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On the Disambiguation of Passively Measured In-home Gait Velocities from Multi-person Smart Homes

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Abstract

In-home monitoring of gait velocity with passive PIR sensors in a smart home has been shown to be an effective method of continuously and unobtrusively measuring this important predictor of cognitive function and mobility. However, passive measurements of velocity are nonspecific with regard to who generated each measurement or walking event. As a result, this method is not suitable for multi-person homes without additional information to aid in the disambiguation of gait velocities. In this paper we propose a method based on Gaussian mixture models (GMMs) combined with infrequent clinical assessments of gait velocity to model in-home walking speeds of two or more residents. Modeling the gait parameters directly allows us to avoid the more difficult problem of assigning each measured velocity individually to the correct resident. We show that if the clinically measured gait velocities of residents are separated by at least 15 cm/s a GMM can be accurately fit to the in-home gait velocity data. We demonstrate the accuracy of this method by showing that the correlation between the means of the GMMs and the clinically measured gait velocities is 0.877 (p value < 0.0001) with bootstrapped 95% confidence intervals of (0.79, 0.94) for 54 measurements of 20 subjects living in multi-person homes. Example applications of using this method to track in-home mean velocities over time are also given.

Keywords

Gait; passive infrared (PIR) motion detectors; smart homes; unobtrusive monitoring; walking speed

1. Introduction

Gait velocity is an important predictor of cognitive function, mobility and age-related adverse outcomes [29], especially in elderly populations [26]. Gait velocity has been shown to slow prior to cognitive decline [6, 35], has been shown to predict dementia [34, 35] and cognitive decline [24], and slows coincident with dementia [3, 33] even at early stages. Gait velocity has also been used by itself [16] and with other measures of lower-extremity function to predict future disability [16, 17, 27]. Further studies have linked gait velocity to cognition [22] and executive function [5, 8].

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Dr. Hayes has a significant financial interest in Intel Corporation, a company that provided funds to purchase some of the computers used in this study. Intel Corporation may have a commercial interest in the results of this research. This potential conflict has been reviewed and managed by OHSU.

Recently, a smart home based method for unobtrusive and continuous measurement of in-home gait velocity based on passive infrared sensors (PIR) was proposed and validated [18] as an effective means of monitoring gait velocity much more frequently than is commonly done in the clinical setting. However, the method as proposed only works well for single resident dwellings or situations where a resident is known to be alone for a majority of the time since the passive nature of the sensors used does not provide information about who is being measured. In order to generalize the utility of this methodology, the problem of disambiguating the collected velocities must be solved.

A number of methods have been proposed to solve this type of problem, mostly under the framework of tracking multiple residents in the smart environment [7]. Recent examples include using wireless network based solutions [13] to track a person's location, pedestrian dead-reckoning [15, 25, 32] systems alone or with fiducials, and using vision based systems [14, 21, 31]. While these methodologies have shown some success, they usually require that subjects wear or carry special devices or tags or allow cameras to be placed in the home. Requiring devices to be worn is problematic – especially for older people – as forgetting to wear a device or to place a device on a charger regularly can cause the system to fail. Additionally, vision based systems tend to be computationally costly and require significant overhead to set up and monitor all locations in the home. Camera based systems also tend to collect potentially more invasive data than passive devices. As a result, these approaches are not currently suitable for unobtrusive in-home monitoring. Other, more promising work has used Naïve Bayes classifiers [9] and hidden Markov models to assign individual sensor events to different residents [10–12, 28]. These approaches have shown success; however, these algorithms require significant amounts of annotated training and/or test data prior to being implemented. In the homes we monitor, acquiring enough annotated data to properly train and/or test these algorithms is both costly, disruptive and invasive (e.g., may require camera visualization) for the subjects. Further, neither approach takes full advantage of the structure inherent in the gait velocity datasets. In this paper we address the problem by using Gaussian mixture models to model the underlying distribution of the gait velocity data into a number of components corresponding to the number of residents in the home. We combine this with infrequent clinical timed walk measurements to assign the GMM components to the correct resident. This is done by preserving the ordering present in the clinical data (i.e., the fastest GMM component is associated with the fastest clinical walker, etc.). This approach exploits the inherent structure present in the gait velocity data set caused by different subject's walking abilities and preferences. It also allows us to replace the difficult problem of assigning individual walking events to the correct resident with the problem of modeling the underlying distribution of gait velocities. The relevant gait parameters can then be estimated directly from the mixed data and tracked longitudinally.

