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].

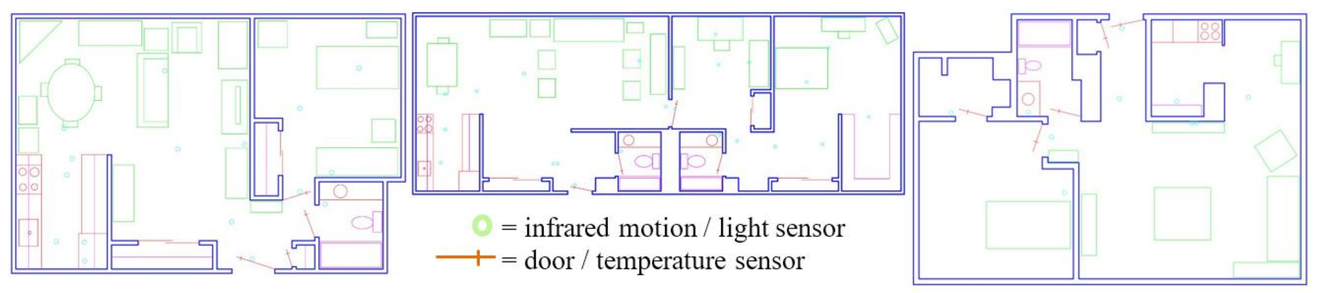

Figure 1. Sensor layouts. Smart home floorplan and sensor layouts for three testbeds (left to right: SH1, SH2, and SH3).

Timestamp/Identifier/Message	Sensor Location	Activity
2014-06-15 03:38:28.094897 M009 ON	BedroomMotion	Sleep
2014-06-15 03:38:29.213955 M009 OFF	BedroomMotion	Sleep
2014-06-15 03:38:17.814393 M015 ON	BathroomMotion	Bed-Toilet
2014-06-15 03:38:58.584179 M015 OFF	BathroomMotion	Bed-Toilet
2014-06-15 03:39:17.814393 M009 ON	BedroomMotion	Sleep

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.

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 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 (W_{10}).

Smart Home Resident #2 (SH2)

- 91 year old female
- Diagnosed with insomnia during week (W_{11}).

Smart Home Resident #3 (SH3)

- 80 year old female
- Fell in her home during week 8 (W_8).

References: [1] Krishnan and Cook, 2014. [2] Prince et al., 2008. [3] Liu et al., 2013. [4] Hido et al., 2010. [5] Refinetti et al., 2007.

Behavior Change Detection

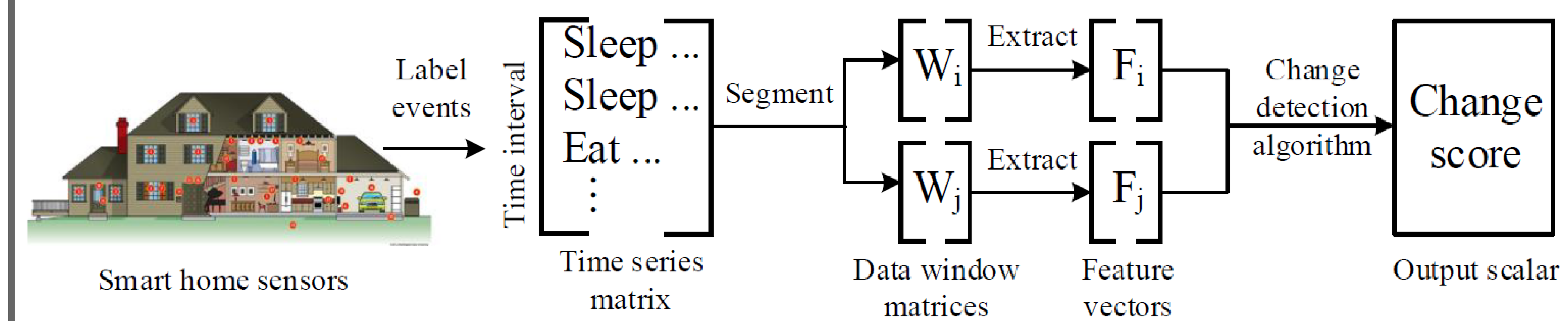

Figure 2. BCD data processing. Activity recognition labels smart home sensor events. Several algorithms process the labeled time series data to produce a change score representing the detected change between two windows of data.

