Real-World Gait Speed Estimation Using Wrist Sensor: A Personalized Approach

Abolfazl Soltani, Hooman Dejnabadi, Martin Savary, and Kamiar Aminian

***Abstract*—Gait speed is an important parameter to characterize people's daily mobility. For real-world speed measurement, inertial sensors or global navigation satellite system (GNSS) can be used on wrist, possibly integrated in a wristwatch. However, power consumption of GNSS is high and data are only available outdoor. Gait speed estimation using wrist-mounted inertial sensors is generally based on machine learning and suffers from low accuracy because of the inadequacy of using limited training data to build a general speed model that would be accurate for the whole population. To overcome this issue, a personalized model was proposed, which took unique gait style of each subject into account. Cadence and other biomechanically derived gait features were extracted from a wrist-mounted accelerometer and barometer. Gait features were fused with few GNSS data (sporadically sampled during gait) to calibrate the step length model of each subject through online learning. The proposed method was validated on 30 healthy subjects where it has achieved a median [Interquartile Range] of root mean square error of 0.05 [0.04–0.06] (m/s) and 0.14 [0.11–0.17] (m/s) for walking and running, respectively. Results demonstrated that the personalized model provided similar performance as GNSS. It used 50 times less training GNSS data than nonpersonalized method and achieved even better results. This parsimonious GNSS usage allowed extending battery life. The proposed algorithm met requirements for applications which need accurate, long, real-time, low-power, and indoor/outdoor speed estimation in daily life.**

***Index Terms*—Low-power, online learning, personalization, real-world gait speed, running and walking.**

I. Introduction

GAIT speed is among the most important parameters to characterize people's daily mobility. It is a primary outcome in ageing and is associated with survival in elderly subjects [1]–[3]. In clinical applications, gait speed is employed to characterize orthopedic diseases, to quantify impacts of intervention, to design functional assessments after treatment, and to predict the risk of falling [4]–[9]. Gait speed is also used in sport to design personalized training sessions and evaluate performance of athletes [10].

For accurate measurement of instantaneous speed, camera-based motion capture systems and instrumented walkways with pressure sensors were introduced [11]–[13]. However, apart from being restricted to the laboratory, these need considerable time for preparation, measurement, and post-processing. Gait features (e.g., step length) greatly differ between free-living and laboratory conditions, one might have shorter gait distances in the latter [14]–[16]. It is shown that few steps of a person in a controlled laboratory setting cannot completely represent his/her real performance during daily life [17]. For objective outcome evaluation, knowledge about patients' mobility in real-world is more important than short clinical visits and tests [18], [19]. Consequently, it is crucial to develop gait speed measurement systems for real-life conditions.

Global Navigation Satellite System (GNSS) is the first choice to measure gait speed in everyday situations. It offers ambulatory speed and position measurements with a very high accuracy (0.05 m/s of error) [20]–[22]. However, the GNSS receiver has high power consumption, which limits its use for a portable device when long duration measurements are required. Furthermore, communicating with satellites may not be possible indoors, near high buildings, narrow valleys, etc.

Inertial sensors (i.e., accelerometer, gyroscope) have been used to estimate gait speed based on the movement of lower and/or upper limbs, like feet [23]–[25], shanks [3], [26]–[28], thighs [29], [30], trunk [31], [32], and waist [33], [34]. In some cases, data captured from multiple sensors (located at different parts of the body) were fused to achieve better performance [35]–[37]. These systems computed the cadence (number of steps per unit time) through the detection of certain events at each gait cycle (e.g., initial and terminal contact or mid-swing of the foot). Step length was also estimated through either modeling of human's gait [26], double integration of acceleration [23] or abstract modeling based on machine learning [30], [33], [38]. Eventually, instantaneous gait speed was obtained by multiplying cadence and step length. The main advantage of such systems was that they provided relatively accurate estimation of gait speed outside the laboratory in free-living environments. They overcame the GNSS problems through reduction of power consumption and being independent of any external sources (i.e., satellites). However, they are not as accurate as the GNSS. They may also suffer from inconvenient sensor fixation (e.g., skin patch or elastic straps), especially when multiple sensors are required, which complicates their use and may need an expert to install on body.

A more convenient approach to estimate gait speed would be to attach inertial sensors to the wrist (e.g., as a wristwatch). This could offer several advantages such as usability, comfort

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and a handy user interface. However, contrary to trunk and legs, the association between wrists movements and locomotion is not straightforward, especially during daily activities. The hand may be motionless (e.g., in the pocket, carrying bag) during locomotion, or moving during rest (e.g., sitting or standing). These "independent" movements of the hand are potentially a serious challenge for accurate wrist-based speed estimation. This is also confirmed by limitations of speed estimation algorithms in many accelerometer-based smartwatches, targeting the consumer market, and probably why the hand has hitherto not been favored for sensor attachment to estimate speed in research or clinical settings [39].

In existing literature, a few methods have recently been introduced to estimate gait speed based on a single wrist-mounted inertial sensor. These methods extracted several features from raw sensor data and then mapped them to gait speed though a linear or non-linear modeling. The features were in general chosen to be indicator of intensity, energy, cadence, mean crossing rate, but statistical features such as mean, standard deviation, mode, and median of acceleration norm have also been employed [20], [40]–[45]. Altitude changes, measured by a barometric pressure sensor, were also used as a feature to improve gait speed estimation in [20]. In order to model gait speed, several machine learning approaches have been investigated such as Gaussian process regression [40], lasso regularized least squares regression [40], [44], regularized kernel method [42], and piecewise linear regression [20].

An important issue in machine learning when designing a model is the training strategy. In general, a subsample of a population is considered to train a general model optimized for all individuals belonging to the entire population. Such an approach does not take into account individual strategies involved in gait modulation, e.g., one might change speed by controlling cadence whereas another might vary step length for the same purpose. Therefore, a population-based training approach cannot perform well for all gait styles and there is a need to personalize the speed model to each individual.

Usefulness of personalization in gait speed estimation has been shown in few previous works [46]–[48]. Generally, they improved estimation of speed through using a reference value (e.g., from GNSS or marked walkway) to collect a bunch of data from each individual user and then calibrated their general speed model to the specific user by applying an offset or scaling factor to the model. However, the main drawback of such approaches was that they collected their personalization data only from a very short walk period or in a controlled setting. Gait speed of a person may vary due to change of seasons, living or working environments, etc. Moreover, all these studies are based on offline personalization, which means that they need all personalization data to once calibrate the speed model.

