

Intelligent Systems for Assessing Aging Changes: Home-Based, Unobtrusive, and Continuous Assessment of Aging

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Objectives. To describe a longitudinal community cohort study, Intelligent Systems for Assessing Aging Changes, that has deployed an unobtrusive home-based assessment platform in many seniors homes in the existing community.

Methods. Several types of sensors have been installed in the homes of 265 elderly persons for an average of 33 months. Metrics assessed by the sensors include total daily activity, time out of home, and walking speed. Participants were given a computer as well as training, and computer usage was monitored. Participants are assessed annually with health and function questionnaires, physical examinations, and neuropsychological testing.

Results. Mean age was 83.3 years, mean years of education was 15.5, and 73% of cohort were women. During a 4-week snapshot, participants left their home twice a day on average for a total of 208 min per day. Mean in-home walking speed was 61.0 cm/s. Participants spent 43% of days on the computer averaging 76 min per day.

Discussion. These results demonstrate for the first time the feasibility of engaging seniors in a large-scale deployment of in-home activity assessment technology and the successful collection of these activity metrics. We plan to use this platform to determine if continuous unobtrusive monitoring may detect incident cognitive decline.

Key Words: Cognitive assessment—Dementia—Home-based clinical assessment—Technology.

ACROSS a broad range of physical, psychosocial, and cognitive outcomes in gerontology and geriatric medicine, it is fundamentally important to be able to detect meaningful change over time. This is especially important for practicing proactive health care and for the timely application of prevention strategies. Current methodologies for detecting clinical change involve relatively brief in-person visits conducted over intervals that may range from every 6 months to every 2 or 3 years. These visits are performed at the convenience of the examiner, and little, if any, direct data are collected during holidays, weekends, or after business hours. Additional methods include mail-in questionnaires or telephone interviews that rely primarily on forced choice queries to elicit self-reports of changes in physical and cognitive function. These are often in the form of “in the last [time interval] did you [experience X]?”

Despite the widespread use of these methodologies, they have significant shortcomings in identifying the full range of potential events or trends of interest. People cannot recall with high fidelity meaningful changes that are infrequent and brief in duration or subtle and evolving slowly over time. Thus, they may fail to sufficiently identify rare and irregularly occurring events (e.g., falls, naps, transient neurological events), which because of their evanescence or infrequent occurrence may be easily forgotten. On the other hand, events or syndromes that progress slowly over time

(e.g., cognitive decline, frailty) often have poor demarcation as to onset and transition to new states making the changeover to a new state difficult to recognize. In general, questionnaires and episodic in-person examinations are inadequate because they depend on recall of events or a snapshot observation of function. They assume that observations recorded during the examination represent the person’s typical state of function for relatively long periods of time prior to the assessment. The observations recorded also are often restricted to indirect inference about how one state or event may relate to another because there is limited precision in the relative time occurrence of events. Thus, the qualities of many activities, such as sleep, exercise, and socialization that may influence health outcomes (and each other), cannot be readily time stamped and then associated with effects on specific outcomes of interest. All these limitations make it highly challenging for a geriatrician and other clinicians to provide precise answers with regard to the many important transitions or events that may occur in cognitive or physical function with aging. Thus, the nature of many current assessment approaches hinders early detection of critical changes that indicate the onset of cognitive or functional decline preceding many important geriatric events or syndromes. Traditional methods make it difficult to identify change or events with detailed temporal precision, intraindividual specificity, and ecological validity.

An alternative approach is to bring assessment into the daily activity of a person in their home environment, which changes the focus of assessment from brief, episodic, or intermittent evaluations prescribed often at the convenience of the evaluator. Ideally, this assessment is performed continuously in real time and with minimal, if any, intrusion on the daily activities of the individual. To achieve this new model, one can draw upon advances in ubiquitous computing and “smart home” technologies that have been in development for several decades. These techniques span the gamut from identifying a person’s general activity based on electrical activity in the home (Berenguer, Giordani, Giraud-By, & Noury 2008; Gupta, Mukhopadhyay, Sutherland, & Demidenko, 2007; Noury et al. 2009) to detailed identification of particular activities using body-worn sensors (Atallah, Lo, Ali, King, & Yang, 2009; Logan, Healey, Philipose, Tapia, & Intille, 2007; Min, Ince, & Tewfik, 2008; Park & Kautz, 2008) to monitoring health status using sensors distributed around the home (Hagler, Austin, Hayes, Kaye, & Pavel, 2010; Hayes et al., 2008; Kaushik, Lovell, & Celler, 2007; SAPHE, 2010; Virone, Noury, & Demongeot, 2002). Other systems seek to understand mobility outside the home as well as inside the home (Michael, McGregor, Allen, & Fickas, 2008; Oswald et al., 2010). More recently, considerable effort has been devoted to identifying the architecture, psychosocial implications, and human–computer interaction requirements for technologies to support telehealth in general and dementia patients and aging-in-place in particular (ENABLE: Hagen et al., 2001 and BETAGT: Claßen, Oswald, Wahl, Becker, & Heusel, 2010). Although these projects have not yet been deployed into clinical trials or large-scale field studies, their observations are of particular relevance to our own research, which seeks to validate the potential of in-home technologies for early assessment of cognitive decline. This article describes a longitudinal community cohort study, Intelligent Systems for Assessing Aging Changes (ISAAC), that is among the first to deploy an unobtrusive home-based assessment in hundreds of seniors homes in the existing community.

