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Abstract: The increasing average age emphasizes the importance of gait analysis in elderly populations. Inertial Measurement Units (IMUs) represent a suitable wearable technology for the characterization of gait by estimating spatio-temporal parameters (STPs). However, the location of inertial sensors on the human body and the associated algorithms for the estimation of gait STPs play a fundamental role and are still open challenges. Accordingly, the aim of this work was to compare three IMUs set-ups (trunk, shanks, and ankles) and correspondent algorithms to a gold standard optoelectronic system for the estimation of gait STPs in a healthy elderly population. In total, 14 healthy elderly subjects walked barefoot at three different speeds. Gait parameters were assessed for each IMUs set-up and compared to those estimated with the gold standard. A statistical analysis based on Pearson correlation, Root Mean Square Error and Bland Altman plots was conducted to evaluate the accuracy of IMUs. Even though all tested set-ups produced accurate results, the IMU on the trunk performed better in terms of correlation ($R \geq 0.8$), RMSE (0.01-0.06 s for temporal parameters, 0.03-0.04 for the limp index) and level of agreement (-0.01 s $\leq$ mean error $\leq$ 0.01 s, -0.02 s $\leq$ standard deviation error $\leq$ 0.02 s), also allowing simpler preparation of subjects and minor encumbrance during gait. From the promising results, a similar experiment might be conducted in pathological populations in the attempt to verify the accuracy of IMUs set-ups and algorithms also in non-physiological patterns.

Keywords: gait; healthy elderly population; inertial sensors; spatio-temporal parameters; accuracy

1. Introduction

Gait analysis consists of quantitatively assessing the human locomotion [1]. The detection of gait events (GEs) allows identifying different cycles and phases inside each walking trial. In normal gait, the heel-strike (HS) indicates the starting point of a gait cycle, and it marks the beginning of the stance phase. The toe-off (TO) marks the beginning of the swing phase [2]. After the identification of the time instants corresponding to GEs, gait spatio-temporal parameters (STPs) can be calculated [3]. The accuracy of gait analysis is strongly affected by the measuring instrumentations. During past decades, several tools have been proposed for gait analysis [4].

Literature endorses optoelectronic systems as the gold standard for the gait analysis. By means of infrared cameras capturing reflective markers positioned on the human body, motion is detected. These systems contribute to high accuracy and precision in measuring gait parameters [5]. Despite the optimal performance, optoelectronic technologies present some critical disadvantages, as the restriction to laboratory settings, the expensive cost, and the required expert operation. Wearable and markerless motion capture devices try to overcome these limitations.

Wearable sensor technologies have shown advantages in measuring human body motion in several applications [6–9]. Inertial sensors based on accelerometers, gyroscopes, and magnetometers [10–12] and foot insoles composed of pressure sensors [13] are examples of wearable devices. In addition to the reduced cost, the good reliability, and the limited invasiveness, these sensors allow the monitoring of human gait outside the laboratory setting and for long time and distances. Despite the great advantages of using inertial sensors for gait analysis, some open issues still exist. Indeed, Inertial Measurement Units (IMUs) require to define a suitable and reliable set-up, possibly with a limited number of units [14]. Moreover, a robust algorithm needs to be implemented for the GEs identification or the compensation of drift errors due to the double integration process when considering position.

Several previous studies focused on the implementation of IMUs set-ups and algorithms for the evaluation of STPs. The main differences among proposals refer to the number of sensors, sensor positioning (trunk, shank, and foot level) [15, 16], measured signals (accelerations and angular velocities) [17, 18], and signal processing methods (peak identification, zero crossing, filtered waveform, and mathematical assumptions) [19–23]. The developed algorithms have been strongly validated with experimental analyses.

