Operationalizing a wireless wearable fall detection sensor for older adults

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***Abstract*—Falls are the leading cause of disability and injury-related deaths among older adults, resulting in over 1.6 million annual emergency hospitalizations in the United States. Fall detection devices often rely on dramatized falls when developing algorithms. This study used tri-axial accelerometers worn by older adult research subjects in order to (1) collect false positive data (2) capture potential fall events and (3) evaluate the usability of the device among this target population. Twelve older adults wore activity monitors while participating in structured and unstructured activities. The study collected data on 120 patient days, yielding 492.5 hours of monitored time. Actigraphy data of annotated activities were used to define parameters for refining the algorithm. No falls occurred during the study, but valuable false positive data were collected. The study also obtained information on the usability of the devices and revealed user perspectives on commercializing the final product.**

Keywords—fall detection; actigraphy; activity monitors; elderly populations

I. Introduction

Falls are the leading cause of disability, injury-related deaths, and emergency hospital admissions for adults over the age of 65 [1-4]. The consequences of falls among older adults also extend to loss of independence and need for long-term care [5]. Fall detection technologies that enable a timely response have the potential to mitigate these health and lifestyle sequelea attributed to falls.

Despite its importance, research on the activity of older adults has been limited [6-7]. Previous efforts at collecting activity data among the older adult population relied on simulated falls to predict and validate algorithms for sensory devices [8-12]. However, both dramatized falls and real falls among younger adults, happen in a very different way than the falls occurring among older adults and therefore are not an accurate representation of the activity that has become a leading public health concern [12]. As a result, sensors designed for older adults are not very sensitive or precise to actual falls.

The primary objective of this research is to refine an existing but incomplete algorithm for detecting falls from activity data collected on a tri-axial accelerometer. This research contributes to the development of a unique device that will send automated alerts when it detects a fall. It is therefore critical that the algorithm is precise enough to accurately discern a fall event but specific enough to distinguish between other movements and true fall events. This study combines observational and actigraphy data using wearable wireless sensors attached to older adult subjects to develop a reliable algorithm for detecting falls in this at-risk population.

A. Accelerometers for fall detection

Studies have used accelerometers to devise thresholds for fall detection algorithms. The different types of accelerometers include a tri-axial accelerometer using two, bi-axial Analog Devices ADXL210 mounted orthogonally to each other [16]. Other accelerometers for fall detection consist of a thigh-set MMA7260Q (74g, 300mV/g) tri-axial micro-machined accelerometer and two analog devices ADXRS150 (71501/s) rate gyroscopes measuring pitch (back positive) and roll (left positive) angular [9-10]. Another position for portable tri-axial accelerometers has been on the lower back to measure accelerations for near falls [11]. Finally, waist-mounted accelerometers with web-tracking capability have also been examined to enhance real-time fall detection [17].

The state of fall detection devices is evolving with an increasing trend in the provision of instantaneous and automatic alerts and use of cellular geopositioning capacities. Automatic fall detection devices are commercially available and transmit fall alerts to caregivers or to a centralized care dispatcher. Companies that provide automatic fall detection alerts include Phillips™, which launched the Lifeline with AutoAlert in 2010 [18] and Wellcore, which exhibited its Mobile Personal Emergency Response System (M-PERS) in 2010 [19]. Halo Monitoring™ has also developed a fall detection device that automatically activates a notification via text, email or phone upon the recognition of falls [20]. This push towards real-time fall alerts also necessitates rigorous research to minimize the inefficient use of resources involved in responses to false positives.

The integration of real-time tracking and communication is another advance in detection. Web-based platforms serve as one medium for enabling real-time monitoring. GPS is being incorporated into devices to more precisely identify fall locations, as demonstrated by products such as ActiveCare's Personal Assistant Link [21]. Other developments include efforts to build fall detection into mobile phones in order to

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expedite data transmission. One example of a mobile phone-based device includes the *PerFall ID*, which proposes to use an Android phone interface [22]. Mobile phone-based fall detection devices have demonstrated a high agreement with traditional external accelerometers in a study using dramatized falls [23]. Results from this study indicated specificity and sensitivity of 0.81 and 0.77, respectively [23]. Finally, Lifecomm™ is developing a Mobile Personal Emergency Response System (MPERS) that enables both cellular communication and GPS-tracking [24].

The fall detection landscape is rapidly changing due to the emergence of complementary technologies and increased need generated by the Baby Boomer driven demographic shift. These enhancements to fall detection systems offer the opportunity to provide more timely care, while also demonstrating the need for continued validation studies.

