Accurate Stride Length Estimation via Fused Radio and Inertial Sensing

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***Abstract*—Stride length estimation has various applications, ranging from pedestrian tracking to individual healthcare. It is usually achieved by inertial sensing, which, however, suffers from large errors due to the noisy readings on the low-cost commodity sensors and unconstrained human walking. Different from prior methods that explore inertial sensors only, in this paper, we present a fused radio and inertial sensing design that estimates fine-grained stride length. Our approach incorporates recent advances in WiFi sensing that underpins walking distance estimation at centimeter accuracy from radio signals. We then present a novel step detection algorithm using inertial sensor readings, which not only counts steps but also reports the time information of every detected step. The proposed algorithm then fuses the time-annotated distance estimates and steps to derive the stride length. The evaluation on a large public dataset shows that our step counting algorithm yields an error of 3%. Furthermore, experiments on commodity hardware with eight users demonstrate an error of about 2 cm in stride length estimation.**

***Index Terms*—Stride length estimation, inertial sensing, WiFi sensing**

I. Introduction

Inertial sensing has been an inexpensive and convenient solution to many mobile applications, such as pedestrian dead-reckoning (PDR) and gait analysis, among many others. It has been employed to support clinical diagnostics to quantify and treat gait impairments, a symptom of may neurological or musculoskeletal diseases that may result in shuffling steps or reduced step length. On the other hand, PDR using low-cost inertial measurement units (IMUs) has been widely studied to offer alternative positioning when GPS is not available. It integrates the moving distance, typically estimated as the number of steps multiplying the step length, and heading information to provide continuous locations.

Despite extensive research, one of the most crucial components that are still open to inertial sensing is accurate estimation of stride length, a critical stride-by-stride parameter to both gait analysis and PDR. Many algorithms have been proposed for step detection, such as zero-crossing, peak detection, and autocorrelation [4]. Stride length estimation, however, is more complicated due to the noisy readings on cheap sensors, varying walking patterns among individuals and over time. Early solutions adopt over-simplified linear/non-linear models that suffer from errors [4]. The majority of prior algorithms perform double integration of acceleration over time, which requires zero-velocity update points for reinitialization and is vulnerable to the noisy sensor data and motion interference [6]. Recent works build neural networks to learn stride length, which, however, requires a large amount of data for training [5]. Other modalities are also employed for stride length estimation, including camera systems [2], pressure sensors [1], etc. These systems, however, are less convenient and usually much more expensive than inertial sensors.

Nowadays, most mobile devices are equipped with inertial sensors as well as multi-antenna WiFi radios. In this paper, we leverage this opportunity and propose to integrate the emerging radio sensing with traditional inertial sensing to achieve precise stride length estimation. The idea is to estimate the walking distance from radio signals while the corresponding steps taken from the IMU data. The proposed approach is built upon a recent work [15], which enables precise moving distance estimation at centimeter accuracy by using only the antenna array on commodity WiFi radios. We employ the virtual antenna alignment approach introduced in [15] and implement it for mobile environments using a commodity WiFi card with two or three antennas. A user simply needs to walk freely with the radio in hand, and the walking distance will be estimated from the measured series of Channel State Information (CSI) of the received WiFi signals. We first introduce a novel time-domain algorithm for step detection based on a finite state machine, which not only counts steps but also reports accurate starting and ending time of each detected step. Many existing approaches fail to obtain such time-annotated steps. Then the stride length can be estimated by dividing the moving distance by the corresponding number of walking cycles during the same period.

Our experiments to validate the effectiveness of the proposed algorithm include two parts. First, we examine the step detection on a large public dataset [4] of 27 people, 130 walks, and 6 different smartphone placements. The dataset contains the time series of IMU data measured on smartphones in typical, unconstrained use while walking. The evaluation on this dataset shows that the proposed step counting algorithm achieves remarkable performance with error rates less than 5% for 90% of all the traces, outperforming 9 different approaches evaluated in [3]. In addition to the accurate step counting, the proposed algorithm also outputs time information of every single step.