More recent studies dealt with the comparison of different IMUs set-ups and algorithms to identify the most accurate and reliable one [23–25]. Mansour and colleagues [23] compared trunk-IMU and shank-IMU methodologies for STPs detection with respect to the force treadmill method. Results highlighted a greater accuracy of algorithms based on the trunk or shank accelerometers instead of shank gyroscopes [23]. Patterson and colleagues [24] evaluated the suitability of three IMUs locations, adding the alternative of a foot-IMU method. GEs detection from IMUs was compared to a standard force platform. Due to the higher level of correlation, results suggested that foot location might be considered the most appropriate methodology for calculating step time in clinical applications [24]. In 2018, Pacini Panebianco and colleagues [25] considered IMUs algorithms in a systematic review. Seventeen algorithms were classified based on sensor position, target signal, and computational approach. Shank- and foot-IMUs algorithms revealed higher accuracy and repeatability in GEs detection and stance time evaluation. However, contrary to a previous study [23], angular velocity-based algorithms showed significantly higher repeatability than acceleration-based ones, for HS and TO detection. The computational approach showed a strong dependency on sensor positioning [25]. However, previous works comparing different methodologies focused on the gait analysis performed by healthy young subjects and estimated a limited number of STPs [23–25]. Generally, healthy elderly subjects implement a compensatory strategy to prevent possible unbalance and loss of control. As a consequence, STPs are expected to be altered in elderly populations with respect to healthy young subjects. Considering that the global median age is increasing, as well as devices/services and studies focusing on active aging, a complete quantitative analysis of gait in elderly populations becomes fundamental, especially to choose the best IMU configuration in terms of accuracy. Furthermore, an elderly population of healthy individuals may constitute a valid “control” group, age-matched with respect to patients showing altered locomotion patterns [26]. To the best of the authors’ knowledge, no previous studies have estimated a large number of STPs by investigating and comparing the suitability of IMU set-ups and algorithms on healthy elderly populations.

The aim of the current study was the comparison of three different IMU set-ups, and correspondent algorithms, to a gold standard optoelectronic system (Gold Std), for the objective evaluation of gait spatio-temporal parameters in a healthy elderly population (> 65 years), walking at three different self-selected speeds (slow, normal, fast). The accuracy of IMUs set-ups and algorithms with respect to the Gold Std was assessed in terms of correlation, root mean square error (RMSE), and level of agreement. These analyses allowed the identification of the most appropriate IMUs set-up and algorithm.

2. Materials and Methods

2.1. Participants

Sixteen healthy elderly subjects (8 males and 8 females) participated in the experiment after giving their written informed consent. Four inclusion criteria were considered: (i) age over 65 years old, (ii) no declared neurological disorders, (iii) no musculoskeletal diseases in the last five years, and (iv) no prostheses.

Population characteristics were:

- Age: 68.3 ± 4.4 years, range 65-79 years;
- Height: 1.6 ± 0.1 m, range 1.48-1.90 m;
- Weight: 68.7 ± 13.4 kg, range 53-109 kg;
- BMI: 25.1 ± 3.0 kg/m^2, range 21-31 kg/m^2.

The study was approved by the Local Institutional Review Board. All procedures were conformed to the Helsinki Declaration.

2.2. Instruments

Two different motion capture systems were considered: an inertial system based on IMUs that considered 3 different set-ups, and an optoelectronic system based on 6 infrared cameras and 9 passive reflective markers, adopted as Gold Std.

2.2.1. Inertial system

Five MTx IMUs (Xsens, The Netherlands) were used for the test. Each of them contained a tri-axial accelerometer (±5 G), a tri-axial gyroscope (±1200 dps), and a tri-axial magnetometer (±75 µT). Noise density, as declared by the manufacturer, is 0.002 m/s^2/√Hz and 0.05 deg/s/√Hz for accelerometer and gyroscope, respectively. IMUs were fixed on the trunk, shanks, and ankles of participants (Figure 1), according to previous literature studies. In particular, the trunk-IMU was placed at T12-L1 level [16, 27], the shank-IMU on the proximal anterior part of the tibia [28, 29] and fixed with Xsens elastic bands. The ankle-IMU was held fixed in correspondence of the free Achilles tendon (above the insertion of the Achilles tendon into the calcaneum) using a tightly wrapped 3M™ Coban™ Self-Adherent Wrap. The position is slightly above the calcaneum, as it was instead in [30, 31].

