Unobtrusive, Continuous, In-Home Gait Measurement Using the Microsoft Kinect

Erik E. Stone*, *Student Member, IEEE*, and Marjorie Skubic, *Member, IEEE*

***Abstract*—A system for capturing habitual, in-home gait measurements using an environmentally mounted depth camera, the Microsoft Kinect, is presented. Previous work evaluating the use of the Kinect sensor for in-home gait measurement in a lab setting has shown the potential of this approach. In this paper, a single Kinect sensor and computer were deployed in the apartments of older adults in an independent living facility for the purpose of continuous, in-home gait measurement. In addition, a monthly fall risk assessment protocol was conducted for each resident by a clinician, which included traditional tools such as the timed up a go and habitual gait speed tests. A probabilistic methodology for generating automated gait estimates over time for the residents of the apartments from the Kinect data is described, along with results from the apartments as compared to two of the traditionally measured fall risk assessment tools. Potential applications and future work are discussed.**

***Index Terms*—Depth camera, fall risk, gait, Kinect.**

I. Introduction

RESEARCH has shown the importance of measuring a person's gait [1] and that the parameters describing locomotion are indispensible in the diagnosis of frailty and fall risk [2]. Additionally, studies have indicated that changes in certain gait parameters may be predictive of future falls and adverse events in older adults [3]–[6] and may precede cognitive impairment [7]. However, current methods for measuring gait, such as observation by a clinician with a stopwatch or evaluation in a physical performance lab, often lead to sparse, infrequent assessments and may not be representative of a person's true functional ability [8].

Systems capable of measuring gait parameters on a continuous basis during normal daily activity could provide invaluable information for a variety of purposes including automated fall risk assessments, early detection of illness or change in health status, and better assessment of progress during rehabilitation or change in medication. Furthermore, such systems could help facilitate targeted medical interventions in a timelier manner leading to better health outcomes.

A number of technologies exist or are being developed for the purpose of continuous gait monitoring [8]–[17]. These technologies range from wearable accelerometer and gyroscope-based devices to arrays of passive infrared (PIR) motion sensors in the home. Based on responses from older adults [18], an ideal system would be unobtrusive and not inconvenience the person being monitored. As such, an ideal system would likely not require the older adult to wear any device or require the presence or help of a technician or clinician.

Vision-based monitoring systems in the home offer a unique set of characteristics to meet these criteria. First, vision-based sensors offer the precision necessary to measure gait parameters such as stride time and stride length, in addition to more coarse measures such as walking speed, without the need for wearable devices. Second, vision-based sensors are ideally suited for environmental mounting, offering continuous, unobtrusive measurement in the home without inconveniencing the patient being monitored. Finally, research has indicated that privacy concerns of older adults to vision-based monitoring systems can be addressed by use of appropriate privacy preserving processing techniques, such as silhouettes [19].

Recently, Microsoft released the Kinect sensor for the purpose of controller free game play on their Xbox gaming system. The sensor uses a pattern of actively emitted infrared light in combination with a CMOS image sensor and IR-pass filter to obtain a depth image that is generally invariant to ambient lighting. The sensor offers a single, low-cost, vision-based sensor device that allows for a three-dimensional (3-D) representation of the environment. Earlier iterations of the paper presented in this paper have investigated algorithms for measuring gait parameters using the Kinect sensor without the use of skeletal tracking, validating the measurements against a Vicon marker-based motion capture system in a laboratory setting, and extending this approach to capture gait in real-world, dynamic environments, specifically the homes of older adults [15]–[17].

This paper presents a methodology for and results from estimating the gait of older adults continuously, in their homes, using a Microsoft Kinect sensor over a period of seven months. First, a discussion of related work is presented. Second, the basic setup and operation of the system is described. Third, a probabilistic methodology for generating automated gait measurements for the residents of the apartments is detailed. Fourth, data captured in the apartments are presented and compared against

Manuscript received October 18, 2012; revised January 28, 2013 and April 23, 2013; accepted May 23, 2013. Date of publication June 5, 2013; date of current version September 14, 2013. This work was supported in part by the U.S. National Science Foundation under Grant CNS-0931607 and in part by the Agency for Healthcare Research and Quality under Grant R01-HS018477. *Asterisk indicates corresponding author.*

*E. E. Stone is with the Electrical and Computer Engineering Department, Center for Eldercare and Rehabilitation Technology, University of Missouri, Columbia, MO 65211 USA (e-mail: ees6c6@mizzou.edu).

M. Skubic is with the Electrical and Computer Engineering Department, Center for Eldercare and Rehabilitation Technology, University of Missouri, Columbia, MO 65211 USA (e-mail: skubicm@missouri.edu).

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TBME.2013.2266341

a set of traditional fall risk assessment tools. Finally, there is a discussion of the results and future work.

II. Related Work

Wearable accelerometer and gyroscope-based devices for measuring gait parameters as well as traditional tests of physical function, such as the timed up and go (TUG) test, has been an area of much research [12], [13]. In [12], researchers showed that a variety of parameters derived from body-worn kinematic sensors provided significant discrimination between patients with and without a history of falls. Although such devices may be ideal for supervised fall risk assessment, the fact that many older adults are reluctant to use wearable devices because they consider them to be invasive or inconvenient [18], combined with the need to change batteries, etc., may make wearable devices problematic for long-term continuous monitoring.

