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ORIGINAL ARTICLE

Estimation of hike events and temporal parameters with body-attached sensors

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Abstract

The analysis of human gait is of fundamental importance for the monitoring and enhancement of athletes' performances. The kinematics and kinetics of human gait are mostly investigated with optical motion capture systems and force plates that require specialised laboratories and limit the possible test conditions. On the contrary, body-attached sensor networks provide an opportunity for long-term acquisitions in unsupervised, naturalistic scenarios. In this study, a wearable sensor network consisting of two wireless dataloggers and two instrumented insoles with eight pressure sensors each is used. Custom algorithms for the automatic detection of hike events and the estimation of the related temporal parameters based on sensors data are presented. The proposed algorithms were tested against laboratory measurements performed on an instrumented treadmill and showed relative errors of less than 2.5% in the estimation of stride time, step time and cadence. Higher relative errors were found in the estimation of stance and swing phases. The developed algorithms were also applied in a field study. In this paper data from one subject are considered. The aim of this research work is to provide an effective sensor-based methodology for the evaluation of gait parameters in naturalistic settings.

Keywords Gait analysis · Wearables · Pressure insoles · Temporal parameters · Hike events

1 Introduction

The acquisition of temporal-spatial parameters of bipedal human locomotion is fundamental for several disciplines. According to Prakash et al. [1], who provided a review of human gait based on the most important articles published in the last 20 years, the main areas of application of gait analysis are clinical diagnosis, geriatric care, rehabilitation, animation and sports. In sports, the analysis of human gait is used to monitor and improve the performance of athletes. For example, Dunn and Kelley [2] used vision-based gait analysis to automatically determine the position and timing of an athlete's foot contacts to calculate stride length, time, and speed.

Gait analysis can be performed with vision-based or sensor-based methods. Vision-based solutions such as Vicon Motion Capture (Oxford Metrics, Oxford, GBR) or BTS GAITLAB (BTS S.p.A., Milano, Italy) are considered the gold standard for accurate reconstructions of human movements. However, the vision-based technologies typically require specialised and often expensive laboratories and are subject to certain limitations, such as occlusions. In contrast, sensor-based gait analysis is usually less expensive and eliminates the need for specialised laboratories. It enables field testing and allows the subject to behave in a more naturalistic way. Sensor-based solutions also allow the analysis of gait kinematics and kinetics, as described by Tao et al. [3]. The gait kinematics are usually captured with inertial magnetic sensors such as the Xsens MTw Awinda (Xsens Technologies B.V., An Enschede, NLD) [4] or the Ultium Motion System (Noraxon USA, Scottsdale, US). Chew et al. [5], for example, used accelerations and angular velocities recorded with an inertial sensor attached to the right shoe

Giuseppe Sanseverino and Dominik Krumm have contributed equally to this work.

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of a runner to determine foot contacts, foot offs and related parameters. Notwithstanding the interesting results of this study, the results were only validated against an optical motion capture system. Therefore, this method only provided an estimate of the kinetic gait parameters and not a direct measurement. Furthermore, this study lacked proof of concept in the field and thus is to be considered valid only under simplified conditions. In example, changes of direction, stopping times and environmental conditions are not considered. Another inertial-based solution was also used by Caporaso et al. [6] to estimate temporal-spatial parameters of racewalking. For this purpose, they used an inertial measurement unit (IMU) attached to the base of the athletes' spine and custom algorithms to detect infringements based on the estimated parameters. However, only kinematic and not kinetic parameters were investigated in their study.

The gait kinetics are usually recorded with force plates that can measure ground reaction forces. As demonstrated by Willems and Gosseye [7], comparable precision can be achieved with instrumented treadmills such as the M-Gait (Motek Medical B.V., Houten, NLD) or the Tandem Treadmill (Advanced Mechanical Technology Inc., Watertown, US). However, these solutions are expensive and tied to a laboratory, which limits the possible test conditions. Pressure insoles are a more cost-effective solution, ensure high flexibility and offer the possibility to perform field measurements. These typically consist of a network of Force Sensing Resistors (FSR) attached to an insole. In a recent study, Howell et al. [8] presented a custom FSR-based insole for kinetic gait analysis and demonstrated the performance of such a low-cost device compared to laboratory measurements using marker-based motion sensing as reference for the lower limb joints moments and force plates as reference for the ground reaction forces (GRF). As a result, they found good agreement between the GRF measured with force plates and the ones estimated with recorded plantar pressure. However, the tests conducted by Howell et al. [8] were bound to a laboratory. Falbriard et al. [9] also used foot-worn inertial sensors to estimate temporal parameters of running in a laboratory study with several participants. Although their algorithms were validated against laboratory measurements carried out on an instrumented treadmill with built-in force plates, no field test was carried out to demonstrate the performance of their methodology.