The objective of this study is to design and validate a method based on a single wrist-mounted accelerometer and barometer for accurate and precise estimation of instantaneous speed during real-world walking and running. We hypothesize that a personalized speed model is feasible and will improve the performance of the system. To this end, when a person is walking or running, we sporadically use the GNSS to acquire few speed

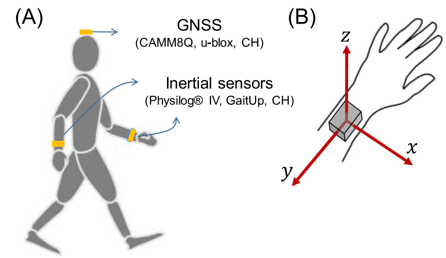

Fig. 1. (A) Sensor configuration of the measurement. A single sensor was fixed on each wrist and the GNSS receiver was used as the reference method. (B) Local coordinate frame of the wrist accelerometer.

data and then we personalize the speed model to the user's specific gait style through online learning. For further improvement, we propose physically meaningful gait features based on the biomechanics of wrist movement during gait. Eventually, we consider requirements of real-time and low-power applications to optimize the gait speed estimation algorithm for subsequent implementation inside a smart wristwatch by proposing a recursive algorithm that uses parsimoniously acquired GNSS samples.

II. Methods

A. Material and Measurement Protocol

Thirty healthy and active volunteers (14 women, 16 men, age 37 ± 9 years old, height 172 ± 10 cm, and weight 68 ± 11 kg) participated in this study. Participants worn two time-synchronized inertial sensors (Physilog IV, GaitUp, CH) on wrists using elastic straps. The proposed method is based on data from a single wrist. However, we recorded data on both wrists to compare the performance of the proposed method between wrists. Fig. 1(A) and (B) show sensor configuration and local coordinate frame of the wrist accelerometer, respectively. Sensors recorded three-dimensional acceleration (range ±16 g) at 500 Hz and barometric pressure at 50 Hz. The accelerometer sensor was calibrated according to [49]. Furthermore, as ground truth, a GNSS receiver (CAMM8Q, u-blox, CH) with an external active antenna (ANN-MS, u-blox, CH) were mounted on the head using Velcro attached to a cap. The GNSS receiver was set to pedestrian mode with a sampling frequency of 10 Hz.

The measurement protocol consisted of outdoor walking and running in free-living conditions lasting around 90 minutes. In order to cover real-life gait diversity, the activities were performed on various terrain conditions, including uphill, downhill and flat. Further, the participants were asked to perform the activities at self-adjusted normal, slow and fast speeds. We manually excluded all rest periods. Fig. 2 illustrates trial types, elevation profile of the track and GNSS speed change during the measurement. A local human research ethics committee had approved the proposed protocol.

B. Reference Values for Speed

The GNSS provided the instantaneous speed at 10 Hz with its corresponding measurement error. We processed the GNSS speed in two steps to obtain the reference values for speed:

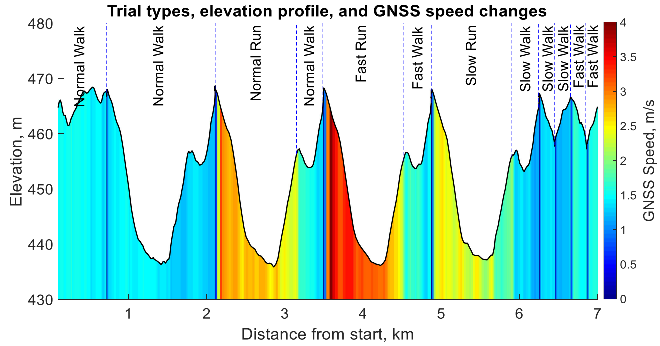

Fig. 2. Trial types and elevation profile of the measurement. Color bar shows one example of how the GNSS speed was changed during a whole measurement for one participant (ID #1).

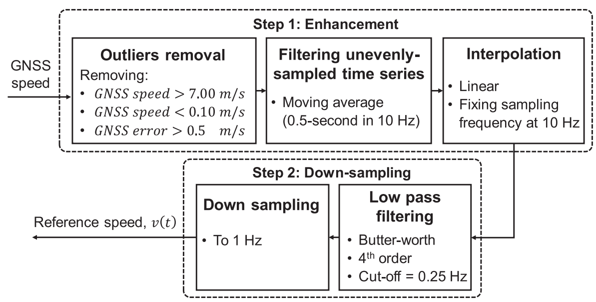

Fig. 3. Processing GNSS speed. Step 1: Enhancing the speed samples. Step 2: Down-sampling the speed to 1 Hz required for the wrist-based algorithm.

enhancement and down-sampling (see Fig. 3). In the enhancement step, first, samples of GNSS speed outside the range of [0.10, 7.00] (m/s) were discarded and not included in neither training nor test. In fact, according to [50], maximum speed of normal and long-term running (e.g., marathon) was less than 6 (m/s). In addition, based on our manual labels, the GNSS speed values were higher than 0.1 (m/s) for all gait periods. GNSS samples with speed less than 0.1 (m/s) corresponded to non-locomotion activities such as shuffling around, standing, sitting, etc. Here, the reported speed values were in the range of GNSS reported error i.e., 0.12 (m/s) (a median error during our measurement), even though the manufacturer reported a speed mean error of 0.05 (m/s) at 30 (m/s). Then, we removed samples with GNSS error higher than 0.5 (m/s), which probably occurred due to the lack of sufficient satellite coverage. This sample removal as well as data loss of the GNSS receiver led to an unevenly-sampled time series for the speed signal. Consequently, we filtered both the speed values and the corresponding time instants using a moving average filter with a width of 0.5-second (in 10 Hz) to obtain a smooth signal. Finally, we used linear interpolation to generate an equally spaced sampled speed time series at 10 Hz. Since the proposed wrist-based speed estimation algorithm needs GNSS speed values at 1 Hz, we designed a down-sampling step. To this end, first, an anti-aliasing fourth-order low-pass Butter-worth filter (with a cutoff frequency of 0.25 Hz) was applied on the signal. Second, the resulting signal was resampled at 1 Hz. The obtained gait speed $(v(t))$ was considered as: (a) actual speed values for the personalization procedure provided in section C, and (b) reference speed for validation in section D.

C. Personalized Wrist-Based Speed Estimation Algorithm

The proposed wrist-based algorithm used the 3D accelerometer signal $(a(t))$, barometric pressure $(p(t))$, and a subset of the reference speed $(v(t))$. Gait speed is the product of step length and cadence. We have already developed an accurate algorithm for cadence estimation [20]. Therefore, instead of modeling gait speed, which involve non-linearity, here, we modeled step length and then multiplied that with cadence. Fig. 4 shows the block diagram of the algorithm. First, recorded signals were segmented and relevant features were extracted to estimate step length. Then the algorithm included two recurrent phases: personalization and estimation. The personalization phase models fluctuations in step length during walking and running that occur due to differences in individual functional ability and specific aspects of the environment. In estimation phase, the personalized model was used to estimate the speed. A more detailed description of the method is provided below.

Segmentation- First, both $a(t)$ and $p(t)$ were low-pass filtered using a fourth-order Butterworth filter at 4 Hz according to [20]. Then, the signals were segmented every second using a 7-second moving window with 6-second overlap to provide segmented acceleration $(A[n])$ and pressure signal $(P[n])$, where n indicates window number. $S_x[n]$, $S_y[n]$ and $S_z[n]$ were denoted as segmented acceleration along axes of the accelerometer (Fig. 1(B)). The length of the window was selected to be long enough to have sufficient data for frequency analysis, and short enough to provide required time resolution.