In [9], researchers developed and validated a method for continuous measurement of in-home walking speed using an array of unobtrusive, environmentally mounted PIR motion sensors. The array of motion sensors is mounted on the ceiling in a hallway, or other natural walking path in the home environment, and allow for the accurate measurement of walking speed when a resident walks along the path. In [8], researchers were able to show that these in-home walking speeds were associated with several neuropsychological and motor performance tests and that they allowed the calculation of previously unattainable metrics of physical function. However, such a PIR-based system does have limitations. For example, in multiresident homes distinguishing between residents can be problematic as the only feature available is walking speed [10]. Furthermore, finely grained measures, such as stride time and stride length, could provide information key to early illness detection as well as automated fall risk assessment.

Much research has also been done in the area of markerless motion capture systems [20], which typically use three or more cameras to construct a three-dimensional model of a person being observed. While such systems have been shown to be quite accurate, the need to position and calibrate multiple sensors, along with the additional required processing power, limits their suitability for low cost, long-term, in-home monitoring.

Recently, researchers have developed several methodologies for examining gait using the Microsoft Kinect sensor. In [21], researchers used the Kinect to characterize the asymmetry of participants' gait while walking on a treadmill, with the goal of using the system as a screening tool in clinical settings rather than in patients' homes. In [22], researchers made use of the Microsoft Kinect SDK and a machine learning framework to generate signals typically seen from wearable gyroscopes. However, due to the limited range of the skeletal tracking built into the Kinect SDK (currently 4 m), such a system would be fairly constrained for monitoring in a home setting.

III. System Overview

In [15], the Microsoft Kinect sensor was evaluated for the purpose of passive, in-home gait measurement in a lab setting. This evaluation consisted of developing algorithms for extracting the gait parameters of walking speed, stride time, and stride length from the Kinect depth imagery and comparing the gait measurements obtained from the Kinect to those from a Vicon marker-based motion capture system. The results of this evaluation showed good agreement, along with good reliability of the measurements from the Kinect. Specifically, the distributions of the percentage error were found to be approximately –4.1 $\pm$ 1.1, 0.0 $\pm$ 2.9, and –2.9 $\pm$ 2.5 for walking speed, stride time, and stride length, respectively.

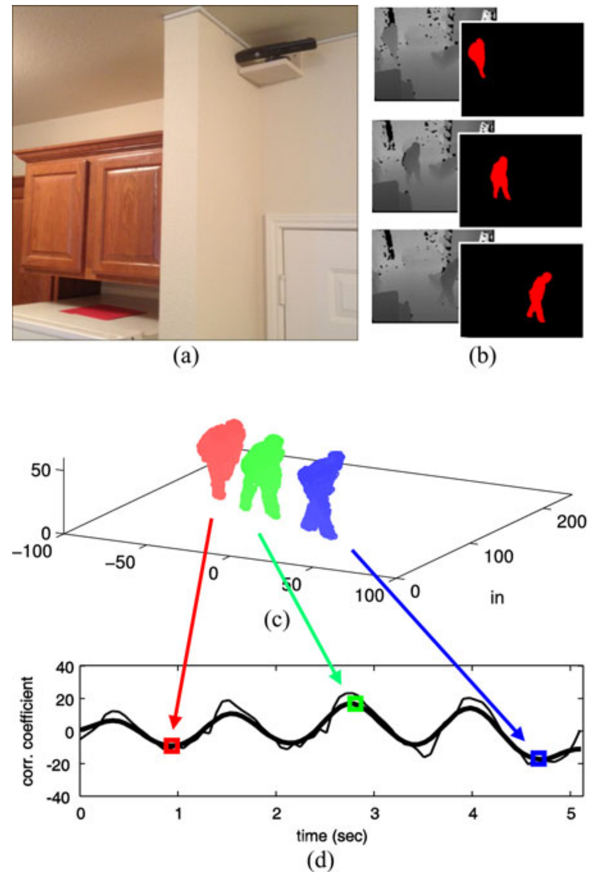

Fig. 1. (a) Kinect and computer (inside cabinet) as deployed in apartments. (b) Example depth images and extracted foreground during a walking sequence in an apartment. (c) Three-dimensional model of person obtained at selected frames using extracted foreground. (d) Plot of correlation coefficient time series of normalized ground plane projections during walking sequence (thin is raw, thick is filtered); used to identify when steps occur. Local maxima correspond to left steps, while local minima correspond to right steps. Algorithm details and parameter definitions can be found in [15].

In this paper, the Kinect sensor and a computer were deployed in the homes of elderly residents at an independent living facility as part of an IRB-monitored human subjects study. Fig. 1 shows the Kinect sensor as mounted in one of the apartments. The Kinect is placed on a small shelf a few inches below the ceiling (height 2.75 m), above the front door. The computer is placed in a cabinet above the refrigerator. This arrangement has proven to be unobtrusive to the residents, with some indicating that they do not notice the equipment after a short period of time.

The Microsoft Kinect SDK and the skeletal tracking it provides, is not used. Instead, the raw disparity values from the Kinect depth stream are processed directly. The main reason for not using the Kinect SDK is the limited range of the skeletal tracking, approximately 1.5–4 m from the Kinect. This range, combined with the positioning of the Kinect, is insufficient to capture walking sequences from beginning to end in many areas of the apartments, whereas the validated approach has been shown to work at distances up to 8 m from the Kinect [15].

A brief description of system operation follows; the reader is referred to [15]–[17] for a more detailed description. First, foreground objects, represented as a set of 3-D points, are identified from each frame using a dynamic background subtraction technique. Next, a tracking algorithm is used to track extracted 3-D objects across multiple frames. Walks are then identified from the path histories of the tracked objects. A set of criteria including path straightness, speed, duration, and distance are used to identify suitable walks from the path histories. This is done online in real time (15 frames per second). Current minimum requirements for a walk are a relatively straight path of at least 1.2 m, with a continuous minimum speed of 12.7 cm/s.

