Detecting Health and Behavior Change by Analyzing Smart Home Sensor Data

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Overview

Smart Home Environments
Smart homes consist of ambient sensors installed in the environment (e.g. motion sensors, door/cabinet sensors) and activity recognition algorithms that assign activity labels (e.g. cook, eat/drink, relax, sleep, enter/leave home) to sensor events [1].

Figure 1. Sensor layouts. Smart home floorplan and sensor layouts for three testbeds (left to right: SH1, SH2, and SH3).

<table>
<thead>
<tr>
<th>Timestamp/Identifier/Message</th>
<th>Sensor Location</th>
<th>Activity</th>
</tr>
</thead>
<tbody>
<tr>
<td>2014-06-15 16:28:26</td>
<td>M909 ONS</td>
<td>Bedroom Motion: Sleep</td>
</tr>
<tr>
<td>2014-06-16 15:28:26</td>
<td>M909 ONS</td>
<td>Bedroom Motion: Sleep</td>
</tr>
<tr>
<td>2014-06-16 15:28:36</td>
<td>M901 ONS</td>
<td>Bedroom Motion: Bed-Toilet</td>
</tr>
<tr>
<td>2014-06-15 15:28:46</td>
<td>M901 ONS</td>
<td>Bedroom Motion: Bed-Toilet</td>
</tr>
<tr>
<td>2014-06-16 15:28:56</td>
<td>M901 ONS</td>
<td>Bedroom Motion: Bed-Toilet</td>
</tr>
</tbody>
</table>

Table 1. Activity recognition example. Sample raw sensor data is automatically labeled by activity recognition algorithms with corresponding activity labels.

Tracking Changes in Behavior
Tracking changes in labeled smart home data can be representative of changes in resident behavior. Often, self-perception and direct measurement of behavior are not congruent [2]. To address this, we propose Behavior Change Detection (BCD) to objectively detect changes in behavior that are indicative of significant health events.

Figure 2. BCD data processing. Activity recognition labels smart home sensor events. Several algorithms process the labeled time series data to produce a change score representing the detected change between two windows of data.

Features such as amount of time spent on each activity and distance traveled in the home are extracted from each window. The features serve as inputs to change detection algorithms, such as RuLSIF [3], virtual classifier [4], and our proposed sw-PCAR algorithm. If the score is significant, change analysis is performed to inspect and explain the source of change.

Case Studies

We collected data in smart homes with older adult residents for multiple years. We investigate 3 residents who experienced a major health event during the time we collected their data in their home:

**Smart Home Resident #1 (SH1)**
- 86 year old female
- Diagnosed with lung cancer and started radiation treatment during week 10 of data collection (W10).

**Smart Home Resident #2 (SH2)**
- 91 year old female
- Diagnosed with insomnia during week (W1).

**Smart Home Resident #3 (SH3)**
- 80 year old female
- Fell in her home during week 8 (W8).

Case Study #1 (SH1)
- Significant changes are detected for each algorithm (see Figure 6 for sw-PCAR scores).
- Number of times left/returned home increased (see Figure 7).

Case Study #2 (SH2)
- Changes exist in days leading up to diagnosis (see Figure 8 for PCAR scores).
- Sleep decreases during this period (see Figure 9).

Case Study #3 (SH3)
- Virtual classifier detects a significant change.
- Daily distance traveled is the most informative feature (see Figure 10).

Behavior Change Analysis

For a change score CS to be significant, we test that the magnitude of change (inter-window change) exceeds the day-to-day variability [5] within each window (intra-window change). We generate a list of all possible daily change scores, DCs, within each window. Next, outlier detection determines if CS is an outlier of DCs. If CS is significant, we analyze features and inspect a decision tree learner to reveal the source of change.

Figure 3. The BCD algorithm.

Figure 4. ExampleRuLSIF change scores. The blue line plots weekly change scores comparing each week to the baseline week (W8). The red line plots the computed significance threshold and the green line denotes an occurrence of a health event.

Figure 5. Change analysis. When a significant change is detected, the data is inspected to identify the source of change.

Impact
Our BCD approach objectively and automatically quantifies changes in activity behavior. The methods are useful data mining techniques for monitoring human behavior for health changes and progress toward health goals.

Future Work
Future work includes performing change analysis on real-world datasets from:
- Different health event categories.
- Vital sign data (e.g. heart rate from wearables).
- Different size windows of time.
- Smartphone applications.

Conclusions


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