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A Radar Sensor for Automatic Gait Speed Analysis in Walking Tests

Daniel Alshamaa, Racha Soubra and Aly Chkeir

***Abstract*—Walking tests can provide an indicator of balance and fragility of people. They measure the gait speed and compare it to reference values related to various pathologies. We propose a radar sensor system that allows the evaluation of the gait speed in these tests in an automatic manner. The proposed approach consists of three phases; a first phase where the system automatically distinguishes the three sections of the test, namely walk #1, turn, and walk #2. Then, a second phase where the obtained signal is processed to evaluate the gait speed of the person. This is done through time-frequency analysis of the radar signal. In order to deal with the non-stationary nature of the radar signals, we consider the short-time Fourier transfer in our time-frequency analysis. The third phase consists in segmenting each walk into three segments, namely an acceleration zone, a measured-gait zone, and a deceleration zone. We provide a segmentation of the walking in order to automatically distinguish these zones. The proposed approach is validated using a Vicon motion-capture system, with a mean RMSE equal to 0.076 m/s. As compared to traditional techniques, our proposed system is automatic and does not require acceleration and deceleration zones.**

***Index Terms*—walking tests, gait speed analysis, radar sensor, repeatability**

I. INTRODUCTION

Walking tests provide a method for the assessment of basic functional mobility and have been also shown to predict frailty [1]. The advantages of these tests are that they are simple, done quickly and involve an everyday activity, which is walking. They consist in having the person walk a certain distance, to turn and then to walk back to the starting position. The objective of such tests is to determine the gait speed of the subject. Physical therapists, as specialists in movement and function, argue that the gait speed can be used as a practical and informative functional sixth "vital sign" for all patients [2]. It can be examined in the same way as we routinely monitor blood pressure, pulse, respiration, temperature, and pain. Theou et al. [3] showed that the walking speed at usual pace was the parameter with the greatest correlation with the frailty index. Montero-Odasso et al. [4] asserted that gait velocity can be a single predictor of adverse events in healthy seniors. The gait speed was also proved to be a relevant predictor, among others, for falls detection [5]. This suggests that deviations from the normal walking speed during free walking may reveal a degree of abnormal walking patterns. These studies suggest that the gait speed is a useful measure for evaluating aging and pathology-related disorders.

Commonly used methods for gait characterization involve the use of motion-capture camera systems or inertial measurements units [6], [7]. The former solution is intrusive and expensive. The latter requires the person to wear special markers where the acceptability of such solutions is always an issue especially for elderly people. The radar sensor has established itself as a reliable instrument for measuring the velocity of moving objects, both in outdoor and indoor environments [8]. In addition to being low-cost and non-intrusive, an advantage of these radars is that they can be placed in the elderly people's homes and acquire data during daily activities to provide continuous rather than periodic monitoring. This increases the chances of detecting any change in the gait characteristics. The privacy of the people is also respected as the radar sensor only measures gait characteristics without any additional information [9]. The radar sensor has shown to be an important device for several applications in the field of biomedical engineering such as fall detection for the elderly and even for cough detection which is an important symptom of Covid19 virus using signal processing and deep learning models [10], [11], [12].

Regarding gait analysis, several works exist that use the radar sensor. Wang et al. [13] proposed an approach with two radars and showed that the movement of each member of the human body can be extracted using this system. A similar work was carried by Cuddihi et al. [14] focusing on separating the leg motion from the torso motion and its relation with the fall risk assessment. A time-frequency analysis is carried out by Seifert et al. [15] on the radar signal to characterize various walking problems and differentiate them from normal walk. Saho et al. [16] used statistical learning to extract various gait velocity parameters from the radar signal. An implementation of the radar with time-frequency analysis for elderly care has been proposed by Rui et al. [17]. Ziegel et al. [18] have proposed an interesting approach for the automation of the TUG test using an ultrasonic sensor. The proposed solution considers however the time required by the subject to complete the test. We show in this paper that the time alone deceives the geriatrician or clinician about the real gait speed of the subject due to the presence of acceleration and deceleration zones. While some works aim to determine the gait speed using a radar and very few others to automate the walking tests, a gap still exists to have a complete framework capable of automatically detecting all the phases, evaluating the instantaneous gait speed, and segmenting the different sections of the walk. In our previous works [19], [20], [21][1], we have studied several aspects of the road to automate these tests. In [19], we studied the existence of acceleration and deceleration zones and their influence on the tests. In [20], we proposed an approach to evaluate the gait speed using a

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[1] Earlier versions of this paper were presented at the three conferences IEEE SAS [19], IEEE BioSmart [20] and IEEE EMBC [21] and published in their proceedings.

radar sensor. In [21], we presented an approach to partition the walking and detect the turn in the tests.

In this paper, we build on these approaches to present a complete framework for an automatic gait speed analysis in walking tests using a smart radar sensor. The contributions of this paper at the methodological level are 3-fold. At first, an algorithm that partitions the three sections of a walking test, namely walk #1, the turn and walk #2 is proposed. Second, an algorithm to exactly evaluate the gait speed of the subject undergoing the test is presented. Finally, an algorithm that segments each walking into three parts; an acceleration zone (AZ), a measured-gait zone (MGZ), and a deceleration zone (DZ) is provided. This segmentation allows to evaluate the real gate speed of the subject, by excluding the AZ and the DZ. At the experimental level, we perform experiments on 22 subjects, collecting a total of 396 walking pattern signals. The proposed approach is validated by a Vicon system and compared to state-of-the-art solutions. A statistical study is also carried out to determine the repeatability of the phases determined through our proposed algorithms.

The rest of the paper is organized as follows. Section II describes the used methods. Section III explains the proposed algorithm to automate gait speed analysis in walking tests. Section IV presents and discusses the obtained results. Finally, section V concludes the paper and provides some perspectives.

