Published in final edited form as:
IEEE Trans Biomed Eng. 2010 April ; 57(4): 813–820. doi:10.1109/TBME.2009.2036732.

Unobtrusive and Ubiquitous In-Home Monitoring: A Methodology for Continuous Assessment of Gait Velocity in Elders

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Abstract

Gait velocity has been shown to quantitatively estimate risk of future hospitalization, has been shown to be a predictor of disability, and has been shown to slow prior to cognitive decline. In this paper, we describe a system for continuous and unobtrusive in-home assessment of gait velocity, a critical metric of function. This system is based on estimating walking speed from noisy time and location data collected by a “sensor line” of restricted view passive infrared (PIR) motion detectors. We demonstrate the validity of our system by comparing with measurements from the commercially available GAITRite® Walkway System gait mat. We present the data from 882 walks from 27 subjects walking at three different subject-paced speeds (encouraged to walk slowly, normal speed, or fast) in two directions through a sensor line. The experimental results show that the uncalibrated system accuracy (average error) of estimated velocity was 7.1cm/s (SD = 11.3cm/s), which improved to 1.1cm/s (SD = 9.1cm/s) after a simple calibration procedure. Based on the average measured walking speed of 102 cm/s our system had an average error of less than 7% without calibration and 1.1% with calibration.

Index Terms

Eldercare; unobtrusive monitoring; ubiquitous computing; gait; walking speed; passive infrared (PIR) motion detectors

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I. Introduction

Improving quality of life and providing adequate medical care for the rising number of elderly while keeping health care costs under control has in recent years become a major problem [1]. Several methodologies have been proposed to address this problem that include the use of technology to develop systems that promote aging in place [2] and the use of pervasive healthcare [3] to help alleviate the burden placed on health care providers. One of the underlying themes of these approaches is to employ technology such as wireless networks combined with novel sensing systems to gather and interpret data in non-health care settings such as the home environment.

Many systems have been proposed that use these methodologies to assist the elderly. For example, passive infrared sensors have been used in-home for the estimation of amount [4] and type [5] of daily activity and in-hospital for classification of patient movements [6]. Other systems have been proposed that detect falls in elders [7], infer activities of daily living (ADLs) [8], use computer interactions to detect cognitive changes [9], and for continuous and unobtrusive in-home behavioral monitoring [10]. Other recent applications of pervasive healthcare and wireless sensor networks for supporting elder healthcare for aging in place include multimodal sensing and computer vision [11,12] while systems for supporting independence in assisted living are described in [13,14]. For completeness we mention that a comprehensive literature review of pervasive computing in health care from 2002 to 2006 is available [15] including applications to eldercare.

One specific measure of particular interest for unobtrusive assessment for health monitoring is walking speed. Walking speed has been shown to be a quantitative estimate of risk of future hospitalization [16]. Slower walking speed has been demonstrated in dementia patients compared to controls [17] and has been shown to precede cognitive impairment [18] and dementia [19], and timed walk has been used as a partial characterization of lower extremity function which has been shown to predict disability [20,21]. Other studies have shown a relationship between walking speed and cognition [22,23]. Current evaluation of walking speed is typically done both infrequently and in the clinic setting which suffers from at least five shortcomings. First, frequent assessment visits are impractical and cost prohibitive since either it is difficult for patients to make frequent trips to a doctor's office or other clinical settings or in the case of research assessments, inconvenient for the research team to visit homes frequently. Second, for longitudinal study each testing session is typically scheduled in increments of six months or a year after a baseline visit making it difficult both to evaluate the validity or stability of baseline measurements and to detect short and long term variability [24]. Third, there may be an intentional [16] change in walking speed in the clinical setting or an unintentional [24] change in abilities during a single assessment. These pacing considerations themselves may have important implications for predicting outcomes [23]. Fourth, infrequent measurements report only the net change between measurement times and cannot distinguish between functional changes occurring slowly over time and abrupt functional changes, which may have different causes. Fifth, infrequent measurements do not detect changes when they happen which may reduce the ability of a clinician to provide intervention or reduce the effect of an intervention. By shifting to continuous in-home monitoring of walking speed from the current paradigm, the effect of all of these short comings can be significantly reduced or removed.

There have been several systems proposed for monitoring walking speed and other gait features outside of the clinical setting [25-27]. These systems typically consist of some wearable combination of gyroscopes and/or accelerometers and have demonstrated accuracy and precision in the field. However, these systems suffer from several limitations such as short battery life, the need to download the data or introduce additional hardware and complexity for wireless data collection, and the inconvenience of both a wearable device and having to remember to wear a device. For these reasons the wearable devices are currently inadequate for long-term, in-home, unobtrusive monitoring.

In order to address these concerns and to improve diagnostic ability for clinicians and researchers, we propose a methodology for continuous in-home monitoring of walking speed using passive infrared motion sensors. Specifically, we describe the hardware preparation and deployment, the techniques for data collection, and the data processing algorithms for continuous in-home assessment of walking speed in elders. Finally, we validate our approach by comparing the results of our method for walking speed estimation with the commercially available GAITRite® Walkway System gait mat.

II. System Description and Data Collection

In this section, we describe the hardware and methodology used to deploy the walking speed measurement system in a residence. A partial description of this system has been described elsewhere [4,10] in the more general context of total activity monitoring, as has a simpler version of the proposed approach [28]. Here we specialize and describe in more detail the specific nature of the walking speed measurement system. We begin by describing the sensors and how they are placed in a residence and follow with a description of the wireless network based data collection.

