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ABSTRACT

Gait velocity and stride length are critical health indicators for older adults. A decade of medical research shows that they provide a predictor of future falls, hospitalization, and functional decline among seniors. However, currently these metrics are measured only occasionally during medical visits. Such infrequent measurements hamper the opportunity to detect changes and intervene early in the impairment process.

In this paper, we develop a sensor that uses radio signals to continuously measure gait velocity and stride length at home. Our sensor hangs on a wall like a picture frame. It does not require the monitored person to wear or carry a device on her body. Our approach builds on recent advances in wireless systems which have shown that one can locate people based on how their bodies impact the surrounding radio signals. We demonstrate the accuracy of our method by comparing it to the gold standard in clinical tests, and the VICON motion tracking system. Our experience from deploying the sensor in 14 homes indicates comfort with the technology and a high acceptance rate.

Author Keywords

Gait velocity; Stride length; Wireless sensing; Device-free sensing; Continuous monitoring.

ACM Classification Keywords

H.5.2. User Interfaces: Input devices and strategies; C.2.1. Network Architecture and Design: Wireless communication

INTRODUCTION

The term "gait velocity" refers to the habitual walking speed adopted by a person in everyday life [21]. Medical research has shown that gait velocity is an important health metric, particularly among the senior population [35, 27]. Walking exercises the nervous, cardiovascular, pulmonary, musculoskeletal and hematologic systems because it requires more oxygen to contract the muscles. Impairment in one of these systems impacts the person's gait velocity [35, 36]. As a result,
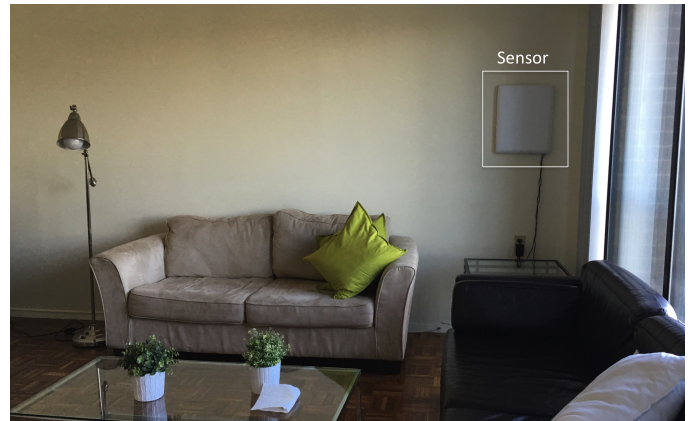

Figure 1. The WiGait sensor is hung on the wall in one of the user's home. It transmits low power radio signals and analyzes how people's motion disrupts surrounding radio signals. The sensor measures the user's gait velocity and stride length from these radio signals and does not require the user to wear a device on her body.

physicians have called "gait velocity" the sixth vital sign [11]. Multiple papers have shown that gait velocity predicts future hospitalization for congestive heart failure [30], chronic obtrusive pulmonary disease [20], and hemodialysis patients [22]. Degradation in gait velocity and stride length are correlated with an increase in fall risk and a decline in one's ability to live independently [9, 26]. Thus, these measurements are included in geriatric assessments [16]. Today, these tests are performed only occasionally during clinical visits. There is a great interest, however, in measuring these metrics more frequently at home [33, 34, 38, 17, 13, 18]. Such measurements would enable continuous health tracking and provide the opportunity for early intervention.

The standard approach for assessing gait velocity and stride length requires a human (typically a clinician) to observe the person and time her movements [16]. Developing a design that is both automated and comfortable for continuous in-home use is challenging. Older adults typically feel encumbered by wearable devices and are uncomfortable using them [12, 32]. Furthermore, wearable wristband activity trackers like FitBit neither measure gait speed nor stride length. Smartphones use GPS to estimate walking distance; but these measurements are not sufficiently accurate [41], and GPS does not work indoors where the elders spend most of their time. Researchers have looked at using Kinect and depth cameras to monitor gait

speed at home [33, 34]. However, such devices have a limited field of view and often raise privacy concerns [14].

In this paper, we aim to deliver a new technology for in-home monitoring of gait velocity and stride length. In particular, we would like a solution that neither requires people to wear or carry sensors on their bodies, nor raises the same privacy concerns associated with visual monitoring via cameras or Kinect.

We observe that recent advances in wireless systems have led to devices that can locate a user based on how their motion disrupts the surrounding radio signals [6, 5, 15]. These technologies transmit a low-power wireless signal, analyze its reflections, and output the position of the people in their vicinity. Since radio signals traverse walls, these systems can localize people even when they are in a different room or occluded by furniture. These systems, however, see the whole body as one point and cannot distinguish body parts or strides. Also, they are unable to measure meaningful gait since they do not distinguish different types of motion: walking vs. cleaning or dressing. In this paper, we leverage these results and explore the feasibility of using radio signals for continuous gait and stride monitoring.

We introduce WiGait, a home sensor that passively and continuously measures gait velocity and stride length by leveraging how a person's motion affects the surrounding wireless signals. The sensor hangs on the wall, like a picture frame (see Figure 1). It does not require the user to wear sensors on her body, walk on predetermined paths, or change her behavior at all. The user goes about her normal life, while the device operates in the background and measures the desired metrics.

The design of WiGait involves the following contributions:

- **Identifying walking traces from other activities:** Simply measuring the velocity from changes in location over time does not yield representative estimates. We need to identify walking periods and separate them from other activities like cleaning, dressing or cooking, which involve taking steps but do not qualify for gait speed measurements.[1] We introduce a low-complexity streaming algorithm that automatically extracts trajectories of walking from activity-focused motion. Our algorithm builds on the diameter-of-a-set problem to analyze the structure of the traveled path and does not require any prior training.