II. METHODOLOGY

A. Apparatus

The wearable Shimmer Device consisted of a tri-axial accelerometer using Freescale MMA7361, 1.5//6g MEMs Accelerometer, 3 Colored Status LEDs, soft-power button and SignalQuest SQ-SEN200 Passive MEMs Omnidirectional tilt and vibration sensor. Each sensor was 53mm x 32mm x 15mm.The Shimmer Device weighed 15g with baseboard for a total of 22g with the enclosure and battery.

Fig.1. Shimmer Device from the front (left) and back (right).

B. Study Procedures

The study used five sensors: one located on each wrist, one on each hip attached to the research subject's pant waistband, and one worn around the neck underneath the clothes. Subjects were equipped with all five sensors for each day of observation. The on-site study coordinator attached the sensors to the study participants in the morning and removed them at the end of each day. Female subjects wore the pendant higher so that the device was resting on their chest. Male subjects wore the pendant lower so that it was hanging well below their shirts. The hip position was similar for all research subjects but depended primarily on the height of the pants or skirts, which varied for both male and female subjects. Wrist straps were much smaller for females because of their narrower wrists.

Fig. 2. Mounting positions of the Shimmer devices on the wrist, hip and neck (left to right).

Information on the activity patterns of the study subjects was based on observed data of structured and unstructured activity. The structured activity was conducted three times over the course of the 12-day study period. The unstructured direct data consisted of 30-minute observations with the study subjectsto monitor daily-life activities. Unstructured activities consisted of the research subject's leisure routine, which consisted of bingo playing, painting and other craft activities.

The study also used self-reported activity history in which the study coordinator asked study subjects how they spent the previous few hours. The questions were adapted from the Physical Activity Scale for the Elderly (PASE) [25] and also included additional questions about what they did at specific times, based on the data that were extracted from the sensors.

C. Study Site

This study was conducted at Jewish Home Lifecare (JHL), a multi-campus nursing facility with locations in Manhattan, the Bronx, and Westchester County. This study recruited from the Manhattan and Bronx campuses focusing on long-term care populations, assisted-living populations, and adult day care populations. The study was approved by the JHL Institutional Review Board in January 2011.

D. Subject Selection

In an effort to capture daily life activity and fall data, this study used a convenience sample of subjects determined to be at high-risk for falling. The study involved two rounds of recruitment. Recruitment was initially focused on long-term nursing home residents and sub-acute care residents. The second round extended eligibility to assisted living and outpatient adult day programs. The inclusion criteria for participating in the research included the following:

- High-risk for falls, defined as having fallen in the past three months or fallen twice ever;
- Age 66 years or older;
- Full time resident of long-term stay nursing, sub-acute nursing units, assisted living facility or at least twice-weekly, community-dwelling visitors of Adult Day Care;
- Mobile, not requiring the use of an assistive ambulatory device;
- No extensive time planned off-site over the course of the study period;
- Standard Mini-Mental State Exam score ≥ 15;
- English speaking.

E. Ethical Considerations

Ethical considerations for selecting research subjects with a high risk for falls were taken into account. This was an observational study and research staff members were trained in geriatric fall protocol. Study subjects conducted activities that formed part of their daily routine, and no activities were used to induce falls.

F. Measurement Tools

Usability and comfort were measured qualitatively, through daily study subject feedback, and through a formal entrance and exit interview with the study coordinator. The study also collected baseline characteristics on research subjects to obtain demographic information, capabilities for activities of daily living, physical ability, daily routine/schedule, and levels of participation in facility activities. This information was collected using the following assessment tools.

- A study-specific demographic assessment was used to capture basic socio-demographic information (available upon request).
- The Snellen Eye Chart, a commonly used tool for screening visual acuity, was used to administer the basic vision test.
- The Pelli-Robson Contrast Sensitivity Chart was used to administer the Contrast Sensitivity Test.
- The Mini-Mental State Examination (MMSE) [26] was used to assess cognitive impairment.
- A Physical Performance Battery for older adults, which included a grip strength test, the Tinetti Balance and Gait analysis [27], and a timed ten meter walk, was used to assess physical capacity. The Physical Activity Questionnaire assessed physical activity during the past two weeks, functional status including pain, energy, level of independence with activities of daily living, and bladder function. It also included a geriatric depression scale that measured feelings from the previous week.
- The Frailty Test assessed the strength of the older adults. Frailty was identified when three or more of the following criteria were present: unintentional loss of at least ten pounds in the past year, self-report of exhaustion, extremely weak grip strength, slow walking speed over fifteen feet, and low physical activity as measured by calories expended per week.