We demonstrate the validity of this method by computing correlation between the mean of the GMM components and the clinical walking speed measurements in data from homes with two residents when the clinical walking speed measurements are separated by at least 15 cm/s. We discuss the remaining sources of variability not accounted for by the linear regression model, discuss some implementation issues employing this methodology as part of a complete monitoring system, and conclude with an application to tracking in-home gait velocities over time followed by a discussion of future work.

2. Methods

In this section we describe the subjects, methods, data, and data analysis used in this work. We start by describing the collection and estimation of in-home walking speed data, follow with a description of Gaussian mixture models and how they were applied to this data, discuss the subject population and the clinically administered timed walk, and end the

section by discussing the methods of data analysis employed to validate the GMM based approach.

2.1. In-home Gait Velocities

A thorough description of the in-home data collection and estimation of gait velocities is described elsewhere [18]; here we give a brief description of the main components. A sensor line consists of a linear array of four passive infrared motion sensors (MS16A, ×10.com) with restricted field of view (± 4 degrees). This set of sensors is installed on the ceiling of a residence with approximately 61cm between each sensor pair in a confined area such as a hallway or other corridor. This arrangement is used to prevent the sensor from firing unless a resident is passing directly below the sensors and causes a subject to walk linearly through the sensor line. When a subject passes through the sensor line, a sequence of individual sensor identifiers is transmitted wirelessly to a WGL 800 wireless transceiver connected to a computer in the residence that timestamps the data. These data are then stored locally and are also transmitted securely over the Internet to a database where they can be accessed for analysis. Prior to estimating velocities, we exclude sensor line data if the sensor line sensors do not fire sequentially and if the differences in time between adjacent sensor line sensors normalized by the physical difference between them do not match within the expected tolerance of noise in the sensors. These two criteria are in place to prevent estimation of gait velocity in situations where the subject is not walking at an approximately constant velocity, as is the case if the subject stops in the middle of the sensor line and then continue through or does not pass through the entire sensor line. For each set of sensor line sensor firings, total least-squares is used to make an estimate of the velocity. The final result is a set of estimated velocities and time of walk for each home.

2.2. Gaussian Mixture Models and Gait Velocity

Mixture models are commonly employed models for the underlying distribution of a data set that is known or assumed to consist of data drawn from more than one distribution. A subclass of these models, Gaussian mixture models, (GMM) involves the additional assumption that the data are generated by more than one Gaussian distribution. In other words, the underlying distribution of the data is assumed to have the form

$$f_X = \sum_{k=1}^K \alpha_k N(\mu_k, \sigma_k^2) \quad (1)$$

where $N(\mu, \sigma^2)$ is the normal distribution with mean μ and variance σ^2 , and the mixture

parameters α_k satisfy the constraints $\alpha_k \geq 0$ and $\sum_{k=1}^K \alpha_k = 1$. These constraints ensure that the mixture is itself a probability distribution. In the case of two people in the same house, $K=2$.

The parameters, $\{\alpha_k, \mu_k, \sigma_k^2\}_{k=1}^K$, for a GMM are typically estimated from a data set using the expectation-maximization (EM) algorithm which is well understood and described in many places, for example [4].

With the in-home gait velocities, a mixture model is a natural choice since the collected velocity data is known to be generated from more than one source. Under the assumption that there is an underlying distribution of possible velocities each resident can walk and if data is excluded when other people are in the home (e.g., visitors), then each gait velocity measurement can be assumed to come from one of the residents. As a result, the data can be modeled as being drawn independently and identically distributed from the underlying

mixture distribution with fixed parameters on a short time scale (the size of the data window used to fit the model) and variable model parameters on a longer time scale (i.e., the parameter estimates can change over time).

