Radar-Based Passive Step Counter and Its Comparison with a Wrist-Worn Physical Activity Tracker

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September 17, 2024

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Abstract. Inspired by novel applications of radio-frequency sensing in healthcare, smart homes, rehabilitation, and augmented reality, we present an FMCW radar-based passive step counter. If a person walks or performs other activities, the individual body segments, such as head, torso, legs, arms, and feet, move at different radial speeds. Owing to the Doppler effect, the individual body segments in motion cause distinct Doppler shifts that can be used to recognize and analyze the performed activities. We compute the time-variant Doppler spectrogram of a walking activity of a person and extract the high energy Doppler components that mainly describe the torso movements during walking. From the computed Doppler spectrogram, we then compute the mean Doppler shift. To detect and count steps, we apply the peak detection algorithm to the mean Doppler shift. Our approach is evaluated using a walking activity data set. We have used ground truths and a commercially available wrist-worn human activity tracker to validate the results of our approach. Our results show that our system is capable of passively counting 97.71%–98.51% steps within a 12 m range. Therefore, our proposed system can be used as a passive step counter in indoor environments. Besides, it can also contribute to indoor localization and human tracking applications.

Keywords: FMCW radar · Mean Doppler shift · Peak detection · Spectrogram · Step counting.

1 Introduction

The World Health Organization (WHO) statistics[1] on obesity and overweight reveal that 1.9 billion individuals, 18 years and above, were overweight in 2016. Out of these, 34.2% were obese. Research has shown that the obese people are at higher risk for various diseases and health conditions including hypertension, type 2 diabetes, coronary heart disease, mental illness, sleep disorders, and low quality of life [20]. Regular physical exercise, especially walking, and a healthy diet are among the best ways to treat obesity. Walking is one of the simplest

[1] https://www.who.int/news-room/fact-sheets/detail/obesity-and-overweight

forms of physical activity that can easily be carried out in indoor and outdoor settings. Long term studies have found evidence that regular counselling, step goals, and pedometer-based interventions are useful to increase and maintain walking levels among low active Scottish individuals [10]. Another study [5] reports that pedometer users tend to walk approximately one mile (or 2000 steps) more compared to people who do not use pedometers. According to [23], in WHO European region, people spend just about 90% of their time in indoor environments. Out of which approximately 60% time is spent at home.

The widely available and commonly used pedometers are body-worn and consist of sensors such as accelerometers and gyroscopes. These sensors record the acceleration and variation in orientation due to the walking activity and process the recorded data to count the steps of the user. Moreover, many people use their smartphones with built-in pedometers to count their steps. People need to wear these pedometers all the time for continuously registering their steps, which may be uncomfortable for some people in in-home settings. As studies have shown [10, 5] the pedometers act as a motivational tool for increasing physical activity. Therefore, to promote an active life-style in indoor environments, there is a need to develop a user-friendly step counting system that can unobtrusively count steps of users in in-home settings. In addition to that a passive step counter can also contribute in developing more robust indoor human tracking and localization solutions.

Compared to vision and wearable sensing modalities, the radio-frequency (RF) sensing modality has emerged as an attractive alternative in a lot of applications, such as human activity recognition (HAR) [11, 9], gesture recognition [21], vital signs monitoring [22], and security and surveillance [12]. There exist various reasons that have led to the wide acceptance of RF-sensing in human-centric applications. First and foremost, RF sensing is truly unobtrusive in nature, which means users do not need to wear or carry additional sensors. Moreover, the RF-sensing modality is far more privacy-preserving compared to other available sensing methods such as vision, wearable, and acoustics. In addition to that, the RF sensing can operate in poor lighting conditions, see-through obstacles and its performance is not affected by anthropocentric variations and changes in the environment. Within the context of RF sensing, Wi-Fi and frequency modulated continuous wave (FMCW) radars are commonly used for perceiving human activities. Although Wi-Fi is ubiquitous and low-cost, it offers a lower bandwidth, which results in a lower spatial resolution and therefore Wi-Fi-based activity recognition methods struggle in recognizing fine-grained human activities. On the other hand, FMCW radars generally enjoy much larger bandwidth, which results in higher spatial resolution and thus they can effectively be employed to identify fine-grained human activities with higher precision and accuracy [18]. Besides, FMCW radars are also capable of identifying the range and speed (or Doppler frequencies) of the target. These properties are the key enablers that have led to the wide adoption of FMCW radars for the aforementioned applications compared to Wi-Fi, continuous wave, and ultra-wide-band pulse radars.

