TEMPORAL MODELING OF HUMAN ACTIVITY IN SMART HOMES

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Key words: Smart home, Pattern recognition, Activities of daily living (ADL), Temporal Modeling.

Abstract: Recognition of human activity is a potential challenge to design an effective smart home. The paper proposed a novel algorithm to recognize activities of daily living (ADL) of the resident. It provides analysis and mathematical modeling of temporal intervals of the event. The opposite entity states are used to extract the pattern of event sequence. Each extracted episode represents a distinct task of the resident. Result shows that, the algorithm can successfully identify 135 unique tasks of different lengths with temporal characteristics. The analysis confirms that temporal pattern follows normal distribution which can be modeled by Gaussian function.

Modeliranje človeškega obnašanja v pametnih hišah

Kjučne besede: pametni dom, prepoznava vzorca, dnevne aktivnosti, časovno modeliranje

Izvleček: Prepoznava človeške aktivnosti je potencialni izziv za načrtovanje pametnih domov in hiš. Članek predstavi nov algoritem za prepoznavanje dnevnih življenjskih aktivnosti prebivalca. Omogoča analizo in matematično modeliranje časovnih intervalov posameznih dogodkov. S pomočjo posebnih algoritmov ugotavljamo časovni vzorec posameznih dogodkov. Vsak ugotovljen dogodek predstavlja specifično nalogo prebivalca. Rezultati so pokazali, da algoritem lahko uspešno prepozna 135 edinstvenih dogodkov, ki so različno dolgi. Analiza potrjuje, da časovni vzorec sledi normalni razdelitvi, ki jo lahko oblikujemo po vzoru Gaussove funkcije.

1. Introduction

Smart home research requires understanding of human behavior and reorganization of the patterns of the activities of daily living (ADL). Early projects in this area hardly try to understand psychosomatic nature of human. Those projects simply employed intelligence to the household appliance without considering psychological understanding. Projects by Mozer /1/, Vainio *et al.* /2/, Adlam *et al.* /3/, Das *et al.* /4/ suffer from these types of limitation.

Previous trends of smart home failed to achieve anticipated improvement. Recently, researchers realized that the study of human behavior should be the initial step to conduct smart home research. Current trends show that most of the recent projects are involved in identification of ADL. The House_n group at MIT developed PlaceLab to study human activities in ubiquitous environment /5/. To acquire user information, the house is occupied with numerous wire, light, pressure, temperature, water and gas sensors. The project used video and audio retrieval devices to create vast amount of real life data. The goal of the project is to study human behavior, influence of technology on the people and how technology can be utilized to simplify user interaction with the environment.

Noguchi *et al.* used a summarization algorithm to track the resident by segmenting sensory data /6/. Segments are classified by room states and summarized for activity detection. Isoda *et al.* applied C4.5 algorithm to build spatiotemporal context of the user /7/. The system used sensors and RFID tag to define task models and user behavioral pattern at any moment that is matched with the recently detected states.

Ma *et al.* utilized Case Based Reasoning (CBR) to make a context aware system /8/. CBR uses previous activities and interactions to provide the solution of current problem. De Silva *et al.* applied multimedia technology to implement an audiovisual retrieval and summarization system /9/. They used a large number of cameras to create personalized video clips by hierarchical audio clustering and video handover. The system can track people, extract key frame, localize sound source and detect lighting change.

Zheng *et al.* used self-adaptive neural network (SANN) to classify activities of daily living /10/. For the purpose, they proposed a Growing Self-Organizing Map (GSOM) based on Kohonen self-organizing map with adaptive architecture. Virone *et al.* applied statistical predictive algorithms to model circadian activity rhythms (CARs) and their deviation /11/. Zhang *et al.* proposed snow-flake data model to classify ADL from the observed pattern and temporal information /12/. The model utilized probabilistic distribution and applicable for multiple inhabitants.

```
initialize episode_database:= null
initialize window:= null
initialize window_length:= desired_episode_length

loop
        wait for the next event e
        add e to the window
        if length(window) = window_length
                If window[1]= on state and window[window_length]=opposite state of window[1] event
                        add window to the episode_database or update frequency count
                        add time interval between the states to the episode_ database
                remove window[1] and update window index
forever
```

