

Published in final edited form as:

*Alzheimers Dement.* 2008 November ; 4(6): 395–405. doi:10.1016/j.jalz.2008.07.004.

## Unobtrusive assessment of activity patterns associated with mild cognitive impairment

T.L. Hayes<sup>1,3,\*</sup>, F. Abendroth<sup>2,3</sup>, A. Adami<sup>4</sup>, M. Pavel<sup>1,3</sup>, T.A. Zitzelberger<sup>2,3</sup>, and J.A. Kaye<sup>1,2,3</sup>

<sup>1</sup>Department of Biomedical Engineering, Oregon Health & Science University

<sup>2</sup>Department of Neurology, Oregon Health & Science University

<sup>3</sup>Oregon Center for Aging and Technology, Oregon Health & Science University

<sup>4</sup>Department of Computer Science, Universidade de Caxias do Sul

### Abstract

**Background**—Timely detection of early cognitive impairment is difficult. Measures taken in the clinic reflect a single snapshot of performance that may be confounded by the increased variability typical in aging and disease. We evaluated the use of continuous, long-term and *unobtrusive* in-home monitoring to assess neurological function in healthy and cognitively impaired elders.

**Methods**—Fourteen older adults 65 years and older living independently in the community were monitored in their homes using an unobtrusive sensor system. Measures of walking speed and amount of activity in the home were obtained. Wavelet analysis was used to examine variance in activity at multiple timescales.

**Results**—More than 108,000 person-hours of continuous activity data were collected over periods as long as 418 days (mean  $315 \pm 82$  days). The coefficient of variation in the median walking speed was twice as high in the MCI group ( $0.147 \pm 0.074$ ) as compared to the healthy group ( $0.079 \pm 0.027$ ;  $t_{11} = 2.266$ ,  $p < 0.03$ ). Furthermore, the 24-hour wavelet variance was greater in the MCI group (MCI:  $4.07 \pm 0.14$ , Healthy elderly:  $3.79 \pm 0.23$ ;  $F = 7.58$ ,  $p < 0.008$ ), indicating that the day-to-day pattern of activity of subjects in the MCI group was more variable than that of the cognitively healthy controls.

**Conclusions**—The results not only demonstrate the feasibility of these methods, but also suggest clear potential advantages to this new methodology. This approach may provide an improved means of detecting the earliest transition to MCI compared to conventional episodic testing in a clinic environment.

### Keywords

Assessment of cognitive disorders/dementia; MCI (mild cognitive impairment); Cognitive aging; Technology and aging; In-home assessment

---

Address correspondence to: Dr. Tamara L. Hayes, Department of Biomedical Engineering, Oregon Health & Science University, 3303 SW Bond Ave., CH13B, Portland, OR 97239. Voice 503.418.9315, Fax 503.418.9311, email hayest@bme.ogi.edu.

**Publisher's Disclaimer:** This is a PDF file of an unedited manuscript that has been accepted for publication. As a service to our customers we are providing this early version of the manuscript. The manuscript will undergo copyediting, typesetting, and review of the resulting proof before it is published in its final citable form. Please note that during the production process errors may be discovered which could affect the content, and all legal disclaimers that apply to the journal pertain.

**Disclosures:** The authors report no conflicts of interest.

## 1. Background

Early detection of cognitive decline preceding the onset of dementia or functional impairment is important for many reasons [1,2]. Cognitive changes in the elderly may have immediately remediable causes, such as medication complications or unsuspected medical illnesses. Failure to recognize some of these causes in a timely manner may lead to irreversible damage. Mild cognitive decline can also be an early indicator of dementia and timely recognition of cognitive impairment provides an opportunity to focus on strategies for treatment, compensation, and coping [3,4], and may allow an individual to maintain greater independence than would otherwise be the case. In addition, early recognition is an opportunity for those with irreversible decline to proactively plan for their future and avoid being forced into crisis management.

Unfortunately, early detection of cognitive impairment is problematic, since patients may be unaware of their impairment, or if noted, uncomfortable discussing their concerns. In addition, cognitive testing is not a routine part of an elder's visit to their physician. Fully 50% of people age 75 or older seeing a primary care practitioner have no diagnosis or evaluation of their memory complaint [5,6], and in fact even the patient or family report memory problems in only a small percentage of cases where the patient has clinically detectable cognitive impairment [7]. Thus, alternative means of identifying early cognitive decline are needed.

Further confounding our ability to detect cognitive decline early are the facts that both cognitive and motor functional measures in the elderly become increasingly more variable as people age [8–10], and that this variability increases differentially in Alzheimer's disease (AD) and other neurological disorders [11]. For example, variability in mobility measures such as walking speed or stride length have been shown to increase with age, and even more so in AD and other dementias [8,10]. Measures taken in the clinic reflect a single snapshot of performance that may be confounded by such variability – identification of a decline may require many visits over months or years to obtain an accurate picture of true changes. As can be seen in Figure 1, test scores taken during a periodic clinic visits (left panel) may show changes in performance that do not reflect true change, but are instead simply reflective of normal variability for each subject. The true trend is clearly apparent when many more measures are available. We hypothesized that measures taken consecutively in an elder's home, on a frequent or continuous basis, would provide a much better picture of true functional performance. Not only would such an approach allow better understanding of normal daily variability for an individual, but change in the variability itself could herald cognitive decline.

Clearly, frequent or continuous measures of cognitive function would be difficult to collect using conventional time- and location-restricted methods. However, motor measures such as walking speed and movement-related activity may be better suited for continuous measurement because they are part of an individual's normal daily functioning. It is becoming increasingly evident that motor and activity measures, which are important measures of functional ability in the elderly [12–14], are also correlated with cognitive function [15]. Even measures as simple as gait speed or timed walking have been shown to be independent predictors of cognitive impairment [16–20]. However, the precise relationship between motor and cognitive function in aging and cognitive decline is not well understood, and further research is needed to better understand this relationship.

Recent research has shown that intraindividual variability in motor measures such as walking tasks correlates with cognitive performance [8,21]. These studies have examined frequent (e.g. biweekly) clinic-based measures such as timed walking, and have suggested that the short-term variance (week-to-week) in motor measures may be a sensitive indicator of cognitive health. These latter studies underscore the value of assessing intraindividual variability through more frequent measures. However, conducting frequent clinic-based assessments is

impractical and labor-intensive. Alternatively, the collection of measures of motor activity gathered in the home on a continuous basis can be done unobtrusively and automatically, without requiring the presence or involvement of a health care provider. Furthermore, measures gathered in the home may be more representative of an individual's normal daily functioning.

To determine the feasibility of using continuous measurement of motor activity for early detection of cognitive decline, we carried out a cross-sectional study in which we gathered measures of walking speed and of total movement within the home, using unobtrusive in-home technology. Two groups of community-dwelling elders were compared – those with mild cognitive loss and those who were cognitively healthy.