To detect motion we used the X10 model MS16A (X10.com) passive infrared motion sensor which emits a unique programmable bit code at 310 MHz when motion is detected. We restricted the field of view of each motion sensor to ±4 degrees and installed four sensors sequentially on the ceiling (average height of 2.54 m) approximately 61cm apart in a confined area such as a hallway or other corridor. This combination tends to force a resident to walk linearly through each sensor pair in the sensor line and ensures that each sensor will only fire when someone passes directly below. Limiting the field of view precisely and placing sensors in exact locations is not possible, and therefore there is some variability in the physical locations which cause the sensors to fire, as will be discussed shortly. Fig.1 shows how these sensors look from a resident's point of view when entering the sensor line.

To collect the wirelessly transmitted sensor firings, we use a WGL 800 wireless transceiver connected to a desktop computer installed in the residence. Simultaneous sensor firings or other interfering sources can result in lost data due to collisions at the wireless transceiver. However, these have been shown to be minor, with a less than 2% overall data loss [4]. The computer timestamps the sensor firings and the data pair is both stored locally and sent via a secure Internet connection to a central database for analysis.

Our experience with the described technology comes from the deployment and monitoring of approximately 250 Portland (OR, USA) metropolitan area homes and retirement community dwellings from between 6 months to over 2 years in ongoing studies. We have instrumented both single and multi person dwellings and have collected data from over 1,200,000 walking events from single person homes with minimal technical challenge or sophistication needed for setup. Installation of the complete system (including additional technologies described elsewhere [4]) takes an average of 1.5 to 2 hours with 2 people. Deploying only the equipment necessary to measure walking speed (computer, sensors, wireless transceiver, and internet) is estimated to take 1 person approximately 1 hour – if the home already contains an Internet-connected computer, this could be done in 20 minutes. The technologies are managed remotely using custom systems management software that supports data viewing, remote software updates, and remote computer reboots if needed. Other issues, such as replacing motion sensor batteries (battery life is about 1 year) or changing sensors if they become unreliable or defective can typically be handled in a very short visit to the residence, typically 10-15 minutes. Overall, we have found the system has been simple to install, unobtrusive in the sense of both passive sensor technology and minimal outside intervention, and easy to maintain.

III. Data Modeling and Analysis

In this section we introduce and discuss both the proposed linear model and the estimator for determining the gait velocity from noisy motion sensor data. We start by describing how to determine the precise spatial separation of the sensors from the sensor firings since they will not, as mentioned, be the same as the measured values due to a combination of installation variability and differences between individual sensors. We then use this information to model the walking speed as a linear function of the measured data degraded by two sources of additive noise. The first source of noise is in units of distance and is due to the sensor firing in slightly different locations during each pass through the sensor line. This error is based on the field of view and sensitivity of an individual sensor. The second source of error is in units of time and is due to the discrepancy between when a sensor fires and when the computer timestamps the firing, which generally causes positive time errors. We conclude the section by proposing a walking speed estimator that minimizes the combination of these errors followed by a discussion of model calibration in the presence of ground-truth data versus estimating the calibration factor when ground-truth data is unavailable.

A. The Linear Model

We start by assuming the sensors are placed at physical positions $\{\tilde{x}_i\}$ in some spatial coordinate system. For a particular walking event the sensors fire at times $\{t_i^k\}$ where k indexes the particular sensor line walking event and i indexes the particular sensor which fired. We then define $\{x_i\}$ to be the average position at which the walker is when the ith sensor fires. In other words, for a particular walking event the ith sensor fires when the walker is at some random location $\{x_i+\varepsilon_i\}$ with the errors $\{\varepsilon_i\}$ being independent random variables with zero expected value. Fig. 2 illustrates this arrangement.

The differences $\{x_i - \tilde{x}_i\}$ represent likely biases due to the field of view of the sensor and the direction of movement as shown in fig. 2. For the sake of simplicity we restrict the present discussion to the analysis of movement in one direction.

Now assuming a walker moves with some known velocity v through a sensor line and we have some absolute reference time, $\{\tau_i\}$ can be defined as the time at which the walker is expected to be at location $\{x_i\}$ and trigger the ith sensor. If we now include the errors in detection location $\{\varepsilon_i\}$ explicitly in the measured time we find that the measured times should be $\left\{\tau_i+\frac{\varepsilon_i}{v}\right\}$.

By further assuming that there is some random delay $\{\eta_i\}$ between when a sensor fires at location $\{x_i + \varepsilon_i\}$ and when the computer time-stamps the sensor firing data, the measured time can be written as $\{t_i^k\}=\left\{\tau_i^k+\frac{\varepsilon_i^k}{v^k}+\eta_i^k\right\}$ where the $\{\eta_i\}$ are independent random variables with some common non-negative expected value and the explicit dependence on the measured time from both position errors and time errors is shown.

Now, consider an event k to comprise a person walking past the line of sensors with a constant, but unknown velocity v^k. Then for any pair of sensors, i,j we have $x_j - x_i = v^k\left(\tau_j^k - \tau_i^k\right)$, from which we find:

$$\left(x_j + \varepsilon_j^k\right) - \left(x_i + \varepsilon_i^k\right) = v^k\left[\left(t_j^k - \eta_j^k\right) - \left(t_i^k - \eta_i^k\right)\right]. \tag{1}$$

Using (1) we can solve for the velocity v^k, for any three sensors i,j,m:

$$v^k = \frac{\left(x_j - x_i\right) + \left(\varepsilon_j^k - \varepsilon_i^k\right)}{\left(t_j^k - t_i^k\right) + \left(\eta_i^k - \eta_j^k\right)} = \frac{\left(x_m - x_j\right) + \left(\varepsilon_m^k - \varepsilon_j^k\right)}{\left(t_m^k - t_j^k\right) + \left(\eta_j^k - \eta_m^k\right)} \tag{2}$$

