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Towards a Passive Low-Cost In-Home Gait Assessment System for Older Adults

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Abstract

In this paper, we propose a webcam-based system for in-home gait assessment of older adults. A methodology has been developed to extract gait parameters including walking speed, step time and step length from a three-dimensional voxel reconstruction, which is built from two calibrated webcam views. The gait parameters are validated with a GAITRite mat and a Vicon motion capture system in the lab with 13 participants and 44 tests, and again with GAITRite for 8 older adults in senior housing. An excellent agreement with intra-class correlation coefficients of 0.99 and repeatability coefficients between 0.7% and 6.6% was found for walking speed, step time and step length given the limitation of frame rate and voxel resolution. The system was further tested with 10 seniors in a scripted scenario representing everyday activities in an unstructured environment. The system results demonstrate the capability of being used as a daily gait assessment tool for fall risk assessment and other medical applications. Furthermore, we found that residents displayed different gait patterns during their clinical GAITRite tests compared to the realistic scenario, namely a mean increase of 21% in walking speed, a mean decrease of 12% in step time, and a mean increase of 6% in step length. These findings provide support for continuous gait assessment in the home for capturing habitual gait.

Index Terms

computer vision; gait analysis; eldercare technology; webcam; passive monitoring; walking speed; step time; step length

I. Introduction

Gait characteristics have been linked with a variety of medical conditions in clinical research [1, 2]. We are particularly interested in gait analysis for fall risk assessment in elderly people [3,4] as part of the ongoing work towards building an integrated in-home health monitoring system for seniors [5]. Falls are a major cause of morbidity among the elderly, and in almost all incidences of falls, some aspects of locomotion have been implicated. While monitoring the regular day-to-day activities of seniors, we realized that it could be extremely beneficial to study their gait, as walking is one of the most natural physical activities and can be conveniently and easily accommodated into an older adult's routine. A change in the gait profile over time may indicate that a person is more at risk of falling. Thus, monitoring older adults' walk on a daily basis using smart-home technologies, such as camera monitors and walking sensors, can provide essential information on the changes of functional status.

Continuous gait assessment has clear advantages over the clinic-based tests that may not always provide an accurate and complete picture of the elder's true physical condition, since the tests can only be done on a limited interval; furthermore, many older adults are never assessed for fall risk in any setting. Also the clinical walkway is not representative of the complex environment within which an elderly person must function. There is a need for a low-cost passive sensor system to provide a reliable, quantifiable method of monitoring gait parameters in seniors' daily activities. Such a system can potentially be used to recognize elderly people at risk of falling, identify diagnostic measures that are predictors of fall-prone elderly, detect subtle gait changes early so that effective interventions can be made in a timely manner to prevent or reduce severe health outcomes, and accurately measure the effects of medical interventions.

In the next section, we discuss related work in this field. Section III gives a detailed description of the gait analysis methodology. Section IV presents validation experiments and results conducted in the research lab and in a retirement community. Section V describes the in-home realistic scenario testing of the system with elderly participants. We offer discussion in Section VI, and conclude in Section VII.

II. Related Work

Fall risk assessment of community-dwelling older adults based on functional assessment instruments [6] has become common, and is most widely performed by physical therapists in an outpatient setting. Studies have shown that these clinical tests can be subjective and sometimes inconsistent, especially when the testers are inexperienced [7,8]. In addition, they are usually not administrated often enough to identify problems while they are still small to facilitate timely interventions. Therefore, new technologies are necessary to give a more detailed gait and balance assessment.

A gait laboratory [9] typically uses a combination of these technologies to evaluate the biomechanics of gait: a marker-based motion capture system, force plates, an electromyography system, and a pressure sensitive electronic walkway. The systems used in a gait laboratory provide very accurate descriptions and models of gait. However, these expensive systems must be installed in appropriate rooms and can only be operated by specially trained personnel. There is, therefore, a clear need for an inexpensive, unobtrusive and easy-to-use system, which allows continuous and quantitative analysis of gait patterns outside the lab.

With the advancements in technology, researchers have attempted to deploy different techniques for continuous gait assessment with varying degrees of obtrusiveness. Among the most studied techniques are those using wearable accelerometers and gyroscopes. The

sensors have also been employed for different purposes: monitoring activity, assessing standing balance, detecting falls, capturing postural orientation, classifying activities, and estimating metabolic energy expenditure [10]. Many wearable systems have demonstrated accuracy and precision, but suffer from limitations such as short battery life, the need to download the data or introduce additional hardware for wireless data collection, and the inconvenience of both a wearable device and having to remember to wear a device. For these reasons, wearable devices are currently inadequate for long-term, in-home, unobtrusive monitoring.

Recently, more research focuses on the unobtrusive home monitoring of elders to determine speed of walking to detect early changes in cognitive function. Low-cost passive sensor systems for gait assessment, such as inexpensive passive infrared (PIR) motion sensors, are used for continuous and unobtrusive assessment of mobility and walking speed in the home [11]. However, such systems can provide only walking speed as the single gait parameter. A home based footmat system using Flexiforce sensors is proposed in [12] to capture gait characteristics of people especially elderly in their daily life. Both of the above systems face challenges such as tracking individuals in multi-occupant dwellings.

Video sensors are a rich source of information that can be used for gait analysis; vision-based gait analysis has been an active research topic in the computer vision community. Applications for vision-based gait analysis fall into the following categories: gait recognition as a biometric, gait classification to distinguish between different types of activities such as walking, running and jumping, and as an assessment tool in elder care, rehabilitation and sports activity. A good background review on vision-based human motion analysis techniques is provided in [13,14]; both model-based and non-model based methods are used. For the model-based method, a human body shape model, such as stick models, contour models and volumetric models, is established to match real images to the predefined model, and thereby extracting the corresponding features once the best match is obtained. For the non-model based method, image structure correspondence between successive frames is based upon features related to prediction, velocity, shape, texture and color, etc. Some studies have been done on silhouette-based human gait analysis using two dimensional silhouettes [15–17]. In most of the studies, either people are limited to walk normal to the viewing plane, as major gait information is available in a sagittal view, or walking directions have to be restricted because the test images need to be taken from roughly the same viewing angle as the training images.

Considering the limitation of the existing systems, and addressing the need of in-home gait assessment as described, we have developed an inexpensive two-camera system using a three dimensional human representation to eliminate the constraint of a controlled walking path [18,19]. The idea of approximating an object's shape from intersection of visual cones has been introduced by Baumgart [20]. Problems existed such as concavities which were later described by the visual hull [21]. Today the idea continues to be widely used as a basis for many approaches to 3D photography, or the acquisition of high-quality geometric and photometric models of complex real-world objects [22, 23].

In our work, we are assisted by volunteer elderly residents at TigerPlace, a retirement community with the aim to help residents age in place, stay active, and remain healthy.

III. Gait Analysis Methodology

The system overview of the webcam gait assessment system is shown in the diagram of Fig. 1. Each component is further discussed in detail in the following sections. The computationally expensive parts of the system are the voxel reconstruction from silhouettes.

Currently the system utilizes the graphics processing unit (GPU) to speed execution and can run in real time at up to 8 frames a second.

A. 3D Voxel Reconstruction from Silhouettes

Silhouette extraction is performed first to segment the human body from the background. This is not only a necessary step for the voxel reconstruction, but also protects the privacy of the residents. The ultimate goal for this technology is to monitor elderly persons' gait patterns in their homes. Our studies conducted in TigerPlace have shown that this type of silhouette shape extraction can alleviate privacy concerns associated with the use of cameras [24].

