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Automated Technology for In-home Fall Risk Assessment and Detection Sensor System

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Abstract

Falls are a major problem for older adults. A continuous, unobtrusive, environmentally mounted in-home monitoring system that automatically detects when falls have occurred or when the risk of falling is increasing could alert health care providers and family members so they could intervene to improve physical function or mange illnesses that are precipitating falls. Researchers at the University of Missouri (MU)Center for Eldercare and Rehabilitation Technology are testing such sensor systems for fall risk assessment and detection in older adults' apartments in a senior living community. Initial results comparing ground truth fall risk assessment data and GAITRite gait parameters with gait parameters captured from Mircosoft Kinect and Pulse-Doppler radar are reported.

Falls are a major problem in older adults. One in every three people over the age of 65 falls each year and 2 million are treated in emergency rooms for fall-related injuries (Centers for Disease Control, 2013). Researchers have studied falls, fall risk assessment, and interventions to prevent falls. However, their methods require that research staff or clinicians complete multi-factorial assessment of fall risk (Parrell et al, 2001) or that people maintain logs of falls, wear devices that measure changes in positions that could indicate a fall (Boissy, Choquette, Hamel, & Noury, 2007) or activate an alarm when they need assistance (Curry, Tinoco, & Wardle, 2003). A continuous, unobtrusive, environmentally mounted in-home monitoring system that automatically detects when falls have occurred or when the risk of falling is increasing could alert health care providers and family members so they could intervene to improve physical function or mange illnesses that are precipitating falls. Researchers at the University of Missouri (MU) Center for Eldercare and Rehabilitation Technology are testing such sensor systems for fall risk assessment and detection in older adults' apartments in a senior living community.

Environmentally Mounted Fall Sensor System Overview

Fall risk assessment sensor systems have been installed in apartments of older adults at TigerPlace, an independent senior living community. The fall risk assessment sensor system consists of a Pulse-Doppler range control Radar, a Microsoft Kinect (developed for a gaming system), and two web cameras. The radar is installed in a decorative wooden box next to the front door of the apartment. The Kinect is located on a small shelf over the front door, near the ceiling. To preserve the privacy of the research subject, only the depth image (an image where the value of each pixel depends on its distance from the camera) from the Kinect and the radar data are continuously captured. Gait parameters are calculated on a daily basis from the Kinect data. The first system was installed on June 9, 2011 and is still active providing over one and a half years of continuous data for system development and improvement.

The Pulse-Doppler radar and Kinect systems were developed and tested in a MU research laboratory before being deployed in the homes of older adults. Gait parameters are extracted from the radar and Kinect systems using sophisticated algorithms developed by engineering research team members. The Pulse-Doppler radar system was created by collaborators at GE Global Research laboratories. For testing of the sensor systems, a Vicon optical motion capture system was used as ground truth. The Vicon system uses infrared markers worn by test subjects and a system of cameras to precisely measure limb and torso movements.

Methods

Sample for Laboratory Development of the Systems

Fifteen test subjects (8 women, 7 men) ranging in age from 23-67 (mean 56.53, standard deviation 11.51) performed a series of walks (fast, slow, normal) and fall risk measures in the laboratory. The Pulse-Doppler radar estimates the velocity, stride length, and stride variability and they compare very well with the estimates from the Vicon with the exception of a walk to simulate a post-stroke patient where the feet are shuffled (Yardibi et al., 2011). In addition, the Kinect validation using the Vicon system demonstrated good agreement between gait parameters of stride time, stride length, and velocity calculated using the Kinect data and those obtained from Vicon (Stone & Skubic, 2011).

Sample for Field Testing in Homes of Elders

After initial development and testing in the laboratory, the fall risk assessment sensor systems were deployed in the homes of residents at TigerPlace, a senior retirement community, to test the system in a real-world environment with older adults. To maintain a continuous sample in 10 apartments, the sensor system has been installed in 14 apartments. Seventeen people (10 women, 7 men) signed IRB approved informed consent and have been monitored including 3 couples. The age of the research subjects range from 67 to 98 (average 87.5, standard deviation 7.94). Six people have been discharged during the first year and half of deployment for the following reasons: one person died, one moved to a nursing home, a couple withdrew for personal reasons, and another couple moved to an assisted living facility. Eleven people including one couple remain in the study.