## 2. Methods

### 2.1 Subjects

All subjects provided informed consent to participate. Protocol and consent forms were approved by the Oregon Health and Science University Institutional Review Board. Fourteen older adults (aged  $89.3 \pm 3.7$  years) were recruited from ongoing studies at the NIA - Layton Aging and Alzheimer's Disease Center (LAADC) (OHSU IRB #1487). All participants were ambulatory adults aged 65 years or older, living independently and alone in the community. Subjects were clinically assessed during regular LAADC visits using a standardized battery of tests consisting of neurological and psychometric assessments, including tests of motor performance. Neurologic tests of motor function consisted of Tinetti gait and balance scales [22], finger tapping, timed one-leg standing, the motor portion of the Unified Parkinson's Rating Scale (UPDRS) [23] and timed walk [17]. Subjects were classified into one of two groups based on their scores on the global Clinical Dementia Rating (CDR) scale [24] and the Mini-Mental State Examination (MMSE) [25]: a *healthy* group ( $n=7$ ; CDR = 0, MMSE  $\geq 24$ ) and a *MCI* (Mild Cognitive Impairment) group ( $n=7$ ; CDR = 0.5, MMSE  $\geq 24$ ). All subjects were continuously monitored for at least 6 months. Demographic and functional characteristics of each group are shown in Table 1.

### 2.2 Procedures

To collect continuous activity data, an unobtrusive activity assessment system was installed in the home of each participant. The system used X-10 motion sensors and contact sensors to monitor activity in the home as well as comings and goings from the home. X10 is an international and open industry standard for communication among electronic devices used for home automation. The sensors transmit data at 310MHz, and the original protocol was designed to use household electrical wiring as a carrier for the digital signal. Unfortunately, this approach introduces significant noise into the signal – for example, fluctuations in the power level (for example, due to a refrigerator compressor turning on) can introduce false positives and extra bits into the data stream. As a result, past studies which used household wiring to carry the signal experienced significant levels of false positives and false negatives. A more robust approach, which was used in this study, is to collect the sensor firings using a wireless transceiver (WGL 800, WGL Designs) connected directly to a computer installed in the subject's homes. Collisions due to multiple sensors firing and other sources of 310MHz noise may result in garbled data (representing false negatives, since the original signals are lost); these types of errors were quantified by tracking the number of invalid signals received. In our previous studies, the data loss due to these errors was 1.9% [26]. While false positives are theoretically possible (simultaneous modification of 12 bits due to noise or collision could result in the creation of a new valid sensor code), we used sensor codes with little similarity that to further reduce the likelihood of this rare event.

Three configurations of sensors were used to gather data about movement and activity in the home. First, passive infrared pyroelectric motion sensors (MS16A, x10.com) were placed in every room at locations expected to pick up the participant's movements restricted to that room. These sensors fire once every 6 seconds as long as movement is detected. Because these sensors are sensitive to changes in heat sources, sedentary activities such as reading may not cause the sensors to fire, whereas activities involving arm, body, or leg movements (folding laundry, making meals, using the bathroom, moving between rooms) will result in regular firing. Clearly, differentiating from continuous motion involving mild exertion (such as folding laundry) and high exertion activities (such as jogging on a treadmill) is not possible with these sensors. However, the sensors do capture well differences in daily activities typical of this population. Second, magnetic contact sensors (DS10A, x10.com) were placed on each door of the home to track visitors and absences from the home. Third, to estimate walking speed, motion sensors with a restricted field of view were installed along a hallway so they would fire only when someone passed directly in front of them (restricted to  $\pm 4^\circ$  field of view, or about  $\pm 6.5$  cm at a distance of 90cm from the sensor). All data were time-stamped at the computer and uploaded nightly via automated dial-up to the project data center.

## 2.3 Analysis

**2.3.1 Data preparation**—Sensor data were first cleaned to remove redundancy (each sensor sends 5 identical signals each time it detects motion to reduce the potential loss of data due to simultaneous transmission of multiple sensors). Then, days in which multiple people were in the home, or in which excessive data errors occurred, were removed from the analysis, as follows. Periods in which more than one person was likely to be present in the home were identified by examining door openings and activity in the home, and days in which these periods occurred were excluded from the analysis. In addition, because collisions and errors in the data can influence our estimates of daily counts, we excluded those days in which the number of such errors were extreme outliers. Specifically, days in which the percentage of data errors was more than 3 standard deviations above the mean for that home were excluded from the analysis. Finally, full days in which the subject was away from home were also excluded from analysis.

Paired comparisons were made using a t-test unless otherwise indicated. All data cleaning and analyses were performed using Matlab standard, wavelet, and statistical packages (The Mathworks Inc., Natick, MA).

**2.3.2 Estimates of walking times**—Walking times were estimated for each subject as described previously [26]. Briefly, three restricted-field motion sensors were placed along a hall or path of frequency traffic in the home. If the restricted field sensors are  $s_1$ ,  $s_2$  and  $s_3$ , then each time the sensors fired in the order  $(s_1, s_2, s_3)$  or  $(s_3, s_2, s_1)$  without another intervening sensor firing, the subject was considered to have walked along the restricted-field path and the difference in firing times  $d_t = |s_1 - s_3|$ , was calculated as the observed sample of the walking time. The walking times for each subject were normalized to a distance of one meter. Walking times more than three standard deviations from the norm for this age group were excluded from analysis, since in some homes there was a cupboard or other distraction along the sensor line at which subjects would stop, resulting in very long (and non-representative) walking times. The median walking time was then calculated for each one-week period in which at least seven measures were taken. The median walking time was used because it is more robust to outliers, and because we were particularly interested in typical walking times for each subject. Walking times were compared across groups using data from the 26 contiguous weeks of monitoring common to all subjects (January-June). The coefficient of variation (CoV) of the median walking times was also calculated over the 26 intervals and compared across subjects using a t-test. One MCI subject (S3) fractured her femur near the start of the study and was not ambulatory for an extended period during the study; her data were excluded from this analysis.

In four other homes (S2, S8, S11, S12) there was not a hall in the home that restricted the motion along the sensor line. Therefore, it was possible to approach the sensor line from other angles, which may have impacted the measurement of walking speed. Therefore, we analyzed the data both with and without these additional homes.

Previous work has shown that the elderly have decreased mobility and activity in the latter part of the day [27]. We hypothesized that our subjects would walk more slowly in the late afternoon and evening, with the consequence that our data would show increased walking times in the latter half of the day. We were also interested in whether or not this increase would be greater for subjects with MCI. To this end, the observed data were analyzed for each subject by comparing median walking speed in the period 6am-3pm (morning) to those in the period 3pm-6am (evening), over the entire monitoring period, using a Bonferroni correction [28] for comparisons of multiple outcome measures. In addition, we compared the difference between the evening and morning walking times between groups.