Behavior is represented by a matrix of activity-labeled time intervals for each day. The data is segmented into windows, W_i and W_j, where i and j denote the start of each window containing n days.

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.

Algorithm 7 BCD(X, n, $offset$, adv_i, adv_j)

```
Input: X = time series data
Input: n = window length in days
Input: offset = number of days separating windows
Input: adv_i = number of days to advance the first window
Input: adv_j = number of days to advance the second window
Output: V = vector of change scores
Initialize: i = 1 and j = 1 + offset
for each pair of windows to compare, W_i and W_j of time series X:
    W_i = X[i : i + n − 1]
    W_j = X[j : j + n − 1]
    Compute CS = F(W_i, W_j)
    Determine if CS is significant
    Identify the type of change that is exhibited
        Manual inspection of change
        Unsupervised inspection (change analysis)
    Append CS to change score vector V
    i = i + adv_i
    j = j + adv_j
end for
return Change score vector V
```

Figure 3. The BCD algorithm.

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.

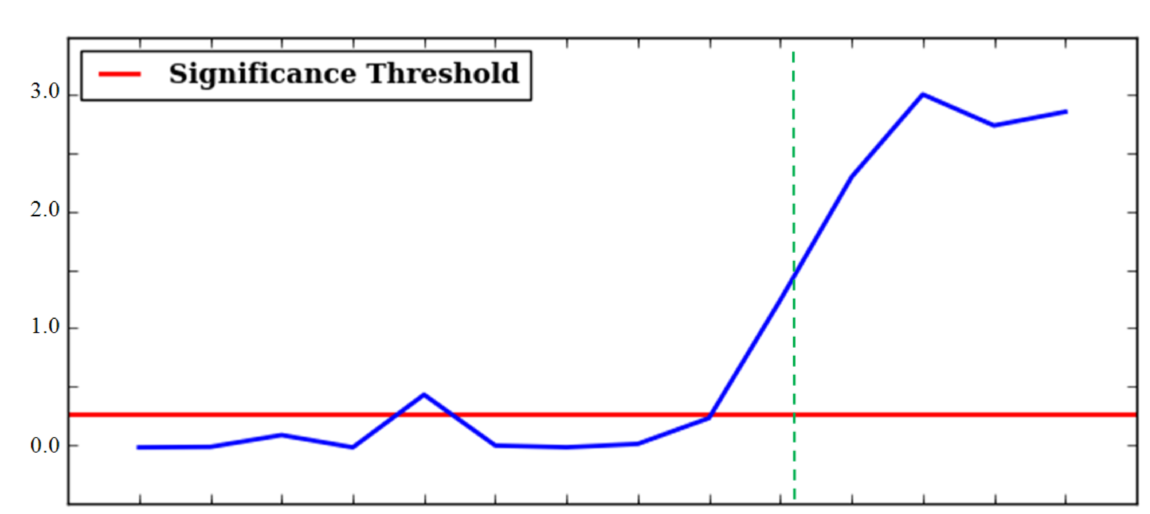

Figure 4. Example RuLSIF change scores. The blue line plots weekly change scores comparing each week to the baseline week (W_1). The red line plots the computed signifiance threshold and the green line dentoes an occurrence of a health event.