Feature extraction- In order to represent walking and running, we defined various numbers of features based on biomechanics of wrist movement (such as energy, periodicity, posture, etc.) as well as statistics (like mean, median, standard deviation, kurtosis, etc.). We employed LASSO (least absolute shrinkage and selection operator) feature selection method according to [51] to create the best possible features sets for walking and running using training dataset. As we expected, since movement and posture of the wrist during walking and running are different, two different sets of features were chosen. Consequently, it is necessary to distinguish between walking and running before using the proposed method. In this study, we labeled manually walking and running periods. For running, four features were chosen as follows:

$\mathbf{Cad}[\mathbf{n}] =$ *Cadence:* Locomotion cadence has a high correlation with the step length and was estimated based on the algorithm proposed in [20].

$\mathbf{Alt}_{\boldsymbol{\Delta}}[\mathbf{n}] =$ *Altitude change of the path:* During running, gait speed may change with the slope of the path, e.g., longer (shorter) flying phase when running on downhill (uphill) compared to level running. Altitude change of the path was computed within window number n from barometric pressure as the slope of a line fitted to $(-1) \times P[n]$ using the least squares method,

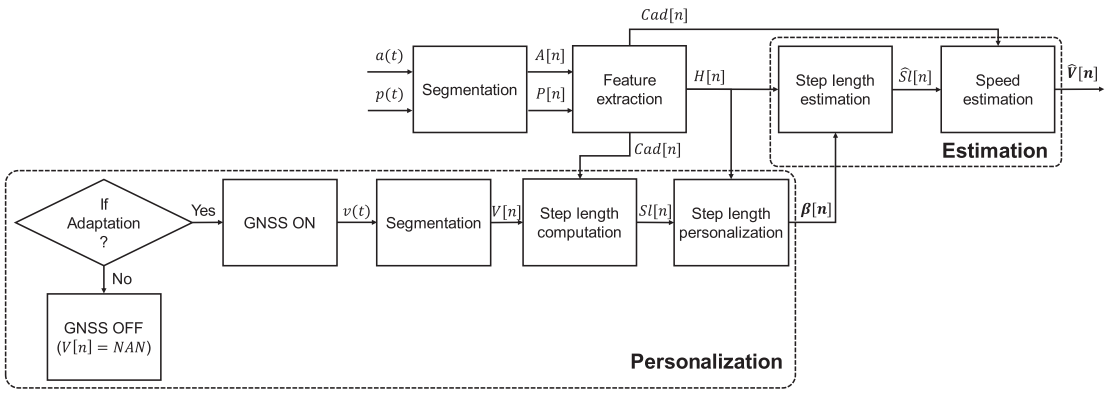

Fig. 4. Block diagram of the proposed method. Data were first segmented and relevant features were extracted. During the personalization phase, the step length model was personalized using the extracted features and limited number of speed data sampled randomly for each individual during daily life. In the estimation phase, the step length was estimated using the extracted features and the most updated model resulted from personalization phase. Eventually, the speed was calculated using the estimated cadence $(Cad[n])$ and the step length $(\widehat{Sl}[n])$.

according to (1).

$$Alt_{\Delta}[n] = -\frac{\sum_{i=1}^{q}(i-\bar{i})\left(P^{i}[n]-\bar{P}[n]\right)}{\sum_{i=1}^{q}(i-\bar{i})^{2}} \times F_s \qquad (1)$$

where q is the number of samples within window number n, F_s is the sampling frequency, and $P^i[n]$ is the *i*-th sample of the pressure vector within window number n. In addition, $\bar{P}[n]$ and $\bar{i}$ are computed based on (2) and (3).

$$\bar{P}[n] = \frac{1}{q}\sum_{i=1}^{q} P^{i}[n] \qquad (2)$$

$$\bar{i} = \frac{1}{q}\sum_{i=1}^{q} i \qquad (3)$$

$\mathbf{E_{S_y}[n]}$ = *Energy of acceleration along axis y:* When a person increases his step length, the range of hand movement may increase as well, which leads to an increase in the energy of the acceleration signal along the longitudinal axis of the hand (y in Fig. 1B). $E_{S_y}[n]$ was estimated using standard deviation according to (4).

$$E_{S_y}[n] = std\left(S_y[n]\right) \qquad (4)$$

$\mathbf{Jerk[n]}$ = *Mean absolute jerk:* During locomotion, repetitive impacts at the step frequency appear on the wrist acceleration. The mean absolute value of jerk (time derivative of acceleration) provides information about the load changes of such impacts. We hypothesized that the mean absolute value of jerk (adopted from [52]) of axis y would be correlated with step length during running. Equation (5) shows how to compute this feature within window n where $S_y^i[n]$ is the *i-th* sample of vector $S_y[n]$.

$$Jerk[n] = \frac{1}{q}\sum_{i=1}^{q}\left|S_y^{i}[n]-S_y^{i-1}[n]\right| \qquad (5)$$

In conclusion, the feature vector for running $(h_{run}[n])$ was defined by (6). Our data revealed non-linearity between altitude change and step length. Therefore, we also included the square of $Alt_{\Delta}[n]$ to the running feature vector.

$$h_{run}[n] = [1\ Cad[n]\ Alt_{\Delta}[n]\ E_{S_y}[n]\ Jerk[n]\ Alt_{\Delta}[n]^2] \qquad (6)$$

For walking step length estimation, two new walking-specific features were chosen through LASSO supporting the fact that the nature of arm movement during walking and running gives rise to fundamental differences in wrist-recorded acceleration. For instance during walking, the extended arm and forearm lead to a sort of pendulum swing movement of the wrist in the relative transvers plane of the wrist ($< x, z >$) whereas during running the flexed forearm prevents such a transverse swing. Therefore, in addition to $Cad[n]$, $Alt_{\Delta}[n]$ and $Jerk[n]$, we defined the following two new walking-specific features:

$\mathbf{I_s[n]}$ = *Intensity of hand swing:* it is the energy of acceleration in the transversal plane relative to the wrist $< x, z >$, computed through (7). Owing to the cylindrical geometry of the wrist, our combined use of data from both axes, forming the transversal plane, makes this feature robust to sensor rotation which may sometimes occur during walking.

$$I_s[n] = std\left(\sqrt{S_x[n]^2 + S_z[n]^2}\right) \qquad (7)$$

$\mathbf{\overline{Norm}[n]}$ = *Mean of acceleration norm:* During walking, amplitude of trunk movement is related to the step length [31]. In walking, we can consider the arm as a moving pendulum, which swings about the shoulder joint. We hypothesized that the back and forth movement of the arm, relative to the trunk, would have an average value associated with trunk movement. The feature was obtained from (8).

$$\overline{Norm}[n] = mean\left(\sqrt{S_x[n]^2 + S_y[n]^2 + S_z[n]^2}\right) \qquad (8)$$

For walking the feature vector $(h_{walk}[n])$ was defined according to (9).

$$h_{walk}[n] = \left[1\ Cad[n]\ \ Alt_{\Delta}[n]\ \ Jerk[n]\ I_s[n]\ \overline{Norm}[n]\right] \qquad (9)$$

Personalization phase- In the personalization phase, we propose to calibrate the step length model for each user by sporadically sampling the GNSS signal during daily life. The GNSS samples along with the corresponding features were used to calibrate the step length model.