Fig. 1: Pseudocode of the proposed algorithm

Park *et al.* combined computer vision and RFID sensors to recognize ADL at multiple levels of detail /13/. The system builds a dynamic Bayesian network and can identify coarse-level and fine-level ADL. In 2008, Rashidi *et al.* developed CASAS at Washington State University /14/. It uses Frequent and Periodic activity miner algorithm to discover frequent and periodic activity patterns. Lu *et al.* built CoreLab, a location aware activity recognition system /15/. Instead of using simple sensors, CoreLab employs ambient-intelligence compliant objects (AICO) to detect contact, pressure, power usage and motion. It can cluster ADL by utilizing an enhanced version of naive Bayes classification method.

The major problem related to data classification algorithm is deciding the exact starting and ending point. Researchers try to solve the problem using time frame. But there is a chance to count noisy information because the time frame doesn't consider actual data flow. Others try to implement LZ78 data compression rule but it also has the same short fall. The proposed algorithm solely considers appliance states which can accurately identify ADL and temporal characteristics.

2. Methodology

Human activity is a collection of well defined tasks. The tasks can be as simple as coffee making activity, cooking sequence, watching TV or reading books. Some consist of complex long patterns like using the kitchen, toilet and so on. Classification of the task and event according to temporal and location information is an important prerequisite to develop a reliable and sustainable smart home.

Task isolation process requires accurate clustering of unique episode. For the purpose, the actual stating point and ending point of the activities should be properly defined. In the proposed algorithm, a novel clustering method has been developed based on opposite state modeling.

Suppose, we need to identify the living room activities. The activity may be started with the turning ON of the living room light. Then the resident switched ON the TV. After watching the TV program for a while, he turned it OFF. The activity is ended by switching OFF the living room light. Therefore, there is a specific starting point and ending point of the living room activity which are turning the living room light ON and OFF respectively. If we consider cooking activities, there also has a starting point which is turning ON the cooker. And the ending point is the OFF states of the cooker. Similarly, we can classify each and every activities of the resident by considering the ON-OFF states of home appliances.

Fig. 1 shows the pseudocode of the algorithm. It maintains a window to track the events according to the sequence of occurrence. The window is a fixed length array which is defined by the programmer according to desired episode length. The first event of the window is compared with the current event to determine the pattern. If they represent the

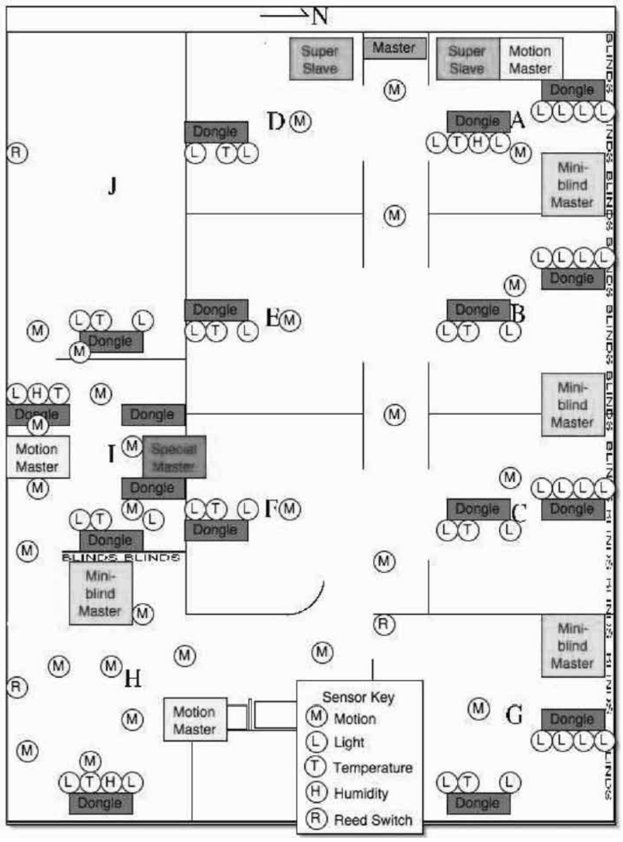

Fig. 2: MavLab interior map and sensor locations.

opposite state of the same entity, then the whole window is added to the episode_database. In case of existing episode, the algorithm updates the frequency count. It also stores the time interval between the states into the database. The episode_database provides the classified episodes, number of their occurrence and a series of temporal intervals.

