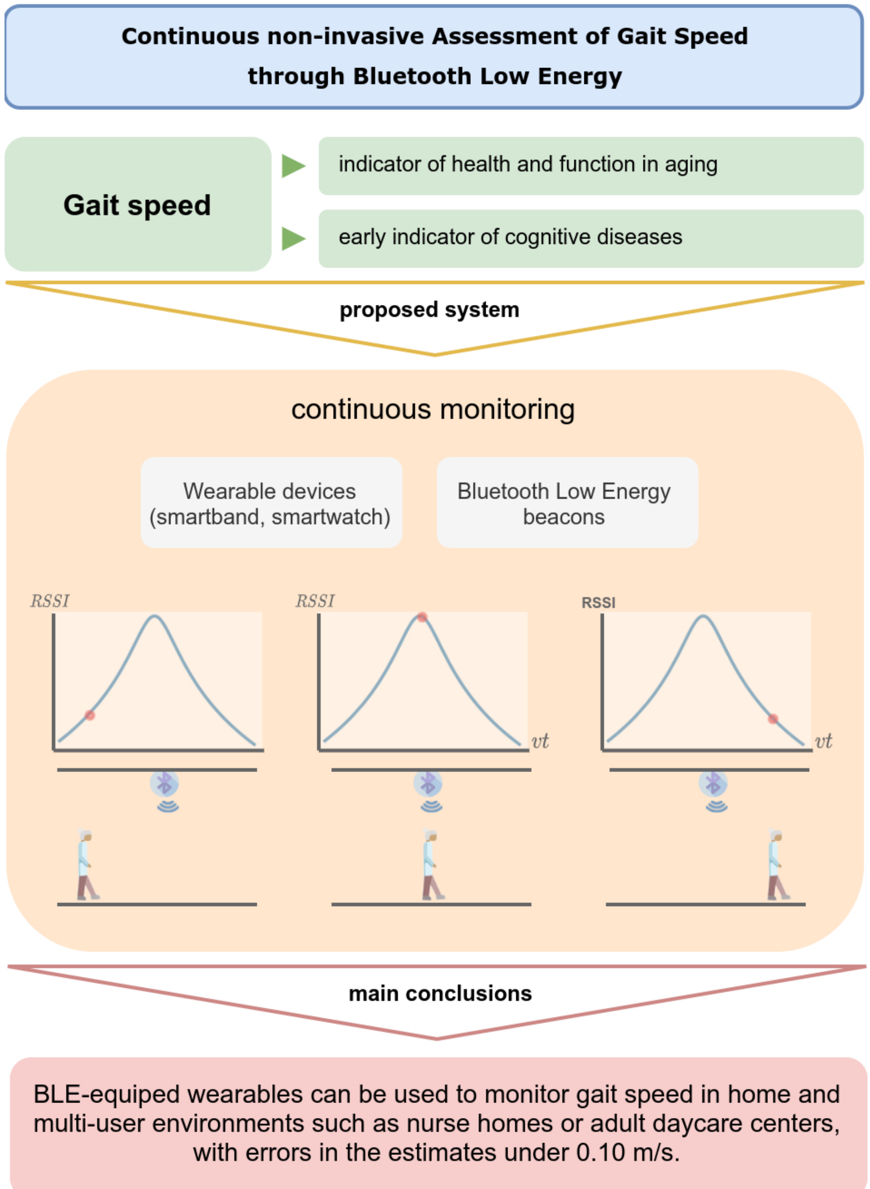

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Continuous non-invasive Assessment of Gait Speed through Bluetooth Low Energy

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***Abstract*—In the near future, as a consequence of the increasing percentage of elder people with respect to the total population, developed countries will face significant stress on their healthcare systems. The onset of some diseases associated with aging, such as dementia or cognitive decline, has been associated with a number of factors that can be detected in advance, thus offering the possibility of an early intervention to delay their onset. Specifically, several studies have shown a correlation between slower gait speed and serious cognitive diseases such as Alzheimer's disease. In this work we present a method, based on Bluetooth Low Energy (BLE), capable of detecting the user's walking speed in a continuous and non-invasive way, providing a useful tool for the monitoring and early detection of this type of diseases. The proposed method estimates the gait speed with an average error of less than 10 cm/s, and is capable of providing continuous non-invasive monitoring of the gait speed of users while they conduct their usual life routines, without any additional requirements other than wearing a smartwatch or an activity band with inertial sensors and BLE capabilities.**

***Index Terms*—Ambient Assisted Living, Bluetooth Low Energy, Gait Speed**

I. Introduction

Population aging is a global phenomenon. In the next thirty years, the number of people over the age of 65 is expected to double, from 700 million to 1.5 billion. The share of the population aged 65 years or over will increase from 9% in the year 2019 to 16% in the year 2050 when it is expected that one in six people worldwide will be aged 65 years or over [1]. Evidence suggests that people entering older age now are healthier than previous generations and that this trend will continue in the next decades. Worldwide, a person who reaches the age of 65 years in 2015-2020 can expect to live an additional 17 years on average. By 2045-2050, that number is expected to increase to 19 years.

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Older adults have greater health and long-term care needs than the rest of society. Health systems have not been oriented toward these needs in the past and may have difficulties responding to the new demographic reality and the associated changes in population health. More than ever, a smaller proportion of people, those of working age, will be responsible of providing and financing these health care systems for their older adults.

In this scenario, it is desirable to promote quality health-related services that allow the elderly to have the opportunity to continue living actively and independently for as long as possible. Information and communication technologies can play a key role in this context, since they can support remote health services. In addition, technological advances make it possible to introduce this type of services in a non-obtrusive manner, providing quality in-time information to physicians or caregivers, with minimal invasiveness. This kind of assistive technologies are framed in the paradigm of Ambient Assisted Living (AAL) [2], which aims to support the aging population allowing their stay as much as possible within the home environment.

AAL integrates technologies and services focused on offering assistance in health problems such as fall risk, chronic diseases, medication management or depressive disorders, among others. It provides valuable information both for the detection of obvious and immediate problems, such as falls, and for the detection of gradual changes in daily routines or in the physical and psychological conditions of the users.

Identifying potential risk factors may reveal opportunities for early intervention. Making better use of technology to stress disease prevention and early detection is key to meet the needs of future societies. In the cognitive diseases area, for example, where the number of cases is predicted to double every 20 years, future treatments could target diseases in their earliest stages, before irreversible brain damage or mental decline has occurred.