Although the distribution of the gait velocity should theoretically be defined only on the positive real numbers, e.g., such as the gamma distribution, our initial analysis suggested that a Gaussian distribution provided a better approximation to the data. We hypothesize that this was due to the significantly higher statistical efficiency in parameter estimation for the Gaussian distribution as well as due to the procedure for removing outliers described below.

Once the GMM was selected as a viable model for these data, all gait velocities from each home (inclusionary criteria of subjects are discussed below) within ± 1 month of each clinical timed walk assessment was collected. Sets of gait velocities for each direction through the line were used as separate estimators of gait velocity and were treated separately as described in [18]. Before fitting the model, outliers were identified and removed from each data set as data that fell outside of the range ($Q1 - 1.5IQR$, $Q3 + 1.5IQR$) where $Q1$ and $Q3$ are the first and third quartiles, respectively and IQR is the inter-quartile range. Each of the resulting data sets was then fit with a GMM if at least 20 walks were available during the interval of interest. The number of required walks was set as the minimum number of data points needed to obtain a reasonable estimate of the underlying distribution. Each mixture component was then assigned to a corresponding subject in the home by assigning the component that preserved the ordering present in the clinical data (i.e., the fastest GMM component is associated with the fastest clinical walker, etc.).

2.3. Subjects and Clinically Assessed Timed Walk

Subjects were selected from a subset of the Intelligent Systems for Assessing Aging Changes (ISAAC) cohort (described in more detail elsewhere [23]) composed of fifty-four residents living in 27 multi-person homes where all subjects in the home are tracked clinically. This subject population had a mean age of 81.9 years at baseline enrollment ($SD = 5.13$, range = 66.8 – 90.4), and 28 were female. The age at each clinical assessment of walking speed varied across the dataset used in the study, since these subjects have been tracked longitudinally for up to three years. Where yearly follow-up assessments were available for subjects, they were used in this analysis. For our initial analysis, we included only those subjects where the clinically measured difference in gait velocity was at least 15 cm/s. Histograms and kernel density estimates of gait velocity distributions where the clinical speeds are less than 15 cm/s frequently appear unimodal and are thus not generally suitable to be modeled by a GMM. Additionally, this separation helps prevent confusion in assigning the GMM components to the correct subjects (i.e., the fastest GMM component is associated with the fastest clinical walker, etc.). This is because there would need to be a relatively large change in all subjects' in-home speeds with respect to the clinical speeds in order to overcome this 15 cm/s difference and be associated with the wrong component. We also excluded subjects where the smallest of the mixture parameters in the GMM was less than 0.08 (meaning that that subject accounted for less than 8% of the model), and those cases without data to estimate the model parameters. This resulted in a total of 20 subjects (43% of the initial subject pool) all living in two person residences and 54 in-home mean/clinical speed data pairs. These 20 subjects had mean age of 81.8 ($SD=3.6$, range = 75.5 – 88.8); 10 were female.

The timed walk is a 15-foot out and back walk timed by a trained clinician where the clinically tracked parameters include the time-to-walk (i.e., complete the entire 30 ft path), number of steps, and steps per second. The subjects are told to walk at their normal pace. This test is administered as part of a motor systems assessment that also includes the finger tapping test, timed standing on one leg, timed chair stands, and grip strength. This test was

administered at the baseline visit and during yearly follow-up visits. In order to facilitate comparison of the results of the timed walk to our in-home gait velocities, we converted the timed walk to the average velocity over the 30 ft. interval, neglecting the time it took the resident to turn around as this time was not measured clinically.

2.4. Data Analysis

In order to investigate and validate the relationship between the modeled GMM mixture components and the associated clinical walking speeds, we fit a linear regression model to the data using the GMM mean values as predictors of the timed walk velocity. We also calculated the correlation coefficient of the regression model and tested the hypothesis that the correlation was positive against the null hypothesis that the correlation was not positive (one sided t-test). By examining the distribution of the residual errors from the regression model, we were also able to identify additional sources of variability not explained by the linear model. Finally, we analyzed the results of using GMMs longitudinally by using GMMs periodically (every 4 months) over the course of the entire in home monitoring period and comparing the estimated GMM mean components with available clinical measurements.

