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Capturing Habitual, In-Home Gait Parameter Trends Using an Inexpensive Depth Camera

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Abstract— **Results are presented for measuring the gait parameters of walking speed, stride time, and stride length of five older adults continuously, in their homes, over a four month period. The gait parameters were measured passively, using an inexpensive, environmentally mounted depth camera, the Microsoft Kinect. Research has indicated the importance of measuring a person's gait for a variety of purposes from fall risk assessment to early detection of health problems such as cognitive impairment. However, such assessments are often done infrequently and most current technologies are not suitable for continuous, long term use. For this work, a single Microsoft Kinect sensor was deployed in four apartments, containing a total of five residents. A methodology for generating trends in walking speed, stride time, and stride length based on data from identified walking sequences in the home is presented, along with trend estimates for the five participants who were monitored for this work.**

I. Introduction

RESEARCH has shown that the parameters which describe locomotion are indispensible in the diagnosis of frailty and fall risk [1] and that the measurement of a person's gait is of importance to a variety of health conditions [2]. Clinical research has indicated that changes in gait parameters such as walking speed may precede cognitive impairment [3], and that variability in stride parameters may be predictive of future falls in older adults [4-5]. These studies are just a small subset of the research indicating the importance of measuring gait parameters.

Given these findings, it would seem that regular, frequent measurement of gait would be a common practice. However, current technologies for gait measurement, such as timing with a stop watch or evaluation in a performance lab, often lead to infrequent assessments which may not be representative of a person's true ability [6]. Thus, inexpensive systems which can continually monitor gait in typical real-world settings, such as the home, would greatly facility the use of gait information in clinical care.

A variety of technologies are being developed and investigated to address this need. Wearable devices for measuring gait, in addition to other physical measures of performance, based on accelerometers and/or gyroscopes are an area that has received significant attention. Although it has been shown that measures derived from body-worn sensors are useful in a variety of contexts [7], including fall risk assessment, feedback from older adults indicates that many consider them to be invasive or inconvenient [8]. Ultimately, more investigation is needed to assess the usability and reliability of these devices as a continuous, long-term monitoring tool.

In [6], researchers were able to demonstrate the benefits of a passive, in-home gait monitoring system that uses an array of passive infrared (PIR) motion sensors to capture walking speed. These benefits included showing that in-home walking speed was associated with several neuropsychological and motor performance tests. However, such systems are not capable of the fine grained measurements necessary to capture parameters such as stride time and stride length which could be necessary for tasks such as early illness detection, or in-home fall risk assessment.

Vision-based monitoring systems offer a potential solution which addresses both the need for fine-grained, detailed measurements and the need for passive, environmentally mounted hardware that does not require those being monitored to wear any devices or worry about changing batteries, etc. Furthermore, research has indicated that privacy concerns older adults may have to vision-based monitoring systems can be addressed through the use of privacy preserving processing techniques [9].

Recently, Microsoft released the Kinect sensor to allow controller free game play on its Xbox system [10]. The sensor, which utilizes a pattern of actively emitted infrared light and an infrared sensitive camera, is capable of generating a depth image (*an image in which the value of each pixel depends on the distance to what is being viewed*) independent of visible lighting. This yields a three-dimensional (3D) view of the world, day or night, using a single low-cost device. Earlier work investigating the Kinect for passive gait measurement in home environments has shown the potential of this sensing platform [11-12].

This paper presents initial results of capturing trends in three habitual, in-home gait parameters for five residents living in four different apartments using the Microsoft Kinect sensor. First, Section II presents a brief overview of the system deployed in the four apartments, which are part of an independent living facility for older adults, and provides a quick summary of previous work conducted to validate the approach. Section III describes the framework for analyzing the data collected in the apartments and generating trend estimates in the habitual, in-home gait parameters over a four month period. Finally, Section IV provides a brief discussion of the potential impact of the work, along with avenues for future investigation.

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II. SYSTEM OVERVIEW

In [11], the Microsoft Kinect sensor was evaluated for the purpose of passive, in-home gait measurement in a lab setting. The results of this evaluation showed good agreement between gait parameters obtained using the Kinect and those measured using a Vicon marker-based motion capture system. More recently, algorithms necessary for extending the earlier approach into dynamic real world environments were developed and initial in-home gait measurement results were presented [12]. Furthermore, the impact of visitor walks was found to be negligible. A brief overview of the system is given below.