The appearance of difficulties in walking denotes a significant point as an indicator of health and function in aging and disease [3]. Several studies have confirmed an association linking gait speed (GS) to many major health-related outcomes including hospitalization, falls, nursing home placement, mobility disability, and cognitive diseases such as Alzheimer's disease [4]–[6]. Gait control is a complex system that involves the integration of multiple systems including motor, perceptual, and cognitive processes. As dysfunctions in these systems lead to a slowing of gait, walking speed is a commonly used measure in health care research. Gait speed has been found to be a consistent risk signal for adverse outcomes in older people. The measurement of gait speed is quick, reliable, sensitive, and easy [7]–[10], and therefore it is often included in clinical and epidemiological research studies [5], [6], [11]. In addition to sex and age, it is used to monitor the functional capacity of older adults and to forecast their rate of age-related decline [12]. For example, for subjects with abnormal walking speed, an improvement of 0.1 m/s or more is a useful predictor for well-being, while a decrease in the same amount is linked with poorer health status, more disability, longer hospital stays, and increased medical costs [13], [14].

Medical practitioners generally assess gait speed by manually measuring the time taken by the subject to travel a given distance [3], but there is great variation in the protocols used for measurement, since methods and distances are diverse, and usually, they depend on the purpose of the test. In most cases, distances range from 4 to 10 meters, with 10 meters being the most common distance chosen. The accuracy of measuring gait speed over distances less than 4 m, especially when starting motionless, has been questioned [11]. The standard approach requires a clinician observing and timing a subject while he or she is following a predefined path. This procedure may introduce errors due to the use of a manual stopwatch to estimate the time and, especially, to the fact that users being evaluated and under the observation of a clinician may introduce a bias by instinctively trying to perform well. If possible, conducting the measure three times during the examination, with a period of rest between trials, and taking the average value will provide a more accurate measurement of actual gait speed [15].

However, this procedure for gait speed monitoring may not be practical for continuous monitoring. It takes time and resources, and it can only be performed with the physical presence of both the patient and the practitioner. In-home monitoring would be a good alternative, especially in situations where on-site visits to the practitioner are discouraged, as is currently the case due to the COVID-19 pandemic. By providing continuous in-home tracking of gait speed, it would be possible not only to detect sudden changes but also gradual modifications along time that may denote a progressive decay in health. This would reveal opportunities for early intervention as well as be used to monitor the progression of known diseases, contributing to increasing older adult's ability to live independently.

Wearable devices have become a standard part of life for consumers, as they are widely available, comfortable, and often inexpensive. Devices such as wristbands or smartwatches are examples of available products that can provide innovative solutions for healthcare problems. These wearable devices incorporate several sensors, a subset of which can be used for medical applications. The current generation of wearables can monitor oxygen saturation and blood pressure, besides levels of daily activity or quality of sleep. Accurate and unbiased data gathered from wearables can help doctors to make more informed healthcare decisions and offers them a way of monitoring their patients remotely. Some of these products also mount Inertial Motion Units (IMU) that can identify the activity the user is performing (walking, running, standing still, etc) and count steps. These devices collect information about the users' activities and habits and transmit it so that other devices (usually smartphones or tablets) can process it. The connectivity of such wearables generally relies on Bluetooth Low Energy (BLE) technologies. BLE is excellent for wearables because it is very energy efficient, secure, and inexpensive [16].

In the present work, we present a gait speed estimation method based on BLE, and composed of a set of beacons deployed on the ceiling and a smartwatch worn by the subject. Our goal is to enable continuous monitoring of the gait speed both in home environments and in nursing homes or other facilities were older adults may live alone or in company. To this end, the beacons are placed in a frequently traversed location, such a corridor, where users usually walk at a constant speed. The main contributions of this research are:

- We present a method to continuously monitor gait speed based on the deployment of a set of BLE beacons and the use of a BLE equiped wearable device such a smartwatch or an activity band.
- We verify that BLE can be used to monitor gait speed in home environments with good accuracy. The experiments performed show an error in the estimates under 0.10 m/s.
- The proposed method is suitable both for private homes and for multi-user environments such as nurse homes or adult daycare centers, where multiple users can be monitored simultaneously.

The rest of the paper is organized as follows: In Section II we analyze previous works related to continuous gait speed estimation. In Section III we introduce the related technologies and proposed method for gait speed estimation. In Section IV we describe the data set used and the experiment setup. In Section V we present the result obtained, which are discussed in Section VI.

II. Related work

Several schemes have been proposed to enable in-home monitoring of gait speed. Some of them, such as those based on the use of video cameras, raise privacy concerns and only provide directional coverage with Line-Of-Sight (LOS) conditions. Other approaches, based on the deployment of Wireless Sensor Networks (WSN) or motion sensors, are able to estimate human's gait speed but they are not able to distinguish between users. This makes these solutions inappropriate for situations where there may be more than one person involved, such as nursing homes, people not living alone, receiving visits, etc.

Measuring GS is a difficult task that requires a system with enough precision to detect small variations in measurements taken at very different times. Initially, GS was measured only in clinics using a stopwatch. Apart from the lack of precision, it is a very time-consuming task, and incapable of effectively detecting GS changes from one visit to the practitioner to another [17], [18]. For this reason, new different technologies were introduced to measure GS effectively in clinical environments. Researchers have opted to use vision-based systems to have a precise measurement of the GS and other kinetic parameters related to gait and posture. The Kinect system, developed by Microsoft, has been used in several clinical research for walking and GS control [19], [20]. Makihara et al. [21] used a depth camera to measure the walk of the participants over a green chroma wall. Their results were published with a database of gait and posture information with data from more than 200 participants. Using similar systems, Fukuchi et al. [22] and Schreiber et al. [23] provided clinical databases of GS measurement of healthy individuals. These systems require an especial place to perform the measurements, specially trained personal, and their price is usually very high. As mentioned in the previous section, the ideal scenario is to measure GT in the day-to-day patient's environment. Therefore, the system must be implemented in non-controlled scenarios, like residential care facilities and user's houses, where complex and expensive systems can not be installed.

Ultrasound technology has also been used in this context. In [24] the distance between an emitter and a transponder carried by the user was calculated using an ultrasonic signal. The set of distance measurements was used to calculate the average instantaneous speed of the transponder. In [7], a set of ultrasonic distance sensors were used to detect the presence at a particular time and calculate the GS. More advanced ultrasonic systems can calculate the speed from the phase shift, as proposed in [25] or using the Doppler's effect, as proposed in [26].

