31st Annual International Conference of the IEEE EMBS
Minneapolis, Minnesota, USA, September 2-6, 2009

Unobtrusive assessment of walking speed in the home using inexpensive PIR sensors

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Abstract—**Walking speed and activity are important measures of functional ability in the elderly. Our earlier studies have suggested that continuous monitoring may allow us to detect changes in walking speed that are also predictive of cognitive changes. We evaluated the use of passive infrared (PIR) sensors for measuring walking speed in the home on an ongoing basis. In comparisons with gait mat estimates (ground truth) and the results of a timed walk test (the clinical gold standard) in 18 subjects, we found that the clinical measure overestimated typical walking speed, and the PIR sensor estimations of walking speed were highly correlated to actual gait speed. Examination of in-home walking patterns from more than 100,000 walking speed samples for these subjects suggested that we can accurately assess walking speed in the home. We discuss the potential of this approach for continuous assessment.**

I. Introduction

Mobility and activity are important measures of functional ability in the elderly [1]. However, it is becoming increasingly evident that mobility measures may also be important independent predictors of the later onset of dementia. This has been shown both generally as overall slowing (bradykinesia) or loss of trunk and lower extremity automaticity ("parkinsonism" or gait disturbance) measured by clinical signs on motor rating scales [2] and more specifically related to gait speed or timed walking [3, 4].

Unfortunately, standard tests of cognition and physical slowing are typically administered only when an elder has become significantly impaired [5], essentially precluding early detection of change, and hence precluding restorative or preventive intervention. Furthermore, clinic-based assessment of function at periodic intervals may not provide an accurate picture of an elder's true function, since individuals have "good days" and "bad days". A promising new approach to early detection of cognitive decline in the elderly is to use unobtrusive technology to do continuous assessment of activities that may be predictive of the onset of cognitive changes.

A number of researchers have begun to investigate methods of remotely monitoring the activity of people in their homes for extended periods of time [6-8]. For example, in a study conducted in the homes of 8 elderly people monitored for 2-20 months, a single pyroelectric motion detector in each room was used to map typical patterns of activity [8]. Recently, we found that variability in walking speed was significantly greater in a group of elderly subjects with Mild Cognitive Impairment, as compared to healthy elders [9]. In that study, we measured walking speed in the home over a six-month period on a continuous basis, using restricted-field pyroelectric infrared motion sensors (PIR sensors). The results of that study suggested that continuous assessment of walking speed in the home may have the capacity to capture changes that are indicative of early cognitive decline, and we are currently conducting a large-scale longitudinal study of 237 community-dwelling seniors to test that hypothesis [10].

This Oregon Center for Aging and Technology (ORCATECH) study is focused on the use of intelligent in-home technologies for detecting early cognitive decline. We are using unobtrusive, commercially-available sensors (X10 MS16A PIR motion sensors and X10 DS10 contact sensors, X10.com) to collect continuous data about activity in the home. One of the key outcome measures in the study is walking speed. Walking speed is measured by distributing four restricted field motion sensors in a row along the ceiling of a hall or path of frequent traffic in the home. Conceptually, these sensors fire only when somebody walks directly under them, and therefore one can estimate walking speed from the difference in firing times of sensors along the walking line provided an accurate measurement of the distance between the sensors is made. In order to restrict the field of view, IR-opaque tape is placed over the Fresnel lens, leaving a narrow window. These sensors have a field of view of about ±4 degrees, corresponding to ±6.5cm at a distance of 90cm from the sensor. However, the use of the tape reduces the sensitivity of the sensor, so that sometimes the sensors will fail to fire. In addition, the placement of the

This study was funded by NIA grants P30AG024978 P30AG08017, and R01AG024059.

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Some of the computers used in the homes of subjects in this study were paid for by Intel Corporation. Dr. Hayes has a significant financial interest in Intel Corporation, a company that may have a commercial interest in the results of this research and technology. This potential conflict has been reviewed and managed by OHSU.

tape is not precise, and therefore accurate measurement of the location of movement that causes the sensor to fire is not possible. Therefore, it was important for us to evaluate the accuracy with which we can measure walking speed with these sensors.