IMUs on the trunk (TRN), right ankle (ANK_R), and left ankle (ANK_L) were oriented with the *x*-axis (x_{TRN}, x_{ANK_R}, and x_{ANK_L}) pointing downward, the *y*-axis (y_{TRN}, y_{ANK_R}, and y_{ANK_L}) directed toward the participant's right side and the *z*-axis (z_{TRN}, z_{ANK_R}, and z_{ANK_L})

pointing in the direction opposite to gait. IMUs on right (SHA_R) and left (SHA_L) shanks were oriented with the *x*-axis (x_{SHA_R}, x_{SHA_L}) pointing downward, the *y*-axis (y_{SHA_R}, y_{SHA_L}) directed toward the participant's left side, and the *z*-axis (z_{SHA_R}, z_{SHA_L}) pointing in the direction of gait (Figure 1). During the initial standing posture, IMUs were fixed to human body segments with their axes aligned, as much as possible, to the anatomical axes.

IMUs were connected in a chain through cables. In addition, the trunk-IMU was also connected to the Xbus Master, the control unit sending synchronous, sampled, and digital data to the PC via Bluetooth. Data were acquired through the Xsens proprietary software MT Manager with a sampling frequency of 50 Hz.

2.2.2. Optoelectronic system

The optoelectronic system was composed of two V120:Trio tracking bars (OptiTrack, USA) and 9 passive reflective markers with a diameter of 14 mm. Each bar was self-contained, pre-calibrated, and equipped with three infrared light cameras. Six markers were fixed on the feet of participants with adhesive tape (Figure 1): on the right (TOR) and left (TOL) toes, on the right (MAR) and left (MAL) lateral malleoli, and on the right (HER) and left (HEL) heels. Other 3 markers (A, B, and C) were placed on the floor, in order to define a Global Coordinate System (GCS) [32]. GCS originates in B and the *X*-axis was defined as the walking direction (Figure 2).

Each bar was connected to a separate PC. Data were acquired with the OptiTrack proprietary software Motive at a sampling frequency of 120 Hz.

**** Figure 1 near here ****

**** Figure 2 near here ****

2.3. Protocol

The experimental test was conducted indoor. First, a linear walking path of 6 meters was marked on the floor. Then, the two OptiTrack bars were positioned at the sides of this path, one in front of the other, at 6.5 m of distance. A capture volume of 2.5 m × 3.5 m was obtained (Figure 2), providing that cameras could capture approximately 3 gait cycles. A static recording was performed with OptiTrack bars, to obtain the coordinates of markers A, B, and C on the floor (Figure 2). Afterwards, the three markers were removed.

Subsequently, participants were asked to walk barefoot on the marked path, at 3 different self-selected speeds: slow, normal, and fast. For each speed, subjects performed 26 back-and-forth transiting in front of the cameras, in order to have at least 30 valid gait cycles. The order of the 3 speed-conditions was randomized for every subject. Data were acquired, at the same time, with the two motion capture systems. To synchronize the systems, subjects were asked to hit the floor with their right heel at the beginning of the acquisition, in order to identify an external common event.

2.4. Signal processing and data analysis

Signals from the two motion capture systems were synchronized in time through the right-foot hit event: the maximum peak of the ANK_R-IMU *x*-acceleration was shifted to overlap the minimum value of the HER marker vertical coordinate. Then, gait events were detected and spatio-temporal parameters were evaluated from data of both motion capture systems. Statistical analysis was performed to compare data from different set-ups and algorithms. Customized Matlab® routines were developed to implement all the signal processing steps and data analysis.

2.4.1. Gait events detection

The assessment of spatio-temporal parameters was based on the identification of two events: the impact of the heel on the floor (HS: heel strike), and the detachment of the toe from the floor (TO: toe off). The sequence of these gait events allows segmenting gait cycles (GC) and detecting the GC sub-phases (stance and swing) [2]. The detection of HS and TO, in both marker trajectories and IMU signals, was performed considering previous literature works [33][32][34][35][21][30][36]. These methods were chosen because of their several positive aspects: the suitability on both healthy and pathological subjects, the easiness of implementation, and the reduced number of analyzed signals. Differently from [33][32][34][35][21][30][36], raw (unfiltered) IMU data were used for gait events identification. In addition, only peak timing was considered and not their amplitude. Therefore, no IMU calibration during the data acquisition, neither IMU tilt correction in the post processing were applied since a perfect alignment with respect to the anatomical axes is not necessary [37].

