A wearable multi-sensor system for real world gait analysis

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Abstract— **Gait analysis is commonly performed in standardized environments, but there is a growing interest in assessing gait also in ecological conditions. In this regard, an important limitation is the lack of an accurate mobile gold standard for validating any wearable system, such as continuous monitoring devices mounted on the trunk or wrist. This study therefore deals with the development and validation of a new wearable multi-sensor-based system for digital gait assessment in free-living conditions. In particular, results obtained from five healthy subjects during lab-based and real-world experiments were presented and discussed. The in-lab validation, which assessed the accuracy and reliability of the proposed system, shows median percentage errors smaller than 2% in the estimation of spatio-temporal parameters. The system also proved to be easy to use, comfortable to wear and robust during the out-of-lab acquisitions, showing its feasibility for free-living applications.**

I. INTRODUCTION

Recent literature has shown the relevance of characterising an individual's mobility in real-world conditions for a complete assessment of typical motor abilities [1,2]. This requires the use of activity monitors, *e.g.* devices including a single inertial measurement unit (IMU), that can be used without causing discomfort thanks to its limited invasivity. In this sense, the most convenient body positionings are trunk and wrist [3]. However, those locations present criticalities for the analysis of gait in terms of reliability, since the farther from the contact point the IMU is placed, the more difficult the estimation of gait-related parameters is. In this respect, the trunk is far from the ground but near to the centre of mass while the wrist is far from both ground and centre of mass. Although the scientific community is actively working on developing and improving algorithms for the above-mentioned solutions, algorithms validation is still performed in the laboratory while capturing simple gait tasks in spatially and temporally limited observation windows [4,5]. Testing single-sensor algorithms outside the laboratory would require a wearable system that is robust and accurate enough to be used as reference in validating other wearable technologies, *i.e.* a mobile gold standard

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(mGS). Ideally, a mGS system should include sensors that are able to directly detect the foot-ground contact. Moreover, it should be based on an optimal sensor's redundant configuration for drift reduction, enable statistical accuracy improvement and, also, be easy to be integrated with third-party devices.

With this aim, we developed a new wearable multi-sensor system (INertial module with DIstance Sensors and Pressure insoles, INDIP), which integrates multiple IMUs with pressure insoles (PIs) and time-of-flight distance sensors (DSs) [6,7], and the relative algorithm for the estimation of gait metrics. Exploiting the redundancy of information provided by different working principles, taking advantage of the latest technologies and state of the art algorithms, the INDIP system could represent a mGS ("best available" reference) for real-world gait assessment applications. In this work, we present the INDIP, both in terms of hardware and algorithms, along with a preliminary validation on five healthy participants showing the results from both in-lab and out-of-lab experiments.

II. MATERIALS AND METHODS

A. System description – INDIP system

The INDIP system includes three IMU (fs=100 Hz), two plantar pressure insoles (16 force resistive sensing elements, fs=100 Hz) and two time-of-flight distance sensors (range=0.2 m, fs=50 Hz). Each IMU includes a 3D accelerometer (±16 g), a 3D gyroscope (±2000 °/s) and a 3D magnetometer (±50 Gauss). Data are processed by an ARM® 32-bit Cortex®-M4 CPU and stored in an on-board 128 MB flash storage for up to twelve hours of data logging. The system allows the synchronisation with third-party devices via an external trigger.

B. Experimental set-up

The INDIP system was validated against the stereo-photogrammetric system (SP) during lab-based acquisitions to assess its accuracy. Then, data were collected during 2.5h out-of-lab acquisitions to evaluate its capabilities, robustness and usability in real-world conditions. Validation experiments have been carried out recruiting healthy participants at both the University of Sassari (Italy) and the University of Sheffield (UK). Ethics approval was granted by the University of Sheffield's ethics committee (Application 029143). All participants provided written informed consent, before taking part to the acquisitions. In this paper, preliminary results obtained from five participants (4 males and 1 female, age 35±8.9 years) from both in-lab and real-world data acquisitions are presented and discussed. For the in-lab experiments, each participant was equipped with SP markers and the INDIP system. The lower back IMU was positioned using an elastic belt, PIs were inserted in the shoes, feet IMUs were fixed to the shoe

Figure 1: a) INDIP foot positioning (MIMU, PI, DS); b) INDIP lower back positioning.

instep using a clip. The DSs were attached asymmetrically, pointing medially, with elastic belts to the shanks to avoid mutual interference (Fig. 1). A total of 12 markers were used: four markers on each foot, and four markers placed on a rigid cluster used as support also for the lower back IMU. For the free-living acquisition, participants were equipped with the INDIP system only (Fig. 1).