Walking speed is computed for every identified walk as it relies on the movement of the centroid of the 3-D point set representing an object. The height of the individual walking is computed as the average of the maximum value in the vertical direction measured at each frame of the walk. Due to issues such as occlusion of the legs and bad segmentation, stride parameters cannot be extracted for every identified walk. Stride parameters are only extracted for walks for which at least five steps could be identified which met three screening criteria used to eliminate invalid sequences: 1—the steps were extracted in the correct temporal order (left, right, left, right, etc.), 2—the maximum amplitude of the correlation coefficient time series did not exceed 90, and 3—the difference between the maximum and minimum stride times was less than the average stride time. The reader is referred to [15] for a detailed explanation of the algorithms and the definition of the correlation coefficient.

IV. Methodology

The output of the Kinect system is a dataset in which each entry corresponds to a walk identified in the apartment. For this paper, each entry is associated with the following features: height of the person, walking speed, and, if possible, average stride time, and average stride length, in addition to the time the walk occurred. Thus, each walk x_i is initially associated with either two or four features:

$$x_i = \begin{cases} \{h, s\}, & \text{if no stride data} \\ \{h, s, st, sl\}, & \text{else} \end{cases} \quad (1)$$

where h, s, st, and sl are height, walking speed, stride time, and stride length, respectively.

In order to include the information from walks without stride parameters in the computations, which due to furniture placement, etc., may make up the majority of walks in some apartments, stride time and stride length values are estimated for the walks lacking them using the mean of the three nearest neighbors with stride information.

As the systems are deployed in real-world environments, this dataset will include walks from all the residents of the apartment, as well as any visitors. As such, before any gait measurement estimates can be performed, a procedure for identifying walks from the specific resident (s) is necessary.

A. Resident Model Estimation

The current approach makes the assumption that each resident will create a cluster, or mode, in the dataset, representing their typical, in-home, habitual gait. These clusters are modeled as Gaussian distributions in the four-dimensional (4-D) feature space. The basic procedure is to fit a Gaussian mixture model (GMM), $\lambda = \{\rho_r, \mu_r, \Sigma_r\}$, $r = 1, \ldots, K$, with the number of distributions K equal to the number of residents in the apartment to the dataset $X = \{x_1, \ldots, x_N\}$

$$p(x_i|\lambda) = \sum_{r=1}^{K} \rho_r g(x_i|\mu_r, \Sigma_r) \quad (2)$$

where $g(x|\mu_r, \Sigma_r)$, $r = 1, \ldots, K$, are the multivariate Gaussian distributions, and ρ_r, $r = 1, \ldots, K$, are the mixture weights.

The Gaussian distribution representing each resident is used to identify walks from that resident. Any walk whose likelihood given a distribution is greater than a threshold is assumed to be from the resident that the distribution represents, and is used in computing gait parameter estimates for that resident. The classification is done independently for each distribution. Thus, a walk could be included in the estimates of more than one resident, if the distributions overlap. The steps of model initialization and updating are described later and illustrated in Fig. 2.

1) Resident Model Initialization: The mean of each distribution in the GMM is initialized by matching it to a mode in the dataset. Modes are identified by locating local maxima in a smoothed 4-D histogram. The heights of the residents, which are measured *a priori,* are used to associate each of the distributions to one of the identified modes. If too few modes that match the known heights of the residents are found to allow a unique correspondence between modes and distributions, then multiple distributions may be initialized to the same mode, resulting in the same estimate being used for multiple residents in an apartment.

If no modes are found that closely match the known height of a resident, than the model cannot be initialized. Such a case would indicate that more data are needed to initialize the model, or that the resident does not walk frequently enough in the apartment to allow such a modeling approach. The covariance matrix of each distribution is initialized to a predefined value (a diagonal matrix with variances of (2.5 cm)^2, (7.5 cm/s)^2, (0.05 s)^2, and (7.5 cm)^2, for height, walking speed, stride time, and stride length, respectively), and each distribution starts with equal weighting in the GMM.

2) Resident Model Updating: Given a dataset of walks, an iterative process is used to update the model parameters. First, all data points with a Mahalanobis distance greater than D (2.85) from the GMM are pruned from the dataset. This step rejects outliers from the estimate. Second, an expectation–maximization (EM) algorithm is used to update the model parameter estimates, given the current model estimate as a starting point. These two