Before silhouette extraction can occur, an accurate background model must be acquired. The background is defined as any non-human static object. Images are pre-processed for pixel noise removal, features based on histograms of texture and color are extracted, and the mean and standard deviation of a single Gaussian is recorded for each pixel. After the background model is initialized, regions in subsequent images with significantly different characteristics from the background are considered as foreground. Areas classified as background are also used to update the background model. Shadows are removed using a modified Hue, Saturation, and Value (HSV) color space procedure [25].

A voxel is a three dimensional volume element (a non-overlapping cube) resulting from the discretization of the environment. In this work, the voxel resolution is 1×1×1 inch (2.54 cm). Our three-dimensional human model, called voxel person, is constructed in voxel space by back projecting silhouettes from multiple camera views based on camera calibration performed *a priori*. The camera calibration including intrinsic and extrinsic parameters is done using the Camera Calibration Toolbox from [26]. Given the intrinsic and extrinsic camera model, the calibrated view vector of each pixel in each camera can be determined for silhouette back projection. Back projection of the silhouette of a single camera i resulted in voxel set $\boldsymbol{v}_b^i$. The back projection of the two silhouettes $\{\boldsymbol{v}_b^1, \boldsymbol{v}_b^2\}$ are combined by intersection, forming a three dimensional human model $\boldsymbol{v}_t = \boldsymbol{v}_b^1 \cap \boldsymbol{v}_b^2$. The voxels that belong to voxel person at time t are $\boldsymbol{v}_t = \{v_{t,1}, v_{t,2}, \ldots, v_{t,p}\}$, where the center position of the ith voxel $v_{t,i} = (x_i, y_i, z_i)$. An illustration of silhouette extraction and the voxel person reconstruction process is shown in Fig.2. Our goal is not to build a highly detailed body representation, but to obtain features that could be used to extract useful gait parameters. We build a relatively low resolution voxel model without explicitly tracking body parts and joints. It is computationally efficient, suitable to run unsupervised in real world environments for long time periods, and helps to preserve the residents' privacy.

The above discussion is based on the assumption that good human silhouettes are available. In an unstructured daily living environment, it is inevitable to have artifacts such as moving objects, and lighting changes. A method has been proposed by Stone [27] to improve silhouette extraction using the following two features. The *connected component usage* (*CCU*) is used to remove voxel objects that are the result of intersecting connected components from different real world objects. The *voxel objects volume* is used to remove voxel objects which are either too small such as a small moving object, or too large to be human such as artifacts resulting from quick, large scene changes due to lighting changes or large moving objects.

The system aims to monitor seniors in a single or dual-resident environment. Color histograms of each connected component representing a person in the silhouette images are used to differentiate one person from another in a two-person scenario as shown in Fig. 3.

B. Video Segmentation for Gait Analysis

When presented with a large amount of video information of a person's daily activities, it is necessary to locate the images suitable for gait analysis. Even though occlusion is a common issue facing computer vision approaches, unlike critical monitoring such as fall detection, it can be overcome in our application, as long as some good walking sequences can be identified. When this technology is deployed in a home, identifying a few good gait sequences a day would be sufficient to serve the gait monitoring purpose

```
Algorithm 1: walking sequences selection
For each input frame
 If (a good voxel frame according to rule 1–3)
  If (continuous)
   Add to the current existing walk sequence
  Else
   Start a new sequence
   Keep the previous sequence if the length is greater
   than T_t second
```

We propose to use the voxel person's velocity, foot region projection and height features to segment the input video into walking sequences. The criteria of 'good' voxel frame input used in Algorithm 1 is defined based on the following rules:

1. velocity is above a predefined threshold T_v,
2. projection of foot area is above threshold T_f,
3. voxel person height is above threshold T_h

Rule (2) is to ensure the foot regions are not occluded. And rule (3) is to ensure the person is in a standing position. The selection of threshold may vary slightly from person to person as the person's height and average walking speed vary. In our experiment, we have chosen T_f=300cm^2, T_v=25cm/s, and T_h= 0.85*height. In addition, the walking sequence length threshold T_t= 3 seconds as used in Algorithm 1.

C. Extraction of Gait Parameters

The gait parameter definitions commonly used in clinical gait analysis are listed below for reference purposes. These definitions are used by the GAITRite system (CIR Systems Inc.), one of the ground truth systems, and only used to guide our webcam system's proper estimation of these parameters.

Walking speed/Velocity Distance traveled divided by the ambulation time.

Step time Time elapsed from first contact of one foot to the first contact of the opposite foot.

Step length The step length of the right foot is defined as the distance between the center of the left foot to the center of the right foot along the line of progression.

In this paper, unless specified, the step time and step length are the averages of the right and left feet. With the low frame rate (5fps) and low voxel resolution (1 inch cube), the webcam system is not able to detect the exact first contact of the foot and the center of the foot as

stated in the clinical definitions, but rather, as shown later in the section, relies on the variation of the 3D reconstructed foot region for step recognition, then computes the associated gait parameters. In the time domain, each step time segment based on the first foot contact used by the GAITRite is likely not to align exactly with the one estimated by the webcam. However, through the study, we have found that this exact alignment of the two systems is not critical in determining the statistical average step time and step length. The low-cost webcam system is able to accurately estimate these gait parameters compared to the ground truth.

Walking Speed / Velocity—The voxel set belonging to the voxel person at frame t is $\boldsymbol{v}_t = \{v_{1,t}, v_{2,t} \ldots, v_{p,t}\}$, with voxel center position of voxel $v_{i,t}$ *at* (x_i, y_i, z_i).The voxel person centroid $\boldsymbol{C}_t$ at time t is:

$$\boldsymbol{C}_t=\frac{1}{P}\sum_{i=1}^{P}\boldsymbol{v}_{i,t} \quad (1)$$

where P is the total number of voxels belonging to the voxel person at frame t. The centroid represents the 3D location of the person at a given time. The distance D_t a person traveled from frame t-1 to t in 2D space is computed as equation (2).

$$D_t=\|\boldsymbol{c}_t(x,y)-\boldsymbol{c}_{t-1}(x,y)\| \quad (2)$$

The average velocity V can be computed as $V=\frac{\sum_{t=T}^{T'}D_t}{(T'-T)}$, where the time interval (T'-T) is obtained from the image time stamp information.

Step Recognition for Step Time and Step Length—In order to compute step time and step length, the steps must first be accurately recognized. The voxels with a height below 4 inches from the ground plane are used to capture foot motion. They are projected onto the 2D space as shown in Fig. 4 (a) and (c). The solid line represents the length from the front of one foot to the end of the other foot. It is projected along the walking direction, which is obtained from the voxel person's centroid in adjacent two frames of the current frame. As illustrated in Fig. 4(b), this length alternatively expands (shown as peaks) and contracts (shown as valleys) over time as the person's feet spread and close during the gait cycle. The number of steps S is obtained directly from the number of peaks representing the number of gait cycles (Fig. 4b). The average step time T_s of a walk sequence is then calculated as

$$T_s=\frac{T'-T}{s} \quad (3)$$

The average step length L is then calculated as:

$$L=V*T_s \quad (4)$$

D. Reference Systems: Vicon and GAITRite

To validate the web camera system, we used both a Vicon motion capture system with a high degree of precision [28] and a GAITRite mat with proven reliability and validity [29] as ground truth. Gait parameters are extracted for the Vicon system, while the GAITRite software outputs the results.