As we know, the electromagnetic waves emitted by the FMCW radar reflect off both static and moving objects present in the environment. Owing to the Doppler effect, different movements of a moving object result in distinct Doppler shift patterns [8]. Various studies have demonstrated that these distinct Doppler shift patterns can effectively be exploited to not only discern humans [19, 7], animals [3], and vehicles [13, 15] but also to recognize different human activities [9, 11, 16, 18], such as walking, sitting, standing, running, jumping, etc.

In this paper, we investigate the novel idea of using Doppler shifts caused by a walking person to count the number of steps and provide preliminary results. As we know, the human walk is cyclic in nature and during each step-to-step transition, the moving body segments exhibit repetitive cycles of movements. Thus, a cyclic gait pattern will manifest itself in velocities (or cyclic Doppler variations) of the body segments. We first process the recorded RF sensing data of a walking activity to reduce the noise impact, and then we compute the spectrogram of the data. The spectrogram shows the time-variant micro-Doppler patterns associated with movements of different human body segments, such as torso and legs. Next, we compute the time-variant mean Doppler shift from the spectrogram. Finally, we apply a peak (or valley) detection algorithm to detect and count the number of steps. We use a human walking activity data set to evaluate our approach. We use ground truths to validate the results of our approach. Besides, we also use an accelerometer-based wrist-worn step counter to compare the performance of our radar-based step counter with an existing off-the-shelf step-counter.

Our results show that the proposed step-counter can count 97.71%–98.51% steps in a 12 m range. Note that, to accurately count the number steps, it is crucial to first identify when a person is walking. This information can be obtained using a HAR recognition system developed in our previous works [16–18], which is able of recognizing the walking activity with almost 100% precision and recall. This work enable us to combine HAR and passive step counter to develop a solution that is not only able to recognize human activities but also capable of implicitly counting the steps.

The rest of the paper is organized as follows. In Section 2, we describe the basic principle of FMCW radar systems, explain the various steps of radar signal processing, and present expressions for computing spectrogram and mean Doppler shift. The details of our experimental setup and data collection process are given in Section 3. The results of our approach are presented in Section 4. The limitations of this work are presented in Section 5. Finally, in Section 6, we conclude this work and present its future outlook.

2 System Description and Radar Signal Processing

In this work, we have used an FMCW radar system as an RF sensor to capture the micro-Doppler effects caused by a walking person. The FMCW radar uses a synthesizer to generate a frequency modulated (FM) electromagnetic wave (known as chirp), which is transmitted in the environment via a transmit antenna T_x [22]. The instantaneous frequency of the chirp changes linearly over a fixed time period (know as sweep time T_{sw}) by a modulating signal [6]. The transmitted signal $s_{T_x}(t')$ can be expressed as [1]

$$s_{T_x}(t') = \exp[j2\pi(f_0 t' + \frac{\alpha}{2}t'^2)] \tag{1}$$

where f_0 indicates the start frequency, α is the chirp rate, and t' denotes the fast-time. The chirp rate is expressed as $\alpha = (f_1 - f_0)/T_{sw}$, where f_1 stands for the stop frequency. The bandwidth B of the radar is the difference between the stop frequency f_1 and the start frequency f_0, i.e., $B = f_1 - f_0$. The transmitted wave reflects from different static and moving scatterers that are present in the environment, as shown in Fig. 1. The reflected electromagnetic wave is received by the receive antenna R_x with a time delay $\tau = 2R/c$, where R is the distance of the scatterer from the radar and c is the speed of light [22]. The received electromagnetic wave $s_{R_x}(t')$ that is reflected from a single scatterer is a τ delayed version of the transmitted signal [1]