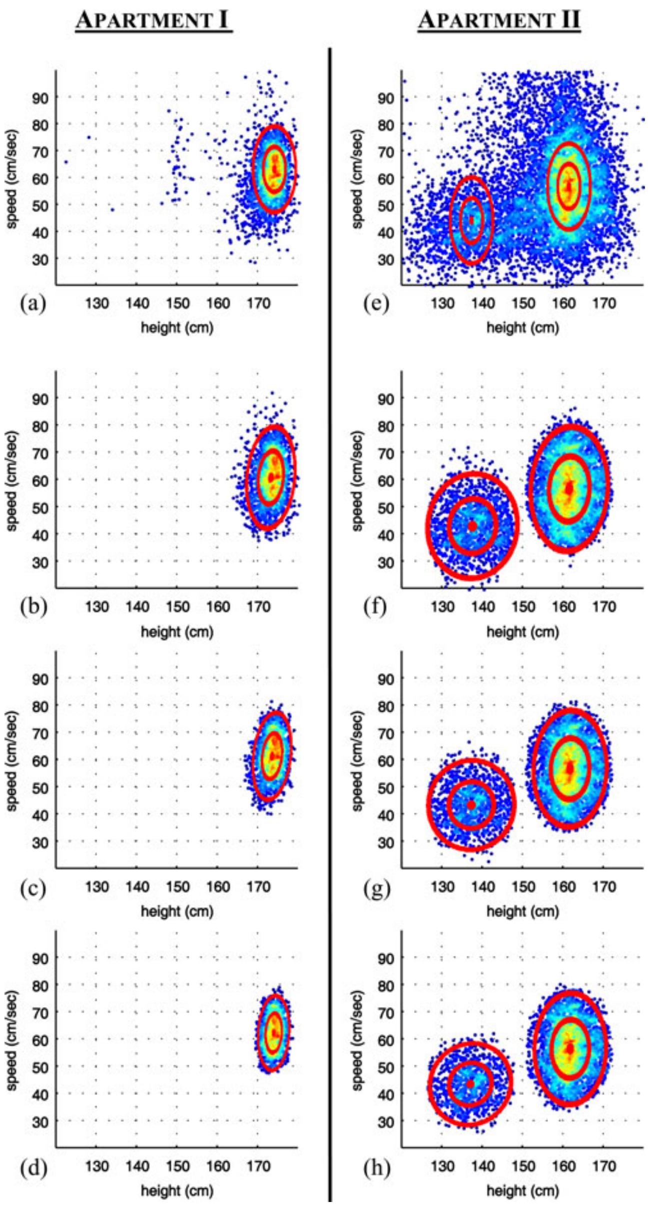

Fig. 2. Illustration of model initialization and updating for two apartments. Each dot corresponds to a walk identified in the apartment over a six-week time period. (a) and (e) Resident model initialization using clinically measured height(s) and *a priori* covariance matrix; (b), (c), (f), and (g) refinement of model based on dataset (after iterations 1 and 3), and (d) and (h) final estimate. In (a) and (e), the entire dataset is displayed; for the rest the pruned dataset is displayed. Although only two dimensions are shown, the process uses all dimensions of the dataset.

steps are repeated until the change in the negative log likelihood is less than ε, or a maximum number of iterations have occurred.

Following this iterative procedure, if the absolute change in the mean of a distribution is above a threshold, or the height associated with the distribution is no longer close to the known height, which is updated slowly over time, of the resident the distribution represents, the update is rejected. If the change in the mean is acceptable, then the covariance matrix is scaled, if necessary, to meet a set of constraints that bound its range.

a) Gait Parameter Estimates: Given a resident model, $\theta_r = \{\mu_r, \Sigma_r\}$, estimated from a dataset, $X = \{x_1, \ldots, x_N\}$, walks belonging to the resident are selected from a dataset $Y = \{y_1, \ldots, y_M\}$ (typically a subset of X), based on their likelihood given θ_r:

$$f(y_i|\theta_r) = g\left(y_i|\mu_r, \sum_r\right) \Big/ g\left(\mu_r|\mu_r, \sum_r\right). \qquad (3)$$

All walks with likelihood greater than or equal to threshold T (0.135) are assumed to be from the resident the model represents. This set of selected walks A_r is used to estimate in-home, habitual, gait parameters for the resident, assuming its cardinality $|A_r|$ is greater than α_r

$$\alpha_r = \rho_r \eta(wn)\beta \qquad (4)$$

where ρ_r is the mixture weight of θ_r in λ, η is the percentage of dataset X used in the final estimate of λ, w is the median number of walks per day in the apartment calculated from dataset X, n is the number of days dataset Y spans, and β is a constant parameter (β = 1/6 for this paper). If this threshold on the cardinality of A_r is not met, then no estimate is made as the number of walks from the resident in Y is insufficient.

Assuming $|A_r| > \alpha_r$, the weighting, u_i, for each walk, $a_i \in A_r$, is computed as follows:

$$u_i = \frac{\min(\text{walk length}(a_i),\ t_l)}{t_l} \qquad (5)$$

where t_l is a constant (2.1 m). Equation (5) reduces the contribution of short walks, which are not as useful for measuring gait parameters. The final estimate, g_est_r, is a weighted average of all walks $a_i \in A_r$

$$g\_est_r = \frac{\sum_{i=1}^{|A_r|} u_i a_i}{\sum_{i=1}^{|A_r|} u_i}. \qquad (6)$$

The upper and lower quartiles of A_r are used as a gauge of variation. This is shown in Figs. 3 and 4.

Earlier work using three weeks of labeled data and a preliminary version of this methodology proved very effective at selecting walks from the resident in single resident apartments, and in multiple resident apartments where the residents' modes were sufficiently separated as a result of differences in the measured parameters [16]. Specifically, in three single-resident apartments, 100% of the labeled walks used to compute gait parameters were from the resident of the apartment. In a two-resident apartment where the residents' modes were well separated, 94.6% of the labeled data used to compute gait parameters for the first resident were from the first resident, and 97.7% of the labeled data used to compute gait parameters for the second resident were from the second resident. As one would expect, the automated gait parameter estimates matched very closely to those computed manually using all the labeled walks of the residents. In the future, additional features, such as shape descriptors, could be added to improve walk classification in apartments with multiple residents who have similar physical characteristics.

3) Trends: Trends in the gait parameters of a resident are computed by applying the resident model estimation and gait parameter estimation steps with a sliding window approach.

