obtained from the WBB. The features we considered are computed as in [32], and represent: the root mean square distance (RDIST) from the mean; the 95% confidence ellipse area (CEA), and the mean velocity (MVELO).

Fig. 5 (b)-(d) presents a comparison of the results obtained with the two techniques, showing very good correlations of the computed features.

In the second experiment, we have recorded a population of eight healthy subjects performing a series of dynamic exercises, i.e. items, also drawn from common clinical balance scales, with the single sensor attached to the subjects' back at the level of L3-L4 by means of a strap-on band being wirelessly acquired by a laptop. Subjects were simultaneously recorded using a SIMI Motion 3D (Simi Reality Motion Systems GmbH, Germany), a passive marker motion capture system with 4 synchronized cameras. The X, Y and Z coordinates of two markers (placed on the subjects at the level of L3-L4 and Th10 respectively) were acquired at a frequency of 100 Hz and used to compute roll and pitch angles of the trunk. The selected exercises were the following: 1) stand-up (SU); 2) sit down (SD); 3) place each foot alternately on a stool while standing unsupported (SOS); 4) reaching forward while standing (RF).

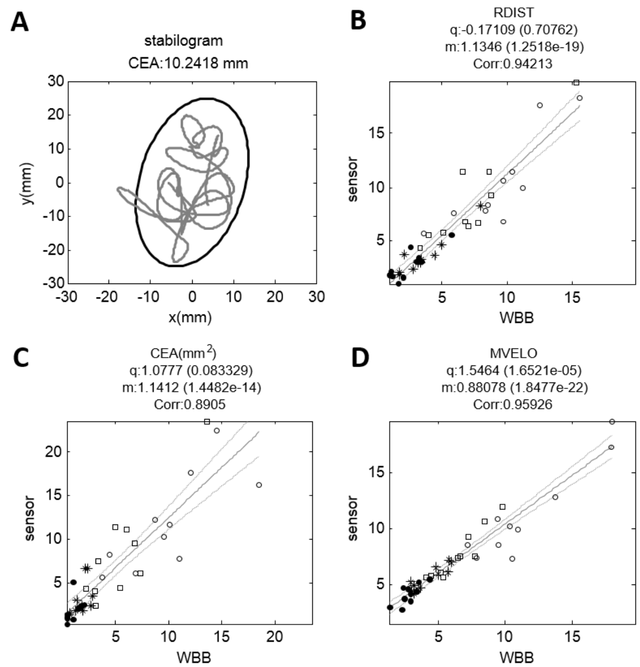

Fig. 5 (a) Stabilogram of projected CoM displacement (gray line) for the subject in Fig. 4 (b), (d) and ellipse including 95% of data (dark line). (b),(c),(d) RDIST, CEA, MVELO, respectively. The parameters computed from sensor data are plotted against those computed from BB data. Points represent SEO, stars SEC, squares SEOF and circles SECF. The slope, the intercept of the linear regression and the Pearson's correlation coefficients are reported.

Again, the first two items were drawn from the Tinetti test [5], whereas the last two were drawn from the Berg balance scale [6]. Sensor's data were also acquired at 100 Hz sampling frequency (setup as in the scenario 1). We estimated the orientation of the worn device, and hence of the trunk, using the Kalman filter algorithm in [33] and the sensor signal model reported in [34]: the estimate is based on the integration of the angular velocity provided by the gyroscope, with a correction based on the inclination computed using data from the accelerometer for compensating integration errors. These data were then compared to the roll and pitch trunk inclination angles computed based on the SIMI Motion data. An example of such comparison on a representative subject is shown in Fig. 4: panel (e) shows the pitch angle computed from the sensor mounted on the subject's lower back together with the trunk inclination computed based on the SIMI Motion data during a SU exercise. The difference in inclination that can be noted at the end of the exercise may be due to the sensor taking into account the lumbar curvature in standing upright, whereas the straight line between the L3-Th10 markers neglects it. Panel

(f) shows the roll angles during a SOS exercise (computed based on the raw signals shown in Fig. 3 (a, b)). Table III presents the median value of Pearson's linear correlation coefficients and confidence intervals between the two signals, for all items considered (pitch angles are shown for the SU, SD, RF items, whereas roll angles are considered for the SOS).

V. Conclusion

We have developed a custom IMU sensor aimed at monitoring human movement in several scenarios of interest for both the scientific and the clinical fields, ranging from long term balance assessment, i.e. a Holter monitor for balance, to kinematic analysis of multiple limb movements for monitoring the execution of full body gestures or exercises, in the general context of movement control, balance assessment and fall prevention. We have validated the device for its use as a balance monitoring tool by simultaneously recording healthy subjects performing exercises drawn from commonly used balance assessment scales, with both our device worn at the level of L3-L4 and reference instrumentation.

TABLE II. Static exercises correlation coefficients

Static	CorrX			CorrY		
	median	2nd Q- 1st Q	3nd Q- 2st Q	median	2nd Q- 1st Q	3nd Q- 2st Q
SEO	0.5980	-0.1539	0.3043	0.7795	-0.0502	0.0435
SEC	0.8658	-0.3461	0.0559	0.7588	-0.0746	0.1220
SEO_F	0.9143	-0.0495	0.0403	0.5894	-0.3888	0.1431
SEC_F	0.9331	-0.1307	0.0207	0.6932	-0.1345	0.0655

TABLE III. Dynamic exercises correlation coefficients

Dynamic	Corr		
	median	2nd Q- 1st Q	3nd Q- 2st Q
SUpitch	0.9690	-0.0872	0.0039
SDpitch	0.9947	-0.0641	0.0011
RFpitch	0.9926	-0.0120	0.0021
SOSroll	0.9462	-0.0085	0.0088

The data relative to the four quiet standing exercises were compared based on the estimated CoM displacements and on features commonly used for sway path evaluation. The comparison between the CoM's X and Y displacements computed based on the data acquired by our device and by the Nintendo Wii Balance Board in the SEC, SEO_F, SEC_F conditions show good to very good correlation coefficients. The X coordinate, in particular, shows very good correlation coefficients in those exercises where relatively larger body oscillations are present, and a good correlation in the other cases, in which only small oscillations are expected in healthy subjects. We further tested whether the data acquired using the proposed device allowed reliable computation of the figures that are commonly used for evaluating posturography data, thus comparing the mean velocity, the root mean square distance and the 95% confidence ellipse area computed on the WBB COP data with its estimate based on the IMU and found very good correlations. Finally, data relative to the four dynamic exercises were compared based on estimated trunk inclination angles computed using the IMU and the SIMI Motion 3D data. We found very good correlations between the angles of interest of all considered items.

These experimental tests strongly argue for the reliability of the proposed sensor in such configuration. The system (single unit for short-term acquisition, first scenario) is being used in an experimental campaign where both its quantitative measurements, and expert examiners' judgments are recorded while a group of patients and controls carry out motor tasks, i.e. items, drawn from the most common clinical balance scales (e.g., Tinetti test, Berg Balance Scale, BESTest).

In the tests we performed the proposed device has proven comfortably wearable by the subjects and easy to use by the operators. We are currently developing a proper computational framework for analyzing the data acquired while performing the selected set of exercises in order to identify appropriate behavioral features allowing to classify the individuals in terms of their fall risk [35]. Quantitative features describing balance control abilities are thus used for patients' fall risk classification.

Acknowledgment

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