ISAAC has several long-term project goals that include the following: (a) to determine if continuous unobtrusive monitoring of motor and cognitive activities detects incident cognitive decline in seniors living in typical community settings, (b) to develop and use novel algorithms and assessment techniques for detecting motor and cognitive change in these community settings and to test in situ evolving sensor technology, and (c) to identify the monitoring needs of, and optimal communication channels for, lay individuals and health care professionals. Here, we describe our initial experience in deploying and capturing the activity measures of interest with this in-home continuous assessment approach. Accordingly, we have restricted our report to 4-week continuous monitoring periods centered on the day of conventional scale administration and provide

examples of the unique metrics that may be derived from this embedded systems methodology. Other initial work on algorithm development related to analysis for detection of clinically relevant change as well as work related to attitudes and beliefs of seniors surrounding the use of this in-home assessment approach are found in Hagler (2010), Hayes and colleagues (2008), Jimison and colleagues (2006), and Wild, Boise, Lundell, and Foucek (2008). The research platform utilizes continuously active unobtrusive technologies to bring the locus of assessment into real time as events occur throughout the daily life in the home and community. Although the system may enable assessment of a wide range of relevant health states and changes, the initial design has focused on enabling assessment and detection of change in functions that are major forces leading to loss of independence, namely cognitive impairment and problems with mobility.

METHODS

The community-wide, scalable home-based assessment platform and protocol were developed and pilot tested by the Oregon Center for Aging and Technology (ORCATECH) at Oregon Health & Science University (OHSU) beginning in 2004. This initial platform development was conducted in the ORCATECH Living Laboratory, which is a population of 30 community-dwelling seniors who agree to participate in a variety of research studies related to the use of in-home technologies for health monitoring, intervention, and support of independent living. Within this group of seniors, we first examined usability, feasibility, and reliability of the technologies and methods before wider dissemination to the larger study cohort described later.

Participants

All participants were recruited from the Portland, Oregon metropolitan area and provided written informed consent before participating in study activities. The protocol was approved by the OHSU Institutional Review Board (IRB #2353). Enrollment began in March 2007 and continued on a rolling basis until September 2009. Eligibility criteria included being a man or woman aged 80 years or older (or 70 years or older for non-Whites and for individuals residing with a participant aged 80 years or older), living independently (cohabitation with a companion or spouse was allowed but not with a formal caregiver), in a larger than one-room “studio” apartment, and cognitively healthy (Clinical Dementia Rating [CDR; Morris, 1993] score ≤ 0.5 ; Mini-Mental State Examination [MMSE; Folstein, Folstein, & McHugh, 1975] score > 24) and in average health for age (well-controlled chronic diseases and comorbidities or none at all). There were 10 participants with MMSE scores ≤ 24 at baseline and 5 participants with CDR scores of 1 at baseline (see Table 4) who were included in the study because they lived with a spouse or partner who was participating in

the study and met eligibility criteria. Medical illnesses with the potential to limit physical participation (e.g., wheelchair bound) or likely to lead to untimely death over 35 months (such as certain cancers) were exclusions. Participant enrollment not only focused on seniors living in retirement communities but also included seniors living in free-standing single-family homes. To facilitate recruitment, senior center administrators, retirement community facility directors, and managers were contacted concerning the study, and formal community presentations were conducted to enhance awareness of the project. Potential participant pools were created at the end of presentations, and follow-up calls were made within 2 weeks to interested parties. Participants were also recruited from lists of current OHSU Layton Aging & Alzheimer's Disease Center research participants who have been followed longitudinally in other projects.

Clinical Assessment Procedures

Participants were assessed in-home at baseline, at 6-month intervals (by telephone), and during annual in-home visits with research personnel who administered standardized health and function questionnaires and physical and neurological examinations. Health assessment consisted of a review of medical histories, medication lists, and completion of the modified Cumulative Illness Rating Scale (CIRS; Linn, Linn, & Gurel, 1968 and Miller et al., 1992). In addition to these assessments, participants were queried with regard to their attitudes and beliefs about home monitoring using a 35-item questionnaire (Gressard & Loyd, 1986; Woodrow, 1991) that assessed views of computer and technology use, types of data of importance to the participant, and issues of privacy and security. Participants were also administered a 20-item questionnaire that assessed computer use self-efficacy (Busch, 1996). Health, cognitive, behavioral, and functional assessments are summarized in Table 1.

