Gait evaluation using inertial measurement units in subjects with Parkinson's disease

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We investigated whether a wearable system based on a commercial Inertial Measurement Unit (IMU) can re-liably provide the main spatiotemporal gait parameters in subjects with Parkinson's disease (PD), compared to a gold-standard optoelectronic motion capture system. The gait of 22 subjects with PD (Age: 69.4 (6.1) years; UPDRS-III: 28.0 (9.2)) was recorded simultaneously with an optoelectronic system and a commercial IMU-based wearable system. Eight spatiotemporal parameters describing the step cycle (cadence, velocity, stride length, stride duration, step length, stance, swing and double support duration) were compared between the two systems. The IMU and the optical system reported comparable gait parameters, with the exception of walking velocity (optical system, 0.72 (0.27) $m{\cdot}s^{-1}$ vs. IMU: 0.86 (0.26) $m{\cdot}s^{-1}$, $p < 0.05$). Although most parameters detected by the two systems were not statistically different, some of them like stride length, double support and step duration showed notable root mean square and mean absolute errors. In conclusion, the algorithm embedded in the current release of the commercial IMU requires further improvements to be properly used with subjects with PD. Overall, the IMU system was sufficiently accurate in the assessment of fundamental gait spatiotemporal parameters. The fast and simplified data re-cording process allowed by wearables makes this technology appealing and represents a possible solution for the quantification of gait in the clinical context, especially when using a traditional 3D optoelectronic gait analysis is not possible, and when subjects are not fully cooperative.

Keywords:
IMU
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Gait parameters
Gait analysis

1. Introduction

Parkinson's disease (PD) is a chronic neurodegenerative disorder characterized by motor impairments including limb tremor, decreased movement speed and amplitude, increased limb stiffness and gait disturbances (Stamatakis et al., 2011). In 2005, in Western Europe's five and World's ten most populated nations, representing 2/3 of the World population, the number of individuals with PD aged over 50 was between 4.1 and 4.6 million. This number is expected to reach 8.7–9.3 million by 2030 (Dorsey et al., 2007).

Gait disorders as the impairments in walking, turning, crossing obstacles or performing simultaneous motor and cognitive tasks are the most disabling symptoms of PD. The increase of the motor dysfunctions as the disease progresses requires to quantitatively evaluate and monitor gait impairments over time. Instrumented Gait Analysis (GA) is commonly used to obtain kinematic, kinetic and spatiotemporal parameters, and thus a quantitative picture of the gait function. In particular, spatiotemporal parameters are widely used in the clinical context, as they objectively describe the main events of the gait cycle and reflect the ability of the patient to fulfil the general requirements of gait, i.e. weight acceptance, single limb support and the advancement of the swing limb (Bugané et al., 2012). Several studies documented spatiotemporally the main features of gait in PD: reduction of stride length, often accompanied by lower walking speed (De Souza et al., 2011) and by the attempt to extend the double support phase (Sofuwa et al., 2005); absence of "heel strike", due to the typical flat foot support

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(Sofuwa et al., 2005); troubles in changing direction during turning (Morris et al., 2001; Nutt et al., 2011). In particular, Morris et al.(Morris et al., 2001) highlighted that turning can be even more frequent than forward walking, especially in confined environments such as dwellings.

To date, optical motion analysis systems (3D-GA) have been widely recognized as the gold standard in measuring gait parameters (Stamatakis et al., 2011). Through the computation of spatiotemporal, kinematic and kinetic parameters, traditional optoelectronic systems provide the essential information on the functional status of a subject. However, a clinical gait test also requires specialized personnel, considerable equipment and time, in most cases allows for the assessment of just a few steps, and patients need to be transferred to an in-strumented laboratory (Muro de la Herran et al., 2014). These con-straints may represent critical issues, especially in the context of PD, where the gait function of patients is characterized by a great varia-bility, due to physical fatigue and to pharmacological treatments (O'Sullivan et al., 1998). Thus, optoelectronic marker-based systems are not always optimal for patients' monitoring in daily-life conditions, and for the assessment of gait fluctuations throughout the day (Muro de la Herran et al., 2014).