G. Data processing and analysis

The sensors automatically collected actigraphy data and stored it on the Shimmer device. The data was uploaded daily onto a secure laptop once all observations were completed. Data analysis was performed using MATLAB to correlate collected acceleration data with annotated information on observed activity.

Activity data collected from the monitors were visually and statistically compared with researcher accounts of movement. This comparison allowed us to determine parameters for defining key aspects of the signal, including acceleration frequencies, as well as other physical characteristics of the signal. These parameters allowed us to classify certain signals that might resemble a fall event as non-falls, thereby improving the specificity of the device.

III. Results

A. Study Subjects: Population Characteristics

The study was comprised of ten full-time study subjects contributing twelve non-consecutive days of activity data each and two part-time study subjects contributing six non-consecutive days of activity data each for a study total of 120 monitored days of activity captured. The number of monitored hours varied per day depending on the subject's schedule. The average number of collected hours per day was 4.76 hours with a standard deviation of 3.21 hours. Our sample population drew heavily from short-term senior centers. As a result, the number of observation hours was limited to the amount of time each study subject stayed at the facility during the day.

The study population was 36% male and 64% female with an average age of 79.3 years (66 years to 91 years). 36.4% of the population characterized themselves as Caucasian/white, 36.4% as Hispanic, and 27.2% as African American/black. All study subjects were insured through Medicare. The highest level of education within the study population was a high school diploma. The majority of the study subjects were widowed and all had been at JHL for at least two years (average 7.3 years; standard deviation 10.2 years.). All but one of the study subjects used a walking aid on a regular basis: seven subjects used a walker with wheels and three used a cane.

The average MMSE score was 23 out of 30 with a standard deviation of 4.08 (low: 17; high: 29). All subjects were oriented to time and place while none of the study subjects had total registration and recall. The average Geriatric Depression Scale score was 2 out of 15 with a standard deviation of 4.25 (low: 0 high: 6). All study subjects were evaluated on the Tinetti Balance and Gait scale with the average balance score of 7.8 out of 16 with a standard deviation of 4.25 and an average gait score of 5.7 out of 12 with a standard deviation of 2.99 (total low: 1 total high: 20). The average 10 meter walk time was 12.2 seconds with a standard deviation of 3.06 (low: 6.7seconds high: 18.5 seconds). 18.2% of the study population could complete the 1 Chair Stand test and only one study subject could complete the 5 Chair Stand test. 72.7% of the study population could stand unassisted while only one study subject could complete the tandem stand unassisted.

All study subjects were on the internal JHL High Alert List for being "at high risk" for falling. The study populations average score on the Fall Efficacy scale was 35.5 out of 100 with a standard deviation of 13.02 (low: 20 high: 63). The average score on the Morse Fall scale was 68.4 out of 125 with a standard deviation of 7.49 (low: 55 high: 75). 9.1% of the study population had a fall within the three months prior to the start of the study, 27.3% of the study population had a fall within the 12 months prior to the start of the study, and 36.4% of the study population has had what they described as "a life changing fall."

All study subjects had at least one co-morbidity that was a risk factor for falling: hypertension, diabetes mellitus, benign prostate hyperplasia, schizophrenia, or depression. Two study subjects had four of the five diagnoses. The majority of study subjects took between eleven to fifteen medications daily and no study subjects took fewer than two medications a day.

B. *Perfecting the Algorithm*

Earlier rounds of laboratory testing informed the design of an algorithm with 95% sensitivity to dramatized falls. However, additional validation was needed to assess and improve specificity in this population. 492.5 hours of activity data were collected, consisting of both structured and unstructured activities. As described above, structured activities were performed in the presence of the study coordinator as she noted the time and types of movements involved in the activity. The most valuable data captured were (1) standing up from a seated position (2) walking (3) laying down and (4) standing up from a reclined position. These data were instrumental in understanding the difference between fall and non-fall events because they could be clearly identified within the actigraphy data and used to define and eliminate "non-fall events" in the algorithm.

Each study subject was asked to engage in these four activities as often as possible throughout the study period. Other structured activity data were used to characterize specific activities within the collected actigraphy data such as eating, drinking and writing. The unstructured activity data were used for defining the noise in the background of the actigraphy data. Having over 400 hours of daily-life older adult activity facilitated the creation of a baseline that enabled detection of an "event" within the noise.