Then to evaluate the performance of stride estimation, we

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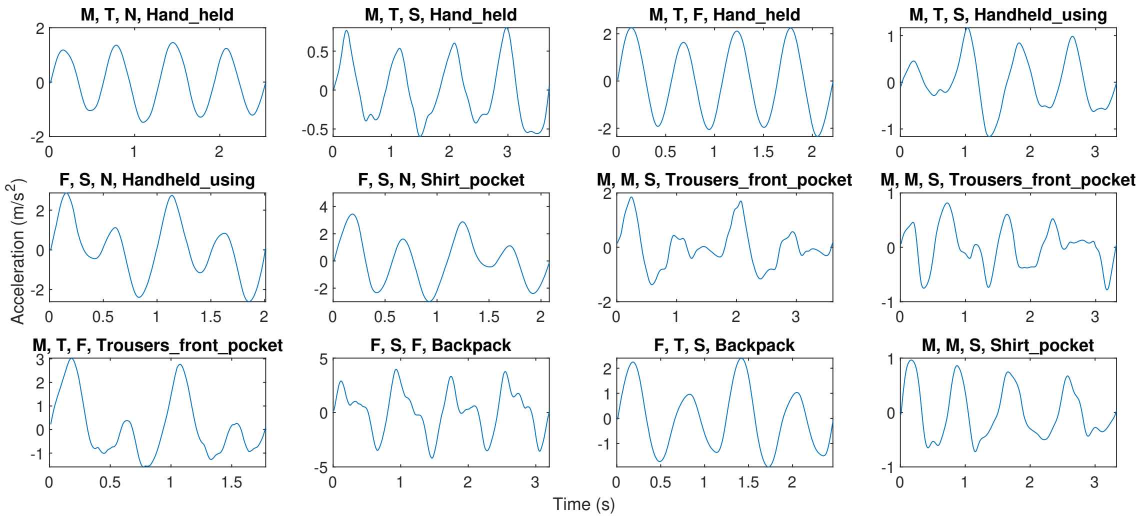

Fig. 1: Different step patterns resulted from different subjects, speeds, and sensor placements. Each figure shows the acceleration series of 4 steps (*i.e.*, two stride cycles) and is named in the format as Gender (M: Male, F: Female), Height (T: 180cm-189cm, M: 170cm-179cm, S: 150cm - 169cm), Speed (N: Normal, F: Fast, S: Slow), Placement. The data have been detrended and smoothed.

implement and experiment with the proposed algorithm on commodity hardware. We collect data using an embedded iMX7 board, which is equipped with an off-the-shelf IMU and a commodity WiFi chip that reports CSI. We recruit eight users who are asked to walk normally while holding the device in hand. Both CSI and sensor data are collected during their walking. Notably, the stride length is estimated with a median error of around 2 cm.

In summary, our core contributions are as follows:

- As far as we are aware, this is the first fused radio-inertial sensing approach for accurate stride length estimation. Attributed by radio sensing, the approach is robust to noisy sensor data and free of accumulative errors that conventional methods undergo in distance estimation.
- We propose a novel time-domain step detection algorithm based on FSM, which reports not only step number but also the timing information of each step.
- We extensively evaluate the proposed algorithm on a large public dataset as well as an experimental prototype. The results show high accuracy for both step detection and stride length estimation.

The rest of the paper is organized as follows. We present the algorithm in §II, followed by experimental evaluation in §III. We discuss future work in §IV, review the literature in §V and conclude in §VI.

II. Stride Length Estimation

A. Precise Step Detection and Counting

There are many algorithms developed for step detection using inertial sensors [7], [16]. Conventional methods usually focus on counting how many steps have been taken given a sequence of accelerometer readings. To obtain precise stride length, however, we need not only the step number but also the exact starting and ending time of each step so that we can later calculate the precise moving distance during the specific stride period via radio signals (as detailed in the next section).

To achieve step detection with accurate timing information, we propose a time-domain approach based on a Finite State Machine (FSM). The key insight is that a normal human walking cycle, albeit varying over individuals and speeds, submits to a typical template viewed from the inertial data. A stride cycle consists of two phases: the stance and swing phases, which can be further decomposed into seven stages [9]. The stance phase starts with the initial heel contact of one foot and ends when the same foot's toe leaves off the ground. The swing phase follows immediately with the action of the leg swinging forward and lasts until next heel contact. Intuitively, a stride cycle consists of two steps, and the stride length is accordingly defined. In this work, however, we do not differentiate two consecutive steps and thus calculate the *step length* as stride length, which is, on average, half of the commonly defined stride length. Ideally, during a step, the acceleration induced by walking motion will first increase to a large value, then decrease down to negative values, and finally returns to approximately zero. A typical and ideal acceleration change during a step is shown by the first figure in Fig. 1, while the other figures show how the patterns vary over different individuals, walking speeds, and sensor placements.