1. *Optoelectronic system algorithm.* HS was defined as the first-time sample of the plateau in the heel-marker X-trajectory (Figure 3). TO was defined as the first sample after the plateau in the toe-marker x-trajectory [32, 33]. An additional check was performed verifying that HS and TO, identified through the horizontal coordinates (X-trajectory), matched the minimum peaks of the vertical coordinates (Y-trajectory) of markers on heels and toes. The double-check was implemented to strengthen the identification of gait events, which might be more challenging in elderly subjects. Considering that the markers on the left/right malleolus were visible only from the corresponding bar of the same side (lateral view), this was used to distinguish between left and right strides during gait.

2. *Inertial system trunk-IMU algorithm*. GEs were identified from the raw signal of the trunk IMU z-acceleration (a_z_{TRN}) (Figure 4A). In detail, the maximum peaks of this signal were identified as HS events, as suggested in [34]. Moreover, minimum peaks of the same signal were identified as TO events, as proposed by [35]. Afterwards,

based on [32][36], the distinction of right and left GEs was performed through the trunk-IMU angular velocity around the vertical axis (ω_x_{TRN}), by evaluating the alternance of positive and negative values corresponding to HS instants.

3. *Inertial system shank-IMU algorithm*. This algorithm was applied to the identification of gait events from the y-angular velocities of the two shank-IMUs (ω_y_{SHA}) [21]. HS events were identified as the peaks following the upward concaves, while TO events were identified as the peaks preceding the upward concaves (Figure 4B-C), as proposed by [21].

4. *Inertial system ankle-IMU algorithm*. The last algorithm was applied to identify gait events from y-angular velocities of the two ankle-IMUs (ω_y_{ANK}), as suggested by [36]. HS and TO events were detected as peaks following and preceding the upward concaves, respectively (Figure 4D-E).

**** Figure 3 near here ****

**** Figure 4 near here ****

2.4.2. Spatio-temporal parameters

From the detected gait events, 9 gait STPs and the average gait speed were calculated (Table 1). Except for average speed and limp index, all the other parameters were assessed separately for the right and left sides. Gait STPs were calculated for each gait cycle of each participant. For each gait speed, the STPs were then averaged across subjects.

**** Table 1 near here ****

2.4.3. Statistical analysis

Shapiro-Wilk test was implemented to verify the normal distribution of data ($p > 0.05$). To have ecological testing, slow, normal, and fast speeds were self-selected by each participant, and not paced by a metronome. For this reason, the values of gait speeds were estimated for each trial of each participant. In addition, for each subject, the intra-subject variation of speed was calculated as it follows:

$$\%\ speed\ variation_k = mean\left|\frac{(v_i - \bar{v})}{\bar{v}}\right|_k \times 100$$

where k=1:3 represents the walking-speed conditions of the subject (low, normal, fast), i=1:26 represents the walking trials of the subject (for a specific walking-speed condition k), $\bar{v}$ represents the average speed among the walking trials (for a specific walking-speed condition k).

The mean value resulted lower than 12% across the population, at each specific walking speed. Moreover, statistical differences among speeds were assessed with one-way ANOVA and post-hoc Tukey test (independent variable: group of elderly subjects; dependent variables: slow, normal and fast speeds). The level of significance was fixed at α=0.05. For each spatio-temporal parameter, mean and standard deviation values were calculated across the population, separately for each speed condition. In addition, the standard error was estimated to allow a direct comparison with the values obtained from studies considering a different sample size. Left and right sides were considered separately to assess the gait symmetry in all subjects. Subsequently, a two-way MANOVA (α=0.05) and a post-hoc Tukey test were used to test the effect of the speed of the measurement system and of their interaction on STPs.

The accuracy of IMU algorithms was assessed by evaluating the level of correlation, the RMSE and the level of agreement with respect to the gold standard. The level of correlation was calculated through the Pearson correlation coefficient. Consistently with the literature, the positive correlation was considered strong with a coefficient of correlation $R \geq 0.7$ [38]. The RMSE was estimated for all spatio-temporal parameters. The level of agreement was obtained with a Bland-Altman style analysis for all STPs. The Bland-Altman plot represents the mean of measures (x-axis) with respect to their differences (y-axis). The error was calculated as the difference between the mean value estimated with the optoelectronic Gold Std and the mean value estimated with each IMUs algorithm. The sign of the error value allowed to identify an over-estimation (negative sign) or an under-estimation (positive sign) of each IMU algorithms. Mean and standard deviation values of errors were evaluated for all parameters. Limits of Agreement (LoA) were included to depict the range of variability of the IMUs values that could be expected in comparison with the gold standard.