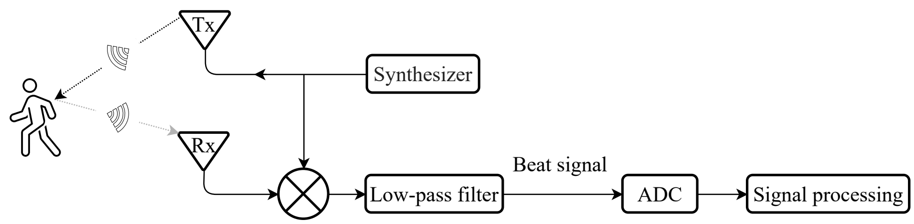

Fig. 1. A block diagram of an FMCW radar system.

$$s_{R_x}(t') = a\exp[j2\pi(f_0(t' - \tau) + \frac{\alpha}{2}(t' - \tau)^2)] \tag{2}$$

where symbol a in (2) represents the amplitude, which depends on the physical properties of the system, such as the transmission losses and the radar cross-section of the scatterer. As per the principle of the FMCW radar, the transmitted signal $s_{T_x}(t')$ and the received $s_{R_x}(t')$ signal are mixed together and passed through a low pass filter to obtain the so-called beat (or intermediate frequency) signal which can expressed as [1, 22]

$$s_b(t') = a\exp[j(2\pi\alpha\tau t' + 2\pi f_0\tau)] = a\exp[j(2\pi f'_b t' + \psi)] \tag{3}$$

where f'_b is the beat frequency and ψ is the phase of the beat signal. The beat signal is then sampled by an analog to digital converter (ADC). The output of ADC is stored in an $n \times m$ matrix s_b, where n denotes the number of samples per sweep (or fast-time data) and m represents the number of transmitted sweeps (or chirps). For the following discussion, we consider the beat signal s_b as a function of fast-time t' and slow-time t, such as $s_b(t', t)$. As shown in (3), the fundamental frequency of a single point moving scatterer is present at $f'_b = \alpha\tau$. Therefore, we can obtain the range information of a scatterer by computing the fast Fourier transform (FFT) of the beat $s_b(t', t)$ with respect to fast-time data, i.e.,

$$S_b(f_b, t) = \int_0^{T_{sw}} s_b(t', t) exp[-j2\pi f_b t'] dt'. \tag{4}$$

The Doppler frequency of the moving scatterer is estimated over a series of continuously transmitted sweeps (or chirps). The result obtained after applying the FFT according to (4), undergoes an additional FFT (known as the Doppler FFT), which is applied on the windowed range profile along the slow-time, i.e.,

$$X(f_b, f, t) = \int_{-\infty}^{\infty} S_b(f_b, t) W_r(x - t) exp[-j2\pi f x] dx \tag{5}$$

where $W_r(\cdot)$ indicates the rectangular window function, x is the running time, and f denotes the Doppler frequency. The short-time Fourier transform (STFT) of the range profile provides us with the range and Doppler information of the moving scatterer. To obtain the time-variant Doppler frequencies, we agglomerate the range information as follows

$$X(f, t) = \int_0^{f_{b,\max}} X(f_b, f, t) df_b \tag{6}$$

where $f_{b,\max}$ denotes the maximum beat frequency that an FMCW radar can resolve [14]. In the next step, we compute the spectrogram $S(f, t)$, which is defined in [4] as the absolute square of $X(f, t)$, i.e.,

$$S(f, t) = |X(f, t)|^2. \tag{7}$$

The spectrogram presents the time-varying micro-Doppler signature of the moving scatterer. Finally, the time-variant mean Doppler shift $B_f(t)$ is computed as

$$B_f(t) = \frac{\int_{-\infty}^{\infty} f S(f, t) df}{\int_{-\infty}^{\infty} S(f, t) df}. \tag{8}$$

3 Experimental Setup and Data Collection

In this work, we considered an indoor environment, where we used the Ancortek SDR-KIT2400T2R4 [2] (SDR-KIT) as shown in Fig. 2 to collect RF sensing data. The SDR-KIT is a software-defined FMCW radar that operates in the K-band within 24–26 GHz. The SDR-KIT consists of two transmit and four receive units where two T_x and four R_x antennas can be connected.

