Assessing Older Adult's Gait Speed with Wearable Accelerometers in Community Settings: Validity and Reliability Study

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Abstract. We present the preliminary results of a validity and reliability study of two different state-of-the-art algorithms to estimate the gait speed of older adults in free-living conditions from the data collected by the ActiveUP wearable device. We described the ActiveUP wearable sensor together with its integration in a smart environment for frail and pre-frail older adults via an edge-computing architecture. A cross-sectional observational study was conducted. A sample of 18 people, 77.89 (6.47) y.o. 11 women, was recruited and their movement signals were recorded during short (2.4 m) and long (6 m) walking bouts. Validity, agreement, and reliability were assessed with Pearson's correlation coefficient, with SEM and Bland-Altman limits of agreement (LOA), and with an ICC(A, 1) model of the intra-class correlation coefficient, respectively. Validity and reliability seemed to be good. However, the small size of our sample results in broad confidence intervals for the estimators. The agreement seems not to be good enough to trigger therapeutic responses. More studies are necessary to test whether the threshold for clinical tests is applicable under free-living conditions.

Keywords: gait speed · wearabe accelerometer · validity · reliability

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1 Introduction

The World Health Organization defines healthy aging as "the process of developing and maintaining functional ability that enables well-being in older age" [1] (p. 28). This definition emphasizes that healthy aging is more than the simple absence of disease. It is now widely recognized that functional impairment, rather than disease, is the main risk factor for disability and death [2] and that it is the main factor that explains the increase in cost for social and health systems. Older adults with functional impairment and their families make an intensive use of health and social services [3]; and this presents a major challenge in providing the health services that older people need while maintaining the sustainability of the system. The path to disability is a gradual process of functional loss [4]. During this process, even years before developing a disability, older adults show characteristic signs of a syndrome known as frailty [4]. Frailty is a state of increased vulnerability to adverse outcomes due to a reduction in the ability to respond to stressors, even if they are of low intensity [5]. However, frailty can be prevented and also reversed [6]. In fact, there are validated tools to detect frailty and effective interventions to manage it [5]. Frailty is evaluated by trained geriatricians or geriatric nurses in specialized care. However, specialized care does not have enough resources to screen the entire older population; the identification of new and more efficient forms of detection and screening remains a challenge [7].

The use of wearable automatic sensors has been proposed as a way to assess the functional status of older people without involving specifically trained personnel [8]. Gait analysis is one of the most studied applications of wearable sensors; and gait speed is one of the five markers of frailty in the most widely used frailty model, the Linda Fried phenotypic model [4]. Gait sensors have been used to implement instrumented versions of standard clinical tests. For example, they have been used to estimate the value of gait speed and some other kinematic variables in walking tests of different lengths [9,10]. The usability of wearable sensors for instrumented walking tests has not been tested in older adults in unsupervised home settings. However, the favorable experience of Cobo et al. with their body sensor for instrumented sit-to-stand tests [11] suggests that instrumented walking tests with wearables could be suitable for this scenario.

Gait sensors have also been used to go a step further and estimate gait speed without interfering with people's daily activities. Recent studies using wearable accelerometers to collect gait signals under free-living conditions can be found in the scientific literature [12–14]. The wearable sensors described in these studies were located on the waists of the participants or on their lower backs through elastic or adjustable belts. Their algorithms processed the acceleration signals to identify sustained walking bouts and then provided an estimate of gait speed for each bout. They report good results. However, there are still some challenges to overcome. On the one hand, although a relationship between daily gait speed measurements and functional impairment has already been observed [10,15], more studies are still needed to find out which estimation methods best capture the onset of functional changes and which quantitative thresholds best quantify their intensity. On the other hand, sensor measurements must be readily available to older adults' physicians to assess their functional status and make therapeutic decisions when appropriate. Smart environments can connect these gait speed sensors to third-party services via the Internet of Things (IoT) to provide personalized, anticipatory and adaptive services in many areas, such as energy management, health care, quality of life (independent and assisted living), or social isolation [16,17]. However, sensors in a smart environment require connectivity, which adds a load to the computation and energy constraints of the devices.

In the present paper, we describe the ActiveUP wearable sensor as an IoT device integrated in an edge-computing architecture; and present the preliminary results of a validity and reliability study of three different state-of-the-art algorithms to estimate gait speed in free-living conditions from the data collected by the ActiveUP wearable device.

2 Methodology

We conducted a prospective cross-sectional observational study to assess the validity and reliability of three different state-of-the-art algorithms for the estimation of gait speed under free-living conditions. A sample of older adults was recruited and their movement signals were recorded during short and long walking bouts 2.4 m and 6 m long, respectively. The study was carried out according to the Declaration of Helsinki and the protocol was approved by the Ethics Committee of the University Hospital of Getafe (CEIm21/41).