3. Results

When analyzing the recorded signals, two male participants had to be excluded, since less than 30 valid gait cycles were acquired. Therefore, the subsequent analysis was performed on 14 subjects (6 males and 8 females).

Slow (0.74 ± 0.14 m/s), normal (0.92 ± 0.16 m/s) and fast (1.23 ± 0.22 m/s) self-selected speeds were significantly different (one-way ANOVA, $p < 0.001$). The post-hoc Tukey test revealed significant difference among all the speeds ($p < 0.001$ in the comparison of slow-fast and normal-fast; $p = 0.03$ in the comparison slow-normal). Table 2 reports the mean and standard deviation of STPs, as derived from Gold Std, trunk-IMU (TR), shank-IMUs (SH), and ankle-IMUs (AN) systems. Table 3 reports the results of the two-way MANOVA to test the effect of speed ($p \leq 0.001$ for all STPs, except for limp index), the effect of the used measurement system ($p \leq 0.001$ for swing time), and the effect of speed-system interaction ($p > 0.05$ for all STPs). The Tukey post-hoc test revealed significant differences among all speeds. Considering the IMU systems, the ankle-IMU produced significant differences for right and left stance time and swing time ($p < 0.001$), in all speed conditions, while the trunk-IMU revealed significant differences for left and right swing time only at fast speed. Figure 5 shows STP mean and standard error at each walking speed and it sums up the obtained statistically significant differences.

Table 4 shows the Pearson correlation coefficient (R) between the gold standard and each of the three IMUs set-ups (trunk: $0.81 \leq R \leq 0.99$, shank: $0.53 \leq R \leq 0.99$, ankle: $0.87 \leq R \leq 0.99$) for temporal parameters, averaged between right and left sides. In addition, Figure 6 depicts the graphical representation of the correlation. Table 5 shows the RMSE values for all STPs and all walking speeds. To further compare the accuracy of the different measurement systems against the gold standard, Figure 7 reports Bland-Altman plots, for each STP and walking speed.

**** Table 2 near here ****

**** Table 3 near here ****

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4. Discussion

The aim of the present work was the comparison of gait spatio-temporal parameters obtained by three different IMUs configurations and a gold-standard optoelectronic system. STPs were evaluated in a healthy elderly population walking at three different self-selected speeds (slow, normal, and fast). The accuracy of the three IMUs configurations was assessed based on: the level of correlation, the RMSE and the Bland Altman plots. Due to the significant difference among speeds (p-value $\leq$ 0.001), the following analyses were conducted separating the gait trials in the three walking-speed conditions.

Mean and standard deviation values of STPs (Table 2 and Figure 5) are consistent with those reported by previous studies [34, 39], typical of a physiological gait. In particular, the limp index, which quantifies gait symmetry, shows a value close to 1 for every investigated subject (Table 2 and Figure 5), as it is expected in a healthy population.

The dependence of STPs from speed is well documented in literature [14, 40, 41]. In this work, all STPs except for the limp index demonstrate a significant influence of gait speed (Table 3 and Figure 5). Moreover, always in accordance with the literature [42], the limp index is not affected by gait speed in this population of healthy elderly subjects. Due to these previous considerations about the limp index and the confirmed symmetry, STPs of right and left sides were averaged. Considering the dependence of STPs from the adopted measurement system, only swing time demonstrate a significant influence (Table 3). The ankle-IMU revealed differences in stance time and swing time with respect to the Gold Std, at all speed conditions (Figure 5). Hence, the ankle-IMU can be considered the less appropriate configuration in detecting gait sub-phases. The absence of a significant interaction between speed and system (Table 3) highlights the validity of the results independently from the adopted measurement system.

Overall, strong correlations between IMU estimations with respect to Gold Std are found almost in every configuration (Figure 6 and Table 4). More specifically, trunk- and ankle-IMUs show Pearson correlation coefficients in the range 0.81-0.99. The shank-IMUs also show strong correlations (>0.7), except for the swing time at normal speed (0.53) and the stance time at fast speed (0.69).