In the framework of this work, the potential of Body-Attached Sensor Networks (BASN) for bipedal human locomotion analysis was to be further investigated. Although many solutions were proposed to estimate gait parameters using wearable sensors, no studies were found in which such technologies were tested outside laboratories in unsupervised, long-term field studies. Thus, the aim of this work was to develop an algorithm that enables long-term monitoring of human movements in unsupervised, naturalistic settings (e.g. during a hike) using wearable sensors.

2 Methods

The study was divided into two experiments. The first experiment, conducted in a laboratory, served to design the algorithm for automatic hike event detection and to compare its results against a reference system. The second experiment took place in the field and was intended to demonstrate that the novel algorithm works error-free in practice. The data records for both experiments can be accessed from the Open Science Framework (OSF) [10, 11].

2.1 Participant

One male (age 37 years, height 1.80 m, body mass 71 kg) volunteered to participate in both experiments and provided written informed consent. The study was approved by the institution's ethics committee (reference number #101525731) and was in accordance with the Declaration of Helsinki. The criteria for participation was a healthy, athletically active individual between the ages of 18 and 50 years with a shoe size between 36 and 47 EUR. Participation in the study was excluded if the applicant had an acute lower extremity injury or one that had occurred within the previous 6 months.

2.2 Equipment

The Gait Real-time Analysis Interactive Lab (GRAIL, Motek Medical B.V., Houten, NLD), two BASNs consisting of a small (48 × 30 × 18 mm), lightweight (34 g) and portable sensor node[1] [12] and a pair of pressure insoles (Smart footwear sensors/HD 002, IEE, Echternach, LUX) were used to collect bipedal locomotion data on a treadmill during the laboratory experiment (Fig. 1). The sensor node consisted of a central processing unit that enables data acquisition and pre-processing, a wireless data logger, flash memory, a battery (1.5 Wh), and an integrated 3-axis accelerometer and gyroscope. The pressure insoles were operated via the sensor node using a plug-in connector. This particular BASN was also used for the field experiment. Measurements with the BASN can be performed without external devices (e.g., computer, smartphone, etc.), and the collected data can be stored on the internal memory and later downloaded to a computer using the appropriate software (Envisible sensors). The GRAIL consisted of a dual belt treadmill with

[1] The sensor node is currently a research product. However, it will be commercially available in the next future (https://www.envisible.de/).

Fig. 1 Body-attached sensor networks (BASN) consisting of a sensor node and a pressure insole, and a participant walking in the Gait Real-time Analysis Interactive Lab (GRAIL). The pressure sensors are located under the insole of the shoe. The sensor node is attached either to the shoe using double-sided adhesive tape or to the test person's sock

integrated force plates mounted on a two degrees of freedom motion frame, a fall protection to attach a harness, a 180° cylindrical projection screen, wide-angle and short-throw projectors, a motion capture system, and operator software such as D-Flow and Vicon Nexus 2. The motion capture system consisted of 10 optoelectronic cameras (Vantage, Oxford Metrics, Oxford, GBR).

2.3 Procedure

The participant wore tight-fitting sportswear and a harness to fasten the safety belt prescribed for the treadmill. The participant's running shoes (size 43 EUR) were equipped with size large (L) pressure measurement insoles. The sensor nodes were attached to the lateral side of each participant's running shoe using adhesive tape. After ensuring that the BASNs were operating correctly and the two force plates integrated into the treadmill were set to zero, the participant went onto the treadmill where he was hooked into the treadmill's safety system. The experiment started with a two-minute warm-up at a speed of 3 km/h, followed by a one-minute rest. The participant performed three three-minute exercise tasks in succession, i.e. walking at 4 km/h, hiking at 6 km/h and running at 9 km/h. There was a one-minute rest before the measurement ended. Data from the BASNs were recorded at 100 Hz and from the force plates at 1000 Hz. The systems were not synchronised. However, it was attempted to start the two different measurement systems as simultaneously as possible.

The field experiment took place in a flat urban area with an overall slope of 50 m and moderate traffic. The participant was asked to undertake a 7.5 km hike using the same shoes and BASNs already used for the laboratory experiment. Neither a hiking pace nor a time limit was given. The recordings were started and stopped by the participant. The BASN data were recorded at 100 Hz.

2.4 Data processing and algorithm

The force plate data was exported to MATLAB (R2020b, The MathWorks, Inc., Natick, MA, USA) via a self-written m-file using the Vicon Nexus pipeline "Run MATLAB Operation". The force data was down-sampled from 1000 to 100 Hz. The BASN data, accessible as an "envisible" file with tab-delimited values, was exported to MATLAB. The data of the individual pressure sensors, which are available as voltage values in the unit V, were converted into pressure values with the unit bar using the supplier's calibration curve. Since the sensor is only calibrated for a measuring range between 100 mbar and 7 bar, values smaller than 100 mbar were set to zero. The pressure sum was calculated from the eight channels of the respective pressure measurement insoles. The time delay between the force plates and the BASNs was determined by calculating the normalized cross-correlation between each pair of signals and their signals aligned accordingly. Since the measured values of the force plates were noisy due to the measurement technique used, all negative values for the vertical ground reaction force were set to zero.