For these reasons, research is moving towards the development and employment of portable devices based on Inertial Measurement Units (IMUs) for the assessment of GA parameters. These devices enable the real-time assessment of spatiotemporal parameters in real-life environments, indoor and outdoor, thus overcoming the typical limitations of laboratory measurements. Moreover, IMUs are cheaper and more practical than full GA systems; only a relatively fast preparation of the patients is required, as the sensor is placed on the body (typically on the waist) by means of an elastic belt. Data can be easily transferred via Bluetooth to the dedicated software. These features broaden the range of its potential users. However, commercial IMU-based systems for gait analysis also have limitations, such as the lower number of computable parameters (especially in terms of kinematics) due to the single unit usually worn, reduced accuracy and precision, and increased susceptibility to noise and external factors.

Recently, the performance of inertial sensors in detecting spatiotemporal gait parameters has been compared to optoelectronic systems in healthy subjects (Bugané et al., 2012; Mariani et al., 2010). Further, applications of IMUs in rehabilitation and in recovery of patients' mobility have been reported (Bugané et al., 2012; Bauer et al., 2015; Cimolin et al., 2016; Godfrey et al., 2008; Larivière et al., 2013; Rueterbories et al., 2010; Schwesig et al., 2011); in several studies, IMUs have been used to assess the gait performance in PD subjects (Jochen et al., 2013; Sant'Anna et al., 2011; Weiss et al., 2015). However, no study ever investigated the agreement between spatiotemporal parameters simultaneously computed with 3D-GA and IMUs in a population of patients with PD. In the current study we aimed at investigating whether a commercially available inertial sensor can reliably provide basic gait spatiotemporal parameters in PD during level walking.

2. Methods

2.1. Participants

Twenty-two older adults aged 60–80 years and diagnosed with PD were involved; they signed a written informed consent to participate in the study. Participants' anthropometrics and clinical data are shown in Table 1. Participants with liver, kidney, lung, or heart diseases, diabetes, or other causes of autonomic dysfunction were excluded. The present study was conducted in accordance with the guidelines on human experimentation (Declaration of Helsinki, 1964) and did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Table 1
Participants' anthropometrics and clinical data (n = 22, 12 males and 10 females).

Characteristics	Mean (SD)
Age [years]	69.4 (6.1)
Height [cm]	162.1 (12.4)
Weight [kg]	76.6 (15.0)
H&Y	3.00 (0.50)
UPDRS III	28.00 (9.25)

2.2. Data collection

All the trials were recorded at the Motion Analysis Laboratory of Hospital San Raffaele, Tosinvest Sanità, Cassino (FR, Italy). IMU and the optoelectronic motion data were recorded at the same time.

A marker-based optoelectronic system (SMART, BTS SpA, Milan, Italy) was taken as the ground truth. It was composed by eight optoelectronics cameras, recording at a sampling frequency of 100 Hz the three-dimensional coordinates of 22 spherical passive markers (diameter: 14 mm), placed on the subject's skin at specific landmarks, according to the Davis protocol (Davis et al., 1991). Two synchronized force platforms (Kistler, Germany) detected Ground Reaction Forces (GRF). Before data acquisition, system calibration was performed under the manufacturer's guidelines, and all the trials were acquired by the same operator to avoid inter-examiner variability.

The commercial portable device was made up by the BTS® G-Sensor (BTS SpA, Milano, Italy), communicating with the receiving unit (personal computer) via a Bluetooth link, and by a software, BTS® G-Studio, for data recording, processing, reporting and storage. The IMU includes a triaxial accelerometer (16 bit/axes, up to 1000 Hz) with multiple sensitivity (± 2, ± 4, ± 8, ± 16 g), a 16-bit triaxial magnetometer (± 1200μ T, up to 100 Hz), and a triaxial gyroscope (16 bit/axes, up to 8000 Hz), with multiple sensitivity (± 250, ± 500, ± 1000, ± 2000°/s). Proprietary algorithms fuse sensors data at 200 Hz. The previously validated "Walk" protocol within the G-Studio software was used (Bugané et al., 2012): this protocol requires the sensor to be placed at the L5 level by means of a provided elastic belt, with the power connector pointing upwards and the logo facing out. The position of the sensor has to be kept vertical to correctly define the reference system. The final report obtained using the IMU provides all the spatial-temporal gait parameters and the pelvic tilt angles.