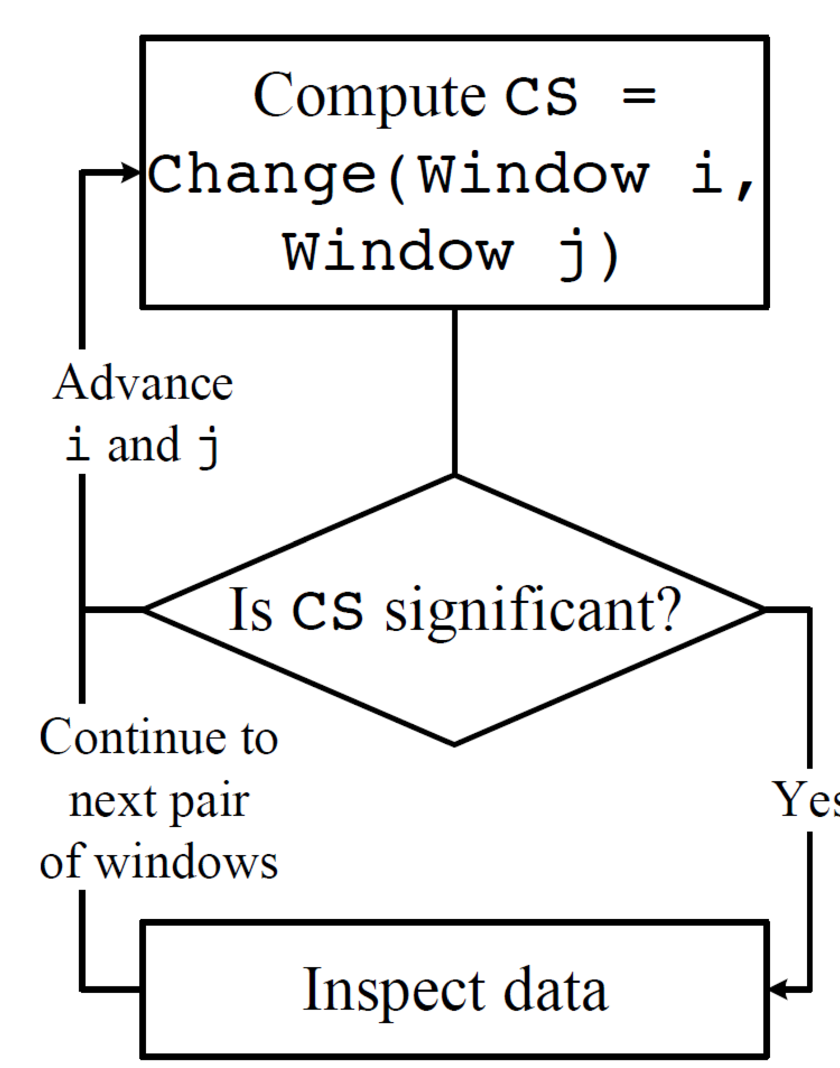

Figure 5. Change analysis. When a significant change is detected, the data is inspected to identify the source of change.

Results

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 sw-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).

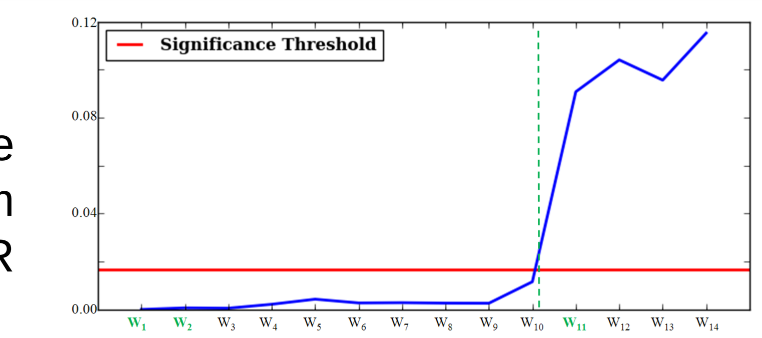

Figure 6. SH1 sw-PCAR change scores.

