A novel method for in-home Gait Speed estimation in Health Monitoring Using Bluetooth Low Energy

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***Abstract*—Gait speed (GS) is a crucial parameter in the evolution and diagnosis of degenerative illnesses. Nowadays, it is measured in clinical environments where it is impossible to keep track of all patients due to the lack of resources. The development of GS measurement systems for in-home environments could solve this problem, but current methods present, at least, one of these problems: they require expensive hardware, are intrusive for the patient, or are imprecise. A novel method to measure GS in these scenarios using Bluetooth Low Energy and smart wearable devices is proposed in this work. The proposed system is inexpensive, non-intrusive, and its precision is comparable to the current state of the art methods. This system could be commercialized as part of an in-home health monitoring system.**

***Index Terms*—Bluetooth Low Energy; Gait Speed; Health Monitoring**

I. Introduction

Gait speed (GS) is a significant parameter, along with sex and age, in predicting the appearance of degenerative illnesses like Parkinson and Alzheimer [1]. Since the sooner these are predicted and treated, the better the patient's development, it is essential to detect changes in it as soon as possible. Usually, GS is only measured in clinical environments, where specialized doctors measure GS and other kinematic parameters (posture, muscle contractions, and gait direction) using an expert vision-based system.

Simultaneously, the population of people aged 65 or more is expected to double in the next twenty years worldwide [2]. Since this group has more health-related issues than any other, current health care systems must adapt to face this future reality. In this context, the traditional GS measurement in clinics and hospitals will not be able to track all their patients simultaneously [3]. Therefore, the monitoring of GS in risk patients should be carried in their residences. This change will allow monitoring more people automatically while saving time and effort in hospitals.

Despite all the recent technological developments in this topic [4], there is no standard GS measurement system for multi-resident environments. Current developments present several problems; high-precision systems are too expensive, and therefore only used in clinical environments or specific research projects [4]. The systems developed specifically for in-home monitoring are intrusive, which has been proved to affect the patient's behavior while measuring [5]. The current non-intrusive systems cannot distinguish between different persons, which is crucial in correctly evaluating each patient's evolution [6]. Therefore, an affordable and non-intrusive technological alternative is needed to monitor GS in a multi-resident home.

A new method to measure GS from the received signal strength (RSSI) measurements from Bluetooth Low Energy (BLE) beacons is proposed in this work. The Internet of Things (IoT) orientation of BLE makes its design inexpensive compared with other systems and non-intrusive because it works with wearable commercial devices already familiar to all users, like smartphones and smartwatches. Our method is tested using the BLE-GSpeed database [7], which contains BLE RSSI measurements from different smartwatches and persons while walking through a straight walk. The experimental data can be found in the Zenodo repository [8].

The remainder of this paper is organized as follows. In section II, different works in the same field are described. In section III, the proposed method and methodology are presented. In section IV, the experimental set-up is described. Results are detailed in Section V. A discussion about the key elements in the method is presented in Section VI. Finally, the conclusions and future works are summarized in section VII.

II. Related works

The traditional approach to measure GS was to measure the time the patient took to walk some distance with a stopwatch, which, apart from the lack of precision, had become obsolete when compared with current systems [9]. In clinical environments, where apart from the GS, more information is extracted from the measurements, vision-based systems are commonly used [10]. The Kinect system, developed by Microsoft, has been used for this task by different health researches [11, 12]. Its precision requires training personal to operate it, and its prices are very high. Similarly, depth-cameras have also been used to estimate the GS [13].

More technologies have been tested when building GS systems for in-home environments. For example, ultrasonic sensors have been used estimating the time of flight [14]. Passive infrared sensors (PIR) are also used when working as

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presence sensors. A set of PIR sensors placed in the ceiling alongside a hallway can record the detection times and use the distance between sensors to estimate the GS. A complete description of the mathematical steps of this method can be found in [15]. The same architecture can be used with any other technology when working as presence sensors, as in [16], where the same idea is repeated using ultrasonic sensors. Following the same procedure, Chapron et al. [6] proposed an indoor BLE positioning system to determine which patient is closest to the PIR sensors, correctly assigning the measurements to each user.