II. Methods

A total of 22 subjects (12 men and 10 women) aged between 23 and 69 underwent the experiments. Among the subjects, five are older than 65 of which two are diagnosed as frail. The characteristics of the subjects are summarized in Table I. The subjects were given a detailed description of the objectives and requirements of the study prior to the experiment.

TABLE I: Subjects characteristics

Characteristics	Men (12)			Women (10)		
	Me	min	max	Me	min	max
Age (years)	32	23	69	30	23	67
Height (cm)	177	173	202	161	159	175
Weight (Kg)	82	71	102	54	50	64

Me, median; min, minimum value; max, maximum value

The subjects walked back and forth along a straight walkway. The distance between the radar and the start of the walkway was around 20 cm. The covered distance was varied between 3, 4, 4.5 and 5 meters. These walkway lengths have been suggested in previous studies to evaluate the gait speed in walking tests [22]. We will refer to the walk away from the radar by walk #1 and to the walk towards the radar by walk #2. The person walks a certain distance, 3 to 5 meters according to the test, turns, returns back to the starting position. To study different environmental conditions, the lighting was changed from full to dimmed and the objects surrounding the experimental setup in the room were displaced along the trials. The participants were verbally instructed to walk at three paces; slow, usual, and fast. The test was carried out three times in continuous sessions. This resulted in 18 measurements per subject (3 for each pace $\times$ 3 for each session $\times$ 2 for back and forth). The total number of measurements for the 22 subjects is thus 396. The complete experimental setup is shown in Fig. 1. A Doppler radar sensor MDU1130 was used in order to evaluate the gait speed. The radar emits a signal with a frequency of 9.9 GHz and a theoretical range of 15 meters, although practical experiments demonstrated a range of around 10 meters only. The MDU uses separate transmit and receive antennas. As well as improving the sensitivity of the unit by providing isolation between transmit and receive paths this features also permits the shape of the coverage pattern to be optimised. The coverage pattern of the standard unit is 72° horizontally and 36° vertically, with the connection tab facing downwards. This represents the angular coverage over which the sensitivity is at least 70% of the peak sensitivity directly in front of the MDU. The signal was filtered using Butterworth band-pass filter to remove the noise and the unwanted frequencies. The sampling rate was chosen to be 250 Hz as will be explained later. The oscilloscope, measuring the output signal, was used to record the data on a Universal Serial Bus (USB). Here, an oscilloscope of type Tektronix MDO03104 was used. It has 4 analog channels with a vertical resolution of 8 bits, a bandwidth up to 1 GHz, a sampling rate of 5 Gegasample/s and a record length of 10 Megabytes. Once the data are recorded on the USB, they were transferred to the computer where processing took place.

In order to validate the results obtained using the radar sensor system, we used a Vicon system installed in the experimental area, as shown in Fig. 1. The Vicon system allows for a very accurate measurement of movement using reflective markers and infrared cameras. The cameras emit infrared light signals and detect the reflection from the markers attached to the participants. Based on the angle and time delay between the original and reflected signals, it tracks the movement trajectories of the reflective markers in 3D space. The Vicon system implemented in this work is a comprised of 8 cameras of type Bonita 10 that has the following specs; A frame Rate up to 250 fps, a resolution of 1 megapixel (1024 $\times$ 1024), a Lens Operating Range up to 13 meters, an Angle of View Wide of 70.29° $\times$ 70.29° and Angle of View Narrow of 26.41° $\times$ 26.41°.

The radar and Vicon systems were synchronized through infrared barriers. When the subject traverses the first barrier, both the radar and the Vicon system start acquiring data. The subject then traverses the second barrier, turns, traverses it in his/her way back and walks till his starting point. Once the subject traverses the barrier, acquisition automatically stops. Both systems were also synchronized at the level of sampling frequency. The role of the Vicon system is only to validate the results obtained by the radar system. The true gait speed is computed using the Vicon through the 3D location information about the torso marker attached to the participant. We represent the torso by the average between the four markers, two on the shoulders and two on the waist as shown in the video attached in the supplementary material. The position of the marker, thus

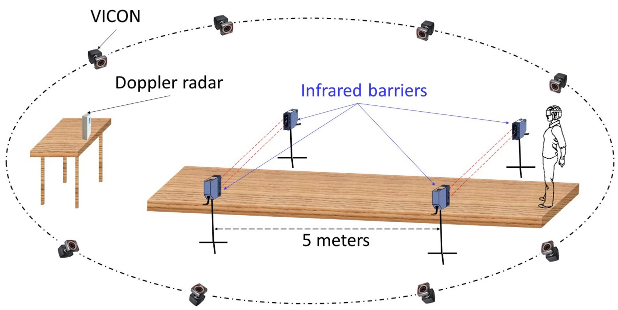

Fig. 1: Experimental setup.

the subject, at instant t is $x[t], t \in \{0, \ldots, D\}$, D being the number of points recorded by the Vicon, $D = \frac{100}{250}L$. Here, L is the number of points recorded by the radar as described above. The instantaneous exact speed using the Vicon is thus,

$$V[t] = \frac{x[t + \Delta t] - x[t]]}{\Delta t}, \tag{1}$$

such that $\Delta t = 0.01 sec$ is the time between two samples.

III. Proposed Algorithm

The objective of the proposed approach is to develop a complete automatic algorithm for gait speed analysis in walking tests. The algorithm is composed of three phases, as explained in the following. Walking tests are normally composed of a walk in one sense, a turn and a walk in the other sense to return to the initial position. To automate this process, we partition the walking into three walks, walk #1, the turn and walk #2. The second phase is the evaluation of the gait speed that is the aim of the walking test. However, in our tests, we noticed the presence of the three zones of the walking pattern, an acceleration zone, a normal zone, where the gait speed is measured and a deceleration zone. For that reason, a third phase is added, which is the automatic segmentation of walking.