The vertical ground reaction forces were used to determine the reference events of the different activities. For this purpose, the maxima of the individual steps of a foot were first determined. Based on these maxima, the foot contact (FC) and the foot off (FO) were determined as reference events. The foot contact corresponded to the time at which the vertical ground reaction force last reached a value less than or equal to 5 N before the maximum was reached. The foot off corresponded to the time at which the vertical ground reaction force first reached a value of less than or equal to 5 N after the maximum was reached. Events that could not be assigned to an active movement phase, e. g. because the experiment also contained pauses, were automatically removed using a threshold value. The threshold was calculated as the mean plus 1.96 times the standard deviation of the difference between the foot contact events of one side.

The events based on the BASNs, on the other hand, were determined using the pressure sum and an alternative procedure. In this procedure, the state levels of a two-level rectangular waveform were first estimated for the summed pressure signals. These two levels were used as input variables to obtain the transition metrics of the two-level waveform. The foot contacts and foot offs were then determined as the linearly interpolated times at which the signal crossed the previously calculated lower reference with positive and negative polarity, respectively. The pauses were removed analogously to the described procedure of the reference events.

Using the determined events, the individual cycles were separated and the corresponding temporal parameters, i.e. stride time (i.e. time between successive ipsilateral foot contacts), step time (i.e. time between contralateral and subsequent ipsilateral foot contact), cadence (i.e. number of strides per unit time), stance phase (i.e. time between ipsilateral foot contact and subsequent ipsilateral foot off relative to the ipsilateral cycle/stride time) and swing phase (i.e. time between ipsilateral foot off and subsequent ipsilateral foot contact relative to the ipsilateral cycle/stride time), were calculated. The cycles were normalised to 101 data points so that the mean and standard deviation could be determined and plotted on a graph. The cycles and events were further grouped into the individual activities, i.e. all activities, walk, hike and run. By assigning each pressure sensor to the forefoot, midfoot, or rearfoot, the plantar pressures of each foot segment were determined separately.

2.5 Statistical analysis

Mean and standard deviation were determined for the temporal parameters and for the normalised force and plantar pressure cycles. The force values were normalised to the body weight for better visualisation. In addition to the absolute values for the temporal parameters, the relative measurement deviations (f) were also calculated to determine the validity. The measurement deviation represents the deviation of the measurement value "estimated" by the algorithm from the "correct" measurement value based on the force plate data. To assess the bias and precision of the algorithm the Bland and Altman's limits of agreement (LoA) method [13] was used.

3 Results

An algorithm to automatically detect the hike events using the BASNs was successfully designed. The algorithm can be accessed from OSF [11]. Based on the events obtained during the laboratory experiment from the pressure measurement insoles using the algorithm, temporal parameters were calculated and compared with the reference parameters which were based on the force plate data (Table 1). For the stride time, the largest relative error was 0.2%. The cadence also had an error of less than 1%. The step time had a relative error of less than 2% except for the activity "running" (− 2.50%). The largest relative errors were found for the stance and swing phases with the highest error being 10.77%.

The LoA method (Fig. 2) revealed no systematic bias and no heteroscedasticity, i.e. the variability is not depending on the magnitude of the mean values, for the five temporal parameters evaluated. Most of the individual differences between the methods (Δ) were within the 95% limits of agreement (± 1.96 standard deviation). However, for each of the five temporal parameters evaluated, there were individual difference that fell outside these limits.

The left and right stance phase is about 60% for all activities. This is evident from both the force data and the pressure data, where the values drop to 0 N/kg and 0 N/cm^2 respectively (Fig. 3). The course of the kinetic data (force or pressure) changes visibly depending on the activity (Fig. 4). While an "M-curve" can be seen for walking at 4 km/h and hiking at 6 km/h, the curves for running at 9 km/h show a dominant so-called active force peak and a small passive force peak at the beginning. The passive force peak is particularly pronounced for the right ground reaction force during running (Fig. 4g). The standard deviations for segmented activities are relatively small compared to the curves for all activities. Based on the temporal parameters derived from the events as well as on the curves, no noteworthy differences in symmetry between the left and right side can be identified for the tested participant.