3. Results and discussion

To evaluate the algorithm, we used practical smart home date from MavHome project /16/. The project used X10 based devices for home appliance control. There are more than 60 X10 appliances which are divided into 16 zones and identified by a unique id number. Fig. 2 shows MavLab interior map and sensor locations.

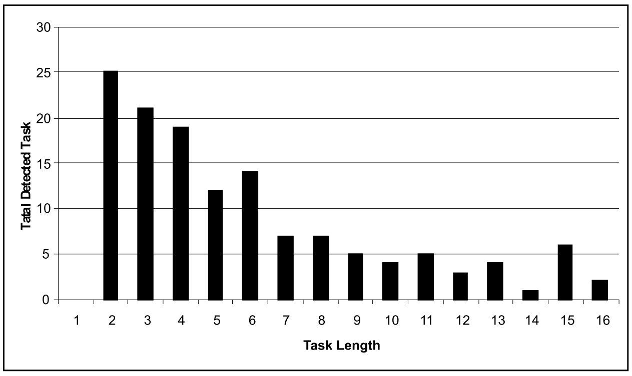

Fig. 3: Total number of activities according to episode length.

Table 1: Temporal Analysis of Events

Event Id	Mean(s)	Median(s)	Mode(s)	Standard Deviation (s)
Event-1	60	60	60	0
Event-2	386	240	180	311
Event-3	72	60	60	27
Event-4	570	300	240	514
Event-5	600	540	none	275

The information from the X10 device has been fed into the algorithm as input and it successfully identified activities of various lengths. The lower pattern length indicates simple task and higher length represents complex activities. Fig. 3 illustrates identified patterns for various lengths. The algorithm has identified total 135 tasks. Small length activities are frequent and more than long tasks. For 2, 3,4,5,6 length episode, the algorithm can classify 25,21,19,12 and 14 distinct activities respectively. The number of total tasks reduced to less than 10 if the episode length exceeds 6 events. For example, if the episode consists of 10 events than the total activities reduce to 4. Results show that, the proposed algorithm can identify different length of activity pattern utilizing opposite state episode boundary.

The algorithm stores the temporal intervals of the event in the *episode_database*. The same event takes different duration of time. To measure central tendency of the temporal intervals, we calculated mean, median and mode of the durations. Standard deviation shows the deviation from the mean value. Table I gives an idea about temporal characteristics of the event intervals.

Temporal duration of smart home events follows normal distribution and it can be described by using Gaussian distribution function (eq. 1).

$$\varphi(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\left[\frac{(x-\mu)^2}{2\sigma^2}\right]} \qquad (1)$$

Here, $\varphi(x)$ is the probability density function, σ = standard deviation and μ is the mean of observed temporal data. Fig. 4 illustrates an event with σ =0.45 minute and μ =1.2 minute.

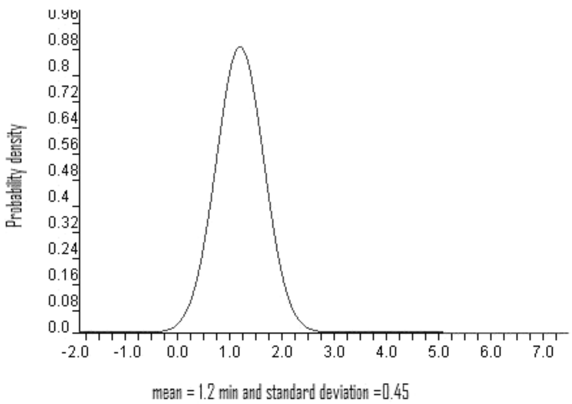

Fig. 4: Total Temporal intervals follow normal distribution

4. Conclusions

The paper presents an innovative method to detect activities of daily living. Unlike other methods, it is based on dual state entity extraction which considers the common data flow of smart home event sequence. Result proves that, it can successfully classify 135 activities of various lengths. It provides temporal analysis and modeling of smart home user activities. Event duration follows normal distribution which can be modeled by the Gaussian function. The model can be used to predict temporal behavior of the resident.

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