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The commercial 3D motion analysis system, Vicon MX, allows for very accurate measurement of movement, using reflective markers and 7 cameras simultaneously. The cameras send out infrared light signals and detect the reflection from the markers attached to the toe of both shoes. Based on the angle and time delay between the original and reflected signals, it tracks the movement trajectories of the reflective markers in 3D space. The Vicon cameras sampled at 50Hz, and were properly calibrated according to the manufacturer's instructions prior to data collections. The key in analyzing the Vicon data is the accurate detection of the contact of the footfall by monitoring the foot markers' location $\boldsymbol{M}$(t) at time t. A footfall is a momentarily stationary location of the foot based on a threshold:$|\boldsymbol{M}(t) - \boldsymbol{M}(t\text{-}1)| < threshold$ The *threshold* is set to 2 mm in each of the 2D directions. Once the footfalls are identified, the gait parameters can be easily extracted.

The commercial GAITRite system used in the experiment is an electronic walkway that comprises a series of pressure activated sensor pads inserted in a grid. The sensors are placed 1.27 cm apart with a total of 18,432 sensors. Spatial and temporal footfall data from the activated sensors are collected by on-board processors and transferred to the computer with application software that calculates various gait parameters for individual footfalls as well as an overall average for each parameter. The average step time and step length for the GAITRite used in the later analysis is obtained through the average of these parameters' readings of the right and left feet. The sampling rate of the system is 120Hz.

IV. Validation Experiments

The purpose of the validation experiments was to determine the accuracy, reliability, and validity of the web cameras gait analysis system. The validation experiments have been conducted in two stages: (1) in a lab setting with both the Vicon motion capture system and the GAITRite as ground truth, then (2) with elderly residents in a realistic home environment at TigerPlace using the GAITRite as ground truth.

A. In-lab Validation

Experimental Setup—Experiments were conducted in the lab, where subjects walked across the GAITRite mat of effective length 16 ft (4.9m) at various speeds while the Vicon motion capture cameras recorded the motion of reflective markers attached to the toe of both shoes as well as the back of the subjects, and two calibrated web cameras captured the images (see Fig. 2a). Unibrain Fire-i digital cameras were used. The images are recorded at a frame rate of 5 frames per second, with an image resolution of 640×480 pixels.

Thirteen healthy subjects (age 25–60, mean 36.8, SD 14.8) from the research team participated. Subjects were instructed to walk in various walking patterns, including normal speed, fast, slow, and limping. Each subject was tested multiple times for each walk. In total, there are 44 test runs. The experiment has incorporated a wide range of subject age and gait parameters to test the system's reliability and validity.

Results—The test results are shown in Fig. 5; Tables I and II list the comparison among the web camera, GAITRite and Vicon systems for walking speed, step time, step length respectively. Intra-class coefficients (ICCs) of the type (2,1) and the repeatability coefficient (RC) were used to evaluate the level of agreement between the Webcam and Vicon, and between the Webcam and GAITRite. The Bland and Altman repeatability coefficient was calculated as 1.96 times the standard deviation of the difference between the two systems under comparison. The difference of the two measurement systems is expected to be less than this coefficient with a probability of 95%. The repeatability coefficient was also calculated as a percentage of the average values of the two measurement systems. Paired t-tests were used to determine the systematic difference between the two systems.

Gait parameters obtained from the tests cover a large variation: velocity ranges from around 40 to 180 cm/s, step time from around 0.4 to 1s, and step length from 27 to 180 cm. An excellent agreement between the Webcam system and Vicon, as well as between the Webcam and GAITRite systems are achieved. Mean values of all gait parameters are very close. Paired t-test results showed that the differences between the two measurement systems under comparison are not statistically significant ($p > 0.05$ for all comparisons). ICC of 0.99 demonstrated an excellent level of absolute agreement between the two systems under comparison. RC is also small in magnitude further indicating close agreement between the systems. For example, the absolute RC of 4.4 cm/s for velocity in Table I indicates that the expected maximal difference between the two measurement systems would be 4.4 cm/s on 95% of occasions.

The set of validation experiments was designed to put the web camera system under test with some extreme walking patterns as demonstrated by the large variation in the gait parameters. The test results provide confidence in the performance of the system for a variety of gait patterns. Through the in-lab experiments, we have learned that a camera frame rate of 5 frames per second is sufficient for accurate step detection. Based on Nyquist-Shannon's theorem, the Nyquist sampling rate needs to be twice the highest signal frequency, which would translate to a 0.4s step time for our web camera system. Our results have shown that all the subjects' step times are longer than 0.4s. Considering the technology application for elderly people, the current frame rate is adequate to capture the step time accurately.

In addition, one test was performed specifically to verify the performance of the system while the person is walking in various directions with respect to the camera locations and in a non-straight, non-controlled walk path. In this test, a participant is asked to wander around in a 10×8 ft area. The participant walked a distance of 73 feet (22m). Because of the random walking nature, a comparison of average velocity was made between the webcams (77.4 cm/s) and the Vicon (77.6cm/s) only. Therefore, we believe the system is well suited for an in-home environment where the person's walk is not confined to a fixed path with respect to the cameras.

B. In-Home Validation with Elderly Participants

Experimental Setup—To further validate the system in more realistic daily living settings with the target population, we conducted the following experiments with elderly volunteers at TigerPlace. Eight TigerPlace residents (age 81–94, mean 87, SD 4.3) have been recruited to participate in the experiments. All provided informed consent. Some of them walk independently and some use a cane. The GAITRite mat was moved to TigerPlace, and used as ground truth for the validation experiments there. We placed the GAITRite mat at different angles with respect to the cameras to test the camera systems performance under various viewing angles. The participants were instructed to walk on the GAITRite mat at their preferred speed while web cameras recorded images.

Results—The validation experiment results from the TigerPlace testing are shown in Table III. Compared to the results from the in-lab testing, the gait parameters have a much smaller range of variation due to the subject age range and the fact that subjects were asked to walk in their preferred velocities. ICC and RC revealed that the webcam system has an excellent match with the GAITRite system. These results give us confidence in the web camera system performance and accuracy in a realistic daily environment.

V. Testing With Elderly Participants In A Realistic Scenario

A. Study Overview

The purpose of this study is to simulate normal daily activities in order to investigate the feasibility of developing and eventually deploying such vision technology for continuous eldercare gait assessment in the home.

Ten elderly volunteers (4 females, 6 males, age 83–98, mean 90, SD 5) from TigerPlace were again recruited to participate in a scripted scenario with realistic daily activities with only web cameras recording. All provided informed consent. The scenario involves a two person environment and is designed to include common everyday activities that also provide the type of information needed to assess physical function of older adults.

In the *repairman* scenario, the elderly resident enters the door, walks into the room, then returns to the door to pick up the newspaper, and comes back to the room. The resident sits down and starts to read the newspaper, but remembers his glasses. He stands up, retrieves his glasses, and comes back to sit down in the chair. The resident reads the newspaper, then stands up, and comes to the middle of the room, stretches in the forward and lateral directions. The repair person knocks on the door and comes in. The resident stands and chats with the repair person for 30 sec. The repair person puts down his tool box and goes to check the window that needs to be fixed. The resident steps around the tool box and leaves the room.

The scenario is explained to each volunteer resident in detail before the recording. A research team member plays the repairman role and is present to provide step by step instructions during the data collection. The residents are not required to memorize any step. Each resident completed two runs of the same scenario consecutively, with each run taking 5 minutes or so depending on the subject's speed. Volunteer residents are given gift cards for their participation and seem to enjoy their roles as paid actors. An example of a participant in a scenario run is shown in Fig. 3.