The newly developed algorithm based on data from the BASNs was also successfully applied to the data collected in the field from a hike. During the approx. 70-min hike with an average speed of 6.2 km/h, a total of 4180 valid steps were detected. The mean stance phase was 60.6% for the left and 59.1% for the right side (Fig. 5). The plantar pressure curve, which envelopes the signal from all eight sensors of a pressure insole, is similar for both feet. The curve for segmented foot areas is also similar, except for the midfoot area. While the right midfoot area drops off shortly after reaching the peak, the left midfoot area shows a second smaller peak. The representation of all individual

Table 1 Temporal parameters derived from the vertical ground reaction forces of the integrated force plates and from the pressure sensor signals of plantar pressure insoles

	Left					Right				
	Force plate		Pressure insole		Error	Force plate		Pressure insole		Error
	Mean	SD	Mean	SD	f	Mean	SD	Mean	SD	f
Stride time (s)										
All	1.02	0.18	1.02	0.18	− 0.02%	1.02	0.18	1.02	0.18	− 0.02%
Walk	1.15	0.02	1.15	0.02	0.08%	1.15	0.02	1.15	0.02	0.19%
Hike	1.01	0.03	1.01	0.01	0.03%	1.01	0.01	1.01	0.01	0.08%
Run	0.81	0.02	0.81	0.02	0.10%	0.81	0.02	0.81	0.01	0.07%
Step time (s)										
All	0.51	0.09	0.52	0.09	1.72%	0.51	0.09	0.50	0.09	− 1.71%
Walk	0.58	0.02	0.59	0.01	2.05%	0.57	0.02	0.56	0.01	− 1.70%
Hike	0.51	0.02	0.52	0.01	2.03%	0.51	0.02	0.50	0.01	− 1.86%
Run	0.40	0.02	0.41	0.01	2.76%	0.41	0.01	0.40	0.01	− 2.50%
Cadence (strides/min)										
All	60.8	10.6	60.8	10.5	− 0.04%	60.8	10.6	60.8	10.5	− 0.03%
Walk	52.2	0.9	52.1	0.7	− 0.09%	52.2	1.0	52.1	0.9	− 0.19%
Hike	59.2	1.6	59.2	0.7	− 0.08%	59.2	0.8	59.1	0.7	− 0.08%
Run	74.1	1.7	74.1	1.3	− 0.12%	74.1	1.6	74.1	1.1	− 0.09%
Stance phase (%)										
All	55.0	13.0	52.9	11.4	− 3.89%	55.3	12.7	52.4	11.7	− 5.26%
Walk	64.9	1.3	61.8	0.8	− 4.80%	65.0	3.0	61.3	0.8	− 5.79%
Hike	62.1	2.8	59.5	0.8	− 4.31%	62.0	1.0	59.0	0.7	− 4.81%
Run	37.4	1.9	37.4	1.9	0.06%	38.0	1.6	36.4	1.9	− 4.26%
Swing phase (%)										
All	45.0	13.0	47.1	11.4	4.76%	44.7	12.7	47.6	11.7	6.50%
Walk	35.1	1.3	38.2	0.8	8.88%	35.0	3.0	38.7	0.8	10.77%
Hike	37.9	2.8	40.5	0.8	7.07%	38.0	1.0	41.0	0.7	7.83%
Run	62.6	1.9	62.6	1.9	− 0.04%	62.0	1.6	63.6	1.9	2.61%

Given are the mean and standard deviations of the parameters separated by activities (all $n=652$, walk $n=153$, hike $n=176$, run $n=221$) and side (left, right) as well as the relative errors between the two approaches

pressure curves separated by foot area shows that not all normalised gait cycles (about 20 cycles) of the over 4000 recorded cycles were correctly recognised (Fig. 6). Nevertheless, it is noticeable that the standard deviation is rather low (Fig. 5).

4 Discussion

Laboratory tests results demonstrated that the developed algorithms can successfully detect events, namely foot contacts and foot offs, and deliver good estimation of temporal parameters for walking and hiking. Indeed, the relative errors between temporal parameters calculated with the reference system (GRAIL) and the one estimated with BASNs were always lower than 2.5% for stride time, step time and cadence. On the contrary, the estimation of stance and swing phase presents higher relative errors (up to 10.77%). Good agreement between temporal parameters calculated with the reference system and the one estimated with BASNs are also detected when the data related to all activities are not differentiated. The activity running is characterized by higher errors in the estimation of stride time, step time and cadence.

