Gait Phases Detection in Elderly using Trunk-MIMU System

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Abstract: The increasing interest towards wearable Magnetic Inertial Measurement Units (MIMUs) for gait analysis is justified by their low invasiveness, confirmed repeatability and complete independence from laboratory constraints. However, some crucial doubts about the identification of a suitable sensor set-up and algorithm in different gait conditions and populations still exist. In this context, the principal aim of the present study was to investigate the effect of different walking conditions on the accuracy of gait phases detection with a trunk-MIMU system. Eleven healthy elderly subjects performed gait trials in four different walking conditions (fast speed, normal speed, slow speed and normal speed with dual-task). A stereophotogrammetric system was adopted as gold standard. The accuracy of the estimation of stance and swing phases was evaluated from the comparison of trunk-MIMU to the stereophotogrammetric system. Mean error values smaller than 0.03 s confirmed the accuracy of the trunk-MIMU algorithm for an elderly population. Consequently, trunk-MIMU system can be considered suitable for the characterization of gait phases in elderly subjects regardless of walking conditions.

1 INTRODUCTION

During the last decades, different applications highlighted the central role of locomotion in human daily activities, generating a strong interest towards gait analysis. Several studies have been directed to assess standard gait patterns (Davis 1997), to identify the conditioning factors (Hebenstreit et al. 2015), to select systems and set-ups (Benndorf, Gaedke, and Haenselmann 2019), as to characterize human gait phases and kinematics (Kadaba et al. 1989). In particular, clinical gait analysis is usually aimed at monitoring rehabilitation processes (Moon et al. 2017), characterizing normal and pathological locomotion (Prakash, Kumar, and Mittal 2018; Shirakawa et al. 2017) and verifying therapeutic treatments (Gastaldi et al. 2015). The objective measurement of gait parameters supports clinical experts during the observational assessment of gait. Human locomotion can be mainly described by the identification of two gait events: the heel strike (HS) and the toe off (TO). In detail, the detection of gait events allows first to divide each walking trial into consecutive cycles, then to estimate different gait phases. The gait cycle (GC) of each limb can be mainly divided in stance and swing phases. The first one starts with the load acceptance from the foot and lasts the entire time the foot is in contact with the ground, while correspondingly the limb bears part or whole human weight. The swing phase depicts the time period of foot oscillation without floor contact. Durations of stance and swing phases are expressed as percentages of the GC duration. Generally, in healthy adults the stance phase represents approximatively the 60% of the GC, while the swing phase the 40% of the GC.

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Stance and swing phases can be crucially influenced by gait velocities, external disturbs or dual-tasks (Liu et al. 2014). In addition, previous studies highlighted the aging effect on gait phases (Aboutorabi et al. 2016). Healthy elderly people demonstrated a compensatory strategy to overcome instability and loss of control through the variation of spatio-temporal parameters. The percentage duration of the stance phase is increased, entailing a reduced percentage duration of the swing phase. More in general, in clinics, altered patterns of locomotion are assessed by a different percentage distribution of time in the two phases (Trojaniello et al. 2014). Another important aspect of pathological gait is the symmetry between right and left limbs. However, reduced symmetry is not clearly associated with age in healthy elderly populations (Aboutorabi et al. 2016).

During past decades, several tools have been used for the analysis of human locomotion, especially to add an objective measure to the observational gait evaluation (Akhtaruzzaman, Shafie, and Khan 2016). Literature confirms optoelectronic systems as the gold standard technology thanks to their high accuracy and precision. Several improvements, methodologies and innovative biomechanical models are proposed nowadays to be implemented with optoelectronic systems for deeper kinematic and dynamic investigations (Panero, Gastaldi, and Rapp 2018). However, these systems have some crucial disadvantages, as the cost, the restriction to the laboratory environment and the required expert operation.