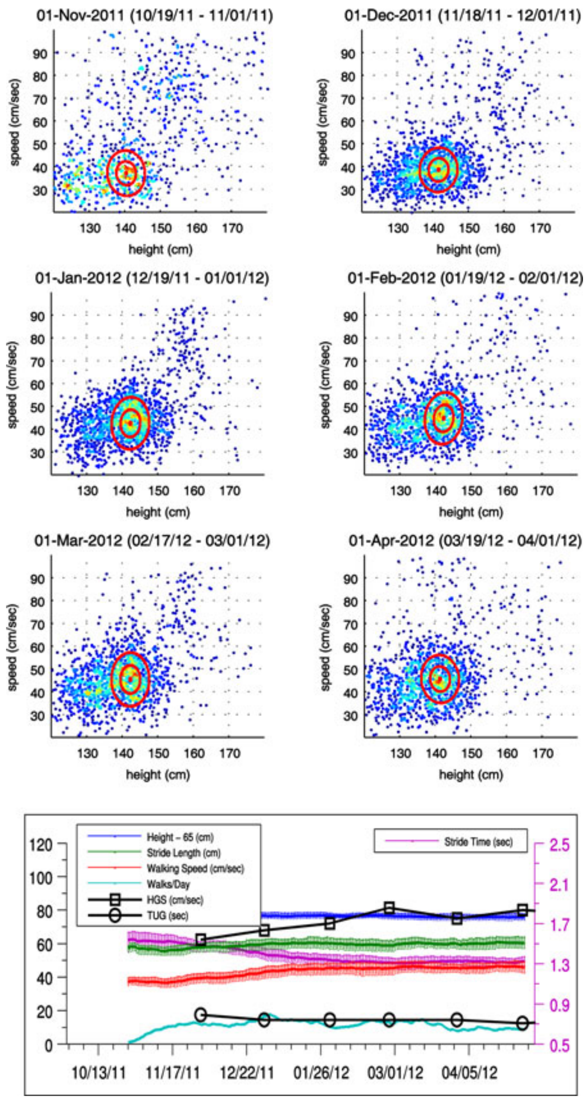

Fig. 3. Illustration of sliding window approach used to generate trends in gait parameters for an apartment. (Top) Change in resident model over six months time period. Plots show current model estimate and two weeks of walk data from specified time period. (Bottom) Parameter trend estimates over six month period. Error bars extend from the lower quartile to upper quartile. A six-week window was used for the model estimation step, and a two-week window was used for the parameter estimation step.

The resident model is initialized and updated using data from a given time period (typically two to six weeks). Next, the gait parameter estimation step is performed using some subset of the data used for model estimation (typically the most recent one to two weeks). The window for both the model estimation and gait parameter estimation steps are moved forward one day, and the process is repeated, with the previous model estimate being used as the starting point for the update procedure. The end result is a time series of daily gait parameter estimates representing the trend in gait parameters, and a model estimate that adapts to the data over time. This is illustrated in Fig. 3.

For this paper, window sizes of six weeks and two weeks were used for the model and gait parameter estimation steps, respectively. These were selected such that, for all apartments, a sufficient number of walks were included to allow accurate resident modeling, and to smooth the gait trends so long-term changes were emphasized over short-term fluctuations. Ideally, these windows sizes would be varied based on the number of walks that occur in an apartment, how well separated the modes of the residents are, and what information is to be extracted, i.e., short-term changes or long-term trends.

V. Results and Analysis

The Kinect system with walk identification and gait measurement has been deployed in 12 apartments with 15 residents as part of an ongoing, IRB approved, study. The apartments are located in an independent care facility for older adults, in the actual homes of the residents. Ages of the residents range from 67 to 97 years, and six are male. Multiple residents used an assistive walking device during some part of the study.

For this analysis, data from the Kinect systems is shown along with two traditional fall risk assessment tools: habitual gait speed (HGS) and TUG time [23], as measured by a clinician. The HGS and TUG tests are conducted using a walking path of 10 feet, and HGS is an average of two walks. These tests, along with others such as the short physical performance battery (SPPB) [24], are administered in the homes of the participants on a monthly basis as part of a fall risk assessment protocol. This monthly assessment protocol forms a best estimate, using traditional measures, of the participant's level of physical function and fall risk. These data are used for comparison purposes against the in-home Kinect data. However, all of these clinically assessed measures are not recorded every month for every resident due to participant unavailability and/or the participant being physically unable to complete the assessments. This difficulty in collecting data on a monthly basis further illustrates the need for passive, continuous monitoring.

Fig. 4, in addition to Fig. 3, provides visualizations of the data for a selected subset of residents of the 12 apartments. In the majority of the cases, the in-home gait parameter trend lines are generally stable, suggesting little or no change in the physical function of the residents during the study. Fig. 4(a) serves as a representative example for these cases. However, two cases in which changes are indicated in the in-home gait data, along with two cases involving multiple residents in an apartment, have been selected for visualization and additional discussion.

The first of these cases is shown in Fig. 3. This resident was admitted to the hospital needing femur surgery on September 3, 2011 (before monitoring was active) and returned to her apartment after rehab on October 25, 2011. Upon returning to her apartment, the resident continued intensive physical therapy while using an assistive walking device for a short period of time, before eventually making a full recovery. This period of recovery is captured in the gait parameter data as increasing walking speed and decreasing stride time, and in the standard fall risk measures as increasing HGS and decreasing TUG time. This case illustrates the potential effectiveness of these systems for continuous, in-home rehabilitation monitoring.