More recently, radio-frequency signals have also been used to measure GS. The Widar system, proposed in [17], uses commercial Wi-Fi networks to estimate the subject's speed and orientation wearing a custom receiver. In [18], Zhang et al. use the WiSpeed system that 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. [19] build the GaitWay system, which can measure GS using a custom Wi-Fi transmitter and receiver to analyze the multipath effect using the received signal. Despite their promising results, these systems require extra specialized and expensive hardware to operate.

GS can also be assessed using inertial sensors from wearable devices. In [20], a high-precision accelerometer is used with orthogeriatric patients to study their responses to different treatments against Parkinson. A similar experiment is presented in [21] using an accelerometer and a gyroscope from a custom wearable device attached to the legs and belt of participants. These systems require high-precision custom wearables that the patients must actively use, interfering with how they behave. The low-cost inertial sensors embedded in smartwatches and smartphones provide very noisy measurements, which lead to underestimations of the GS [22].

III. Proposed Method

The proposed method uses the Received Signal Strength Indicator (RSSI) from a BLE beacon. RSSI is a magnitude that measures the signal's attenuation between transmitter and receiver on a logarithmic scale. Fig. 1 shows a representation of the experiment, with the distances that take part in it. Let d be the distance between the receiver and the beacon at any time, h the distance between the average height of the receiver and the ceiling, and x the user's position in the hallway with respect to the vertical projection of the beacon over the floor. It is assumed that h is constant for each walk and that d and x are time-dependent. The dependence $x = x(t)$ and $d = d(t)$ are considered implicitly in all equations. Equation (1) models the dependence between the RSSI and the distance where α is the path loss exponent, d_0 is a reference distance (usually taken as 1 m), and $RSSI_0$ the RSSI measurement at that distance.

$$RSSI = RSSI_0 - 10\,\alpha\,\log_{10}\left(\frac{d}{d_0}\right) \tag{1}$$

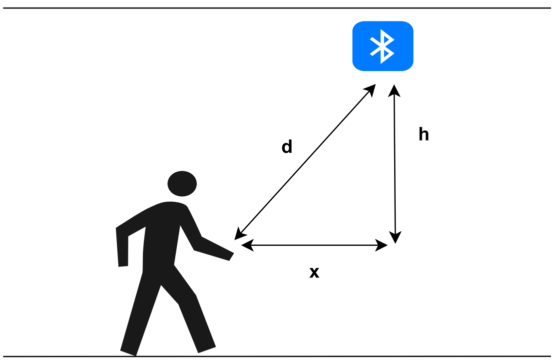

Fig. 1. Diagram with the transmitter, user's position, and the distances considered in the method.

To take into account the user's position, the distance d can be expressed as a function of h and x as $d = \sqrt{x^2 + h^2}$ which transforms (1) into (2).

$$RSSI = RSSI_0 - 10\,\alpha\,\log_{10}\left(\frac{\sqrt{x^2+h^2}}{d_0}\right) \tag{2}$$

The BLE beacon is placed in the center of a hallway. Preferably, the beacon is in the ceiling facing toward the floor to minimize the user's shadowing effect while walking. The receiver, a smartwatch or a smartphone, is carried by the user with their Bluetooth capabilities activated. Along the user's walk, the device records the RSSI measurements taken at different random times. The main idea is to use the RSSI rate of change to estimate the user's speed numerically. The time derivative is taken in (2), which becomes (3).

$$\frac{d(RSSI)}{dt} = \frac{-10\,\alpha}{\log(10)}\,\frac{x}{(h^2+x^2)}\,\frac{dx}{dt} \tag{3}$$

From this last equation the user's speed can be estimated, as shown in (4).

$$\frac{dx}{dt} = \frac{-log(10)\,(h^2+x^2)}{10\,\alpha\,x}\,\frac{d(RSSI)}{dt} \tag{4}$$