3. Results

The regression model using the GMM means to predict clinically assessed gait velocities is shown in fig. 1. The correlation was found to be 0.877 (p value < 0.0001) with bootstrapped 95% confidence intervals of (0.79, 0.94). The linear function from the in-home modeled means to the clinically measured velocities was $\hat{v}_{Clinical} = 1.08v_{GMM} + 11.4$. Example fits of GMMs compared to histogram representations of the data are shown in figs. 2 and 3. The number of bins used for the histogram was the largest integer less than the square root of the number of data points. Fig. 4 shows the results of a linear regression when the data is not restricted to come from subjects with at least 15 cm/s separation in clinical speeds. In this case, the correlation coefficient is 0.54 (p value < 0.0001) with bootstrapped 95% confidence intervals of (0.40, 0.66). The best fit line is $\hat{v}_{Clinical} = 0.6v_{GMM} + 44.5$. Figs. 5 and 6 show the results of fitting a GMM with two components to data where the clinically measured speeds are not separated by at least 15 cm/s.

As an application of the proposed approach to modeling walking speeds in multi-person residences, we also used GMMs to estimate the in-home mean velocities of two different homes with two subjects per home at four month intervals chosen to coincide with clinically assessed gait velocities. These results are shown in figs. 7 and 8 where the in-home GMM mean velocity estimates have been adjusted according to the regression line discussed earlier. Additionally, linear interpolation has been used to give a coarse continuous estimate of mean velocity over the considered interval. Some slowing was seen for all subjects.

4. Discussion

The high correlation of 0.877 between the in-home GMM estimated mean velocities and clinically assessed velocities demonstrates the effectiveness of this method. Also, figs. 2 and 3 visually show the closeness of fits between the peaks of the component densities in a GMM and the clinically assessed speeds. Nominally, this method accounts for 77% of the variability present in the data with 95% bootstrap confidence intervals of (62%, 88%). The residual variability not explained by the linear fit had mean 0 and SD = 15.1 cm/s. We believe that there are two main sources of variability comprising these residuals (ignoring both the small error associated with fitting the GMM and the error associated with using a stopwatch to measure the timed walk) –measurement variability due to the sensor line and variability between subjects' preferred in-home velocity and clinically assessed velocity. In

a description of the PIR based sensor line used here [18], it was shown that the variability of the uncalibrated sensor line has a standard deviation of 11.3 cm/s. This source of error seems to account for most of the residual variability. Further, the difference between a person's clinically measured speed and in-home preferred speed introduces additional error. This can be caused by inter-rater variability, fatigue levels of the subject at the time of the test, and a subject's response to the instructions (i.e., being coached to walk at a "normal" speed). The remaining variability not explained by these two sources of error is something that may itself have clinically useful information and is currently not well understood.

The necessity of having at least a 15 cm/s separation between the clinically assessed walking speeds was presented and discussed briefly above. In an effort to better demonstrate the need for this requirement and to show a shortfall of this approach as a general solution to the problem, we demonstrate what happens when this requirement is not fulfilled. Figure 4 shows the regression line and spread of the in-home/clinical data pairs when this requirement is not enforced. The correlation drops from 0.877 to 0.54 and the explained variability drops from 77% to 29%. Additionally, the regression line changes to $\hat{v}_{Clinical} = 0.6v_{GMM} + 44.5$, demonstrating the larger contribution of a constant term and the smaller contribution of the estimated velocities as the best predictor of clinically assessed velocities. When we use the proposed methodology only on subjects with speed differences which violate the 15 cm/s assumption the correlation drops to 0.073 showing that there is almost no linear relationship between the clinical and in-home walking speeds in these subjects. This is partially due to the assignment of the fastest clinical walker to the fastest in-home component no longer being justified and partially due to model errors discussed below. This demonstrates that violating the 15cm/s difference in clinical speed threshold significantly degrades algorithm performance and makes the proposed methodology insufficient for estimating component walking speeds.

