Smart Home-Based Longitudinal Functional Assessment

Prafulla Dawadi
Diane J. Cook
School of Electrical Engineering
and Computer Science
Pullman, WA, USA
{pdawadi,cook}@eecs.wsu.edu

Maureen
Schmitter-Edgecombe
Department of Psychology
Washington State University
Pullman, WA, USA
schmitter-e@wsu.edu

Abstract
In this paper, we investigate methods of performing automated cognitive health assessment from smart home sensor data. Specifically, we introduce an algorithm to quantify and track changes in activities of daily living and in the mobility of a smart home resident over time using longitudinal smart home sensor data. We use an automated activity recognition algorithm to recognize a smart home resident's activities of daily living from the generated sensor data, and introduce a Compare and Count (2C) algorithm to quantify the changes in everyday behavior. We test our approach using a longitudinal sensor dataset that we collected from 18 single-resident smart homes for nearly two years and study the relationship between observed changes in the sensor-based everyday functioning parameters and changes in standard clinical health assessment scores. The results suggest that we may be able to develop sensor-based change algorithms that can predict specific components of cognitive and physical health.

Author Keywords
Functional Assessment, Longitudinal Data, Smart Home

ACM Classification Keywords
H.2.8. [Information Systems]: Database-Data mining; I.2.6. [Computing Methodologies]: Artificial

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Introduction

Smart home technologies can be beneficial for monitoring health changes and for providing interventions to sustain or improve human health. The goal of this project is to develop functional assessment algorithms based on smart home technologies to assess the cognitive and functional health of a resident based on automatically-detected activities of daily living (ADL) parameters using longitudinal smart home data. Activities of daily living (ADL) such as sleeping, grooming, and eating are essential everyday functions that are required to maintain independence and quality of life. Decline in the ability to independently perform ADLs has been associated with a host of negative outcomes, including placement in long-term care facilities, shorter time to conversion to dementia, and poorer quality of life for both the functionally impaired individuals and their caregivers [9–11].

In this work, we develop functional assessment algorithms for unconstrained environments. Our algorithm does not require changes in the environment or in a residents routine. As a result, it offers an ecologically valid method to assess the cognitive and physical health of an individual [2, 8].

Smart Home Test bed

We test our ideas in 18 actual smart home test beds. The smart home test beds are single-resident apartments, each with at least one bedroom, a kitchen, a dining area, and at least one bathroom. The sizes and layouts of these apartments vary from one apartment to another. The apartments are equipped with *motion sensors* on the ceiling and *door sensors* on cabinets and doors. Figure 1 shows a sample layout and sensor placement for one of the smart home test beds.

The residents complete their daily activities in their (smart) apartments. While residents carry out their daily routines, smart home sensors continuously monitor their behavior. The CASAS middleware collects the sensor events and stores the data on a database server. Figure 2 provides a sample of the raw sensor events that are collected and stored. Each sensor event is represented by four fields: date, time, sensor identier, and sensor message.

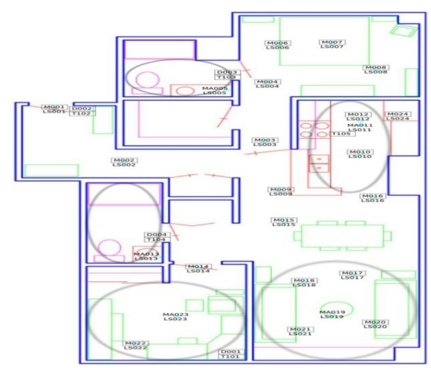

Figure 1: CASAS Longitudinal smart home floor plan and sensor layout.

```
2010-01-29 15:32:48.35166 M010 OFF
2010-01-29 15:33:50.25128 D006 ON
2010-01-29 15:34:51.47531 M014 ON
2010-01-29 15:35:51.49961 M013 ON
```

Figure 2: Sample raw and activity annotated sensor data. Sensors IDs starting with M are motion sensors and IDs starting with D are door sensors.

Related Work

The relationship between in-home sensor-based measurements of everyday abilities and corresponding clinical measurements has been explored using statistical tools and visualization techniques. For example, Paavilainen et al. [12] monitored the circadian rhythm of activities for older adults living in nursing homes using the IST Vivago WristCare system. They compared the changes in activity rhythms with clinical observations of the health status of subjects. In a separate study, these researchers [13] monitored changes in the sleep pattern of demented and non-demented individuals over a 10-day period.