Recently, wearable sensor technologies such as Magnetic Inertial Measurement Units (MIMUs) have shown promising results in measuring human body motion with limited cost and invasiveness, with a good reliability and without laboratory constraints (Cereatti, Trojaniello, and Croce 2015; Digo et al. 2020; Petraglia et al. 2019; G. Yang et al. 2019). The use of wearable systems may be more suitable for monitoring the subject for longer observation periods and during daily activities. However, some open issues related to MIMUs still exist, such as the definition of a suitable and reliable set-up (S. Yang and Li 2012) and the implementation of a robust algorithm for gait phases identification (Caldas et al. 2017) that can be used in different conditions. Several previous studies have proposed MIMUs set-ups and algorithms to assess gait parameters both in healthy and pathological subjects.

A previous pilot study has been conducted with three healthy young subjects performing gait trials for the evaluation of two MIMUs set-ups and associate algorithms for gait events detection (Panero et al. 2018). In the first set-up one MIMU was positioned on the trunk, while in the second set-up two MIMUs were fixed on heels. Results have demonstrated the suitability of the two MIMUs set-ups and algorithms, but the set-up involving the trunk-MIMU showed the best accuracy and simplest usage. Considering these results and concentrating on the trunk-MIMU set-up, the analysis has been extended to a larger population of healthy elderly subjects, in order to validate the robustness of the algorithm in different walking conditions.

Consequently, the aim of the current study deals with the analysis of gait speeds and conditions effects on the accuracy of gait phases detection with a trunk-MIMU system. Eleven healthy subjects over 65 years old performed gait trials in four different walking conditions. Stance and swing phases have been monitored as outcomes of interest. Accuracy and error quantification, obtained from the comparison of trunk-MIMU results with an optoelectronic reference system, are analysed.

2 MATERIALS & METHODS

2.1 Participants

Eleven healthy elderly subjects (4 males and 7 females) participated in the research 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 internal prostheses. The study was approved by the Local Institutional Review Board. All procedures were conformed to the Helsinki Declaration. Mean and standard deviation values of subjects' age, height, weight and Body Mass Index (BMI) are reported in Table 1.

Table 1: Subjects' data (mean ± standard deviation).

Age (years)	Height (m)	Weight (kg)	BMI (kg/m^2)
68.8 ± 5.0	1.6 ± 0.1	70.3 ± 14.9	25.8 ± 3.1

2.2 Instruments

Two motion capture systems were adopted for the study: an inertial system consisting of one MIMU and a stereophotogrammetric system composed of six infrared cameras and nine passive reflective markers.

2.2.1 Inertial System

One MTx MIMU (Xsens, The Netherlands) containing a tri-axial accelerometer (range ±5 G), a tri-axial gyroscope (range ±1200 dps) and a tri-axial magnetometer (±75 μ T) was used for the test. The MIMU was fixed on trunk (TRN) of participants at the level of T12-L1 vertebrae, with an elastic band provided by the Xsens kit. The sensor was oriented with the vertical x-axis pointing downward, the medio-lateral y-axis directed to the right side of participants and the anterior-posterior z-axis pointing in the opposite direction of the gait (Figure 1A). The MIMU was connected to the Xbus Master, the control unit able to send 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 Stereophotogrammetric System

The stereophotogrammetric system adopted for the test was composed of two V120:Trio tracking bars (OptiTrack, USA) and nine passive reflective markers with a diameter of 14 mm. Each bar was self-contained, pre-calibrated and equipped with three cameras able to detect infrared light.

Six markers were fixed on feet of participants with adhesive tape (Figure 1B): two on toes (right toe = TOR, left toe = TOL), two on malleolus (right malleolus = MAR, left malleolus = MAL) and two on heels (right heel = HER, left heel = HEL). Other three markers (A, B and C) were placed on the floor in order to define the Global Coordinate System (GCS) in which to report data recorded by the bars (Panero et al. 2018). Each bar was connected to a separate PC. Data acquisition was made with the OptiTrack proprietary software (Motive) with a sampling frequency of 120 Hz.

2.3 Protocol

The experimental test was conducted indoor. The two OptiTrack bars were located one in front of the other parallel to a 6-meters linear walking path traced on the floor. Consequently, the obtained captured area was 2.5 m x 3.5 m, to guarantee the acquisition of at least three steps for each transition in front of the cameras. A static recording was made to obtain the coordinates of the three fixed markers A, B, C on the floor (Figure 2).