B. Gait Assessment with a Realistic Scenario

The walking sequences are segmented automatically from the scenario videos using algorithm 1. During the two-person scenes, the two persons are differentiated and tracked using color features of the foreground components in the silhouette image. There are 13–15 segmented walk sequences for each subject in each test run. For each walk sequence, the gait parameters of average velocity, step time and step length are extracted. These parameters are then summarized to obtain the mean and standard deviation for each participant, as presented in Fig. 6. The gait parameters of a separate clinical GAITRite test conducted apart from the webcam system study for these participating residents during the same time period, were also collected and are shown in Fig. 6 for comparison purpose.

Fall risk assessment—Fig. 6 clearly displays the gait parameters of the ten participants over a short term monitoring. Such information can be used for fall risk assessment to identify older adults with a high risk of falling.

First, as seen in Fig. 6(a), the walking speed for the ten elderly participants in the scenario ranges between 34.8 to 74.5 cm/s. ID5, who uses a cane walks substantially slower (mean=37.9cm/s, SD=4.4cm/s) than the rest of the participants whose walking speeds are near or above 60 cm/s within 1 standard deviation. It has been reported that walking speeds ≤ 60 to 70 cm/s are strong risk factors for poor health outcomes for community dwelling older adults [30,31]. Second, participant ID5's step time is among the longest and his step length is among the shortest in the group. Finally, the continuous monitoring has revealed

that ID5's walking speed has little variation (with a smaller standard deviation), but his step time and step length have larger or comparable variations (with a larger standard variation) compared to other participants in the group. It implies that he consistently walks slowly, or in another words, he is not able to walk faster, but his walk has a lot of variation in terms of step time and step length. From studies shown in [4,32], low walking speed, short step length and large stride-to-stride variation are all warning signs of a faller, or someone at higher risk of falling that may need medical intervention.

This study has clearly demonstrated the potential capability of the webcam system for gait analysis in fall risk assessment. It could be used to provide a clear day-to-day picture of the person's gait status, and can be used by clinicians to screen fallers in a timely manner.

Scenarios vs. clinical-based tests—Through this study, it has been observed that the clinical tests have a mean increase of 21% in walking speed, a mean decrease of 12% in step time, and a mean increase of 6% in step length compared to the scenario tests. Six participants including one female and five males have substantially faster walking speed in clinical testing than in the scenario. Five of them (ID4, 6, 7, 8 10) have a clinical test walking speed above the 95% confidence interval (CI) of the scenario speed. The faster walking speed was achieved by taking faster and larger steps based on the information from Fig. 6 (b–c). The clinical walking speed of the other four participants' (ID 1, 2, 3, and 5) followed closely to their mean speed in the scenario.

The scenario data show that velocity has a Pearson correlation coefficient of 0.55 on average with the walking distance. This implies a moderate correlation between the two, namely that the subjects walk somewhat faster when they walk a longer distance. The walking distance in the scenario runs is 5.97 m (SD 1.26m), while in the clinical GAITRite tests it is 4.40m (SD 0.20 m). All subjects participated in the scenario in the same room, with a similar walking distance. Considering that the walking distance in the scenario is on average longer than in the GAITRite runs, we believe the walking distance is not a major contributing factor for the difference observed in walking patterns. The participants who walk faster in clinical tests are the ones who have a higher walking speed in their gender group. So they are able to walk faster when they are being tested, while the slow walkers seem to stick with their mean speed. We hence believe that the walking patterns change between the short term continuous scenario monitoring vs. the one time clinical tests, could possibly be the Hawthorne effect, which is a form of reactivity wherein subjects improve some aspect of their behavior while being measured simply in response to the fact that they are being watched, not in response to any particular experimental manipulation [33,34].

The above findings provide support of the importance and advantage of continuous gait assessment in a daily living environment versus a snapshot clinical testing.

VI. Discussion

The proposed low cost webcam based in-home gait assessment tools have been validated and shown to accurately estimate the walking speed, step time and step length compared with ground truth GAITRite and Vicon systems in the lab and in the realistic living environment, with intra-class correlation coefficients of 0.99 and repeatability coefficients between 0.7% and 6.6% for walking speed, step time and step length even with the limited frame rate and voxel resolution.

We have further tested this practical gait assessment tool in a senior housing environment with volunteer residents in a scripted scenario, and compared their gait parameters with clinical test results. We have found that clinical tests have a mean increase of 21% in

walking speed, a mean decrease of 12% in step time, and a mean increase of 6% in step length compared to the scenario tests. The difference in gait patterns observed provides further support of the importance and necessity to have an in-home daily gait assessment tool that can monitor the older adults' gait continuously. The system can provide real pictures of the seniors' gait status while in their own environment which are very valuable, and currently unavailable to clinicians.

Our proposed system includes two low-cost webcams and a GPU computer, estimated today at about $1000. With the technology development, the cost of the system will continue to drop and performance will continue to improve. It can eventually be deployed widely at a low cost. In the long-term, the system is less expensive than repeated clinical testing, and provides more detailed daily results.

Gait speed can serve as a geriatric vital sign [35]. Slow walking speeds are associated with poor general health, falls, low physical and cognitive functioning and other adverse health outcomes in older adults [36]. Recent studies show that gait speed was associated with survival [37], and may help predict the risk of short-term complications following cardiac surgery [38] in older adults. We see great potential in using this low cost system for health monitoring besides the fall risk assessment. Although this study only demonstrated short term monitoring, we foresee using the gait assessment tools developed in this research for longitudinal studies and detecting the trends and changes of gait characteristics.

Assistive devices used for walking impose challenges in the video based gait analysis. Several elderly participants in the study used a cane which did not affect the performance of the system. Although not specifically studied, walkers are expected to have little effects on speed estimation. However, the step time and step length cannot be accurately estimated using the method descried here because the foot area cannot be accurately reconstructed.

Long term in-home monitoring is expected to be more challenging than the lab setting and the short term in-home monitoring demonstrated in the study, due to the complexity of the real world environment. The work reported here is a first step towards investigating the feasibility of using such a system in an unstructured home setting. Although the positive results demonstrated the feasibility of deploying such systems in an elderly resident's home, there are issues to be addressed in our future research. One of them is resident identification. With the rich information from video images, we are working to develop algorithms using color, static and dynamic gait information, such as height, speed, and body shape to differentiate residents in a multi-resident apartment, and to differentiate residents from visitors. Occlusion could be another issue in a clustered home environment. As mentioned earlier, the system is not expected to perform gait assessment on every single walking sequence. It is sufficient to identify and analyze a few good walking sequences a day using the rule-based video segmentation approach proposed. Strategic placement of the web cameras, such as a hall way or other open living areas in the home, can also help to optimize the system's performance. In many of the cases when the human bodies are partially occluded by furniture, often the feet regions from the web cameras' view, walking speed can still be estimated properly, but steps cannot be recognized using the proposed method. We are in the process of testing the system in 10 senior apartments for two years and will report the results as the study proceeds.

VII. Conclusion

In this study, we have proposed and validated a low cost webcam system for passive and continuous in-home gait assessment. Using 3D voxel data without explicitly tracking human body parts is computationally efficient, eliminates the constraint of walking path direction,

helps to preserve the residents' privacy, and makes this technology especially suitable for passive, long term use in an unstructured daily living environment. Our findings include: (1) The system has achieved a high accuracy based on in-lab and in-home validation with ground truth; (2) The system provides a clear overview of the person's daily gait parameters, and has a good potential to be used to identify people at high risk of falling; (3) Large differences in gait patterns have been observed between the in-home tests vs. clinical tests. The above findings support the feasibility and necessity of deploying such systems in an elderly home.