2.1 Participants

Subjects were eligible for the present study if they:

- met ALL the following INCLUSION CRITERIA:
  - subjects 70 years or older,
  - subjects able to walk, with or without mobility aids (such as canes or walkers).
- did not meet ANY of the following EXCLUSION CRITERIA:
  - subjects unwilling or unable to give their consent,
  - subjects unable to understand the researchers' commands or the questionnaires. This criterion was tested asking subjects to point to the device on/off button and to describe the meaning of the light that turned on after pressing it.
  - Clinically unstable subjects in the judgment of the investigator.

2.2 Apparatus

The ActiveUP Wearable Sensor. This sensor is a device of 10 × 7 cm that includes a 6 degree-of-freedom inertial measurement unit (IMU). Figure 1 shows three pictures of the sensor. The device comprises an ESP32 microcontroller with WiFi and BT interfaces onboard, an MPU-6050 GY-521 IMU with an I2C interface, a DS3231 Real Time Clock, a Micro-SD card module with an SPI interface, a TP4056 Lipo charger with a USB type-C interface, an RGB LED, and a commutator. The microcontroller samples linear acceleration and angular velocity 18 Hz in each of the three spatial directions and stores the data on an SD card for subsequent transmission.

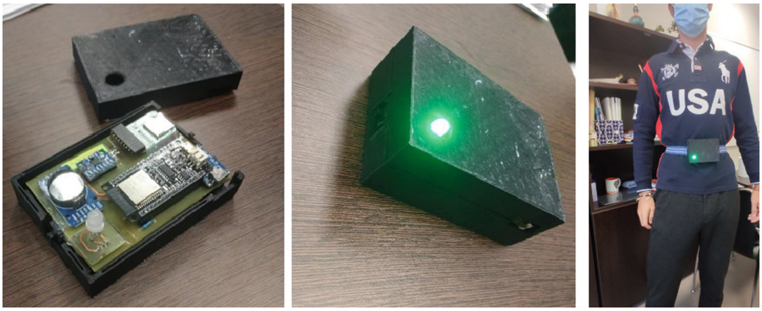

Fig. 1. The ActiveUP wearable sensor. View of the prototype PCB (left). View of the operative device (center). Subject wearing the device (right).

The ActiveUP wearable sensor has been integrated into an edge computing architecture as shown in Fig. 2. The architecture is a wireless network that comprises sensors, an edge node, and a gateway with an Internet connection. The edge node has been implemented on a Raspberry Pi and includes a message broker, local storage, and some data processing modules. The message broker redirects sensor data to authorized interested parties (in-home and external) via a publish/subscribe mechanism. Data processing modules transform raw data into clinically relevant information, thus reducing the amount of information that must be transmitted over the Internet.

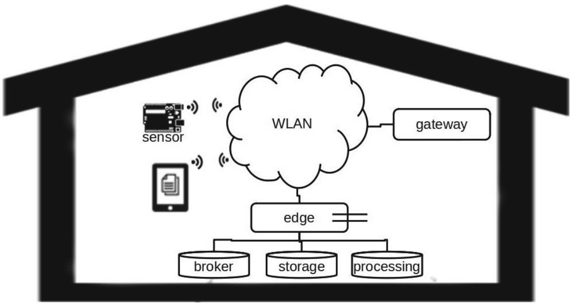

Fig. 2. Edge-computing architecture for the ActiveUP home system.

The Gait Speed Algorithms. We processed the signals collected with the ActiveUP sensor with three state-of-the-art algorithms to estimate the gait speed of older adults.

Mueller's Algorithm. Mueller et al. described an algorithm specifically designed for older adults who walk at a slow speed [13]. The algorithm uses a Short-Time Fourier Transform (STFT) to divide the acceleration signal on each axis into 2.5-s-long overlapped windows. Then, windows are kept or discarded based on the plausibility of their dominant frequency and trunk inclination. Finally, the algorithm applies a Hilbert transform on each axis and estimates gait speed by entering the amplitude values into a previously fitted linear regression model. They do not provide a precise description of some of the steps of the algorithm. Thus, we implemented our own adaptation by applying the following criteria:

1. we computed the STFT step by splitting the signal into 2.5-s windows with a 50% overlap (empirical value).
2. We used the highest frequency in a window as the dominant frequency, regardless of the axis.
3. We removed windows with a dominant frequency below 0.5 Hz (empirical value).
4. We did not use the angle of the trunk to remove any windows because it resulted in a decreased performance.
5. We did not apply the Butterworth filter in the sixth step because the filter parameters were not described.