Participants were first asked to hit their right heel on the floor to define an external event to synchronize the stereophotogrammetric system and the inertial system. Subsequently, subjects walked barefoot on the linear path in four conditions. In the first three conditions, they were asked to walk at different self-selected speeds: fast, normal and slow. In the fourth condition, participants were involved in a dual-task condition at self-selected normal speed. While walking, they were asked many questions about their lives and habits. For each walking condition, all subjects performed 26 transitions in front of the cameras. The order of the four sets of walking conditions was randomized for all subjects. Coordinates of markers and signals of MIMUs were acquired at the same time with the two motion capture systems.

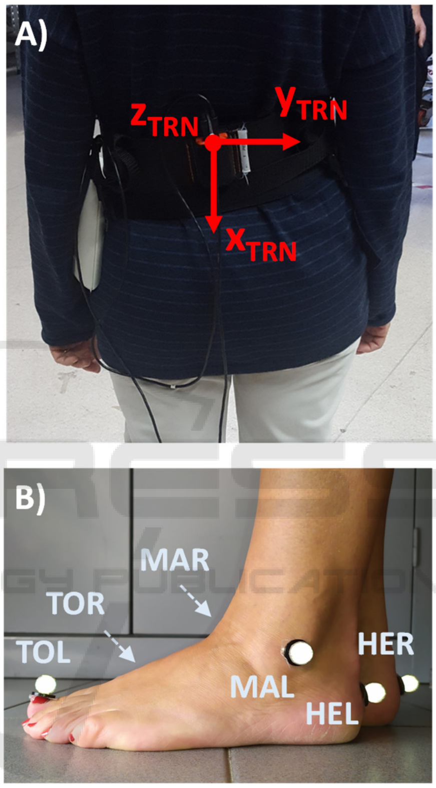

Figure 1: Configuration of trunk-MIMU (A) and markers (B) on body of participants.

2.4 Signal Processing and Data Analysis

Signal processing and data analysis were conducted with customized Matlab routines. Considering the static recording of markers on the floor, a transformation matrix was built and used to express in the GCS all markers trajectories collected during gait sessions. Afterwards, the temporal synchronization of data from the two motion capture systems was guaranteed through the initial impact of the right foot on the floor (Panero et al. 2018). Gait events were then separately identified from data acquired by the MIMU system and the optoelectronic system. This detection was made with two algorithms inspired by previous literature works. Considering the optoelectronic system, HSs and TOs were identified from horizontal and vertical coordinates of heels and toes markers, respectively (Panero et al. 2018; Veilleux et al. 2016). Since each bar captured the lateral view of one side of the body, markers on malleolus were used to distinguish between right and left sides during gait. As regards the MIMU system, gait events were identified from the anterior-posterior acceleration signal of trunk-MIMU. More in detail, HSs and TOs were detected as maximum and minimum peaks of this signal, respectively (Panero et al. 2018; Zijlstra and Hof 2003). In addition, the distinction between right and left gait events was made by considering the alternation sign of trunk-MIMU angular velocity signal around the vertical axis (McCamley et al. 2012; Panero et al. 2018).

For each subject, a total number of gait cycles between 150 and 300 was collected. First, for each participant in each testing condition, the average walking velocity was calculated as the ratio between the total gait path and the travel time. Then, for each testing condition, inter-subjects mean and standard deviation of walking speed values were estimated. Afterwards, using gait events obtained with both algorithms, spatio-temporal parameters of stance and swing times were assessed for each gait cycle of each participant in all walking conditions. For both stance and swing times, mean and standard deviation values were calculated intra- and inter-subjects for both right and left sides. Moreover, the symmetry of participants was evaluated by estimating the limp index as the ratio between right and left stance times. According to this confirmed symmetry, values of stance and swing times were averaged between right and left sides and represented through bar diagrams. In addition, stance and swing durations were estimated as percentages of the GC, in order to evaluate the effect of age on gait phases distribution.