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References

1. Hodgins D. The Importance of Measuring Human Gait. Medical Device Technology. 2008; vol. 19:44–47.
2. Perry, J. Gait Analysis: Normal and Pathological Function. Thorofare, NewJersey: SLACK Inc; 1992. ISBN 978-1-55642-192-1.
3. Tinetti ME, Speechley M, Ginter SF. Risk Factors for Fallers Among Elderly Persons Living in the Community. New England Journal of Medicine. 1988; Vol. 319:1701–1707. [PubMed: 3205267]
4. Barak Y, Wagenaar RC, Holt KG. Gait Characteristics of Elderly People with a History of Falls: A Dynamic Approach. Physical Therapy. 2006; vol. 86(no. 11):1501–1510. [PubMed: 17079750]
5. Skubic M, Alexander G, Popescu M, Rantz M, Keller J. A Smart Home Application to Eldercare: Current Status and Lessons Learned. Technol and Health Care. 2009; vol. 17(no. 3):183–201.
6. Perell KL, Nelson A, Goldman RL, Luther SL, Prieto-Lewis N, Rubenstein L. Fall Risk Assessment Measures an Analytic Review. Journal of Gerontology. 2001; vol. 56:761–766.
7. Krebs DE, Edelstein JE, Fishman S. Reliability of Observational Kinematic Gait Analysis. Physical Therapy. 1985; vol. 65(no. 7):1027–1033. [PubMed: 3892553]
8. Brunnekreef JJ, van Uden CJ, van Moorsel S, Kooloos JG. Reliability of Videotaped Observational Gait Analysis in Patients with Orthopedic Impairments. BMC Musculoskeletal Disorders. 2005; vol. 16:17–25. [PubMed: 15774012]
9. Alwan, M.; Felder, RA. Eldercare Technology for Clinical Practitioners. Totowa, NJ: Humana Press; 2008. ISBN 978-1-58829-898-0.
10. Yang C-C, Hsu Y-L. A Review of Accelerometry-Based Wearable Motion Detector for Physical Activity Monitoring. Sensors. 2010; vol. 10:7772–7788. [PubMed: 22163626]
11. Hagler S, Austin D, Hayes TL, Kaye J, Pavel M. Unobtrusive and Ubiquitous In-Home Monitoring: A Methodology for Continuous Assessment of Gait Velocity in Elders. IEEE Transactions on Biomedical Engineering. 2010; vol. 57(no. 4):813–820. [PubMed: 19932989]
12. Low, KH.; Tani, JW.; Chandra, T.; Wang, P. Initial Home-Based Foot-Mat Design & Analysis of Bio-Gait Characteristics to Prevent Fall in Elderly People; Conf Proc IEEE Robotics and Biomimetics; 2009. p. 759-764.
13. Aggarwal JK, Cai Q. Human Motion Analysis: A Review. Computer Vision and Image Understanding. 1999; vol. 73:90–102.
14. Moeslund TB, Hilton A, Kruger V. A Survey of Advances in Vision-Based Human Motion Capture and Analysis. Computer Vision and Image Understanding. 2006; vol. 104:90–126.
15. Collins, RT.; Gross, R.; Shi, J. Silhouette-based Human Identification from Body Shape and Gait; Proc. IEEE Intl Conf on Automatic Face and Gesture Recognition; 2002. p. 366-371.

16. Wang L, Tan T, Ning H, Hu W. Silhouette Analysis-Based Gait Recognition for Human Identification. IEEE Tran on Pattern Analysis and Machine Intelligence. 2003; vol. 25(no. 12): 1505–1518.
17. Bouchrika I, Nixon MS. Model-Based Feature Extraction for Gait Analysis and Recognition. Lecture Notes in Computer Science. 2007; vol. 4418:150–160.
18. Wang F, Stone E, Dai W, Skubic M, Keller J. Gait Analysis and Validation Using Voxel Data. IEEE EMBS. 2009:6127–6130.
19. Wang, F.; Stone, E.; Dai, W.; Banerjee, T.; Giger, J.; Krampe, R.; Rantz, M.; Skubic, M. Testing an In-Home Gait Assessment Tool for Older Adults; Conf Proc IEEE EMBS; 2009. p. 6147-6150.
20. Baumgard, BG. PhD thesis. University of Stanford; 1974. Geometric Modeling for Computer Vision.
21. Laurentini A. The Visual Hull Concept for Silhouette-Based Image Understanding. IEEE Transactions on Pattern Analysis and Machine Intelligence. 1994; vol. 16:150–162.
22. Esteban CH, Schmitt F. Silhouette and stereo fusion for 3D object modeling. CompVis and Img Understandi. 2004; vol. 96:367–392.
23. Furukawa Y, Ponce J. Carved Visual Hulls for Image-Based Modeling. Int Journal of Computer Vision. 2009; vol. 81:53–67.
24. Demiris G, Oliver DP, Giger J, Skubic M, Rantz M. Older Adults' Privacy Considerations for Vision Based Recognition Methods of Eldercare Applications. Technol and Health Care. 2009; vol. 17:41–48.
25. Luke RH, Anderson D, Keller JM, Skubic M. Human Segmentation from Video in Indoor Environments Using Fused Color and Texture Features. Technical Report, University of Missouri. 2007 [Online]. Available: http://www.eldertech.missouri.edu/files/Papers/LukeRobert/HumanSegmentation.pdf.
26. Bouguet J-Y. Camera Calibration Toolbox for Matlab. 2010 [Online] Avaliable: http://www.vision.caltech.edu/bouguetj/calib_doc/.
27. Stone EE, Skubic M. Silhouette Classification Using Pixel and Voxel Features for Improved Elder Monitoring in Dynamic Environments. IEEE Pervasive Comput and Commun Workshops. 2011:655–661.
28. Windolf M, Gotzen N, Morlock M. Systematic Accuracy and Precision Analysis of Video Motion Capturing Systems – Exemplified on the Vicon-460 System. J of Biomech. 2008; vol. 41:2776–2780. [PubMed: 18672241]
29. Webster KE, Wittwer JE, Feller Julian F. Validity of GAITRite Walkway System for the Measurement of Averaged and Individual Step Parameters of Gait. Gait and Posture. 2005; vol. 22:317–321. [PubMed: 16274913]
30. Montero-Odasso M, Schapira M, Soriano ER, Varela M, Kaplan R, Camera LA, Mayorga LM. Gait Velocity as a Single Predictor of Adverse Events in Healthy Seniors Aged 75 Years and Older. J Gerontol A Biol Sci Med Sci. 2005; vol. 60:1304–1309. [PubMed: 16282564]
31. Studenski S, Perera S, Wallace D, Chandler JM, Duncan PW, Rooney E, Fox M, Guralnik JM. Physical Performance Measures in the Clinical Setting. J Am Geriatr Soc. 2003; vol. 51:314–322. [PubMed: 12588574]
32. Brach JS, Studenski SA, Perera S, VanSwearingen JM, Newman AB. Gait Variability and the Risk of Incident Mobility Disability in Community-Dwelling Older Adults. Journals of Gerontology: Series A. 2007; vol. 62:983–988.
33. Parson HM. What Happened at Hawthorne? Science. 1974; vol. 193:922–932.
34. De Amici D, Klersy C, Ramajoli F, Brustua L, Politi P. Impact of the Hawthorne Effect in a Longitudinal Clinical Study: The Case of Anesthesia. Control Clinical Trials. 2000; vol. 21(no. 2): 103–114.
35. Fritz S, Lusardi M. Walking Speed: the Sixth Vital Sign. Journal of Geriatric Physical Therapy. 2009; vol. 32:46–49. [PubMed: 20039582]
36. Graham JE, Fisher SR, Berges IM, Kuo YF, Ostir GV. Walking Speed Threshold for Classifying Walking Independence in Hospitalized Older Adults. Phys Therapy. 2010; vol. 90:1591–1597.
37. Studenski S, Perera S, Patel K, Rosano C, Faulkner K, Inzitari M, Brach J, Chandler J, Cawthon P, Connor EB, Nevitt M, Visser M, Kritchevsky S, Badinelli S, Harris T, Newman AB, Cauley J,

Ferrucci L, Guralnik J. Gait Speed and Survival in Older Adults. J Am Mel Ass. 2011; vol. 305:50–58.