A. Partitioning the walking

At first, we aim to partition the walking into three sections, walk #1, turn and walk #2. The relationship between the relative velocity of the person and the Doppler frequency shift f_d is governed by the following equation,

$$v = \frac{c \times f_d}{2 f_0}, \tag{2}$$

where $c = 3 \times 10^8 m/s$ is the speed of light and $f_0 = 9.9$ GHz is the frequency of the emitted signal of the Doppler radar MDU1130.

In order to partition the walking into three sections, we propose a forward-backward algorithm that scans the radar signal to determine the gait speed, and thus estimates the position of the person. In the forward algorithm, the system determines the distance corresponding to walk #1. In the backward algorithm, the system divides what is left from the measured signal into the turn and walk #2. Suppose the instructed distance is d meters and the whole measured signal is $r[l], l \in \{1, \ldots, L\}$ points. As the person starts walking, the system scans the radar signal several times at constant intervals. Suppose the number of points collected at each scan is Y. The Y-points signal is converted into the frequency domain using the Fourier transform (FT),

$$R[f_j] = \sum_{l=0}^{Y-1} r[l] e^{-i2\pi f_j l}, \tag{3}$$

where $f_j = \frac{j}{Y}, j = 0, \ldots, Y-1$. This equation yields the Fourier transform $R[f_j]$ of the time signal $r[l], l \in \{1, \ldots, L\}$ on all frequencies $fj = \frac{j}{Y}, j = 0, \ldots, Y-1$. The signal $r[l]$ is multiplied by $e^{-i2\pi f_j l}$ so that it is transformed from the time domain to the time-frequency domain. The median frequency f_m is used with equation (2) to determine the average speed $\Delta V_{t-1,t}$ of the person between two scans. The position of the person is thus deduced at each scan instant,

$$x_t = \Delta V_{t-1,t} \times t + x_{t-1}, \tag{4}$$

$x_0 = 0$ being the initial position of the person. Once x_t becomes equal to the instructed distance d, the system partitions the first section, which corresponds to walk #1. The system continues scanning until the end of the walking test. At this time, the system considers a backward algorithm to partition walk #2,

$$x_t = x_{t+1} - \Delta V_{t,t+1} \times (t+1), \tag{5}$$

such that $x_L = 0$. Once the system finds that $|x_t|$ is equal to the instructed distance d, it partitions walk #2. The turn is deduced as what is left between walks #1 and #2 from the original signal $r[l]$.

B. Evaluation Of the gait speed

After automatically partitioning the walk using the approach proposed in Section III-A, we obtain 3 signals corresponding to the three walks. The objective of the walking tests is to evaluate the gait speed of the subject. This section aims to determine the gait speed in each one of the three walks. We consider one of the walks, perhaps walk #1 and develop the algorithm allowing to evaluate this gait speed. The same algorithm applies for the two walks.

The signal generated by the radar has a very small amplitude, in the order of millivolts. For that reason, an electronic circuit is placed at the output of the radar with two objectives. The first objective is to amplify the signal with a gain $A = 3.6 \times 10^3$, resulting in a signal in the order of volts. The second objective is to act as a pass-band filter between the cutoff frequencies 5 Hz and 100 Hz. These frequencies correspond to the Doppler shift in case of minimum and maximum walking speeds of people respectively. The 5 Hz corresponds to the minimum speed $v_{min} = 0.075 m/s$ and the 100 Hz corresponds to the maximum speed $v_{max} = 1.5 m/s$ according to equation (2). In the measurement of the Doppler shift, the sampling frequency is set to $f_s = 250$ Hz. This is to respect Shannon's theorem, where the sampling frequency must be at least double the maximum frequency of the analog signal in order to guarantee reconstruction.

The L-points signal obtained from the Doppler radar sensor after sampling $r[l], l = 0, \ldots, L-1$ is displayed in the time domain after passing through the electronic circuit described above. The raw signal resulting from the walking of one person is shown in Fig. 2. The amplitude of the signal decreases as the person walks away from the radar, due to the attenuation of the power of the distance. The signal is converted into the frequency domain using the Fourier transform (FT),

$$R[f_j] = \sum_{l=0}^{L-1} r[l] e^{-i2\pi f_j l}, \tag{6}$$

where $f_j = \frac{j}{L}, j = 0, \ldots, L-1$. The fast Fourier transform (FFT) is an efficient way of computing the FT. Applying it to the signal of Fig. 2 results in the signal shown in Fig. 3.

However, the FT does not allow us to examine instantaneously the gait speed, but rather indicates the frequency components over the walked distance. For that reason, we convert the signal $r[l]$ from the time domain to the frequency domain as a function of time using the discrete-time short-time Fourier transform (STFT) [23]. The STFT computes the FFT over periods of time by dividing the signal into overlapping time segments. It is defined as follows,

$$X[n,k] = \sum_{m=0}^{M-1} r[n+m] w[m] e^{-ik2\pi m/M}, \tag{7}$$

where $w[m]$ is the window function, commonly Hanning or Gaussian, n referes to the time domain, k referes to the frequency domain, and M is the window length. In this work, a Hanning window is considered as recommended in [24], defined as follows,

$$w[m] = \frac{1}{2}\left(1 - \cos\left(\frac{2\pi m}{M-1}\right)\right), m = 0, \ldots, M-1. \tag{8}$$

An important issue in STFT analysis is the selection of the window length M. In fact, the time-frequency resolution of the spectrogram depends on this selection. A large window results in high spectral resolution but low temporal resolution, whereas a small window results in the opposite. Nisar et al. [25] propose an empirical model that adaptively selects the window length,

$$M = \frac{3B \times f_s}{\lambda}, \tag{9}$$

such that B is the size of the main lob of the window, and is equal to 4 for the Hanning window, and λ returns the frequency where the power spectral density (PSD) is concentrated, computed as follows,

$$\lambda = \sum_{l=0}^{L-1} P_l \times A_l, \tag{10}$$

P_l being the normalized power spectral density of point l, and A_l the amplitude of P_l. The spectrogram of the signal of Fig. 2 using the obtained window is shown in Fig. 4. The PSD of each segment is computed as follows,

$$P_n = \frac{1}{M}\left|\sum_{m=0}^{M-1} r[n+m] w[m] e^{-if2\pi n}\right|^2. \tag{11}$$