Gait speed can also be assessed using inertial sensors from wearable devices carried by the patients. In [27], the use of the accelerometer sensor was evaluated with orthogeriatric patients using a custom wearable placed inside the belt buckle. A similar experiment was presented in [28] using an accelerometer and a gyroscope from a custom wearable device attached to the legs and belt of participants. Their results are published as a database for clinical purposes [29] but without data from the sensors. In a clinical environment, Beck et al. [30] used a high-precision accelerometer to study the evolution of a group of Parkinson's disease patients. These last works are focused on the clinical interpretations of the GS, not on the technology. Most of these systems require high-precision custom wearables that must be actively used by the patient. Low-cost inertial sensors. like the ones embedded in smartphones and smartwatches, return imprecise measurements due to their associated noise. These devices systematically underestimate GT with non-precise estimation [18], which limits their use for patient tracking.

More recently, electromagnetic signals have also been used to measure the speed of a moving object. In [8] the interaction between a radio-frequency signal and the human body was used to determine the GS. The results obtained were quite precise, but the system was not able to differentiate between users. The Widar system, proposed in [9] used commercial Wi-Fi networks to estimate the speed and orientation of the subject wearing a custom receiver. In [10] Zhang et al. presented the WiSpeed system, which works using electromagnetic waves' statistical theory to establish a correlation between an object's speed and the measurements in the receptor's physical layer. Chenshu et al. [31] built the GaitWay system, which can measure GS using a custom Wi-Fi transmitter and receiver to analyze the multi-path effect using the received signal. Compared to other works, the GaitWay system can work in non-line-of-sight conditions. Based on a similar approach, Wang et al [32] used the same information to detect a walking event in indoor scenarios with a commercial Wi-Fi system.

Hagler et al. [33] proposed an in-home gait speed monitoring system based on a set of passive infrared (PIR) sensors placed on the ceiling. Detection time and sensor positions are transmitted to a server where the GS is calculated. This system report an average error of 0.071 m/s (SD = 0.113 m/s) without calibration, but it does not support authomatic identification of the user. Following a similar design, in Chapron et al. [34] gait speed is also measured using a set of PIR sensors. In this work, user differentiation is addressed using a BLE tag associated with a wearable device for positioning the user. Thus, if there are two or more users nearby, the system is not able to link the estimated speed to the matching subject.

Finally, the authors in [35] proposed a method for gait speed estimation based on the deployment of a set of BLE beacons on the ceiling, and a wearable device worn by the user. Authors of this work published a data set for gait speed estimation through BLE technologies, and provided baseline results. In the present work we make use of the same data set and propose an improved method that increases the system accuracy.

Despite all the new technology developments, there is not a standard system for gait speed tracking and measurement in in-home environments. High-precision and complex systems are too expensive to be installed in usual spaces. On the other hand, in in-home scenarios, the systems can not distinguish between different residents unless an external system is used for identification. The works developed for clinical purposes are classified according to their technology in Table I.

TABLE I
REFERENCE OF CLINICAL OR DEVELOPED TO ASSIST CLINICAL WORKS WITH THE TECHNOLOGY.

Technology	Reference
Ultrasound	[7], [24]
Radio-Frequency	[8]–[10], [31], [32]
Inertial	[18], [27]–[30]
Vision-based	[21]–[23], [36]
Infrared	[33]
BLE	[35]

III. Methods

A. Bluetooth Low Energy

Bluetooth Low Energy technology has been designed for periodic transfer of little amounts of short-range data. Its main strength is its very low energy consumption, which allows it to be embedded in small devices with low-charge and small batteries. BLE remains cost-effective with a significant battery lifespan. Thus, its energy efficiency makes it one of the most compatible options for battery-powered wearable devices' connectivity and preferred to less efficient alternatives such Bluetooth or WiFi, especially for utilization in cases where only state data has to be exchanged. Wristbands, smartwatches, or smart clothing are examples of wearable devices that take advantage of BLE to keep a good equilibrium between battery duration and connectivity.

BLE operates in the Industrial, Scientific and Medical (ISM) band included in 2.4-2.5 GHz, the same used by WiFi. In particular, the BLE radio band goes from 2.4000 GHz to 2.4835 GHz and is divided into 40 channels. Three of these channels (37, 38, and 39) are reserved for advertising packets, whereas the other 37 are used to exchange data with connected devices.

A BLE device can play four different roles, i.e. master, slave, advertiser, and scanner, and can communicate using two main modalities: connection and broadcasting. Connection mode is used to provide a private, permanent and periodical data exchange of packets between two devices. In broadcasting mode, advertising packets are sent from a single device to any scanning device in the listening range, either with the purpose of discovering slave devices available for connection or to advertise to devices that do not need an active connection. Devices may play two roles in this scenario; the broadcaster, also known as the advertiser, which periodically sends advertising packets to any device available to receive them, and the observer, or scanner, which continuously scans available advertising packets.

The advertising interval designates the rate at which the advertising packets are sent. For non-connectable broadcasting, the broadcaster advertisement packets' time interval can be set as low as to 100ms plus a random delay on each advertising of 0-10 ms. This configuration allows a device to send a maximum of 9 advertising packets every second. On the other hand, the scanner device must set a scan interval, i.e., the rate at which the scanner's radio turns on, and a scanning window, that is the time the device keeps on scanning for each scan interval.

Even though it uses the 2.4 GHz radio band that is also used by WiFi, the BLE protocol defines very short duration messages to reduce battery consumption. Messages can be either data messages or advertisement messages. The latter are needed to enable any form of communication and carry a payload that can be used to broadcast information such as sensor state. Since BLE has been proposed to be used for indoor location purposes [37], [38], its use could be extended to also provide the speed of a user in an indoor environment. For fingerprinting-based positioning, the received signal strength indicator (RSSI) of each advertisement can be used to form a signature for each location. For speed estimation, assuming it is constant, it should be possible to determine the actual speed from the RSSI evolution over time.

B. Gait speed estimation

The main purpose of this work is to assess the reliability of estimating the gait speed of a subject through a wearable device that continuously monitors the RSSI value received from a set of ceiling-mounted BLE beacons deployed in a place where users may pass regularly at a constant speed, such a hallway. BLE can be used to estimate the distance between nodes of the network. The RSSI value provided by radio-frequency modules represents an indication of the power strength of the transmitter signal perceived by the receiver node. The RSSI value received at a particular location can be modeled as a function of the logarithmic distance between the receiver and the emitter, plus a set parameters related to environment attributes and devices' characteristics. This analytical model allows estimating the position of a device, the scanning node, knowing the received RSSI value data and the position of the emitting node. The path loss model describes the relationship between the signal strength and the distance to the emitter as follows:

$$RSSI = RSSI_0 - 10\gamma \log_{10} \frac{d}{d_0} + X_g, \tag{1}$$

where:

- $RSSI$ is the received signal strength at a distance d from the beacon.
- $RSSI_0$ is the received signal strength at the reference distance (1 meter) from the beacon.
- d is the distance between the receiver and the beacon.
- d_0 is the reference distance (1 meter)
- X_g is a random variable with zero mean, reflecting arbitrary variations (in decibel-milliwatts) caused by fading, multi-path effect, etc.
- γ is the path loss exponent, which represents the rate at which the RSSI decreases with distance. Value is normally in the range of 2 to 6 [39]. The actual value depends on the specific propagation environment.