C. Experimental protocol

The lab-based protocol included different motor tests characterized by an increasing complexity. For the purposes of this study, four tasks executed at comfortable self-selected speed were considered (Fig. 2):

- Straight walk along a 5m path.
- L-test: the participant is asked to sit in a chair, stand up, walk straight, turn at a curved 90°, walk straight, turn again at a curved 180°, follow the circuit back to the chair and sit down.
- Surface test: the participant is asked to stand at the starting point and walk the circuit, passing over the carpeted mat, by turning around the cones and finish at the marked end point. The circuit is repeated twice.
- Hallway test: the participant is asked to stand at the starting point and walk to the other end of the walkway, stepping up and down off a step halfway through the path. At the end of the walkway, the participant will complete a sharp 180° turn and walk back along the walkway (again stepping up and down off a step) until reaching the end point.

The out-of-lab protocol included acquisition of data during unsupervised free-living for 2.5h, asking participants to perform the following activities: rise from a chair and walk to another room; walk to the kitchen and get something to drink; walk up and down stairs; walk outside for a minimum of 2 minutes; walk up and down an inclined path, if outside.

D. Data processing

A preliminary calibration procedure was applied to each of the INDIP sensors according to [8,9]. Before each data acquisition, all IMUs underwent to a 60s static acquisition to compute the bias of the gyroscope [10]. A trigger-based synchronisation procedure was applied to align the SP and INDIP data.

Spatio-temporal parameters were calculated from the INDIP data combining the information provided by different types of sensors, according to the following six main steps:

(i) *static/dynamic activity periods recognition*: used to discard the intervals in which there is no movement. The subject is "active" if the standard deviation of acceleration of
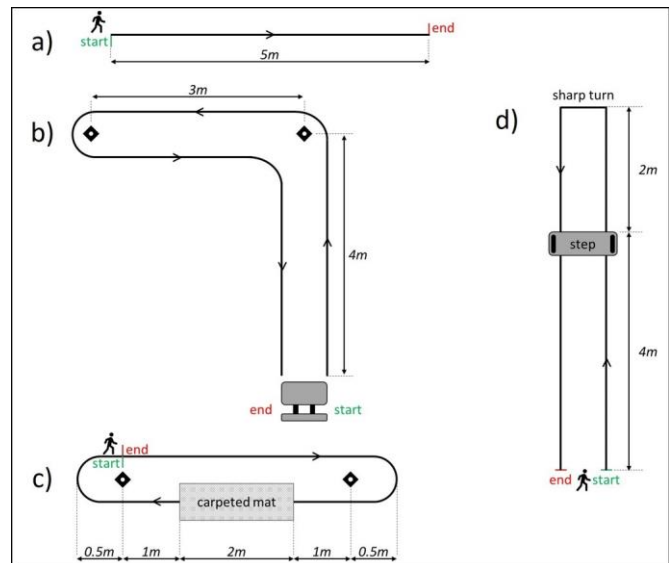

Figure 2: a) Straight walk; b) L-test; c) Surface test; d) Hallway test.

both lower-back and at least one foot is above an empirical threshold (0.7 and 2.1 m/s^2, respectively) [11,12].

(ii) *initial contact (IC) and final contact (FC) events detection*: based on PI and foot IMU, which are used separately to detect gait events. Then, results are combined, giving priority to PIs in case of events detected with both methods. The PIs method applies a cluster-based approach to describe foot contacts in a finer way. Specifically, a first derivative approach is used to identify rising/falling minima [13], used as reference points. Then, for each possible IC/FC, a sub-group of three rising/falling minima is selected, corresponding to the activation/deactivation of neighboring sensors. An IC corresponds to the third rising minimum of the subgroup, while an FC corresponds to the third falling minimum of the subgroup. For the IMU method, the algorithm proposed by Trojaniello et al. [14] was adapted to foot positioning.

(iii) *computation of spatial variables from feet-IMUs:* a Madgwick filter [15] is applied to inertial data, to provide reliable orientation estimates [16,17]. This algorithm uses the instants when the foot is stationary to re-initialize the orientation, thus limiting the integration period as well as the orientation drift. To minimize the convergence time, the orientation is initialized with an algebraic quaternion using the accelerometer measurements only, as described in Valenti et al. [18]. Then, velocity and displacement are obtained with a direct and reverse integration approach [14].

(iv) *stride identification and selection:* right and left strides are initially detected from the ICs. A stride selection is then performed by applying conditions on minimum and maximum stride duration, minimum stride length and maximum stride height. At this stage, DSs are used as "stride counters" and give additional information about the reliability of each measure [7].

(v) *definition of continuous walking periods (CWPs)*: these are defined by merging the information relating to right and left strides. Each CWP represents a gait portion with a minimum of two left and two right strides. For the in-lab acquisitions, each trial corresponds to a CWP.

(vi) *calculation of gait metrics:* these are computed for each CWP and include start and end time instants, duration, average cadence, path length and strides number. Stride duration, stride length and stride speed values, which are initially computed at stride level, are also averaged at a CWP-level to obtain additional gait metrics relative to that gait portion (i.e., average stride duration, average stride length and average stride speed).

For the SP-based method gait metrics were identified using skin-marker trajectories; IC and FC events were estimated as described in [19].

