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
Intelligence-Learning

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.

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 individual's 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 $(t_1, t_2)$,

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

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.

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>
<thead>
<tr>
<th>Variable name</th>
<th>Type</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>TUG</td>
<td>Numeric</td>
<td>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.</td>
</tr>
<tr>
<td>RBANS</td>
<td>Numeric</td>
<td>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.</td>
</tr>
</tbody>
</table>
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>
<thead>
<tr>
<th>Group</th>
<th>Variable</th>
<th>Features</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>Mobility</td>
<td>Total distance traveled, #Sensor triggered</td>
</tr>
<tr>
<td>II</td>
<td>Sleep</td>
<td>Sleep duration, #Sensor events in sleep</td>
</tr>
<tr>
<td></td>
<td>Bed toilet transition</td>
<td>Bed toilet transition duration, #Sensor events in bed toilet transition</td>
</tr>
<tr>
<td></td>
<td>Cook</td>
<td>Cook duration, #Sensor events in cook</td>
</tr>
<tr>
<td></td>
<td>Eat</td>
<td>Eat duration, #Sensor events in eat</td>
</tr>
<tr>
<td>III</td>
<td>Relax</td>
<td>Relax duration, #Sensor events in relax</td>
</tr>
<tr>
<td></td>
<td>Personal hygiene</td>
<td>Personal hygiene duration</td>
</tr>
<tr>
<td></td>
<td>Leave Home</td>
<td>Leave home duration</td>
</tr>
</tbody>
</table>
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, $* < 0.05$)

<table>
<thead>
<tr>
<th></th>
<th>Sleep</th>
<th>Mobility + Leave Home</th>
<th>ADL</th>
<th>Sleep + Mobility</th>
<th>Sleep + ADL</th>
<th>Mobility + ADL</th>
<th>ALL Features</th>
</tr>
</thead>
<tbody>
<tr>
<td>RBANS</td>
<td>0.11</td>
<td>0.02</td>
<td>0.36</td>
<td>0.07</td>
<td>0.43*</td>
<td>0.20</td>
<td>0.41*</td>
</tr>
<tr>
<td>TUG</td>
<td>0.16</td>
<td>0.43*</td>
<td>0.16</td>
<td>0.16</td>
<td>0.01</td>
<td>0.24</td>
<td>0.10</td>
</tr>
</tbody>
</table>

Algorithm 1 2C Algorithm

Input: Clinical Assessment data (CA)
Input: Smart Home Sensor data (SH)

1: $W = 6$ $\triangleright$ Window Size $W = 6$ months
2: $T_1 = 1$
3: repeat:
4: Place window of size $W$ at $T_1$
5: $CH_2 = 0; CH_1 = 0$ $\triangleright$ Change counters
6: for all $T_i, T_j \in W$ and $T_i < T_j$ do
7: Calculate: $CH_1 = \text{changeSH}(T_i, T_j)$
8: Calculate: $CH_2 = \text{changeCA}(T_i, T_j)$
9: Store: $(T_i, CH_1, CH_2)$
10: end for
11: $T_1 = T_1 + W$ $\triangleright$ Next Time Point
12: until $T_1 < (T_n - W)$
13: Accumulate $CH_1$ and $CH_2$
14: Use learning algorithm to model $CH_1$ and $CH_2$

- 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).

References