The second of these cases is shown in Fig. 4(b). This resident was monitored beginning in October 2011. He used an assistive walking device almost exclusively while he was included in the

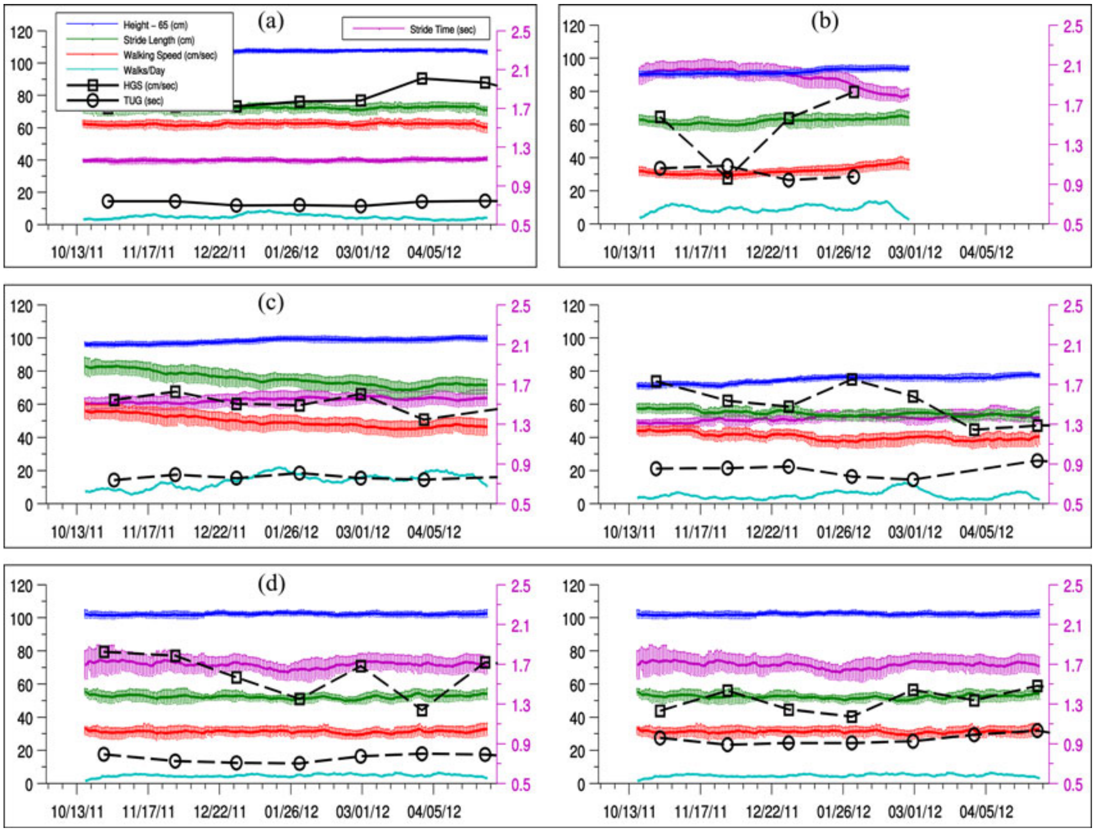

Fig. 4. Gait parameter trends for selected subset of residents included in the study. Each box corresponds to an apartment and each graph to a resident. Error bars extend from lower quartile to upper quartile. In (d), the same mode (and thus model) is used to represent both residents as two separate modes are not differentiable in the data. A six-week window was used for the model estimation step, and a two-week window was used for the parameter estimation step.

study, had a small apartment with one viable walking path, and had a number of visitors such as aides and family in addition to cleaning staff. Given this environment, the Kinect system was still able to successfully identify walks of the resident and generate stride parameter estimates.

At the end of February 2012, he left for an extended stay at another facility before returning to his apartment for two short time periods during April and May that were separated by a hospitalization. He ultimately passed away, in his home, near the end of May 2012. During these short returns to his apartment, this resident was mostly bedbound, resulting in too few data points for updated gait parameter estimates to be made. Using the methodology described in Section IV, he appears to have a noticeable decrease in stride time prior to his initial departure from the apartment. Although this is a single case, changes of this nature could potentially be used to generate automatic alerts to care providers indicating possible health changes.

The last two of these cases are shown in Fig. 4(c) and (d) and are residents from multiresident apartments included in the study. In the case of Fig. 4(c), which also corresponds to Apartment II in Fig. 2, the residents are of sufficiently different heights to allow modeling of their individual modes in the data from their apartment, with no overlap of the distributions, given a time window of six weeks. The large number of walks in the apartment further facilitates clear identification of the modes.

In the case of Fig. 4(d), the residents are very similar in height, within 5 cm, and physical function. Furthermore, due to the size and layout of their apartment, very few walks, only 13% of the number found in the previous case, are identified. Thus, the same mode is used to represent both residents as their individual modes are not discernable in the data. This last case illustrates the need for additional features, such as shape descriptors, for accurate walk classification in multiresident apartments with residents of similar physical characteristics and/or multiresident apartments with few data points.

Finally, as the graphs in Figs. 3 and 4 indicate, clinically measured HGS can differ substantially from the continuous, habitual, in-home walking speed measured by the Kinect. This is consistent with other findings that suggest every day, in-home activity differs from that observed during explicit performance testing [8], [11].

VI. Discussion

As shown in Section V, the Kinect-based gait analysis systems deployed in the apartments of elderly residents in an independent living facility were able to continuously, unobtrusively identify walks and automatically generate in-home gait parameter estimates for the residents. This was achieved in both single- and multiresident homes and in the presence of visitor walks. Furthermore, stride parameters were obtained from walks of residents who used an assistive walking device. Lastly, the potential cost of the Kinect-based systems is relatively minimal.

An earlier analysis [16] indicated that a methodology of fitting a GMM with the number of distributions equal to the number of residents to the 4-D feature space formed by walking speed, stride time, stride length, and height was successful in filtering out the majority of walks which did not belong to the resident(s), thus allowing accurate gait parameter estimates to be made. This approach was more thoroughly developed and presented in this paper. However, this approach relies on the resident(s) walks in the apartment forming a mode in the feature space.