The annual neuropsychological examination included the following battery of tests tapping multiple cognitive domains: Attention and concentration (Digit Span Forward; Wechsler, 1981; Digit-Symbol; Wechsler, 1981; and Trail Making Part A), Processing speed (Simple & Choice Reaction Time and Crossing-off test), Working memory (Digit Span Backward; Wechsler, 1981; Letter-Number Sequencing; and Digit Sequencing), Memory (Logical Memory Delayed; Wechsler, 1987; Visual Reproduction; Wechsler, 1987; CERAD Word List; Wechsler, 1987; and CERAD Visual Figures Recall; Welsh, Breitner, & Magruder-Habib, 1993), Language (WRAT-R; Jastak & Wilkinson, 1984; and Boston Naming Test; Welsh et al., 1993), Executive function (Category Fluency; Jastak & Wilkinson, 1984; Trail Making Part B, Stroop Test, Letter Fluency, and Odd Man Out task), and Visuospatial construction (Picture Completion; Wechsler, 1981; and Block Design). A subset of this assessment battery is part of the Uniform Data Set of the

Table 1. Assessment Follow-up Schedule^a

Assessment	6-month follow-up	Annual follow-up
Medical History and Physical Examination		+
Oregon Brain Aging Study Memory Questionnaire (Kaye et al., 1994)	+	+
Personal & Family History		+
Physical/Neurological Examination		+
FAQ (IADL)	+	+
Older Americans Resources and Services (OARS) OARS ADLs (Fillenbaum & Smyer, 1981)		+
CDR (Morris, 1993)	+	+
Geriatric Depression Scale (Seikh et al., 1986)	+	+
MMSE (Folstein et al., 1975)		+
Uniform Data Set of the National Alzheimer's Disease Center (UPDRS) UPDRS (Fahn et al., 1987), Motor Scales (Lang & Fahn, 1989; Tinetti, 1986)		+
Neurobehavioral Cognitive Status Examination		+
Neuropsychological Examination (see text)		+
Telephone Interview of Cognitive Status (Crooks et al., 1999)	+	
CIRS (Parmelee, Thuras, Katz, & Lawton, 1995)		+
SDSQ (Tractenberg, Singer, & Kaye, 2005)	+	+
Technology Attitudes Questionnaire		+
Laboratory Studies/Genotyping (apolipoprotein E)		+

Note: ^aTICS is administered at 6 months for most participants; those with severe hearing impairment receive in-person assessment with MMSE. CDR is completed at 6 months based on telephone interview with the participant only; if there has been a change in cognitive status, a collateral informant is also interviewed. SDSQ is administered online every 6 months. ADL = activity of daily living; CDR = Clinical Dementia Rating Scale; CIRS = Cumulative Illness Rating Scale; FAQ = Functional Assessment Questionnaire; IADL = instrumental activities of daily living; MMSE = Mini-Mental State Examination; SDSQ = Sleep Disturbance Symptom Questionnaire.

National Alzheimer's Disease Coordinating Center (Morris et al., 2006, <http://www.alz.washington.edu>).

Tests of motor performance included the Tinetti gait and balance scales (Tinetti, 1986), chair stands (Csuka & McCarty, 1985; Guralnik et al., 1994), timed 9-m walk at comfortable pace (Podsiadlo & Richardson, 1991), grip strength (measured with a Jamar Dynamometer; Csuka & McCarty, 1985), finger tapping (using a reciprocating manual counter; number of strokes per 10 s; Camicioli, Howieson, Oken, Sexton, & Kaye, 1998), timed one-leg standing (under two different conditions: eyes open and eyes closed; Duncan et al., 1990), and the motor section of the Unified Parkinson's Disease Rating Scale (Fahn, Elton, & Members of the UPDRS Development Committee, 1987). The standardized conventional assessments were established to identify incident cognitive decline (mild cognitive impairment or dementia) and to compare the conventional annually acquired measures with the automated continuous data acquired on a daily basis. Biological samples were obtained from each participant to measure apolipoprotein E genotype and other biomarkers that may affect health and cognitive status.

Sensor and Computer Installation

Collection of continuous activity data using an unobtrusive activity assessment system was achieved by installing



Figure 1. Examples of two home layouts with coverage of sensors indicated. Red boxes (S): locations of passive infrared motion detectors; green rectangles (D): contact sensors on exit/entry doors and refrigerator doors; blue boxes (W): sensor lines for measuring walking speed; HC: home computer location. See text for details of how sensor locations were chosen.

several types of sensors in the home of each participant. Metrics assessed by the sensors include total daily activity, time out of home, and walking speed. Floor plans of each residence were drawn to provide a map of sensors placed throughout the home (Figure 1).

In order to detect movement, wireless passive infrared motion sensors (MS16A X10.com) were placed in rooms frequently trafficked by participants (bedroom, bathroom, kitchen, living rooms, and hallway-entry areas). These sensors were used to assess general activity by location. Walking speed was estimated as described previously (Hagler et al., 2010) using data from sensors positioned sequentially on the ceiling approximately 61 cm apart in areas such as a hallway or other corridor (light blue boxes; Figure 1). These sensors were modified so that they had a restricted field view of $\pm 4^\circ$, only firing when someone passed directly within their path. Wireless magnetic contact sensors (DS10A; X10.com) were placed on each door of the

home to track visitors and absences from the home. Data from all sensors were received by a dedicated research laptop computer placed in the participant's home (not the participant's personal computer), then time stamped and stored in an SQL database. All data were automatically uploaded daily to a central database in the project data center.