Other researchers have, like this study, considered the relationship between sensor based activity performance and cognitive and physical health assessment derived using standard clinical scores. For example, Robben et al. [16, 17] studied the relationship between different high-level features representing the location and transition patterns of an individuals indoor mobility behavior, namely the frequency, duration and times of selected mobility patterns, with the Assessment of Motor and Process Skills (AMPS) scores [5]. Similarly, Suzuki and Murase [20] compared indoor activities and outings with Mini-mental State Examination (MMSE) scores [6]. However, none of these groups considered parameters reflecting the performance of activities of daily living.

In our earlier work, we established a correlation between smart home sensor-based performance measures of simple and complex ADLs and validated performance measures derived from direct observation of participants completing the ADLs in a smart home [3, 4]. However, those performance measures were derived using sensor data collected from cross-sectional studies conducted in a smart home laboratory setting. We extend this prior work by investigating the relationship between continuous longitudinal sensor data collected from 18 single-resident smart homes and their clinical assessment scores obtained by performing standard clinical assessments biannually with the smart home residents.

Participants

Participants included 18 older adult residents (4 females, 14 males) from a senior living community. All participants were 73 years of age or older ($M = 84.44$, $SD = 5.06$, range $73 - 92$), and had a mean level of education of 17.33 years ($SD = 2.03$, range $12 - 20$). At baseline, participants were classified as cognitively healthy, at risk for cognitive difficulties, or experiencing cognitive difficulties.

Standard Neuropsychological Tests

Clinical tests were administered every six months to residents of our smart home test beds. As detailed in Table 1, these tests included measures of walking speed (TUG), and a global measure of cognitive status (RBANS). The administered clinical tests are standardized and validated measures. Using repeated measurements obtained from biannual clinical tests, we create a clinical dataset that contains two different measurement variables (features).

Modeling Activities of Daily Living Parameters

In this study, we model a subset of automatically-labeled resident daily activities including sleep, leave home, bed to toilet, cook, eat, relax, and personal hygiene. We also capture and model a resident's total mobility in the home using smart home sensor data.

The raw sensor data captured from smart home sensors do not contain activity labels. We use an *activity recognition algorithm* to map sensor event sequences to activity labels. Activities of daily living such as cooking and eating can be recognized using the sensor data from environmental sensors such as motion sensors [18].

To model the activities performed by smart home residents, we calculate how much time a resident spends (activity duration) while performing each of the activities and the number of sensor events they generate while carrying out these activities. Similarly, we model a resident's mobility using two features: the number of sensor events the resident triggers as they move throughout their home and the total distance that is covered by their movement. We note that all these features are aggregated over a day time frame. For example, we calculate the time spent sleeping and number of sensors triggered while sleeping in a day. For each individual, we calculate these features for the entire data collection period.

Changes in clinical assessment data

The measurements in biannual standard clinical data are numeric values. We define a change in clinical assessment data from one time point t_1 to another time point t_2 as the difference between the clinical assessment scores at those given time points. For any time point pair (t_1, t_2),

$$\text{clinical assessment change}(t_1, t_2) = abs(CA(t_2) - CA(t_1))$$

where $CA(t_1)$ and $CA(t_2)$ represents clinical assessment data at time point t_1 and t_2.

We administer the standard clinical tests every six months because they are resource intensive. Thus, t_1 and t_2 are always six months apart.

Table 1: Variables in standard clinical dataset

Variable name	Type	Description
TUG	Numeric	Timed Up and Go [14] . This test measures *basic mobility skills*. Participants are tasked with rising from a chair, walking 10 feet, turning around, walking back to the chair and sitting down. The TUG measure represents the time it took participants to complete the task.
RBANS	Numeric	Repeatable Battery for the Assessment of Neuropsychological Status [15].This *global measure of cognitive status* was developed to identify and characterize cognitive decline in older adults. The RBANS measure is the Total Scale score.

Changes in smart home longitudinal data

We divide the longitudinal sensor data into bins of one-month time slots since features in the longitudinal smart home sensor data are continuously gathered. We then use a Hotelling T-test [7] to compare one month (a single bin) of sensor data with another month (another bin) of sensor data to detect changes. For any time point t_1, t_2,

$$\text{sensor based change}(t_1, t_2) = \text{Hotelling}(EV(t_1), EV(t_2)).$$

where EV(t_1) represents everyday functioning sensor data for month 1 and EV(t_2) represents everyday functioning sensor data for month 2.

Compare and Count(2C) Algorithm

The Compare and Count (2C) algorithm is a sliding window algorithm that accumulates changes observed in a

Table 2: Everyday Functioning Longitudinal Dataset

Group	Variable	Features
I	Mobility	Total distance traveled, #Sensor triggered
II	Sleep	Sleep duration, #Sensor events in sleep
	Bed toilet transition	Bed toilet transition duration, #Sensor events in bed toilet transition
III	Cook	Cook duration, #Sensor events in cook
	Eat	Eat duration, #Sensor events in eat
	Relax	Relax duration, #Sensor events in relax
	Personal hygiene	Personal hygiene duration
	Leave Home	Leave home duration

window. We initialize a change counter C that maintains a *change score*. 2C slides a window of size W over these bins. We choose a window size of W = 6 months because clinical tests are administered biannually. The bins that fall in this window are compared with all other bins. Depending on the time resolution and type of data, we compare bins using the notion of change defined in previous sections. Algorithm 1 explains the algorithm.