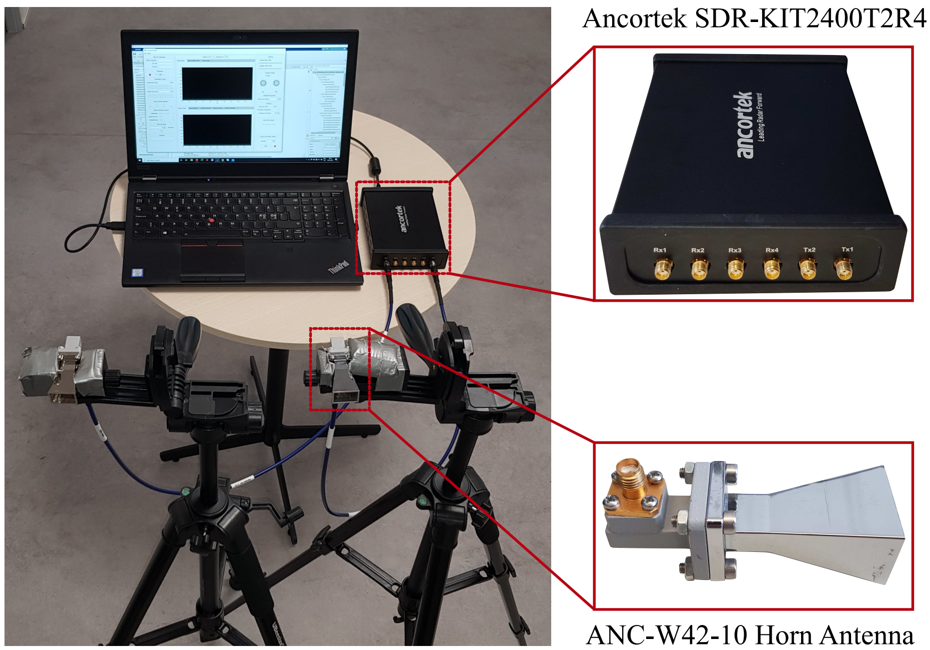

Fig. 2. Hardware setup for collecting radar-sensing data in the presence of a walking person.

Within the scope of this work, we only used a single transmit and a single receive unit. The T_x and R_x antennas were connected to the SDR-KIT using 1 m RF cables. We attached the T_x and R_x antennas to two separate tripods and set the height of both antennas to 110 cm from the floor. The SDR-KIT is connected to a laptop using a universal serial bus cable. The laptop runs a program that provides a graphical user interface (GUI) to interact with the SDR-KIT. Using the GUI, the users can set different parameters of the radar and issue commands to start and stop recording the data. The recorded data are in the form of ADC samples and stored on the laptop. We placed our hardware setup in a corridor as shown in Fig. 3. We used the co-located[2] antenna configuration, and set the bandwidth B, centre carrier frequency f_0, and sweep time T_{sw} to 250 MHz, 24.125 GHz, 1 ms, respectively.

We collected walking activity data from two participants. For the first participant, we recorded walking activity data in two separate sessions. In the first session, we asked the participant to walk in front of the T_x and R_x antennas from Point A to Point B, as shown in Figs. 3. The distance from Point A to Point B was 8 m, where the participant needed to take exactly 10 steps at a normal walk pace to cover this distance. The participant walked in total 150 times from

[2] By co-located antenna configuration, we mean that the T_x and R_x antennas were placed close to each other, as can be seen in Fig. 3.

(a) (b)

Fig. 3. Indoor radar sensing of a person walking along a floor: (a) antenna configuration and (b) walking activity.

Point A to Point B and 150 times back from Point B to Point A. This actually provides us the ground truth, as we know, the participant took 3000 steps while walking back and forth between points A and B. For the second session, we asked the participant to walk from Point A to Point C, which are shown in Fig. 3(a). The distance from Point A to Point C was 12 m. To walk 12 m distance, the participant needed to take exactly 15 steps at a normal walking speed. In the second session, the participant again walked 3,000 steps, by walking 100 times in each direction. In each session, the data corresponding to each walk were stored in a separate file to keep the size of each data file manageable. This means, we stored the walking RF data in 300 files in the first session and in 200 files in the second session.