Online Assessment

Each participant received a desktop computer (or could choose to use their own), and Internet broadband services were provided in order to facilitate data acquisition and participation in all study activities. Participants received computer training based on their computer familiarity as determined by an assessment of computer experience administered at the first training session. Research personnel observed participants to determine if tasks outlined in Table 2 were completed without prompting. The scale used

Table 2. Elements Assessed for Computer Proficiency

1. Turn on the computer
2. Navigate the mouse on the screen
3. Open the Microsoft Word program
4. Type the given sentence correctly
5. Print this document
6. Save this document
7. Close the Microsoft Word program
8. Reopen the document
9. Delete the document
10. Retrieve the document from the recycle bin
11. Open an Internet browser
12. Go to the OHSU Web site using the Web site address
13. Click on the "About OHSU" link
14. Open an e-mail program
15. Open an e-mail in the inbox
16. Reply to an e-mail (using the "Reply" button)
17. Send a new e-mail using the address book
18. Send a new e-mail using the new e-mail address
19. Delete an e-mail
20. Turn off the computer

Note: OHSU = Oregon Health & Science University.

in the assessment to determine computer proficiency included 2 = *no prompting necessary*, 1 = *some prompting necessary*, and 0 = *unable to complete the task*. A score of 40 indicated high computer proficiency.

Participants who were unable to send and receive e-mail or who requested instruction were invited to participate in six training sessions conducted over 3 weeks using a standard curriculum with individual tutoring administered as needed. Participants were considered computer literate once they were able to reliably send and receive e-mail. Participants received a weekly online health questionnaire to complete that asked questions about behaviors that could affect activity patterns. Questions covered nine areas concerning medication changes, falls, injuries, health changes, emergency room visits, depression, changes to living space, vacations, and visitors. Computer use was monitored through keystroke logins, mouse movements, and time on computer. In addition, participants were provided a suite of games to play at their discretion that were designed to potentially identify cognitive change based on individual game playing performance over time (Jimison et al., 2006). Responses from the health questionnaire were monitored using an online database and project tracking software, "The Console," which was created to examine the status of daily data transfer and quality (Hayes, Pavel, & Kaye, 2009). The software also provides a secure interface to access data summaries and plots of activity that alert staff to equipment malfunction (e.g., dead sensor battery), changes in behavior pattern (e.g., decline in sensor firings), and noncompliance (e.g., failure to complete the weekly health questionnaire). Each home monitoring system is remotely accessed for trouble shooting or software upgrades.

Continuous Metrics of Change

Primary metrics for assessment are total activity during the day and at night, number of walks per day, median walking

speed, time out of the home per day, and computer use (proportion of days with computer use and total time spent on the computer per day). Total activity in the home was estimated by the mean number of sensor firings per day. Total nighttime activity was estimated by the mean number of sensor firings between 9 p.m.–6 a.m. The walking speed was estimated as the median walking speed per day as derived from the firing times of the walking line sensors (Hagler et al., 2010). The number of walks per day was determined using the same walking data. Time out of the home was calculated by identifying periods of at least 15 min between door openings when there was no activity in the home and summing over all such periods in the day. In addition, the weekly health questionnaire data were summarized into a life events inventory.

Statistical Analyses

Baseline demographic and clinical characteristics and continuously assessed metrics (4-week windows) over time are presented for the overall cohort as well as by age groups (young old: age <85 years vs. oldest old: age ≥85 years). Differences between the two age groups were assessed using *t* tests or the Wilcoxon rank sum test for continuous variables or by using Pearson's chi-square test or Fisher's exact test for categorical variables depending on the distributions of the variables. Medians are presented for variables with skewed distributions. The age group differences in continuous metrics of change were examined controlling for sex, MMSE, body mass index (BMI), and CIRS, using ordinal linear regression models. All summaries and analyses were performed using SAS 9.2 software (SAS Institute, Inc., Cary, NC).

RESULTS

A total of 265 participants were initially enrolled in the ISAAC study. Of those enrolled, 32 participants lived in a residence with another participant who declined to fully take part in the assessment protocol or who failed to meet eligibility requirements for full implementation of the in-home protocol. Two hundred and thirty-three participants underwent the full clinical assessment and had the research technology platform installed in their homes. To date (April 2, 2010) the cohort has been followed for a mean of 142 ± 27 weeks. Since baseline, one couple moved out of the metropolitan area requiring withdrawal from the project. Twenty-three participants (18 homes) have moved to a new residence but continue to be followed (with reinstallation of the research platform in their new home). To date, 17 participants (6%) have subsequently withdrawn from participation. Nine withdrew immediately due to household changes, uneasiness with sensors, and feeling overwhelmed by study procedures. Eight withdrew later on due to health problems or having a busy personal schedule. Fourteen participants have died. A summary of participant characteristics

Table 3. Participant Baseline Demographics

	Full cohort N = 233	Young old N = 136	Oldest old N = 97	p value
Age (mean ± SD)	83.3 ± 5.7	79.8 ± 4.5	88.2 ± 2.7	NA
Education (years)	15.5 ± 2.6	15.4 ± 2.9	15.6 ± 2.3	0.65
Gender (% women)	73	75	71	0.51
Race/ethnicity (%)				
White	80	71	93	<0.0001
Black	15	24	3	
Asian	5	5	4	
Socioeconomic status ^a	50.5 ± 11.1	50.1 ± 11.7	51.1 ± 10.2	0.68
Single-person household (%)	52	46	60	0.04
Computer user (%)	94	96	90	0.04
Attended computer training (%)	86	87	86	0.78