FSM design Based on an in-depth understanding of the walking cycle, we elaborate on an advanced FSM to characterize the acceleration transitions for step detection. As shown in Fig. 2, the proposed FSM contains five different states:

- `S_ZC`: The initial and default state when a zero-crossing is detected;
- `S_PK`: The state when the acceleration tops a peak;
- `S_P2V`: The state that a zero-crossing occurs when the

acceleration decreases from the peak to a potential valley;

- `S_VL`: The state at an acceleration valley;
- `S_DT`: The state that a step is claimed.

To determine the state transition, we define six basic events, which are all identifiable from the inertial sensor data.

- `E_PK`: A peak is detected;
- `E_VL`: A valley is detected;
- `E_ZC`: A zero-crossing is observed;
- `E_FPK`: A "far" peak is detected after a previous `E_PK` event without any intermediate events, but with a large time difference exceeding a threshold;
- `E_FVL`: A valley similarly defined as `E_FPK`;
- `E_TIMEOUT`: A timeout event will trigger if the FSM stays on one state for too long.

The first three events characterize the key properties of acceleration patterns during walking, while the latter three are derived from the first three coupling with time information to combat noises and non-walking motion interference.

By default, the algorithm stays on its current state until an event occurs, depending on which it will either transit to another state or remains unchanged. Each state only transits upon the specific events as marked in Fig. 2. All the states except for the default `S_ZC` is associated with a timeout event. State `S_DT` will return to `S_ZC` with any new data arriving. `E_FPK` and `E_FVL` are introduced to handle the cases of two consecutive peaks or valleys caused by noisy sensor readings and user motion interference. For example, if a subsequent peak is too close to a former one, the algorithm will treat it as distortion during walking and keep the same state; otherwise, it is more like random motion, and the state is reset to `S_ZC`.

The design of the proposed algorithm achieves many strong sides. For each detected step, the algorithm outputs the timing information of the detected step: The time point of the corresponding `S_ZC` is the starting time, while the time it enters `S_DT` implies the ending time. The algorithm is efficient, with only a few states. It decomposes the relatively noisy sensor readings as several essential events, which can be identified without relying on many subject-dependent parameters, such that it does not heavily rely on the absolute accelerations.

Sensor data processing The raw sensor data are processed into a series of events-of-interests as inputs for the above FSM. A key challenge here, however, is that the ideal acceleration pattern of a step will greatly vary over different walking patterns and device locations (*e.g.*, hand-held, in the pocket, or the backpack, etc.). Moreover, the sensor data is noisy and could drift over time. Fig. 1 illustrates several different patterns of the walking cycles, including normal, distorted, or biased ones.

To handle various sensor patterns, we perform a series of preprocessing steps. The accelerometer reports 3D sensor values along its x-axis, y-axis, and z-axis for every sample, denoted as $\mathbf{a} = (a_x, a_y, a_z)$. The reported accelerations are in the device frame (rather than the earth's frame) and contain both motion-induced and gravity-forced components. We need to compensate for gravity and transform the accelerations into

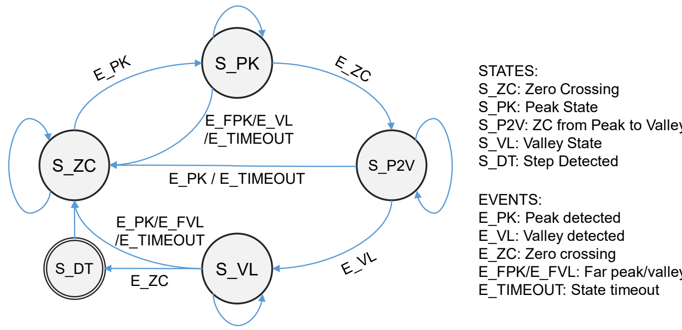

Fig. 2: A Finite State Machine (FSM) for step detection.