A preliminary field test was performed to test the effectiveness of the proposed methodology in practice. Indeed, laboratory studies have considerable simplifications, such as: (i) running on a treadmill means moving in one direction only, whereas in reality one has to change direction to turn or overcome obstacles, (ii) stopping times (e.g. at traffic lights, pedestrian crossings) do not play a role, (iii) the numerous and often small changes in the slope of a track cannot be faithfully reproduced, and (iv) environmental conditions such as temperature and humidity variations or the presence of obstacles are not taken into account. All of the above-mentioned limitations can affect the estimation of the temporal parameters of gait. Since the average speed of the runner during the field test happens to reflect the speed used the activity hiking in the laboratory

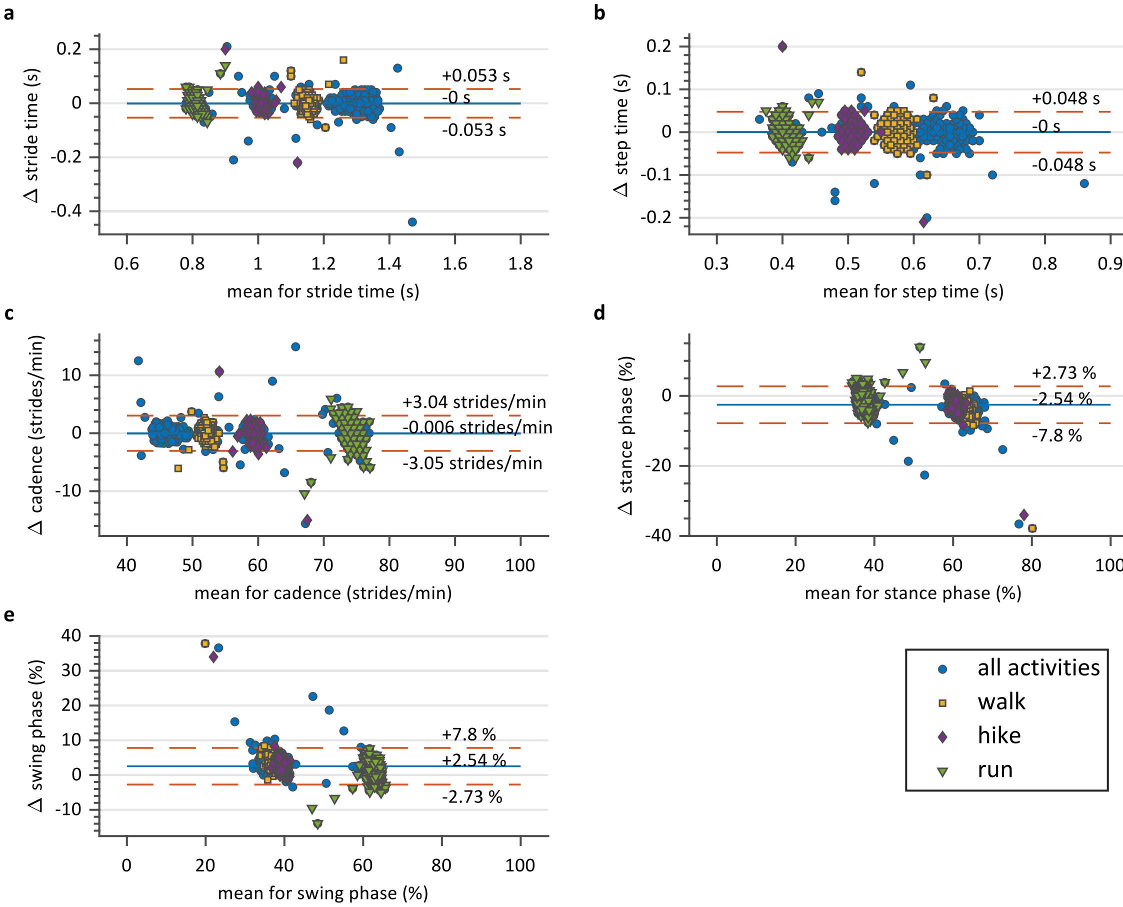

Fig. 2 Bland–Altman plots for the temporal parameters derived from the force plates and the pressure insoles. **a** stride time, **b** step time, **c** cadence, **d** stance phase, and **e** swing phase