Note: ^aHollingshead Scale (Hollingshead, 1975).

based on age group at baseline is presented in Table 3. Clinical characteristics of the cohort at baseline are summarized in Table 4. The mean age of the cohort is 83 years with a mean of 15.5 years of education. Seventy-three percent are women, and 20% are minority participants. Half of the participants in our cohort live alone; oldest old were more likely to live alone than young old ($p = .04$). Overall, 94% were considered computer users when baseline assessments were completed and 86% of the group attended a computer training class. A computer user was any participant for whom we collected some computer activity data. At baseline, the median MMSE score for the cohort was 29. The median Functional Assessment Questionnaire (FAQ) (Pfeffer et al. 1982) score was 0. Oldest old had lower BMI ($p < .001$) and higher Tinetti Balance scores ($p < .001$) than young old.

Table 4. Participant Baseline Clinical Characteristics

	Full cohort N = 233	Young old N = 136	Oldest old N = 97	p value
MMSE (median ± SD)	29 ± 2.0	29 ± 1.8	28 ± 2.2	0.01
Clinical Dementia Scale (%)				
0	191 (84)	111 (84)	80 (83)	0.81
0.5	32 (14)	19 (14)	13 (14)	
1	5 (2)	2 (2)	3 (3)	
GDS (median)	1 ± 1.3	0 ± 1.4	1 ± 1.3	0.14
FAQ (median)	0 ± 2.9	0 ± 3.4	0 ± 2.0	0.51
CIRS	21.0 ± 3.1	20.9 ± 3.5	21.2 ± 2.6	0.10
BMI (kg/m ²)	26.9 ± 4.9	27.9 ± 5.3	25.6 ± 3.9	<0.001
UPDRS (median)	0 ± 1.6	0 ± 1.0	0 ± 2.2	0.06
Stopwatch walking speed (cm/s)	84.0 ± 25.2	87.0 ± 27.3	79.8 ± 21.3	0.07
Tinetti Gait (median)	0 ± 1.4	0 ± 1.4	0 ± 1.4	0.19
Tinetti balance (median)	2 ± 4.2	1 ± 3.9	3 ± 4.4	<0.001
Chair stands (s)	9.5 ± 5.5	9.4 ± 5.3	9.6 ± 5.8	0.76
Grip strength (dynes)	21.2 ± 8.5	22.3 ± 8.8	19.7 ± 7.8	0.04

Note: BMI= body mass index; CIRS = Cumulative Illness Rating Scale; FAQ = Functional Assessment Questionnaire (administered for instrumental activities of daily living); GDS = Geriatric Depression Scale; MMSE = Mini-Mental State Examination; UPDRS = Parkinson's Scale.

Examples of continuous activity for two participants with different activity patterns are presented in Figure 2. The spiral plots indicate unique patterns of activity over 180 days of monitoring, such as sleeping behavior, nighttime movement, consistent periods away from the home, and the locations where the participant spends their most time.

A summary of the life events reported by participants on their weekly online health form covering a mean 142-week follow-up period is given in Table 5. A vast majority of