**2.3.3 Estimates of daily activity**—As previously mentioned, our activity measures reflect the amount that a subject moves throughout the home. Although some subjects were active outside the home, our data are restricted to in-home activity. In order to compare in-home activity levels across subjects, we determined the number of sensor firings during all periods in which the subject was home, using door openings and lack of activity in the home to identify when the subject was out of the home. We also calculated the mean number of outings per day, and the average time spent outside the home per day, for each subject. Daily activity counts were normalized to the number of firings per minute based on the time the subject was in the home. The coefficient of variation of activity was then calculated for each subject over the first 26 monitoring weeks during which the subject was home and the data were valid.

In addition to these estimates of daily activity, wavelet analysis (a common method of decomposing a time-varying signal at multiple resolutions) was used to examine differences in 24-hour activity variance over time for each group of subjects [29,30]. Specifically, the data were divided into 6 consecutive 4-week periods, and wavelet analysis was done for each subject over each period. This transformation of the data produces a set of wavelet coefficients corresponding to specific time scales, including 3 hours, 6 hours, 12 hours, and 24 hours. The variance in these coefficients over each 4-week period therefore provides a measure of the amount of variance in activity at each of those time scales. The wavelet variance at a time scale of 24 hours (reflecting daily variance) was compared over the periods and between groups using a mixed model repeated-measures ANOVA to examine trends in the variance over time [31].

### 3. Results

More than 108,000 person-hours of continuous activity data were collected during this study. These data were collected unobtrusively for up to 418 days (mean  $315 \pm 82$  days) without requiring the subjects to wear any devices or to interact with research staff during the monitoring period.

#### 3.1 Data cleanup and errors

The number of days of data removed from analysis due to a disproportionate amount of collisions and data error ranged from zero to 27, but did not differ between groups (MCI:  $10.3 \pm 9.3$  days removed, healthy:  $7.8 \pm 6.4$  days removed). For the remaining days, the amount of error as a percentage of total daily activity was  $1.1 \pm 2.3\%$  across all homes (range 0.1–8.5%). However, the amount of error was much greater in two of the homes (S15 = 2.3% and S8 = 85%). In S15 the collisions were due to overlap of the field of view of two sensors in the den; in this home, the subject spent about 5% of her time in the den sitting at the computer, and thus

total overall activity for this subject was likely only slightly underestimated. In the case of S8, the subject lived in a mid-sized RV (recreational vehicle), and the data errors appeared to be due to the placement of the antenna receiving the data. Thus, some data from each sensor was lost, and total activity was certainly underestimated. However, in this home the distribution of collisions throughout the day was evenly distributed.

### 3.2 Comparison of subjects by conventional measures

All subjects were ambulatory and had normal motor function as assessed clinically and measured by the motor function scales. There were no significant differences between the groups in modified UPDRS (healthy  $1.9 \pm 2.3$ ; MCI:  $1.9 \pm 2.0$ ,  $p=0.87$ ) or the clinic-measured 9 m timed walk (healthy:  $14.5 \pm 3.7$  seconds; MCI:  $15.6 \pm 5.5$  seconds,  $p=0.78$ ). However, the MCI group had higher Tinetti Gait (healthy:  $0.33 \pm 0.52$ ; MCI  $1.6 \pm 1.5$ ,  $p=0.08$ ) and Tinetti Balance scores (healthy:  $2.5 \pm 1.4$ ; MCI:  $7.1 \pm 3.9$ ,  $p=0.02$ ).

### 3.3 Comparison of walking speed

Comparison of week-to-week normalized walking times (time to walk 1 meter) and the week-to-week coefficient of variation for the walking times revealed no differences in median or mean walking times of participants in the MCI group as compared to the healthy elderly group (Healthy elderly:  $1.76 \pm 0.52$  secs/m versus MCI:  $1.70 \pm 0.60$  secs/m;  $t_{11} = -0.194$ ,  $p=0.43$ ). In addition, median walking times did not change over the six-month monitoring period for either group. However, the coefficient of variation in the median walking times was twice as high in the MCI group ( $0.147 \pm 0.74$ ) as compared to the healthy group ( $0.079 \pm 0.027$ ;  $t_{11} = 2.266$ ,  $p<0.03$ ). As is apparent from Table 2, the homes without halls did not differ from those with halls. Analysis of the data excluding the homes without halls also showed similar median walking times between groups ( $t_7 = 0.142$ ,  $p=0.45$ ), and a significantly greater coefficient of variation in median walking times for the MCI group as compared to the healthy group ( $t_7 = 2.257$ ,  $p<0.03$ ). Not surprisingly, both the median walking times and the coefficient of variation in walking times were correlated with the Tinetti Balance scores (medians:  $r=-0.45$ , CoV:  $r=0.75$ ).

We also looked at the morning and evening walking speeds for each subject. Figure 2 shows the median morning and evening walking times for each subject, over the 6 month period. Most of the MCI subjects had longer walking times in the evening, as compared with the healthy controls. The difference between evening and morning walking times was significantly greater for the MCI subjects than the healthy elderly (MCI:  $0.31 \pm 0.08$  secs/m versus healthy elderly:  $0.057 \pm 0.01$  secs/m;  $t_7 = 1.19$ ,  $p=0.05$ ).

### 3.4 Comparison of measures of daily activity

Table 2 summarizes the activity counts, which reflect intensity of activity in the home, for all subjects. Figure 3 shows typical activity for each subject during the monitoring period. These graphs show the considerable differences across subjects in the variability in their activity. The asterisks in this figure indicate those subjects with the greatest variance in their daily activity. In general, MCI subjects were somewhat more active than their healthy counterparts, although this difference was not statistically significant (MCI:  $0.85 \pm 0.14$  counts/minute, healthy:  $0.64 \pm 0.16$ ;  $t_{12} = 1.03$ ,  $p=0.16$ ). In one case (S7), a cognitively healthy subject also had high day-to-day variance in their daily activity measure. This subject had severe visual and hearing impairments and seldom left their home; however, is not clear how this may have influenced his activity in the home. MCI subjects were also less likely to go out of the home than the healthy elders (MCI:  $0.96 \pm 0.67$  outings per day, healthy:  $2.03 \pm 1.43$  outings per day), and spent less time on average out of the home each day (MCI:  $62.0 \pm 70.9$  minutes per day, healthy:  $198.0 \pm 142.3$  minutes per day), but the differences between individuals were much greater

than that between groups. There was also no difference in the coefficient of variation of the daily activity between the groups.