the earth's reference frame. Fortunately, modern IMUs have done an excellent job in extracting the gravity component as a fusion sensor (usually named as gravity sensor) based on the accelerometer and gyroscope or magnetometer, which reports a gravity vector $\mathbf{g} = (g_x, g_y, g_z)$. Thus, we can easily obtain the magnitude of the projected acceleration free of sensor orientation as:

$$a = \frac{\mathbf{a} \cdot \mathbf{g}}{||\mathbf{g}||}. \tag{1}$$

Given a time series of the acceleration magnitude, denoted as $A = [a(t_1), a(t_2), \cdots, a(t_M)]$ where $a(t_i)$ is the reading at time t_i, we further detrend the gravity and potential sensor drifting by removing the moving average trend. Since we do not need to process the data online for stride length estimation, we employ a relatively long window of 2 s to calculate the moving average. Afterward, we further smooth the detrended data with a window of 0.25 s.

Then we perform zero-crossing and peak detection to identify all the events-of-interests from the data series (valley detection is done in the same way as peak detection by multiplying the data by -1). The processing results in a time series of events, denoted as $E = [e(t_1), e(t_2), \cdots, e(t_Q)]$ where $e(t_i) \in \{\mathtt{E\_PK}, \mathtt{E\_VL}, \mathtt{E\_ZC}\}$ is the event occurs at time t_i. Note that the events are sparse over the time series A since typically there are three `E_ZC`, one `E_PK`, and one `E_VL` within a standard step. This event series is then fed into the FSM for step detection. The other three events, *i.e.*, `E_FPK`, `E_FVL`, `E_TIMEOUT`, are detected inside the FSM by examining timestamps of two consecutive `E_PK`, `E_VL` and the duration of the state itself, respectively. For example, an `E_FPK` occurs if $e(t_{i-1}) = e(t_i) = \mathtt{E\_PK}$ and $|t_i - t_{i-1}| > th_{\text{max\_gap}}$, where $th_{\text{max\_gap}}$ indicates a threshold that can be determined by human walking behavior.

By involving events (that is, specific relative patterns in the acceleration series) rather than absolute acceleration thresholds, the proposed FSM is more generalized and robust to different walking patterns and sensor locations. Fig. 3(a) shows an example of the step detection results, which counts every step precisely with timing information.

B. Walking Distance Estimation with WiFi

To accurately estimate the walking distance at the centimeter level, we borrow the idea of the virtual antenna alignment approach [15] with a focus on hand-held mobile scenarios. Virtual antenna alignment is recently introduced in [15] for precise measurements of moving distance, heading direction, and rotating angle. The core idea is to track the moving speed by utilizing rich indoor multipath as virtual antennas. In this work, we need merely the moving distance estimation and implement it with two or three antennas on one WiFi card.

Take a two-antenna line array as an example. When the array moves along the line joining them, there will be one antenna following the trajectory of the other. The particular moving speed determines the time delay for the following antenna to hit the same location the other has traveled (*i.e.*, the two antennas are virtually aligned) and thus observe the same (similar) multipath profiles. As in [15], the time delay can be estimated by

$$\Delta t(t) = |\underset{k\in\{-l,\cdots,l\}}{\arg\max}\ \eta(H_i(t), H_j(t+k))|, \quad (2)$$

where $H_i(t)$ is the CSI measurement at time t, l specifies the search window $[t-l, t+l]$, and η is the Time-Reversal Resonating Strength (TRRS) calculated as

$$\eta(H_i, H_j) = \frac{|H_i^{\mathrm{H}} H_j|^2}{\langle H_i, H_i\rangle\langle H_j, H_j\rangle}, \quad (3)$$

where $(\cdot)^{\mathrm{H}}$ denotes the conjugate transpose.

With Δt, the array's moving speed can be immediately derived as

$$v(t) = \frac{\Delta d}{\Delta t(t)}, \quad (4)$$

where Δd is the corresponding antenna separation known in advance. And the moving distance is thus calculated:

$$d = \int_0^T v(t)dt, \quad (5)$$

where T is the time duration of moving.

