Smart Home Automation with User Activity Prediction

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Abstract -Smart homes are one of the Internet of Things domains intended to support and aid the residents through various smart services. These services require accurate context inferences using daily activity patterns and environmental properties. To satisfy such a need with battery-powered sensors, various duty cycling schemes were introduced. In this letter, we propose an activity-aware sensor cycling approach that makes the best tradeoff for duty cycle adjustments by exploiting the predictable behavior of residents, thereby significantly improving the activity detection accuracy at a marginal increase of the energy consumption. Evaluation results demonstrate that it achieves up to 99% accuracy of activity detection and extends the network lifetime by supporting balanced energy consumption among sensors. We formulate and solve the activity prediction problem in the framework of imitation learning and reduce it to a simple regression learning problem.

Index Terms – Smart Homes, Activity Prediction, Energy Management, Raspberry Pi.

1. INTRODUCTION

With the advent of Internet of Things (IoT), Wireless Sensor Networks (WSNs) are envisioned as an integral part of our daily environments to enable a broad range of smart applications from health-care to energy savings. With huge commercial prospects and rapid development of information and communication technology in recent years, smart environments have become a very active research topic. Smart home is a branch of ubiquitous computing in which the information-perceiving and information-processing units remain invisible in the surroundings to create a pervasive environment. People spend a significant amount of time in their houses, and this has drawn researchers to promote integration of all possible services with traditional homes.

Providing intelligence to the home appliance is a critical problem in designing an intelligent system. The design architecture strongly depends on a system's perception of the environment and its behavior based on observation. Smart homes, the next emerging research area in the field of artificial intelligence (AI), depend on effective usage of AI algorithms for reliable performance.

Conventional duty cycling minimizes the active time of sensors by having them to sleep when not in use. Despite the amount of energy saved, however, it may not be suitable for many IoT applications since important activities can be missed when sensors are inactive. To simultaneously meet the needs of both accuracy and energy efficiency, predictionbased duty cycling schemes were introduced.

In a sequence, where multiple nested episodes are possible, SPEED only considers the inner most episode for identifying context frequencies, which results in reduced prediction accuracy. Our proposed algorithm overcomes the limitations mentioned above and results in better prediction with a faster convergence rate. Also, resource management and concurrent activity scheduling is an important functionality of any multiresource Smart Home solution having more resources of same type (multiple TV sets). The better the resource management, the better is user experience in a Smart Home. For example, consider a smart home solution deployed in a 2 user (User1, User2) environment. Assume there are 2 TV sets installed in a smart home, one in living room and another in bed room of User1. Consider that based on the past history of User1 activities, there is a prediction that Sunday 7:30pm, a scheduled TV show to be watched by User1. At the same time User2 has a weekly show scheduled at 7:30pm on Sunday. So in this situation, smart home should be able to allocate living room TV set to User2 and suggest User1 to watch show in bed room. This idea provides an algorithm to handle concurrent activities in Smart Home environment through resource management.

2. RELATED WORK

In this section, a brief discussion of related sequence prediction algorithms is presented.

Bhattacharya and Das proposed the LeZi Update algorithm to track user mobility using the concept of the LZ78 data compression algorithm . LeZi Update constructs a decision tree using LZ78 dictionary contexts and predicts the possible user location based on a PPM-style algorithm.

Gopalaratnam and Cook improved the LeZi Update, creating the ALZ algorithm, by increasing the convergence rate [1]. Instead of parsing data directly from LZ78 dictionary words, it uses a variable- length window to reduce the data loss across phase boundaries.

Davison and Hirsh developed the incremental probabilistic action modeling (IPAM) algorithm to predict the next user

command in a UNIX shell prompt . IPAM stores the probabilities of each event in a table and updates the table according to the weighted probability regarding the immediate past command.

3. SMART HOME ARCHITECTURE

The architecture of a Smart Home can be accurately depicted as four layers:-

- Physical Layer
- Communication Layer
- Information Layer
- Decision Layer
- 2.1. *Physical Layer:*

This layer contains the basic hardware within the house including individual devices, transducers, and network hardware.

2.2. *Communication Layer:*

This layer includes software to format and route information between agents, between users and the house, and between the house and external resources.

2.3. Information Layer:

This layer gathers, stores, and generates knowledge useful for decision making.

2.4. Decision Layer:



Figure 1 Smart Home Architecture

This layer selects actions for the agent to execute based on information supplied from other layers.

Perception is a bottom-up process. The sensors monitor the environment (e.g. the temperature of the home) and, if necessary, transmit the information to another agent through the communication layer. The database records the information in the information layer, updates its learned concepts and predictions accordingly, and alerts the decision layer of the presence of new data.

The execution is a top down process. The decision layer selects an action (e.g. adjust the temperature to a lower value) and relates the decision to the information layer. After updating the database, the communication layer routes the action to physical layer. The physical allocates action to the appropriate effectors to execute

4. MOBILITY MODEL

The Smart Home coverage area is partitioned into zones or sectors. Location management involves keeping track of the user movement. When Smart Home needs to contact an inhabitant, the system initiates a search for the target terminal device by polling all zones where it can possibly be found. All terminals listen to the broadcast page message, and only the target sends a response. The restrictions imposed by sensor characteristics like limitation due to infrared technology sometimes may become unavoidable. Also, to avoid location uncertainty of the inhabitant, a periodic update of the inhabitant's location needs to be captured. The most probable current position is predicted by update information and the last known position. In this section all the results and the discussions should be made.