For the second participant, the walking activity data was recorded only in a single session. Just like the first participant, the second participant walk 12 m from Point A to Point C. To walk 12 m distance, the second participant needed to take exactly 17 steps and walked 59 times back and forth between points A and C. The data corresponding to each walk was stored in a separate file. This means, the second participant took a total of 1,003[3] steps while walking

[3] Note that, our goal is to compare the total number of steps taken by a participant in reality with the total number of steps recorded by the wrist-worn activity tracker and

back and forth between Points A and C. Also, to compare the results of our approach with commercially available activity trackers, we asked the participants to wear a Garmin Forerunner 935 watch on the non-dominant wrists to register the steps taken during data recording sessions. The watch uses its internal 3-axis acceleromter to measure dynamic arm movement and translates each complete arm swing into two steps.

4 Step Detection and Step Counting Results

We processed each recorded walking activity data file. At first, we removed the impact of ambient noise by subtracting the sample mean from the raw radar data. Besides, the mean subtraction also removes the contributions of fixed scatterers to a certain extent. Moreover, we applied a high-pass filter to fully remove the contributions of fixed scatterers, such as walls, ceiling, and furniture. Thereafter, we estimated the range of the moving scatterers by computing the range-FFT as presented in (4). From the range-profile (see Fig. 4), we can observe that the person was first standing still for the first three seconds at a distance of 2.4 m distance from the radar, and then the person started walking away from the radar's T_x and R_x antennas. The person walked for 6.5 seconds and covered a distance of approximately 8 m. The last five seconds of the range-profile plot show that the person stood still at a distance of 10.24 m. The range-profile is

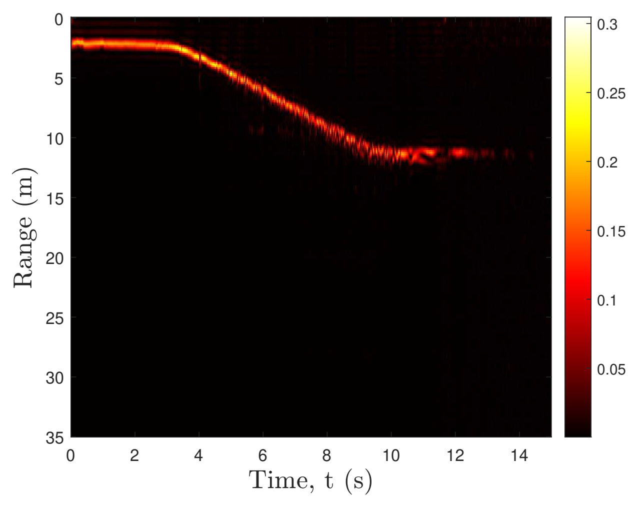

Fig. 4. The measured range profile of an 8 m long walking activity performed by the first participant.

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the proposed radar-based step counter. Therefore, each participant does not need to take the same number of steps.

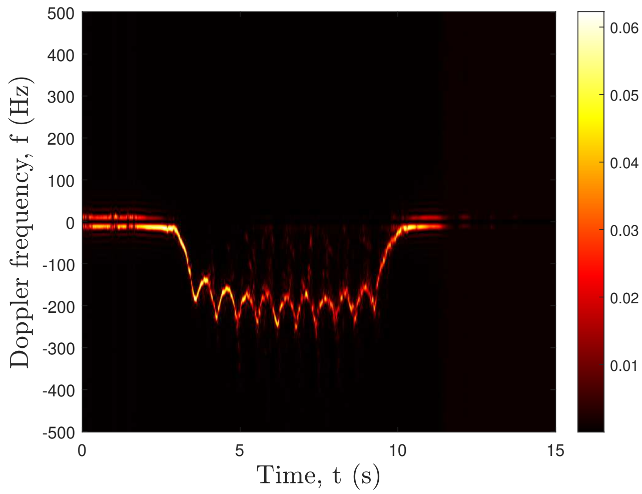

Fig. 5. The spectrogram of an 8 m long walking activity performed by the first participant. Note that, the negative Doppler shift is due to the fact that participant was walking away from the away from the co-located T_x and R_x antennas.

useful for determining how the distance of a walking person changes over time. However, the number of steps cannot directly be counted from the range profile. We use the spectrogram method to extract the micro-Doppler signature of the walking activity from the range profile, as presented in (5)—(7). The spectrogram of the walking activity is shown in Fig. 5, which gives an impression of the micro-Doppler signatures associated with different limbs in motion during the walking activity. The negative frequencies in the micro-Doppler signatures are due to the fact that the person is walking away from the T_x and R_x antennas of the radar.