We now economize the notation and define $\varepsilon_{ji}^k \equiv \varepsilon_j^k - \varepsilon_i^k$ and $\eta_{ij}^k \equiv \eta_i^k - \eta_j^k$ for i,j,m. Rewriting (2) yields:

$$\begin{aligned} &\left(x_j - x_i\right)\left(t_m^k - t_j^k\right) + \left(x_j - x_i\right)\eta_{jm}^k + \left(t_m^k - t_j^k\right)\varepsilon_{ji}^k + \varepsilon_{ji}^k\eta_{jm}^k \\ &= \left(x_m - x_j\right)\left(t_j^k - t_i^k\right) + \left(x_m - x_j\right)\eta_{ij}^k + \left(t_j^k - t_i^k\right)\varepsilon_{mj}^k + \varepsilon_{mj}^k\eta_{ij}^k. \end{aligned} \tag{3}$$

Taking the expectation of both sides and using the facts that: $E_k\left\{\varepsilon_{ij}^k\right\} = 0$, $E_k\left\{t_i^k\varepsilon_j^k\right\} = 0$, and $E_k\left\{\varepsilon_j^k\eta_i^k\right\} = 0$ for $i \neq j$, results in:

$$\begin{aligned} &\left(x_j - x_i\right)E_k\left\{t_m^k - t_j^k\right\} - E_k\left\{t_j^k\varepsilon_j^k\right\} + E_k\left\{\varepsilon_j^k\eta_j^k\right\} \\ &= \left(x_m - x_j\right)E_k\left\{t_j^k - t_i^k\right\} - E_k\left\{t_j^k\varepsilon_j^k\right\} + E_k\left\{\varepsilon_j^k\eta_j^k\right\}, \end{aligned} \tag{4}$$

which simplifies to:

$$\frac{\left(x_j - x_i\right)}{\left(x_m - x_j\right)} = \frac{E_k\left\{t_j^k - t_i^k\right\}}{E_k\left\{t_m^k - t_j^k\right\}}. \tag{5}$$

From this we may conclude that:

$$\left(x_j - x_i\right) \propto E_k\left\{t_j^k - t_i^k\right\} = E_k\left\{\Delta t_{ij}^k\right\}. \tag{6}$$

The expected value of the random variable Δt_{ij}^k can therefore be used to estimate the spatial separation of the sensors up to a scale factor by computing the average values over a large number of events.

By explicitly writing (6) with the proportionality constant c we have:

$$\left(x_j - x_i\right) = cE_k\left\{\Delta t_{ij}^k\right\}. \tag{7}$$

Here c has a ready interpretation as the speed a person would have to walk in order for the sensors to register time differences equal to the average time differences calculated from the training data set.

Let us look more closely at the estimated spacings $(x_j - x_i)$. Considering fig. 2 again, we see that the sensor line is effectively hovering at some height between the ceiling and the floor. In the figure it has been drawn at the top of the head. Let us imagine that we knew the actual mean firing position for each sensor as a function of the height above the floor, so that if the sensor is triggered by motion at a height h it will typically be triggered at a position x_i (h). In addition, the body itself does not move at a single constant velocity v during gait, but rather different segments move with various velocities over the course of the gait cycle. The effect of this is that the values $\{\tau_i\}$ (which are the actual measurements) reflect triggering at various heights due to different body segments. In effect, all these factors are averaged over to produce effective sensor spacing based on the subject's height and style of walking together with the sensor characteristics. We expect that for people of similar heights, as well as reasonably similar styles of gait, that the estimated effective sensor spacing $(x_j - x_i)$ should be close in value.

B. Estimation of Gait Velocity

When we estimate the gait velocity we must consider two sources of measurement error. First, there is the combined error for sensors i,j resulting from detecting the walker at positions away from the mean detection locations x_i, x_j which we denote by ε_{ij} Second, there is the combined error for sensors i,j resulting from errors in time-stamping the moments at which each sensor fired. This is represented by η_{ij}. In general, these two types of errors should be given different weights in accordance with the relative variability captured by the spatial and temporal covariance matrices of the error terms ε_{ij} and η_{ij} [29]. The relative weighting of the temporal error term relative to the spatial error term is represented by the parameter ρ. We proceed initially by assuming that the calibration factor c and the weighting factor ρ are known values and derive an estimator for the walking velocity, $\hat{v}$ through the sensor line. With this estimator, we then proceed to consider situations in which we know the actual walking velocity, v and consider the estimator now as a function, $\hat{v}(c,\rho)$, which arises when one calibrates the line using a set of data where the velocities are known. Finally we consider the case where c,ρ are not known and use information from the physical set up of the sensors to estimate a value of c. In this last case we assume that weighting of the errors is a general value across all reasonably similar sensor lines and so take the value for ρ obtained from our calibrated experiment described in the next section.