The data from the study contained over 4,500 potential fall events that met the initial conditions for a fall defined by a magnitude event. Windows of false positive data were extracted to generate a false positive range to enhance the fall positive and fall detection algorithms. Even though valuable structured and unstructured activity data were captured, no falls occurred during the study period. As a consequence, there were no true positive data available to refine the algorithm.

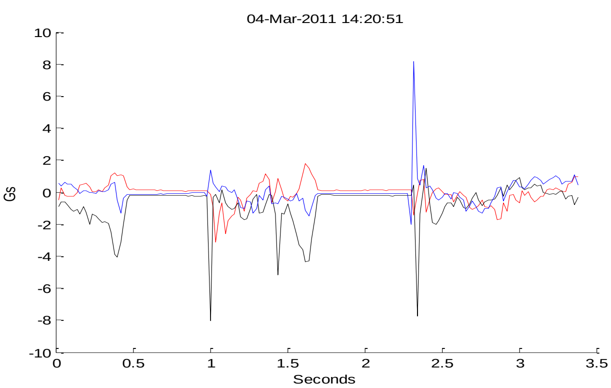

Fig. 3. Extracted false positive event representing a drop.

C. *Usability*

The secondary objective of this research was to determine the usability and overall comfort of the fall detection devices. The question of usability and comfort is particularly important because personal technology is not ubiquitous in the target population (older adults) and the devices must be charged, placed properly on the body, and worn at all times in order to effectively detect falls [28].

Of the three device form factors (wrist, hips, and pendant), 75% of the male study subjects preferred the hip sensor, 25% of the male study subjects preferred the wrist sensor, and no male study subjects preferred the pendent sensor. 71.4% of female study subjects preferred the pendent sensor although subjects mentioned that they wished it was lighter and did not swing back and forth as much. The other 28.6% of female subjects preferred the hip sensor and no female study subjects preferred the wrist sensor, stating that it was too bulky and would hit against furniture easily during daily activities. For overweight and obese study subjects, the hip sensor would dig into the side and cause discomfort. For thin and frail study subjects, the wrist sensor would slide up and down the arm causing some skin irritation, catching on clothing, and on occasion banging against furniture. The number of devices that needed to be worn may have influenced study recruitment. Two approached patients declined to participate because they did not want to wear five devices.

All twelve study subjects said that they would participate in a similar study in the future. The most common reasons were feeling a sense of community from participating, helping to advance the science of fall detection and activity monitoring, and helping to alleviate fear of future falls.

No study subjects mentioned any feeling of stigma from wearing the devices within the nursing facility. 83.5% of the study subjects stated that they would feel comfortable wearing the devices in public. One male and one female subject stated that they would be self-conscious wearing the devices in public but would do so if it was medically relevant or if they feared injury from falling.

Because study subjects were wearing prototypes that were charged, placed, and maintained by the study coordinator, there were no data regarding device maintenance or placement from the study subject's perspective. All study subjects voiced some concern about understanding the technology of the devices and being able to remember to wear them at all times.

The majority of the subjects (58.3%) described their concern as mild, 25% of the subjects described their concern as moderate, and only 16.7% described their concern to high. The two subjects who were highly concerned were ten and eleven years older than the study population average. The study subjects with the most concern about remembering to wear the devices were the female subjects with the lowest MMSE scores. On the other hand, the male subjects were not very concerned about remembering to wear the devices.

IV. CONCLUSION

A. Algorithim development

Activity data collected during this study were used to (1) check the amount of false positives that occur during typical use of the device, (2) define what types of false positives occur during typical use of the device, (3) characterize false positive events using subject demographics and more annotated information, and (4) provide more data for a machine learning algorithm to classify false positives as false positives. Because older adults move very differently than the general population, it was important to capture as many daily activities as possible in a variety of different settings: full-time nursing home, assisted living facility, and adult day programs.

Although the study was not able to capture a true positive event, the actigraphy annotations provided critical information in establishing a baseline repository for false positives. Parameters derived from the study data were defined by changes in orientation, free fall, energy expenditure associated with the same interval, and magnitude of acceleration from the impact of the fall. A proprietary machine learning algorithm was used to define the separations and parameters based on the physical characteristics of the visualized data. This study protocol did not use dramatized falls. However, laboratory-based research that was conducted prior to this study collected data from dramatized falls to develop the basis for the algorithm design.