Among spatio-temporal parameter, Stride time and Step time show the highest Pearson correlation coefficients with respect to Gold Std.

Considering the walking-speeds, the highest correlation with the Gold Std was found at slow speed. Indeed, the walking speed influences the waveform of acceleration and angular velocity. At slow speed, signals show clearer peaks in correspondence of the gait events.

The presented results are consistent with those reported in a previous work [24] for slow and normal speeds, in which only the step time parameter was considered.

The estimation of RMSE comparing IMU systems and the gold standard demonstrates the accuracy of all the applied algorithms. As Table 5 shows, all algorithms produced small RMSE values (0.01-0.07 s for temporal parameters, 0.02-0.04 for the limp index). The evaluation of gait spatio-temporal parameters tends to be more accurate for faster walking speeds in accordance with [23]. In Bland Altman plots (Figure 7), errors were estimated as differences between Gold Std and IMUs values. The sign of differences indicates an underestimation (+) or an overestimation (-) of values. Overall, the trunk-IMU provides the best accuracy (both in terms of 95% LoA and bias), except for the stride time at slow speed. On the contrary, the shank IMUs shows the worst performance (both in terms of 95% LoA and bias). The ankles-IMUs algorithm shows the largest bias (mean error) in most parameters and speed conditions. However, all three IMU locations provided an accurate (low mean error) and repeatable (low standard deviation error) estimation of spatio-temporal parameters, when comparing the obtained results with [24] and [25].

Overall, the three IMU set-ups showed a good accuracy, although slight differences could be observed among their measurements. The position of the sensors has an impact on the recorded linear acceleration and angular velocity. Since all the algorithms are based on these signals for gait events detection, the results might be influenced by positioning. Indeed, even if sensors are placed in correspondence of the same anatomical landmark for every subject, the axes orientation of IMU sensors can be affected by the anatomical characteristics of each tested subject. Nevertheless, as already mentioned in the description of the algorithms, the gait event recognition is based on the peak timing, and not on their amplitude.

This should mitigate the influence of the sensors positioning on the final results. However, peaks might be less pronounced and thus less easy to detect. Consequently, detection errors might be larger. In the present study, shank-IMU positioning, and its y-axis orientation are related to the flat plane of the tibia, which might differ among subjects, potentially influencing the results. Moreover, heel-strike and toe-off gait patterns are intrinsically subject-dependent and this could be reflected in an easier or more difficult GE recognition. Similarly, the choice of positioning the ankle-IMU on the Achilles tendon might influence the final results. The alternative choice of positioning the ankle-IMU over the bony prominence of the first cuneiform might reveal a higher level of stability and repeatability [43]. However, the free Achilles tendon was chosen as sensor positioning because it is easier and less invasive. To obviate the possibility of sensor movement, tightly wrapped bands were used to prevent relative movement between foot and sensor, although less. For all the above considerations, the identification of GEs may have a time shift due to the adopted IMU configuration. In the case of a systematic error, some STPs (i.e., stride and step time) are not affected. Regarding STPs (i.e., swing and stance time) that are affected by a systematic error, it should be mentioned that clinical applications often focus their interest on estimating the variation of STPs between different gait sessions. Such variations can still be detected if the same IMU configuration is used.

Some study limitations can be highlighted. The experimental population size was small. In addition, gait trials were performed in a laboratory setting, due to the necessity of using the optoelectronic system as gold standard. This resulted in a constrained gait path (non-ecological), which can be overcome by using plantar sensors as gold standard, to allow measuring in different settings, conditions, and longer time periods.

5. Conclusions

All the tested IMU set-ups demonstrated good performance for gait analysis in healthy elderly. Despite all the IMU configurations produced a good level of accuracy, the trunk-IMU system seems to outperform the ankle-IMU and shank-IMU. In addition, the use of a single inertial measurement unit might be beneficial in terms of ease of use, simplicity of signal processing, and cost. This may be of help for the monitoring of daily activities and tele-rehabilitation through wearable technology. In addition, the faster preparation of patients represents a key aspect, especially for clinical gait analysis.

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