In this study we compared walking speed as measured using PIR sensors to ground truth measures taken using the commercially available GAITRite® Walkway System gait mat. These results were then compared with walking speed as measured using the clinical gold standard test of a 10 meter timed walk, and with in-home walking speeds measured using PIR sensors on an ongoing basis.

II. Methods

A. *Data Collection for technology evaluation*

Eighteen subjects, including five with Mild Cognitive Impairment, participated in the experiment; all subjects provided informed consent. A single walking line was set up in a conference room at the facility in which the participants live. A GAITRite® Walkway System gait mat was placed on the floor along the walking line, and six restricted-field IR sensors were placed on the ceiling at a height of 2.6m at two foot (.61m) intervals. Subjects were instructed to walk at their normal walking speed, at a fast walking speed, or at a slow walking speed. Subjects walked along the walking line fifteen times at each speed. 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. PIR sensor data during the walking speed test was lost for five subjects due to operator error; therefore, the calibration of the walking speed described below excluded the data from those subjects. However, we did compare their gait mat results and in-home results.

B. *Derivation of walking speed from IR sensor data*

The motion sensors used in this study are maximally sensitive to movement across their field of view. If the motion sensors were placed precisely and the sensor firing response were always the same, one could use the times between sensors to directly calculate walking speed. By mounting them on the ceiling, we avoid the problem of the angle of approach to the sensor itself. However, the sensors have variability in their response to heat change, and the restriction of the Fresnel lens to a narrow field of view is imprecise. Therefore, the precise position at which movement triggers the sensor cannot be measured. Instead, we have developed a method for estimating the distance between the sensors; these distances can then be used to calculate walking speed along the sensor line.

Let the physical location of sensor i be $\tilde{x}_i$. Due to variability in the restriction of the field of view of the sensor, assume that the actual location at which an ideal sensor would be triggered is x_i, where the difference $\tilde{x}_i - x_i$ varies with the sensor and the direction of movement. We model the actual response of the sensor to movement as a random variable $\{e_i\}$ with zero expected value, such that the location of movement which triggers the sensor is at random locations $\{x_i + e_i\}$. Thus, for a person moving at constant velocity v_k during any particular walk k between two sensors, their velocity v_k can be calculated as:

$$v_k = \frac{\left(x_j + e_j^k\right) - \left(x_i + e_i^k\right)}{\left(t_j^k - t_i^k\right)} = \frac{\left(x_j - x_i\right) + \left(e_j^k - e_i^k\right)}{\left(t_j^k - t_i^k\right)},$$

where t_i^k and t_i^k are the firing times of sensors i and j respectively, and the equation holds for any pair of sensors in the firing line. If their velocity is constant during any given walk through the sensor line, then for three sensors (*i, j, k)* we have

$$\frac{\left(x_i - x_h\right) + \left(e_i^k - e_h^k\right)}{\left(t_i^k - t_h^k\right)} = \frac{\left(x_j - x_i\right) + \left(e_j^k - e_i^k\right)}{\left(t_j^k - t_i^k\right)} \quad (1)$$

for all walks k. Since $\{e_i\}$ and $\{t_j\}$ are independent random events for $i \neq j$,

$$E\left\{t_j^k e_i^k\right\} = E\left\{t_j^k\right\} E\left\{e_i^k\right\} = 0.$$

Rewriting equation (1) and taking the expectation value of both sides we get

$$\left(x_i - x_h\right) E\left\{t_j^k - t_i^k\right\} = \left(x_j - x_i\right) E\left\{t_i^k - t_h^k\right\}.$$

Thus, for a large number of walks along the sensor line, the mean difference in firing times of the sensors provides a scaled estimate of the distance between the sensors,

$$\Delta x_{ij} = c \sum_{k=1}^{K} \Delta t_{ij}^k. \quad (2)$$

This estimate can then be used to calculate the walking speed v_k through the sensor line on any given run k. The scaling constant c must be determined through calibration. For our technology evaluation experiments, the gait mat provided the ground truth measures of velocity to calibrate the sensor line used in that experiment.

C. *Collection of in-home walking speed estimates*

The 18 subjects who participated in the technology evaluation experiment are enrolled in the longitudinal study, and therefore walking speed along a sensor line is collected on an ongoing basis in their homes. A four PIR-sensor walking line was placed along a hall or commonly used path in each home, and the physical distance between the sensors was recorded. Sensor firings were sent to a wireless receiver connected to a computer in the home, where they were time-stamped and then uploaded daily to the research database.