B. Reasons for Lack of Fall Data

The lack of captured falls was most likely the result of the short study period and the characteristics of the study population resulting from the eligibility criteria. In particular, the study made use of a high cognitive threshold in order to ensure study subjects could follow the activity protocol. As such, the study may have been biased away from subjects at very high risk for falling.

The structured-activity component of the protocol required subjects to be able to both follow directions and be mobile in order to sit, stand, walk, and recline. Furthermore, at the end of each day, study subjects were asked to recall their activities and report any fall events. In order to ensure that subjects were able to fully participate in the study, there was a high MMSE requirement. Having a high MMSE score as a criterion for eligibility disqualified older adults with dementia from participating in the study. Consequently, our cognitive requirements excluded a subpopulation of older adults with a higher risk of falling than the broader population of older adults [29].

C. User Perspectives

As described in the usability section above, the overall study was well received by the subjects. Once enrolled subjects were engaged, they freely voiced their opinions about the usability of the device, fear of falling, desire to maintain independence, health concerns, and struggles of aging.

Fear of falling was more common among female study subjects and subjects who had previously experienced a fall that resulted in hospitalization. Fear of falling was not correlated with age. All the study subjects cited a desire to maintain independence as a motivator for wearing a fall detection device. One subject stated, “Knowing that there is a person out there looking out for me is comforting… being able to get medical attention without having to call for it is reassuring.” Another subject mentioned that such a device would provide comfort to his daughter who “often worries about [him] being alone.”

Over the course of the study, several subjects discussed the trials of aging and the need for a device for effective fall detection. One study subject was concerned that the devices would be inadvertently set off during routine daily activities: “I would be nervous it would go off when it is not supposed to.”

The cost of the device and related fees affected the likelihood of the study subjects purchasing a similar device: “I would wear one – if it was not too expensive.” Having the devices offered through Medicare services was popular among the study subjects, not only for lessening the financial burden of the device but also because it would lend creditability to the percent effectiveness and medical relevance of the device.

D. Next Steps

Although the dangerous effects of falls are well documented, there are limited activity data available for capturing true positives within this population. Furthermore, the metrics for characterizing actigraphy data and classifying activity events, particularly in older adults, are poorly developed. This study has helped advance the research, but studies that capture true positives (falls) are required to perfect the fall detection algorithm.

The next steps for this would research include applying the algorithm to actigraphy data collected during a longer study with more subjects who are at higher risk for falling. More data could enhance the characterization of older adult activity data, such that accelerometers could distinguish between activities performed by older adults using a walking aid and those with unassisted mobility. Also, further research should provide a deeper analysis of older adult actigraphy so that patterns can be elicited to predict activity preceding a fall event.

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REFERENCES

[1] N. de Rekeneire et al., “Is a fall just a fall: Correlates of falling in healthy older persons: The Health, Aging, and Body Composition Study,” J AmerGeriatrSoc, vol. 51, pp.841-846, 2003.

[2] W. Graafmans, G. Wijlhuize, S. Pluijm and L. Bouter,“Daily physical activity and the use of a walking aid in relation to falls in elderly people in a residential care setting,” Z GerontolGeriatr,vol. 36,pp. 23-28, 2003.

[3] E. Ribom, E. Grundber and H. Mallmin,“Estimations of physical performance and measurements of habitual physical activity may capture

men with high risk to fall: Data from the MrOs Sweden cohort," Arch GerontolGeriatr,vol. 49, pp. e72-276, 2009.

[4] Center for Disease Control. Home and recreational safety: Fall among older adults [Online]. http://www.cdc.gov/HomeandRecreationalSafety/Falls/adultfalls.html. Accessed November 20, 2010.

[5] National Institute on Aging. NIH senior health [Online]. http://nihseniorhealth.gov/falls/aboutfalls/03.html. Accessed November 20, 2011.

[6] I. Bautmans, B. Jansen andB. Van Keymolen,"Reliability and clinical correlates of 3D-accelerometry based gait analysis outcomes according to age and fall risk," Gait Posture,vol. 33, pp. 366-372, 2010.

[7] A.K. Bourke, P. van de Ven andA.E Chaya,"Testing of a long-term fall detection system incorporated into a custom vest for the elderly,"IEEE Eng Med Biol Soc., pp.2844-2847, 2008.

[8] P. Boissy, S. Choquette and M. Hamel,"User-based motion sensing and fuzzy logic for automated fall detection in older adults," Telemed J E Health,vol. 13(6), pp. 683-693, 2007.