In contrast, wavelet analysis, which allowed us to examine the variance at different time scales, showed significant differences between the groups. The wavelet variance was higher in the MCI group than in the healthy elderly group at all times scales (Figure 4A), and in particular at the 24-hour timescale. A repeated-measures ANOVA of 24-hour wavelet variance, calculated for six consecutive four-week periods, showed a significant difference between groups (Figure 4B, MCI:  $4.07 \pm 0.14$ , Healthy elderly:  $3.79 \pm 0.23$ ;  $F_{1,60} = 7.58$ ,  $p < 0.008$ ), but no effect over time periods. This indicated that the day-to-day pattern of activity of subjects in the MCI group was more variable than that of the cognitively healthy control group. Since the CoV of the daily activity measure over the entire 6-month period did not differ, this greater variability at specific timescales suggests that the *patterns* of variance differ between the groups, with the healthy elders showing a more consistent pattern of activity throughout the day.

#### 4. Discussion

The results presented here provide a first look at continuous motor and activity measures derived from the normal daily activities of community-dwelling elders. By continuously monitoring elders using unobtrusive wireless technologies in the home, we have been able to identify a set of activity parameters that may differentiate individuals with mild cognitive impairment from their healthy counterparts. The use of unobtrusive in-home technologies allowed us to observe activity parameters of individuals over an extended period of time without interfering with their daily activities. Thus, unlike brief, periodic clinical visits, our measures factor in the natural daily variability in an individual's health, mood, and energy level. This objective, continuous documentation of daily activity affords us insights into differences in activity levels between MCI and healthy elderly that could not be easily identified using a typical cross-sectional study design.

The normalized mean walking times for both groups, 1.8 s/m (0.56 m/s), were somewhat longer than what has been reported in the literature [17,32], where healthy elderly typically walk about 0.7–1.2 m/s (equivalent to 0.85–1.4 s/m) in timed walk tests in the clinic. We hypothesize that the desire to perform well during a clinical testing situation leads subjects to walk faster than their normal daily pace. In contrast, because we obtain continuous measures over a period of months, our data reflect a more natural walking pace. As discussed above characteristics of natural mobility observed over time may reflect systematic variations that would otherwise be interpreted as random effects.

Although one might anticipate longer walking times in the MCI group, this was not the case. Rather, our data indicated that the MCI subjects slowed more in the evening than did their healthy counterparts, and the amount of slowing was significantly greater for the MCI subjects as compared to the healthy group. This greater slowing rate in the data may reflect increased difficulty in performing motor tasks when tired. Due to our sample size, we were unable to use group comparisons of “slow walkers” and “fast walkers” as has been done in previous studies that suggest that motor slowing (including bradykinesia, gait disturbance, and reduced gait speed or timed walking) may be predictive of the eventual onset of dementia [16–18,20,33]. What is of key importance in assessing motor slowing is not group performance, but rather how much slowing one experiences relative to one's own baseline. In our study, we did not see significant slowing in any of the subjects over the 6 month period. However, the greater coefficient of variation in walking times in the MCI subjects as compared to healthy controls, coupled with their greater slowing in the evenings, suggests that variability in this motor

measure may be more strongly correlated with their cognitive impairments than absolute walking speed.

Of even more interest than the differences in walking speed were the differences in the wavelet variance of activity levels. The wavelet analysis indicated that the intra-group variability in the wavelet variance was smaller in the MCI group, although the wavelet variance itself was greater at all time scales. This suggests that the wavelet variance may increase as early cognitive decline occurs. More precise specification of trajectories of change in these putative markers of MCI requires confirmation during a longitudinal study. However, this study does demonstrate the ability to collect measures that are sensitive to differences between MCI and healthy elderly, as well as to track changes in these measures over time. Thus, this approach has the potential to be a valuable tool for assessing longitudinal change.

There were several technological limitations of the current study. The primary drawback of the activity assessment system we used for this study is that it cannot reliably determine when multiple people are present in the home. Although we selected subjects for the study who lived alone, and excluded intervals in which multiple people were determined to be present in the home, to be widely useful an activity assessment system must necessarily be equally effective in multi-person homes. Although subjects could maintain a log of visitors, this would be excessively burdensome over long periods, and thus a technological solution is needed. A number of technologies have been proposed to mitigate this problem [34–37]; however, because the participants must wear tags, the system is no longer unobtrusive. We are actively investigating unobtrusive alternatives to simultaneously tracking multiple individuals in the home. In addition, more sophisticated statistical approaches, such as the use of Bayesian networks to model activities, may uncover measures that differentiate the groups more definitively. Also, because the measurement of walking speed was necessarily restricted to the times during which subjects walked down the hall, this approach has limited usefulness in small apartments which lack such a hall. We are now developing new approaches for deriving walking speed data from the other motion sensors distributed around the home [38].

Previous studies of activity in the home have used wrist-worn actigraphs to quantify movement in the home [39,40]. The present study differs from the use of actigraphy in two major ways. First, our approach allows continuous monitoring over months or even years, without requiring compliance by the subject (to wear the actigraph). Second, the in-home sensors provide information about location in the home, as well as capture all types of movements (including walking speed) rather than just arm movements, and therefore these data may be of particular value in interpreting patterns of activity in the home.

Recently, there have been a number of laboratory-based and case study examples of using motion sensors for monitoring acute changes in activity and movement in the home [41–43]. However, to the best of our knowledge this is the first case control study of in-home activity patterns examining the potential clinical relevance of continuous activity assessment. The results strongly suggest that continuous assessment of activity patterns in the home, and in particular variance in daily activity, may provide a useful early marker of MCI. It is highly likely that individuals begin to adjust their behavior and adapt coping mechanisms long before their cognitive decline results in apparent functional loss, or even before an individual recognizes a memory problem. Continuous assessment of in-home activity would allow detection of a change in the consistency of an individual's daily activity patterns that could provide an early warning system for the onset of such cognitive problems, even before the individual was aware of a problem themselves. Furthermore, the combination of information about movement consistency changes and information such as total recent activity, and the proportion of time spent in the bedroom versus other areas of the home, could provide markers of other illnesses including depression, movement disorders, mild stroke, cardiac

decompensation or occult infection. Thus, the results of the current study suggest that unobtrusive, continuous in-home assessment provides a promising new tool for the early detection of clinically relevant changes not only affecting cognition, but for a number of other neurological and general medical conditions.

## Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

## Acknowledgements/Conflicts/Funding Sources

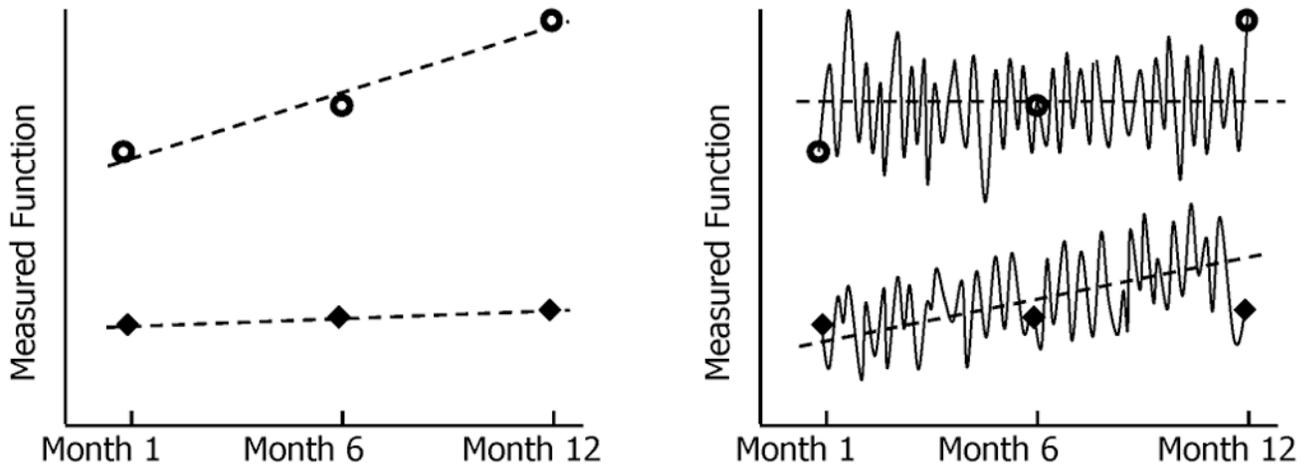
The authors gratefully acknowledge the staff of the Layton Aging and Alzheimer's Disease Center for their help in recruiting participants for this study, and Brad Stenger for his technical assistance in designing and deploying the systems used in this study. This work was funded by a pilot grant from the National Institute on Aging (P30 AG08017). Dr. Kaye's time was partially supported by a Merit Review Grant, Office of Research and Development, Department of Veterans Affairs.

## References

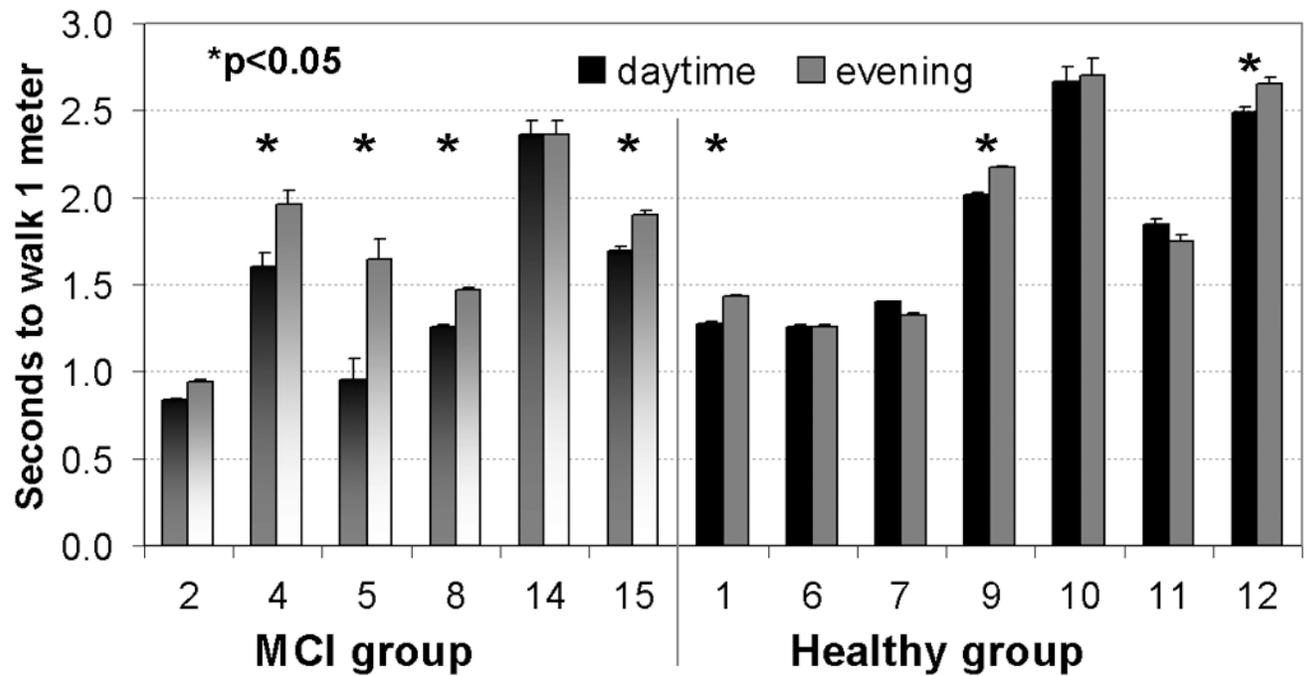
1. Boise L, et al. Diagnosing dementia: perspectives of primary care physicians. *Gerontologist* 1999;39(4):457–464. [PubMed: 10495584]
2. Gwyther L. Family Issues in dementia: Finding a new normal. *Neurologic Clinics* 2000;18:993–1010. [PubMed: 11072271]
3. Quayhagen MP, et al. Coping with dementia: evaluation of four nonpharmacologic interventions. *Int Psychogeriatr* 2000;12(2):249–265. [PubMed: 10937544]
4. Gilmour JA, Huntington AD. Finding the balance: living with memory loss. *Int J Nurs Pract* 2005;11(3):118–124. [PubMed: 15853790]
5. Callahan C, Hendrie H, Tierney W. Documentation and evaluation of cognitive impairment in elderly primary care patients. *American College of Physicians* 1995;122:422–429.
6. Boise L, Neal M, Kaye J. Dementia assessment in primary care: Results from a study in three managed care systems. *Journal of Gerontology: Medical Sciences* 2004;69(6):M621–M626.
7. Ganguli M, et al. Detection and management of cognitive impairment in primary care: The Steel Valley Seniors Survey. *J Am Geriatr Soc* 2004;52(10):1668–1675. [PubMed: 15450043]
8. Li S, et al. Short-term fluctuations in elderly people's sensorimotor functioning predict text and spatial memory performance: The MacArthur Successful Aging Studies. *Gerontology* 2001;47(2):100–116. [PubMed: 11287736]
9. Martin M, Hofer SM. Intraindividual variability, change, and aging: conceptual and analytical issues. *Gerontology* 2004;50(1):7–11. [PubMed: 14654720]
10. Sheridan PL, et al. Influence of executive function on locomotor function: divided attention increases gait variability in Alzheimer's disease. *J Am Geriatr Soc* 2003;51(11):1633–1637. [PubMed: 14687395]
11. Burton CL, et al. Intraindividual variability as a marker of neurological dysfunction: a comparison of Alzheimer's disease and Parkinson's disease. *J Clin Exp Neuropsychol* 2006;28(1):67–83. [PubMed: 16448976]
12. Brach JS, VanSwearingen JM. Physical impairment and disability: relationship to performance of activities of daily living in community-dwelling older men. *Phys Ther* 2002;82(8):752–761. [PubMed: 12147005]
13. Stenzelius K, et al. Patterns of health complaints among people 75+ in relation to quality of life and need of help. *Arch Gerontol Geriatr* 2005;40(1):85–102. [PubMed: 15531026]
14. Montero-Odasso M, et al. Gait velocity as a single predictor of adverse events in healthy seniors aged 75 years and older. *J Gerontol A Biol Sci Med Sci* 2005;60(10):1304–1309. [PubMed: 16282564]
15. Tabbarah M, Crimmins EM, Seeman TE. The relationship between cognitive and physical performance: MacArthur Studies of Successful Aging. *J Gerontol A Biol Sci Med Sci* 2002;57(4):M228–M235. [PubMed: 11909888]