In a sensor line of four sensors i,j,l,m that fire sequentially when a subject walks along the sensor line, we can estimate the walking speed by minimizing the overall error in the dependent and independent variables using the method of total least squares [30] applied to the model:

$$\left(\begin{bmatrix} \rho E_k\left\{\Delta t_{ij}^k\right\} \\ \rho E_k\left\{\Delta t_{jl}^k\right\} \\ \rho E_k\left\{\Delta t_{lm}^k\right\} \end{bmatrix} + \begin{bmatrix} \frac{\rho}{c}\varepsilon_{ij}^k \\ \frac{\rho}{c}\varepsilon_{jl}^k \\ \frac{\rho}{c}\varepsilon_{lm}^k \end{bmatrix}\right)\left(\frac{c}{\rho\widehat{v^k}}\right) = \begin{bmatrix} \left(t_j^k - t_i^k\right) \\ \left(t_l^k - t_j^k\right) \\ \left(t_m^k - t_l^k\right) \end{bmatrix} + \begin{bmatrix} \eta_{ji}^k \\ \eta_{lj}^k \\ \eta_{ml}^k \end{bmatrix}, \tag{8}$$

where we have rewritten the linear equations in matrix notation, used the fact that $\eta_{ji}^{k}=-\eta_{ij}^{k}$ to keep the noise term in (8) in the standard additive form, and used the estimate of the spatial sensor separation as in (7). We proceed assuming that c,ρ are fixed and known constants for the sensor line.

To compute the velocity estimates, we now construct a matrix containing as column vectors the distances between adjacent sensors, and the time differences between adjacent sensor firings:

$$M^{k}(\rho)=\begin{bmatrix} \rho E_{k}\left\{\Delta t_{ij}^{k}\right\} & \left(t_{j}^{k}-t_{i}^{k}\right) \\ \rho E_{k}\left\{\Delta t_{jl}^{k}\right\} & \left(t_{l}^{k}-t_{j}^{k}\right) \\ \rho E_{k}\left\{\Delta t_{lm}^{k}\right\} & \left(t_{m}^{k}-t_{l}^{k}\right) \end{bmatrix}. \tag{9}$$

This matrix may be factored per the singular value decomposition into a trio of matrices $A^k(\rho)$, $B^k(\rho)$, $\Sigma^k(\rho)$ so that the equation $M^k(\rho) = A^k(\rho)\Sigma^k(\rho)B^{k*}(\rho)$ is satisfied. Letting $B_{12}^{k}(\rho)$, $B_{22}^{k}(\rho)$ denote the appropriate elements of the matrix $B^k(\rho)$, the estimated velocity is given by:

$$\widehat{v}^{k}=-\frac{c}{\rho}\frac{B_{22}^{k}(\rho)}{B_{12}^{k}(\rho)}. \tag{10}$$

C. The Calibrated Sensor Line

Taking the weighting factor ρ still to be fixed and known, we now treat the calibration factor c as a variable whose value we may estimate using known velocity data. We are given a set of training data consisting of sensor firing times $\left\{t_{i}^{k}\right\}$ and true gait velocities $\{v^k\}$ for a sample set of walks through the sensor line. We assume the actual walking speeds and the estimated walking speeds satisfy the linear model:

$$v^{k}+\omega^{k}=-\frac{\widehat{c}}{\rho}\frac{B_{22}^{k}(\rho)}{B_{12}^{k}(\rho)}, \tag{11}$$

where the $\{\omega^k\}$are independent random variables with zero expected value. By collecting all the measurements $v^{k}, b^{k}(\rho)=\frac{B_{22}^{k}(\rho)}{B_{12}^{k}(\rho)}$ into vectors v,$b(\rho)$, we can estimate the calibration factor with linear least squares:

$$\widehat{c}=-\rho\frac{v^{T}v}{v^{T}b(\rho)}. \tag{12}$$

If we knew the actual value ρ we would be done at this point as we could estimate the calibration factor c given the measured time and velocity values. However, where we do not know the actual value of ρ, we would like to choose a value which yields the best performance of the method for estimating velocities. In particular we would like to find a value of ρ which gives the best performance across many sensor-lines. Let us consider the calibration factor for the nth sensor-line as a function of ρ, that is:

$$\widehat{c}_n(\rho) = -\rho \frac{v_n^T v_n}{v_n^T b_n(\rho)}. \tag{13}$$

We may consider the set of velocity estimates also as functions of ρ:

$$\widehat{v}_n^k(\rho) = -\frac{\widehat{c}_n(\rho)}{\rho} b_n^k(\rho) = \left(\frac{v_n^T v_n}{v_n^T b_n(\rho)}\right) b_n^k(\rho). \tag{14}$$

This expresses the estimated velocity for the kth walk along the nth sensor-line $\widehat{v}_n^k(\rho)$ entirely in terms of the measured time, the measured velocity, and the unknown parameter ρ. The weighting factor may now be found as a value which gives the best sensor-line performance on average.

In practical situations where calibration data are not available we use an average value of ρ determined from existing data. In particular, we found that the average value that minimized the estimation error in our controlled experiments, described in the next section, was ρ = 0.75.

D. The Uncalibrated Sensor Line

If the velocity is not known, then the training data set will contain only the sensor firing times $\left\{t_i^k\right\}$. In this case we must estimate the value for c using the values for the physical sensor positions $\{\tilde{x}_i\}$. Choosing any pair of sensors i,j we may make the estimate:

$$\widehat{c} = \frac{\tilde{x}_j - \tilde{x}_i}{E_k\left\{\Delta t_{ij}^k\right\}} \tag{15}$$

We would like to choose our pair of sensors so that the expected value $\tilde{x}_j - \tilde{x}_i$ is as near in value as possible to the distance between mean detection positions $x_j - x_i$. In general the expected error will be minimized by choosing the pair consisting of the outermost sensors of the line.

We do note that care should be taken when using the uncalibrated sensor line cross-sectionally, especially over small samples, as the individual instantiations of a sensor line can have sizable differences between $\hat{c}$ and c as shown in fig. 5.

