Measuring In-Home Walking Speed using Wall-Mounted RF Transceiver Arrays

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***Abstract*— In this paper we present a new method for passively measuring walking speed using a small array of radio transceivers positioned on the walls of a hallway within a home. As a person walks between a radio transmitter and a receiver, the received signal strength (RSS) detected by the receiver changes in a repeatable pattern that may be used to estimate walking speed without the need for the person to wear any monitoring device. The transceivers are arranged as an array of 4 with a known distance between the array elements. Walking past the first pair of transceivers will cause a peak followed by a second peak when the person passes the second pair of transceivers. The time difference between these peaks is used to estimate walking speed directly. We further show that it is possible to estimate the walking speed by correlating the shape of the signal using a single pair of transceivers positioned across from each other in a hallway or doorframe. RMSE performance was less than 15 cm/s using a 2-element array, and less than 8 cm/s using a 4-element array relative to a gait mat used for ground truth.**

I. Introduction

Assessing changes in mobility in the home is important for monitoring the health status of people with chronic illness and for enabling seniors to live independently. Gait metrics including walking speed are important indicators of health for seniors [1,2,3,4]. Abbellan et al. [3] performed an extensive review of the literature and evaluated all longitudinal studies that examined walking speed at baseline followed by a longitudinal monitoring of physical and mental health status. They concluded that gait speed as measured under normal life conditions is a consistent risk factor for disability, cognitive impairment, falls and / or mortality. Buracchio et al. [5] showed that a downward trajectory of gait speed precedes cognitive decline and even presage Alzheimer's disease. Dodge et al. [6] showed that in-home assessment of walking speed can be used to distinguish people with mild cognitive impairment (MCI) and those without MCI.

Estimating walking speed within a real-world environment is important because current estimations done within a clinic are oftentimes non-representative of a person's true walking speed. Walking speed is typically measured within a clinical setting through a test such as the *Timed 25-Foot Walk* which requires a patient to walk as quickly as possible on a well-marked 25-foot course. The duration of the walk is measured by a clinician and used as a metric of mobility and leg function. Measuring walking speed in a clinical environment has been shown to be an inaccurate estimate of real-life walking speed; patients oftentimes walk faster in a clinic than they do in their daily lives. Furthermore, clinical testing occurs infrequently, whereas in-home gait measurement can provide real-time estimates of walking speed as an indicator of the patient's health under real-world conditions.

Other groups have described methods for passively estimating gait speed within the homes. Pavel et al. [7] showed how infrared (IR) sensors arranged in a line on the ceiling could be used to estimate walking speed. In this system, as a person walks beneath ceiling mounted IR sensors arranged in a line, the sensors would fire synchronously. The velocity of the subject could be estimated using the distance between the sensors. Hagler et al. [8] followed up on this work and showed that by restricting the field of view of these walking line sensors, an accuracy of 9 cm/s standard deviation of error could be achieved relative to a GAITRite walking mat[1]. Low et al. [9] proposed an in-

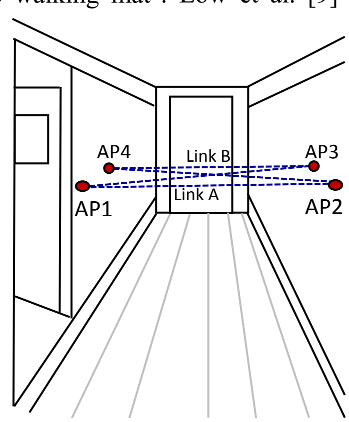

Figure 1. Access points are arranged along a hallway. As a person walks between APs 1 and 2 (Link A), signal strength between those two APs (shown as a line with an arrow) will drop. As the person continues walking down the hallway, the signal strength between AP 3 and AP4 (Link B) will drop.

subject longitudinal studies, absolute measures of speed for different systems are less accurate due to issues with in-home calibration.

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home walking mat for estimating gait speed and showed how it could be used to estimate fall risk. Walking mats suffer from wear and tear and may be a trip hazard for seniors. Use of video cameras has also been described as a method for estimating walking speed. Wang et al. [10] showed that walking speed estimates using an in-home video camera system were close in accuracy to gait mat estimates. The same group used the Microsoft Kinect 3-d camera for in-home estimate of gait speed and fall risk [11]. However, there are privacy issues with using video cameras and many subjects within our living laboratory cohort will not use them.

In this paper we describe a new method for estimating walking speed passively within the home using a small array of wall-mounted radio transceivers. The sensors have the advantage of being low-cost, unobtrusive, and easy to install, while still providing accurate estimates of walking speed. The person being monitored need not wear or carry any device. The transceivers, referred to as access-points (AP), are arranged as shown in Fig. 1.