- **Extracting gait velocity and stride length from walking traces:** To extract clinically meaningful gait metrics, it is important to eliminate periods of acceleration and deceleration at the beginning and end of a walking period. This task is complicated by the fact that acceleration-deceleration happens within each step in a walk. We develop an algorithm that iteratively zooms in on the path, removes the initial acceleration and final deceleration, and extracts the stable phase of the walk which it uses to measure the user's gait velocity. It then analyzes the periodicity of the stable phase of the walk to measure stride length.

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[1]One of the authors is a geriatrician who practices gait assessment.

- **Integration with radio hardware:** We have implemented our algorithms and integrated them with a radio design called WiTrack [6, 5] to deliver a stand-alone sensor that is easy to deploy and use at home.

To evaluate WiGait's accuracy we compare it to the clinical test [16] and the ground truth motion from the VICON system [3]. Among the eighteen subjects who participated in this experiments, the average error rates are 1.9% and 4.2% for the gait velocity and stride length respectively. To evaluate acceptance of WiGait monitoring, we deployed the device in 14 homes. During the deployment, we explained to the subjects the operation of the device and the data it outputs, and asked for their consent. The subjects were receptive and did not raise privacy concerns, neither during the deployment nor throughout the later months. In contrast, when asked about replacing the device with a device that monitors gait using a camera, only three of the subjects agreed to the monitoring.

We believe that WiGait fills a need for continuous in-home gait monitoring and allows computing devices to play a bigger role in ensuring the safety and well-being of older adults, hence addressing a key problem for modern societies.

BACKGROUND AND RELATED WORK

Interest in gait velocity for geriatric care has surged significantly over the last decades. In 2011, Studenski et al [35] published a study that tracked gait velocity of over 34,000 seniors over a period of 6 to 21 years. They found that predicted survival based on age, sex, and gait speed was as accurate as predicted based on age, sex, chronic conditions, smoking history, blood pressure, body mass index, and hospitalization. This has motivated much research into health tracking and risk assessment based on gait speed. The following years have led to many papers that point to the importance of gait velocity as a predictor of degradation and exacerbation events associated with various chronic diseases including heart failure, COPD, kidney failure, stroke, etc. [30, 20, 22, 36]. In the US, there are 13 million seniors who live alone at home [1]. Gait speed and stride length are particularly important in this case since they provide an assessment of fall risk, the ability to perform daily activities such as bathing and eating, and hence the potential for being independent.

Gait velocity is typically measured by a clinician during medical visits. The senior is asked to walk comfortably for a distance of a few meters (usually 4 to 10 meters) [16]. The first and last meters are typically ignored to allow for acceleration and deceleration. A clinician measures time using a stopwatch and computes the person's gait velocity. Normal walking speeds are around 1m/s. Values lower than 0.6m/s indicate falls and hospitalization risks, whereas values below 0.4m/s indicate functional impairment, severe fall risk, and some walking disability [11, 27]. Changes in gait velocity are particularly important since they indicate a sudden decline or recent recovery [24]. Changes of 0.05 m/s have been deemed clinically meaningful [29]. Stride length is typically measured by counting steps over a particular distance. The value is correlated with fall risk, frailty and the ability to age at home [26, 31].

Rehabilitation centers, clinics, and hospitals may also use automated systems for measuring gait speed and stride length. Many places have GAITRite [2], which is a pressure mat attached to a computer system. Some rehabilitation centers have a VICON motion tracking system, which is a set of infrared cameras mounted on the ceiling [3]. Tracking is done by attaching infrared markers to the person's limbs and body parts. Some institutions use LEGSys [10] which requires five inertial sensors attached to the shanks, thighs, and lower back. None of these systems however, are easy to deploy or comfortable enough for continuous use at home.

Wristband activity monitors from companies like FitBit and Jawbone cannot measure gait velocity or stride length. These devices measure the number of steps. People, however, have different step sizes. In fact, FitBit explicitly states on its website that they calculate stride length using a person's height and gender, which they multiply by the number of steps to obtain walking distance.[2] Smartphones and advanced models of FitBit use GPS outdoors to measure distance. However, GPS's margin of errors is too high for measuring gait velocity and stride length, particularly for indoor environments where the elderly spend the vast majority of their time.

There is much interest in continuous monitoring of gait speed at home. Researchers proposed using Kinect and depth cameras for continuous in-home monitoring of gait [33, 34, 38]. While this approach is easy to use, many people may choose not to use the device for privacy concerns for themselves or other family members sharing their living space [14]. Researchers also mounted multiple infrared sensors on the ceiling in seniors' homes and tracked when the person crossed the sensors' field of view [17, 13]. Such an approach, however, requires a significant deployment effort. For seniors in assisted living or nursing homes, researchers have used wearable sensors which exchange beacons with infrastructure sensors to locate the person [18]. These approaches are possible in institutionalized settings where the staff can ensure the older person carries her sensor and the environment is equipped with the beacon readers.

In contrast to the above work, WiGait infers a person's gait by analyzing the radio signals reflected off her body. It builds on past work on device-free motion tracking using RF signals. Past work in this domain falls into two classes: The first class does not measure gait speed or stride length. This includes work that compares the RF signal against a prior database of labeled measurements to classify activities [40, 23] or classify people [42]. It also includes work that measures the user's position [6, 5, 15, 7], or her vital signs [8].

The second class measures a form of gait speed and strides, but only in a restricted setting and with active user participation [39, 19, 37]. This work does not allow the user to move freely or perform other activities. It requires the user to walk on a predefined path in a predefined direction. This limitation is because the technique relies on Doppler shift, which measures only the relative speed projected on the line connecting the user and the sensor. The calculated gait speed and stride

length become incorrect if the sensor is moved with respect to the predefined line, or if the user sways from the marked path due to visual or cognitive impairment.