If the user's speed is constant, the right term of (4) must be constant in the beacon's proximity. Unfortunately, RSSI measurements are very sparse due to the noise introduced by different effects such as the switch from different channels in the communication protocol and the multipath effects in complex indoor environments [23]. A weighted moving average filter is applied to smooth the raw RSSI values. The apply filter is the convolution of the RSSI raw measurements with a triangle signal. Let r_i be the i-th RSSI measurement taken at time t_i. The filtered RSSI, f_i, is given by (5), where t_h is the half-time window average size. This value is taken as 15 % of the RSSI data size.

$$f[i] = \frac{1}{\sum\limits_{k=-t_h}^{k=t_h} w[k]} \sum_{j=i-t_h}^{j=i+t_h} r[j]\,w[j-i] \tag{5}$$

Where w_j are the weights given the normalize triangle discrete signal with the same size that the moving average window, as shown in (6).

$$w[k] = \begin{cases} 1 - \frac{|k|}{t_h} & |k| \leq t_h \\ 0 & otherwise \end{cases} \tag{6}$$

Fig. 2 shows the evolution of the RSSI against time while the users are walking along the hallway. The continuous blue line is the predicted RSSI using (1), the red circles are the raw RSSI measurements, and the black points are the filtered RSSI.

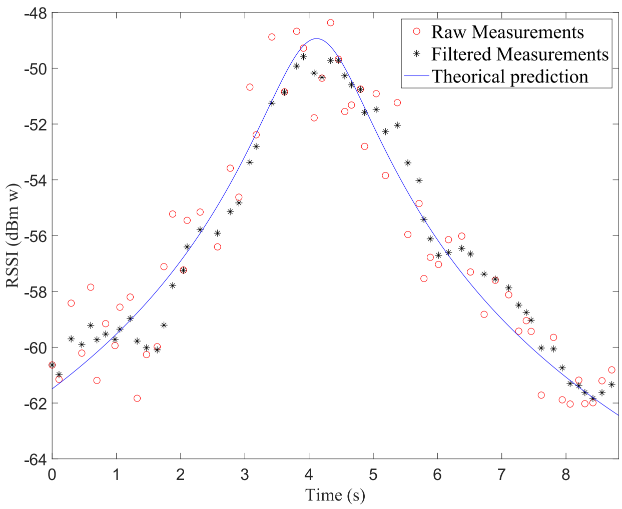

Fig. 2. Raw measurements (red circles), theoretical prediction (blue), and filtered RSSI (black line and points).

The numerical derivative, dr_i is computed using the difference between consecutive elements, as shown in (7). Theoretically, there must only be measurements with the same frequency as the BLE beacon's transmission frequency; however, some consecutive measurements may have a minimal increment in time. These measurements affect the numerical derivative and are eliminated from the filtered data. Finally, for the same reason, the numerical derivative is filtered again using the same filtering process. Fig. 3 shows the RSSI derivative, following the same filtering process used with the raw measurements.

$$dr[i] = \frac{f[i+1] - f[i]}{t[i+1] - t[i]} \tag{7}$$

The speed is calculated following the discrete-time variant of (4) i.e. (8) where x_i is the estimated position of the user at time t_i using the filtered RSSI and equation (2).

$$v[i] = \frac{-log(10)\,(h^2 + x[i]^2)}{10\,\alpha\, x[i]\, dr[i]} \tag{8}$$

The final estimation is approximately constant, as shown in Fig. 4, therefore, the average value of all the estimations is considered as the final GS.