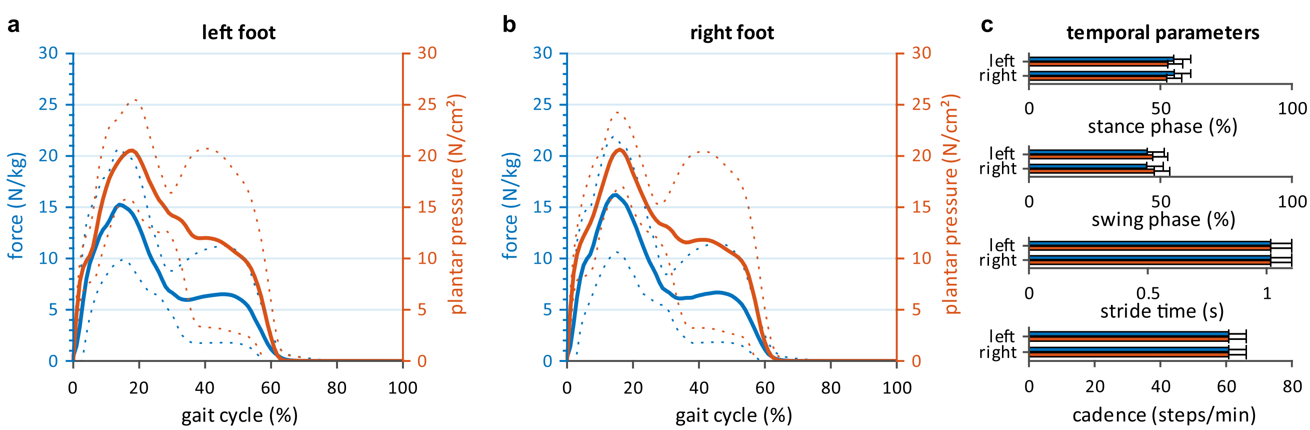

Fig. 3 Curve representation of the signals recorded by means of force plates and pressure measurement insoles, aggregated in normalized gait cycles without differentiation by activity, as well as bar graphs of the temporal parameters derived from them, i.e. stance phase, swing phase, stride time and cadence. **a** mean and standard deviation of normalised forces and summed plantar pressure signals for the left foot and **b** right foot, **c** mean and standard deviation of the temporal parameters for the left and right foot calculated using force place data (blue bar) and estimated using plantar pressure (orange bar) (color figure online)