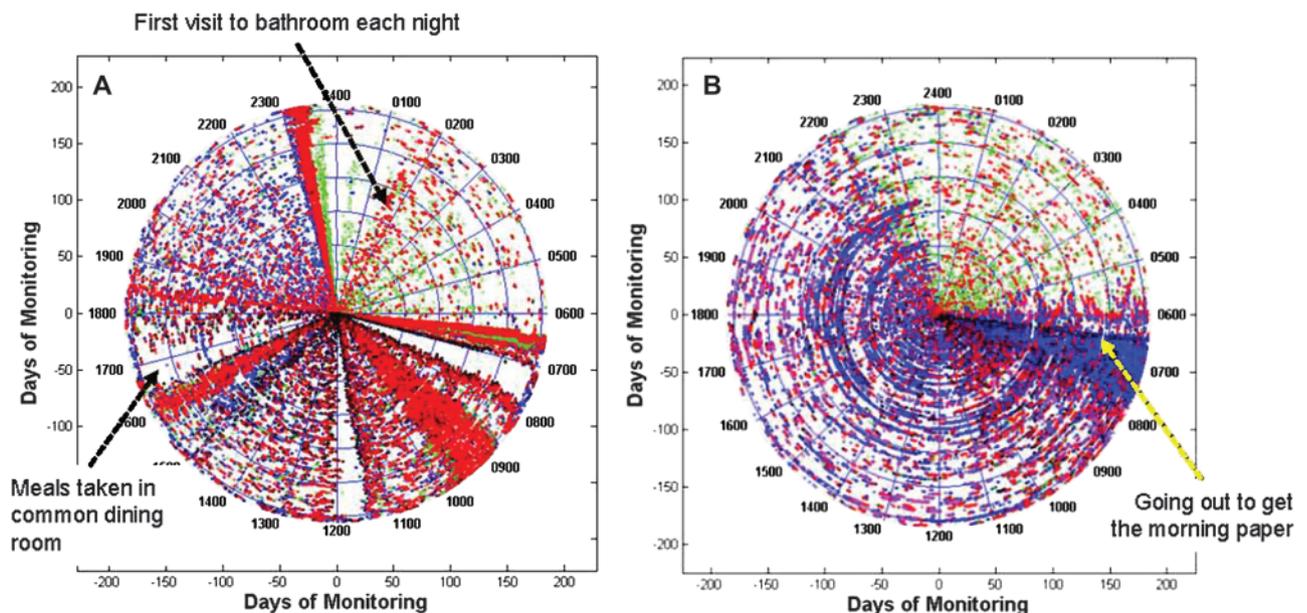


Figure 2. Spiral plot showing activity in two homes over 180 days of monitoring. Each day's activity forms one concentric circle in the plot, with the timing of sensor firings indicated by the 24-hr clock (midnight at the top and noon at the bottom). The solid blue concentric circles represent 30-day markers. The colors indicate where the sensor fired: red = bathroom, green = bedroom, blue = living room, black = front door. (A) This participant lives in a Continuing Care Retirement Community and takes meals in the common dining room, falls asleep at about the same time every night, and gets up most nights at the same time to use the bathroom. (B) This participant lives alone in the community, has more irregular sleep patterns, and leaves her home much less often.

Table 5. Health and Activity Events Reported Using Electronic Weekly Health Form During Study Period

	Full cohort N = 233	Young old N = 136	Oldest old N = 97	
	N (%)	N (%)	N (%)	p value
Accident or Injury	145 (62)	79 (58)	66 (68)	.12
Fall	130 (56)	66 (49)	64 (66)	<.01**
Hospitalization or Emergency room visit	82 (35)	45 (33)	37 (38)	.43
Depression or distressed	85 (36)	47 (35)	38 (39)	.47
Physical problem	193 (83)	108 (79)	85 (88)	.10
Cancer	10 (4)	6 (4)	4 (4)	1.0
Cardiac issue	26 (11)	10 (7)	16 (16)	.03*
Stroke	8 (3)	5 (4)	3 (3)	1.0
TIA	3 (1)	1 (1)	2 (2)	.57
Moved residence	23 (10)	15 (11)	8 (8)	.48
Death of a loved one	12 (5)	5 (4)	7 (7)	.24
Participant deceased	14 (6)	6 (4)	8 (8)	.22

Note: * $p < .05$; ** $p < .01$ based on the Bonferroni multiple comparison adjustment.

participants used the online health form to report various physical problems (83%). During the study, over half of all participants reported at least one fall, and over one third (35%) reported at least one trip to the hospital or emergency room. Oldest old were more likely to report a fall event ($p < .01$) and cardiac issues ($p = .03$) compared with the young old.

The continuous measures are summarized in Table 6 for a subset of the participants. Because algorithms to disambiguate the data from multiple residents in the home are still under development, for this initial analysis, we focused on the 76 single-person homes with complete data around a 4-week consecutive period that corresponds to a period spanning the 2 weeks preceding and the 2 weeks following the first annual visit. Age group differences were examined by controlling for sex, BMI, and CIRS. On average, participants walked past their in-home sensor line 22 times a day. The mean walking speed was 61.0 cm/s, whereas fast walking was 96.0 cm/s and slow walking was 36.2 cm/s (defined as the participant's median speed of walks $>1 SD$ above or below their mean velocity). On average, participants left their home twice a day for a mean of 208 min (total for the day). Overall, participants spent less than half (43%) of their days on the computer, but on days when the computer was in use, they averaged 76 min per day.

DISCUSSION

These results demonstrate for the first time the feasibility of engaging seniors of advanced age in a relatively large-scale research deployment of home-installed activity assessment technology. They further show that independently living older persons can engage in continuous unobtrusive monitoring for long periods of time to derive salient metrics of interest for aging research and health care. Of note, recruitment of the sample was not difficult, likely supported

Table 6. Summary of Continuously Assessed Metrics (4-week window) for a Subset of Full Cohort Living Alone (mean $\pm SD$ given)

	Cohort subset N = 76	Young old N = 30	Oldest old N = 46	p value ^a
Walking metrics				
Number of walks/day	21.9 \pm 15.2	20.8 \pm 14.4	22.6 \pm 15.9	.52
Walking speed (cm/s)	61.0 \pm 17.1	62.4 \pm 19.5	60.1 \pm 15.5	.33
Fast walking speed	96.0 \pm 22.9	99.8 \pm 24.7	93.4 \pm 21.5	.22
Slow walking speed	36.2 \pm 12.3	35.7 \pm 12.9	36.5 \pm 12.0	.62
Activity metrics				
Number of outings/day	2 \pm 1.2	1.8 \pm 1.4	2.1 \pm 1.1	.70
Time out of house/day (min)	208 \pm 145	222 \pm 182	197 \pm 111	.44
Total activity	1,502 \pm 572	1,587 \pm 554	1,443 \pm 584	.08
Nighttime activity	253 \pm 138	286 \pm 143	229 \pm 131	.13
Computer use metrics				
Days with computer use (%)	43 \pm 29	41 \pm 28	46 \pm 31	.38
Daily computer session (min)	76 \pm 48	65 \pm 33	87 \pm 59	.51

Note: ^a p values based on the Bonferroni multiple comparison adjustment; activity is measured as number of sensor firings total and during nighttime (9 p.m.–6 a.m.); p values reflect adjustment for sex, Mini-Mental State Examination, body mass index, and Cumulative Illness Rating Scale.

by the provision of a personal computer, free broadband access, and instruction in how to effectively use their computer. The methodology has been well received with a low withdrawal rate of about 2.6% per year. Further supporting acceptability, 23/24 participants who had to change residences choose to have the systems reinstalled in their new homes after their move. The one case where the system was not reinstalled was because the move was to a remote area that made performing the conventional in-person annual assessments unfeasible.