WiTrack: Finally, WiGait's algorithms are integrated with the WiTrack radio to deliver a stand-alone gait monitoring sensor. We refer the reader to [6, 5] for a detailed description of WiTrack. For the purpose of this paper, it is sufficient to know that WiTrack is a device-free location tracking radio technology. It transmits a low power signal (1000x lower than WiFi), analyses its reflections, and outputs the locations of the surrounding people. It works across walls, spans a radius of 30 to 40 feet, and can concurrently locate up to 4 moving people. It should be noted that WiTrack (as well as other device-free localization radios) returns only one location for the whole body. Any motion of the body or its limbs registers as a change of location. WiTrack outputs a measurement every 0.02s. Its median accuracy for 3D localization is 13 cm in the x and y dimension, and 21 cm for elevation measurements [6].

For the rest of this paper, we focus on scenarios with one person, though the same analysis can be applied to each person identified by WiTrack.

DESIGN OF WIGAIT

WiGait is a home sensor for monitoring gait velocity and stride length. WiGait measures these metrics without requiring the person to carry or wear any sensor. It leverages that body motion affects the surrounding radio signals. WiGait incorporates recent advances in radio-based localization, particularly the ones described in [5] and named WiTrack version 2.0. It augments RF-based localization with algorithms for separating walking periods and extracting a person's gait speed and stride length. The whole design is built as one sensor, which hangs on the wall like a picture frame, as shown in Figure 1. The sensor box contains both the radio and a single board computer that implements the various algorithms. Once the sensor is turned on, it communicates with an app on the user's cell phone via bluetooth. The user can then connect the sensor to the Internet to allow the data to be stored in the cloud. The sensor does not need any additional calibration.

In order to extract meaningful gait velocity and stride length, WiGait operates in three steps as follows:

1. Identify walking periods where the user walks from an origin to a destination and separate them from other activities that result in motion (e.g., cleaning, searching, dressing.)

2. Extract the stable phase within each walking period and separate it from the acceleration and deceleration phases.

3. Analyze the time series data to compute gait velocity and stride length.

We explain each of these steps below.

Walking Period Identification

At first, it might seem that one can estimate gait velocity by recording changes in location and dividing by the time taken to perform the motion. Such an approach, however, does not yield meaningful gait for two reasons. First, radio-based

localization abstracts the human body as a single point, i.e., a person lifting his hand will be registered as a change of location. Second, even if we ignore all in-place motion, we still need to separate pure walking from changes in location due to other activities.

Thus, our first task is to identify periods of pure walking and separate them from being stationary, moving in place, or performing some activities. Our algorithm takes as input a stream of locations over time from a radio-based localization system. The algorithm operates in two stages. In the first stage, the algorithm identifies periods during which the person was either stationary or moving in place, and ignores them. In the second stage, the algorithm processes the remaining moving periods to eliminate the ones that include activities other than walking.

(a) Identifying stationary periods or in-place motion: To identify stationary or in-place periods, the algorithm estimates the diameter of a circle that bounds all the location points within an observation window. The observation window slides over the stream of location data. For each window, we consider the set of location points in that window. If the diameter of the set of points is less than some threshold B, then the window is considered as stationary or moving-in-place. We set the default size of the sliding window to 4s and B to 1.6m because a walking speed of less than $0.4m/s$ can be considered as a severe walking disability [27].

To implement the above logic, we need a streaming algorithm that takes a stream of location points and computes the diameter of the set of points in a sliding window. Computing the diameter of a set of points is a standard computation problem and has both exact and approximate solutions [25]. Since WiGait has to work continuously, it is important to maintain low computational complexity. Hence, we use an approximate algorithm which operates as follows. To compute the diameter of a set of points in 2D, we first pick k lines in the plane and project all points on those lines. For each line, we calculate the maximum distance between any two projected points on the line. The diameter of the set is approximated as the maximum of all maximum distances computed for all lines. This algorithm has a complexity of $O(kn)$, where n is the number of points in the set and its approximation error decays as $\frac{1}{k^2}$.

For the streaming version of the algorithm, we can make it even more efficient by storing the projected points on each line in a binary search tree. Whenever the window slides by one location point, we insert the projected point in the tree corresponding to each projection line and remove the old projected point from each of the trees. With the tree structure, we can easily access the *min* and *max* projected points along each projection line for the current sliding window in $O(\log n)$. If no projection has $max - min > B$, the current window is labeled as stationary/in-place. Since insertion, deletion, and finding *max* and *min* take $O(\log n)$ operations, this streaming algorithm has a complexity of $O(k \log n)$ per point. We provide a pseudo code of the approximate diameter estimation algorithm in Algorithm 1. Figure 2 illustrates how the estimated diameter increases as the user starts walking and remains below B when the person is stationary.

Algorithm 1: Approximate Diameter Estimation

Input : A sequence of 2D points, window size
Output : A sequence of approximate diameters
1 $d = []$;
2 **for** *each new point p* **do**
3     $max_{diff} = 0$;
4   **for** *each projection line l* **do**
5   p_l = project p on line l;
6        $queue_l$.push(p_l);
7        $tree_l$.insert(p_l);
8   **if** $queue_l.size >$ *window size* **then**
9           $p_{l,old} = queue_l$.pop();
10           $tree_l$.delete($p_{l,old}$);
11   **end**
12        $diff_l = tree_l$.max() - $tree_l$.min();
13   **if** $diff_l > max_{diff}$ **then**
14           $max_{diff} = diff_l$;
15   **end**
16   **end**
17   d.append(max_{diff})
18 **end**
19 **return** d

(b) Identifying walking periods: By removing the stationary and in-place periods, we segment the stream of data into moving periods. In order for a moving period to be a walking period, it should satisfy two conditions. First, the stretch of motion should exceed a few meters in order to allow for acceleration, stable walking, and deceleration. In our setting, we require the motion to exceed 4 meters since it is common to use a 4m walking test indoors [16]. Second, the motion should be pure walking and no other activities.