5. PREDICTION ALGORITHMS

The prediction algorithm aims to construct a universal predictor or estimator for determining the next user action. The scheme creates a dictionary of zone ids treated as character symbols and uses the dictionary to gather statistics based on movement history contexts, or phrases.

5.1 LZ78 Algorithm

The LZ78 data compression is an incremental parsing algorithm based on the Markov model. The LZ78 is used only as a system that breaks up a given sequence (string) of states into phrases.

initialize dictionary := null

initialize phrase w := null

loop

wait for next symbol v

if ((w.v) in dictionary):

w := w.v

else add (w.v) to dictionary w := null increment frequency for every possible prefix of phrase endif forever

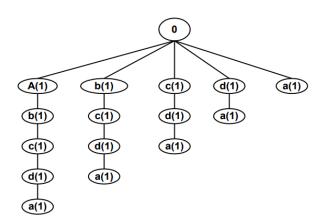


Figure 2 Worst case scenario of the algorithm

5.2 Active LeZi Algorithm

The Active LeZi is an on-demand algorithm that is based on Markov models and primarily stores the frequency of input patterns in a trie according to the compression algorithm LZ78.

The length of the longest phrase seen in a classical LZ78 parsing is chosen as equal to the length of window at each stage. The reason for selecting this window size is that the LZ78 algorithm is essentially constructing an order-k-1 Markov model, where k is equal to the length of the longest LZ78 phrase seen so far.

initialize dictionary:= null initialize phrase w:= null initialize window: = null initialize Max_LZ_length = 0 loop wait for next symbol v

if ((w.v) in dictionary):

$$w := w.v$$

else

add (w.v) to dictionary update Max_LZ_length if necessary w:= null endif add v to window if (length(window) > Max_LZ_length) delete window[0] endif

Update frequencies of all possible

contexts within window that includes v

forever

5.3 SPEED

SPEED is an adaptive sequence prediction algorithm. Its performance depends on the episode isolation criteria as well as the number of episode occurrences in smart homes. SPEED generates a finite-order Markov model and makes predictions using an algorithm based on PPM.

initialize Max_Episode_Length : = 1

initialize window : = null

loop

```
wait for next symbol E
```

add E to the window queue

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e := opposite (E)
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loop

search every i th element of the window for e

where, i:=1 to length(window) -1

if window(i) = e

episode := window (i : end)

if length(episode) > Max_Episode_Length

Max_Episode_Length := length(episode)

end

window := window(end - Max_Episode_Length+1: end)

add or update frequencies of all possible contexts within the episode

where, maximum context length = Max Episode Length

end

forever

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forever

SPEED is the first sequence prediction algorithm that is based on human activity patterns inside smart homes. Previously proposed algorithms are based on general sequence patterns and are not concerned about the psychological behavior of the people inside homes.

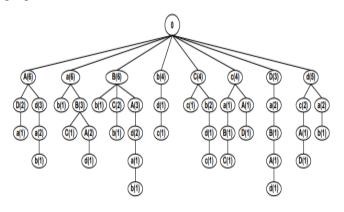


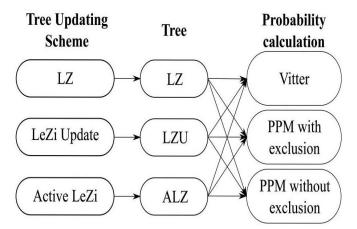
Figure 3 SPEED Algorithm Space Tree

6. PERFORMANCE ANALYSIS

The evaluations of performance of Prediction Algorithms, the following metrics are used in the literature:

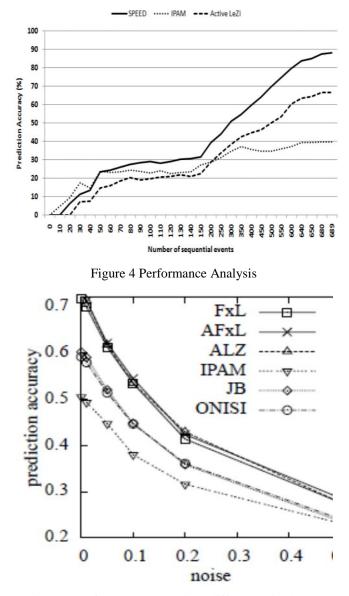
- Prediction accuracy
- Prediction probability
- Applicability

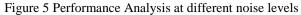
The prediction accuracy and probability are computed by assigning a score to every prediction made by the algorithm and averaging over the number of predictions made by the algorithm.



The characteristics of the input sequences plays an important role to find which algorithm is best suited to requirements of the application. The most important parameters are:

- Dataset size available for training
- Distribution of repetitive sequences
- Noise in the repetitive sequences





7. CONCLUSION

In the paper, the concept of a Smart Home and necessary steps in implementing its logic is discussed. The skeletal architecture for implementation of a Smart Home provides an approach to its deployment. The prediction algorithms play key role in providing the intelligence for a smart home by mining the sensed environmental and human activity data. We initially discuss in details regarding the algorithms, the fall backs. We then cover in brief how few of the fallbacks have been considered in the following algorithms. Some enhancements to these algorithms have also been reviewed. The exclusive pattern isolation rule ultimately performed better than the other algorithms. This is because the amount of knowledge it contains is higher, its memory is better organized, and it uses multi-order knowledge to make decisions.

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