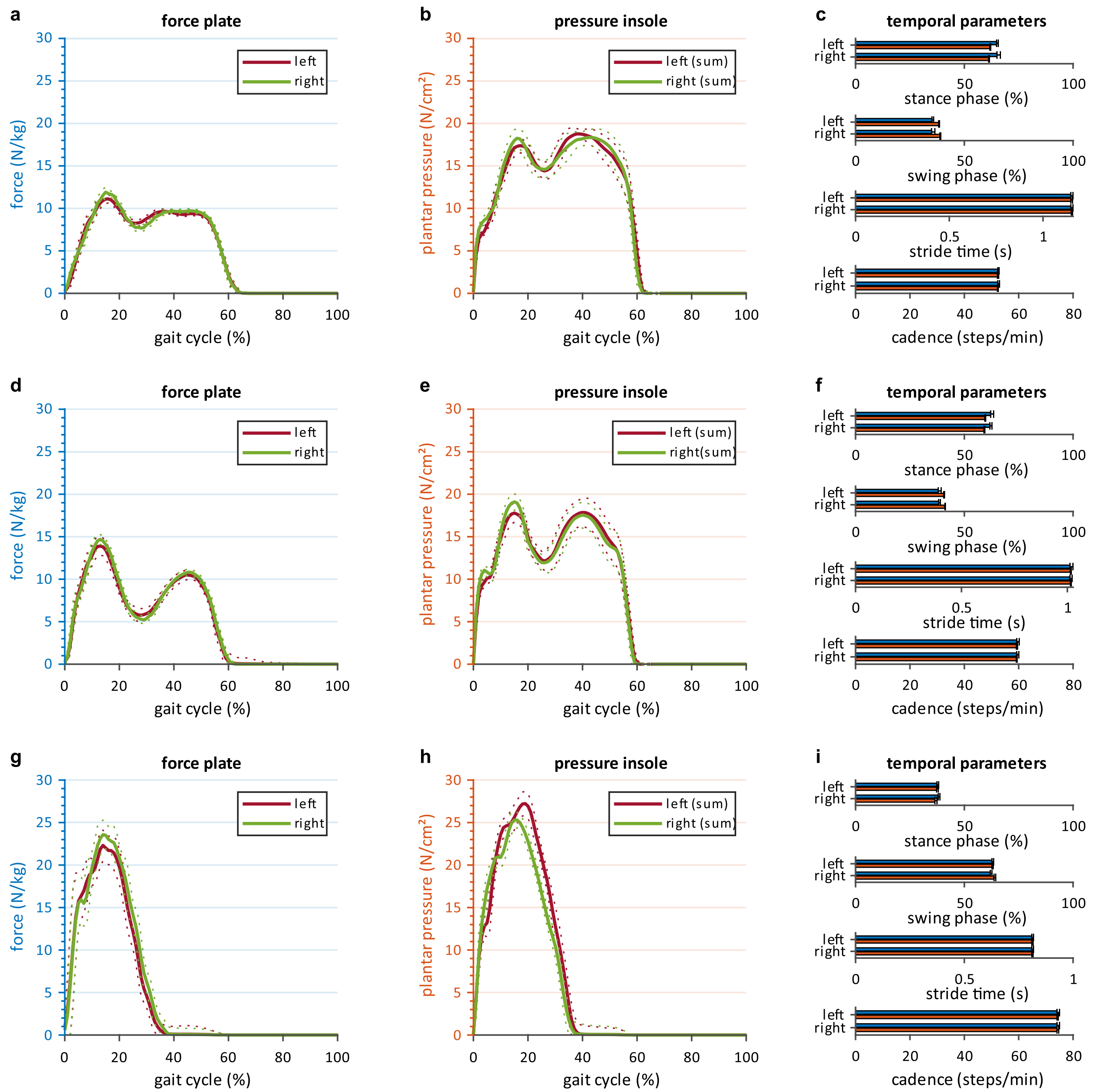

Fig. 4 Curve representation of the signals and bar graphs of the temporal parameters separated by activity, i.e. walking with 4 km/h (**a**, **b**, **c**), hiking with 6 km/h (**d**, **e**, **f**) and running with 9 km/h (**g**, **h**, **i**). The left column represents the mean and standard deviation of normalised forces separated by foot side and aggregated in normalized gait cycles for **a** walking, **d** hiking and **g** running. The middle column represents the mean and standard deviation of summed plantar pressure signals separated by foot side and aggregated in normalized gait cycles for **b** walking, **e** hiking and **h** running. The right column represents the mean and standard deviation of the temporal parameters separated by foot side calculated using force place data (blue bar) and estimated using plantar pressure (orange bar) for **c** walking, **f** hiking and **I** running

test (6 km/h), the two experiments can be compared very well. The pilot field study, showed the strength of BASNs in the analysis of long-term acquisitions in unsupervised, naturalistic settings. Highlighting how wearable sensor networks represent a flexible and suitable alternative to complex and expensive laboratory solutions. Furthermore, through the use of pressure insoles the BASNs, object of this study, is also capable of delivering additional qualitative information on the foot areas in contact with the ground, that is not possible with inertial-based solutions like the one proposed by Falbriard et al. [9].

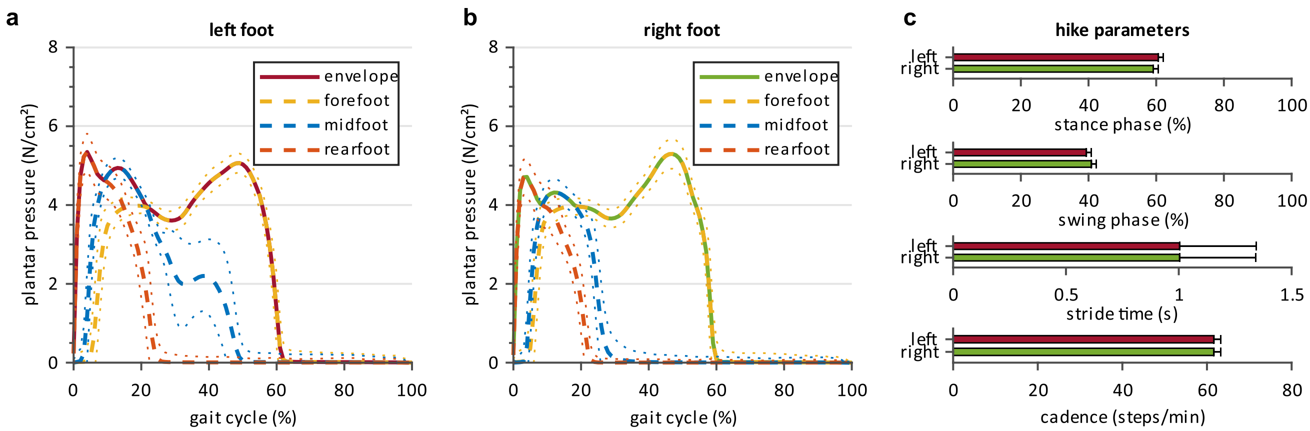

Fig. 5 Plantar pressures for normalized gait cycles ($n=4180$) and hiking parameters of the subject during a hike with an average speed of 6.2 km/h, **a** envelope, mean, and standard deviation of plantar pressure separately by foot segments for the left foot and **b** the right foot, **c** mean and standard deviation of the hiking parameters for the left and right foot