Whether the moving period has covered an area that spans more than 4m can be checked using the diameter set algorithm, as before. However, since each moving period has a fixed starting point that does not slide, the complexity can be optimized further. In particular, we do not need to keep the projected points in a tree. It is sufficient to keep two variables, the *min* and *max* along each projection and update these variables as we consider each new point in the window. This makes the computational complexity $O(k)$ per point.

Next, we want to check if the moving period reflects pure walking as opposed to other activities that involve taking steps while doing other things. Here we use a heuristic. Our intuition is that walking is a very systematic and periodic process where the person repeatedly puts one foot down after the other. Thus, a trace of pure walking shows a significant periodicity that corresponds to the movement associated with each step. Thus, we look at the Fast Fourier Transform (or FFT) of the velocity over time and expect the FFT to spike at a frequency that corresponds to the step size. We will elaborate on this point further as we explain how we compute the stride length.

If the moving period passes all of the above checks, it is considered a walking period and we use it to measure the person's gait. It is possible that we may have some false
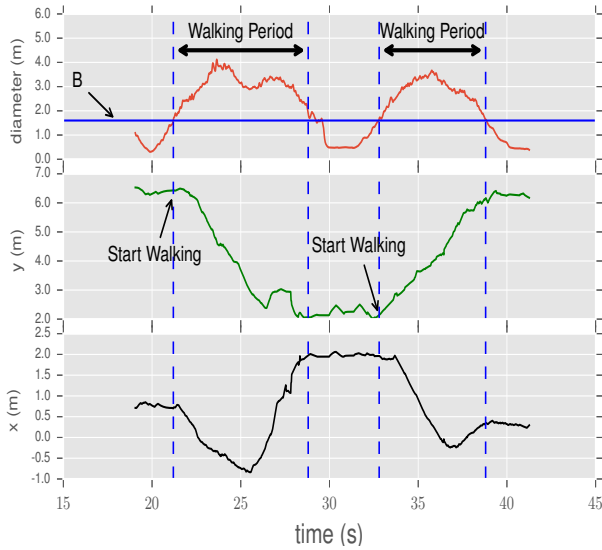
Figure 2. The top graph shows the change in diameter over a period in the middle of the experiment. Boundary B was shown to cut the walking period of the person. The other two graphs plot the change of x coordinate and y coordinate over the same time period.

positives and false negatives. However, since a clinician needs only the average gait over days, we have enough statistical data to extract the average and deal with some misclassification errors.

Stable Phase Extraction

After identifying the walking periods, WiGait zooms in on each such period to extract the stable phase and separate it from the beginning and the end of a walk. To help explain the problem, we show the velocity of a user's walking period in Figure 3.

A walking period consists of three phases: the acceleration, stable, and deceleration phase. The velocity increases in the acceleration phase when the user takes her first few steps, and decreases in the deceleration phase when she gets closer to the destination. While the overall trend of the velocity is clear in these phases, the velocity does not increase and decrease monotonically as shown in Figure 3. Instead, as the user steps forward, the velocity oscillates within each step. We often observe bigger and less stable oscillation of the velocity in the acceleration and deceleration phases. Between the two phases, there is a stable period when the velocity oscillates around a stable value. In clinical tests, the gait velocity of a person is defined as the velocity during this stable phase of a walk [28]. Thus, to extract meaningful gait information, we need to identify the stable phase in each walking period.

WiGait uses an iterative algorithm to identify the stable phase within a walking period. It starts with the whole walking period as the initial estimate of the stable phase and refines the estimation in each iteration until convergence. It assumes that in the stable phase, the velocity oscillates around a stable velocity v_s that can be bounded by $v_s - dv$ and $v_s + dv$. In each iteration i, it computes the estimated stable velocity v_i

by taking the median velocity across the current estimate of the stable phase and comparing it to v_{i-1}. If the difference is smaller than δ, the algorithm finishes and returns the current estimate as the stable phase. Otherwise, it takes the longest consecutive period in the current stable phase estimate that has a velocity above $v_i - dv$ as the new estimation. Our default settings are $\delta = 0.001$ m/s and $dv = 0.45$ m/s, which are chosen based on empirical results with multiple walking traces.

The algorithm converges because the actual stable velocity is higher than the average velocity in the acceleration and deceleration phases. The estimated stable velocity v_i increases in each iteration as we zoom in closer to the stable phase, and eventually converges to the actual stable velocity. On average it takes around 3 to 4 iterations to converge. Figure 3 shows an example output of this algorithm. In this example the algorithm converges in the third iteration when $|v_3 - v_2| < \delta$. Thus, the longest period above $v_2 - dv$ is returned as the estimated stable phase.