The accuracy of the MIMU algorithm was evaluated as the relative error between the mean value estimated with the optoelectronic system and the mean value obtained with the MIMU system, for each participant. Subsequently, inter-subjects mean values of errors were calculated in all walking conditions. The sign of the error allowed the differentiation between overestimation (negative sign) and underestimation (positive sign) with respect to the reference value. Finally, a stem graph representation was adopted in order to compare errors for both stance and swing times in different walking conditions.

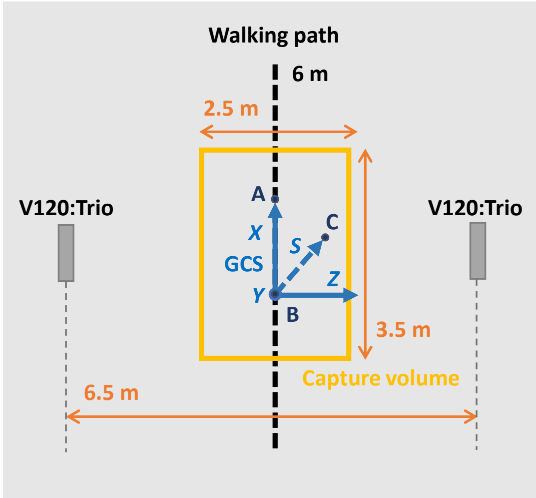

Figure 2: Top view of the setting with distance between OptiTrack bars, measures of the capture volume, length of walking path and GCS definition.

3 RESULTS

Table 2 depicts average and standard deviation values of walking speed (m/s) for the tested population in all the four conditions.

Table 2: Inter-subjects mean and standard deviation values of walking speed (m/s) in four conditions.

Speed (m/s)	Mean ± St. Dev.
Fast	1.16 ± 0.16
Normal	0.87 ± 0.12
Slow	0.74 ± 0.14
Dual	0.82 ± 0.15

Figure 3 shows inter-subjects mean and standard deviation values of stance and swing times (s) estimated with both OptiTrack and trunk-MIMU in all walking conditions. In Figure 4, two stem graphs represent mean errors for stance and swing times in all walking conditions (red circle for fast speed, green diamond for normal speed, blue square for slow speed and black pentagram for dual-task).

Table 3 contains inter-subjects mean and standard deviation values of limp index, stance duration (% GC) and swing duration (% GC) obtained from the two algorithms in all walking conditions.

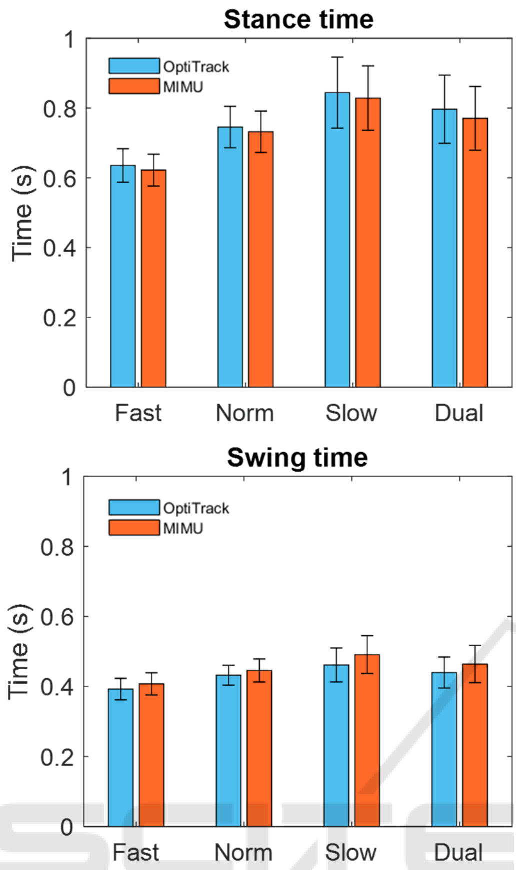

Figure 3: Stance time and swing time estimated in different walking conditions with OptiTrack (blue) and trunk-MIMU (orange) systems.