16. Marquis S, et al. Independent predictors of cognitive decline in healthy elderly persons. *Arch Neurol* 2002;59(4):601–606. [PubMed: 11939895]
17. Camicioli R, et al. Motor slowing precedes cognitive impairment in the oldest old. *Neurology* 1998;50(5):1496–1498. [PubMed: 9596020]
18. Richards M, Stern Y, Mayeux R. Subtle extapyramidal signs can predict the development of dementia in elderly individuals. *Neurology* 1993;43:2184–2188. [PubMed: 8232926]
19. Wilson RS, et al. Parkinsonianlike signs and risk of incident Alzheimer disease in older persons. *Arch Neurol* 2003;60(4):539–544. [PubMed: 12707067]
20. Atkinson HH, et al. Predictors of combined cognitive and physical decline. *J Am Geriatr Soc* 2005;53(7):1197–1202. [PubMed: 16108938]
21. Strauss E, et al. Intraindividual variability in cognitive performance in three groups of older adults: cross-domain links to physical status and self-perceived affect and beliefs. *J Int Neuropsychol Soc* 2002;8(7):893–906. [PubMed: 12405540]
22. Tinetti M. Performance-oriented assessment of mobility problems in elderly patients. *Journal of the American Geriatrics Society* 1986;34:119–126. [PubMed: 3944402]
23. Fahn, S.; Elton, R., et al. Unified Parkinson's disease rating scale. In: Fahn, S., et al., editors. *Recent Developments in Parkinson's Disease*. Florham Park, NJ: Macmillan Healthcare Information; 1987. p. 153-163.
24. Morris J. The clinical dementia rating (CDR): Current version and scoring rules. *Neurology* 1993;43:2412–2414. [PubMed: 8232972]
25. Folstein M, Folstein S, McHugh P. "Mini-mental state" - a practical method for grading the cognitive state of patients for the clinician. *Journal of Psychiatric Research* 1975;12:189–198. [PubMed: 1202204]
26. Hayes, TL.; Pavel, M.; Kaye, JA. An unobtrusive in-home monitoring system for detection of key motor changes preceding cognitive decline. 26th Annual International Conference of the IEEE Engineering in Medicine and Biology Society; San Francisco, CA. IEEE; 2004.
27. Renfrew JW, Pettigrew KD, Rapoport SI. Motor activity and sleep duration as a function of age in healthy men. *Physiol Behav* 1987;41(6):627–634. [PubMed: 3441533]
28. Weisstein, EW. Bonferroni Correction. [cited; Available from: <http://mathworld.wolfram.com/BonferroniCorrection.html>]
29. Sekine M, et al. Discrimination of walking patterns using wavelet-based fractal analysis. *IEEE Trans Neural Syst Rehabil Eng* 2002;10(3):188–196. [PubMed: 12503784]
30. Najafi B, et al. Ambulatory system for human motion analysis using a kinematic sensor: monitoring of daily physical activity in the elderly. *Biomedical Engineering, IEEE Transactions on* 2003;50(6):711–723.
31. Fleissx, FleissJL. *The Design and Analysis of Clinical Experiments*. John Wiley & Sons, Inc.; 1986. Repeated Measurements Studies; p. 46-90.
32. Murray MP, Kory RC, Clarkson BH. Walking patterns in healthy old men. *J Gerontol* 1969;24(2):169–178. [PubMed: 5789252]
33. Wilson R, et al. Parkinsonianlike signs and risk of incident Alzheimer disease in older persons. *Archives of Neurology* 2003;60:539–544. [PubMed: 12707067]
34. Manapure, S., et al. A comparative study of radio frequency-based indoor location sensing systems; Proceedings of the 2004 IEEE International Conference on Networking, Sensing & Control; 2001 Mar. p. 21-23.
35. Kaemarungsi, K.; Krishnamurthy, P. Properties of indoor received signal strength for wlan location fingerprinting. 1st Annual International Conference on Mobile and Ubiquitous Systems: Networking and Services; Cambridge, MA. IEEE; 2004.
36. Feldmann, S., et al. An indoor Bluetooth-based positioning system: Concept, implementation and experimental evaluation. Proceedings of the International Conference on Wireless Networks, ICWN'03, Jun 23–26 2003; Las Vegas, NV, United States. Bogart, GA 30622, United States: CSREA Press; 2003.
37. Castro, P., et al. *Ubiquitous Computing*. Atlanta, GA: 2001. A probabilistic room location service for wireless networked environments.

38. Pavel, M., et al. Mobility assessment using event-related responses; Transdisciplinary Conference on Distributed Diagnosis and Home Healthcare; Arlington, VA. 2006.
39. Kochersberger G, et al. The reliability, validity, and stability of a measure of physical activity in the elderly. *Arch Phys Med Rehabil* 1996;77(8):793–795. [PubMed: 8702373]
40. Van Someren EJW. Actigraphic monitoring of movement and rest-activity rhythms in aging, Alzheimer's disease, and Parkinson's disease. *IEEE Transactions on Rehabilitation Engineering* 1997;5(4):394–398. [PubMed: 9422465]
41. Sixsmith A. An evaluation of an intelligent home monitoring system. *Journal of Telemedicine & Telecar* 2000;6(2):63–72.
42. Scanail CN, et al. A review of approaches to mobility telemonitoring of the elderly in their living environment. *Annals of Biomedical Engineering* 2006;34(4):547–563. [PubMed: 16550450]
43. Virone G, Noury N, Demongeot J. A system for automatic measurement of circadian activity deviations in telemedicine. *IEEE Transactions on Bio-Medical Engineering* 2002;49:1463–1469. [PubMed: 12542242]