Fig. 1a shows a representation of the theoretical evolution of the RSSI signal when a user wearing a receiver device is walking at a constant speed along a straight line which passes below a BLE beacon. If we assume that the receiver is moving at a constant speed in the presence of a ceiling-mounted emitting device (see Fig. 1b), equation 1 can be expressed as follows:

$$\begin{aligned} RSSI &= RSSI_0 - 10\gamma \log_{10} \frac{\sqrt{d_h^2 + d_v^2}}{d_0} + X_g = \\ &= RSSI_0 - 10\gamma \log_{10} \frac{\sqrt{(d_{ini} - vt)^2 + d_v^2}}{d_0} + X_g, \end{aligned} \tag{2}$$

where:

- d_h and d_v are, respectively, the horizontal and vertical distances from the receiver to the emitting beacon.
- v is the horizontal speed of the receiver device.

- t is the time elapsed since the start of the walk.
- d_{ini} is the initial horizontal distance between receiver and device.

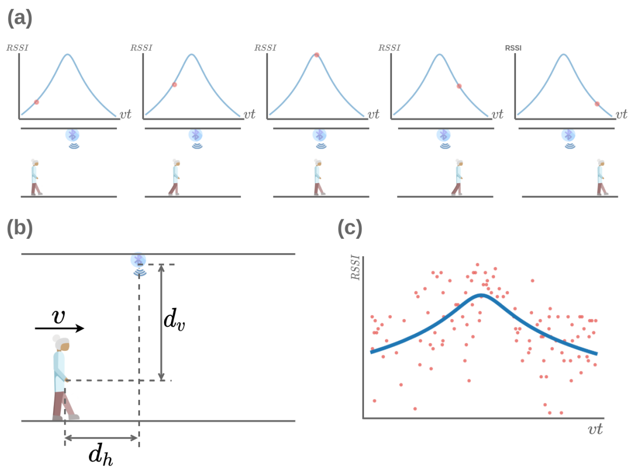

Fig. 1. a) Theoretical evolution of RSSI during a walk, b) distances between the user and the beacon and c) RSSI data received during the walk (red circles) and fitted path-loss curve (blue thick line)

Figure 1c shows a real example of RSSI data (red circles) received from the emitter when the user follows the path at a constant speed. It also shows a path loss curve fitted to the data (blue solid line). Received RSSI signals are subject to noise due to interferences, multi-path effects, signal fluctuations, overlapping channels and other environment characteristics. Even though the received signals are affected by these unpredictable factors, finding a good fit to a path loss-like function is generally possible if there is enough data. The following equation defines the general function to fit:

$$\widehat{f}(t) = \widehat{RSSI}_0 - 10\widehat{\gamma}\log_{10}\left(\sqrt{(\widehat{d}_{ini} - \widehat{v}t)^2 + \widehat{d}_h^2}\right) \quad (3)$$

where the $\widehat{\ }$ symbol represents that the parameter is an estimation. For example, even though the actual value of $RSSI_0$ is fixed for a particular beacon, its real value may still be affected by the state of the beacon's battery. So, the estimated value of $\widehat{RSSI}_0$ represents the same characteristic adjusted to fit the data. Likewise, parameter γ incorporates the particular conditions of the environment. These conditions change dynamically (obstacles such as another user standing nearby, different positions of the wearable for different users, etc.) so for each walk, the value of the adjusted parameter may be different. Even though these parameters take different values for different scenarios, or even for the same scenario with different environment characteristics, they are bound to a certain range due to their physical meaning. For this particular problem, we consider that these parameters can take any value inside the given range with a continuous uniform probability distribution.

To find the best fit of the objective function to the given data we use the Gauss-Newton algorithm to solve a non-linear least squares problem. Consider a set of m datapoints $(x_1, y_1), (x_2, y_2), ..., (x_m, y_m)$, which in this particular case represents pairs of timestamps (x_i) and preceived intensities (y_i), and a given model function $y = f(x, \beta)$, which in this case is the proposed path-loss function 3. Function $f(x, \beta)$ not only depends on x but also on a set of n parameters, $\beta = (\beta_1, \beta_2, ..., \beta_n)$, with $m \geq n$. The goal is to find the vector β of parameters such that the curve fits best the given data in the least squares sense, that is, by minimizing the sum of squares:

$$S = \sum_{i=1}^{m} r_i^2 \quad (4)$$

where the residuals r_i are given by:

$$r_i = y_i - f(x_i, \beta) \quad (5)$$

for $i = 1, 2, ..., m$.

The minimum value of S occurs when the gradient is zero. Since the number of parameters in the model is n, there are n gradient equations:

$$\frac{\partial S}{\partial \beta_j} = 2\sum_i r_i \frac{\partial r_i}{\partial \beta_j} = 0 \quad (j = 1, ..., n) \quad (6)$$

In a nonlinear system, the derivatives $\frac{\partial r_i}{\partial \beta_j}$ are functions of both the independent variable x and the parameters β, so in general these gradient equations do not have a closed solution. Initial values must be chosen for the parameters and then, they must be refined iteratively, that is, the values are obtained by successive approximation. The iterative optimization method assumes a quadratic model as a local approximation to the objective function, and takes repeated steps in the direction of the steepest descent, which is the opposite direction of the approximate gradient of the function at a given point.

Trust-Region-based methods (TRM) comprise a set of numerical optimization techniques suitable for problems where the optimization parameters are constrained inside a range. These methods are based on the restriction of the step size in the steepest descent direction, in an effort to maintain the validness of the quadratic approximation. Once the step size is determined, if a notable decrease is gained after the step forward, then the model is considered to be a good representation of the original objective function. On the contrary, if the improvement is too small, then the model is not considered as a good representation of the original objective function within that region. For each iteration, the size of the trust region is updated depending on the improvement previously made.