Firstly, the INDIP based-method was validated against the SP method using outcome results from in-lab experiments. For each gait metric at CWP level, the absolute percentage difference between INDIP and SP value was computed and then median percentage error, 25th percentile and 75th percentile across all the tests for all the subjects. Secondly, an evaluation of INDIP performances in real-world conditions was carried out by looking at system usability, capabilities and robustness. In this case, mean and standard deviation were computed considering all the CWP detected during the 2.5h acquisition for all the participants.

III. RESULTS

Results obtained from the comparison of INDIP and SP systems across the four in-lab tasks performed by the five healthy subjects are presented in Table I. Results regarding gait metrics obtained from the INDIP system for out-of-lab acquisitions are illustrated in Table II.

IV. DISCUSSION

In the INDIP preliminary validation against SP method, extremely low median percentage errors were achieved in the estimate of start and end instants (median percentage error 0.86% for the start, 0.21% for the end), duration (0.24%), average cadence (0.14%), and length (1.01%) for the identified continuous walking periods. Also for stride-level parameters, *i.e.,* average stride duration (0.14%), average stride length (1.21%) and average stride speed (1.10%), the median percentage error was very low, confirming the results of our previous study [20]. Moreover, both SP-based and INDIP-based methods detected the same number of strides. All the other variables showed a 25th percentile below 1%. The 75th percentile was lower than 1% for CWP end (0.65%), average cadence (0.32%) and average stride duration (0.32%); lower than 2% for start instant (1.09%), duration (1.22%), length (1.9%). Slightly higher differences were observed for average stride length and speed (2.49% and 2.52%, respectively). Previous studies focused their attention on validation of wearable systems including one or more sensors. The work from Li and colleagues [21] validated a multi-sensor system including, for each foot, a force sensor, an IMU and a range sensor using the SP system as reference system, but errors were 9.34% for stride length and 5.90% for stride velocity. In [22], Agostini et al. compared the performances of two IMUs with those of a footswitch-based system (STEP 32 footswitches), obtaining errors below 5% for cadence and stride time; and in [23], validated two feet-mounted IMUs against SP system obtaining average errors of 5.9% for stride length and 6.3% for stride speed. Panero et al.

TABLE I.   MEDIAN PERCENTAGE ERROR, 25TH PERCENTILE AND 75TH PERCENTILE FOR CWP PARAMETERS

Parameter	Median percentage error (%)	25th percentile	75th percentile
Start	0.86	0.46	1.09
End	0.21	0.14	0.65
Duration	0.24	0.07	1.22
Average cadence	0.14	0.07	0.32
Path length	1.01	0.49	1.90
Average stride duration	0.14	0.04	0.32
Average stride length	1.21	0.90	2.49
Average stride speed	1.10	0.70	2.52
Strides number	0	0	0

TABLE II.   MEAN AND MEAN STANDARD DEVIATION OF CWP PARAMETERS FROM INDIP SYSTEM FOR OUT-OF-LAB

Parameter	Mean ± Mean Standard Deviation
Duration (s)	70.60±144.42
Average cadence (steps/min)	80.06±21.67
Length (m)	76.82±169.93
Average stride duration (s)	1.38±0.27
Average stride length (m)	1.05±0.24
Average stride speed (m/s)	0.84±0.29
Strides number	114.37±246.86

[24] validated two methods, reporting only average error values obtained while using a single lower back IMU (0.01s on stride time) and for two shank mounted IMUs (0s on stride time). Fusca et al. [25] used a lower back IMU, obtaining average percentage errors of 5.7% for stride time, 4.9% for cadence, 13.5% for stride speed. All those studies considered only straight walking, while our in-lab testing protocol was very complex and conceived to stress the INDIP system. Except for the straight walk test, all motor tasks have been designed to include a variety of movements which are common in daily life, such as sitting on a chair, turns, different surfaces and obstacles (i.e., the carpeted mat and the step). Therefore, the errors obtained are extremely low considering the high variability that could be expected. Moreover, a structured sensitivity analysis was performed to optimise the gait metrics and to maximally improve our implementation.

The INDIP system can provide a variety of gait metrics by exploiting the redundancy of information provided by different types of sensors. This is done, for example, to increase stride detection specificity: each stride is identified from gait events detected with both PI and IMU algorithms

and then checked also using the DS. Only Li et al [21] proposed a similar solution but with very high errors compared to our results.

Results from out-of-lab experiments (Table II) show that the INDIP-based method can provide the same gait metrics as the in-lab experiments also of the free-living acquisition. Out-of-lab experiments were carried out without technical issues (no system crashes, unexpected events, data loss or uncompleted acquisitions). The system resulted to be comfortable and easy to use for every participant, since it required no interaction at all, which is also a great advantage for a mGS.

V. Conclusion

A novel multi-sensor wearable solution for the identification of continuous walking periods and the estimation of relevant gait metrics within them has been presented. Preliminary results obtained in five healthy subjects are very encouraging. An extensive validation of the INDIP system on more participants and a larger set of motor tasks including simulated daily activities is currently in progress. Moreover, future developments include the validation of the proposed system in a similar fashion (i.e., in-lab/out-of-lab acquisitions) on both healthy participants and people affected by different mobility impairments.

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