The steps above allow us to identify walking periods of interest and focus on time intervals where the gait information is meaningful. In the next section, we describe how WiGait extracts gait velocity and stride length from the data in these windows.
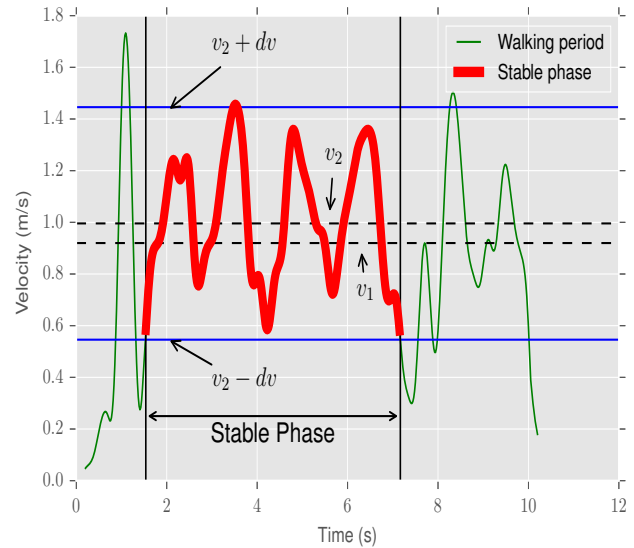

Figure 3. This figure shows changes in velocity over time for a walking period. Our estimated stable walking phase is extracted and highlighted in the figure.

Gait Velocity and Stride Length Estimation

In this section, we describe how WiGait computes the gait velocity and stride length from location data in the stable phase.

Gait Velocity

The velocity of a user at time t is defined as the averaged displacement of location samples in a T second window.

$$v(t) = \frac{\sum_{i=n}^{n+m-1} \sqrt{(x_{i+1} - x_i)^2 + (y_{i+1} - y_i)^2}}{T},$$

where n is the sample index corresponds to time t, m is the number of samples in a T second window, and x_i and y_i are the locations of the user at the ith sample. WiGait uses the estimated stable velocity of the stable phase as the gait velocity of a walking period. For the analysis in this paper, $T = 0.2$ seconds is chosen empirically.

In order to estimate the velocity more accurately, one needs to consider how the signal interacts with the human body. As the user walks, different parts of the body reflect the signal back to our setup at different times [4]. Since WiGait builds on top of a wireless localization system that abstracts the entire human body as a single point, we observe fluctuations in the location data that happen at a smaller time scale than the steps. These variations are due to the fact that the reflection point on the person's body switches from one body-part to another in consecutive measurements (e.g., from the chest to the arm.) In other words, one location point may refer to the location of the person's chest, but the next may be his left leg. To mitigate the effect of this variation on calculating the gait velocity, WiGait applies a Gaussian filter with a window size smaller then the average human step size on the data before calculating the velocity.

Stride Length
WiGait estimates the stride length by first estimating the stride frequency. Although the system abstracts the human body as a single point, we can still measure the stride frequency by observing how the velocity and location change over time. For each step taken by the user, the velocity first increases then decreases. Also, the human body naturally sways as one walks, which changes the reflection point on the user's body and thus the elevation returned by the localization system. Figure 4 shows how the velocity and elevation z of a user changes while she walks. Note that we can see how each step is correlated with changes in the velocity and elevation.
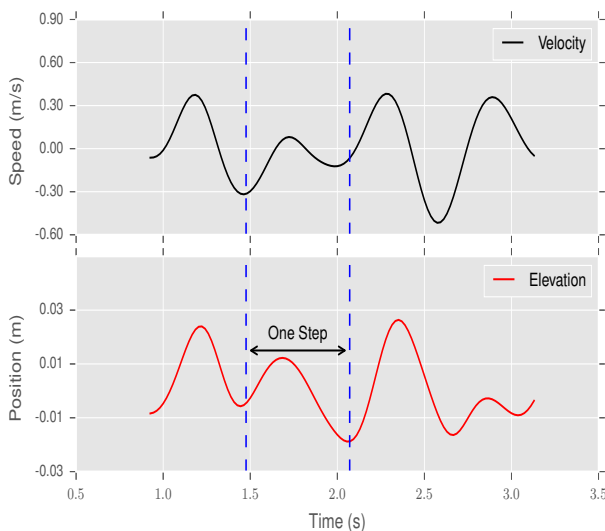

Figure 4. This figure shows the velocity and elevation over time during a stable phase within a walking period. We estimated and removed the low frequency trend in this figure.

To calculate the stride frequency, we take the Fast Fourier Transform (FFT) of both the velocity and elevation values in the stable phase. We then combine the normalized FFT responses from both of them:

$$X_c[f] = \frac{X_v[f]}{\sqrt{\sum_i X_v[f_i]^2}} + \frac{X_z[f]}{\sqrt{\sum_i X_z[f_i]^2}},$$

where $X_v[f]$, $X_z[f]$, and $X_c[f]$ are the responses at frequency f for the velocity, elevation, and combined signal respectively. The intuition is that both elevation and velocity oscillate at the same frequency. However noise can cause other frequencies to spike. By averaging the two spectrums, the correct frequency is emphasized since it is shared, whereas the noise is de-emphasized. We then choose the strongest periodic component in the response as the stride frequency. Figure 5 shows an example of the combined FFT response. The figure also compares it with the correct stride frequency as computed using the VICON motion system (details of the experimental setup and the VICON system are described in the evaluation section.) Note that depending on the way the person walks, there could be an additional low frequency trend in the velocity and elevation signals. To prevent this from affecting our estimation of stride frequency, we estimate and remove the trend of the signals before taking the FFT.