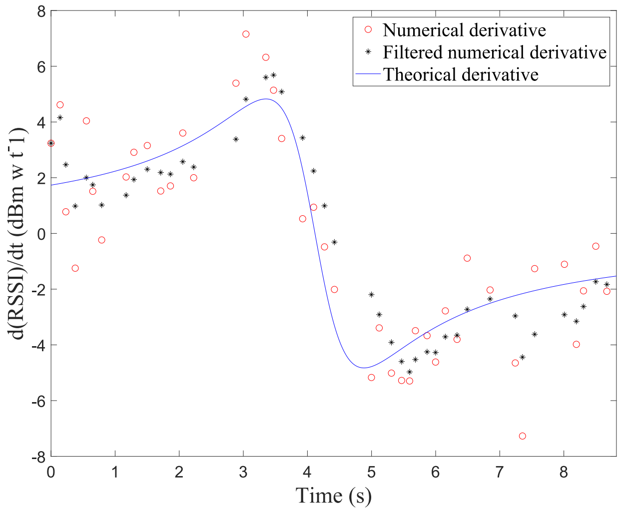

Fig. 3. Derivative with respect to time of the RSSI along the walk. Red raw estimation, blue theoretical prediction and black filtered approximation.

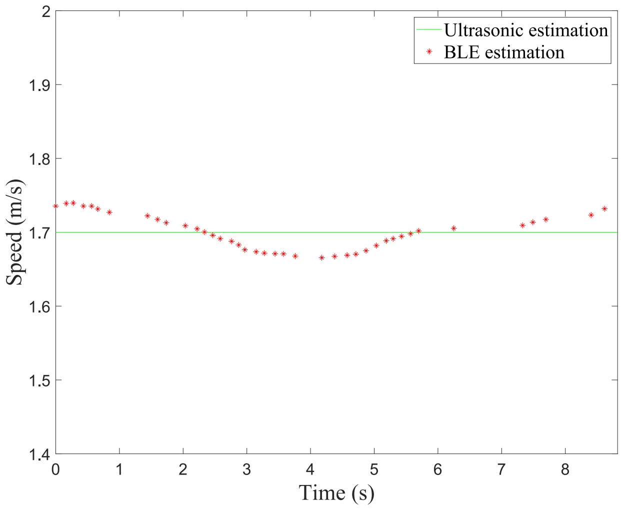

Fig. 4. GS estimation and real value in the beacon's proximity.

IV. BLE-GSpeed Database

To test the proposed method the BLE-GSpeed database [7] is used. This database provides raw RSSI BLE measurements from weareble devices and real time GS measurements. The experimental set-up is explained in this section. The BLE beacons used in the BLE-GSpeed were the IBKS Plus [24], and the IBKS 105 [25], both by Accent Systems. These beacons are designed to broadcast different signals (slots) simultaneously, but only one per beacon was used for this experiment. The emission parameters were configured to be the same for all beacons, with their maximum possible transmission power, +4 dBm, and smallest transmission frequency, 100 ms. There were 23 beacons, but not all of them were used in all the experiments. A total of 13 participants tested the system by walking forward and backward along the hallway in each experiment. Each participant wore four different Android smartwatches, two in each arm. A custom Android application was developed to detect the BLE advertising signals, store the RSSI values, and send them to a central server for later analysis.

A set of ultrasonic detectors connected to an Arduino Uno board was used as the ground truth system. The sensors were placed in the walls and identified when the user was in front of them. Five of these sensors were placed along the hallway, one every 3.5 m. The Arduino board recorded the measurements of the sensors and sent the information to the central server. Following the description of [15], the sensors' position and the detection times can be used to compute the user's gait speed. The hallway was more than 20 meters long, but the sensor area was approximately 10 meters long. Users started and stopped walking before and after the area covered by the sensors to avoid the acceleration effects at the begin and end of the walk. The GS estimation with this set of sensors is considered as the real GS of each participant.

To select the parameters of (1) the RSSI measurements with the same timestamp as the ultrasonic sensor detections and the distances between the sensors and the beacons, depicted in Fig of [7] were used. The before mentioned data was adjusted to (1) using the least square error method. It was assumed that since the configuration of all the beacons were the same, the same parameters held for all the beacons. The values used for parameters in (1) are $\alpha = 3.1$ and $RSSI_0 = -49$ dBm w. For each set of measurements (user, walk, watch, and beacon), the number of measurements varied from 20 to 80 measurements.