IV. Experimental Verification

A. Experimental Description

27 subjects (9 male and 18 female, aged 75 to 95 years, mean age 85.2 years, 145cm to 185cm in height, average height 164.8 cm) participated in the experiment; all provided informed consent. The experiment was conducted in a common use room at the facility where the participants live. A single sensor line of eight (8) restricted-field PIR motion

sensors was placed on the ceiling with sensors physically spaced at 61cm (2ft) intervals. The ceiling height was 240cm (7.8ft). Beneath the sensor line an 854cm (14ft) long GAITRite® Walkway System gait mat was placed so that the ends of the mat aligned with the outermost sensors. Participants were instructed to walk at self-determined “slow”, “normal”, and “fast” walking speeds. A total of 30 walks were recorded for most participants such that each participant walked five times at each of the three speeds in the two directions available along the sensor line. Five participants did a larger number of walks (36, 42, 42, 44, and 46) but their larger group of walks included the basic 30 which all participants did. Their precise walking speed for each trial was calculated using the gait mat data. Firing times were collected for each PIR sensor during each trial and used to determine the accuracy of the PIR sensors for measuring walking speed.

Based on our experience with several hundred homes, a reasonable sensor line configuration which may be installed under the space constraints of typical small homes consists of four sensors placed in a line at approximately 61cm (2ft) intervals. The choice of four sensors was influenced by a few different factors. First, since the sensors are known to be noisy, we wanted multiple measurements of the walking speed to use in our estimator to reduce estimator variance. Experiments showed, for example, that moving from three sensors to four sensors reduced variance by a factor of approximately 3.8. Second, due to space constraints in the homes and retirement communities we found that four sensors are all that would reliably fit in most homes. Third, the probability of an individual sensor firing is approximately 0.937. With four sensors in place and assuming we use walks where either three or four sensors fire, we can capture almost 98% of walking events in the home. Finally, we note that using two sensors in not sufficient as this causes equation (8) to reduce to a single equation with a single unknown which can be solved exactly, and therefore does not allow mitigation for known noise effects. In accordance with this we have considered sensor data in groups of four adjacent sensors. Thus our line of eight sensors is treated as five individual sensor lines. Furthermore as there is no reason to suppose that the effective sensor spacing is the same in the two directions along which the line may be walked, – in the “forward” or “return” direction through the line (with respect to the experimenter) – we evaluated each direction independently.

For each sensor line of four sensors in each direction only those walking events in which all 4 sensors fired were considered for the purposes of calculating the effective sensor spacing and calibration factor. However, to estimate the velocity for walking events we used all the sensor line data in which 3 or 4 of the 4 sensors fired.

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B. Experimental Results

A total of 882 walks from the 27 participants (mean age 85.2 years) were recorded during this experiment with 441 in the “forward” direction and 441 in the “return” direction (as referenced by the experimenter). The numbers of “slow”, “normal”, and “fast” speed walks were the same in either direction for each given participant. The 8 ceiling-mounted PIR sensors were divided into 5 sensor lines of 4 sensors with a regular 61cm (2ft) physical spacing for analysis. In the “forward” direction the sensor lines had all four sensors fire 350 ± 36 times, and in the “return” direction all 4 sensors fired 330 ± 29 times. The effective sensor spacing for each sensor line was calculated and normalized as in the foregoing using only the events where all 4 sensors fired.

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Participants walked in the “forward” direction with a speed of 104 ± 30.6cm/s, and in the “return” direction with a speed of 100 ± 29.3cm/s as measured by the gait mat. We estimated velocity using a sensor line only in those cases where 3 or 4 of the 4 sensors in the line fired. Fig. 3 shows the directional walking speed estimates versus the measured values for the combined sensor line data after calibration using velocity data from the gait mat. Fig.

4 shows the directional walking speed estimates using estimated calibration factors. In both figures the “return” direction is differentiated from the “forward direction” by introducing a negative sign on all the velocity estimates. Additionally, in both figures the line $x = y$ (corresponding to perfect estimation) has been plotted as a dashed line to demonstrate that both calibrated and uncalibrated estimates are distributed around the correct values. Further, the distribution of points in fig.4 is wider than in fig. 3 demonstrating that the calibration procedure does improve estimation. Also, of particular note is the fact that distribution of estimates in both figures is more centered and densely packed around the true value in the “return” direction, indicating that velocity estimates in the “return” direction are better than in the “forward” direction (i.e., the same sensors performed better in one direction than in the other).

To be more precise about the discussion of the walking speed estimates, we denote the estimated speed for the kth walk through sensor line i for both directions by $\widehat{v}_i^k$ and the actual speed by v^k. The accuracy of the system was evaluated by computing the average difference $\left\{\widehat{v}_i^k - v^k\right\}$. For the case of the calibrated sensor lines the mean of this difference is 1.1cm/s and the standard deviation is 9.1cm/s. In the case of the uncalibrated sensor lines the mean is 7.1cm/s, and the standard deviation is 11.3cm/s.

Figure 5 shows the relationship of the estimated calibration factors to the true (measured) calibration factors, with the line $x = y$ drawn for comparison. This shows that the uncalibrated sensor line with $\hat{c}$ as in (15) tends to underestimate the true calibration factor, this making the velocity estimates slightly higher than in the calibrated case. This also demonstrates the need to be careful when comparing uncalibrated sensor line estimates cross-sectionally.

V. Discussion

The proposed system for unobtrusive and continuous monitoring of in home walking speeds has been shown to accurately estimate velocity when compared to the GAITRite® Walkway System gait mat standard. The mean estimation errors of 7.1cm/s and 1.1cm/s for the uncalibrated and calibrated sensor lines when compared to the average speed of 102cm/s result in average errors of 6.96% and 1.08%, respectively. Further, the standard deviations of the error distributions for the uncalibrated and calibrated sensor lines are 11.1% and 8.92% when compared to the average speed of walking. This shows that each individual estimate is accurate, and local averaging and other statistical techniques can be used to increase precision (reduce the error variance further).