The system consists of a single Microsoft Kinect sensor and a computer. For this work, the Kinect has been mounted on a small shelf near the ceiling above the front door of the apartment being monitored and the computer has been placed in a cabinet above the refrigerator. This arrangement is shown in Figure 1 (a) and is used in all the apartments in this study. This arrangement helps minimize the intrusiveness of the system, as the cabinet hides the computer from view and the Kinect is kept out of the way by mounting it near the ceiling.

Due to the placement of the Kinect near the ceiling (which has a height of 9 feet), along with the need for a large operating range (greater than 6 meters) in order to capture walks in the apartments, skeletal tracking is not used. Instead, a dynamic background modeling algorithm allows for extraction of foreground objects through background subtraction using only the depth imagery from the Kinect. The three-dimensional (3D) point clouds of these foreground objects, formed using the known intrinsic and extrinsic parameters of the Kinect, are then tracked over time. This process is illustrated in Figure 1 (b-d). Only objects which meet a size threshold are tracked by the system.

Identification of walking sequences happens online, in real time, at 15 frames per second, using the histories of the tracked objects. A set of criteria based on speed, length, duration, and straightness is used to differentiate walks from other movements, as well as eliminate curved walks which would contain erroneous estimates for the gait parameters. A state machine diagram documenting the walk identification algorithm is shown in Fig. 2. In order to minimize the impact of capturing the beginning or end of a walk on the estimated speed, only the middle half of a walk is used in the computation of walking speed. Given the 3D point cloud of a person for each frame in a walking sequence, steps are extracted, and stride parameters estimated, from the time series of the correlation coefficient obtained from the normalized ground plane projections of the 3D point cloud. This is shown in Figure 1 (e); see [11] for details.

Finally, stride parameters cannot be extracted for every identified walk due to issues such as occlusion, segmentation problems, etc., and walks with less than six steps are often problematic for use in estimating stride parameters. Thus, stride time and stride length are only computed for walking sequences for which at least six valid steps can be identified.

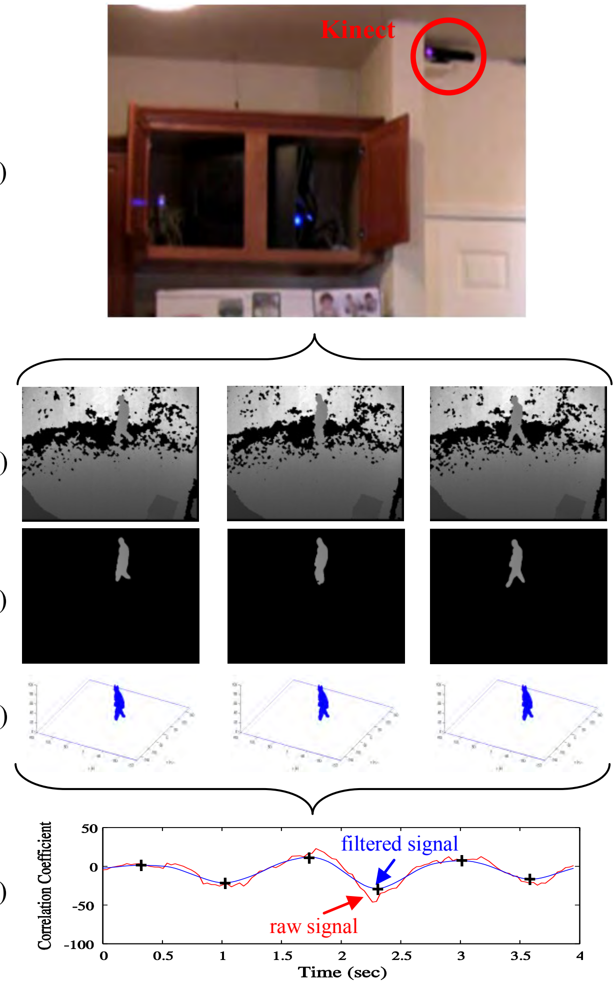

Fig. 1 (a) Kinect system and computer as deployed in apartments. (b) Example depth images from a Kinect during a walking sequence. (c) Extracted foreground corresponding to the depth images. (d) Three-dimensional model of person obtained using foreground and calibration parameters. (e) Plot of correlation coefficient time series of normalized ground plane projections during a walking sequence; used to identify when steps occur. Local maxima correspond to left steps, while local minima correspond to right steps (see [11] for details).