38. Afilalo J, Eisenberg MJ, Morin JF, Bergman H, Monette J, Noiseux N, Perrault LP, Alexander KP, Langlois Y, Dendukuri N, Chamoun P, Kasparian G, Robichaud S, Gharacholou SM, Boivin JF. Gait Speed as an Incremental Predictor of Mortality and Major Morbidity in Elderly Patients Undergoing Cardiac Surgery. J Am Coll Cardiol. 2010; vol. 56:1668–1676. [PubMed: 21050978]

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James M. Keller (F'00) received the Ph.D. in Mathematics in 1978. He holds the University of Missouri Curators' Professorship in the Electrical and Computer Engineering and Computer Science Departments on the Columbia campus. He is also the R. L. Tatum Professor in the College of Engineering. His research interests center on computational intelligence: fuzzy set theory and fuzzy logic, neural networks, and evolutionary computation with a focus on problems in computer vision, pattern recognition, and information fusion including bioinformatics, spatial reasoning in robotics, geospatial intelligence, sensor and information analysis in technology for eldercare, and landmine detection. His industrial and government funding sources include the Electronics and Space Corporation, Union Electric, Geo-Centers, National Science Foundation, the Administration on Aging, The National Institutes of Health, NASA/JSC, the Air Force Office of Scientific Research, the Army Research Office, the Office of Naval Research, the National Geospatial Intelligence Agency, the Leonard Wood Institute, and the Army Night Vision and Electronic Sensors Directorate. Professor Keller has coauthored over 400 technical publications.

Jim is a Fellow of the Institute of Electrical and Electronics Engineers (IEEE) and the International Fuzzy Systems Association (IFSA), and a past President of the North American Fuzzy Information Processing Society (NAFIPS). He received the 2007 Fuzzy Systems Pioneer Award and the 2010 Meritorious Service Award from the IEEE Computational Intelligence Society (CIS). He has been/is a distinguished lecturer for the IEEE CIS and the ACM. Jim finished a full six year term as Editor-in-Chief of the *IEEE Transactions on Fuzzy Systems*, followed by being the Vice President for Publications of the IEEE Computational Intelligence Society from 2005–2008, and since then an elected CIS Adcom member. He is the IEEE TAB Transactions Chair and a member of the IEEE Publication Review and Advisory Committee. Among many conference duties over the years, Jim was the general chair of the 1991 NAFIPS Workshop and the 2003 IEEE International Conference on Fuzzy Systems.

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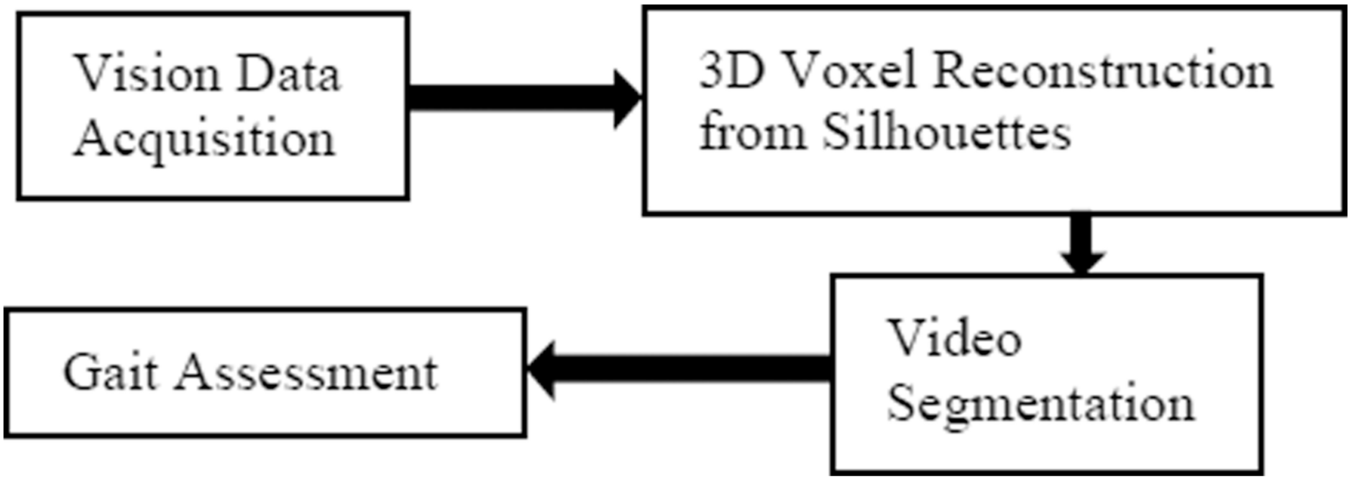

Fig. 1.
Webcam gait assessment system overview.