GNSS sampling and segmentation- To keep power consumption low, it is important to restrict the usage of GNSS to a minimum but still have enough number of speed data. Ideally, GNSS should be used when a significant change in user gait pattern occur. In this study, as a first attempt for GNSS data selection, we used random sampling. The speed $v(t)$, obtained through random GNSS sampling and segmented as $V[n]$ (similar to the segmentation rule described above), along with the corresponding feature vector $h_{walk}[n]$or $h_{run}[n]$, constituted our personalization data set.

Step length computation- $Sl[n]$ is the actual step length computed through (10) for each window n from the personalization data set. In equation (10), $V[n]$, $Cad[n]$, and $Sl[n]$ are GNSS speed (m/s), cadence (steps/min), and step length (m), respectively.

$$Sl\,[n] = 60 \times \frac{V\,[n]}{Cad\,[n]} \tag{10}$$

Step length personalization- $H[n]$ and vector $SL[n]$ were defined as the feature matrix and the actual step length vector, respectively, from the start of personalization up to time n.

$$H\,[n] = \begin{bmatrix} h\,[1] \\ \vdots \\ h\,[n] \end{bmatrix} \tag{11}$$

$$SL\,[n] = \begin{bmatrix} Sl\,[1] \\ \vdots \\ Sl\,[n] \end{bmatrix} \tag{12}$$

We chose a linear approach to model the step length by assuming a quasi-linear relationship between our features and the step length. Moreover, this approach decreased computational cost and facilitated the implementation on a wearable device. More importantly, the linear model needs much less training data than non-linear models, thereby, reducing GNSS usage time. This leads to a reduction in power consumption of the system. Step length was modelled according to (13).

$$SL\,[n] = H\,[n]\,\beta + \varepsilon \tag{13}$$

where β is a column vector providing model coefficients. According to the conventional least squares approach, we have:

$$\beta = \left(H[n]^T H\,[n]\right)^{-1} H[n]^T SL\,[n] \tag{14}$$

Equation (14) needs all personalization data from the beginning of personalization up to time n, which this consumes a lot of memory space and requires much computation. Therefore, a recursive least squares (RLS) fitting approach was employed which provided an acceptable computational cost for the system and was able to work in real-time. Moreover, RLS worked in an online fashion avoiding store all seen personalization data, thereby, reducing memory usage.

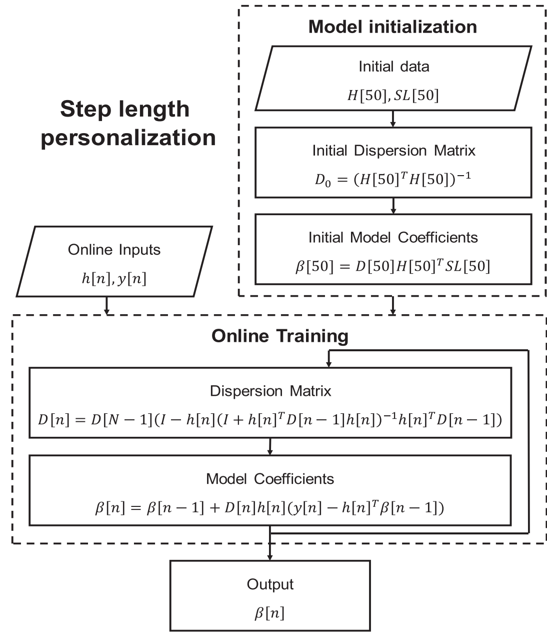

Fig. 5. Block diagram of the proposed step length personalization according to recursive least squares. For each individual, the step length personalization consists of model initialization (using first 50-second of GNSS data) and online learning based on recursive least squares. The output of the block diagram is the most updated model coefficients, $\beta[n]$.

Let $H[n-1]$ and $\beta[n-1]$ be the matrix of features and model coefficients vector up to time $(n-1)$, respectively. In order to compute the coefficient vector at time n ($\beta[n]$) in an online fashion, RLS approach is used based on (15).

$$\beta\,[n] = \beta\,[n-1] + D\,[n]\,h\,[n]\left(Sl\,[n] - h[n]^T \beta\,[n-1]\right) \tag{15}$$

where $h[n]$ and $Sl[n]$ are respectively the feature vector and the actual step length of personalization data set in time n. In addition, $D[n]$ is defined in (16).

$$D\,[n] = \left(H[n]^T H\,[n]\ \right)^{-1} \tag{16}$$

We computed $D[n]$ in a recursive way according to (17) where only the matrix $D[n-1]$ and the personalization data at time n were needed. $K[n]$ is defined according to (18).

$$D\,[n] = D\,[n-1]\left(I - h\,[n]\,(I + K\,[n])^{-1} h[n]^T D\,[n-1]\right) \tag{17}$$

$$K\,[n] = h[n]^T D\,[n-1]\,h\,[n] \tag{18}$$

Fig. 5 depicts a detailed block diagram for the proposed step length personalization method. For each subject, the first 50-second (experimentally adjusted) of personalization data set was used to build an initial model $(H[50], SL[50], D[50], \beta[50])$, named "*Model initialization*". Then, the initial model was adapted to every new personalization sample during "*Online Learning*".

Estimation phase- When GNSS data were not used (e.g., GNSS receiver was off), the vector of updated model coefficients $(\beta[n])$, resulted from personalization phase, and the extracted

TABLE I
ERRORS OF PERSONALIZED SPEED ESTIMATION ALGORITHM FOR DAILY WALKING AND RUNNING UNDER VARIOUS SPEED RANGES AND TERRAIN CONDITIONS ON EITHER BOTH OR SINGLE WRIST