As a person walks between a transmitting and receiving AP, the link Received Signal Strength (RSS) is attenuated because the body absorbs the RF energy. The time-difference between peak drops in RSS energy as a person crosses links can be used to estimate walking speed. Estimation using only a single link is also possible by analyzing the shape of the measured RSS waveform. Note that this new array configuration for detecting walking speed can be used as either a stand-alone sensor or part of a more complete passive tracking and mobility system currently under development. The complete system uses the same AP receivers positioned throughout the home allowing for passive tag-free localization [12,13,14].

II. METHODS

A. Hardware and system configuration

The system we have developed for measuring walking speed consists of 4 RF transceivers arranged on the walls of a hallway as shown in Fig. 1. Testing was performed at the OHSU Point of Care Laboratory (PoCL), a simulated apartment consisting of three rooms: a bedroom, bathroom and combined kitchen / living room filled with furniture and appliances typical for a home environment. The hallway was simulated by mounting the transceivers on wooden polls at a height of 1 m. The distance separating all APs was also 1 meter. This mock configuration was necessary to allow placement of a GAITRite gait mat (CIR Systems Inc., Sparta NJ) to capture walking speed groundtruth.

The transceivers used were manufactured by EmbedRF (Portland OR) and were programmed to transmit data at 905 MHz with a transmission rate of 20 Hz (Fig. 3).

AP1 initiates the communication by sending a data packet to both AP2 and AP3. Both AP2 and AP3 then send a packet to AP4, which acts as a hub consisting of a transceiver connected to a laptop computer. A link is defined as a signal transmission between two APs. Link A is the RSS path between AP1 and AP2; Link B is the RSS path between AP3 and AP4. There are also two additional cross-link RSS paths available; however, these were not used for this initial study.

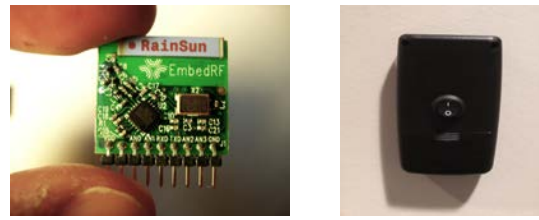

Figure 2. (a) EmbedRF 915 MHz, wireless transceiver used for the access-points and hub (1.5 grams, 10 payload byte, 50 ft range). (b) Enclosure used to hold the transceiver and mount on the wall.

Periodic transmission enables all APs to function at very low power levels (i.e. sleep whenever not transmitting) and last for up to a year on a single set of batteries, making the device ideal for a home monitoring application. When these devices are installed in a home, the Hub can be connected to a Wifi router that will forward the information to an aggregating microcontroller in the home and send up to a cloud server. The total cost of the 4 APs is less than $150 as compared to over $10,000 for a GAITRite system.

B. Two-Link walking speed estimation (4 APs)

An example of what the RSS signals look like when a subject walks past each of the two straight-across paths, Link A and B, is shown in Fig.3. Notice that the RSS crossing Link A peaks first. We define Δt to be the time difference between the first peak and the second peak. The estimate of the walking speed is given directly as $v_{time} = \Delta d/\Delta t$, where Δd is the distance separating the links (Δd =1m in our set-up).

Prior to getting an estimate for Δt, it is first necessary to locate the peaks. A peak detection algorithm is used that finds local maximums in the signal (MATLAB findpeaks function). This algorithm detects about 80% of the peaks accurately. However, some of the peaks exhibit double-peak behavior, which is likely due to the leg or arm swing influencing the RSS measurement. To account for this we locate signal crossing on either side of the original peak where the level rises above or below 75% of the peak amplitude. The midpoint between these crossings is used as

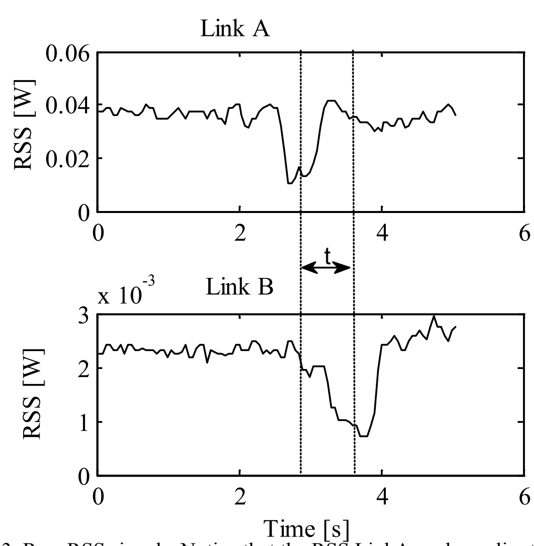

Figure 3. Raw RSS signals. Notice that the RSS LinkA peaks earlier than the RSS crossing Link B.