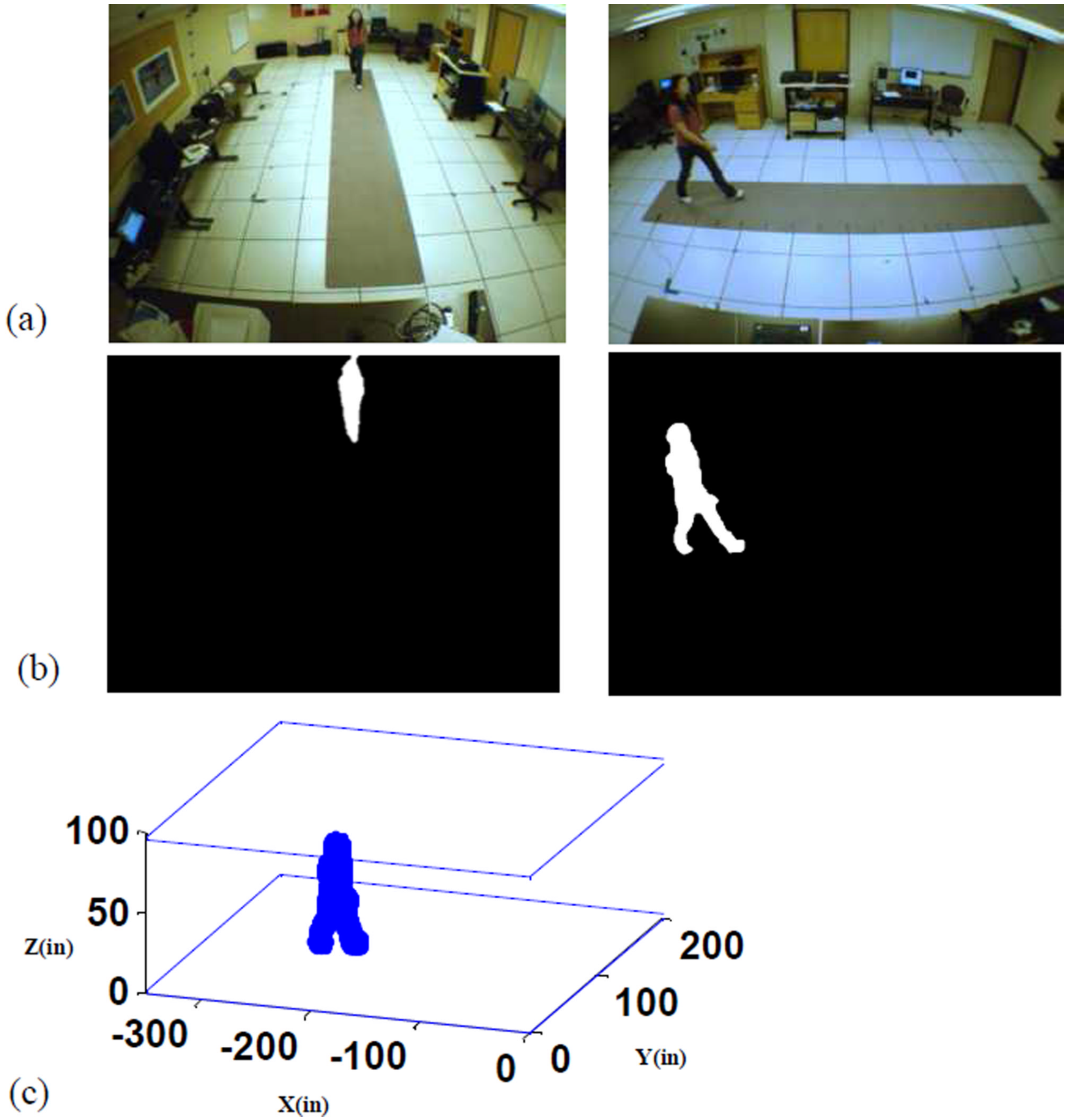

Fig. 2.

(a) Two raw camera images monitoring the same scene of one subject is walking on the GAITRite in the lab (b) Human silhouettes (c) The reconstructed three-dimensional voxel person.

Fig. 3.
An elderly participant during an in-home scenario test (see section V). Color features are used to track the human in a two-person scenario.

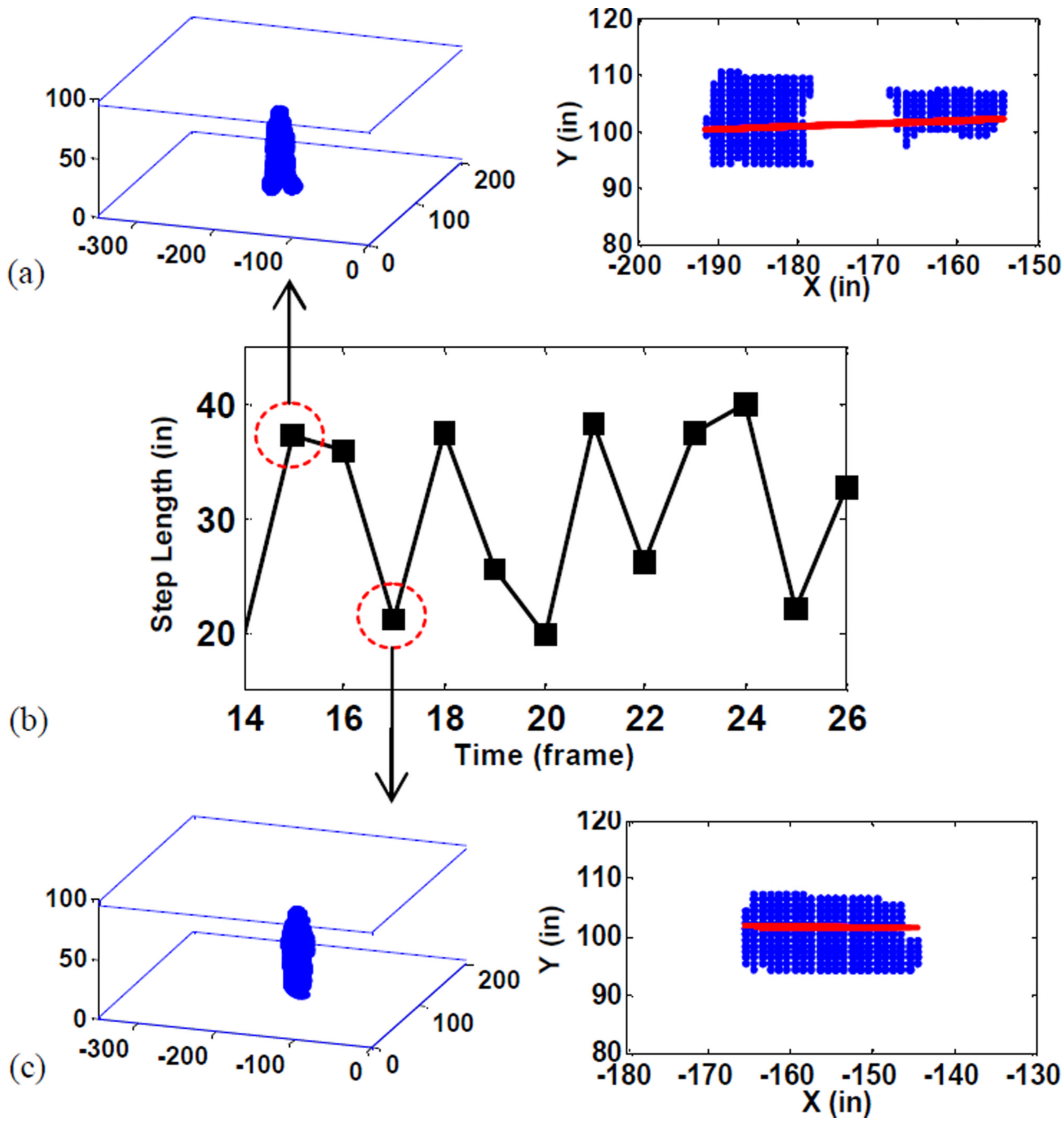

Fig. 4.
(a) An illustration of a peak frame, i.e., feet are apart. Left: voxel person representation, Right: top view of the foot region projection (b) Step length variation at different frames (c) An illustration of a valley frame, i.e., feet are together. Left: voxel person representation, Right: top view of the foot region projection.