The high energy component of the spectrogram (see Fig. 5) can be associated with the micro-Doppler signature of the repetitive movement of the torso. Whereas, the low energy components are due to the movements of the feet, legs, and arms. We threshold the spectrogram to remove these low energy components and then compute the time-variant mean Doppler shift (see Fig. 6) by using (8). The minima of the time-variant mean Doppler shift coincides with the steps of the person. If the person is walking towards the T_x and R_x antennas of the radar, the Doppler shift will be positive and each peak of the mean Doppler shift will indicate a step of the person.

We apply the Matlab's "`findpeaks`" algorithm to detect the peaks of the time-variant mean Doppler shifts that correspond to the steps. By default, the "`findpeaks`" peak detection algorithm will detect all peaks of the mean Doppler shift. Therefore, to prune peaks that do not correspond to the true steps, we set the four parameters of the "`findpeaks`" algorithm, i.e., minimum peak height, minimum peak separation, minimum peak prominence, and minimum peak

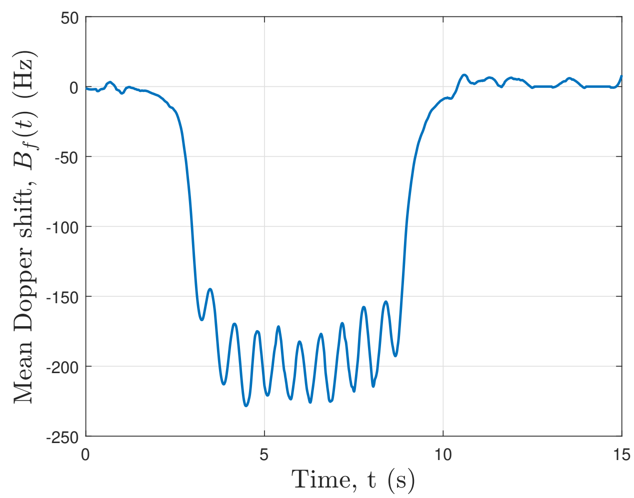

Fig. 6. The time-variant mean Doppler shift of a person walking away from the co-located T_x and R_x antennas.

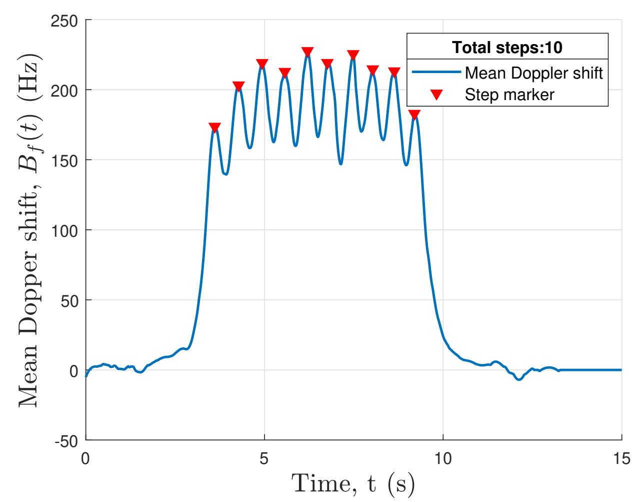

Fig. 7. The steps identified by the peak detection algorithm for the case that the person walks towards the co-located T_x and R_x antennas. Each identified step is marked by the ▼ symbol.

height difference to 20, 0.005, 15, 0.001, respectively. We use the exhaustive grid search approach to optimize the aforementioned parameters of the peak detection algorithm. As shown in Fig. 7, the peak detection algorithm is able to correctly identify steps in the time-variant mean Doppler shift. We iterate over all recorded

Table 1. A comparison of the step-count results of the Garmin Forerunner 935 activity tracker and our FMCW radar-based approach.