These positive results demonstrate the feasibility of the proposed method and address several deficits in the current paradigm of assessing gait episodically or in clinic settings. First, with this system the variability of walking speed can now be monitored continuously over the short term (e.g., walk-to-walk variability) in addition to longer time scales (e.g., month-to-month yearly) without expensive and inconvenient clinic visits. Second, subjects in high-risk groups can be monitored more closely and rapidly than is currently feasible. Third, researchers can have access to more frequent measurements of walking speed, which facilitates the refinement and better understanding of walking speed as it relates to health outcomes and correlations presently in the literature that are based on single or infrequent measurements. Fourth, wide scale analysis of multiple subjects can be performed relatively easily which we anticipate will open further areas of population-based research and diagnostic ability not discussed here. We do note that while our proposed system is less expensive than repeated clinical visits, the cost of the sensors, computer, internet service, and transceiver may currently be cost prohibitive for studies that might involve thousands of subjects who are widely dispersed. However, since historically the cost of equipment and services has continued to drop as better and faster technology becomes available in the marketplace, it is likely that deployment of these kinds of systems to larger cohorts will be facilitated. In addition, less expensive motion sensors may work adequately and simple application specific computers may be built cheaper than off the shelf models which could be deployed today. Further work is needed to identify the most cost efficient approaches to maximize scalability of in-home assessment platforms.

One of the largest challenges to the broad use of our approach to continuous monitoring of walking speed, and to in-home monitoring in general, is the differentiation of multiple residents. This problem is typically addressed by requiring the participants to wear or carry some type of radio frequency identification (RFID) tag. We are currently working on both pattern recognition and model-based approaches to distinguish between multiple residents based on the walking events. This will allow the expansion of this methodology from single resident homes to multiple resident dwellings without the need for additional equipment or hardware.

Future work will address comparisons of the in-home continuous method with standard clinical tests of walking, mobility, and physical performance such as the Short Physical Performance Battery, Unified Parkinson's Disease Rating Scale, and various other timed walks of different durations (e.g., 4-meter, 10-meter, 400 meter) thus facilitating interpretation of these established clinical metrics with our new framework. Other future work will include relaxing the assumption that velocity is fixed over a walking event in order to measure the step-to-step variability in each walking event. In this case the velocity of the *k*th walking event becomes some function of time $v(t)$. Retaining our definition of the error $\{\varepsilon_i\}$ above we find that the time at which the sensor fires may be expressed as $\{\tau_i + \upsilon_i\}$, where $\{\upsilon_i\}$ satisfies:

$$\varepsilon_i = \int_{\tau_i}^{\tau_i+\upsilon_i} v(t')dt'. \tag{16}$$

The values $\{\eta_i\}$ are still defined as above which gives a relation to the measured time values of $\left\{t_i^k\right\} = \left\{\tau_i^k + \upsilon_i^k + \eta_i^k\right\}$. Finally, for any pair of sensors we have the relation:

$$\left(x_j + \varepsilon_j^k\right) - \left(x_i + \varepsilon_i^k\right) = \int_{t_i^k - \eta_i^k}^{t_j^k - \eta_j^k} v^k(t')dt'. \tag{17}$$

which generalizes (1). We anticipate that adjusting the model along the lines of (16) will allow us to derive additional gait parameters from the current and future data.

VI. Conclusion

In this paper we have proposed a new system for continuous in home assessment of walking speed based on PIR sensors and a wireless network for data collection. We have shown that this method is both accurate and precise when compared to the standard of the GAITRite® Walkway System gait mat. This method allows the convenient in home collection of a large number of walking events otherwise gathered infrequently in a clinical setting. Since walking speed has been shown to be an indicator or predictor of many diseases and other health issues such as cognitive decline and hospitalization, we feel that the continuous monitoring of this measure and its applications is an important and useful area of future research.

Acknowledgments

The authors would like to thank the volunteer subjects who participated in this research and the staff from the Oregon Center for Aging & Technology who assisted in this study.

This work was supported in part by the National Institute of Health and the National Institute on Aging under Grants R01AG024059, P30 AG024978, and P30AG008017. This work was also partially funded by Intel Corporation.

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Fig. 1.
A motion sensor line for measuring walking speed where the four sensors are placed 0.61 m apart and are installed on a ceiling typically 2.54 m high.