For the smart home data, we obtain a collection of change scores by running the 2C algorithm independently on features that represent different activities of daily living. Similarly, we run this algorithm on clinical assessment datasets to obtain change scores in clinical assessment scores. The change scores in activities and clinical assessment data comprise our final training dataset. The *change score* of an activity and its corresponding *change score* in the clinical assessment data represent a data point in our training set. We formulate the problem of finding relationships between the *change scores* in the everyday behavior and clinical assessment data as a learning problem, in which we want to correlate changes in clinical assessment scores with changes in everyday behavior.

Performance of Learning Algorithm

We aggregate changes of all individuals observed at different time points to build the training set for our learning algorithm. Using this training set, we learn the relationship between changes observed in the smart home behavior and the changes in standard clinical assessment scores. In our current work, we use a Support Vector Machine as our learning algorithm [1,19]. We evaluate our learning algorithm using leave one out cross validation and evaluate it by calculating the correlation coefficient (r). The objective of the experiment is to identify the strength of the relationship between different changes observed in everyday functioning and the standard clinical assessment scores. Table 3 summarizes the absolute value of the correlation coefficients between different feature subsets and standard clinical assessment scores. These scores were obtained using SVM and linear kernel. We observe that:

- The global clinical measure of general cognitive functioning (i.e., RBANS total score) correlated

Table 3: Average correlations between changes in smart home data and clinical change scores based on SVM predictions using linear kernels($\alpha = 0.005$ with Bonferroni correction for *n* sample groups, $* < 0.05$)

	Sleep	Mobility + Leave Home	ADL	Sleep + Mobility	Sleep + ADL	Mobility + ADL	ALL Features
RBANS	0.11	0.02	0.36	0.07	0.43*	0.20	0.41*
TUG	0.16	0.43*	0.16	0.16	0.01	0.24	0.10

Algorithm 1 2C Algorithm

```
Input: Clinical Assessment data (CA)
Input: Smart Home Sensor data (SH)
W = 6                                  ▷ Window Size W = 6 months
T_1 = 1
repeat:
    Place window of size W at T_1
    CH_2=0; CH_1 = 0;                  ▷ Change counters
    for all T_i,T_j ∈ W and T_i < T_j do
        Calculate: CH_1 = changeSH (T_i, T_j)
        Calculate: CH_2 = changeCA(T_i, T_j)
        Store: (T_i, CH_1, CH_2)
    end for
    T_1 = T_1 + W                      ▷ Next Time Point
until T_1 < (T_n − W)
Accumulate CH_1 and CH_2
Use learning algorithm to model CH_1 and CH_2
```

significantly with the smart home sleep and activity change scores.

- The correlation between the clinical measure of mobility (i.e., TUG scores) and the combined sensor-based mobility + leave home change score was statistically significant; the TUG also showed the highest correlations with the change scores that included mobility.

We note that the correlations between the combined set of changes in everyday functioning and the changes in the clinical assessment scores are weak. Rather it appears that there is some specificity to the change scores that can be captured by different aspects of the sensor data. More specifically, the measure of walking speed showed the strongest relationship with sensor measures of mobility, while the measure of global cognitive health showed the strongest relationships with sensor measures of sleep and everyday activity performance. Our data suggest that we may be able to develop sensor-based change algorithms that can be specific to different components of cognitive and physical health.

These results are promising and they indicate that smart home technologies have the potential to be used to assess and predict the cognitive and physical health of patients. Future research is needed to further explore the strengths and weaknesses of algorithms for analyzing smart home data.

In our future work, we will extend our method to extract information that can provide clinically relevant information to clinicians. Our main objective is to develop learning algorithms that can detect early indications of cognitive and physical health decline by monitoring everyday behavior of a resident using smart home sensors.

Conclusions

In this paper, we presented an approach to model the everyday functioning of a smart home resident using longitudinal sensor data collected from an unconstrained smart home setting. We introduce a 2C algorithm to model the changes in the individual's behavior. To validate change scores, we correlate them with the changes in standardized clinical scores. We found a statistically significant correlation between changes in sleep and activities of daily living and changes in a clinical measure of global cognitive health. We also found a statistically significant relationship between mobility change scores and changes in the clinical measure of mobility (i.e., TUG).

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