PhD Forum: Extracting Similar Patterns of Behavior with a Network of Binary Sensors

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ABSTRACT

The aging population is continuously growing and this results in increasing the demands for using technologies to help to manage the rapidly growing sector of the elderly population. To contribute in this effort, we propose a method that can find similar patterns of behavior for extended durations. Our method uses motion sensors as a privacy-aware alternative to cameras. We compute three initial parameters to extract similar patterns of behavior: (1) movement in spot; (2) movement between rooms; and (3) movement within rooms. The three parameters demonstrate good similarity indicators for finding patterns of behavior between each pair of days.

Keywords

Aging-in-Place, Behaviour Analysis, Motion Sensors

1. INTRODUCTION

Thanks to the rapid development of sensor devices and the low cost of computers and electronic devices, the research of human behavior analysis is not limited to the use of cameras anymore. Motion sensors are popular choice among researchers due to their ability to maximize the privacy of the subjects while still providing information regarding the subjects' behavioral patterns [4]. There are several smart environments based on motion sensors that aim at monitoring a list of daily activities [1, 2]. CASAS [1] is an ongoing project for a number of years, it aims at monitoring a list of daily activities to evaluate completeness of daily tasks in order to detect signs of dementia.

In general, there is a lack of collecting long-term monitoring data due to privacy issues, and there has not been many studies dedicated to long-term behavior anaylsis and health monitoring on the order of months or years [5]. In the following sections, we describe the set of indicators that we would like to extract to find similar patterns of behavior between each pair of days. These indicators will help us in our future research to identify common activities, and provide insights on well-being.

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2. DESCRIPTION OF DATASET

The CASAS dataset [1] contains 619 days of data from a smart apartment testbed. The sensor network deployed in the smart apartment is composed of PIR motion, door and temperature sensors. The PIR sensors were installed in two configurations: (1) local sensors to precisely localize the user with a relatively small detection radius of 8 ft, and (2) area sensors to detect the presence of the user anywhere inside a room. The layout of the smart is shown in Figure 1. The small circles represent the local sensors, and the large diffuse circles represent the area sensors.

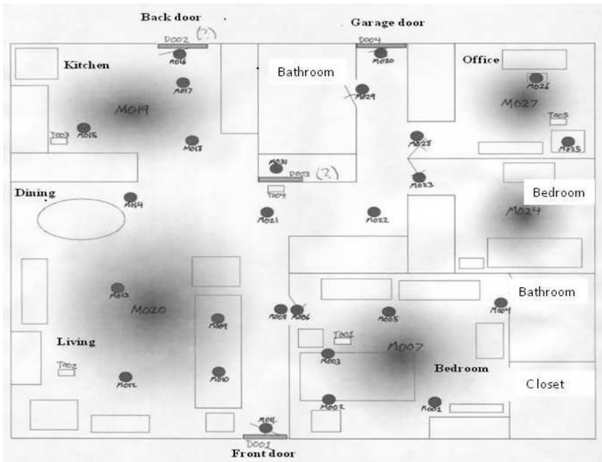


Figure 1: The CASAS smart apartment layout [1].

3. SIMILARITY INDICATORS

Let each day be divided into an equal number of equal time slots. The duration l of each time slot is in minutes. For each time slot the three similarity indicators are computed:

- Level of Activeness (LoA) indicator represents a measure of the local movement in a spot. LoA is computed every T_0 seconds as follows:

$$LoA_{T_0} = \begin{cases} max(\#\text{triggers by any sensor}) \text{ if } \Delta < \phi \\ 0 \text{ otherwise} \end{cases}, \quad (1)$$

where T_0 is the time interval in seconds, ϕ the diameter of the area sensor and Δ is the position of the triggered local sensor within ϕ. The LoA_c for a time slot c is computed accordingly:

$$LoA_c = \sum_{i=1}^{n} LoA_{T_{0_i}}, \qquad (2)$$

where $n = \frac{l}{T_0}$ is the number of the time intervals inside the time slot.

- The Level of Movement (LoM) between rooms indicator represents the time t spent in seconds inside each room RID:

$$LoM_c = \{(RID_1, t_1), ..., (RID_m, t_m)\}, \qquad (3)$$

subject to the following constraint:

$$\sum_{i=1}^{m} t_i = l. \qquad (4)$$

- Position heatmap h indicator captures the movement within a room or a number of rooms.

Let CC be the constant cost that describes the cost of not having activities happening in the same number of rooms N:

$$CC = \frac{\sum_{q=1}^{N} \sum_{r=1}^{N} |d_{q,r}|}{N} \qquad (5)$$

The similar patterns of behavior between each pair of days i and j are extracted as follows:

$$LoA_{i,j} = \frac{|LoA_i - LoA_j|}{|LoA_i + LoA_j|} \qquad (6)$$

$$LoM_{i,j} = \begin{cases} \sum_{r=\{RID_1,...,RID_m\}} |LoM_i^{(r)} - LoM_j^{(r)}| & \text{if } N_i = N_j \\ \text{CC} & \text{otherwise} \end{cases} \qquad (7)$$

$$D_{i,j} = \begin{cases} EMD(h_i, h_j) & \text{if } N_i = N_j \\ \text{CC} & \text{otherwise} \end{cases} \qquad (8)$$

$$E_{i,j} = \frac{LoA_{i,j}}{MAX_{LoA_{i,j}}} + \frac{LoM_{i,j}}{MAX_{LoM_{i,j}}} + \frac{D_{i,j}}{MAX_{D_{i,j}}}, \qquad (9)$$

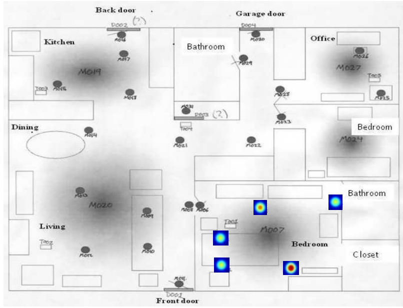
where EMD is the earth mover's distance [3] in Equation 8. Finally, the most similar patterns of behavior between days i and j are found by taking the minimum value for each row in $E_{i,j}$ (most similar from i to j).

4. RESULTS

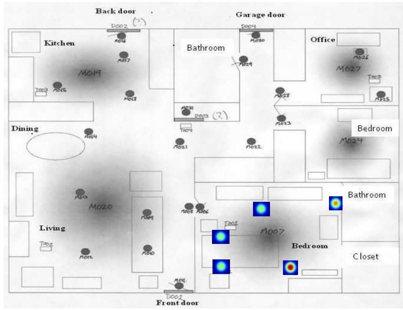
We used the CASAS dataset to show examples of behavioral patterns using the computed similarity indicators. T_0 and l were set to 10 seconds, and 15 minutes respectively. Figure 2 shows an example of bed-to-toilet behavior pattern over two consecutive days. For example, on the first day, Nov 4, a large portion of time was spent moving from the bed to toilet, yet on the next day, the same appreciable amount of time was spent.

5. CONCLUSION

In this work, we have used the CASAS dataset to derive three similarity indicators: (1) Level of Activeness (LoA) which measures the movement in spot; (2) Level of Movement (LoM) which measures the movement between rooms; and (3) position heatmap which measures the movement within room. As far as the future work is concerned, we aim at using different probability graphical models to identify common behaviors using the extracted similarity indicators.



(a)



(b)

Figure 2: Heatmaps for bed-to-toilet behavior pattern (a) Nov 4 2010 from 05:30 to 05:45, (b) Nov 5 2010 from 04:15 to 04:30.

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