In multiple instances, gait parameter estimates were able to be made from residents using assistive walking devices. This is largely due to the fact that the assistive devices do not significantly occlude the legs of the resident, especially when the resident is walking away from the Kinect. As a result, few points, as compared to the number of points returned from the legs, are returned from the assistive device, causing little impact on the gait measurement algorithms.

The precision of the Kinect measurements has been found to decrease significantly with distance [15], [27], and strong sunlight has been found to overpower the Kinect. As shown by the results in [15], the issue of decreasing precision does not prevent the accurate measurement of gait parameters given the algorithms used here. Additionally, the position of the Kinect on an interior wall, such that a person walking will, generally, be between the Kinect and the source of sunlight allows measurements to still be made with limited complications (the hair and head of a person may not return measurements).

The graphs shown in Fig. 2 and the top of Fig. 3 indicate large variances in the height of the residents, beyond what one might expect. This large variance is due to a number of factors, including: whether a resident is wearing shoes, whether strong sunlight is preventing measurements of the hair and/or head, changes in a resident's posture from one walk to another, the accuracy of the floor plane estimation used to judge height, and, finally, the precision of the Kinect measurements themselves. Whereas the algorithm that extracts stride parameters averages together many pixels from each leg, the height of a person at each frame is, essentially, dependent on a single measurement. These factors can cause significant variation depending on the apartment.

The size and layout of an apartment, the positioning of the Kinect, and the amount of clutter (furniture, etc.) in the environment, can greatly impact the number and quality of the walks identified. Care must be taken to position the Kinect such that is has an unoccluded view of at least one regularly used walking path. For this paper, the area in front of the door above which the Kinect was mounted was always clear, yielding at least one walking path in each apartment.

Additional research is being conducted to investigate the quantitative relationship between the habitual, in-home gait parameters measured by the Kinect systems and the traditional, clinically assessed fall risk assessment protocols. As indicated by the graphs in Fig. 4, these traditional measures tend to show significantly more variation from month to month than the in-home gait parameters measured using the Kinect. A number of studies have investigated the test–retest reliability of the TUG test among various populations of older adults, and found significant intraindividual variation between sessions [25], [26]. Therefore, even though these traditional performance measures are useful for detecting changes in populations, their usefulness for detecting changes in an individual is limited. Even relatively large changes may not indicate a true change in physical function, but simply reflect normal variation, or noise, in the measure itself. The improved stability of the continuous, in-home gait parameter estimates may make them more suitable for this change detection than these traditional measures.

Finally, current goals include: developing automatic, daily fall risk assessment reports, evaluating the usefulness of in-home gait measures for detecting early signs of changes in health status (including additional parameters not discussed in this paper such as stride-to-stride variability), developing methods for presenting the gait information back to residents in a clear, understandable format, and providing the information to nurses or care providers as part of an existing eldercare health alert network.

Acknowledgment

The authors would like to thank the members of the Eldertech team at the University of Missouri for their assistance in installing the systems described in this paper.

References

[1] D. Hodgins, "The importance of measuring human gait," *Med. Device Technol.*, vol. 19, no. 5:42, pp. 44–7, Sep. 2008.

[2] M. Runge and G. Hunter, "Determinants of musculoskeletal frailty and the risk of falls in old age," *J. Musculoskeletal Neuron. Interactions*, vol. 6, pp. 167–173, 2006.

[3] B. E. Maki, "Gait changes in older adults: Predictors of falls or indicators of fear," *J. Amer. Geriatr. Soc.*, vol. 45, no. 3, pp. 313–320, 1997.

[4] J. M. Hausdorff, D. A. Rios, and H. K. Edelberg, "Gait variability and fall risk in community-living older adults: A 1-year prospective study," *Arch. Phys. Med. Rehabil.*, vol. 82, pp. 1050–1056, 2001.

[5] Y. Barak, R. C. Wagenaar, and K. G. Holt, "Gait characteristics of elderly people with a history of falls: A dynamic approach," *Phys. Therapy*, vol. 86, no. 11, pp. 1501–1510, 2006.

[6] M. Montero-Odasso, M. Schapira, E. R. Soriano, M. Varela, R. Kaplan, L. A. Camera, and L. M. Mayorga, "Gait velocity as a single predictor of adverse events in healthy seniors aged 75 years and older," *J. Gerontol. A Biol. Sci. Med. Sci.*, vol. 60, pp. 1304–1309, 2005.

[7] R. Camicioli, D. Howieson, B. Oken, G. Sexton, and J. Kaye, "Motor slowing precedes cognitive impairment in the oldest old," *Neurology*, vol. 50, pp. 1496–1498, 1998.

[8] J. Kaye, N. Mattek, H. Dodge, T. Buracchio, D. Austin, S. Hagler, M. Pavel, and T. Hayes, "One walk a year to 1000 within a year: Continous in-home unobtrusive gait assessment of older adults," *Gait Posture*, vol. 35, no. 2, pp. 197–202, 2012.

[9] S. Hagler, D. Austin, T. Hayes, J. Kaye, and M. Pavel, "Unobtrusive and ubiquitous in-home monitoring: A methodology for continuous assessment of gait velocity in elders," *IEEE Trans Biomed. Eng.*, vol. 57, no. 4, pp. 813–820, 2010.

[10] D. Austin, T. L. Hayes, J. Kaye, N. Mattek, and M. Pavel, "On the disambiguation of passively measured in-home gait velocities from multi-person smart homes," *J. Ambient Intell. Smart Environ.*, vol. 3, no. 2, pp. 165–174, Apr. 2011.

[11] F. Wang, "Motion analysis for in-home gait and balance assessment using inexpensive video sensors," Ph.D. dissertation, Univ. Missouri, Columbia, MO, USA, Jul. 2011.