The main problem is that when a GMM is used with two components it will fit two components to the data regardless of whether this is a reasonable model. As can be seen in figs. 5 and 6, a single Gaussian may fit these unimodal data better than a mixture. In these cases a single Gaussian is a more appropriate model, but this model would not help us separate the gait velocities of the two subjects generating the data. When a two component GMM is fit to unimodal data such as those shown in figs. 5 and 6, one component tends to model much of the data while the remaining component ends up modeling a seemingly spurious component that likely does not reflect a mode associated with walking. Thus fitting an incorrect model to the data is primarily what reduces the correlation between the clinical data and the in-home data as shown in fig. 4. We do note that in certain situations (for example, low variance in both component distributions) a two component GMM can successfully fit the data. However, since the model cannot be applied automatically to all the data we use the threshold of 15 cm/s.

To understand why the gait velocity distributions appear unimodal for small separations in clinical walking speed requires a closer look at the errors in the data described above. As mentioned there is some difference between a person's clinically measured and in-home walking speeds. However, this effect is much smaller than the variability in sensor line velocity estimates. Specifically, the large variance in the in-home gait velocity system estimates significantly reduces the ability to resolve peaks in component gaits that are too close together. The effect of the large sensor noise is to smear the two component distributions into a seemingly unimodal distribution which is not well modeled by a multiple component GMM. This effect could be mitigated by more precise sensors deployed in the sensor line at the cost of a more expensive in-home monitoring system. With more accurate sensors, the threshold of 15 cm/s could presumably be reduced to a threshold associated only with the difference between clinically measured and in-home preferred velocities.

Another source of error that must be taken in to account for the proposed methodology is any error that may occur in the sensor line sensors over time. In our implementation, we used sensors off-the-shelf with no sensor calibration in our sensor lines. Because of this, we identified the battery level as the most likely candidate for sensor error as a lower battery level would presumably reduce the sensitivity of the associated sensor. In order to determine whether the battery level had any effect on the walking speed distributions, we analyzed gait velocity data from the two weeks prior to a battery change (after the sensors had been in-home one year on average) and compared this to the data from the two-weeks following a battery change in five homes where the batteries were changed in all four sensor line sensors. We used the Kolmogorov-Smirnov test at the 5% level to compare these data and found insufficient evidence to support a difference in the before and after battery change distributions. However, we do note that if there was an unexpected change in sensor performance for any reason, the velocity of all residents in a given home would be affected in the same way. This is because the sensor line for a given home is used by all residents of that home. For this reason we do not believe that issues with the sensor line will affect the quality of the result from the GMM algorithm although it may affect the quality of the estimated gait velocities.

Another factor that gives insight into the relationship between the in-home data and the clinically assessed data is the regression line, $\hat{v}_{Clinical} = 1.08v_{GMM} + 11.4$. This line shows that in the clinical setting, a subject will walk faster on average than in the home. Also, due to the small offset value, the clinical speeds are almost directly proportional to their preferred in-home speed, especially for faster walkers.

In the clinical literature, time-to-walk is sometimes reported instead of velocity. To give some comparison between the 15 cm/s velocity restriction and a corresponding restriction in time-to-walk 30 ft, we give values for a nominal time-to-walk. Average values of an elderly population time-to-walk 30 ft are between 13–16 seconds. Assuming a time-to-walk of 13 seconds (velocity of 70 cm/s) for a typical subject, the constraint for a faster walker to be separated by 15 cm/s would correspond to a time-to-walk of about 10.7 seconds, and the constraint would be a difference of 2.3 seconds. Considering the constraint for a slower walker, the fastest resolvable time would be 16.6 seconds (55 cm/s) corresponding to a difference of 3.6 seconds.

This approach enables tracking of trends and declines in function over time. In the two homes that we examined for trends over time, the separation of speeds between subjects is clearly maintained in the in-home estimates. Further, the general trends in clinical speeds seem to be maintained in the in-home GMM based mean estimates, although the clinical estimates do not match up exactly (due to un-modeled errors described above). As our subjects continue to be monitored in-home, we will collect more longitudinal data and be able to validate more fully the efficacy of this approach. We also note that the variance, mixture parameters, and other statistics of the estimated distributions can also be tracked and may have predictive power.