In [7], a method to determine the GS from RSSI BLE measurements is proposed as a baseline to start using the database. Their method detects the RSSIs' highest value for each beacon and associates it with the time in which the user is right under the beacon. Combining all the beacons' positions and the timestamp of their peaks, the user's GS can be calculated. The average error obtained with this method is 0.25 m.

V. Results

Considering the walks in each direction as different experiments, there is information from 764 walks. For each one, there is data from 4 smartwatches and between 19 and 23 beacons, depending on the walk. Data from a single user in a walk, and a single smartwatch and beacon pair, is considered as the input of the system. Fig. 5 shows the cumulative distribution function of the error when computing the GS with the proposed method and comparing it with the estimation obtained with the ultrasound system. Table I shows the mean value of the error, the relative error, and the standard deviation of the error for each smartwatch (SW).

TABLE I
MEAN ERROR, STANDARD DEVIATION AND MEAN RELATIVE ERROR FOR ALL THE EXPERIMENTS AND EACH SMARTWATCH.

	SW 1	SW 2	SW 3	SW 4	All
Error (m/s)	0.25	0.30	0.24	0.25	0.26
σ (m/s)	0.2	0.2	0.2	0.2	0.2
Relative Error(%)	26.8	32.1	32.3	27.5	28.6

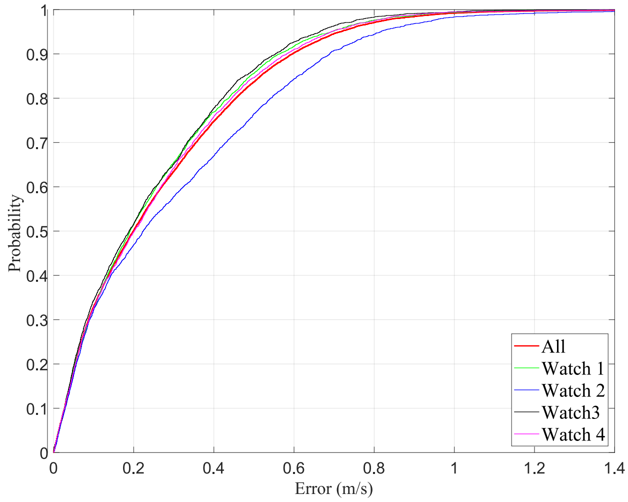

Fig. 5. CDF of the error in the GS prediction with each smartwatch and all of them combined.

The relation between the error in the estimations and the real speeds is now studied. Fig. 6 shows the average relative error of the BLE estimation for each velocity detected with the ultrasonic sensors. This figure shows that the relative error range increases with speed computed with the ultrasound system (ground truth).

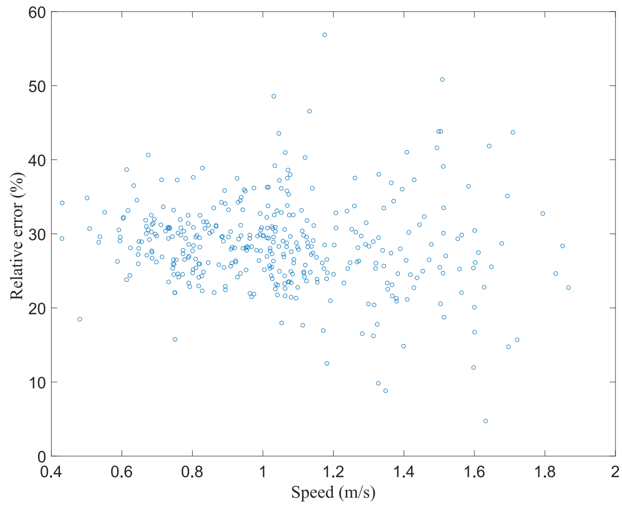

Fig. 6. GS measures with the ultrasound system (ground truth), and the relative error for each estimation with the BLE system.

The results of the method are studied for different users and beacons. Fig. 7 and Fig. 8 show the error distribution for each user and beacon respectively. In these plots, the standard deviation for each subset is indicated with the errorbars. In both cases, no significant statistical differences can be found.