Considering our scenario of stride length estimation, the user needs to hold the device in hand to increase the chance of virtual antenna alignment while walking. As demonstrated in [15], the virtual antenna alignment can tolerate a deviation angle of 15° gracefully during moving. This is a critical property that makes it applicable to hand-held mobile scenarios: Even during walking, a cooperative user can hold the device relatively stably with little chance of producing significant deviation beyond 15°. As shown in Fig. 3(b) and (c), the walking speeds can be accurately tracked when a user is normally walking while holding the WiFi device in hand.

C. *Estimating Stride Length*

Fig. 3 shows an example of the steps detected by inertial sensing and walking distance (speed) estimated by WiFi-based sensing. More generally, given a walking trace, suppose we have detected a series of N steps $S = [s_1, s_2, \cdots, s_N]$, each step s_i starting at time t_{i-1} and ending at time t_i, and have estimated the corresponding instantaneous speed series $V = [v(t), t = 1, 2, \cdots, T]$. It is then straightforward to derive the average stride length L as

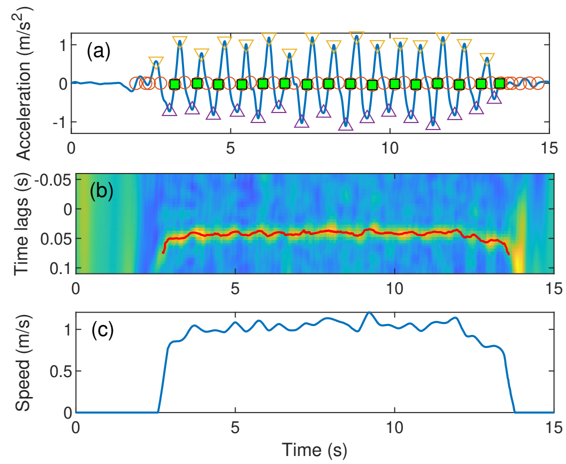

Fig. 3: An illustration of inertial-based step counting (a) and radio-based distance estimation (b) and (c). (a) Green squares denote the detected steps, triangles denote peaks and valleys, and circles indicate zero-crossing points. (b) The TRRS matrix with identified antenna alignment delays (red line). (c) The estimated speeds.

$$L = \frac{\int_0^T v(t)dt}{N}. \quad (6)$$

The estimation can be improved to be more robust to different lengths of the walking traces and/or varying stride lengths during a walking instance. Particularly, we can additionally calculate the stride length by using only the first k steps with k ranging from 1 to N:

$$L^k = \frac{\int_0^{t_k} v(t)dt}{k}, k = 1, 2, \cdots, N. \quad (7)$$

Then we can take the median value as the estimate, *i.e.*, $L = \mathrm{Med}_k(L^k)$.

With the instantaneous speed estimation and the fine-grained step detection, we can even calculate the step-by-step stride lengths, rather than merely the average value. Specifically, the stride length for the ith step can be obtained as the moving distance within that step: $L_i = \int_{t_{i-1}}^{t_i} v(t)dt$. Such fine-grained data would be useful for analyzing the variations of one's walking.

The fused radio and inertial sensing method contributes a distinct novel solution to the stride length estimation problem. It is immune to the noisy sensor readings, and the accumulative errors clung to the double integration approach. It is insensitive to sensor orientation and placement locations. And most importantly, it achieves high accuracy attributed by the precise step detection mechanism and the fine-grained distance estimation.

III. Experimental Evaluation

A. *Methodology*

Our evaluation consists of two part: performance validation on a large public dataset of walking data and prototype eval-