As noted, the provision of online capabilities was likely a facilitating factor in enrollment and retention of participants. The use of the home computer is also of major value to the conduct of this kind of research methodology, providing both basic information needed to interpret ongoing activities (e.g., knowing if furniture has been moved that might affect activity patterns) and as a means to collect more accurate data about relevant health-related events that cannot currently be readily inferred by remote sensing. The accuracy of the rates of several of these weekly self-reported events is difficult to confirm. It is well documented, for example, that self-report of a fall is increasingly more poorly recalled with increasing intervals between the fall event and the query (Fleming, Matthews, Brayne, & Cambridge City over-75s Cohort (CC75C) study collaboration, 2008; Ganz, Higashi, & Rubenstein, 2005). Thus current standards for studying fall frequencies in the community recommend using weekly queries usually conducted by a mail-in card or diary with phone call reminders for late cards. We report here the first known instance of using weekly online reporting of falls (and other events) in seniors (Table 5). We found an annual falls incidence of 42%, which is in line with what would be anticipated in an active aging cohort—somewhat higher than the reported literature of about 30% per year (Ganz, Bao, Shekelle, & Rubenstein, 2007) possibly due to

our frequent assessment. We did not include a weekly mail in report card system in addition to our online system, so we cannot directly compare the two methods. However, the online reporting system may have some advantage in that the time of completion of the report is time stamped, thus allowing one to quantify how close to the reported fall event the actual report is made.

The incidence of the other reported life events was slightly lower compared with national averages reported elsewhere (Horner et al., 2009; Kleindorfer et al., 2005; Lloyd-Jones et al., 2010). This may be expected because our cohort is composed of relatively healthy volunteers free from dementia (mean CIRS score of 21 and minimum to maximum possible scores are 14–70) at baseline. Nevertheless, it is also possible that current epidemiologic methodologies using single self-reports of events over a year or administrative databases may both underestimate (e.g., falls) or overestimate (e.g., medication adherence) some outcomes. The weekly online reporting system may provide an advantage in this regard for capturing the incidence of certain conditions of interest that may have significant public health importance. For example, studies have shown that approximately half of all patients who experience a transient ischemic attack (TIA) fail to report it to their health care providers (Johnston et al., 2003), although approximately 15% of all strokes are heralded by a TIA (Hankey, 1996). One can envision being able to not only have more accurate reporting of these events but for those where timely treatment is critical, such as for thrombolytic therapy, one may begin to examine the reporting of the time of onset of a transient neurological attack more precisely relative to key events such as when a person last rose from bed at night and the subsequent timing of appropriate thrombolytic therapies. Thus, although the focus of this study was not on surveying detailed health status or providing interventions, it points to the use of online reporting methodology in other future studies of what might be called real-time epidemiology and more precisely time-stamped intervention and outcomes research.

We report here for the first time basic continuous in-home activity metrics (Table 6) for an aging population encompassing summary activity measures (total activity counts, nighttime activity, number of outings per day, and time out of the house) as well as measures of specific activities (walking speed, number walks per day, and computer use). There are no current standards for reporting these data. Inherently, these continuous data were not designed to be used as a single point of measurement, such as the in-person baseline and annual measures. We propose that the 4-week time window of continuous activity that is centered around the single in-person assessment time point (composed of mean data of 2 weeks prior and 2 weeks after the in-person assessment) may be a practical summary metric for future studies, which may wish to compare single time point measures to continuous data. The 4-week window balances adequate opportunity to observe several cycles of typical or

routine activity (e.g., encompassing generally four weekends) against longer time intervals that may capture significant longer term time trend changes secondary to environmental or biological transitions or events. In this context, it is of obvious interest for future studies to examine in detail the capability afforded by continuous monitoring to focus measures on many specific time frames using the same data set that are either biologically driven such as circadian epochs or socially constrained such as work weeks and holidays. The latter is of particular interest because the vast majority of clinical research is performed during business hours. Thus, we have little direct knowledge of performance or activity during these off hours. Continuous in-home assessment has the potential to efficiently inform this gap. Future work will examine the general stability and changes over time relative to these multiple time frames of interest.