In most cases, the trust-region is defined as a spherical area in which the trust-region subproblem lies. For optimization problems where parameters are constrained, the *dogbox* algorithm [40], an extension of Powell's [41] dogleg method, defines a rectangular hyperbox shape for the trust-region to deal with bounded parameters.

For this particular matter of estimating the constant speed of a receiving device using the path loss function, we use the Gauss-Newton method with the dogbox algorithm to find the best fit for a given series of received RSSI signals and a set of constrained parameters. As a result, the value obtained for the parameter $\hat{v}$ will represent the speed of the device. In the general case when there may be more than one beacon installed, an approximation of the speed can be estimated as the average of the values obtained for each beacon. Given a set of k beacons, the speed of the device is calculated as follows:

$$\hat{v} = \frac{\sum_{i=1}^{k} \hat{v}_i}{k} \tag{7}$$

where $\hat{v}_i$ is the speed obtained from the path loss fit for the i^{th} beacon.

IV. Experiments

A. Data

We use the BLE-GSpeed data set [35] to evaluate the proposed method. This data set contains data recorded in a hallway (see Fig. 2) at the Universitat Jaume I in Castellón, Spain. The data consist of RSSI signals from a total of 19 BLE beacons of two different models (10 iBKS 105 and 9 iBKS plus) that were mounted on the ceiling of the hallway, with a separation of 30 centimeters between them. All beacons were aligned forming a straigth line. Beacons of both models were installed alternatively, therefore the separation between two beacons of the same model is 60 centimeters.

Fig. 2. Beacons deployed on the ceiling of the corridor.

The data acquisition process consisted on a total of 13 subjects, 11 males and 2 females, aged between 18 and 55, performing several walks in both directions along the hallway. The subjects were instructed to keep their walking speed constant during the process. Each user completed several walks at different speeds, from very slow to fast. The minimum speed recorded was 0.43 m/s and the maximum 1.87 m/s. During the data acquisition process, the subjects wore four smartwatches, two on each wrist. Fig. 3 shows: a) the distributions of speeds recorded by each user, b) the percentage of walks recorded by each user, and c) the overall distribution of speeds in the data set. The actual speed of the users was determined by a set of ultrasonic sensors attached to the wall at an height of 0.7 meters. For a particular walk, the wall-mounted sensors provided the timestamps at which the user passed in front of them. For each pair of consecutive ultrasonic sensors, the actual speed of the user was determined as the cocient between their distance and the difference of the timestamps at with the user passed in front of each one. The resultant speed was calculated as the average of all measurements, but only when their discrepancies are less than 5 cm/s, with the aim to only taking into account those walks executed at a constant speed.

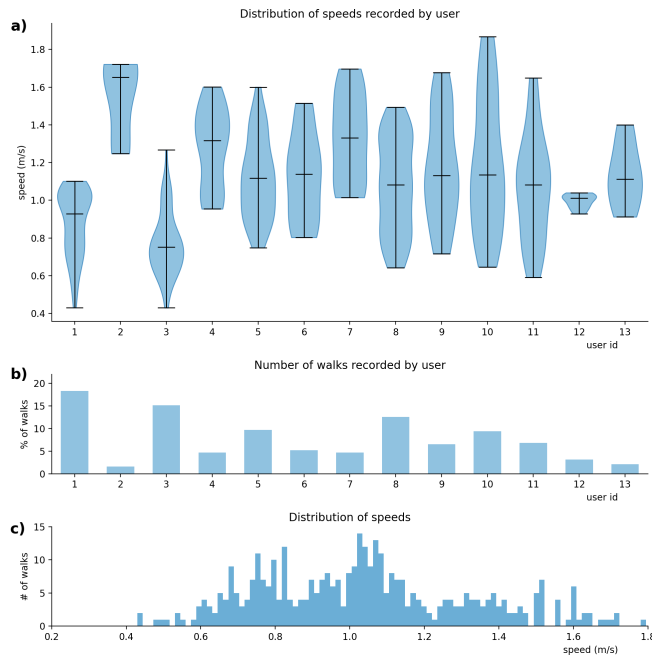

Fig. 3. (a) Speeds by user, (b) percentage of walks by user and (c) distribution of speeds in the data set.

Each row of the data set represents a scan result, and is composed of the following fields:

- *mac*. The MAC address of the detected beacon.
- *rssi*. The RSSI value obtained for the beacon.
- *device*. A four character descriptor for the smartwatch that performed the scan.
- *timestamp*. The time stamp at which the scan was received.
- *user*. The id of the user that was performing the experiment.
- *direction*. A number (0 or 1) indicating the direction of the walk.
- *walk_id*. An number that identifies each walk.
- *speed*. The actual speed of the user, in m/s.

B. Proposed method and experiment setup

The proposed method relies on the presence of a number of ceiling-mounted BLE beacons, and on the subject wearing a BLE-capable device equiped also with an accelerometer. The goal is to obtain reliable estimations of the user's gait speed when he or she is walking below the beacons at a constant speed. This constant speed restriction can be verified from the accelerometer readings [42] by assuming that step signatures equally distanced in time reveal a constant walking pace. Once this condition is met, the gait speed estimation is obtained from the fluctuation of the intensities at which each beacon is perceived by the smartwatch during the walk.

The objective of the experiments is to evaluate a method for gait speed estimation that is valid for as many scenarios as possible, regardless of the attributes of the environment and the physical characteristics of the user. The particular attributes of different scenarios and users affect the values of the parameters that determine the properties of the signal propagation, therefore the only assumption we will make on the values of these parameters is that they are inside a certain margin where any value is equally probable. These bounds take the following values for each of the model parameters:

- $\widehat{d}_v$: We consider that the vertical distance between the receiver (smartwatch) and the beacon is within the interval from 2 to 3.5 meters.
- $\widehat{d}_{ini}$: The initial horizontal distance from the receiver to the emitting beacon is whitin the interval from 2 to 10 meters.
- $\widehat{RSSI}_0$ Values for this parameter can be in the interval from -85 to -20.
- $\widehat{\gamma}$: This parameter can take values in the interval from 0.5 to 3.0.
- $\widehat{v}$: The gait speed will be in the interval from 0.2 to 2.0 m/s.