The frequencies having the highest power are the frequencies corresponding to the movement of the main body of the

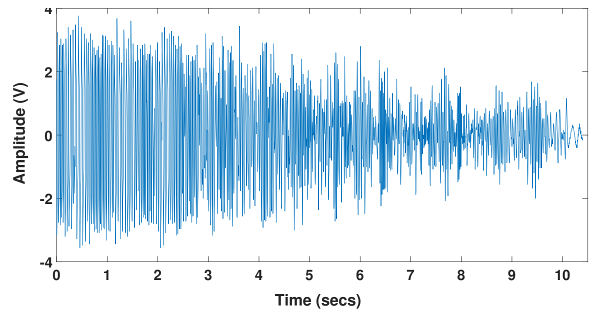

Fig. 2: The raw radar signal of walk #1.

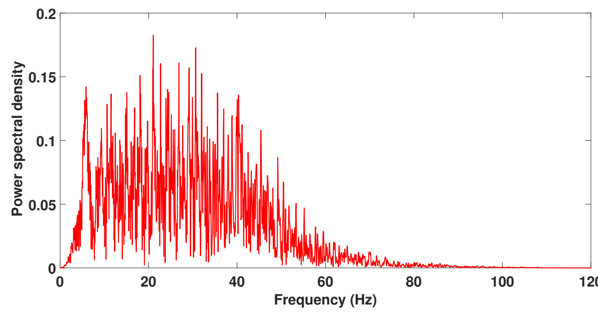

Fig. 3: The FFT of the radar signal.

person. Other frequencies correspond to the movement of other parts of the human body such as hands and legs. Hence, in order to determine the speed of the person walking, the frequency having the highest power in each segment is determined,

$$f_n^H = \operatorname*{argmax}_f P_n. \tag{12}$$

Once the frequency having the highest power in each segment is determined, it is replaced in equation (2), along with the other parameters, to compute the instantaneous gait speed,

$$v_n = \frac{3 \times 10^8}{2 \times 9.9 \times 10^9} \times f_n^H. \tag{13}$$

C. Automatic segmentation of the walking

A zoom-in on the frequencies having the highest power in Fig. 4 shows that there is a significant difference between frequencies, thus speed, at the start, middle, and end of the walking pattern. The speed of the start and end phases of the walking do not correspond to the real movement of the person. Rather, they are times needed by each person to reach his or her normal speed, or the speed demanded in the walking test. The three phases of the walking, i.e. start, middle, and end, are respectively referred to as an acceleration zone, measured-gait zone, and a deceleration zone. Considering the walking as a whole leads to an inexact evaluation of the gait speed.

A solution generally adopted by clinicians is to leave a certain distance before and after the region where the gait speed is to be measured. This distance is normally taken as 2 meters and might vary from 1.5 to 5 meters. This distance allows the person to accelerate and reach the demanded speed, as well as to decelerate and stop. However, this solution is

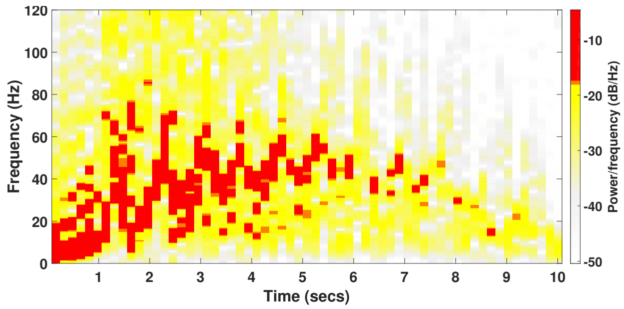

Fig. 4: The spectrogram of the radar signal.

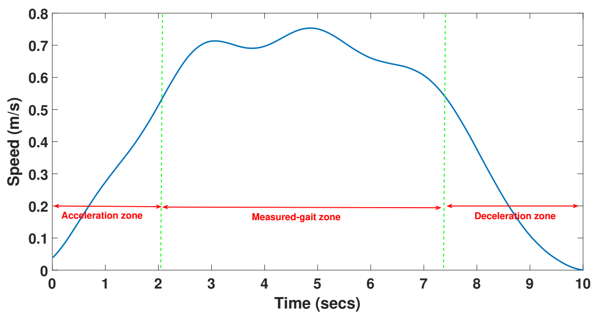

Fig. 5: A segmentation of the walking based on the gait speed corresponding to the frequencies of highest power.

not always feasible due to time, space, and synchronization constraints. Several studies have reported the negative effect of long walks on the acceptability of tests especially by elderly people. Adding 10 meters to guarantee that the measured speed really corresponds to the gait speed of the person, significantly increases the time of the test and might not always be acceptable by the elderly population. That made researchers not consider these acceleration and deceleration zones in their tests in order to increase the acceptability. However, they reported a difference in the gait speed due to this issue. Another constraint is space. A 20 meter distance might not always be available to do a 10-meter test for example. In addition, since we aim to make the device available in homes for continuous collection of data and thus faster detection of disorders, these longer distances are rarely available in rooms of homes. Moreover, a synchronization system is required in order to consider only the MGZ.