In addition to unique capabilities for examining a wide range of time frames of interest, home assessment provides the opportunity to capture activity in the typical environment in which a person lives and thus is likely to represent a more relevant measure of real-world function. Thus, for example, we note that the walking speeds obtained at home are slower on average than those obtained when an examiner asks an individual to “walk at your usual pace” (Stopwatch Speed). We have previously shown that individual participant walking speeds obtained with the in-home sensor line are highly correlated ($r = .99$) with speeds obtained with a GAITRite walkway system gait mat (ground truth; Hagler, 2009; Hayes et al., 2009). Thus, it is likely that in-person-supervised walking speeds represent faster walking than is actually more commonly present when ambulating at home. Interestingly, when we classified fast walks at home (median speed of walks $>1 SD$ above or below mean velocity), these walking speeds were closer to what is usually obtained in the supervised setting. This differential experience with directly observed single measures compared with unobtrusively obtained measures in the home also has implications for self-report versus actual sensed activity data in that seniors, for example, may self-report activity because they perceive they are more active than they are. Critical future studies will need to compare in detail how participants’ continuously sensed data predicts self-reported health-related data, such as outcomes related to sleep, mobility, hospitalizations, or mood changes.

It is noted that there are seemingly few differences in raw activity measures comparing the young old with the oldest old groups. This is not surprising and unlikely due to limitations of the measurement techniques as there were also no differences between the age groups on functional or health measures (FAQ, CIRS, and Stopwatch Speed). Thus, the relatively similar functional and activity profiles of the young old and oldest old are likely a reflection of the health of this volunteer cohort especially within the oldest old group. Of note, the oldest old in this cohort had little or no functional disability in activities of daily living, whereas in

population-based studies, up to 75% of the oldest old will be impaired in one or more activities of daily living (Griffith, Raina, Wu, Zhu, & Stathokostas, 2010). This is a reflection of the entry requirements for study that stipulated functional independence so that we could follow changes in our metrics over time that would predict the future development of cognitive and functional impairment. In this light, a limitation of our study is that it is representative of active healthy seniors living independently and willing to have these systems in their homes including using a computer on a regular basis. Nevertheless, the sample makeup, which included 20% minority representation and a large number of oldest old participants, suggests that these groups often considered to be lagging in technology use can be successfully recruited and engaged long term in technology adopting clinical research. The continuous activity measures generated across the age spectrum enrolled in the ISAAC cohort may be considered to represent optimally functioning seniors.

In this initial report of continuously assessed metrics obtained from a large elderly cohort, we chose to present the raw data unadjusted for a number of factors that may affect activity. Future reports will examine these factors and their relation to in home activity in detail. Of potential importance to interpretation of these data is the affect of differences in size and configuration of a residence and “activity opportunity time” or the time spent in the home during which there is an opportunity to record activities. Thus, less total activity recorded per day can simply reflect more time spent out of the house. For some measures, this may not be as important such as for nighttime activity as virtually everyone returns home to sleep at night (missing data from vacations were excluded from our 4-week summaries).

There are many other novel measures of interest that may also be enabled by in-home continuous assessment. Depending on specific research goals, one may readily incorporate, for example, physiologic monitoring (e.g., weight, blood pressure, glucose) or environmental assessment (e.g., temperature, air quality). We collect data on changes to the home environment on a weekly basis, such as changes in the layout of a person’s furniture via the participant weekly online questionnaire system. This provides the opportunity to incorporate new ways to assess the important role of the physical home environment on maintenance of function in these studies (Iwarsson et al., 2004). The emphasis of this summary has been generally on time-based measures. However, the data recorded are also location stamped as well. Thus, the opportunity for assessing where activities occur, and in what patterns, is facilitated. Studies of life-space analysis (Peel et al., 2005) have previously relied on self-report. The opportunity to now more directly assess when, where, and how much activity has occurred by specific location can be achieved with minimal intrusion. Because of the continuous multidimensional nature of the data, new methods of analysis may need to be adapted to fully take advantage of the opportunities afforded by this

research platform. The density of the data and the potential for personal annotation may ultimately provide an opportunity to conduct statistically meaningful “n-of-one” studies. Collection of continuous activity data provides the opportunity to make valuable intraperson comparisons (i.e., comparing current activity patterns with those from six months or one year previous). The ability of individuals to serve as their own controls may be particularly valuable for the oldest old, where the range of functioning in their peer group can be quite large.

In summary, aging care and research is confronted with the challenge of reliably assessing behavior and clinical status across multiple interrelated domains (cognitive, social, physiological, and environmental). Assessing change across these domains is difficult due to the complexity in detecting and identifying events that rarely or infrequently occur as well as those that evolve slowly over time and lack a clear initial onset. The implementation of a fully scaled home-based research platform, such as in ISAAC, provides the opportunity to overcome many of these obstacles and to measure traditional metrics of health research in real time with a precision previously unavailable. This approach is not without challenges. These include (a) rapidly and continuously evolving technology, (b) identifying multiple and changing residents in a home, (c) accounting for out-of-home activity, and (d) scaling beyond circumscribed communities to thousands of homes.

Future developments will include deployment of improved research platforms to larger community-based studies that will support and integrate the evidence-based research already set in motion. This will provide the opportunity to open many new avenues of knowledge ranging from new ways of assessing social engagement to real-time management of chronic disease. The long-term potential of this new research paradigm is to see a convergence in utilization of these now research-focused capabilities into the mainstream of assessment and care. In this way, we hope to achieve true proactive health and personalized medicine based on an individual’s real-time real-world data.

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