For each walk and each beacon a path-loss curve fit of the data has been performed in the following way:

- Since the original RSSI data contains a large amount of noise, we apply a moving average smoothing strategy, with window sizes ranging from 1 to 30, both values included, to smooth the data before fitting. This technique is reported [35] to give good results with this data set. In particular, a value of 13-points width for the smoothing window gives the best results when using beacons of the same model.
- For each walk, smartwatch, mac address (beacon) and window size, we find the best fit to the data using equation 3. The parameter $\hat{v}$ obtained represents the estimated speed of the user. This result is only taken into account when it is comprised in the interval $0.2 < \hat{v} < 2.0$, not only because we want to consider only results that correspond to a feasible user speed, but also because the low scanning rate of the smartwatches may produce insufficient data to achieve a good fit and can generate artifact results that will not represent a proper estimation of the actual speed of the user. Therefore, if the value obtained is in the limit of the fixed range for the $\hat{v}$ parameter, that is, if it is equal to 0.2 or 2.0, it is disregarded.
- If we consider only one beacon to estimate the gait speed, the result is the parameter $\hat{v}$ obtained previously. When we consider two or more beacons, the estimated gait speed will be the average value for all the selected beacons, as described in equation 7.

Following this procedure, for each value of the sliding window we obtain as many estimates of the user's speed as beacons are installed on the ceiling. In this case, considering the 10 beacons of the *iBKS 105* type, we can obtain a maximum of 10 estimates for each run and each window size considered. From these data we can estimate the error made in the speed estimation as a function of the number of beacons considered and the size of the sliding window.

V. Results

Fig. 4 shows a general view of the results obtained for each device, number of beacons and sliding window size, with the horizontal line in the plots marking the 0.1 m/s error value, considering only beacons of model *iBKS 105*. Results for model *iBKS plus* are shown in Fig. 5, but the error is bigger, and therefore this model will not be used in the following experiments.

The restrictions adopted to consider a fit to be valid (see Section IV-B) make it difficult to obtain a successful fit for all the present beacons for all the walks in the data set. Therefore, we consider only groups of between 1 and 9 beacons. The plots display the average errors obtained considering these groups of 1 to 9 beacons out of the 10 installed beacons. The results show the error from the four smartwatches for each window size considered. As can be seen, the best results are obtained for a window size of around 13, which was the same value reported in [35] for their best results.

For a smoothing window of size 13, the individual results obtained for each device, as well as the average results for all of them, are showed in Fig. 6. The plot also shows the percentage of walks for which it has been possible to obtain an estimate of the user's speed. Table II shows the average results for all the devices and also the success rate for each number of beacons considered. For example, when considering a set of 7 beacons of model *iBKS 105*, the average error is 0.0916 m/s, but taking into account only 45% of the total number of walks in the data set. For the remaining 55% the algorithm has not been able to find a satisfactory fit for some of the beacons.

TABLE II
AVERAGE ERROR IN M/S, STANDARD DEVIATION IN M/S AND SUCCESS RATE USING BEACONS OF MODEL IBKS 105. (# BEACONS STANDS FOR NUMBER OF BEACONS)

# beacons	avg. error (m/s)	std. deviation (m/s)	success rate
3	0.1777	0.1545	0.8965
4	0.1493	0.1323	0.8625
5	0.1272	0.1134	0.7912
6	0.1084	0.0956	0.6328
7	0.0916	0.0779	0.4509
8	0.0764	0.0599	0.1950
9	0.0653	0.0496	0.0641

From the previous results, it can be deduced that increasing the number of beacons yields better results but at the cost of obtaining fewer estimates. This point represents a trade-off between the expected precision of the proposed system and the number of measurements that we can obtain. If a number of 7 beacons are placed in frequently traversed locations, it can be expected to get at least one daily prediction with an error below 10cm/s, which may be good enough for continuous monitoring of the gait speed, particularly given the actual

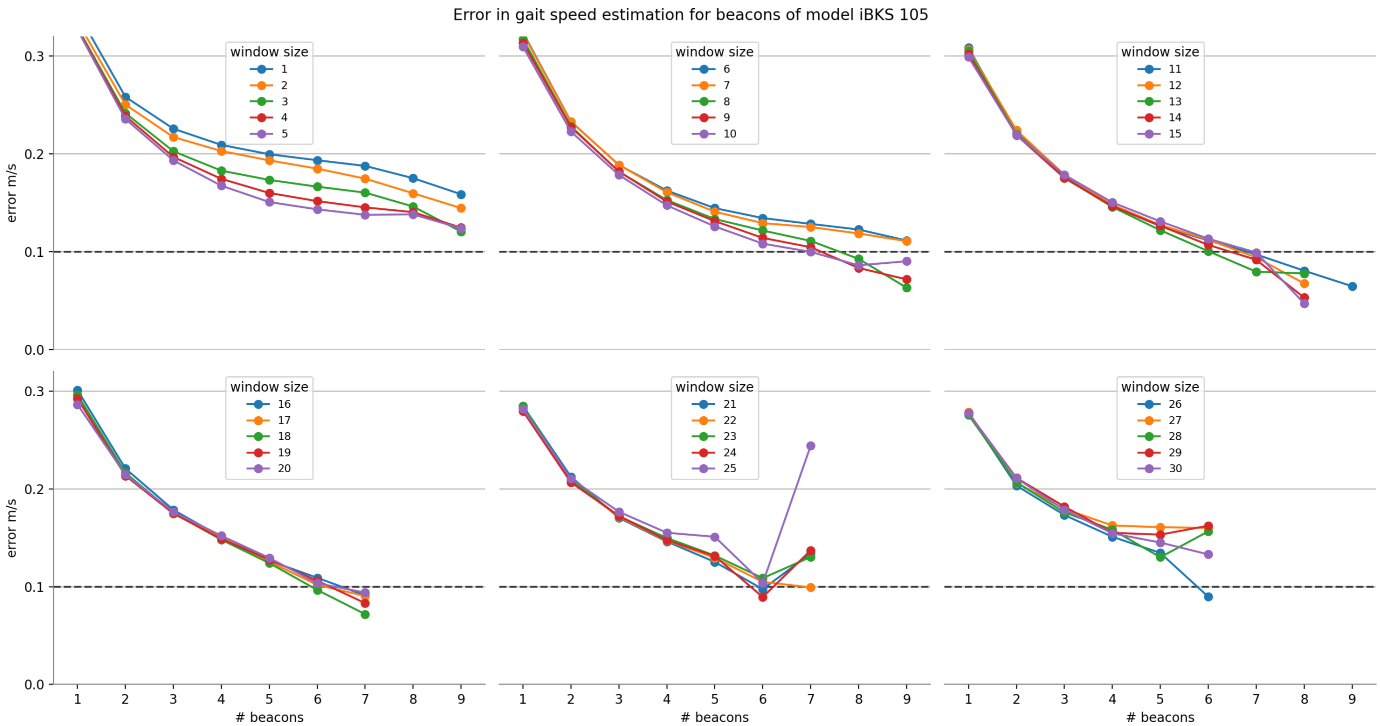

Fig. 4. Error (m/s) in gait speed estimation depending on the number of beacons considered (# beacons) and the size of the smoothing window for beacon model *iBKS 105*.