GaitPy. GaitPy uses a pre-trained binary classifier to detect bouts. Then, it enhances the patterns in the vertical axis with a wavelet-based method to detect heel strikes and toe off events. Finally, the acceleration in the vertical axis is integrated to derive a vertical displacement and an inverted pendulum model is applied to estimate gait speed on a stride-to-stride basis [12]. It is publicly available as an open source Python package [18] at https://github.com/matt002/GaitPy. GaitPy requires sampling frequencies 50 Hz for the input signals. Since the sampling frequency in our device 18 Hz, we had to up-sample the signals with an interpolation filter before applying GaitPy. We used the interp function in Matlab R2022a with a multiplication factor of 3.

Urbanek's Algorithm. Urbanek et al. divide the acceleration signal of each axis with an STFT and rely on the harmonic nature of sustained walking to quantify the local periodicity of the signal within each window. Then, they estimate the fundamental frequency of the observed signals and identify bouts of sustained walking by grouping together windows with low variability of step frequency. Finally, they provide an estimate of cadence (that is, step frequency) for each bout [10]. They thoroughly described their algorithm; therefore, we were able to code our own implementation in Matlab. However, the algorithm has a couple of drawbacks. They report optimal results for a minimum bout duration of 10 s; therefore, performance is expected to degrade for short bouts (2.4 m) and long bouts (6 m) at home. In addition, their algorithm provides estimations of cadence rather than estimations of gait speed. Thus, we only tested Urbanek's algorithm's ability to identify bouts (which is out of the scope of this paper), but did not test its validity and reliability as a gait-speed estimator.

Reference Measurements. The reference measurement of gait speed in short bouts was measured with our previously validated device for 2.4 m walking tests (2.4 mWT) [19]. This device comprises a foldable tape equipped with ultrasound sensors (Fig. 3) and measures the time it takes for a subject to walk along the tape (from the ultrasound sensor at the beginning to the ultrasound sensor at the end). Finally, it reports the average speed of the subject.

Fig. 3. Gait speed sensor for the 2.4 mWT.

In the case of long bouts, we obtained the reference measurements from a standard 6m walking test (6mWT) with a manual stopwatch.

2.3 Procedure

Participants were recruited from the Day Hospital and outpatient clinics of the Getafe University Hospital geriatric service and among relatives and acquaintances of the members of the research team. The day hospital health care personnel and those of external consultations asked patients, after their usual appointment, if they wanted to be informed about a study. Those who accepted went to a separate consultation in which a member of the research team individually explained the study and answered all the questions and doubts they had. In the case of relatives and acquaintances, the different members of the research team contacted them and asked them if they wanted to be informed about a study. They were individually contacted in person or by phone and received an explanation of the study and answers to all their questions and doubts. All of them, regardless of the entry mechanism, received enough time to assess their participation. The possibility of postponing the decision for several days was considered, which is why a contact phone number was provided to clarify doubts or arrange a later appointment for the study. The information related to the study was provided by the physician, nurse, or any other qualified member of the research team. When appropriate, the caregivers of the patients or their family members also received the information.

Subjects willing to participate were screened according to the eligibility criteria. The selected subjects signed an informed consent and were included in the study. Participants included in the study were asked for their consent to video record the data collection session. Those who accepted received an additional authorization sheet to sign. Those who did not accept continued to participate in the study without being recorded. Then the training session and the experimental data collection session took place. If the participant authorized the recording of the session, the recorded timespan was limited to the moments when the participant used the wearable sensor and only captured the image of the participant from the waist down.

During the training session, the participants learned how to operate the device to perform its function.

Data collection involved:

- a questionnaire for demographic and anthropometric data,
- wearing the sensor while taking two gait speed tests (2.4 mWT and 6 mWT),
- a short simulation of daily activities, out of the scope of the present paper,
- an interview about the participants' experience in the use of the technology and their impressions about the sensor,
- and, finally, wearing the sensor while taking two gait speed tests (2.4 mWT and 6 mWT) once again.

During the experiment, a member of the research team took note of the output of the reference measurements. After the data collection session, the collected signals were processed with the algorithms described above and the values of their output were added to the data set.

2.4 Analysis

To characterize the reliability of the measurements, the test-retest reliability was studied. Since gait speed is a continuous variable, the test-retest reliability was estimated by calculating intra-class correlation coefficients (ICC). An ICC (A,1) model was calculated with the icc function in the irr package in the statistical software R, version 4.2.1 [20].

The degree to which two measurements are identical (agreement) was estimated by calculating the standard error of the measurement (SEM). We used SEM estimations to estimate the minimum detectable difference (MDD) and compared it to the minimum difference with clinical significance. SEM and MDD were calculated as described by [21] after performing a repeated measurement ANOVA with the aov function in R. Due to the size of the sample (less than 50), normality was assessed with a Shapiro-Wilk test with the shapiro.test function in R. Homoscedasticity was assessed with a Levene test with the leveneTest function of the car package in R. Upper and lower limits of agreement (uLOA and lLOA) were calculated by conducting a Bland-Altman analysis with the blandr package in R.