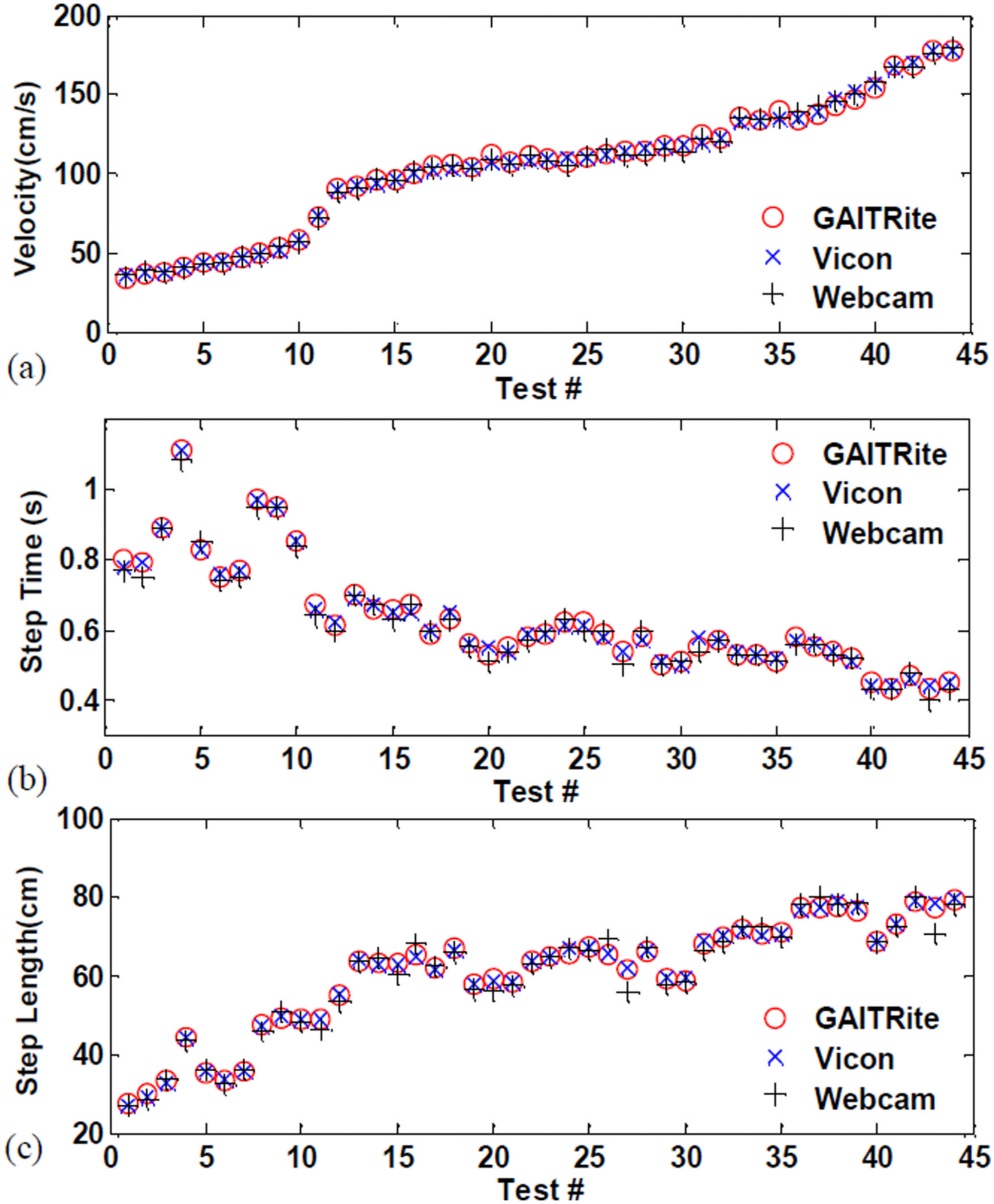

Fig. 5.
In-lab validation results. (a) Velocity (b) Step Time (c) Step Length results for the webcam, GAITRite and Vicon systems. The test runs are sorted by velocity in ascending order.

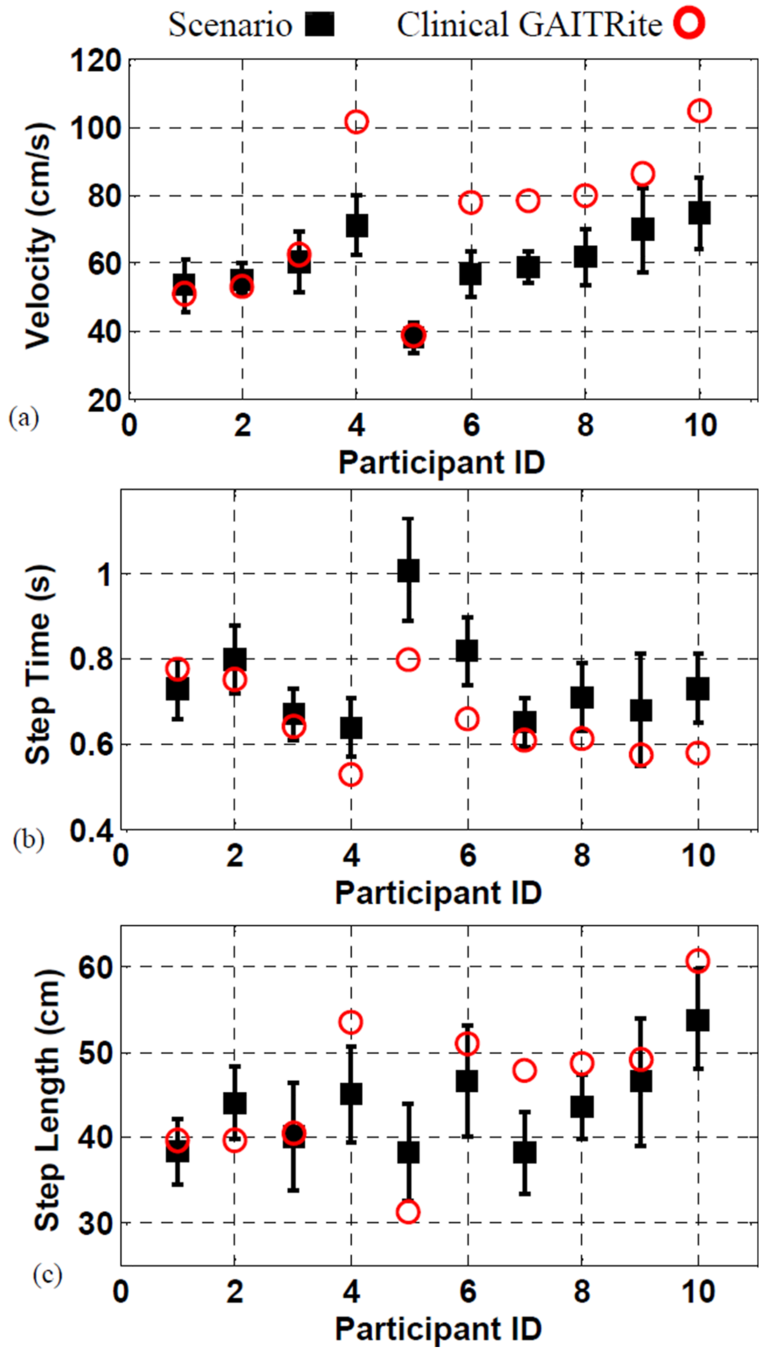

Fig. 6.
Comparison of the scenario results (mean and standard deviation) with a clinical test results using the GAITRite. The participant IDs are sorted based on gender and velocity. Female ID1–4; male ID5–10. (a) Velocity (b) Step time (c) Step length.

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Table I

Webcam and Vicon In-lab Comparison

	Webcam	Vicon	ICC	RC	
	Mean(S.D.)			Absolute	%Mean
Velocity (cm/s)	104.7(40.4)	104.5(40.4)	0.99	4.4	4.2
Step time (s)	0.62(0.15)	0.63(0.15)	0.99	0.03	5.4
Step length (cm)	60.1(14.5)	60.6(14.3)	0.99	4.0	6.6

ICC: Intra-class coefficient; RC: repeatability coefficient

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Table II

Webcam and GAITRite In-lab Comparison

	Webcam	**GAITRite**	**ICC**	**RC**	
	Mean(S.D.)			**Absolute**	**%Mean**
Velocity (cm/s)	104.7(40.4)	104.6(40.4)	0.99	4.4	4.2
Step time (s)	0.62(0.15)	0.63(0.15)	0.99	0.03	4.7
Step length (cm)	60.1(14.5)	60.5(14.2)	0.99	3.8	6.4

ICC: Intra-class coefficient; RC: repeatability coefficient

Table III

Webcam and GAITRite In-Home Comparison

	Webcam	GAITRite	ICC	RC	
	Mean(S.D.)			Absolute	%Mean
Velocity (cm/s)	77.8(8.6)	77.8(8.6)	0.99	2.1	0.7
Step time (s)	0.60(0.07)	0.61(0.07)	0.99	0.03	1.3
Step length (cm)	46.4(4.5)	46.7(4.9)	0.99	1.65	0.9

ICC: Intra-class coefficient; RC: repeatability coefficient