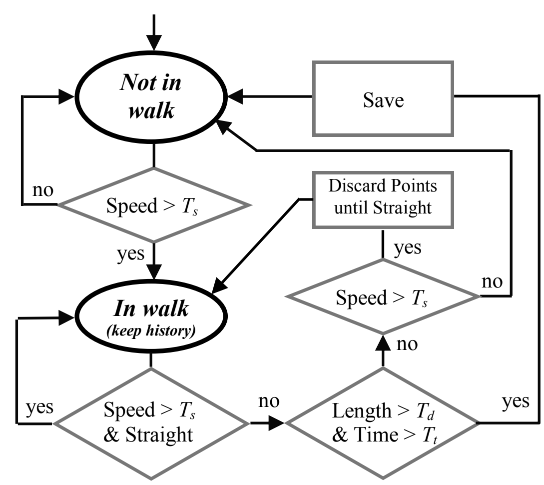

Figure 2: State machine diagram of the walk identification algorithm. The values T_s, T_d, and T_t are thresholds for speed, distance, and time, respectively. These thresholds, along with a straightness criterion, are used to determine the minimum characteristics of walks that are saved. For this work, threshold values were: T_s = 5 in/sec, T_d = 48 in, T_t = 1.0 sec.

III. IN-HOME GAIT PARAMETER TRENDS

Each walk identified in an apartment has either a two (2D) or four (4D) dimensional feature vector associated with it depending on whether stride parameters could be extracted. In both cases, the first two dimensions are the height of the person during the walk, as well as the speed of the walk. In the 4D case, the last two dimensions are the average stride time and stride length for the walk. Thus, each walk, *w*, is represented as follows:

$$w = \begin{cases} \{h, s\} & if\ 2D \\ \{h, s, st, sl\} & if\ 4D \end{cases}$$

where *h*, *s*, *st*, and *sl*, stand for height, walking speed, stride time, and stride length respectively.

In order to estimate values for habitual in-home walking speed, stride time, and stride length, all the walks from a given time period (for this work three weeks) are grouped together and a mode finding algorithm, based on Mean Shift, is used to select a mode in the data which represents the resident. The mode finding is done at a variety of scales, using both the 2D and 4D data simultaneously. The optimal mode is selected based on a criterion that trades off how much of the data is represented by the mode against how compact that set of the data is. In the case of two resident apartments, the algorithm looks for two modes in the data and the criterion function is adjusted, slightly, to favor modes of roughly equal size. Prior work, using a set of labeled ground truth, indicated that such estimates are not significantly affected by visitor walks [12].

By moving the three week period of interest and re-running the mode finding algorithm, values for the habitual in-home gait parameters can be estimated for varying points in time. This process is illustrated, in Figure 3, for a set of four apartments containing a total of five residents. The ages of the residents ranged from 75 to 88, and three were male. The first row of Figure 3 corresponds to the three week time period of Nov. 1, 2011, thru Nov. 21, 2011, and shows scatter plots of the first two dimensions of the walks indentified in the different apartments during this time window (*shown as blue and green dots*), along with the optimal modes found to represent the residents of the apartments (*shown as red circles*). The second row corresponds to the time period Dec. 21, 2011 thru Jan. 10, 2012. Finally, the third row corresponds to the time period Feb. 9, 2012, thru Feb. 29, 2012. (*Note that although Figure 3 shows two dimensions, the mode finding is done in 4D*.)