To verify the validity of the algorithms, we calculated the correlation between their reported speed values and those obtained with the reference methods.

When appropriate, 95% CI are reported. The level of statistical significance was established at 0.05.

3 Results

A total of 18 people were recruited: 77.89 (6.47) y.o., 11 women. Valid signals were obtained for 15 of them: 78.53 (6.71) y.o, 9 women. GaitPy was able to detect walking activity at 2.4 m for 11 subjects only and for 14 of them at 6 m.

Table 1 and Table 2 show the results of the validity, agreement, and reliability analyses for short and long bouts, respectively.

Table 1. Results of validity, agreement, and reliability analyses for short bouts (2.4 m).

	Mueller's	GaitPy
Validity	r = 0.837	r = 0.724
	95% CI = (0.711, 1.000)	95% CI = (0.492, 1.000)
Agreement	SEM = 0.082 m/s	SEM = 0.079 m/s
	MDD = 0.228 m/s	MDD = 0.218 m/s
	95% CI(uLOA) = (0.094, 0.319)	95% CI(uLOA) = (0.066, 0.330)
	95% CI(lLOA) = (−0.362, -0.137)	95% CI(lLOA) = (−0.370, -0.106)
Reliability	ICC(A, 1) = 0.812	ICC(A, 1) = 0.669
	95% CI = (0.532, 0.932)	95% CI = (0.148, 0.899)

Table 2. Results of validity, agreement, and reliability analyses for long bouts (6 m).

	Mueller's	GaitPy
Validity	r = 0.799	r = 0.812
	95% CI = (0.649, 1.000)	95% CI = (0.669, 1.000)
Agreement	SEM = 0.039 m/s	SEM = 0.072 m/s
	MDD = 0.109 m/s	MDD = 0.199 m/s
	95% CI(uLOA) = (0.042, 0.154)	95% CI(uLOA) = (0.046, 0.251)
	95% CI(lLOA) = (−0.176, −0.064)	95% CI(lLOA) = (−0.352, −0.147)
Reliability	ICC(A, 1) = 0.935	ICC(A, 1) = 0.799
	95% CI = (0.814, 0.978)	95% CI = (0.476, 0.931)

4 Discussion

Validity assesses the ability of an algorithm's output to represent the target variable (in this case, gait speed). The point estimates for both Mueller's and GaitPy algorithms suggest that their validity values are good for both short and long bouts. However, their 95% CIs are too broad to support this conclusion. We cannot conclude that their validity is better than moderate; in fact, the lower end of GaitPy's CI for short bouts suggests that its validity could even be poor.

Agreement assesses the ability of an algorithm to provide the same value for multiple measurements on a stable subject. A difference of 0.1 m/s between two clinical walking tests taken two weeks apart is enough to trigger a geriatician's therapeutic response. Only Mueller's algorithm in long bout scenarios is a candidate to comply with such a requirement. It resulted in an SEM of 0.04 m/s and an MDD as low as 0.1 m/s, while the other three cases show an MDD twice as much. However, the widths of the 95% CIs of Bland-Altman's LOAs do not let us conclude that the agreement for Mueller's in long bouts scenarios is good enough to comply. Anyway, the 0.1 m/s threshold has been tested on measurement values from clinical tests. More studies are needed to test whether the same threshold applies to gait speed values estimated from free-living conditions. In fact, differences have already been observed between these two scenarios. For example, the values of gait speed, acceleration, and cadence in free-living conditions have been observed to be lower than those measured with clinical tests [10,13].

Reliability assesses the ability of an algorithm to provide different values for different subjects with different speeds. The point estimates for Mueller's algorithm suggest that its reliability is good for both short and long bouts. In particular, the 95% CI for long bouts let us conclude that reliability is, in fact, good or excellent. On the other hand, the 95% CI for short bouts does not let us conclude that its reliability is better than moderate. The point estimates for GaitPy suggest that its reliability is good for long bouts and moderate for short bouts. However, their 95% CIs suggest that its reliability could even be poor in both cases.

As expected, the overall performance of the algorithms is better for longer bouts than for shorter ones.

The main limitation of this preliminary study comes from its small sample size; which results in broad confidence intervals for the validity, agreement, and reliability estimators. We estimated that subsequent studies require sample sizes from 100 subjects on to be conclusive by running a simulation with synthetic data. We sequentially increased the sample size by adding duplicates of the data until the resulting 95% CIs were narrow enough.

5 Conclusion

Validity and reliability of state-of-the-art algorithms to estimate the gait speed of older adults in free-living conditions seem to be good. However, the results should be taken with caution because the small size of our sample results in broad confidence intervals for the estimators. The agreement seems not to be good enough to trigger therapeutic responses according to the current threshold for clinical tests. However, more studies are necessary to test whether the same threshold applies to gait speed estimations under free-living conditions.

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