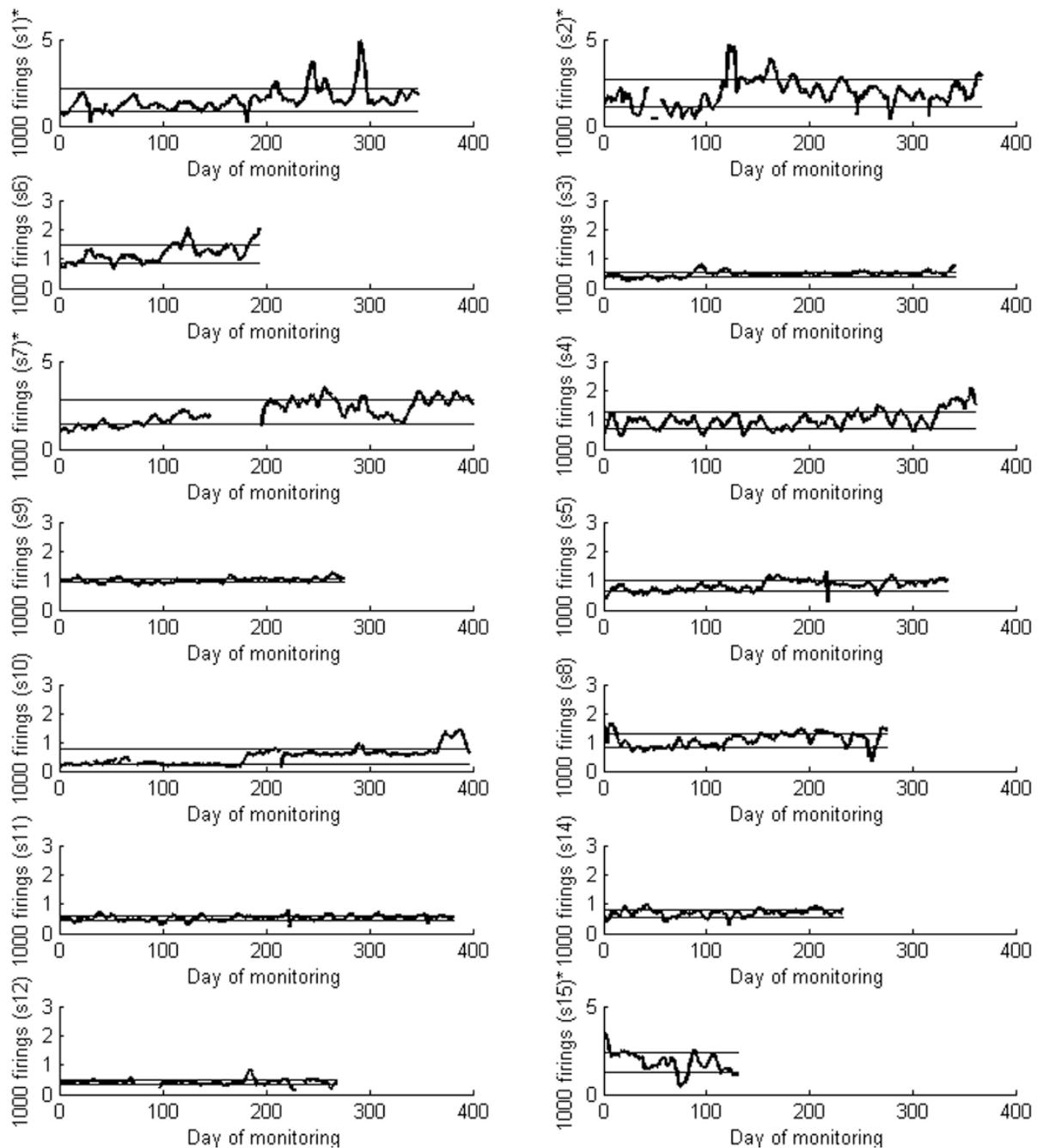


**Figure 1.** Problem with infrequent measurements. In this figure, the left panel depicts test scores taken during a standard clinic visit, taken at 6-month intervals, for 2 patients. The right panel depicts how continuous assessment could reveal a very different picture.