Five trials were acquired with both the optoelectronic and IMU-based systems, asking participants to walk barefoot along a 10-m walkway at their self-selected walking speed. The values of the three central trials were used for systems comparison, in order to get the patients acquainted with the test and to avoid any fatigue effect.

2.3. Data processing

Data collected with the optoelectronic system were processed using two software: BTS® TrackLab and Smart Analyzer (BTS Bioengineering S.p.A., Version 1.10.458.0) were used for the labeling process and to develop a customized routine, which returned the spatiotemporal parameters. Raw kinematic data were filtered with a Butterworth fourth-order low-pass filter (cut-off frequency: 5 Hz); gait events were detected by visually inspecting 3D reconstruction based on GRF – this is the standard procedure for clinical gait analysis tests.

The bundle IMU-system software automatically provides a report with mean and standard deviation (SD) over the assessed gait cycles of the spatiotemporal parameters (for the right and left limb), as well as pelvic obliquity, tilt and rotation traces, time-normalized to the gait cycle duration. In this study, pelvis kinematics was acquired but not considered and further elaborations on inertial data were not performed since our intent was to assess the sensor as it comes in its commercial, end-user form. The G-Studio software implements the following general

Table 2
Median and Interquartile range (IQR) of data obtained from the optoelectronic system (3D-GA) and the Inertial Unit (IMU).

Variable	3D-GA	IMU	p	ES	type-II error	CI_{low}	CI_{high}	RMSE	MAE [%]	Rs
Cadence [step·min^{-1}]	108.6 (17.0)	107.5 (13.5)	0.95	0.028	0.047	−2.21	1.63	4.24	3.0	0.91
Velocity [m·s^{-1}]	0.72 (0.27)	0.86 (0.26)	0.01	0.806	0.006	−0.21	−0.12	0.19	26.6	0.87
Stride length [m]	0.93 (0.30)	1.00 (0.27)	0.23	0.378	0.109	−0.13	−0.02	0.13	12.3	0.84
Stride duration [s]	1.11 (0.22)	1.15 (0.15)	0.40	0.163	0.389	−0.04	0.00	0.07	3.7	0.86
Step duration [%]	45.6 (10.2)	50.00 (4.1)	0.36	0.594	0.002	−7.7	−1.8	10.8	23.5	0.41
Stance duration [%]	63.2 (3.2)	63.9 (5.6)	0.24	0.278	0.265	−1.9	−0.1	3.2	4.0	0.68
Swing duration [%]	37.1 (2.8)	36.0 (5.6)	0.10	0.361	0.254	0.3	2.3	3.5	7.8	0.64
Double support [%]	12.6 (3.0)	12.8 (7.4)	0.14	0.394	0.147	−2.5	−0.1	3.6	25.4	0.64

1-power: Type-II error probability; p: Wilcoxon Signed rank test; $CI_{low/high}$: 95% confidence intervals of the difference between 3D-GA (3D-Gait Analysis) and IMU; ES: non-parametric Effect Size; RMSE: Root Mean Square Error; MAE: Mean Absolute Error; Rs: Spearman Correlation coefficient (all correlations were statistically significant, $p < 0.05$).

algorithms to extract the parameters (Cimolin et al., 2016): along the line of progression, the pattern of pelvic acceleration is predicted by an inverted pendulum model; thus, the forward acceleration component is low-pass filtered and then used to determine the onset of the support phase, as accelerations can be observed after mid-stance and decelerations after initial contact. The step length is estimated based on the amplitude of vertical pelvic displacement and leg length using a simple inverted pendulum model. Vertical displacements were obtained by double integration of the corresponding acceleration component, following high-pass filtering to correct for low-frequency drifts (4th-order zero-lag Butterworth filter at 0.1 Hz). Step lengths were then calculated as $2\sqrt{2lh-h^2}$, where l is leg length and h the vertical displacement. Gait velocity was computed as the ratio between walking distance and duration (Cimolin et al., 2016).