Wrist	Cond.*	Walking error (m/s)						Running error (m/s)					
		RMSE		Bias (median)		Precision (IQR)		RMSE		Bias (median)		Precision (IQR)	
		Median	IQR	Median	IQR	Median	IQR	Median	IQR	Median	IQR	Median	IQR
Both	Slow	0.05	[0.04 0.08]	0.01	[0.00 0.03]	0.07	[0.05 0.08]	0.15	[0.11 0.22]	0.06	[0.02 0.10]	0.17	[0.12 0.25]
	Normal	0.04	[0.04 0.06]	-0.01	[-0.02 -0.01]	0.05	[0.04 0.06]	0.13	[0.10 0.16]	-0.02	[-0.05 0.00]	0.15	[0.12 0.21]
	Fast	0.07	[0.04 0.10]	-0.04	[-0.08 -0.01]	0.06	[0.04 0.11]	0.14	[0.10 0.22]	-0.03	[-0.11 0.03]	0.17	[0.07 0.26]
	Downhill	0.05	[0.04 0.07]	0.01	[-0.01 0.02]	0.06	[0.04 0.08]	0.13	[0.11 0.18]	0.00	[-0.02 0.03]	0.17	[0.13 0.22]
	Flat	0.05	[0.04 0.06]	-0.01	[-0.01 0.00]	0.06	[0.05 0.07]	0.12	[0.09 0.17]	0.01	[-0.03 0.03]	0.16	[0.11 0.22]
	Uphill	0.05	[0.04 0.07]	0.00	[-0.01 0.01]	0.07	[0.05 0.09]	0.15	[0.11 0.21]	0.02	[-0.03 0.05]	0.20	[0.14 0.30]
	Total	**0.05**	**[0.04 0.06]**	**0.00**	**[-0.01 0.00]**	**0.06**	**[0.05 0.07]**	**0.14**	**[0.11 0.17]**	**0.00**	**[-0.01 0.02]**	**0.18**	**[0.14 0.23]**
Left	Total	0.05	[0.05 0.07]	0.00	[-0.01 0.00]	0.06	[0.05 0.07]	0.14	[0.11 0.19]	0.00	[-0.02 0.02]	0.18	[0.14 0.22]
Right	Total	0.05	[0.04 0.06]	0.00	[-0.01 0.00]	0.06	[0.05 0.08]	0.14	[0.12 0.17]	0.01	[0.00 0.02]	0.19	[0.14 0.23]

* Condition: For walking, $v(t) \leq 1.5$, $1.5 < v(t) \leq 1.8$ and $v(t) > 1.8$ (m/s) were considered as slow, normal and fast, respectively. For running, slow, normal and fast were respectively defined as $v(t) \leq 2.5$, $2.5 < v(t) \leq 3.5$ and $v(t) > 3.5$ (m/s). For both walking and running, we defined downhill, flat and uphill as $Alt_\Delta < -0.01$, $-0.01 \leq Alt_\Delta \leq 0.01$, $Alt_\Delta > 0.01$, respectively.

features were used to estimate the step length $(\widehat{Sl}[n])$ in an arbitrary time window n.

$$\widehat{Sl}\,[n] = h\,[n]\ \ \beta\,[n] \tag{19}$$

Finally, gait speed $(\hat{V}\,[n]\ (\mathrm{m}))$ was estimated through (20) using cadence $(Cad[n]$ (steps/min)) and step length $(\widehat{Sl}[n]\ (m))$.

$$\hat{V}\,[n] = \frac{Cad\,[n]}{60} \times \widehat{Sl}\,[n] \tag{20}$$

D. Cross-Validation and Error Computation

The proposed personalized speed estimation method was validated against GNSS data (as reference). For each individual subject, first the data was divided into packets of 10-second. Then, half of packets of each trial were randomly selected for online learning and the other half was selected as the test set. The error between the reference and the proposed method in test data set (personalization data set was excluded) were computed sample-by-sample with a resolution of 1 second. Intra-subjects, Lilliefors test was used to check normality of the speed error. In the case of non-normal distribution, median (as bias), Inter-Quartile Range (IRQ, as precision), and Root Mean Square Error (RMSE) of the speed error were computed for all trials of each subject. Inter subjects, median and IQR of bias, precision and RMSE were reported. The Bland-Altman approach [53] was used to display error plots for estimated speed. To analyze correlations between parameters, we performed Spearman rank correlation [54]. In addition, we used Kruskal–Wallis [55] to investigate whether trials circumstances and/or participant physical condition had significance effects on the speed estimation error.

In order to evaluate the effect of personalization on the speed error, we compared the personalized algorithm to a kind of its non-personalized version. The non-personalized method used the same features and model (i.e., fixed instead of recursive least squares) as personalized but the difference is the way of training, i.e., offline instead of online. To perform a fair comparison, the following procedure was done for an arbitrary subject λ: the personalized method was trained using half of data of the subject λ (randomly selected in time) in an online fashion and tested using the other half of its data. For the non-personalized method, the model was trained on data from all subjects except the subject

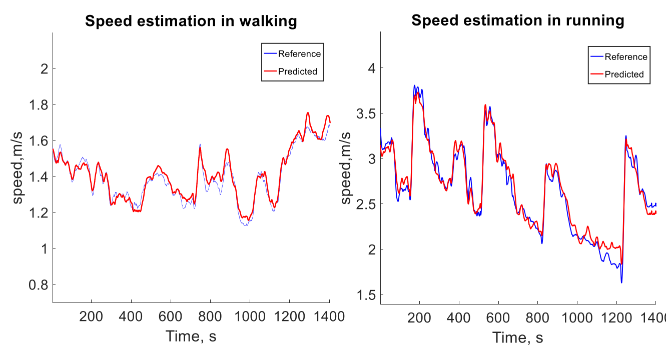

Fig. 6. An illustration of reference and predicted speed values during daily walking and running for a typical subject (ID#1).

λ and then tested on exactly the same test data as personalized method; this process was repeated until each subject had been the test subject exactly once. The error of the non-personalized model was estimated in the same way as personalized model (as described above).

III. RESULTS

We analyzed outdoor activities of 30 participants, both wrists, including a total 41.7 hours of walking and 17.5 hours of running under real-life circumstances. GNSS sensor reported a median speed error of 0.11, 0.11, and 0.12 (m/s) for slow, normal and fast walking activities (see Table I for the definition of different walking), respectively. It also showed a median speed error of 0.16, 0.17, 0.17 (m/s) for slow, normal and fast running, respectively.

A. Personalization Performance

For a typical subject, Fig. 6 illustrates an example of high ability of the proposed personalized method to follow the reference speed under various speed ranges and outdoor circumstances during both walking and running. Lilliefors test showed that instantaneous speed error do not follow normal distribution $(p < 0.001)$. Consequently, for each subject, we computed median (as bias), IQR (as precision), and RMSE of the estimation error in test data set (personalization data set was excluded).

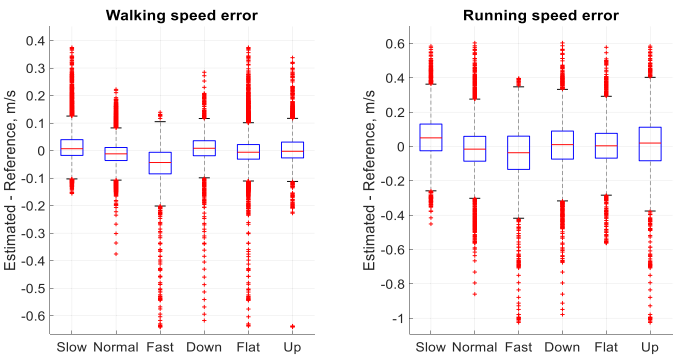

Fig. 7. Boxplot of walking and running speed errors versus trials conditions. Blue boxes and the lines inside are IQR and median values. Dashed lines are whiskers, which show 3/2 of IQR measured from the top and bottom of each box. Red signs "+" also represents the outliers. For information about test conditions, refer to the footnote of Table I.