[12] B. R. Greene, A. O'Donovan, R. Romero-Ortuno, L. Cogan, C. N. Scanaill, and R. A. Kenny, "Quantitative falls risk assessment using the timed up and go test," *IEEE Trans. Biomed. Eng.*, vol. 57, no. 12, pp. 2918–2926, Dec. 2010.

[13] K. M. Culhane, M. O'Connor, D. Lyons, and G. M. Lyons, "Accelerometers in rehabilitation medicine for older adults," *Age Ageing*, vol. 34, no. 6, pp. 556–60, Nov. 2005.
[14] E. Stone, D. Anderson, M. Skubic, and J. Keller, "Extracting Footfalls from Voxel Data," in *Proc Int. Conf. IEEE Eng. Med. Biol. Soc.*, Buenos Aires, Argentina, Aug. 31–Sep. 4, 2010.
[15] E. Stone and M. Skubic, "Evaluation of an inexpensive depth camera for in-home gait assessment," *J. Ambient Intell. Smart Environ.*, vol. 3, no. 4, pp. 349–361, 2011.
[16] E. Stone and M. Skubic, "Passive, in-home gait measurement using an inexpensive depth camera: Initial results," in *Proc 6th Int. Conf. Pervasive Comput. Technol. Healthcare*, San Diego, CA, USA, May 2012.
[17] E. Stone and M. Skubic, "Capturing habitual, in-home gait parameter trends using an inexpensive depth camera," in *Proc Int. Conf. IEEE Eng. Med. Biol. Soc.*, San Diego, CA, USA, Aug. 2012.
[18] G. Demiris, M. Rantz, M. Aud, K. Marek, H. Tyrer, M. Skubic, and A. Hussam, "Older adults' attitudes towards and perceptions of 'smarthome' technologies: A pilot study," *Med. Inform. Internet Med.*, vol. 29, no. 2, pp. 87–94, Jun. 2004.
[19] G. Demiris, O. D. Parker, J. Giger, M. Skubic, and M. Rantz, "Older adults' privacy considerations for vision based recognition methods of eldercare applications," *Technol. Health Care*, vol. 17, pp. 41–48, 2009.
[20] T. B. Moeslund, A. Hilton, and V. Kruger, "A survey of advances in vision-based human motion capture and analysis," *Comput. Vision Image Understanding (CVIU)*, vol. 104, no. 2–3, pp. 90–126, 2006.
[21] H. A. Nguyen, E. Auvinet, M. Mignotte, J. A. de Guise, and J. Meunier, "Analyzing gait pathologies using a depth camera," in *Proc Int. Conf. of the IEEE Eng. Med. Biol. Soc.*, San Diego, CA, USA, Aug. 2012.
[22] M. Gabel1, R. Gilad-Bachrach, E. Renshaw, and A. Schuster, "Full Body Gait Analysis with Kinect," in *Proc Int. Conf. of the IEEE Eng. Med. Biol. Soc.*, San Diego, CA, USA, Aug. 2012.
[23] D. Podsiadlo and S. Richardson, "The timed 'up & go': A test of basic functional mobility for frail elderly person," *J. Amer. Geriatr. Soc.*, vol. 39, pp. 142–148, 1991.
[24] J. M. Guralnik, E. M. Simonsick, L. Ferrucci, R. J. Glynn, L. F. Berkman, D. G. Blazer, P. A. Scherr, and R. B. Wallace, "A short physical performance battery assessing lower extremity function: Association with self-reported disability and prediction of mortality and nursing home admission," *J. Gerontol.*, vol. 49, no. 2, pp. 85–94, 1994.
[25] R. W. Bohannon and K. Schaubert, "Long-term reliability of the timed up-and-go test among community-dwelling elders," *J. Phys. Ther. Sci.*, vol. 17, pp. 93–96, 2005.
[26] E. Nordin, E. Rosendahl, and L. Lundin-Olsson, "Timed 'up & go' test: Reliability in older people dependent in activities of daily living—Focus on cognitive state," *Phys. Ther.*, vol. 86, pp. 646–655, 2006.
[27] K. Khoshelham and S. O. Elberink, "Accuracy and resolution of kinect depth data for indoor mapping applications," *Sensors*, vol. 12, no. 2, pp. 1437–1454, 2012.

Erik E. Stone (S'11) received the B.S. degree in electrical and computer engineering and the M.S. degree in computer engineering, in 2006, and 2009, respectively, from the University of Missouri, Columbia, USA, where he is currently working toward the Ph.D. degree in electrical and computer engineering.

He is currently a Research Assistant at the Center for Eldercare and Rehabilitation Technology, University of Missouri. His current research interests include computational intelligence, computer vision, and pattern recognition.

Marjorie Skubic (S'90–M'91) received the Ph.D. degree in computer science from Texas A&M University, College Station, USA, in 1997, where she specialized in distributed telerobotics and robot programming by demonstration.

She is currently a Professor in the Electrical and Computer Engineering Department, University of Missouri, Columbia, USA, with a joint appointment in Computer Science. In addition to her academic experience, she has spent 14 years working in industry on real-time applications such as data acquisition and automation. Her current research interests include sensory perception, computational intelligence, spatial referencing interfaces, human–robot interaction, and sensor networks for eldercare. In 2006, he established the Center for Eldercare and Rehabilitation Technology, University of Missouri, where he is currently the Center Director for this interdisciplinary team. The focus of the center's work includes monitoring systems for tracking the physical and cognitive health of elderly residents in their homes, logging sensor data in an accessible database, extracting activity and gait patterns, identifying changes in patterns, and generating alerts for health changes.