In order to capture trends in the parameters for each resident, a sliding window approach was applied with a window size equal to three weeks and a step size equal to one day. Results for each resident in the four apartments over a four month period from Nov. 1, 2011, thru Feb. 29, 2012, are shown in Figure 4. The results have been filtered slightly to reduce noise. The total number of walks identified

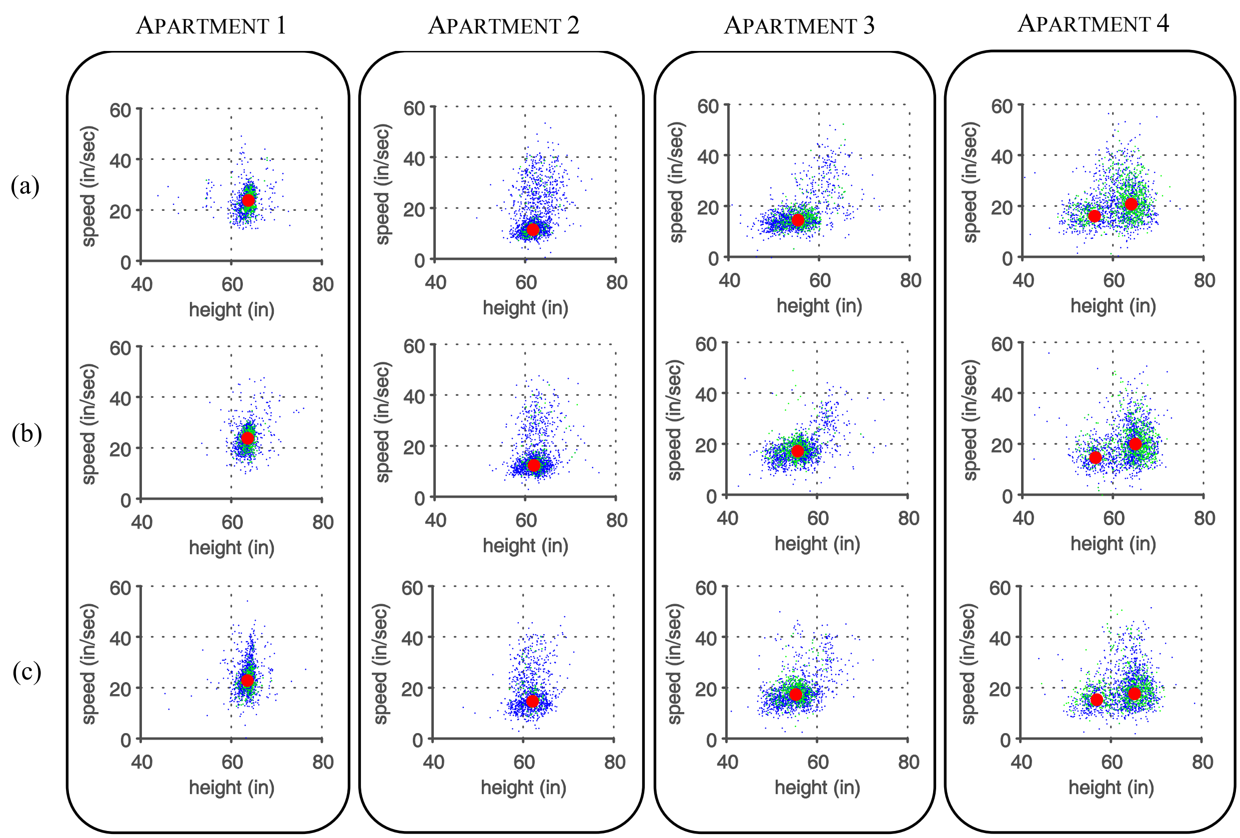

Fig. 3. Scatter plots of the first two dimensions (height and walking speed) of all walks identified in each of four apartments during different three week windows over a four month period. The blue dots represent walks for which only two dimensions are available, while green dots represent walks for which four dimensions are available. The large red dots indicate the modes found to represent the residents of the apartments. (a) Nov. 1, 2011 thru Nov. 21, 2011. (b) Dec. 21, 2011, thru Jan. 10, 2012. (c) Feb. 9, 2012, thru Feb. 29, 2012.

