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Automated Fall Risk Assessment and Detection in the Home: A Preliminary Investigation

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Abstract

Falls are a major problem for older adults. A continuous unobtrusive in-home monitoring system that provides an accurate automated assessment of fall risk and detects when falls have occurred would allow for timely intervention and prevention allowing individual to remain healthier and independent longer. Sensor networks have been installed in apartments of older adult volunteers at TigerPlace, an independent senior living community. Initial results comparing gait parameters captured with a Microsoft Kinect with ground truth clinical fall risk assessments and GAITRite data are presented.

Introduction

Falls are a common problem in older adults. One in every three people age 65 or older falls each year, making falls the most common cause of injuries and hospitalizations for trauma in older adults and the leading cause of death due to injury (Centers for Disease Control 2012). Changes in gait parameters predict increase fall risk (Hausdorff, Ros, and Edelberg 2001; Barak, Wagenaar, and Holt 2006) and gait parameters are important factors in a variety of medical conditions (Hodgins 2008). Researchers have studied falls, fall risk assessment, and interventions to prevent falls. However, to date, their methods require that research staff or clinicians complete multi-factorial assessments of fall risk and that research subjects maintain logs of falls, wear devices that measure changes in positions that could indicate a fall or activate an alarm when they need assistance. A continuous unobtrusive in-home monitoring system that provides accurate automated assessment of fall risk and detects when falls have occurred would allow for timely intervention and prevention allowing individual to remain healthier longer. Researchers at the University of Missouri Center for Eldercare and Rehabilitation Technology are testing sensors system in homes of older adults to detect falls and assess fall risk.

In this paper, we examined the relationship of two ground truth gait parameters (velocity and the functional ambulation profile collected from the GAITRite mat) to various fall risk measures collected by health care professionals completing standard fall risk assessment of elders and gait parameters computed from in-home Microsoft Kinect data. The purpose of the research is to automate fall risk assessment using environmentally placed sensors in the homes of elders so that fall risk can be measured in everyday living activities. In that way, elders themselves can be made aware when fall risk increases and take steps to improve physical function to avoid devastating falls. We also want to discover potentially more sensitive measures of fall risk, much like we have been able to do in early illness detection (Rantz et. al, 2012) using environmentally embedded sensors. The first steps of the research are to automatically capture gait parameters from the sensor system to automatically assess fall risk and compare these to standard fall risk measurements by health care professionals. Data from the initial steps are reported in this paper.

Sensor System and Data Collection

Sensor systems consisting of a Pulse-Doppler range control Radar, a Microsoft Kinect, and two orthogonal web cameras have been installed in apartments of older adults at TigerPlace, an independent senior living community. The sensor system has been installed in 11 apartments. The radar is located in a box by the front door. The Kinect is on a shelf above the front door. A web camera is located on the longest wall of the living room and the other camera is placed on the adjacent wall. The first system was installed on June 9, 2011. The radar and the depth image (an image in which the value of each pixel depends on its distance from the camera) from the Kinect are captured continuously because these images are not personally identifiable. To preserve the privacy of the individuals, the raw images from web cameras are collected only during monthly fall risk data collection of older adult participants that are completed by health care staff. Otherwise, web camera data are captured in the form of extracted silhouettes to preserve the residents' privacy.

A total of 14 people (5 men and 9 women) are being continuously monitored. The average age of the subjects is 85.88 (range 67-97). The monitored group includes 3 couples and the remaining participants are single. Four people have been discharged: one person died, one moved to a nursing home and a couple withdrew from the study for personal reasons.

To test the sensor system, two rounds of data collection take place each month. Each subject completes a Fall Risk Assessment (FRA) in the apartment and a stunt actor completes a series of falls in each of the apartments. The FRA is comprised of six fall risk measures that are valid and reliable: Habitual Gait Speed (HGS) (Bohannon, 1997; Fransen, Crosbie, and Edmonds 1997), Timed Up and Go (TUG) (Podsiadlo and Richardson 1991; Shumway-Cook, Brauer, and Woollacott 2000), Multidimensional Functional Reach (FR) (Newton 2001), Short Performance Physical Battery (SPPB) (Guralnik 1994), the Berg Balance Scale (BBS-SF) (Berg et al. 1992), and the single leg stance (SLS) (Vellas 1997). The first FRA was completed on June 27, 2011. Figure 1 presents the FRA data for 3 of the 14 residents over time. As shown in Figure 1, each of the fall risk measures fluctuate over time for each resident; some move in similar patterns while others do not. Clinical experts on the team interpreted that these are measuring different aspects of fall risk and some have ceiling or floor effects that are impacted by different clinical conditions of each subject.

Gait parameters of step time, step length, stride length, and velocity were computed from the Kinect data at the same time of the FRAs. The methods to calculate the gait parameters are outlined in (Stone & Skubic 2011; Stone & Skubic 2012). The gait parameters extracted from the Kinect data were first validated against Vicon maker-based motion capture system in the laboratory and showed good agreement (Stone & Skubic 2011). The Kinect was then installed in apartments at TigerPlace and gait parameters captured and trends monitored (Stone & Skubic 2012).

GAITRite data were collected on subjects to use as ground truth. The GAITRite portable gait analysis system provides valid and reliable measurements in real time of temporal and spatial parameters of gait including cadence, step length, and velocity (www.gaitrite.com). Gait-related predictors of fall-risk such as analysis of how the foot strikes the surface are also quantified. The 14-foot portable carpet with 16,128 sensors captures gait elements without use of additional sensors. A subject walks across the mat once and the software calculates the gait parameters, such as velocity, and the functional ambulation profile (FAP). The FAP is a summary score (range 0-100) that quantifies the gait based on specific temporal and spatial gait parameters (Nelson 1974).