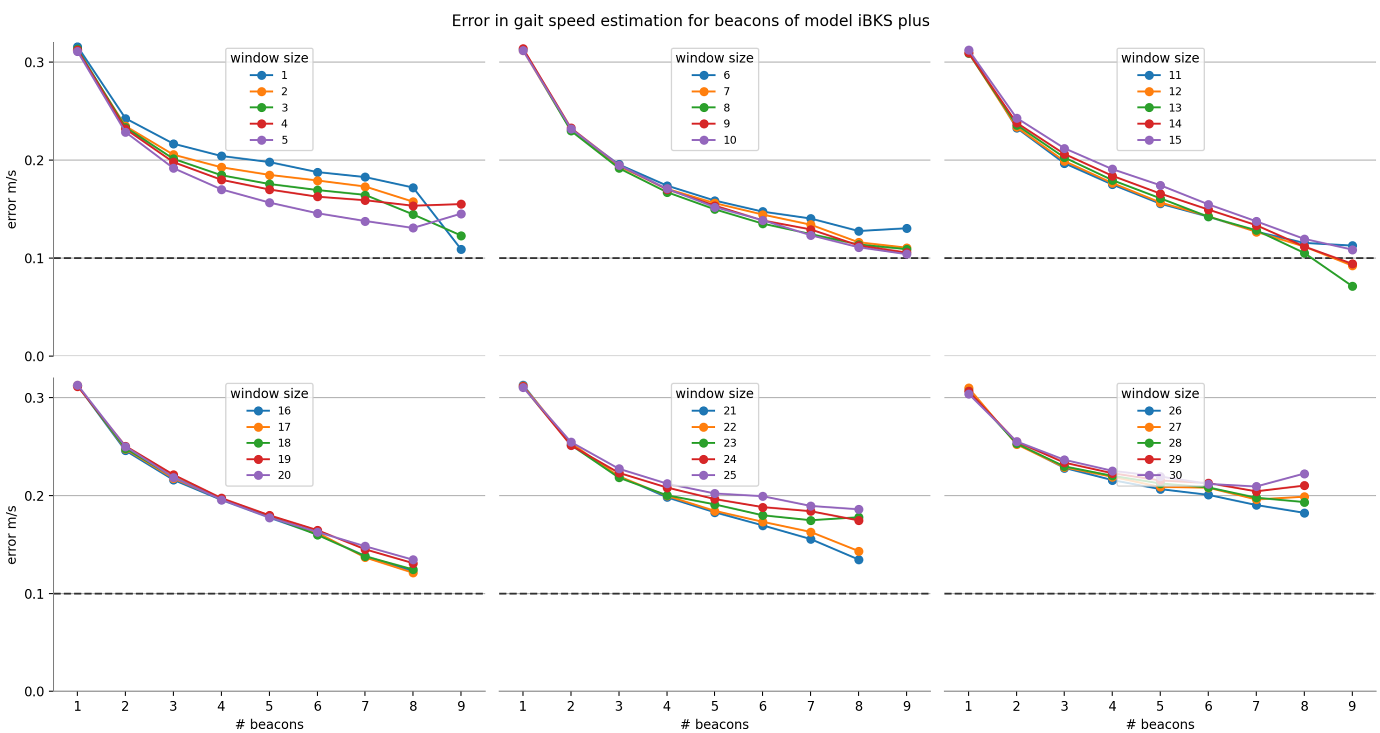

Fig. 5. Error (m/s) in gait speed estimation depending on the number of beacons considered (# beacons) and the size of the smoothing window for beacon model *iBKS plus*.

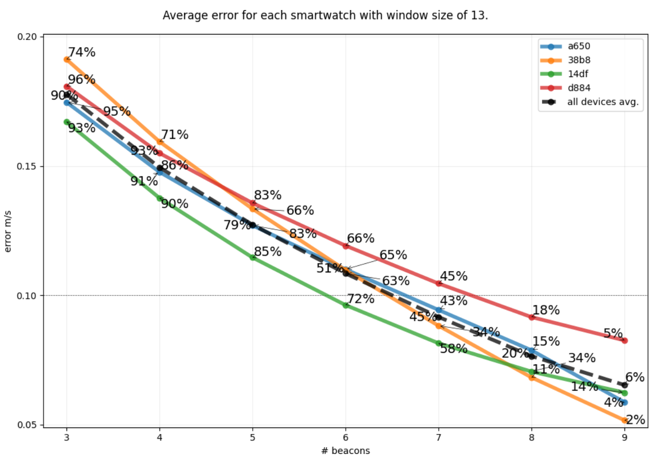

Fig. 6. Average error in gait speed estimation for each smartwatch and number of beacons (#beacons) considered. Numeric values represent the percentage of walks predicted over the total number of walks in the data set.

situation where this assessment is only performed sporadically and on-site.

Nevertheles, in order to increase the number of estimates obtained for a given number of beacons while trying to reduce the prediction accuracy as little as possible, we can calculate the speed by not only considering the maximum number of beacons, but also subsets of the set of beacons in question, for which it may be possible to find an estimate. For example, if the algorithm can not find an estimate for the gait speed of a given walk for a particular set of 7 beacons and a window size value of 13, it may be possible to find an estimate for a subset of 6 beacons, or for the same set of 7 beacons but considering other similar smoothing window sizes such as 12 or 14. Since considering a window size of 13 and the maximum number of beacons is optimal, it is expected that the more we consider smaller subsets of beacons, the worse the results will be, whereas the number of estimates obtained will increase.

Therefore, we define a maximum backtracking value that represents the maximum number of beacons left aside from the original set. For instance, for a set of 7 beacons and a maximum backtracking value of 4, the algorithm will try to find an estimate for the original set of 7 beacons, and if this is not possible, then will try subsets of 6, 5, 4 and 3. The algorithm will also try, for each subset, different values for the smoothing window size, ranging from 8 to 18. If any of these attempts works, the corresponding estimate is assigned, and otherwise it is determined that it has not been possible to find an estimate for this case.