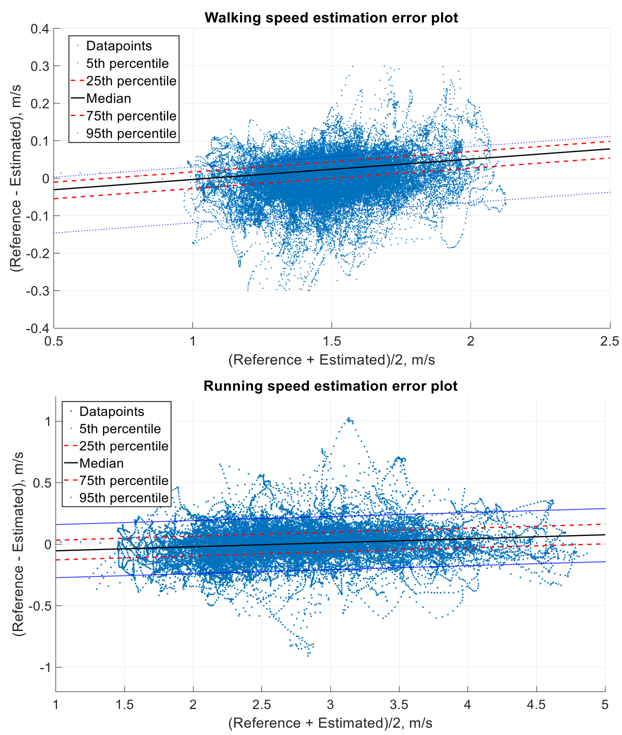

Fig. 8. Error plots for walking and running speed estimation. For walking, the 5th, 25th, median, 75th, 95th percentiles are −0.09, −0.02, 0.00, 0.03, 0.07 m/s, respectively. For running, the parameters are −0.23, −0.08, 0.00, 0.08, 0.22 m/s.

Table I reports inter-subjects median and IQR of RMSE, bias and precision for different conditions of walking and running performed on the track (Fig. 2) on either both or single wrist. Totally, for walking, the proposed personalized method has achieved an RMSE of 0.05 [0.04 0.06] (m/s), a bias of 0.00 [−0.01 0.00] (m/s), and a precision of 0.06 [0.05 0.07] (m/s). For running, it has obtained an RMSE of 0.14 [0.11 0.17] (m/s), a bias of 0.00 [−0.01 0.02] (m/s), and a precision of 0.18 [0.14 0.23] (m/s). Fig. 7 displays distribution of speed error versus trial conditions thorough box plot.

Spearman's test showed a high correlation ($R^2 = 0.96$ for walking and $R^2 = 0.94$ for running) between the reference and predicted speed values. For average speed per person, the correlation coefficients increased to $R^2 = 0.99$ for both walking and running. Fig. 8 illustrates Bland-Altman plot [53] for speed estimation confirming low correlation between the error and estimated speed values ($R^2 = 0.07$ for running and $R^2 = 0.06$ for walking). Kruskal–Wallis test demonstrated a significant effect ($p < 0.001$) for altitude changes of the path and participants on the speed error during walking and running. Lastly, the predicted speed values and age, height and weight for both walking and running were uncorrelated ($R^2 < 0.06$).

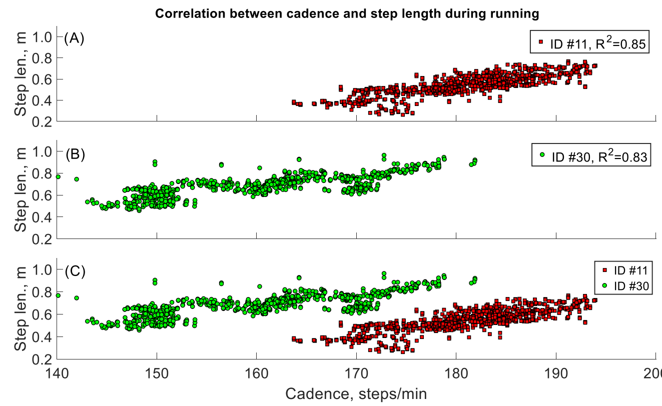

Fig. 9. Importance of personalization for the step length modeling. (A), (B) and (C) show the correlation between the feature *cad* (cadence) and the step length of participants #11 (red squares), #30 (green circles), and both together. R^2 Spearman's correlation values were also indicated for each case.

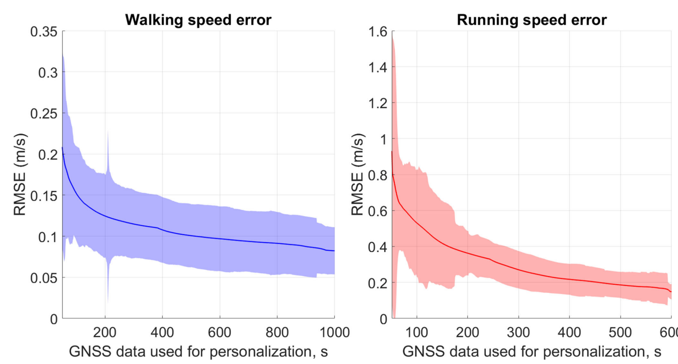

Fig. 10 Evolution of the RMSE error of the proposed speed estimation method over personalization procedure for both walking and running. The dark line and the area are respectively mean and standard deviation of RMSE error over all subjects. *x* axis corresponds to numbers of GNSS data used for personalizing the step length model.

B. Personalized vs Non-Personalized Method

The importance of personalization for step length modeling is demonstrated in Fig. 9. In fact, this example shows how a high correlation ($R^2 > 0.83$) between the individual cadence ($Cad[n]$), as a typical feature, and the individual step length was dropped ($R^2 > 0.12$) when data of the two participants were mixed. Generally, biomechanically-derived features showed different degrees of correlation with step length ranging from $R^2 \in [0.10\ 0.95]$. Nevertheless, each feature has reached

TABLE II
OVERALL PERFORMACE OF PERSONALIZED AND NON-PERSONALIZED APPROACHES FOR SPEED ESTIMATION IN DAILY WALKING AND RUNNING

Methods	#Sub.*	Walking error (m/s)							Running error (m/s)						
		#Samp.*	RMSE		Bias (median)		Precision (IQR)		#Samp.*	RMSE		Bias (median)		Precision (IQR)	
			Med.	IQR	Med.	IQR	Med.	IQR		Med.	IQR	Med.	IQR	Med.	IQR
Non-Personalized	29	70000	0.10	[0.07 0.12]	0.00	[-0.05 0.06]	0.08	[0.07 0.10]	30000	0.31	[0.25 0.42]	-0.02	[-0.20 0.17]	0.31	[0.26 0.39]
Personalized	**1**	**1200**	**0.05**	**[0.04 0.06]**	**0.00**	**[-0.01 0.00]**	**0.06**	**[0.05 0.07]**	**600**	**0.14**	**[0.11 0.17]**	**0.00**	**[-0.01 0.02]**	**0.18**	**[0.14 0.23]**

* Sub. and Samp. are numbers of subjects and samples in training, respectively.

a $R^2 \geq 0.41$ for at least one subject, which higlights the usefulness of all features.