For these reasons, we propose in this study an automatic segmentation of walking for gait speed measurement to divide the signal into three segments, AZ, MGZ, and DZ. Only the gait of the MGZ is then considered and compared to reference values related to the test, sex, age, etc for evaluation and assessment. Since we have three phases to be determined, the problem becomes a detection of two changes in the signal; the first is a change from the AZ to the MGZ, and the second is a change from the MGZ to the DZ. At this level, we have a sequence of speeds $v_1, \dots, v_{\mathcal{W}}, \mathcal{W}$ being the number of windows, $\mathcal{W} = \frac{L}{M}$. We assume here that $v_n, n \in \{1, \dots, \mathcal{W}\}$, changes abruptly two times at unknown instants $\{\tau_1, \tau_2\}$, such that $1 < \tau_1 < \tau_2 < \mathcal{W}$, resulting in three segments, the AZ, the MGZ, and the DZ. We are particularly interested in the changes that affect the mean of the v_n's, since at the end, the mean of the gait speed in the MGZ will be considered as the parameter to be evaluated. This means that a first abrupt change in the mean of the gait speed indicates a transition from the AZ to the MGZ. A second abrupt change in the mean indicates a transition from the MGZ to the DZ. Suppose that the mean of the v_n's is μ_1 before τ_1, μ_2 between τ_1 and τ_2, and μ_3 after τ_2. The means μ_1, μ_2, and μ_3 are not known a priori and are computed once τ_1 and τ_2 are determined. Lavielle [26] adopts a global approach to simultaneously detect these change points, by minimizing a contrast function,

$$(\tau_1, \tau_2) = \underset{\tau}{\operatorname{argmin}}\, J(\tau, v) + \beta pen(\tau). \tag{14}$$

The function $J(\cdot)$ measures the fit of τ with v, and aims to detect the change points as accurately as possible. The penalty term $pen(\cdot)$ with the penalization parameter β are used to determine the optimal number of change points, thus segments, in the sequence. Since here, the number of segments is known a priori to be 3, this term is equal to zero and is thus removed. Following [27], a least square criterion can be considered to detect the changes in the mean, by considering the following contrast function,

$$J(\tau, v) = \frac{1}{\mathcal{W}} \sum_{k=1}^{3} \sum_{i=\tau_{k-1}+1}^{\tau_k} (v_i - \mu_k)^2, \tag{15}$$

such that μ_k is the empirical mean of $\left(v_{\tau_{k-1}+1}, \dots, v_{\tau_k}\right)$. The change points are thus computed using the following simple equation,

$$(\tau_1, \tau_2) = \underset{\tau}{\operatorname{argmin}} \frac{1}{\mathcal{W}} \sum_{k=1}^{3} \sum_{i=\tau_{k-1}+1}^{\tau_k} (v_i - \mu_k)^2. \tag{16}$$

The AZ is then defined as $v_1, \dots, v_{\tau_1}$, the MGZ as $v_{\tau_1}, \dots, v_{\tau_2}$, and the DZ as $v_{\tau_2}, \dots, v_{\mathcal{W}}$. The gait speed of the MGZ can thus be deduced as the average of speeds in this segment,

$$v_{MGZ} = \frac{\sum_{i=\tau_1}^{\tau_2} v_i}{\tau_2 - \tau_1}. \tag{17}$$

The same is done for the other zones in order to compute $v_{AZ} = \frac{\sum_{i=1}^{\tau_1} v_i}{\tau_1}$ and $v_{DZ} = \frac{\sum_{i=\tau_2}^{M} v_i}{\mathcal{W} - \tau_2}$.

The segmentation of the walking based on the gait speed corresponding to the signal of Fig. 4 is shown in Fig. 5. The complete pseudo-algorithm of the proposed approach is presented in Algorithm 1. This algorithm takes as input the raw signal measured by the Doppler radar sensor, and automatically outputs the real gait speed of the person in the realized functional capacity test, corresponding to the gait speed in the MGZ. A matlab code will be made available upon the acceptance of the paper.

IV. Results

The proposed algorithm is executed using Matlab on an i3 Windows PC. It runs in approximately 0.5 seconds but should be done at the end of the data acquisition phase and not in real time. This is because the proposed algorithm requires that the movement ends, so that it partitions the walking into the different phases and then evaluate the gait speed of all zones.

Algorithm 1: Automatic evaluation of the exact gait speed of a person using a Doppler radar sensor.

Input : $r[l]$
Output: v_{MGZ}

$L = \text{length}(r)$;
for $j \in \{0, \ldots, L-1\}$ **do**
  $P_j = \frac{1}{L}\sum_{l=0}^{L-1} r[l]e^{-i2\pi n \frac{j}{L}}$;
  $A_j = |P_j|$;
end
$\lambda = \sum_{j=0}^{L-1} P_j \times A_j$;
$M = \frac{3\times4\times250}{\lambda}$; $\%B = 4; f_s = 250$
$\mathcal{W} = \frac{L}{M}$;
for $m \in \{0, \ldots, M-1\}$ **do**
  $w[m] = \frac{1}{2}\left(1 - \cos\left(\frac{2\pi m}{M-1}\right)\right)$;
end
for $n \in \{0, \ldots, \mathcal{W}-1\}$ **do**
  $P_n = \frac{1}{M}\left|\sum_{m=0}^{M-1} r[n+m]w[m]e^{-if2\pi n}\right|^2$;
  $f_n^H = \text{argmax}_f\, P_n$;
  $v_n = \frac{3\times10^8}{2\times9.9\times10^9} \times f_n^H$;
end
for $\tau_1 \in \{0, \ldots, \mathcal{W}-1\}$ **do**
  for $\tau_2 \in \{\tau_1+1, \ldots, \mathcal{W}-1\}$ **do**
    $J(\cdot) = \frac{1}{\mathcal{W}}\sum_{k=1}^{3}\sum_{i=\tau_{k-1}+1}^{\tau_k}(v_i - \mu_k)^2$;
  end
end
$(\tau_1, \tau_2) = \text{argmin}_\tau\, J(\cdot)$;
$v_{MGZ} = \frac{\sum_{i=\tau_1}^{\tau_2} v_i}{\tau_2 - \tau_1}$;

In order to compare the result obtained by the radar with that of the Vicon, the gait speed of the latter is re-sampled to the same number of points of the former. A comparison between the two is shown in Fig. 6. The smoothness in the Vicon signal is not due to any intentional filtering. However, the proposed algorithm uses windowing of the signal in the time-frequency domain and generates for each window the corresponding gait speed. Each window is thus the average of all the points in a window, where each window has 125 data points corresponding to 0.5 seconds. In this way, the resulting radar signal is down-sampled by a factor of 125. In order to compare the proposed system with Vicon, the Vicon signal was also down-sampled by the same factor of 125. In the down-sampling, the average of the Vicon signal on each window of 125 points was computed and hence the smoothness. The correlation between the gait speeds produced by the radar and those produced by the Vicon is 0.9791 with an average Root Mean Square Error (RMSE) = $0.076m/s$. This low RMSE proves the effectiveness of the proposed approach in evaluating the gait speed in walking tests.