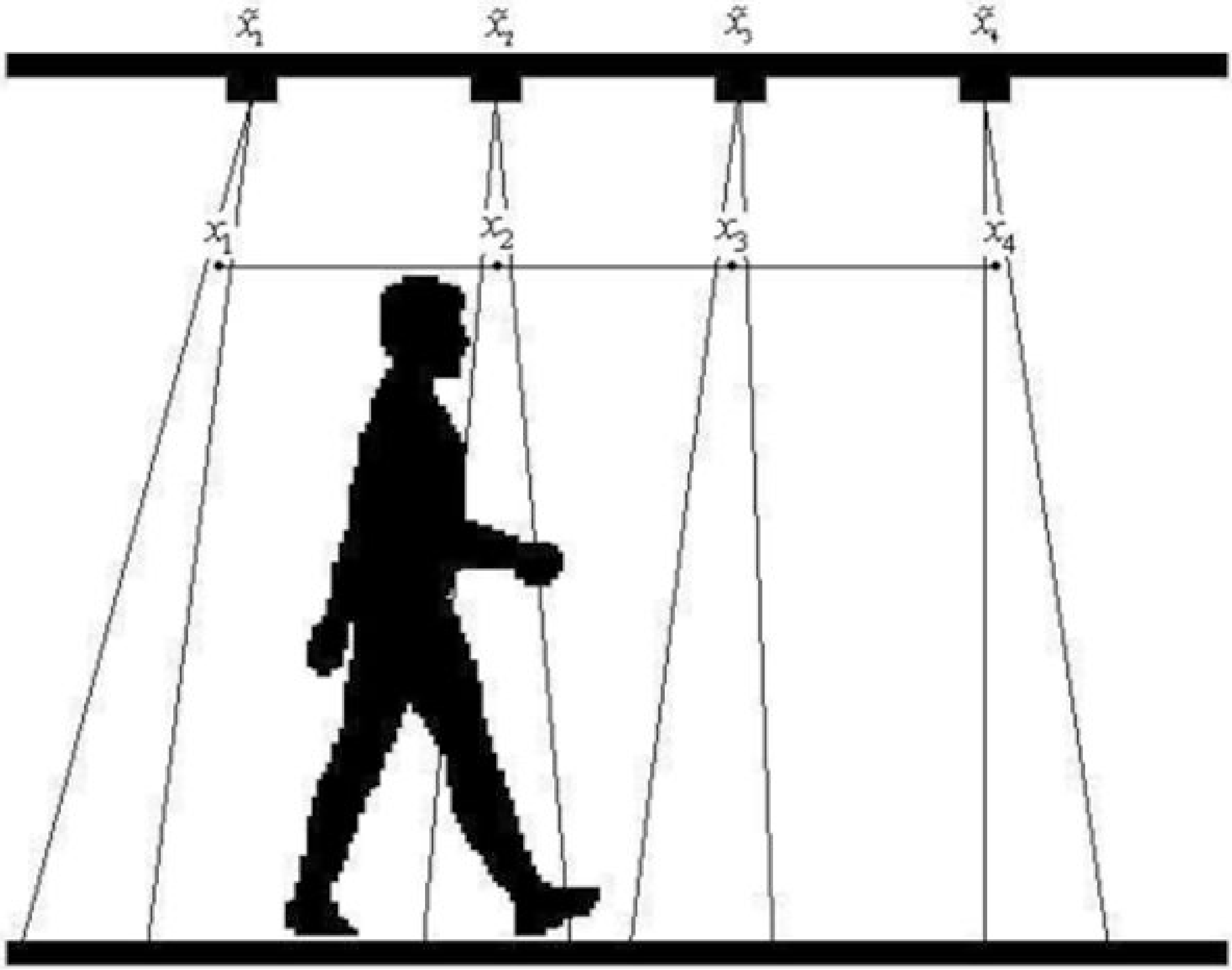

Fig. 2.
Schematic of a person walking through a sensor line containing four sensors with the fields of view and the locations of the $\tilde{x}_i$ and x_i shown.