Fig. 10 indicates the evolution of RMSE of the proposed speed estimation method over personalization procedure. In order to obtain this result, for each subject, training samples were fed one-by-one into the recursive personalization procedure where, after feeding each sample, the most updated model was evaluated through all data in the test set (i.e., half of data of the subject). Then, inter-subjects mean and standard deviation of RMSE were computed as dark line and the shadow in Fig. 10, respectively. According to this figure, using only 600 samples of GNSS for personalization decreased the RMSE value to less than 0.1 and 0.2 (m/s), respectively.

Table II compares overall performance of the proposed personalized method and its non-personalized version, according to average number of samples and numbers of subjects in training to build each model. Both methods are evaluated on test data set which is half of data of each subject (randomly selected) and personalization data set was excluded from error computation. In order to build a non-personalized speed estimation model, on average 70000 and 30000 samples collected from 29 subjects were used for walking and running, respectively. However, for personalized model only 600 and 1200 samples (on average) collected from only one subject were employed for walking and running respectively. Fig. 11 indicates cumulative distribution of RMSE, bias, and precision of the proposed personalized and non-personalized methods. Eventually, Fig. 12 displays the correlation between actual and estimated speed values thorough the proposed personalized and non-personalized methods.

IV. DISCUSSION AND CONCLUSION

In this paper, we devised a personalized approach for accurate speed estimation during walking and running using a wrist-mounted accelerometer and barometer under various real-world conditions. Several terrain conditions as well as speed ranges were considered to test the method.

Our analysis showed that while the correlation between features and step length might be high for when each individual was considered separately, it dropped when we mixed data from two or more individuals (see Fig. 9). Consequently, to provide a more accurate speed estimation, a personalized model was designed for each individual. The personalized model was updated whenever new GNSS data were acquired in order to adapt the model to new gait styles adopted by the user. As depicted in Fig. 10, at the beginning of the personalization procedure,

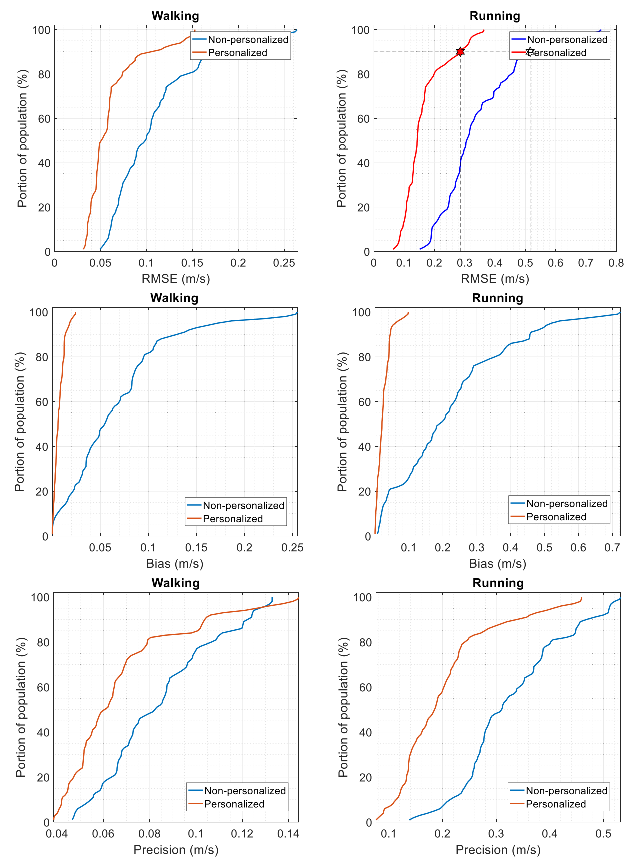

Fig. 11. Cumulative distribution of RMSE, bias and precision of the proposed personalized and non-personalized methods for walking and running. For example on the most top right plot, the red star demonstrates that the RMSE error of the personalized method is less than 0.27 (m/s) for 90% of the population. However, for non-personalized method (i.e., blue star), the RMSE error is less than 0.53 (m/s) for 90% of the population.

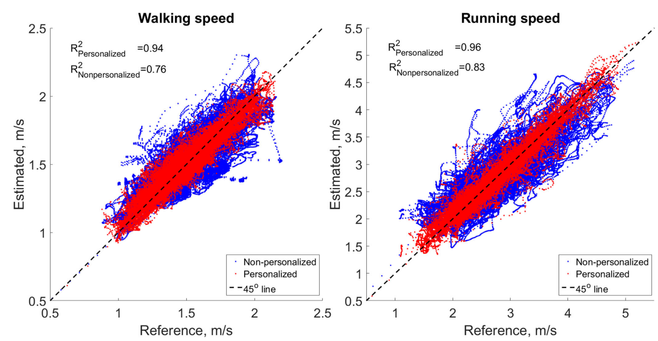

Fig. 12. Estimated speed versus reference for the proposed personalized and non-personalized methods.

the error in estimated speed was quite high since there were not enough data to build a reliable speed estimation model. However, as more and more personalization data were given as input to the online RLS-based learning process, the RMSE were gradually decreasing. The personalized approach relied on the same features and similar rule than non-personalized approach (RLS instead of conventional least square) where only the training data were different. In fact, the personalized model was initialized through training by a small initial data set coming from the participant. An alternative was to train the initial model by the data belonging to the whole population. However, the initial model that we proposed led to a faster convergence of the model and did not require a large training dataset involving high numbers of participants.

The proposed personalized method was able to follow GNSS speed every second under different speed ranges ([0.5 5.2] m/s) and environmental conditions (i.e., uphill, flat, downhill). Compared to GNSS speed, the proposed method has achieved a proper RMSE of 0.05 [0.04 0.06] (m/s) and 0.14 [0.11 0.17] (m/s) for walking and running, respectively. It also provided almost zero bias for both walking and running. Eventually, the method has obtained a very good precision of 0.06 [0.05 0.07] (m/s) and 0.18 [0.14 0.23] (m/s) for walking and running, respectively (see Table I). These errors showed how much the proposed method was different from GNSS speed which itself had a median measurement error of 0.12 (m/s), in spite the low accuracy provided in the GNSS receiver datasheet (0.05 (m/s)). Our algorithm performed better for walking than running, and this was due probably to the greater robustness of the walking features extracted from hand movement. Moreover, the proposed method was also robust enough to have similar performance on both wrists.