Because the GAITRite and FRA data were not collected at the same time or intervals, a 60 day window was used to merge the data sets. If a GAITRite assessment occurred within 60 days of the FRA, the two data points were linked. Figures 2 and 3 illustrate the relationship of the GAITRite and FRA Scores with the Kinect parameters.

Fig. 1: FRA Scores over time

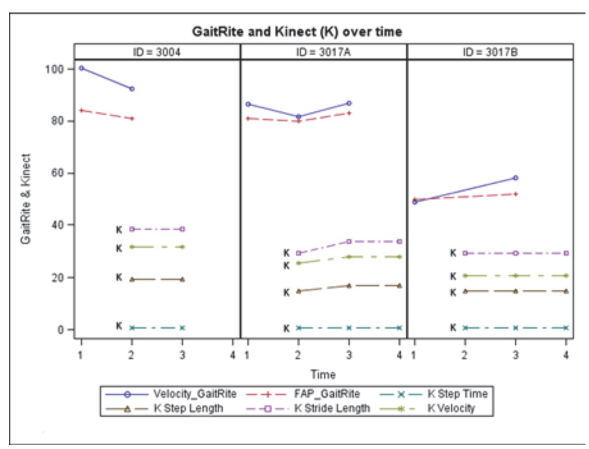

Fig. 2: GAITRite scores and Kinect variables over time

Figure 2 displays the GAITRite velocity and FAP scores and Kinect derived fall risk scores of step time, step length, stride length, and velocity. (Kinect scores are designated by K in Figures 2 and 3.)

In Figures 2 and 3, the variables from the GAITRite and FRA Scores parallel the Kinect variables in many cases, therefore warranting further analyses. An analysis investigating the correlations between the variables in the repeated measure design was completed.

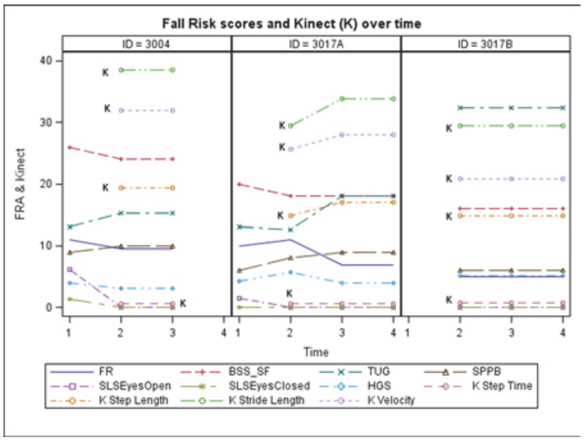

Fig. 3: FRA scores and Kinect (K) variables over time

Results

In Table 1, the key components of fall risk assessments (TUG, SPPB, HGS) are correlated in the expected direction with ground truth of the GAITRite velocity and FAP. The common underlying movement in each of these fall risk measures is gait velocity. In Table 2 we compare Kinect step time, step length, stride length and velocity with GAITRite ground truth. The two parameters with the best relationships in the expected direction to ground truth are step time and velocity (using the more accurate Wolfinger method that incorporates the repeated measure design in the estimation process) (Hamlett et al. 2003). We will continue to explore other parameters that we can measure with the Kinect for potential use in automating fall risk assessment while elders go about normal everyday living activities.

Discussion

Given the positive results of this initial investigation, further exploration is needed. A larger dataset is needed to confirm the results. More sophisticated algorithm using artificial intelligence could greatly increase the accuracy of the results and allow us to capture additional elements of the fall risk assessments.

With additional work and refinement, the system will automatically assess fall risk and detect falls. The system could eventually be deployed as an early warning system in long-term facilities, other congregate housing, and private homes addressing a major problem for older adults allowing them to stay healthy and independent longer.

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GAITRite	Type of Correlation (p-value)	Functional Reach	Berg Balance Scale	Timed Up and Go	Short Physical Performance Scale	Single Leg Stance Eyes Open	Single Leg Stance Eyes Closed	Habitual Gait Speed (10' walk time)
Velocity (cm/sec)	Pearson's Wolfinger Method	.40 (.11) .44	**.60 (.0078)** .66	**-.82 (<.0001)** -.78	**.84 (<.0001)** .87	**.54 (.021)** .55	.17 (.49) .21	**-.81 (<.0001)** -.84
Functional Ambulation Profile (from 100%)	Pearson's Wolfinger Method	.51 (.36) .54	**.57 (.017)** .63	**-.79 (.0002)** -.66	**.64 (.0055)** .70	**.56 (.019)** .56	.18 (.50) .22	**-.54 (.024)** -.62

Table 1: Comparison of GAITRite variables to fall risk assessments (significant results in **bold**)

GAITRite	Type of Correlation (p-value)	Kinect			
		Step Time	Step Length	Stride Length	Velocity
Velocity (cm/sec)	Pearson's Wolfinger Method	**-.62 (<.0001)** -.65	.068 (.81) .11	**.79 (.0003)** .06	.068 (.81) .75
Functional Ambulation Profile (from 100%)	Pearson's Wolfinger Method	-.39 (.16) -.62	.14 (.61) .42	**.66 (.007)** .40	.15 (.61) .69

Table 2: Comparison of GAITRite variables to gait parameters calculated from Kinect Data (significant results in **bold**)

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