The following spatiotemporal gait parameters were compared between the two measurement systems: cadence (steps/min), number of strides per minute; mean velocity (m·s^{-1}), average instantaneous velocity; stride length (m), distance between two consecutive heel strikes (or initial contacts) of the same foot; stride duration (s), time between two consecutive initial contacts of the same foot; step duration (%), time between the initial contact of one foot and the contralateral initial contact, computed as percentage of the stride duration; stance phase duration (%), time from the initial contact to the toe off of the same foot, computed as percentage of the gait cycle; swing phase duration (%), time from the toe off of one foot to the initial contact of the same foot, expressed as percentage of the gait cycle; double support phase duration (%), phase in which both feet touch the ground, computed as percentage of the gait cycle.

2.4. Statistical analysis

SPSS Statistics (version 22, IBM) was used to perform the statistical computations. Data normality assumption was rejected by the Kolgomorov-Smirnov test. Bilateral variables were tested for laterality-driven differences with the Wilcoxon signed rank test; median and Interquartile Ranges (IQR) were computed for all parameters.

The agreement between the IMU and the optoelectronic system was tested using the Wilcoxon signed rank test: alongside the value of α, probability of false positive findings (type-I error), in this research it was important to provide the probability of false negative findings (type-II error for non-parametric tests). The potential tendency of the IMU to underestimate or overestimate gait parameters was analysed computing Confidence Intervals at 95% (95% CI); error measures as the Mean Absolute Error (MAE) and the Root Mean Square Error (RMSE) were computed (Chai and Draxler, 2014). Non-parametric Effect Sizes (ES) were computed to evaluate the practical significance of groups differences; a value of ES smaller than 0.3 was considered small, around 0.5 medium, greater than 0.8 large (Cohen, 1992). Lastly, a Spearman correlation analysis was conducted between the measurements returned by the two systems. The significance level was set at $\alpha = 5\%$ for all tests.

3. Results

No differences between the right and the left side were found for any variable ($p > 0.05$), therefore right and left values of bilateral variables were pooled.

Median and Interquartile Range (IQR) of the variables detected by the two systems are reported in Table 2, as well as the results of the Wilcoxon test, the Confidence Intervals, the error measures (ES, RMSE [%], MAE [%]) and the results of the Spearman correlation. All the gait variables measured with the two systems resulted to be not statistically different, with the exception of the gait velocity ($p < 0.05$); prob-ability of type-II error was lower than 0.2 except for stance/swing and stride duration. Positive, high correlations were obtained for cadence, velocity, stride duration and stride length; positive, moderate correla-tion for the other parameters. All correlations were statistically sig-nificant.

4. Discussion

The present study evaluated the performance of a commercial IMU-based gait analysis system in assessing spatiotemporal parameters during walking in PD subjects, compared to an optoelectronic GA system. The reliability of a sensor depends not only on its accuracy *per se*, but also on its accuracy relative to the variability of the measured system. In healthy subjects, IMU-based measurements were previously found to be sufficiently accurate in the determination of basic gait parameters in 22 healthy subjects (Bugané et al., 2012) and in a cohort of 10 young and 10 old adults (Mariani et al., 2010). However, gait in patients with PD is generally deemed with higher variability than in healthy subjects (Peterson and Horak, 2016; Hausdorff et al., 2003). Thus, it is useful to evaluate the capability of a new commercial IMU system to detect gait parameters in such specific population. Our comparison showed that the IMU was able to reliably measure most spatiotemporal gait parameters, while seemed to be less accurate in computing walking speed. Furthermore, although some parameters detected by the two systems were not significantly different, the error measures associated to their comparison resulted practically not negligible.