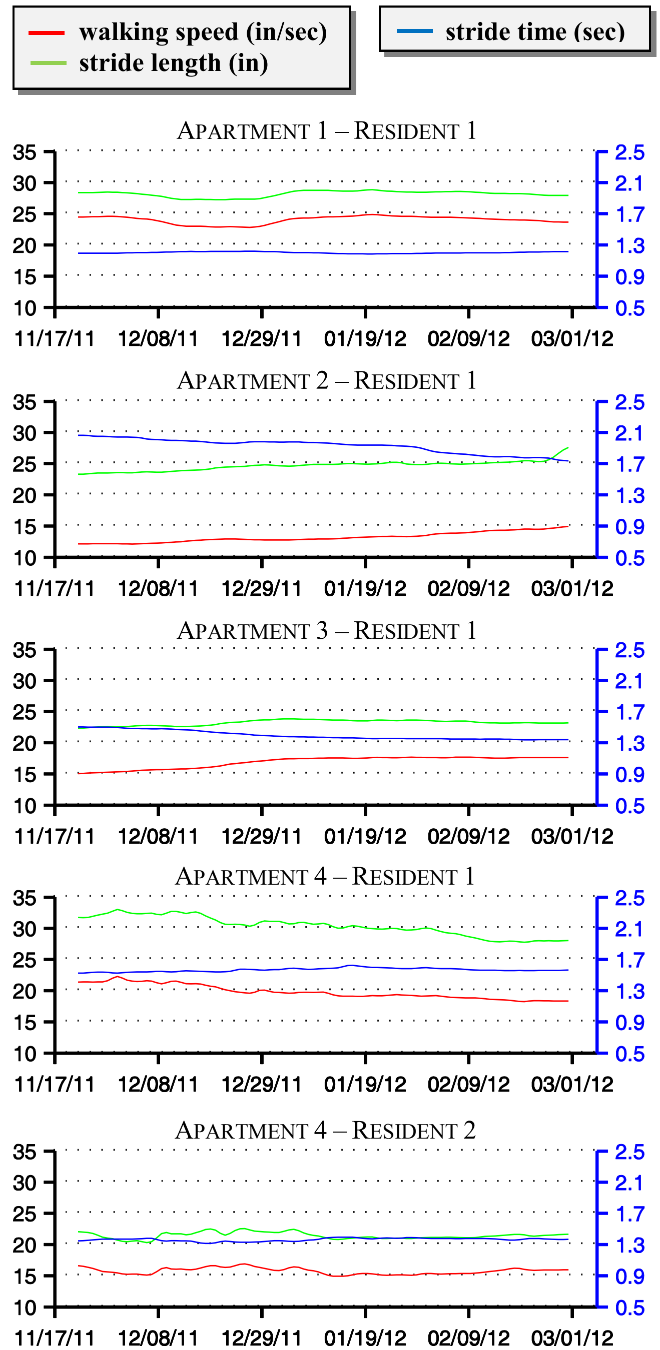

Fig. 4. Trends for the habitual, in-home gait parameters of walking speed, stride time, and stride length for five residents of four apartments computed using data from a four month period, Nov. 1, 2011, thru Feb. 29, 2012. The scale on the left applies to walking speed and stride length; while the scale on the right applies to stride time.

in the apartments during this four month period ranged from 7,199 in Apartment 1, to 27,016 in Apartment 4.

As Figure 4 shows, the trend lines for the residents appear relatively stable. However, there are some noticeable changes. In Apartment 2, the resident's walking speed appears to increase along with his stride length, while his stride time decreases. In Apartment 3, the resident's velocity seems to increase while her stride time decreases. Interestingly, the resident of Apartment 3 underwent femur surgery approximately two months prior to this time period and was recovering. Finally, in the case of Apartment 4, the walking speed and stride length of Resident 1 appears to slow over the four month period while stride time is stable.

IV. Discussion

Kinect based monitoring systems were able to passively and unobtrusively monitor the habitual, in-home gait parameters of five residents in four apartments on a continuous basis over a four month period. An analysis based on a mode finding algorithm combined with a sliding window approach was able to capture trends in these parameters. Such systems could be invaluable for a variety of purposes from in-home fall risk assessment, to early detection of health problems, to improved monitoring of patients during rehabilitation. Future efforts will focus on further evaluating the potential benefits of this technology, as well as refining the algorithms for analyzing the data.

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