[9] M.Kangas, I.Vikman, J.Wiklander, P. Lindgren, L.Nyberg andT.Jämsä,"Sensitivity and specificity of fall detection in people aged 40 years and over," Gait & Posture, vol. 29, pp. 571–574, 2009.

[10] M.N.Nyan, F.E.Tay andE.Murugasu,"A wearablesystemforpre-impactfalldetection," Journal ofBiomechanics,vol. 41, pp. 3475–3481,2008.

[11] A.Weiss, I. Shimkin, N.Giladi and J.M.Hausdorff,"Automated detection of near falls: algorithm development and preliminary results," BMC Research Notes,pp. 3-62, 2010.

[12] A.K. Bourke, J.V. O'Brien andG.M.Lyons,"Evaluation of a threshold-based tri-axial accelerometer fall detection algorithm," Gait & Posture vol. 26, pp. 194–199, 2007.

[13] S.R.Lord, J.A.Ward, P.Williams andK.J.Anstey,"An epidemiological study of falls in older community-dwelling women: the Randwick falls and fractures study," Aust J Public Health,vol. 17(3), pp. 240–5, 1993.

[14] T.W.O'Neill, J.Varlow, A.J.Silman, J.Reeve, D.M.Reid and C.Todd,"Age and sex influences on fall characteristics," Ann Rheum Dis 53(11), pp.773–5, 1994.

[15] B.J.Vellas, S.J. Wayne, P.J. Garry andR.N.Baumgartner,"A two-year longitudinalstudy of falls in 482 community-dwelling elderly adults," JGerontol A Biol Sci Med Sci,vol.53(4), pp.M264–74, 1998.

[16] M.C.Nevitt and S.R.Cummings,"Type of fall and risk of hip and wrist fractures: the study of osteoporotic fractures," The study of osteoporotic fractures research Group. J Am Geriatr Soc,vol.41(11), pp.1226–34, 1993.

[17] Phillips, "How Lifeline Alert Works," [Online] http://www.lifelinesys.com/content/lifeline-products/how-lifeline-works. Accessed April 20, 2012.

[18] G. Ostrovosky, "M-PERS: Wireless Activity Monitor Doubles as Automatic Emergency Notification System," [Online] http://medgadget.com/2010/01/mpers_wireless_activity_monitor_doubles_as_automatic_emergency_notification_system.html. Accessed April 13, 2012.

[19] M. Narayanan et al, "Falls management: detection and prevention, using a waist-mounted triaxial accelerometer," Conf Proc IEEE Eng Med Biol Soc 2007: 4037-4040, 2007.

[20] Halo Monitoring, "Automatic Fall Detection," [Online] http://www.halomonitoring.com/products/for-a-loved-one/automatic-fall-detection. Accessed April 13, 2012.

[21] ActiveCare, "Personal Assistance Link," [Online] http://activecare.com/. Acccessed April 13, 2012.

[22] D. Jiangpeng, X. Bai, Z.Yang, Z. Shen, D. Xuan. "Mobile phone-based pervasive fall detection," Pers Ubiquit Comput. DOI 10.1007/s00779-010-0292-x. 2010.

[23] Age Ageing. R.Y. Lee and A.J. Carlisle, "Detection of falls using accelerometers and mobile phone technology," Nov; 40(6): pp. 690-6. 2011

[24] Lifecomm . Mobile Personal Emergency Response System (MPERS) [Online]. http://www.lifecomm.com/solutions/solutions.html. Accessed April 13, 2012.

[25] R. A. Washburn, K. W. Smith, A. M. Jette, C. A. Janney, "The physical activity scale for the elderly (PASE): Development and evaluation," Journal of Clinical Epidemiology, Vol. 46(2), pp 153–162, 1993.

[26] B.W. Rovner and M.F.Folstein, Mini-mental state exam in clinical practice. Hosp Pract, 22(1A), 1987.

[27] M.E. Tinetti, T.F. Williams and R. Mayewski, "Fall Risk Index for elderly patients based on number of chronic disabilities," Am J Med vol.80, pp.429-434, 1986.

[28] E.Neter and E.Brainin, "eHealth Literacy: Extending the digital divide to the realm of health information," J Med Internet Res. vol.14(1): e19, 2012.

[29] T.Lymker and C.J.Lamoth, "Gait and cognition: the relationship between gait and stability and variability with executive function in persons with and without dementia," Gait Posture,vol.35(1),pp.126-13, 2012.