Table II compares the gait speed obtained using the proposed approach to that obtained using the Vicon system of the different zones at all three paces. We note a generally low RMSE, indicating a high accuracy of the proposed approach in evaluating the gait speed of the different walking patterns. As the table shows, a relatively higher error is noticed at the fast pace and during the acceleration and deceleration zones. In fact, the lower the speed the easier it is for the algorithm to better segment the different zones of the walking pattern and evaluate afterwards the gait speed. Moreover, the relatively larger window of the normal zone of the walking pattern as compared to both the acceleration and deceleration zones compensates for any error in the segmentation algorithm. Even a small error in segmenting the acceleration and/or deceleration zones would be more impactful on the gait speed evaluation in these zones as opposed to the larger normal zone window. In all cases, we focus more on the performance of the proposed system on the normal zone, as this corresponds to the real gait of the person.

TABLE II: Comparison of the gait speed of the different zones at all three paces between the proposed system and Vicon.

RMSE (m/s)	zones		
pace	acceleration	normal	deceleration
slow	0.066	0.063	0.068
usual	0.074	0.068	0.073
fast	0.083	0.079	0.083

Another important aspect to be studied is the sensitivity of the system. It is practically difficult to determine the sensitivity of the system directly by asking the subjects to slightly increase or decrease their walking speed and measure if this change is detected by the system. We determined the average speed on a window of 0.5 seconds by the Vicon and reported the changes between the windows. We then progressively, from the biggest change to the smallest, compared these changes to those of the radar system, also by computing the average speed on 0.5 seconds windows. We noticed that changes greater than or equal to $0.067m/s$ were detected by the radar system. Changes less than this value were not detected. The sensitivity of the system is thus found to be $0.067m/s$.

To validate the segmentation of the walking, we carry a statistical study to determine whether these observations are reproducible in the different phases and for all subjects in all walking patterns. The gait speeds of all participants at the

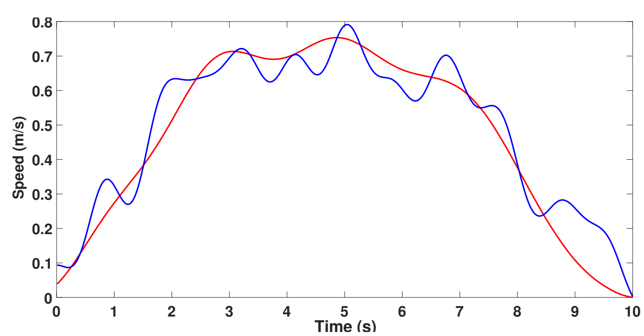

Fig. 6: Comparison between the proposed approach (red) and Vicon system (blue) in evaluating the gait speed.

three walking paces (slow, usual, and fast) and that of each zone of the walking (acceleration, normal, and deceleration) were determined through the algorithm in Section III-C.

To measure the repeatability of these parameters we use the intraclass correlation coefficient (ICC). The ICC estimates and their 95% confidence intervals (CI) are computed based on a 2-way mixed effect model, a single-measurement type, and absolute agreement estimation. This model is chosen since repeated measurement cannot be regarded as randomized samples and it is highly essential to have an agreement between the outputs [28]. As for the type selection, the protocol is planned to be performed in actual applications through a single measurement. The ICC is thus computed as follows,

$$ICC = \frac{MS_S - MS_E}{MS_S + (k-1)\, MS_E + \frac{k}{n}\,(MS_T - MS_E)}, \quad (18)$$

where MS_S is the subjects mean square, MS_E is the error mean square, MS_T is the trials mean square, k is the number of measurements/raters, and n is the number of subjects.

Table III shows the ICCs and their 95% CIs of the various zones of the walking at different paces. The ICC is computed for walk # 1 alone, for walk #2 alone, and for the two walks together. This was done for all three paces. Moreover, in order to evaluate the repeatability of the gait speed of each zone, the ICC is computed for the acceleration, normal, and deceleration zones at the three paces. We are also interested in measuring the variations of the walking from the start till the end. For that reason, we compute the ICCs between different zones of the walking at each pace. Table IV reports these values and their 95% CIs. The numbers in bold in both tables refer to poor reliability (ICC < 0.5). ICCs between 0.5 and 0.75, between 0.75 and 0.9, and greater than 0.90 are indicative of moderate, good, and excellent reliability, respectively [28].

As Table III shows, there is an excellent reliability in almost all zones and patterns at different paces. A poor reliability is however noted in case of both walks at a fast pace. This is due to the variations in the reflected signal by the human body to the radar when considering walks #1 and #2 together. This noise in the measured frequency, mainly coming from the different movement of the legs as viewed by the radar in both walks, leads to a noise in the measurement of the gait speed. This is also validated by the excellent reliability of the whole walking at a fast pace in walk #1 alone and walk #2 alone. This means that the gait speed is also reliable at a fast pace, and the low ICC in the measurement of both walks is due to the variations in the frequency, i.e. rapid movement of hands and legs, as seen by the radar. Another noted poor reliability is in the deceleration phase of walk #1 at usual pace. An interpretation of that might be that participants were unable to repeat their walking in the deceleration zone. A relatively high ICC of the same pattern but for walk #2 (0.87) might indicate that participants anticipated their stop in walk #2 due to the presence of a table in front of them.