Until now, only the information of one beacon has been considered for the GS estimation. The estimation of all the beacons within the hallway can be merged to improve the GS estimation. The average of the estimations from all beacons in each walk is taken as the merge estimation. Fig. 9 shows the

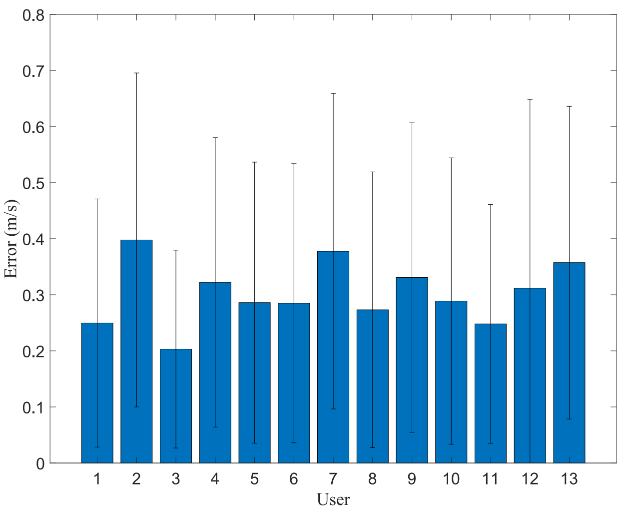

Fig. 7. Average error in GS estimation for each user. The errorbars indicate the standard deviation for each subset.

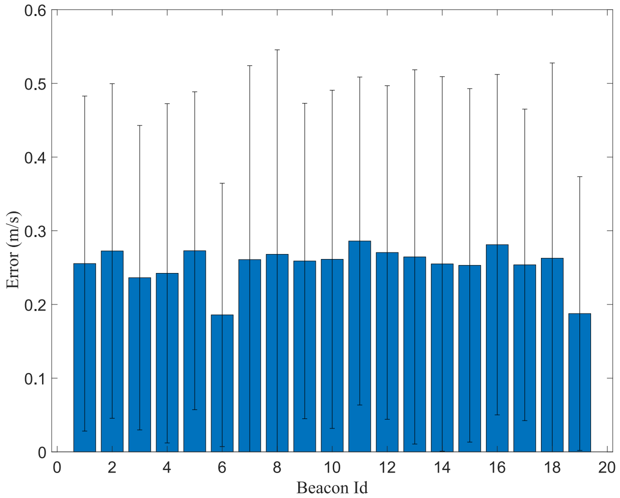

Fig. 8. Average error in GS estimation for each beacon. The errorbars indicate the standard deviation for each subset.

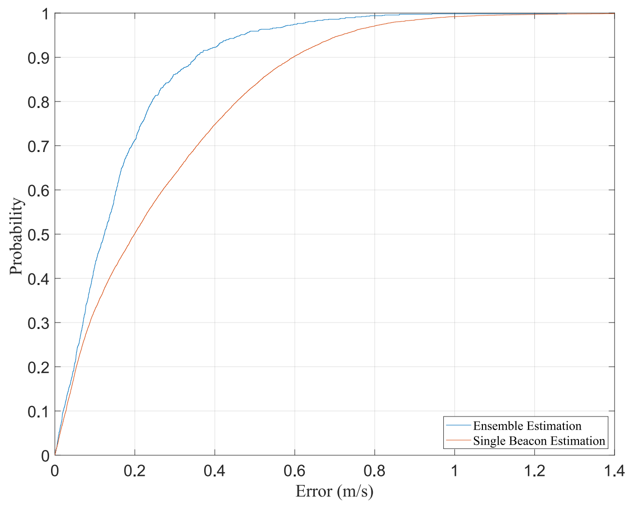

Fig. 9. CDF of the error using each beacon individually (orange) and combining the estimation of all the beacons in each walk (blue).