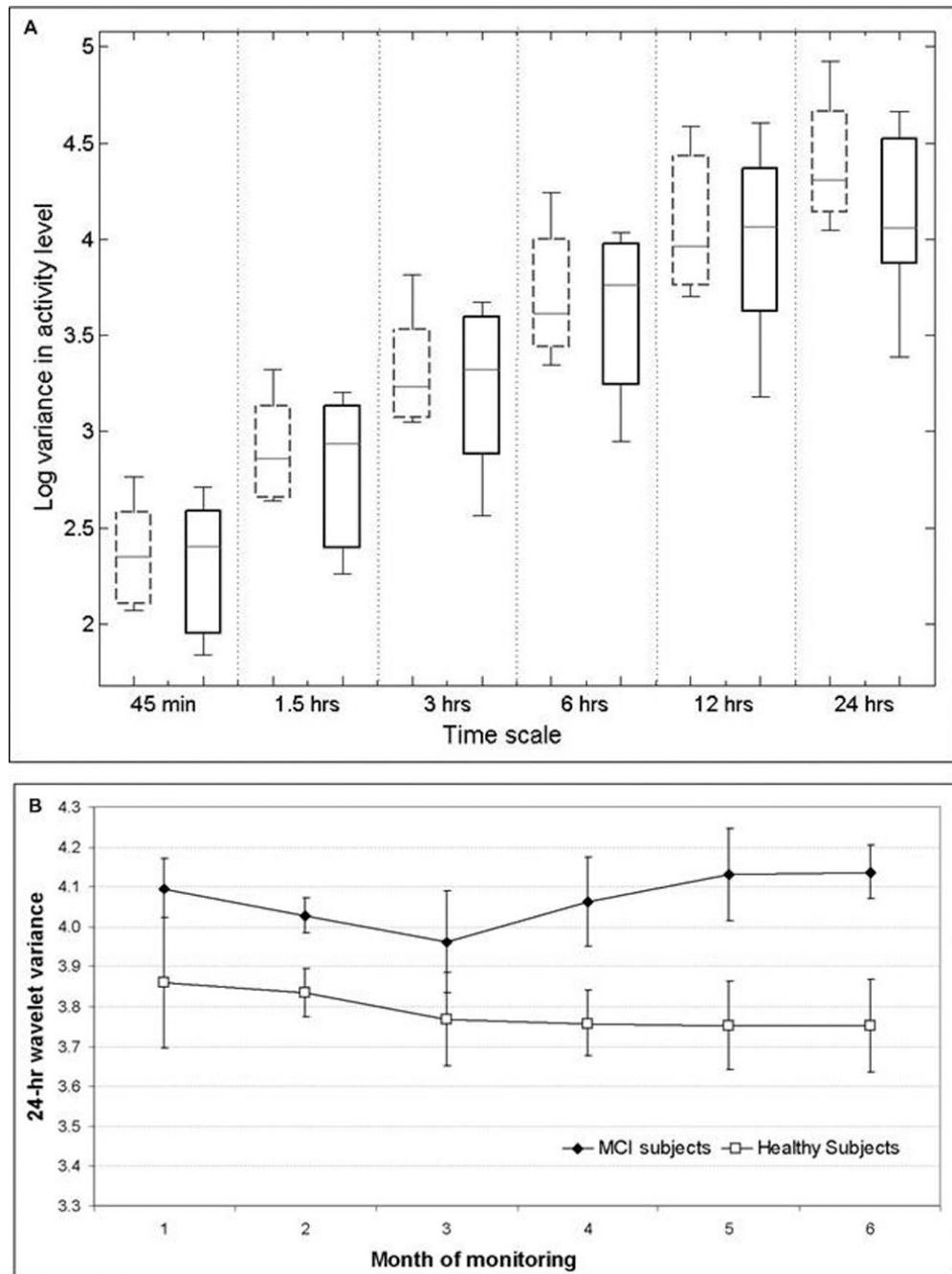
**Figure 2.**

Walking times in the morning and evening, averaged over 6 months, for each subject. Numbers indicate the subject ID's. Across all subjects, the mean walking times were longer in the evening than in the morning, with nine of the twelve subjects showing some slowing later in the day. Comparisons across all walking times in individuals showed that this slowing (reflected in longer walking times) was significantly greater in 7 subjects. Asterisks indicate those subjects whose walking time was significantly increased in the evening.



**Figure 3.**

Daily activity levels for each subject, calculated using a 7-day moving average. The abscissa shows the number of days since start of monitoring; the ordinate shows activity levels, in 1000's of sensor firings. The measure is the number of sensor firings per day. The horizontal green lines indicate one standard deviation above and below the mean. Not all subjects were monitored for the same period of time. Asterisks indicate subjects for whom the Y axis is scaled differently due to a greater variance in the daily activity levels. Missing data indicate absences from home (e.g. subjects S7 and s12); sharp peaks typically correspond to periods in which the subject had an overnight guest in the home (e.g. S1, S2).



**Figure 4.** **Figure 4A.** Box plots of the log variance in the wavelet representation of activity levels across subjects for six time scales. Dashed boxes are MCI subjects; solid boxes are Healthy subjects. **4B.** Plot of the mean of the 24-hour wavelet variance across MCI and healthy subjects, for 6 consecutive months. Solid diamonds are MCI subjects, open boxes are healthy subjects.

**Table 1**  
Demographic and functional characteristics of participants \*

ID	MCI/Norm	Sex	Rms	Educ	Age	MMSE	CDR †	ADL	IADL	mod UPDRS	TIN bal	TIN gait
2 §	M	M	8	17	82.7	27	0.5	0	0	2	1	0
3 ‡	M	F	8	12	91.0	25	0.5	2	3	1	11	1
4	M	M	9	14	92.2	26	0.5	0	1	2	6	3
5	M	F	4	12	90.6	25	0.5	1	1	n/a	12	4
8 §	M	M	2	16	88.3	28	0.5	1	0	3	4	0
14	M	F	7	14	89.5	28	0.5	0	0	5	7	1
15	M	F	7	16	84.8	25	0.5	0	2	3	9	2
1	N	F	6	18	91.9	29	0	0	0	1	3	0
6	N	M	9	16	82.5	27	0	0	0	5	n/a	n/a
7	N	M	8	16	94.3	27	0	0	0	2	5	1
9	N	F	4	16	88.4	28	0	0	0	4	1	0
10	N	F	3	12	90.9	28	0	1	0	7	2	0
11 §	N	F	2	12	88.4	28	0	0	0	1	2	0
12 §	N	F	3	20	93.9	28	0	0	0	0	2	1

\* Group N: healthy elderly, group M: those with mild cognitive impairment. Rms: number of rooms in the home, Educ: years of education, MMSE: Mini-Mental State Exam, CDR: Global Clinical Dementia Rating, modUPDRS: Modified Unified Parkinson's Disease Rating Scale, TINbal: Tinetti Balance measure, TINgait: Tinetti Gait measure, (D)ADL: (Instrumental) Activities of Daily Living.

† p<0.05, significant differences between groups adjusted for multiple comparisons.

‡ Subject 3 excluded from walking speed and 6-month analyses due to an unrelated injury during the study.

§ Subjects 2, 8, 11, and 12 were excluded from walking time analysis due to inappropriate geometry of their homes for unobtrusive measurement of walking speed.

**Table 2**  
Mean walking times and activity levels for all subjects, over a six month period.

Subject	Walking Time		Daily Activity		Mean 24-hr wavelet variance <sup>‡</sup>
	Mean (secs/m) <sup>*</sup>	CoV	Mean (counts/min) <sup>*</sup>	CoV <sup>‡</sup>	
1	1.37	0.071	0.88	0.54	3.89
6	1.29	0.058	0.90	0.37	4.08
7	1.36	0.058	1.35	0.40	4.00
9	2.10	0.049	0.72	0.18	3.82
10	2.69	0.111	0.30	0.69	3.44
11	1.50	0.116	0.49	0.39	3.73
12	1.99	0.089	0.27	0.56	3.55
<b>Healthy</b>	<b>1.76 ± .52</b>	<b>0.079 ± 0.027</b>	<b>0.70 ± 0.15</b>	<b>0.45 ± 0.027</b>	<b>3.79 ± 0.23</b>
2	0.83	0.095	1.39	0.64	4.30
3 <sup>§</sup>	N/A	N/A	0.41	0.45	4.00
4	1.85	0.153	0.68	0.39	4.16
5	1.21	0.290	0.56	0.39	4.08
8	2.09	0.136	0.74	0.36	3.93
14	2.48	0.115	0.51	0.36	3.91
17	1.74	0.090	1.25	0.49	4.12
<b>MCI</b>	<b>1.70 ± .60</b>	<b>0.147 ± 0.074</b>	<b>0.79 ± 0.14</b>	<b>0.44 ± 0.012</b>	<b>4.07 ± 0.14</b>

\* Mean walking times are reported as the mean of the median weekly walking time, normalized to seconds/meter. Mean activity levels are reported in average sensor firings per minute during periods in which the subject was home alone.

<sup>‡</sup> The Coefficient of Variation is for the average sensor firings.

<sup>‡</sup> The 24-hour wavelet variance is an average of the 6 consecutive 4-week measures.

<sup>§</sup> Walking speed data for subject 3 was excluded due to insufficient data. This subject broke her leg during the third week of the study.