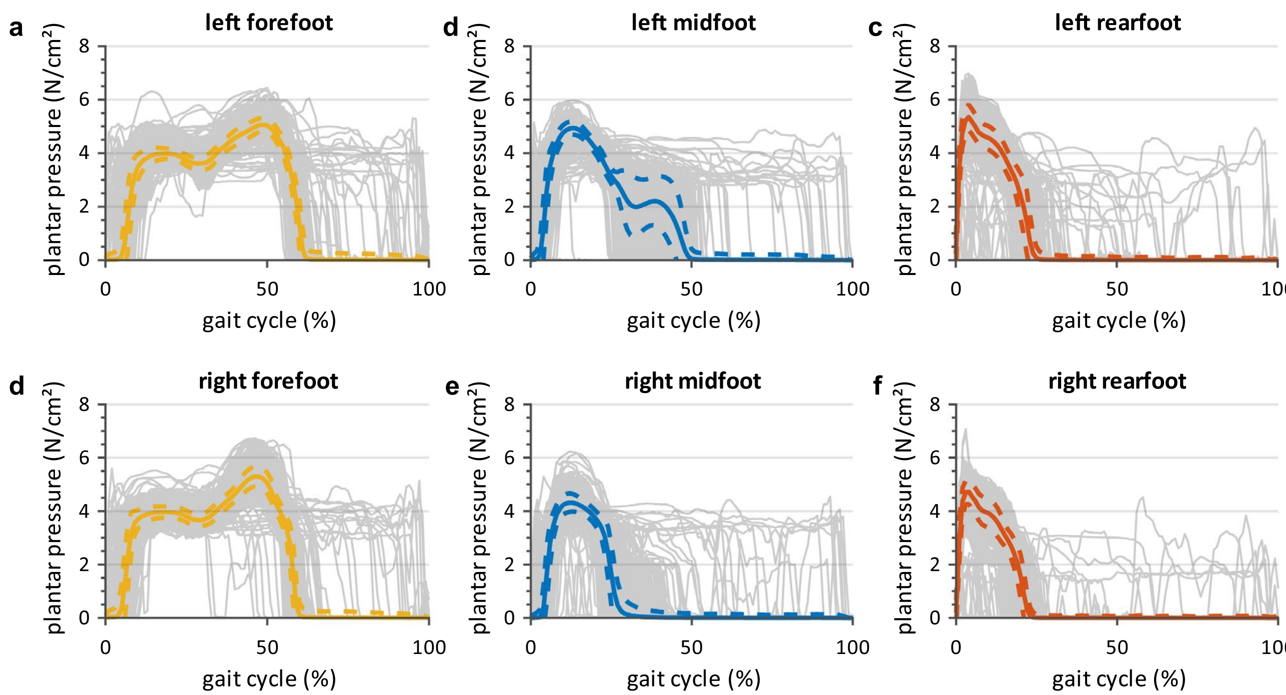

Fig. 6 Individual value, mean value and standard deviation of plantar pressures separated by foot area for all ($n=4180$) normalized gait cycles of the subject during a hike with an average speed of 6.2 km/h, **a** left forefoot, **b** left midfoot, **c** left rearfoot, **d** right forefoot, **e** right midfoot, **f** right rearfoot

Some limitations in the proposed methods have to be acknowledged. The force data collected with the instrumented treadmill and used for the validation of the developed algorithm, suffered from noise and needed to be post-processed to be used. In addition, to obtain comparable results with the force plate and the BASNs, down sampling of data collected with force plate was necessary. Temporal parameters calculated from force plate data with and without down sampling are listed in Online Resource 1. These show that it was feasible to down sample force plate data from 1000 to 100 Hz only when all activities are considered together (Table S1). When analysing each activity separately, the approximation error increases with increasing speed of the participant (Tables S2 to S4). As the force plate and the BASNs were not synchronised, even though the experimenter tried to start the two measurements at the same time, this is a limitation and in future studies the two systems should be triggered to ensure perfect synchronisation.

Furthermore, the proposed field study is meant to be a preliminary proof of concept, indeed, just one person participated in this test and just the activity hiking on relatively flat ground was considered.

5 Conclusion

This work has shown that it is possible to estimate temporal hike parameters using wearable sensors (namely, wireless sensor nodes and instrumented pressure insoles) and customised algorithms. The comparison with reference systems currently used for determining temporal gait parameters has shown that the quality of the estimation decreases with increasing speed and thus less accurate results can be achieved for running activities. Although results obtained with laboratory solutions are more accurate, the use of wearable solutions offers the advantage to estimate temporal parameters during regular training sessions. The effectiveness of the proposed methodology was also tested in a pilot study on the field, demonstrating that Body-Attached Sensor Networks are suitable for long-term acquisitions in unsupervised, naturalistic settings. Further field experiments with more participants, speed ranges and different terrain should be planned to extend the use of this methodology for detecting events and estimating temporal parameters also during running.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s12283-023-00411-x.

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Data availability The data were uploaded to the repository on OSF (Open Science Framework from the Center of Open Science) and can be accessed at the following links: http://osf.io/kcqtf/, http://osf.io/63hjs/.

Code availability The analysis scripts were uploaded to the repository on OSF (Open Science Framework from the Center of Open Science) and can be accessed at the following link: http://osf.io/63hjs/.

Declarations

Conflict of interest SO is a senior consultant for the manufacturer of the sensor nodes used in this study (Envisible GmbH).

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