Unlike during the technology evaluation, we do not have a ground truth measure of walking speed for each traversal of the walking line in the homes. Therefore, our estimates of walking speed between each pair of sensors are based on the physical locations of the sensors $\{\tilde{x}_i\}$.

If the distances between the physical locations $(\tilde{x}_j - \tilde{x}_i)$ were accurate measures of the actual triggering locations $(x_j - x_i)$, then this value could be used to determine the precise walking speed between the sensors based on the firing times. We can adjust our estimates of physical location using equation (2), which provides a scaled estimate of the triggering distances. For a 4-sensor line at physical locations $(\tilde{x}_1, \tilde{x}_2, \tilde{x}_3, \tilde{x}_4)$ we will have twelve pair-wise estimates of the relative distances Δx_{ij} using equation (2) – two for each direction, for each unique pair of sensors. The longest of these, Δx_{14} and Δx_{41}, can be used to provide a nominal scaling factor using

$$\frac{2(\tilde{x}_4 - \tilde{x}_1)}{\Delta x_{14} + \Delta x_{41}} = \tilde{c}.$$

Then, to estimate walking speed through any particular segment we use $\tilde{c}\Delta x_{ij}$ as the distance estimate:

$$\tilde{v}_{ij}^k = \frac{\tilde{c}\Delta x_{ij}}{(t_j^k - t_i^k)}$$

For each home, we calculated the median walking speed, variance in walking speeds, and range of walking speeds in the home for the three month interval immediately preceding the gait mat experiments. We also report the clinical timed walk score for each subject, taken at their enrollment into the study.

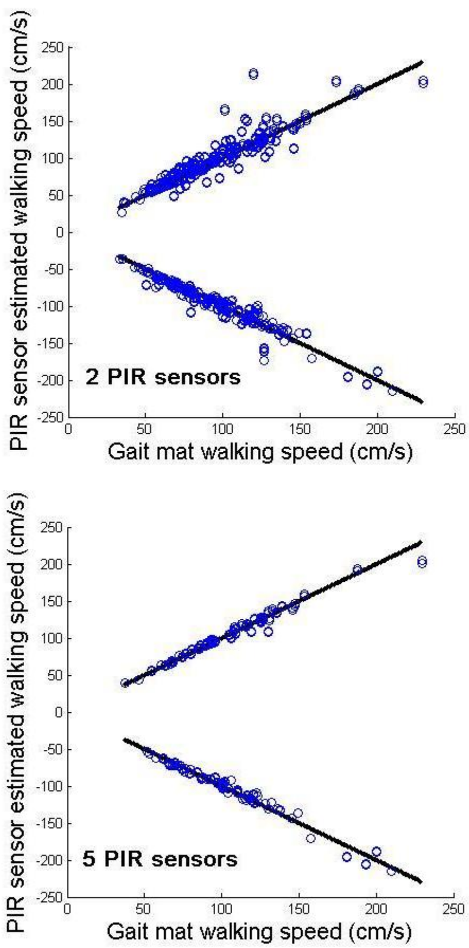

Figure 1. Plot of true walking speed as measured using a gait mat (abscissa) and estimated walking speed from PIR sensors (ordinate). The PIR walking speed is plotted as positive values for movement through the sensor line in one direction, and negative values for movement in the other direction, to allow both to appear on the same plot. The top plot shows all walks through the sensor line in which at least 2sensors fired; the bottom plot shows those walks in which at least 5 sensors fired.

III. Results

A. *Results of gait mat experiments*

Figure 1 shows the comparison between the walking speed as measured by the gait mat and that measured using the motion sensors. The plots show the speed measured using the gait mat (abscissa) against the walking speed estimated using the calibrated scaling constant. We examined the walking speed estimate for cases when two, three, four, or five sensors fired during the run. Although there were fewer instances where all sensors fired, the best results were obtained when all sensors in the line fired. The