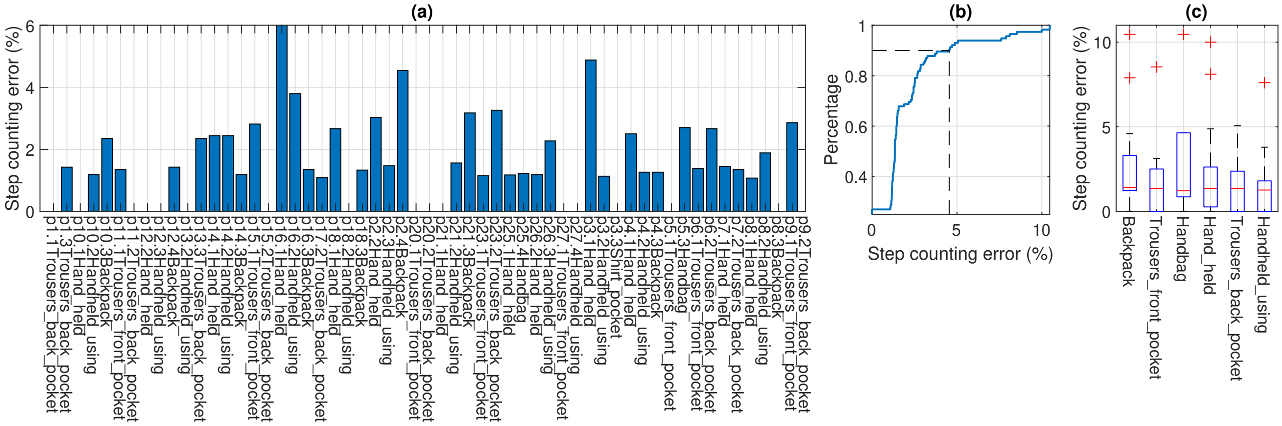

Fig. 4: Accuracy of step detection on a large public dataset.

uation on commodity hardware.

We use the dataset released in [4] for a comprehensive evaluation of the proposed step detection algorithm. The dataset was developed for a fair, quantitative benchmark of standard algorithms for walk detection and step counting. It provides time-annotated sensor traces collected from smartphones in typical, unconstrained use while walking. For each trace, the participant changed the walking speed from normal to fast and then slow paces. The smartphones were placed at different positions (in a front or back trouser pocket, in a backpack/handbag, or in a hand with or without simultaneous typing). More details about the dataset can be found in [4]. The dataset has 130 traces in total, with 27 participants involved and 6 different smartphone placements considered. The ground truths of three persons are missing in the released version, resulting in 117 effective traces for our evaluation.

To further evaluate the end-to-end stride length estimation accuracy, we implemented a prototype with an embedded iMX7 board equipped with a commodity WiFi chip and IMU sensors. We built a data collection tool in C++ to obtain CSI measurements and sensor readings on the device. We recruit eight users (three females and five males) for testing. During experiments, the participants are asked to walk naturally for about 10 meters while holding the device in hand horizontally so that the antenna alignment will take effect. An observer will count how many steps the participant has taken and record as the ground truths. In order to obtain CSI, we set up an Access Point (AP) as the transmitter that sends out packets at a rate of 200 Hz. As noted in [15], the transmitter can be installed anywhere for good coverage, be it Line-Of-Slight (LOS) or Non-LOS (NLOS), and an AP can cover a big area. The receiver, *i.e.*, the iMX7 board, keeps listening for the packets and extracts CSI. The CSI and sensor data are saved locally on the board and then processed on a laptop using Matlab.

B. Performance

We first present the performance of step detection and then evaluate stride estimation.

Step detection: The performance of step detection on the open dataset is shown in Fig. 4. The accuracy over all the traces

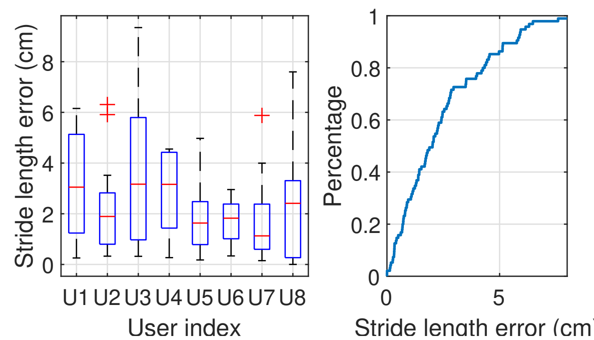

Fig. 5: Accuracy of stride length estimation.

is plotted in Fig. 4(b), and Fig. 4(c) further illustrates the accuracy regarding different IMU placements. For clarity of visualization, we only show a random half of the 117 traces in Fig. 4(a). Since the traces are of different lengths (from 60 to 90 steps), we calculate the relative error, *i.e.*, the errors of steps divided by the actual number of steps. Overall, the proposed algorithm achieves consistently high accuracy over different traces, regardless of different subjects, speeds, and smartphone placements. Specifically, the step counting errors for most of the traces are within 3%, while the 90%tile error is less than 5%. The performance is better than those of all the 9 different approaches evaluated on the same dataset, as reported in [4].