As a final thought, we discuss the use of clinically assessed gait velocities in our approach to disambiguating walking speeds. While the clinical data was used to validate the proposed approach, in the implementation of the approach it was only used to assign the estimated components to the correct person by preserving the ordering of the clinical speeds. Since clinical data may not be available in all commercial and possibly research applications of in-home monitoring, we suggest as an alternative that a timed walk similar to that described above may be performed by a non-clinician. We believe this is an effective alternative to the absence of clinical data since the absolute value of the measurement is not important but

only the relative ordering. As long as errors in administration by a non-expert are systematic, the proposed method should still be applicable.

5. Implementation of the Proposed Methodology as Part of a Smart Home across the Community

In this section we discuss how passive monitoring of walking speed in general and the proposed algorithm fit into a smart home framework for monitoring behavioral patterns of elderly to facilitate aging-in-place. We also discuss the complexity of implementing both the proposed algorithm and the algorithm for estimating walking speeds as well as practical aspects of implementation.

5.1. Passive Sensors in Smart Homes

Many groups have employed PIR sensors in smart environments either alone or with other sensors to instrument the environment passively in order to monitor behavioral patterns attempting to infer activities or behaviors (for example, [2, 19, 30]). In the Intelligent Systems for Assessing Aging Changes (ISAAC) study [23], we have deployed an average of 11 PIR motion sensors per home (in addition to between 1–3 contact sensors monitoring doors and refrigerators) as part of an in-home monitoring network designed to detect functional and cognitive decline early and to support aging-in-place for elders. We currently monitor this sensor data in the homes of 225 older people living in the Portland (OR, USA) metropolitan area. We have had our technology installed in 214 homes most of which are still being monitored. Our sensor network has been installed for up to four years in each home. In each of these homes four of the PIR sensors are restricted field-of-view sensors as described above and are dedicated to the sensor line to measure gait velocity. This allows us to track gait longitudinally in addition to more general activity patterns.

5.2. Real-Time Algorithm Implementation

Our current analysis has focused on post-processing of sensor data that has been transmitted securely over the internet from each of the homes and stored in a database. We have relied heavily on Matlab to access the database and implement our algorithms. However, the algorithms are computationally simple to implement and could readily be coded into a module that operates on the same PC that collects the data in a subject's residence. For example, the total-least-squares algorithm that estimates walking speed for each set of four sequential walking line sensor firings - described in detail in [18] - only requires the singular value decomposition of a 3×2 matrix. If velocities are also estimated when only three of four sensors fire this reduces to a decomposition of a 2×2 matrix. Open source code for numerical linear algebra routines to implement these calculations is widely available and stable algorithms are well understood. As such implementing a routine to estimate the gait velocity in real-time is not difficult. From the set of estimated gait velocities, using the EM algorithm to fit a GMM is also not a complicated calculation and can be done easily. Once parameters have been put in place to select the appropriate data (i.e., selecting a window size for the data, etc...) the EM algorithm can be set to automatically run at selected time periods for which the newly estimated parameters can be transmitted to a database for access by a researcher or health-care provider. In our experience monitoring 214 homes, we have found that being able to process the raw data with these algorithms into a useful format for clinicians and other researchers does not pose issues with either time or complexity.

5.3. Gait Velocities as Part of an In-Home Health Monitoring System

As mentioned previously, gait velocity is a very important predictor of general function, adverse outcomes, and cognitive function, especially in the aging population. As such, the

ability to monitor gait on a regular basis has tremendous potential value. The current clinical paradigm is to measure gait infrequently and in a clinical setting thus making the measurements costly to obtain as well as introducing difficulties for elders who may also have trouble traveling to appointments. Due to the infrequent measurements, it is also difficult or impossible to differentiate between abrupt changes in gait function possibly triggered by acute events or trends in velocity that occur more slowly over time. This is a brief overview of the rationale described in [18] for implementing a method to estimate velocity unobtrusively in the home setting. While there has been success in collecting and analyzing in-home gait velocities [1, 19, 20], much work still needs to be done to expand the relationship between these in-home measured velocities and clinically relevant parameters. However, since gait velocity is related to and sensitive to so many functional deficits, we anticipate that measuring changes in gait will be an important part of any in-home monitoring or pervasive computing system that generates alerts to facilitate early health care intervention. Further, the ability to disambiguate the gait velocity measurements will be an important part of extending any in-home monitoring system to work in multi-resident dwellings.