Methods for Field Testing of Fall Sensor Systems

To validate and improve the fall risk assessment sensor system, each participant completes a monthly fall risk assessment (FRA) doing the steps of commonly used FRA by health care providers. 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. A research assistant scores and records the fall risk measures. In addition to the FRAs, a stunt actor completes a series of falls in each participant's apartment. To protect research subjects from harm, trained stunt actors fall on mats in the apartments each month. The stunt actor falls are necessary because data from actual falls is essential to develop and test computer algorithms for fall detection. The use of stunt actors provides information about how accurate the systems are in detecting actual falls. If the fall detection sensor system is to be widely adopted, it must accurately detect when falls occur.

Another valid source of FRA used in the study is GAITRite data collected for each subject. The GAITRite electronic walkway measures temporal and spatial gait parameters, such as cadence, step length, velocity, and the functional ambulation profile (FAP). The subject simply walks the length of the electronic walkway and the GAITRite system automatically calculates the gait parameters (www.gaitrite.com). The FAP is a summary score that can be used as ground truth for FRA (range 0-100) that quantifies the gait based on temporal and spatial parameters (Nelson, 1974). The GAITRite data is collected every six months; this data is used as ground truth and periodically compared with the other clinical FRA measures.

To further validate the system with data collection in the home environment, a data set was constructed of all monthly clinical FRAs for all subjects (n=17) for 18 months of data collection (n=159 completed FRAs for all clinical measures), Kinect gait data daily measures for the same dates of the FRA, and radar gait measures for the same dates of the FRAs. Three types of correlations were computed using the GAITRite variables of velocity and FAP as ground truth. In order to account for replicate measurements over time, the Bland/Altman approach (Bland & Altman, 1994) and a method suggested by Hamlett et. al. (2003) were used in addition to Pearson's. Commonly used Pearson's correlation coefficients are reported in the tables of results, others are available from the authors upon request.

Results of Field Testing Validation of Automated Assessment of Fall Risk Measures

As a first analytic step, the known valid and reliable GAITRite measures for velocity and FAP scores were used as "ground truth" and correlations were estimated with the FRAs also with known validity and reliability (n=15 with 15 unique subjects). Correlations are in the expected direction for each FRA measure as shown in Table 1. Both velocity and the FAP scores from the GAITRite are highly correlated (in the expected direction) for the Berg Balance Scale (BBS-SF), Timed Up and Go (TUG), Short Performance Physical Battery (SPPB), single leg stance (SLS) (eyes open), and Habitual Gait Speed (HGS).

As the second analytic step, the FRAs were used as ground truth and correlations were estimated with the automated Kinect and radar gait measures that were developed for continuous fall risk assessment. Table 2 displays these results (n=102 with 15 unique subjects). Results show the variables from the Kinect and the radar, collected simultaneously during the FRAs, have correlations consistently in the expected direction with most statistically significant.

As a third step, the limited data set of GAITRite (as ground truth) was correlated with Kinect and radar data collected about the same time, but not simultaneously. A window of plus or minus 2 months was used to merge the data sets. Table 3 displays the correlations of gait parameters of velocity and FAP calculated from the GAITRite; stride time, stride length, and velocity calculated from the Kinect data; and velocity and stride time from the radar. While correlations are in the expected direction, none reached statistical significance. This is likely due to the small sample size (n=15 with 15 subjects). As a final step, correlations were estimated among the Kinect and radar gait parameters (n=102 with 15 subjects). As anticipated, these are correlated in the expected directions and most are statistically significant (see Table 4).

Discussion

Data from this study provides preliminary evidence that work to develop an automated, continuous, unobtrusive, environmentally mounted in-home monitoring system for fall risk assessment is possible and has potential for success. Based on the preliminary findings of this study, normal daily activities in the home can provide measures to detect changes in fall risk that are correlated with commonly used FRA measures. The results from both the Microsoft Kinect and Doppler radar automated algorithms are correlated with ground truth measures of the GAITrite electronic walkway and the commonly used FRA measures by health care providers.