Stride estimation: Now we examine the performance of stride length estimation using our prototype hardware. The distance estimation performance has been thoroughly evaluated in [15]. We directly examine step counting and stride length estimation. Since the participants hold the device stably during the experiments (to allow antenna alignment for distance estimation), the step detection performs perfectly on these data traces. The algorithm achieves 1.5 steps of counting errors. Note that these step errors barely affect stride length estimation since they mostly occur at the beginning or end of the walking and can be trimmed out by finding a stable, continuous period. Thanks to the high accuracy in both distance estimation and step detection, our algorithm yields a great performance in stride length estimation, with a median error of 2.02 cm for eight different users. Fig. 5 illustrates a detailed view of the errors for different users and the overall CDF.

IV. Discussions and Future Work

Here we discuss several limitations and future directions. First, the proposed step detection algorithm achieves excellent performance on walking data. In practice, if unknown motion data (not necessarily walking) are offered, potential false alarms may increase. Thus we need to further improve the robustness in practical scenarios with various sensory data. A promising idea would be to introduce a post-validation step using autocorrelation to reject false alarms. Second, we currently implement the proposed step detection algorithm in an offline form. The next step is to make it online to report steps for real-time streaming data, which may extend the applicability scope of the proposed approach. Third, a further step of our interests is to apply the stride length estimation to PDR for indoor tracking problems. By opportunistically calibrating a user's stride length when WiFi CSI is available, the accuracy of traditional PDR would be greatly improved while the ubiquity remains unimpaired, underpinning a more accurate solution for lightweight, ubiquitous indoor tracking.

V. Related Works

Inertial Sensing Inertial sensing has been widely employed on mobile and wearable devices for many applications. PDR (*a.k.a.*inertial odometry), one of its major applications, utilizes inertial sensors to infer the positions over time. Generally, PDR derives orientation from the gyroscope and/or magnetometer, while inferring moving distance from the accelerometer. Intuitively, the distance could be obtained by double integration of acceleration over time, which, however, results in drastic accumulative errors. To avoid large errors, researchers alternatively estimate steps taken and the step-by-step or averaged stride length. Effective approaches have been proposed for step counting, including peak detection, zero-crossing, autocorrelation, etc., and good performance can be achieved [4]. Stride length estimation, however, remains as a challenge problem for PDR. Existing methods either suffer from errors due to the noisy sensory data [4], [6], [10] or resort to numerous data for training [5]. Differently, we circumvent the noisy sensors and leverage the orthogonal RF sensing for distance estimation, which stands apart from prior works.

RF Sensing Radio signals, initially proposed for communication, have been recently utilized for ubiquitous sensing [11], [13], including activity and gesture recognition [14], vital sign monitoring [19], and indoor tracking [12], [17], etc. Particularly, WiGait [8] achieves accurate stride length estimation but relies on a specialized FMCW radio. WiSpeed [18] passively monitors a pedestrian's speed and so infers the stride length, but assumes only one single moving target. Recent advances have enabled centimeter-accuracy tracking of moving distance using commodity off-the-shelf WiFi devices [15]. This work is built upon the accurate distance estimation introduced in [15] and combines it with inertial sensing to achieve precise stride length estimation. As such, it utilizes the complementary advantages of radio sensing and inertial sensing while overcoming the respective shortcomings, opening up a promising direction of integrated radio-inertial sensing.

VI. Conclusion

In this paper, we present a novel approach fusing radio and inertial sensing for precise stride length estimation. The proposed approach incorporates WiFi-based sensing for walking distance estimation at centimeter accuracy and presents a novel step detection algorithm using inertial data. Combining the two orthogonal dimensions of information, we achieve stride length estimation with a median error about 2 cm. To the best of our knowledge, this is the first work that integrates radio sensing with inertial sensing for stride estimation. Future work continues exploring this promising direction of radio-inertial sensing for PDR, gait analysis as well as other applications.

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