4 DISCUSSIONS

The main aim of the current study was to evaluate how the accuracy and robustness of a trunk-MIMU algorithm in gait phases identification are influenced by four different walking conditions (speeds and dual-task). In order to fulfill this purpose, inter-subjects mean and standard deviation values of walking speeds (Table 2) were calculated. As reported by Aboutorabi and colleagues, a walking speed of 1.30 m/s can be considered the standard reference value for normal walking in healthy adults (Aboutorabi et al. 2016). Moreover, they referred to previous studies showing a loss of gait speed based on age (1.2%/year). In the present work, inter-subjects mean walking speed in normal condition (0.87 m/s) confirms this reduction provoked by age. Moreover, even the registered walking speed in fast condition (1.16 m/s) is lower than the reference value of normal walking speed in healthy adults. In the dual-task condition, walking speed of subjects (0.82 m/s) was lower than the one of normal condition (0.87 m/s), but higher with respect to the slow speed condition (0.74 m/s). This aspect could be justified considering that participants were involved in answering questions and consequently were less focused on walking. Deeper investigation comparing normal and dual-task conditions with a larger population might demonstrate the significance of this difference.

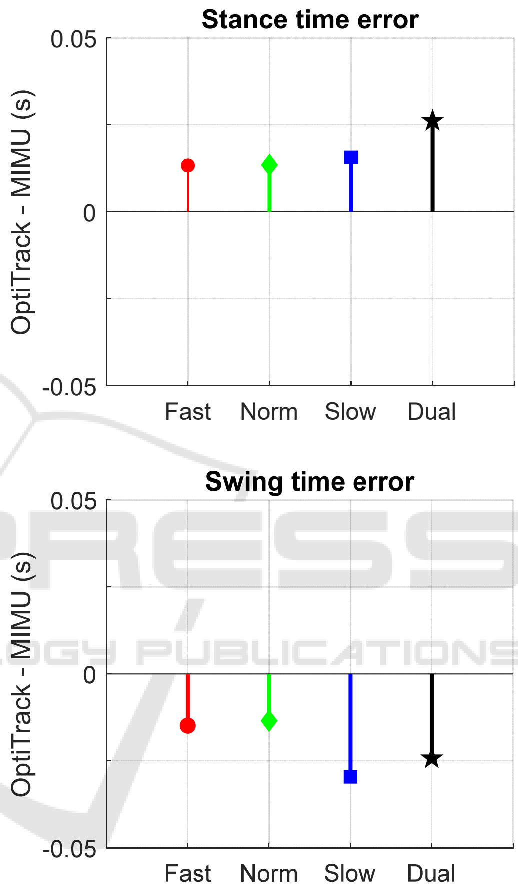

Figure 4: Errors of trunk-MIMU algorithm with respect to OptiTrack for both stance time and swing time in the four walking conditions.

The effect of age on symmetry has been previously investigated by different studies (Aboutorabi et al. 2016). In the present work, the symmetry of participant was evaluated by estimating the limp index in all walking conditions both with trunk-MIMU and OptiTrack (Table 3). Since inter-subjects mean values of limp index were always around 1 as expected in a healthy gait, symmetry of participants was confirmed. Consequently, right and left values of stance time and swing time (Figure 3) and percentage durations (Table 3) were averaged.

Table 3: Limp index, stance duration (%GC) and swing duration (%GC) estimated by OptiTrack and trunk-MIMU systems in all walking conditions (inter-subjects mean ± standard deviation).

	Fast		Normal		Slow		Dual	
	OptiTrack	Trunk-MIMU	OptiTrack	Trunk-MIMU	OptiTrack	Trunk-MIMU	OptiTrack	Trunk-MIMU
Limp index	1.01 (0.03)	1.01 (0.03)	1.00 (0.01)	1.01 (0.03)	1.01 (0.03)	1.00 (0.04)	1.00 (0.02)	1.01 (0.04)
Stance duration (%GC)	61.76 (1.42)	60.44 (1.61)	63.20 (1.66)	62.09 (2.40)	64.57 (1.70)	62.77 (2.01)	64.31 (1.71)	62.39 (2.13)
Swing duration (%GC)	38.24 (1.42)	39.56 (1.61)	36.80 (1.66)	37.91 (2.40)	35.43 (1.70)	37.23 (2.01)	35.69 (1.71)	37.61 (2.13)