Table IV shows a moderate to good reliability between different zones of each walking pattern. The subjects were able to keep a harmony in their walking at low pace (excellent reliability). However, a significant variation between the zones of each pattern is noted at both the usual and fast paces. The lowest reliability is found between the normal and deceleration zones at the fast pace. The low reliability at the fast pace has been explained in the previous paragraph. Moreover, a psychological reason might be pushing the participants to slow down before reaching the line where they were requested to stop. This leads to a significant variation in the gait speed between the normal and deceleration zone. This also explains the reason behind the low ICCs at fast pace in Table III (0.47 and 0.30). The same happens at the start of the walking where the subjects take some time in order to reach their normal speed. Although this can be solved by leaving a distance before and after the walkway as is done in the state-of-the-art methods, this might not always be practical. Space for example is one of the constraints where there is no guarantee to have $> 10m$ long rooms in all indoor environments.

TABLE III: The ICCs of various walking patterns.

ICC (95% CI)		walk		
pace		walk #1	walk #2	both
slow	whole	0.95 (0.91-0.99)	0.98 (0.91-0.98)	0.94 (0.89-0.96)
	acceleration	0.95 (0.86-0.95)	0.97 (0.85-0.93)	0.95 (0.91-0.99)
	normal	0.94 (0.79-0.96)	0.97 (0.82-0.99)	0.95 (0.92-0.98)
	deceleration	0.89 (0.78-0.94)	0.97 (0.82-0.99)	0.93 (0.90-0.97)
usual	whole	0.91 (0.86-0.95)	0.93 (0.91-0.97)	0.89 (0.87-0.92)
	acceleration	0.90 (0.87-0.96)	0.90 (0.82-0.92)	0.91 (0.89-0.98)
	normal	0.96 (0.88-0.98)	0.94 (0.89-0.95)	0.98 (0.95-0.99)
	deceleration	**0.41** (0.31-0.96)	0.86 (0.77-0.96)	0.69 (0.42-0.98)
fast	whole	0.91 (0.86-0.96)	0.93 (0.91-0.99)	**0.46** (0.33-0.97)
	acceleration	0.75 (0.63-0.94)	0.65 (0.54-0.95)	0.71 (0.66-0.95)
	normal	0.58 (0.35-0.92)	0.81 (0.71-0.99)	0.66 (0.52-0.96)
	deceleration	**0.47** (0.29-0.81)	**0.30** (0.18-0.74)	0.57 (0.33-0.97)

walk #1, walking away from the radar; walk #2, walking towards the radar

TABLE IV: The ICCs between zones of walking patterns.

ICC (95% CI)	zones		
pace	acc-dec	acc-normal	dec-normal
slow	0.98 (0.92-0.99)	0.98 (0.93-0.98)	0.96 (0.93-0.99)
usual	0.68 (0.51-0.94)	0.87 (0.81-0.95)	0.68 (0.59-0.84)
fast	0.61 (0.54-0.85)	0.66 (0.77-0.94)	**0.14** (0.05-0.63)
whole	0.77 (0.69-0.95)	0.68 (0.57-0.97)	0.71 (0.66-0.95)

acc, acceleration; dec, deceleration

As a cost-benefit analysis, we note that the system can be deployed in hospitals and clinics for gait speed analysis on daily basis. The system costs around ten dollars including the radar sensor and the electronic circuit to amplify and filter the signal. In return, the proposed system allows for automatic gait analysis without the need to manually partition the walking into phases and each phase into acceleration and deceleration zones. This accelerates the process of realizing the walking tests, reduces the working load of geriatrics and provides a cost-effective solution to extract fine gait-related parameters that help evaluating the ability to move in elderly people.

V. Conclusion

In this paper, we have presented a radar sensor system for automatic gait speed analysis in walking tests. The system automatically partitions the walking pattern into three phases, walk #1, the turn, and walk #2. It then evaluates the instantaneous gait speed of each walking phase. Finally, the system automatically segments each walking phase into three parts, acceleration, normal and deceleration. We have shown that this segmentation has a significant influence on the evaluation of the real gait speed of the person. We have demonstrated that the proposed approach is capable of partitioning and segmenting the walking and evaluating the gait speed of each phase by comparing its performance to a Vicon system on 22 participants and a total of 396 signals. The main advantage of the proposed approach lies in the fact that the different zones and phases are automatically determined and segmented, without the need for additional time, space and synchronization. The proposed system can be used to study the movement of the upper and lower members of the human body to determine the cycle of walking and the length of the step. Another perspective would be combining gait recognition with the current work. This allows for an automatic data recording in hospitals and clinics without the need to manually identify the person doing the walking test.

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References

[1] G. M. Savva, O. A. Donoghue, F. Horgan, C. O'Regan, H. Cronin, and R. A. Kenny, "Using timed up-and-go to identify frail members of the older population," *Journals of Gerontology Series A: Biomedical Sciences and Medical Sciences*, vol. 68, no. 4, pp. 441–446, 2013.

[2] S. Fritz and M. Lusardi, "White paper:"walking speed: the sixth vital sign"," *Journal of geriatric physical therapy*, vol. 32, no. 2, pp. 2–5, 2009.

[3] O. Theou, G. R. Jones, J. M. Jakobi, A. Mitnitski, and A. A. Vandervoort, "A comparison of the relationship of 14 performance-based measures with frailty in older women," *Applied Physiology, Nutrition, and Metabolism*, vol. 36, no. 6, pp. 928–938, 2011.

[4] M. Montero-Odasso, M. Schapira, C. Varela, C. Pitteri, E. R. Soriano, R. Kaplan, L. A. Camera, and L. Mayorga, "Gait velocity in senior people an easy test for detecting mobility impairment in community elderly," *Journal of Nutrition Health and Aging*, vol. 8, no. 5, pp. 340–343, 2004.

[5] J. Verghese, R. Holtzer, R. B. Lipton, and C. Wang, "Quantitative gait markers and incident fall risk in older adults," *The Journals of Gerontology: Series A*, vol. 64, no. 8, pp. 896–901, 2009.