After the stride frequency f_m is estimated, the stride length L can be computed by dividing the gait velocity estimated earlier by the stride frequency.
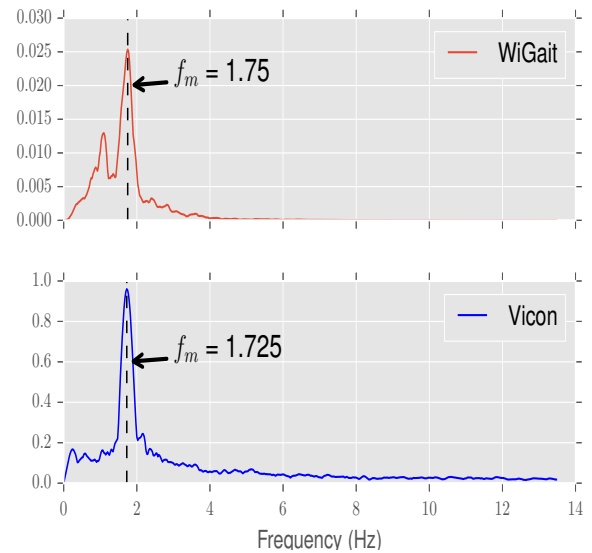

Figure 5. This figure shows the combined FFT of WiGait and FFT taken from Vicon's z value. The highest peak in the FFT is recognized as the subject's stride frequency.

EVALUATION AND RESULTS
We designed a series of user studies to evaluate the accuracy of WiGait in measuring gait velocity and stride length, and the acceptability of using WiGait for continuous monitoring at home. We recruited a total of 25 participants (16 males and 9 females) for the study. The age of the participants ranges from

from 23 to 89, and 7 of them are over 55. 18 of the subjects participated in the evaluation of WiGait in the lab, 14 of the subjects participated in the user acceptability study, and 7 of them participated in both studies. We obtained IRB approval for all studies. For experiments done in the lab, except for the monitored person, we always had another person in the same room who facilitates the experiments. Since the underlying WiTrack radio can separate signals from different people, the presence of a second person in the environment does not affect the results of the monitored person.

Accuracy of WiGait vs. Clinical Test
First, we would like to evaluate the accuracy of WiGait in comparison to the standard clinical test. As mentioned earlier, the clinical test is typically performed by a clinician who asks the person to walk for a fixed distance, and measures the time it takes using a stop watch. To run the standard test, we mark a 7-meter straight line and ask the participant to walk along the line. As recommended, we measure the gait speed over the middle 5-meter stretch, ignoring the first and last meters.

To avoid human error, we use the VICON motion tracking system to accurately measure both walking distance and time. Note that VICON systems are already used by hospitals and rehabilitation centers. The VICON system consists of multiple infrared cameras mounted on the ceiling. It tracks subjects by attaching infrared-reflective markers on their bodies. It has an accuracy of sub-millimeter [3]. The VICON system costs about half a million dollars, and hence it is not appropriate for in-home tracking.

Participants are asked to wear a helmet with infrared markers that can be tracked by the VICON system. The location of the helmet is used as the ground truth location of the user. We also put infrared markers on the feet of the participants to allow the VICON system to track stride length. We place WiGait in the same room as the VICON system. The origin of the VICON system is calibrated such that it is at the same location as WiGait. The total walking area is 6 x 5 m^2, limited by the area where VICON cameras can accurately track the target.

Gait Velocity
We plot the accuracy of gait velocity for different subjects in Figure 6. The accuracy is computed with respect to the clinical test where time and distance were obtained from the VICON. For each subject, the results are averaged over 10 runs. Averaging is recommended for the clinical test to reduce variability across runs. The figure shows that WiGait's accuracy is between 96.0% and 99.8%, across all subjects. To show that WiGait measures gait velocity accurately across different gait speeds, we plot the CDF of gait velocity for all subjects in Figure 7. The 18 subjects in the experiment have gait velocities that range from 0.75 m/s to 1.15 m/s. The above error rate yields an average absolute error of 0.015 m/s to 0.023 m/s in measuring gait velocity, which is accurate enough to detect clinically meaningful changes, i.e., changes at a scale bigger than 0.05 m/s [29].

Stride Length
We also compare the stride length measured by WiGait with the ground truth obtained from the VICON system. Figure 8
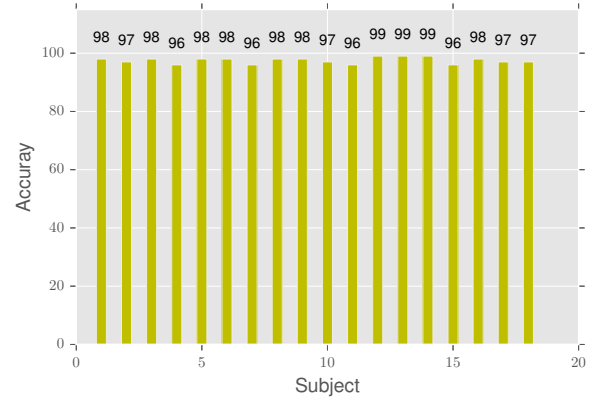

Figure 6. Accuracy of WiGait's gait velocity estimation across different subjects in a standard test. The accuracy values are rounded down to the nearest integer.
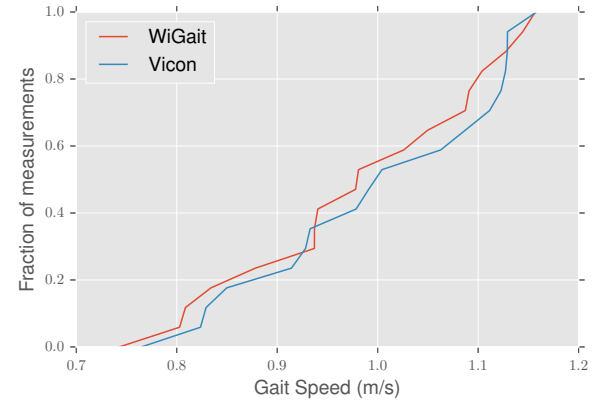

Figure 7. The CDF of the gait velocity of all subjects. The figure shows both the gait velocity estimated by WiGait, and the ground truth.

plots the accuracy of the stride length for each subject, averaged over 10 runs. Across all subjects, WiGait's accuracy varies between 88.4% to 99.3%. The stride length of the individual subjects ranges from 0.56 meters to 0.76 meters, as shown in the Figure 9. The results show that WiGait measures stride length across different ranges with high accuracy.