Low cost, low invasiveness and confirmed repeatability of inertial sensors make them a suitable alternative to optoelectronic systems for gait analysis. Despite large investigations and many applications, some crucial gaps still exist for the identification of a robust and accurate sensor set-up configuration and algorithm that can be applied in different gait conditions and populations. Considering young subjects, the trunk-MIMU solution resulted to be the most suitable one (Panero et al. 2018). In the present study, stance time and swing time have been selected as outcomes of interest for the validation of accuracy and robustness of the trunk-MIMU algorithm and set-up on an elderly population. As Figure 3 shows, both stance time and swing time increase with the reduction of gait speed. In the dual-task condition, values of stance time and swing time are halfway between the correspondent ones of normal and slow speed conditions. Moreover, small standard deviation values depict a repeatability of the measure inside the tested sample of elderly subjects (Pacini Panebianco et al. 2018). Considering the accuracy in gait phases detection with the trunk-MIMU system with respect to the OptiTrack one, bar diagrams of Figure 3 show strong accordance between values of both stance time and swing time in all walking conditions. This correspondence could be evaluated with stem graphs in Figure 4. Smaller errors were obtained for conditions at fast (+0.01 s for stance time, -0.01 s for swing time) and normal speeds (+0.01 s for stance time, -0.01 s for swing time). Stance time error is greater in dual-task condition (+0.03 s), while the greater error for swing time was registered in slow speed condition (-0.03 s). However, in all walking conditions, errors are lower than 0.03 s for both parameters. In addition, stance time is always overestimated (positive sign of errors), while an underestimation interests the swing time (negative signs of errors). This aspect might be justified by the later detection of toe off performed with the trunk-MIMU, probably caused by less clear minimum peaks of the signal. Nevertheless, the overestimation of stance time and the underestimation of swing time demonstrate the constancy of the gait cycle duration. Better performance at fast and normal speeds could be explained by an easier identification of peaks of interest in acceleration and angular velocity signals used for HSs and TOs detection. Despite this aspect, the trunk-MIMU algorithm could be considered accurate for gait phases detection also in elderly subjects.

Considering Table 3, values of stance duration and swing duration obtained as percentages of GC were observed. Reference values of stance duration and swing duration in normal gait are 60% and 40% of the GC, respectively. The current elderly population shows an increased stance duration (around 63% GC for OptiTrack and 62% GC for trunk-MIMU) and a consequent reduction of swing duration (around 37% GC for OptiTrack and 38% GC for trunk MIMU) in normal walking condition. In faster walking speed, the reduction of stance duration with respect to normal speed can be underlined with both OptiTrack (around 62% GC) and trunk-MIMU (around 60% GC), with a resulting increase of swing phase duration. In slow walking speed, the increase of stance duration with respect to normal speed can be underlined with both OptiTrack (around 65% GC) and trunk-MIMU (around 63% GC), with a resulting reduction of swing phase duration. Finally, the walking condition with dual-task shows percentage times distribution similar to the slow speed condition, both for OptiTrack and trunk-MIMU.

5 CONCLUSIONS

In conclusion, the presented analysis confirms that the trunk-MIMU system is suitable for the characterization of gait phases not only in healthy young subjects (Panero et al. 2018), but also in an healthy elderly population. The trunk-MIMU system depicts small errors of stance time and swing time calculation at different walking conditions, revealing its accuracy and robustness. Moreover, the singular MIMU configuration might reveal advantages in terms of ease of use, limited cost and reduced invasiveness. For all these reasons, the trunk-MIMU system demonstrates to be a strategical and potential alternative to traditional stereophotogrammetric systems to evaluate gait phases.

The principal limitation of this study consists in the involvement of a small sample of participants. However, this limit is expected to be overcome in the future, by testing a larger number of elderly subjects and by considering the possibility to identify subgroups based on gender, healthy conditions and specific age.

Future perspectives will concentrate first on the evaluation of additional spatio-temporal parameters, including symmetry indices. Then, plans are to test the same MIMU set-up and algorithm on pathological populations, in order to define a complete protocol for the evaluation of rehabilitation progress and therapeutic treatments benefits.

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