Session	Walking distance	True step count	Steps counted by the Garmin Forerunner 935	Steps counted using the proposed approach
Results of participant 1				
1	8 m	3000	2880 (96.00%)	2948 (98.27%)
2	12 m	3000	2975 (99.17%)	2955 (98.51%)
Results of participant 2				
1	12 m	1003	939 (93.61%)	980 (97.71%)

walking activity data files and accumulate the identified steps in each file. The results of our approach are presented in Table. 1.

For the first participant's 8 m walking scenario, both the Garmin Forerunner 935 activity tracker and the FMCW radar were not able to count all steps. In this case, our FMCW-radar-based approach registered a total of 2948 steps out of the 3000 steps, which are 2.27% more compared to the Garmin 935 activity tracker. For the 8 m walks, our FMCW-radar-based approach and the Garmin 935 activity tracker under-reported 1.73% and 4.0% steps, respectively.

For the first participant's 12 m walking scenario, the step count accuracy of the Garmin 935 activity tracker is 99.17%, whereas the accuracy of our FMCW-radar-based system is 98.51%. We can observe a 3.17% improvement in the accuracy of the Garmin 935 activity tracker for 12 m walks compared to 8 m walks. Whereas, we do not notice a significant change in the performance of our FMCW-radar-based step counter. The radar-based-system performs slightly (0.24%) better for 12 m walks compared to 8 m walks. This is due to the reason that a very slowly taken step does not result in a significant-peak of the time-variant mean Doppler shift. Thus, it cannot be detected as a step by the peak detection algorithm. Such extremely slow steps may occur either at the beginning or at the end of a walk. As, there are fewer start and stop steps in the 12 m walks compared to the 8 m walks, it is therefore plausible that the peak detection algorithm made slightly fewer errors for 12 m walks.

Similarly, upon analysing the step counting results of the second participant, we notice that our radar-based step counter reported a total of 980 steps. Whereas the Garmin 935 activity tracker reported a total of 935 steps. Moreover, we also observe that the step counting accuracy of the Garmin 935 activity tracker significantly varies not only from scenario to scenario but also from person to person. On the contrary, our radar-based step counter reports very similar results for both participants. Note that, for both participants, we used the same thresholds for the `"findpeaks"` algorithm as mentioned earlier in this section.

5 Limitations

Based on the preliminary results (see Table 1), we argue that the radar-based step counter devised in this work can potentially be used for indoor settings step counting applications. However, there are some limitations. Currently, the proposed system can only count the number of steps of a single person walking back and forth in front of the co-located T_x and R_x antennas. To achieve orientation independence, in future, we will use a distributive multiple-input multiple-output (MIMO) radar system. During the experiments, the participants were asked to walk at their routine-life normal walking speeds. In our future work, we will analyse the influence of fast and slow walking speeds on the devised approach.

6 Conclusion and Future Work

In this paper, we proposed an RF-based system to passively count human steps. Our system uses an FMCW radar for its capability to estimate the range and Doppler information of a moving person. We used the spectrogram approach to compute the time-variant mean Doppler shift and then applied a peak detection algorithm to detect and count the steps taken by a person. To evaluate our approach, we used a 24 GHz FMCW radar to record the measurements while a person was walking in front of the T_x and R_x antennas of the radar. We used ground-truths to validate the results of our system. Besides, as a reference, we also used an accelerometer-based wrist-worn physical step counter to compare the performance of our system with one off-the-shelf step counters. The experimental results show that the overall step counting accuracy of our system ranges from 97.71%–98.51% if the walking activity is performed within a range of 12 m. The comparative analysis of the results of our system and the wrist-worn activity tracker (used in this work) demonstrates the reliability of our RF-sensing system. Therefore, our system can potentially be used as an in-home passive step counter and for indoor localization. In future, we will further analyze the Doppler shifts to determine gait stability of walking persons. Besides, we will integrate the step counter developed in this work with our previously developed human activity recognition system, such that our indoor human activity recognition system can implicitly count human steps.

Acknowledgement

This work has been carried out within the scope of the CareWell project funded by the Research Council of Norway (300638/O70).

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