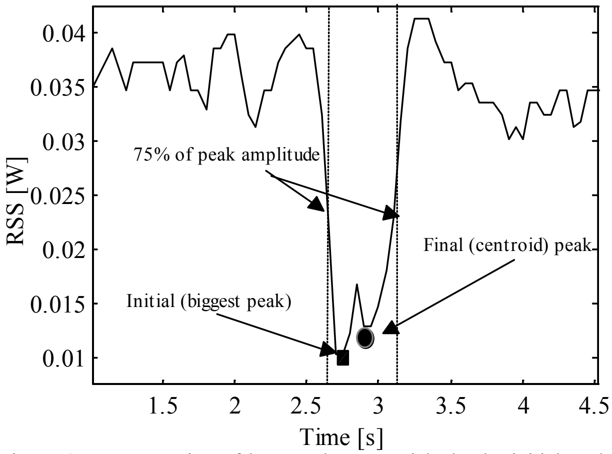

Figure 4. Demonstration of how peaks were picked. The initial peak is shown as a square while the centoid peak (circle) is picked by finding the point where the signal is at 75% of its smallest value.

the final centroid peak. This is shown visually in Fig. 4.

C. Single-Link walking speed estimation (2 APs)

Estimating the walking speed from crossing a single link between only 2 APs is also possible by analyzing the waveform shape. While less accurate than using 4 APs with relative timing information, this configuration may be advantageous for placing the sensor in a doorway.

Fig. 5 shows RSS waveforms for slow, medium, and fast walks. Notice how the RSS waveform is thinner during a fast walk. This makes intuitive sense since it takes less time for the walker to pass by and interfere with the signal.

Instead of using signal width as a feature, our experiments showed that using area was more reliable and correlated better with walking speed. Ideally, area should be linearly related to width. The area, a, is calculated simply as the sum of the absolute RSS values for a 5 second window around the peak location. Walking speed is estimated from area using a linear regression, $v_{area} = \beta_0 + \beta_1 a$, where the coefficient are fit using least-squares. These coefficients provide a subject-dependent scaling factor.

D. Combining timing and area features (4 APs)

The final variant for estimating walking speed using 4 APs is to combine both the timing information and the area features from both links. Specifically, the velocity estimate using combined features is given as,

$$v_{combined} = \beta_0 + \beta_1 a_A + \beta_2 a_B + \beta_3 v_{time}$$

where a_A and a_B are the areas associated with Link A and Link B, and coefficients are again fit using least-squares.

III. Results and Experiments

To evaluate performance, 3 volunteers (subjects A, B, and C) did a total of 60 walks each. Walks were done starting at a slow speed and increasing to a fast speed so that a range of speeds would be covered for each subject. The speeds were approximately regulated by having the walkers carry a metronome and taking a step for each beat of the metronome. The metronome started at 40 beats per minute for the first walk and ended at 99 beats per minute for the 60th walk. The walking speeds as measured by the GAITRite mat ranged from approximately 0.5 m/s to 2 m/s. Note that while the GAITRite mat is used as "ground truth," the walking speed measurement for the GAITRite corresponds to the *average* walking speed over an approximate 4-5 m walking path, whereas our system gives a more "instantaneous" measure of walking speed directly in front of the APs. As a person's speed varies during a single walk, it is expected that our estimates will not match exactly.

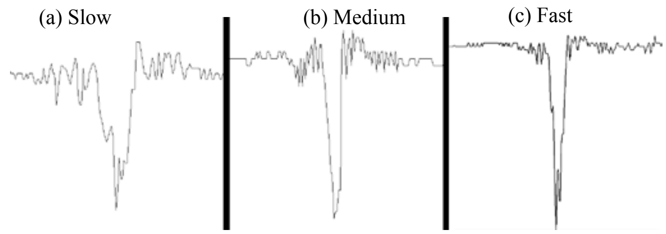

Figure 5. RSS for (a) slow, (b) medium, and (c) fast walking speeds.