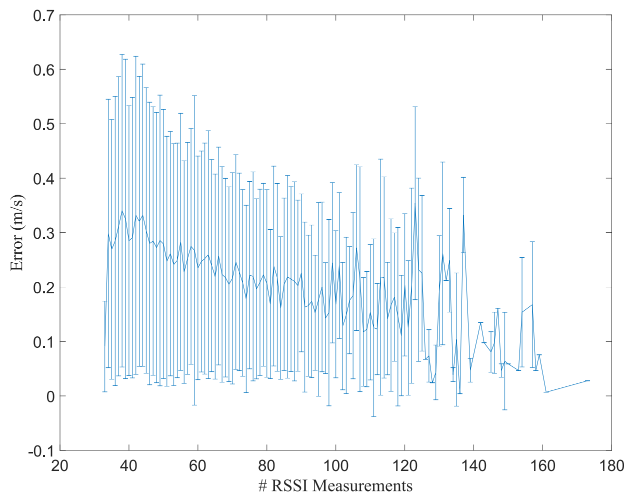

Fig. 10. Evolution of the error with the size of each RSSI data. Errorbars indicate the standard deviation for each subset.

error of the single estimation (orange line) and the ensemble estimation (blue line). The results show that merging different estimations can significantly improve the system's accuracy. The average error of the ensemble estimation is 0.16 m/s with a relative average error of 17%, which is an improvement of more than 25% from a single estimation.

During the data analysis phase, it was noted that the amount of data for each series was significantly different. The larger the dataset, the more information it contains, but also the noisier it usually is. The average error for series with a given size is depicted in Fig. 10 along with its standard deviation, marked with error bars. The average error is approximately constant along all the sizes, however, the standard deviation decrease as the size gets larger.

VI. Discussion

The proposed method is based on filtering the RSSI measurements, which is a complex task due to the random noise. A moving average filter can offer a solution to approximate the actual values, but the filtering parameters must be adapted beforehand for a general situation. The time window length of the moving filter is an important parameter in this method. The maximum of the RSSI or the zero in its derivative are critical features with few points in their surroundings. A large time window could cover these relevant points, shadowing their effects; on the other hand, a small time-window is not enough to reduce the noise, which leads to imprecise estimations. A weighted average is a good trade-off between the different elements, but the filtering process could be improved by testing different kinds of weights. The same is applied to the estimation of the derivative.

Other critical parameters in the system are those of (1), and model the signal's propagation. In this work, the same parameters are assumed to hold for all beacons, but this is not necessarily true. Besides, these parameters must be calculated again if the experiments are repeated in a different environment. In future works, the method's dependency from these parameters will be studied using multi-slot beacons. The GS estimation is done using only information from one pair transmitter-receiver, but the method can be improved by merging information from different transmitters placed in the same hallway, as has been proved in Fig. 9.

Compared with previous similar works, our method performs similarly that the work presented in [7] but only needs one beacon to provide a GS estimation. Since these methods are based on the RSSI measured from each beacon, the lost packages, and the series' size are crucial; therefore, future work must also diminish these two factors' importance. As shown in Fig. 9, the use of more beacons within the same walk can significantly improve the estimation, which is an improvement of over 25 % in precision, when compared with single beacon approach.

VII. Conclusion

In this work, a new system to measure Gait Speed (GS) using a Bluetooth Low Energy (BLE) beacon for in-home environments is proposed. Since the early stages of certain degenerative illnesses are associated with a sudden decay in GS, this system could monitor patients in their residences, detecting these illnesses as soon as possible, significantly reducing the hospitals' work in health monitoring and prevention. The beacon signals are detected by a wearable smartwatch device placed on the user's wrist. The GS is estimated using the numerical derivative of the filtered raw RSSI with respect to time. The proposed system was tested using the BLE-GSpeed database, which provides experiments with 23 beacons, 4 smartwatches, and more than 10 users through different test walks. Final results showed an average error of 0.26 m/s compared with the ultrasound sensors' estimation used as ground truth. The proposed system is non-intrusive since it works with a device already familiar to the user. Besides, it is inexpensive compared with similar current developments, and because of the characteristics of the BLE, it is energy efficient. The algorithm will be improved in future works using multi-slot BLE beacons and the signal propagation model to optimize the filtering algorithm.

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