[6] S. Qiu, Z. Wang, H. Zhao, L. Liu, J. Li, Y. Jiang, and G. Fortino, "Body sensor network-based robust gait analysis: Toward clinical and at home use," *IEEE Sensors Journal*, vol. 19, no. 19, pp. 8393–8401, 2019.

[7] G. Li, T. Liu, and J. Yi, "Wearable sensor system for detecting gait parameters of abnormal gaits: A feasibility study," *IEEE Sensors Journal*, vol. 18, no. 10, pp. 4234–4241, 2018.

[8] K. Saho, M. Fujimoto, M. Masugi, and L.-S. Chou, "Gait classification of young adults, elderly non-fallers, and elderly fallers using micro-doppler radar signals: simulation study," *IEEE Sensors Journal*, vol. 17, no. 8, pp. 2320–2321, 2017.

[9] R. Jaber, A. Chkeir, D. Hewson, and J. Duchêne, "A new device to assess gait velocity at home," in *XIII Mediterranean Conference on Medical and Biological Engineering and Computing 2013*, pp. 1503–1506, Springer, 2014.

[10] A. Singh, S. U. Rehman, S. Yongchareon, and P. H. J. Chong, "Sensor technologies for fall detection systems: A review," *IEEE Sensors Journal*, vol. 20, no. 13, pp. 6889–6919, 2020.

[11] E. L. Chuma, L. L. B. Roger, G. G. de Oliveira, Y. Iano, and D. Pajuelo, "Internet of things (IoT) privacy–protected, fall-detection system for the elderly using the radar sensors and deep learning," in *2020 IEEE International Smart Cities Conference (ISC2)*, pp. 1–4, 2020.

[12] E. L. Chuma and Y. Iano, "A movement detection system using continuous-wave doppler radar sensor and convolutional neural network to detect cough and other gestures," *IEEE Sensors Journal*, vol. 21, no. 3, pp. 2921–2928, 2021.

[13] F. Wang, M. Skubic, M. Rantz, and P. E. Cuddihy, "Quantitative gait measurement with pulse-doppler radar for passive in-home gait assessment," *IEEE Transactions on Biomedical Engineering*, vol. 61, no. 9, pp. 2434–2443, 2014.

[14] P. E. Cuddihy, T. Yardibi, Z. J. Legenzoff, L. Liu, C. E. Phillips, C. Abbott, C. Galambos, J. Keller, M. Popescu, J. Back, *et al.*, "Radar walking speed measurements of seniors in their apartments: Technology for fall prevention," in *2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, pp. 260–263, IEEE, 2012.

[15] A.-K. Seifert, M. G. Amin, and A. M. Zoubir, "Toward unobtrusive in-home gait analysis based on radar micro-doppler signatures," *IEEE Transactions on Biomedical Engineering*, vol. 66, no. 9, pp. 2629–2640, 2019.

[16] K. Saho, K. Uemura, K. Sugano, and M. Matsumoto, "Using micro-doppler radar to measure gait features associated with cognitive functions in elderly adults," *IEEE Access*, vol. 7, pp. 24122–24131, 2019.

[17] L. Rui, S. Chen, K. Ho, M. Rantz, and M. Skubic, "Estimation of human walking speed by doppler radar for elderly care," *Journal of Ambient Intelligence and Smart Environments*, vol. 9, no. 2, pp. 181–191, 2017.

[18] Z. Andreas, K. Peter, M.-O. Robert, and S. Günter, "Automated measurement and subtask analysis of the timed upand-go test in the field of geriatrics," in *2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pp. 1526–1529, IEEE, 2018.

[19] D. Alshamaa, A. Chkeir, R. Soubra, and F. Mourad-Chehade, "Measurement of gait speed using a doppler radar: Influence of acceleration and deceleration zones," in *2019 IEEE Sensors Applications Symposium (SAS)*, pp. 1–5, IEEE, 2019.

[20] D. Alshamaa, A. Chkeir, R. Soubra, and B. Dauriac, "A smart radar system for automatic functional capacity tests," in *2019 3rd IEEE International Conference on Bio-engineering for Smart Technologies (BioSMART)*, pp. 1–4, IEEE, 2019.

[21] D. Alshamaa, A. Chkeir, and R. Soubra, "Gait speed measurement using a doppler radar sensor for in-home functional capacity tests," in *2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pp. 3424–3428, IEEE, 2019.

[22] C. L. Richards, F. Malouin, and C. Dean, "Gait in stroke: assessment and rehabilitation," *Clinics in geriatric medicine*, vol. 15, no. 4, pp. 833–856, 1999.

[23] S. Mohine, B. S. Bansod, P. Kumar, R. Bhalla, and A. Basra, "Single acoustic sensor based time-frequency spectrum sensing approach for land vehicle detection," *IEEE Sensors Journal*, pp. 1–1, 2020.

[24] M. Kojima, S. Obuchi, O. Henmi, and N. Ikeda, "Comparison of smoothness during gait between community dwelling elderly fallers and non-fallers using power spectrum entropy of acceleration time-series," *Journal of Physical Therapy Science*, vol. 20, no. 4, pp. 243–248, 2008.

[25] S. Nisar, O. U. Khan, and M. Tariq, "An efficient adaptive window size selection method for improving spectrogram visualization," *Computational intelligence and neuroscience*, vol. 2016, 2016.

[26] M. Lavielle, "Using penalized contrasts for the change-point problem," *Signal processing*, vol. 85, no. 8, pp. 1501–1510, 2005.

[27] M. Lavielle and E. Lebarbier, "An application of mcmc methods for the multiple change-points problem," *Signal processing*, vol. 81, no. 1, pp. 39–53, 2001.

[28] T. K. Koo and M. Y. Li, "A guideline of selecting and reporting intraclass correlation coefficients for reliability research," *Journal of chiropractic medicine*, vol. 15, no. 2, pp. 155–163, 2016.

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