Accuracy in the Presence of Activity-Based Motion
Next, we would like to evaluate WiGait's accuracy in scenarios similar to those in daily living, where a person moves around and engages in various activities. Ideally, one would like to run these experiments using the data that we obtain from our home deployments. However, in those deployments we do not know the ground truth. Thus, we design an experiment that emulates moving at home and cleaning the space. To emulate a realistic home scenario, we setup desks, chairs and different household items in the same room as the VICON system. The subject is asked to perform certain tasks that involves movement and taking steps. In particular, he/she is asked to clean the desk, sweep the floor, and move items from the desk to the bookcase next to it. Before the start of each experiment, we ask our subject to leave their phone on the table on the other side
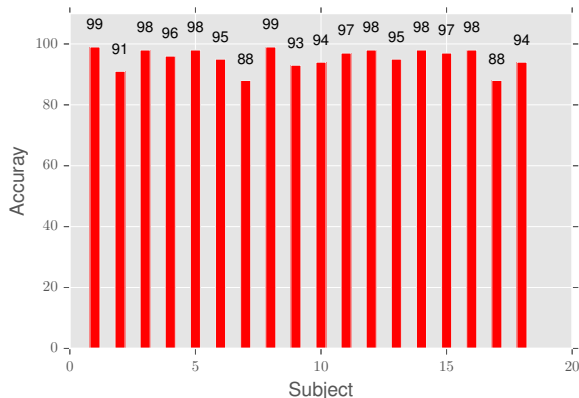
Figure 8. Accuracy of WiGait's stride length estimation across different subjects in a standard test. The accuracy values are rounded down to the nearest integer.
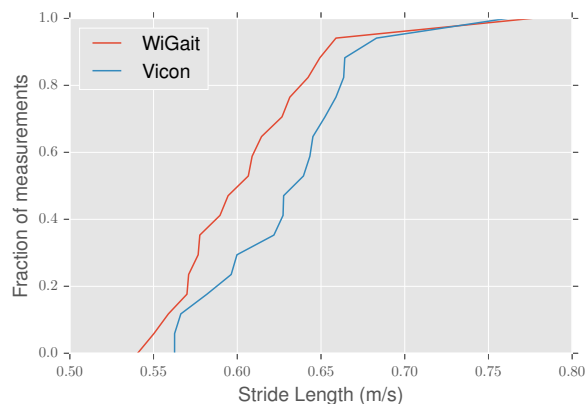

Figure 9. The CDF of the stride length of all sujections. The figure shows both WiGait's estimates and the ground truth.

of the room. During the experiment, we call the subject's phone at random times, unspecified in advance. The subject is asked to pick up the phone whenever it rings and answer the call. Each experiment takes around 15 minutes. The goal of this experiment is to verify that WiGait can correctly separate walking traces from other types of activities, and measures the correct gait speed of the person. The same 18 subjects that participated in the previous experiment participated in this one.

Accuracy of Identifying Walking Periods
Figure 10 shows a representative run of the above experiment. During this period, we called the subject's phone four times which correspond to the four big changes in x and y locations. We can clearly see how these events are reflected in the changes of the estimated diameter of the motion, as shown in the middle row of Figure 10. Each time after the phone was picked up, the subject went back to the other side of the room to finish the assigned tasks. Thus, for each phone call, we see two strong peaks in the diameter values, indicating the two walking periods for picking up the phone and going back to cleaning the desk. The figure also shows that simply looking at

the velocity during a period does not give an accurate estimate of walking periods.

We extract walking periods using WiGait's algorithm described in earlier sections. We compare those walking periods to the ground truth which is obtained manually by having an observer in the room. Since the extracted periods will be further analyzed for separating the acceleration and deacceleration phases, we consider an identified walking period to be correct if it contains the actual walking period with a margin of +/- one second. The recall of identifying walking periods is 100% and the precision is 95.7%.

In choosing the parameters, we make the algorithm more lenient to false positives. More work can be done to determine the best balance between the false positives and false negatives. However, since clinicians need only the average gait metrics over days and the change in these metrics, we can deal with these errors by extracting the average from statistical data collected from long periods of time.
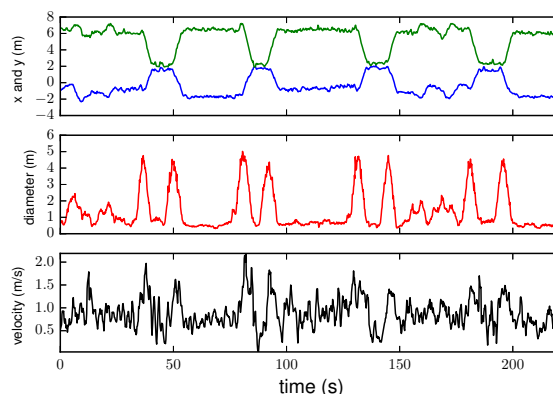

Figure 10. Identifying user's walking periods from activity-based motion using changes in the estimated diameter .

Accuracy of Gait Metrics Extracted from Walking Periods
After verifying WiGait's ability to separate the walking periods from other types of moving activities, we focus on examining the accuracy of gait velocity and stride length extracted from the identified walking periods. Again, we use the VICON system to compute the ground truth. Figure 11 and Figure 12 plot the accuracy of the gait speed and stride length that WiGait measured during the walking periods. The figures show that WiGait's accuracy in computing gait velocity ranges from 95.3% to 99.8% across subjects, while its accuracy in measuring the stride length ranges from 85.9% to 99.8%. The accuracies are overall similar to those obtained from comparing WiGait against the standard test.