Results are summarized in Table 1. As can be seen both the 2 Link timing approach (4 APs) and the 1 Link area approach (2 APs) provide accurate estimates of walking speed. Combining both timing and area features provides the most accurate estimates. For individual subjects the linear regression using area features was fit using the 60 available walking speed trails[2]. We also tested the performance when coefficients were fit on two subjects and then tested on the third subject, as indicated in the "cross-subject calibration" columns in Table 1. In this case performance degrades slightly, indicating that correlation of area features is subject dependent and that individual subject calibration may be necessary for optimal performance.

The scatter plot between the GAITRite velocity and the estimated velocity, v_{time}, using the 2-Link method is shown in Fig. 6 (a). The velocity, v_{area}, predicted using the single-link method is shown below in Fig. 6 (b). And lastly, we plot the velocity, $v_{combined}$, predicted using the combined area and timing difference below in Fig. 6 (c).

TABLE I. RMSE Performance

	RMSE relative to GAITRite (m/s)			
	Subject A	***Subject B***	***Subject C***	***Average***
2 Link timing	0.195	0.053	0.089	0.112
1 Link area	0.168	0.179	0.142	0.162
Timing and area	0.085	0.047	0.103	0.078
	Cross-Subject Calibration			
1 Link area	0.383	0.214	0.280	0.292
Timing and area	0.117	0.061	0.087	0.086

The range of speed and tight correlation between the GAITRite speeds and the estimated speed is shown. Subject

[2] Some of the GAITRite and RSS data for Subject C was corrupted requiring us to manually remove a few of the walking trials during testing.

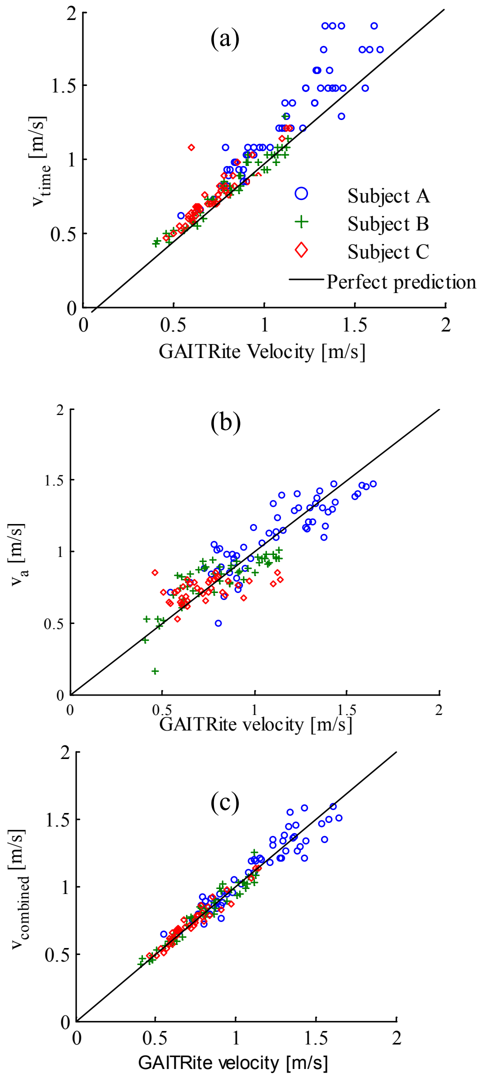

Figure 6. Estimated vs. actual velocity plot using (a) 2-Link timing method, (b) 1-Link method, and (c) combined method.

B, whose RMSE was lowest, walked in a more narrow range of walking speeds as might by typical indoors. Larger errors for subject A occurred during faster walking speeds and may be related to the averaging effect of the GAITRite estimates. The estimated speeds using 2-link timing were slightly biased for Subject A, but were improved after performing linear regression. Subject C exhibited a number of additional outliers (possibly due to corrupted data) that may have affected performance and cross-subject calibration.

IV. Discussion

In this paper we have demonstrated a new method for accurately estimating walking speed within a home environment. Using 2 links with 4 APs placed in a hallway, timing information can be used to estimate walking speed with no calibration required. Improved performance is achieved combining both timing and area features (average RMSE performance was less than 8 cm/s for 3 subjects relative to a GAITRite mat used for ground truth). Using just area shape features, walking speed can also be estimated using only a single link with 2 APs. While this allows for placing the sensors in additional locations such as a doorframe, the single link method requires calibration to a specific user for best performance. A limitation of the work presented here is that the algorithm was only trained and tested on 3 subjects. In the future, we will evaluate on a larger cohort. Future work will also involve refinement of algorithms for improved robustness, alternative approaches to calibration, and long-term testing in the homes of seniors. We are also investigating whether a larger array of APs placed lower to the floor can be used to estimate additional gait features such as footfall and stride length.

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