4.1. Optoelectronic system vs. IMU

The parameters detected by the two systems were comparable, with no statistical significance ($p > 0.05$, Table 2), with the exception of the walking velocity, which was significantly higher in the measurements by the wearable system ($Velocity_{3D\text{-}GA} = 0.72\ (0.27)$ m·s^{-1}, $Veloci\text{-}ty_{IMU} = 0.86\ (0.26)$ m·s^{-1}); the related ES and MAE values were larger than 0.8 and 10%, respectively (Table 2), indicating a practically sig-nificant difference between 3D-GA and IMU.

Although spatiotemporal parameters as stride length, step duration, stance and double support duration did not show statistically significant differences (Table 2), we obtained MAE values higher than 10%; these

constitute notable differences between the accurate measurements detected by the 3D-GA ground truth and those obtained from the wearable system. The stride length and the step duration also showed high RMSE (0.13 m and 11%, respectively). However, most of the boundaries of the percentage change 95% CIs crossed the zero value, indicating a substantial overlapping of the results; consistently, the Spearman correlation analysis showed a good correlation between the two instruments for all measured variables, except for the step duration.

It is worth noting that type-II error probability was fairly high (> 0.2) just for few parameters. This is common when applying non-parametric tests. It should be also considered that the highest values of type-II error probability are matched with p-values higher than 0.1, thus for these variables (stance, swing and stride duration) we cannot state neither the similarity nor the dissimilarity of IMU vs.3D-GA measures.

The inferential and descriptive statistical figures used in this investigation allowed to identify the conditions in which the IMU presented high error measures and/or low correlation coefficient, even when it was not strictly statistically different compared to the optoelectronic system. This study helped to gain a global picture on the performance and reliability of this specific commercial IMU device in detecting gait spatiotemporal parameters in patients with PD.

4.2. Strengths and limitations

Besides a relatively small sample size, the difference detected in some parameters was probably due to the different algorithm used in the two devices to detect gait events. The optoelectronic system para-meters were obtained by evaluating gait cycles separately, while the IMU parameters were computed by the provided software considering a contiguous set of cycles. This may be tricky especially when evaluating pathological gait, where the intra-subject variability can be high. As the IMU data (tri-planar accelerations and angular velocities) are different in nature to the markers trajectories recorded by motion capture systems, algorithms commonly used to compute final parameters are also markedly different and may have introduced additional variability between measures. Third, the partial loss of a pendulum-like gait pattern that may occur in pathological conditions, as in PD (Seyoung et al., 2009), may explain the difference in spatiotemporal parameters observed in this population. This highlights the need to improve the current algorithms, especially when the locomotion function is severely compromised – as in patients with PD.

Despite the discussed limitations, the analysed IMU system represents a promising and viable alternative to the standard gait analysis systems, also in clinical applications. Considering its intrinsic advantages (cheaper purchase price, cheaper cost per recording, portable system, real-life and laboratory-independent setting), there will be growing interest in using inertial in place of optoelectronic systems. This holds even more true when a continuous, daily monitoring of patients is required outside a gait-lab, or when a relevant number of data acquisitions needs to be performed.

Technological advancements in this direction will certainly allow to increase the use of wearable systems also in clinical and research environments. This will provide two major advantages: (a) overcome the intra-individual variability at different times of the day in a single patient due the disease fluctuations, thanks to prolonged recording times; (b) provide the medical staff with technology suitable to make accurate diagnoses, and to develop a more effective targeted therapy, thanks to objective, long-term measurements of treatment outcomes.

5. Conclusion

The main spatiotemporal gait parameters detected by the IMU were mostly comparable to the output of marker-based GA systems. Only one variable (velocity), was significantly higher when measured with the wearable system. Some parameters (e.g. stride length and step duration), although not statistically different, showed moderate values of MAE and RMSE.

However, the results of the comparisons between IMUs and gold standard 3D GA systems were encouraging. In fact, adopting such wearable IMU system can be feasible, especially in routine clinical analysis of PD and whenever a quantitative evaluation is needed, but a traditional Gait Analysis test is not viable. Even if the IMU system overestimated the walking velocity, being aware of this limitation allows to consciously employ the device in cases such as the evaluation of gait pre and post therapies, or to assess changes induced in patients by specific interventions.

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Conflict of interest

The authors declare that there is no conflict of interest.

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