The fall risk assessment sensor system deployed at TigerPlace has the potential to revolutionize fall prevention by measuring fall risk as people go about normal daily living. The system can be refined to send automated “alerts” that fall risk is increasing or provide much needed encouragement that strength training or other exercise-based interventions are actually reducing one’s risk for falls. This system also has potential to keep family members and health providers informed about changes in falls or fall risk affecting an older adult.

This study is also examining environmentally mounted sensors for fall detection; these data collection and analyses are still underway. Non-wearable fall detection would be invaluable in long-term care, hospitals, and congregate senior housing where falls are a major risk. Automatic fall detection would facilitate discovery that a person has fallen, crucial to survival and recovery after falls with injuries, thus enabling older adults to stay healthier longer.

Limitations of this study include the single housing site for sample recruitment, the relatively small deployment in 10 homes, and the limited six month interval for GAITRite ground truth data collection. While monthly data collection of FRAs provides an adequate source for ground truth, overcoming the limited availability of the GAITrite data, future work can include more frequent GAITRite data collection.

In summary, the effort to develop automated technology for in-home fall risk assessment and detection sensor system is advancing new ways to help older adults remain independent as long as possible, an important goal of older people and their families. In addition, it has the potential to reduce costly hospitalization and nursing home stays.

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Table 1

Correlations (Pearson's) between GAITRite Velocity and Functional Ambulation Profile (FAP) and Fall Risk Assessments (FRAs) (n=15 with 15 unique subjects).

GAITRite	Fall Risk Assessments (FRAs) Pearson's correlations						
	FR	BBS_SF	TUG	SPPB	SLS Eyes Open	SLS Eyes Closed	HGS
GAITRite Velocity (cm/sec)	.41(.13)	.52(.045)	-.77(.0008)	.74(.0015)	.15 (.59)	-.0073(.99)	-.76(.0010)
GAITRite	.58(.025)	.60(.018)	-.80(.0003)	.59 (.019)	.32(.24)	.10 (.71)	-.55 (.034)

Table 2

Correlations (Pearson's) between FRAs and Kinect and Radar Variables (n=102, 15 unique subjects)

FRAs	Kinect and Radar Variables				
	Kinect Stride Time	**Kinect Stride Length**	**Kinect Velocity**	**Radar Stride Time**	**Radar Velocity**
FR	-.18.(.07)	.53(<.0001)	.43 (<.0001)	-.30(.002)	.46(<.0001)
BBS_SF	.-.39 <.0001)	.64 (<.0001)	.61(<.0001)	-.31 (.002)	.42 (<.0001)
TUG	.59 (<.0001)	-.61(<.0001)	-. 70(<.0001)	.32 (.001)	-.55 <.0001)
SPPB	-.46(<.0001)	.62 (<.0001)	.65 (<.0001)	-.26 (.008)	.52 (<.0001)
SLS Eyes Open	-.34 (.0004)	.61 (<.0001)	.59 (<.0001)	-.15 (.13)	.26 (.009)
SLS Eyes Closed	-.16(.12)	.30(.0021)	.26(.0074)	-.18(.078)	.31(.0018)
HGS	.36(.0002)	-61(<.0001)	-.58(<.0001)	.30(.0026)	-.46(<.0001)

Table 3

Correlations (Pearson's) between GAITRite Velocity and Functional Ambulation Profile (FAP) and Kinect and Radar Variables (n=15, 15 unique subjects)

GAITRite	Kinect and Radar Variables				
	Kinect Stride Time	**Kinect Stride Length**	**Kinect Velocity**	**Radar Stride Time**	**Radar Velocity**
GAITRite Velocity (cm/sec)	-.19(.49)	.46(.087)	.46 (.087)	-.43 (.11)	.44 (.10)
GAITRite FAP	-.22(.44)	.48(.070)	.45 (.089)	-.59 (.020)	.57 (.027)

Table 4

Correlations (Pearson's) between Radar and Kinect variables (n=102, 15 subjects)

Radar	Kinect Variables		
	Kinect Stride Time	**Kinect Stride Length**	**Kinect Velocity**
Radar Stride Time	.19(.062)	-.21 (.031)	-.18 (.066)
Radar Velocity	-.26 (.0096)	.38(<.0001)	.35 (.0003)