In order to show the power of personalization, we compared the personalized method with its non-personalized version where features, model, and test data were the same and the difference came from training approach. We demonstrated that using 50 times less training samples than non-personalized method (i.e., 600-1200 samples compared to 30000-70000), the personalized method has achieved a better RMSE, bias, and precision. It should be also noted that the personalized method was trained by data of only 1 subject, compared to non-personalized method trained by data of 29 subjects. In particular, by personalization, the IQR of bias dropped by at least ten times, which led to more accurate estimation of average speed within a period of speed measurement. Moreover, the personalization led to a great improvement in the RMSE and precision (at least 3 times), which resulted a precise instantaneous speed estimation. Fig. 11 supports these results by showing that the proposed personalized method performs excellent for almost all types of people where the range of error is very low (e.g., RMSE varies in ranges [0.06 0.36] and [0.03 0.15] (m/s) for walking and running, respectively). On the other hand, the performance of non-personalized method highly varies among different types of people (e.g., RMSE varies in ranges [0.14 0.75] and [0.04 0.26] for walking and running, respectively). Consequently, the personalized model is more reliable than non-personalized method. However, if data of a specific person was not enough to train a reliable personalized model, which depends on the variety of his/her gait styles, the non-personalized method may perform better due to the support of a much higher training data (i.e., higher generalization ability). This issue can be seen in the most bottom left subfigure of Fig. 11 where for a small number of subjects the precision of non-personalized walking speed method was slightly better than the personalized one. Fig. 12 illustrates that through personalization the correlation between reference and predicted speed is increased by more than 23 (%) and 15 (%) for walking and running, respectively. Totally, the results show that the performance of the personalized method was more similar to that of the reference GNSS system than non-personalized one.

In the personalized method, low number of GNSS samples used implies having the GNSS ON for each subject only for few minutes (i.e., 10 minutes). This parsimonious usage of GNSS could be distributed over one or two weeks (e.g., some GNSS samples per day) to obtain enough diversity in the gait styles (different speeds, terrain conditions, etc.) of a user. In this study, we employed a random selection strategy to choose a subset of GNSS samples to personalize the speed estimation model. However, a more smart strategy can be designed (as a prospective of this study) to turn GNSS ON when there is new information in the gait behavior of the user. This leads to capturing the most informative GNSS samples through using the GNSS as less as possible.

In addition to personalization, we defined wrist-based biomechanically-derived features to obtain more accurate speed estimation. These features showed different degrees of correlation with step length depending on the individual's gait style as was illustrated for cadence in Fig. 9. The results determined that each feature reached a $R^2 \geq 0.41$ for at least one subject. This demonstrated that all the proposed features conveyed useful information and had complementary effects. By selecting only a few but relevant gait features, we reduced computation and complexity costs of the step length model, which is important for real-time algorithms implemented on portable devices like wristwatches.

The results highlighted the dependence of the gait speed errors on the speed values: overestimation for low speed and underestimation for high speed (Fig. 8). One possible reason could be due to the limitation of the linear model which was preferred in order to decrease computation and algorithm complexity. Another reason may be the limited number of training samples at low and high speed. This could be confirmed by using non-linear models and increasing sample size. Another issue is the outliers, which can be seen in Fig. 7. One possible reason for these may be the lack of perfect synchronization between the proposed wrist-based speed estimation method and the reference GNSS system. In fact, the wrist-based method used a 7-second sliding window that prevented it from responding to rapid changes of speed, which might be quite probable in real-life situations. Hence, sometimes, there was a time delay between the proposed personalized wrist-based method and the GNSS reference system, especially after immediate speed transitions, which led to generating the outliers observed in our error plots. Apart from this, the GNSS sensor sometimes yielded very noisy data due to low quality of satellite signals or unexpected body movement, which alone can generate outliers. The method presented in Section II-B and Fig. 3, aimed at reducing noise in GNSS data. However, other techniques for better GNNS signal enhancement could be considered.

Compared to previous studies, the proposed personalized speed estimation algorithm has achieved excellent performance even though the sensor placement on the wrist was challenging and measurements were performed in the free-living environment. For walking, the proposed personalized method provides a median error of 0.00 (m/s) and an IQR of 0.06 (m/s) where [20], as one recent non-personalized wrist-based walking speed estimation algorithms, achieved a median error of 0.02 (m/s) and an IQR of 0.18 (m/s) using single accelerometer and barometer sensors. Methods based on foot sensors also have reported a mean error of 0.01 (m/s) and the precision of 0.08 (m/s) for indoor walking [56] where both accelerometer and gyroscope sensors were employed. Moreover, shank and thigh sensors-based algorithms used at least three sensors to provide a precision of 0.10 (m/s) [26]. For running, few works have been introduced to estimate speed using inertial sensors. The proposed personalized method has obtained a median error of 0.00 (m/s) and an IQR of 0.18 (m/s) for running speed estimation. Foot-fixed sensors were used to estimate running speed with a median error of 0.07 (m/s) and range of 0.13 (m/s) [25] where an accelerometer and a gyroscope were used on each foot. Yang *et al.* also estimated running speed on treadmill using an accelerometer and gyroscope shank-mounted sensors with a root mean square error of 0.10 (m/s) [57]. Moreover, [58] tested four different speed estimation algorithms using an IMU implemented into a shoe sole and, in the best case, reported a mean ($\pm$ std) error of 0.03 ($\pm$0.27) m/s for an algorithm based on the foot trajectory estimation.

The proposed method offers a versatile measurement tool that could be used in a variety of target populations. In sport applications, it can be used to help trainers and trainees to optimize their walking/running performances. In clinical applications, the method provides the potential to monitor patients, adults or elderly people. For instance, we have planned to apply this method to a large population to study the effect of various diseases (e.g., obesity, frailty, cardiovascular disorders), or aging on the activity profile of people (i.e., gait speed). However, the proposed method would need to be complemented by other techniques for locomotion-bout detection, to automatically classify gait bouts that could be then used for speed estimation. Our analysis showed that using only one unique model for both walking and running speed estimation could increase the error up to 4 times. Since the proposed personalized method has been optimized for healthy population, it may need some tuning and validation for elderly and patient populations.

To conclude, the present study provided a personalized approach for accurate, precise, and low-power estimation of instantaneous speed during daily-life gait. It demonstrated that personalization leads to a great improvement of speed estimation based on wrist sensor (despite the challenges posed by the sensor location) by achieving results comparable to the GNSS reference. While in free-living conditions, the proposed method were tested on normal gaits where wrists were swinging around the trunk. Further analysis should be done to validate the algorithm under abnormal gaits or where independent arm movements (e.g., hand-in-pocket, carrying a bag, talking with phone) exist. Nevertheless, our previous work showed that the cadence estimation was not affected significantly by these independent movement [20]. As other future work, the proposed algorithm could be improved to manage non-linearity between the chosen features and step length, validated in abnormal gait, integrated with an automatic locomotion-period recognition algorithm (such as methods proposed in [59], [60]), and rendered even lower-consuming through a smart strategy to minimize GNSS usage.

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