Fig. 7 shows the results of this strategy with a maximum backtracking value of 4. Value 0 means that no backtracking has been performed, so this line represents the same estimations obtained previously (Fig. 6 and Table II). The figure shows how increasing the backtracking value increases the error obtained in the estimations, especially in those where there was a low percentage of the total number of walks. However, this technique can be useful if a higher number of walks need to be estimated. For example, as shown in table III, for the case of 7 beacons, using a backtracking value of 1 the error increases very little, from 0.0916 m/s to 0.0976 m/s, whereas the number of correctly estimated walks increases substantially, from 45% to more than 63%. For a backtracking value of 2, the error would be 0.1048 m/s, and the percentage of correct estimates would exceed 79%.

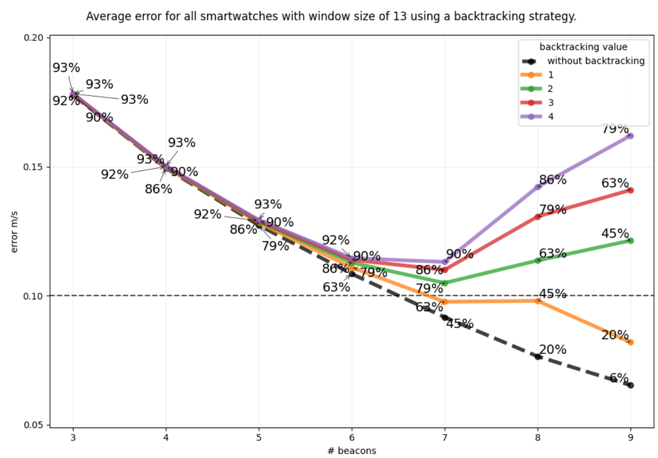

Fig. 7. Average error in gait speed estimation, using the backtracking strategy, with respect to the number of beacons (#beacons) considered. Numeric values represent the percentage of walks predicted over the total number of walks in the data set.

TABLE III
AVERAGE ERROR IN M/S, STANDARD DEVIATION IN M/S, AND SUCCESS RATE USING BEACONS OF MODEL IBKS 105 AND A BACKTRACKING STRATEGY. (*# beacons* STANDS FOR NUMBER OF BEACONS, *max baxk* STANDS FOR MAXIMUM BACKTRACKING VALUE)

max back	# beacons	error (m/s)	std. deviation (m/s)	success rate
0	5	0.1272	0.1134	0.7912
	6	0.1084	0.0956	0.6328
	7	0.0916	0.0779	0.4509
	8	0.0764	0.0599	0.1950
	9	0.0653	0.0496	0.0641
1	5	0.1281	0.1148	0.8625
	6	0.1109	0.0999	0.7912
	7	0.0976	0.0887	0.6328
	8	0.0980	0.0913	0.4509
	9	0.0819	0.0681	0.1950
2	5	0.1286	0.1160	0.8965
	6	0.1127	0.1036	0.8625
	7	0.1048	0.1017	0.7912
	8	0.1135	0.1128	0.6328
	9	0.1213	0.1140	0.4509
3	5	0.1289	0.1168	0.9162
	6	0.1138	0.1064	0.8965
	7	0.1099	0.1118	0.8625
	8	0.1306	0.1344	0.7912
	9	0.1408	0.1353	0.6328
4	5	0.1293	0.1179	0.9299
	6	0.1145	0.1083	0.9162
	7	0.1130	0.1187	0.8965
	8	0.1420	0.1506	0.8625
	9	0.1619	0.1567	0.7912

Finally, table IV shows a comparison between the results obtained with the proposed path-loss fit method and the baseline provided in [35]. Both the error in the estimation of gait speed and the number of beacons needed is lower using the proposed path-loss fit method.

TABLE IV
COMPARISON OF RESULTS WITH BASELINE.

beacon model	baseline error (m/s) & # beacons	path-loss fit error (m/s) & # beacons
iBKS 105	0.0855 (10)	**0.0765 (8)**
iBKS plus	0.1357 (9)	**0.1267 (8)**

VI. Conclusions and future work

From a medical point of view, determining a person's gait speed is important. Both its absolute value and its changes over a period of time can be determinant in the occurrence of medical complications. The possibility of performing continuous measurements of this velocity in a robust, reliable, and non-intrusive manner opens the door to new services for the early diagnosis of degenerative diseases.

This paper proposes the use of BLE beacons located on the ceiling as a way of measuring a person's gait speed, with the only requirement being that the user must wear a device that is capable of reading the intensities at which the beacon signals are received. This should not be an impediment to their adoption, as such devices are already in use today to provide other types of health-related measurements, such as blood oxygen level, a person's physical activity, or sleep characteristics. In fact, since these types of devices are equipped with inertial sensors, they can be used to assist the speed measurement system. This kind of inertial sensors can not be used alone to determine the gait speed, since it depends on unknown variables such as the individual's height and stride length, but they can be used to identify whether the person is walking and whether he or she is walking at a steady pace. This would provide a more complete system for monitoring health-related parameters.

The method presented in this work allows to obtain the walking speed of a person in a non-intrusive way and with a margin of error lower than 0.1 m/s. Moreover, this margin of error can be reduced, at the cost of obtaining fewer measurements, if a more accurate measurement of speed is required. If, on the other hand, the system is configured to detect changes in gait speed over time, one can opt for a lower estimation accuracy but a larger number of measurements. Considering that the proposed method does not need any previous calibration, the results are on a par with other systems based on other types of technologies, such as the results presented in [33], with the added advantage that this method provides continuous monitoring and identification of users while they conduct their usual life routines, without any additional requirements other than wearing a smartwatch or an activity band with inertial sensors and BLE capabilities.

In terms of the quality of the results, the presented experiments substantially improve the results previously presented by the authors using the same database [35], obtaining greater accuracy in the estimation of speed using a smaller number of beacons. Although we consider that the proposed method works well enough to be a useful tool in the early diagnosis of some types of degenerative diseases, it is necessary to study possible improvements of the system to reduce the number of beacons needed to obtain a reliable estimation, as well as the battery consumption of the device due to the need to perform consecutive scans.

A possible alternative to the deployment presented in this work may be to turn the beacons into active devices that are responsible for scanning the signals emitted by the devices worn by the users. This would reduce the power consumption of the wearable devices and would also limit the possibility of installing the beacons anywhere, since they would now require a continuous power supply. This approach can be useful in adult daycare centers or nurse homes where there are a large number of users and all of them usually pass through common areas such as corridors. The different users are identified by their wristbands, but it is the active beacons, using low cost computing platforms such as Arduino or Raspberry Pi, that read the signals emitted by them and process the data to obtain the gait speed estimates.

VII. Reproducibility

The code to reproduce all the plots and experiments described in this work is publicly available at `https://github.com/esansano/gait-speed-monitoring`

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