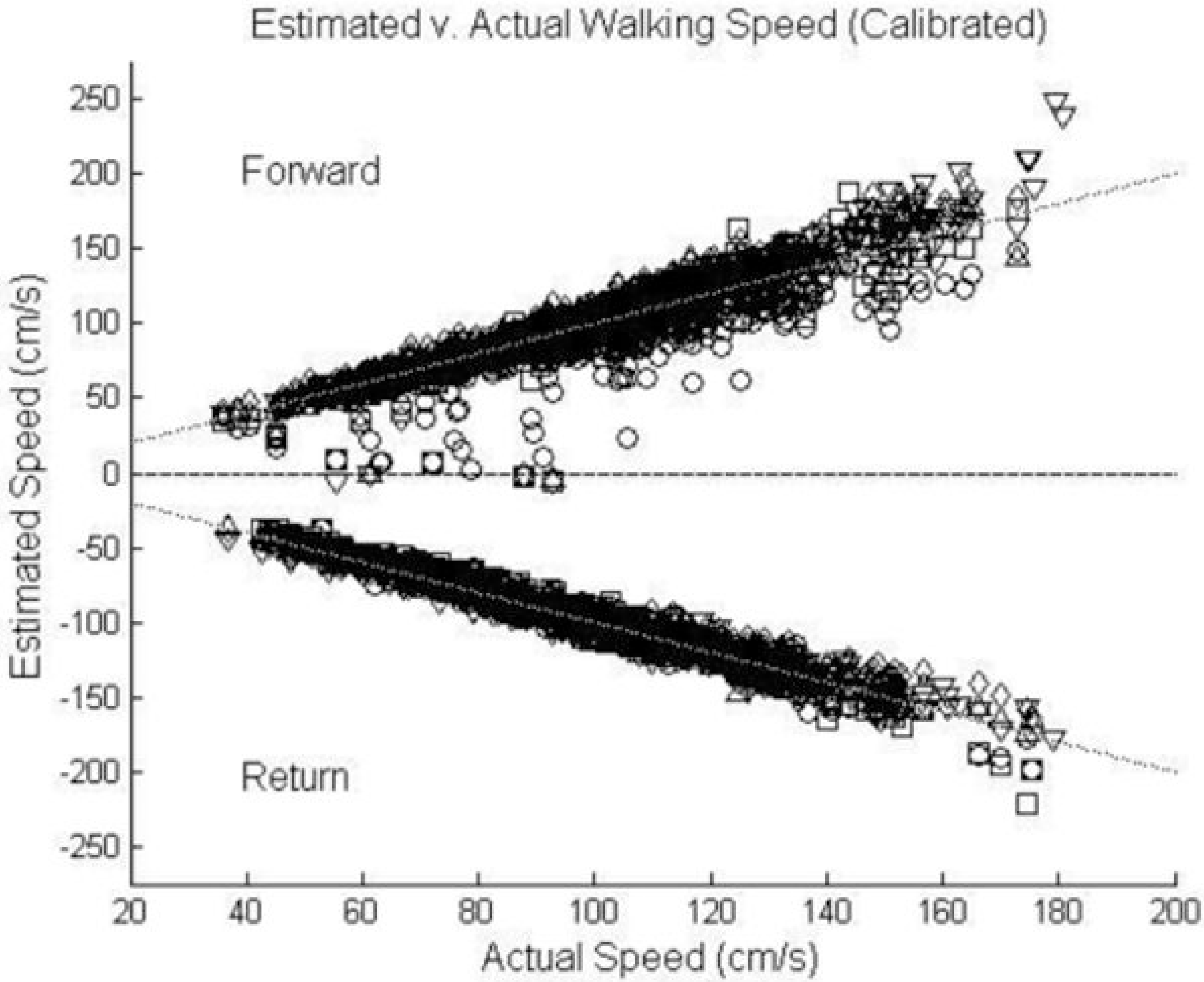

Fig. 3.

Combined walking speed data for all subjects for the 5 sensor lines of 4 sensors (the various shapes indicate data from different sensor lines), using a calibration factor calibrated to the walking speed measured by the gait mat. The sign of the estimated speed differentiates “forward” walks (positive values) versus “return” walks (negative values).

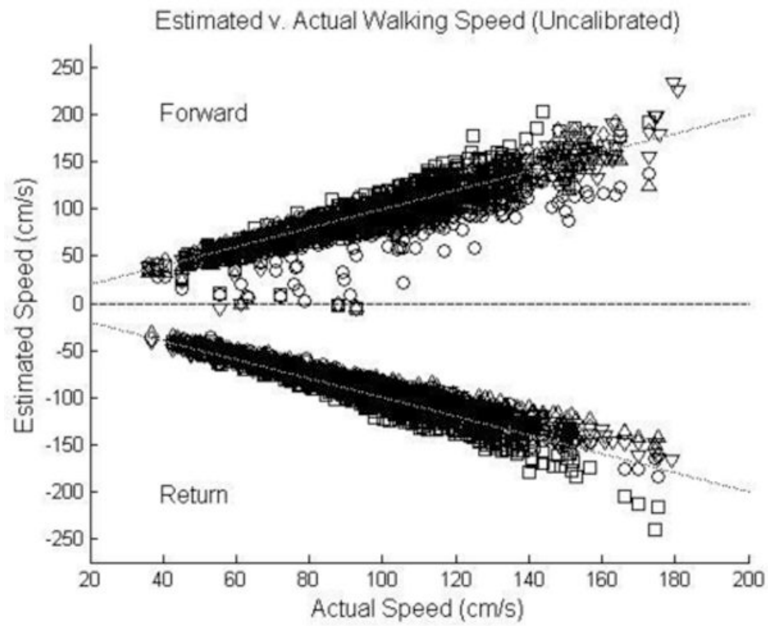

Fig. 4.
Combined walking speed data for all subjects for the 5 sensor lines of 4 sensors (the various shapes indicate data from different sensor lines), using estimated calibration factors. The sign of the estimated speed differentiates “forward” walks (positive values) versus “return” walks (negative values).

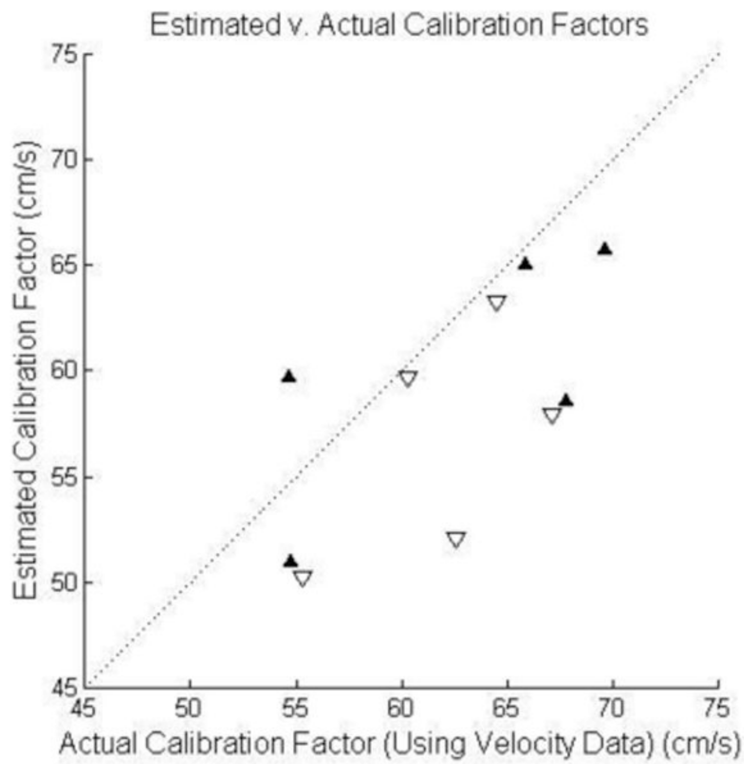

Fig. 5.

Combined calibration factor data (*c* value) for the 10 possible sensor lines (5 "forward" and 5 "return"). The direction the triangle is pointing indicates whether the direction is "forward" (up) or "return" (down).