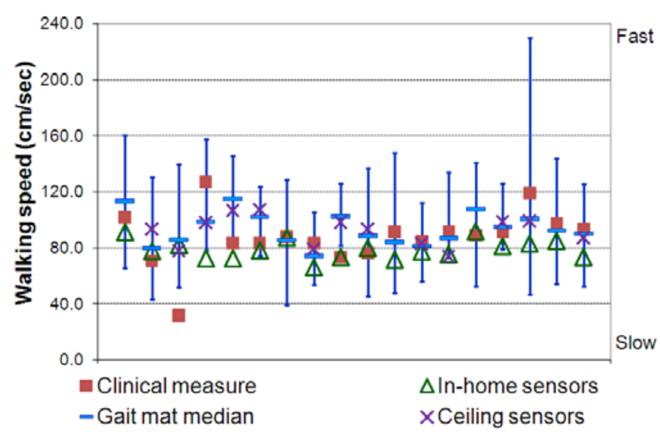

Figure 2. Comparison of gait mat walking speeds, clinical timed walk measures, and in-home walking speeds for all subjects. The blue lines represent the range of speeds for each subject during the gait mat experiment, with the median speed marked by the horizontal line. The X's are the median walking speeds estimated from the ceiling sensors used during the gait mat experiments (13 subjects only). The solid squares are the walking speeds as measured suing the clinical timed walk test, and the triangles are the median walking speed measured over 3 months in the home.

estimated walking speed was highly correlated to the measured walking speed in all cases (2 sensors: r=.93, 3 sensors: r=.96, 4 sensors: r=.97, 5 sensors: r=.99).

B. *Comparison of in-home PIR, clinical, and gait mat measures*

We collected more than 100,000 walking speed samples in three months in the 18 homes, representing from 16 to 204 walking line measures per day on average. The range of speeds observed in the home was more restricted than that during the gait mat experiment. In particular, the mean across subjects of the maximum walking speed during the gait mat experiment was 139.5±26.6 cm/s, versus 99.3±9.2 cm/s in the homes. This is not surprising, since the walking speed in the homes reflects typical daily behavior.

Figure 2 shows the results of the gait mat experiment, clinical timed walk test, and in-home measures for each subject. Interestingly, for most subjects the clinical timed walk was faster than the median walking speed measured during the gait mat experiment, which probably reflects the propensity for subjects to "do their best" when undergoing a clinical assessment. In contrast, the median in-home walking speed was slower than that of the gait mat experiment.

IV. Discussion

This study shows the potential of using simple PIR sensors to measure walking speed in the home. Using the gait mat for calibration, we were able to accurately measure walking speed using PIR sensors, and better results were obtained when more sensors were included in the walking line. The use of the pair-wise distance for our in-home scaling factor provides a slightly biased estimate of walking speed that can be used in the absence of a calibrated scaling factor. We used the longest pair-wise distance because it seems to have the lowest bias since it has the greatest absolute distance.

Clearly, the speed of in-home walks are biased by the participants intention (e.g. rushing to the phone, thinking while walking). However, because we can collect a large number of measures, the variance introduced by these factors would not influence comparisons of walking speeds of an individual over time. For example, a subject who was depressed might show an overall slowing, even if they occasionally speeded up to answer the phone.

The approach does have some limitations. It should be noted that the physical measures for the in-home sensor lines are not precise, and therefore absolute estimates of walking speed in the home would require calibration with a gait mat or other ground truth system. Our method of scaling allows us to use more data, since all pair-wise data can be adjusted based on the scaling factor, but the true scaling factor cannot be determined without calibration. In contrast, comparisons month-to-month or week-to-week within a subject provide accurate measures of change over time. In addition, this approach is only effective if there is a path through the home along which subjects walk on a regular basis. However, because we can use all walking events along the line, even if not all sensors are triggered or the subject does not walk the entire line, we have found that the sensor line does not necessarily need to be located in a hall or restricted path of motion. Finally, in multi-person homes there must be a way of disambiguating which person is walking along the sensor line. We have explored the use of Hidden Semi-Markov Models for this purpose, as well as the use of body-worn identifiers, but we have not found an optimal solution that works in all cases.

In just three month of data collection, we collected an average of 6700 walking speed estimates for each subject. The strength of this approach lies in our ability to collect significant numbers of measurements in a short period of time. This will allow us to track changes due to acute events, as well as trends over time. We are now monitoring more than 200 people, and anticipate that these walking speed data will provide invaluable insights into changes in mobility in community-dwelling elders.

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