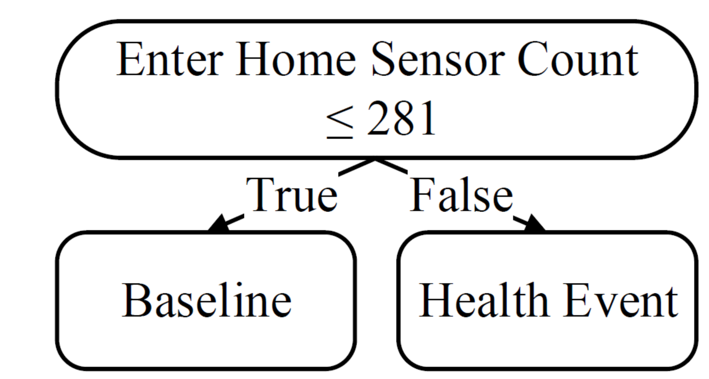

Figure 7. SH1 Decision tree.

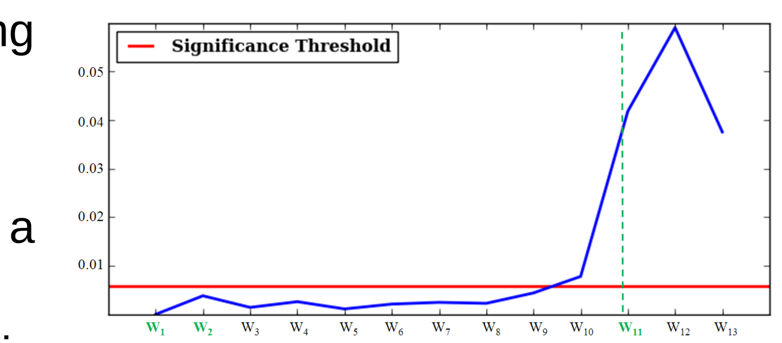

Figure 8. SH2 sw-PCAR change scores.

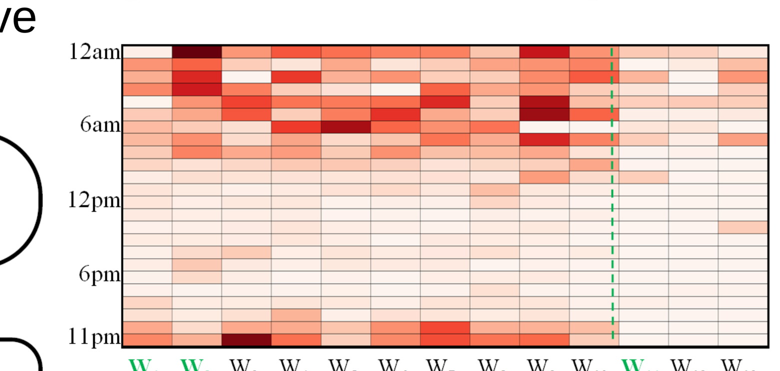

Figure 9. Activity density map for SH2's sleep. Darker colors indicate more time spent sleeping at that hour of the day.

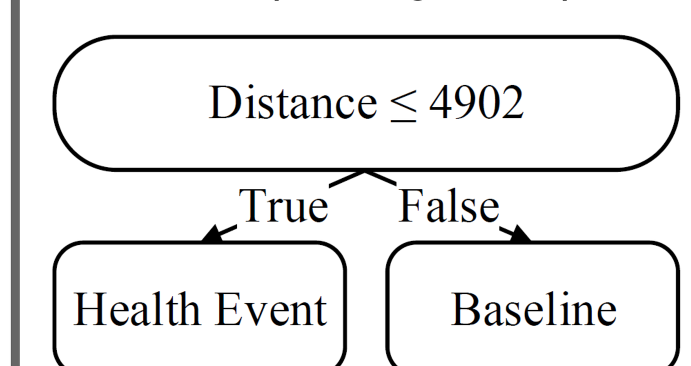

Figure 10. SH3 Decision tree.

Conclusions

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.

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