Note that in general the accuracy in measuring stride length has a higher variance compared to that of measuring gait velocity. The main reason is because measuring stride length requires estimating the periodicity within each walking trace. The periodicity in a walking trace has high variability depending on how the person walks and which parts of her body reflect the signal back to the setup. We believe the accuracy can be

further improved by taking the average of more walking traces from longer monitoring time.
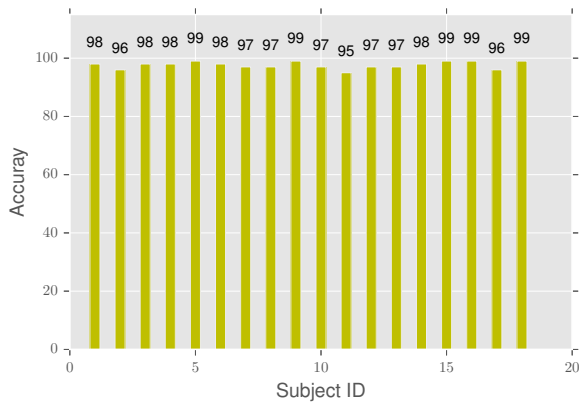

Figure 11. Accuracy of gait velocity in the presence of activity-based motion. The values are rounded down to the nearest integer.
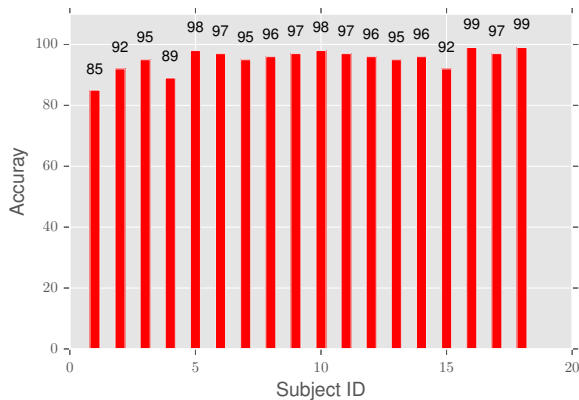

Figure 12. Accuracy of stride length in the presence of activity-based motion. The values are rounded down to the nearest integer.

User's Acceptability Study

We would like to evaluate whether users feel comfortable using WiGait at home. Out of the 25 subjects that we recruited, 14 participated in this study. Their ages range between 23 and 89, and 7 of them are above 55. All of the subjects asked to participate in the home deployment agreed except for one, who raised privacy concerns. Since we have only a total of 14 devices, the rest of the subjects were not asked. None of the subjects was compensated for participating in our experiments.

The study is conducted as follows: we first contact each subject over the phone to schedule a time to visit the subject's home. During the visit, we bring the device and show it to the subject. We read to the subject a consent form that includes the following information:

1. What WiGait does and how it operates.

2. What the output data looks like.

3. What data is being collected and how it is stored.

4. Who has access to the data.

Then, the subject is asked to sign the consent form if she is still interested in participating in the experiment. As mentioned above, all subjects agreed to participate in the deployment and sign the consent forms, except for one person due to privacy issue. For subjects above 70, both the subject and her family caregiver were present and they both were asked for consent.

Seven of the devices were deployed in the living room, 5 in the bedroom of the subject and 2 in a corridor and the entrance area. The choice of location was dictated by the need to maximize the coverage area of the device. None of the subjects objected to a particular location.

One month after the deployment, we contacted the subjects to learn their perception of the device. Eleven subjects were available to take our call, while three were unavailable.[3] We asked each subject two questions. First, we asked them if the device changed the way they normally live. All participants who answered the call replied negatively indicating that the presence of the device did not change their routine. Some said that they were aware of the device in the first couple of days, but soon afterwards it blended into the background.

We also asked whether they would be comfortable if we replace the device with a similar device with one difference: the new device measures gait speed and stride length with a camera or Kinect. Some of the older subjects did not know what Kinect is, so we explained how Kinect works. All subjects except 3 did not agree to replacing WiGait with the new device citing privacy concerns. Of the three who accepted, one wanted the device moved from the bedroom to the living room.

The above results indicate that the device has a high acceptance level, and better acceptance than a camera or Kinect based approach.

CONCLUDING REMARKS

This paper presents WiGait, a home sensor that continuously monitors gait velocity and stride length. It does so by analyzing the interaction of human motion with the surrounding wireless signals. Our results show that WiGait is accurate enough to measure clinically meaningful changes in gait velocity and is capable of measuring gait metrics even when the person moves freely and engages in various home activities. Our user study and home deployment indicate high acceptance of WiGait monitoring at home.

We envision a few directions for future work. First, the algorithms presented in this paper are tested on healthy subjects. Important extensions of this work would consider people with walking disabilities (e.g., Parkinson's Disease and Multiple Sclerosis). Second, we would like to investigate how to obtain the ground truth and extend our results to report accuracy in users' homes. Finally, in this paper, we do not explore the issue of user identification –i.e., being able to automatically identify the monitored person. Some past papers presented mechanisms for identifying users from radio reflections off

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[3]Some were unavailable for health reasons.

their bodies [4, 39], and hence could be incorporated in WiGait. However, more work is needed to simplify those methods and test them in home environments.

We believe our results help develop smart homes that are health-aware and can monitor the safety and well-being of their occupants. Also, WiGait enables new interaction capabilities, and can be incorporated into user interfaces that adapt the environment as the user's health changes, e.g., the environment may encourage the user to exercise more, or alert family and friends for health emergencies.

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