5.4. Scalability

The proposed methodology relies heavily on a separation between gait velocities of multiple residents in the home. In terms of scalability to multi-resident homes, the restrictions become more and more difficult to satisfy for increasing numbers of residents. For example, extending this methodology to three or four person homes should not be problematic, but it would be difficult to find a home with six or more residents that kept a separation of 15cm/s between each resident. For monitoring older people in health care applications this is not too restrictive as most seniors that would benefit from unobtrusive monitoring live in one or two person homes. In the ISAAC study, of the approximately 214 homes that have been or are currently monitored 72 had two residents and only 3 have had more than two people in the home for any length of time. However, this does limit applicability in other situations where measuring gait velocity is desirable.

6. Conclusion and Future Work

In this paper we showed how fitting GMMs to in-home gait velocity data combined with infrequent clinical assessments of velocity can be used to disambiguate in-home walking speeds in multi-person homes. This was done by directly modeling the underlying velocity distribution of each subject. Linear regression and correlation analysis validated this approach by demonstrating a strong linear relationship between the clinical data and the modeled in-home data. We further discussed the sources of variability not captured by the model using this method and provided examples of how this method can be used to estimate and track mean gait velocity in multi-person homes longitudinally. As the clinical assessment data used for this method only provided identification information about which component of the model should be assigned to which resident, we suggested an alternative approach for this step in the absence of this clinical data.

Future work will consist of generalizing the proposed approach or using alternative methods to model in-home speeds when the difference between subjects is less than 15 cm/s. We are also working on separating the variability in subjects' in-home walking speeds from the sensor line sensor noise as gait variability may also be an important predictor of function. This method also needs to be validated in multi-person homes with more than two residents and we are working on clinically tracking walking speed in all subjects in the ISAAC cohort living with more than one additional subject.

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Fig. 1.

Regression line from in-home gait velocities predicting 30 ft. timed-walk velocities (solid line), reference $y=x$ line (dashed line), and raw data points (x's) for subjects where the clinical difference in gait velocity is at least 15 cm/s.

Fig. 2.
Example Gaussian mixture model fit (black line) compared to data histogram (gray bars) with fast (black stem circle) and slow (black stem diamond) clinical velocities superimposed.

Fig. 3. Another example GMM fit (black line) compared to data histogram (gray bars) with fast (black stem circle) and slow (black stem diamond) clinical velocities superimposed.

Fig. 4. Regression line from all in-home gait velocities (i.e., not restricted to a 15 cm/s difference velocity) predicting 30 ft. timed-walk velocities (solid line), reference $y=x$ line (dashed line), and raw data points (x's) for all subjects.

Fig. 5. Example Gaussian mixture model fit (black line) compared to data histogram (gray bars) with fast (black stem circle) and slow (black stem diamond) clinical velocities superimposed for gait velocity data where the clinical speeds are separated by less than 15 cm/s.

Fig. 6. Another example GMM fit (black line) compared to data histogram (gray bars) with fast (black stem circle) and slow (black stem diamond) clinical velocities superimposed for gait velocity data where the clinical speeds are separated by less than 15 cm/s.

Fig. 7. Longitudinal estimates of fast (black line) and slow (black dashed line) in-home gait velocities for two subjects living in the same home. The available clinical measurements of the faster (black diamonds) and slower (black circles) resident are also shown.

Fig. 8.

Longitudinal estimates of fast (black line) and slow (black dashed line) in-home gait velocities for two subjects living in the same home. The available clinical measurements of the faster (black diamonds) and slower (black circles) resident are also shown.