CASASviz: Web-based Visualization of Behavior Patterns in Smart Environments (Demo Proposal)

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***Abstract*—The need to prolong the ability for older adults to live at home independently has become an important area of smart environment research. In this proposal, we demonstrate a web-based visualization system (CASASviz) that integrates monitoring, analysis, and automated recognition of residents' behavior patterns in smart environments. In our data collection module, we collect real sensor data from the CASAS smart apartment testbed. For our data adapter, we translate the raw data to various compatible formats for different visualization applications. In our visualization application module, we visualize resident behavior graphs that allow users to understand their behavior patterns in our smart environments.**

Keywords-smart environments; visualization; heat map; activity graph; behavior patterns

I. Introduction

It has been a long-lasting interesting in developing in-home based technology to improve the quality of care-giving systems, and in turn, to prolong the ability of older adults to live independently at home and avoid institutionalization. Researchers [1] have pointed out that assistive device use and environmental interventions have been shown to be effective strategies in reducing home care costs and in maintaining independence in frail elders. Kiney et al. [2] stated that assistive device use and environmental interventions have been shown to be effective strategies in reducing home care costs and in maintaining independence in frail elders. To assist older adults and people with disabilities to live independently, smart environments [3] have become a very popular research area, which is the consequence of a convergence of technologies in machine learning, data mining, and pervasive computing. In order to understand all the information collected by a smart environment, individuals either need to be trained to read the raw output from the sensors or present the information visually. The goal of the current project is to improve the accessibility of smart environment technology to the public by creating a user-friendly, visualized interface to represent the information gathered from smart home technology (e.g., data from different types of sensors). To achieve this goal, the three following essential objectives shall be met: (1) develop a friendly graphic interface to better represent the data gathered from different sensors in smart home environments, (2) apply data mining and machine learning techniques to analyze, understand, and classify resident behavior patterns, and (3) ensure that the system is compatible with different computation platforms, including Linux, Windows, Mac, and mobile devices.

In view of these requirements, we developed a web-based visualization system, called CASASviz, to represent and explore residents' behavior patterns in our CASAS smart environment. To implement CASASviz, we make use of Scalable Vector Graphics (SVG) [4], which is an application of XML-format that makes it possible to describe two-dimensional vector graphics. SVG graph is compressible, scalable, and can be zoomed without degradation. CASASviz also extends the suffix tree method to look for long-term and abnormal patterns of the residents. To be compatible with different platforms, we use web-based technologies to implement the CASASviz system. Thus, CASASviz can be used on Windows, Linux, and even smart phones without worrying about compatibility. Figure 1 shows the CASASviz interface on an iPhone device.

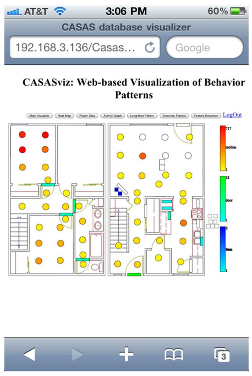

Figure 1. The interface of CASASviz on an iPhone platform.

II. CASASviz System Architeture

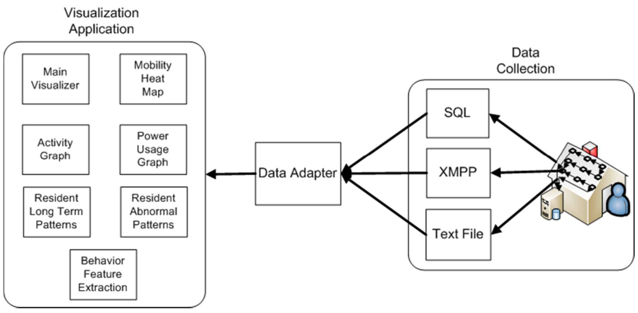

Figure 2. System Architecture of CASASviz system.

Figure 2 shows the system architecture of the CASASviz system. The functionalities of each component are briefly described as follows:

- *The Data Collection module* collects the sensor data gathered from our CASAS smart environment and stores the sensor data in an SQL database or the XMPP middleware. As an option, our system also supports importing the raw data from the data file.
- *The Data Adapter module* provides the interface for accepting different formats of sensor data and translates these sensor data into different compatible formats for various visualization applications.
- *The Visualization Application module* is an integrated web-based interface, which implements seven different visualization applications. We will introduce the details of these visualization applications in the following parts.

A. Data Collection module

The smart home environment testbed that we are using to collect the data is a three bedroom apartment located on the Washington State University campus.

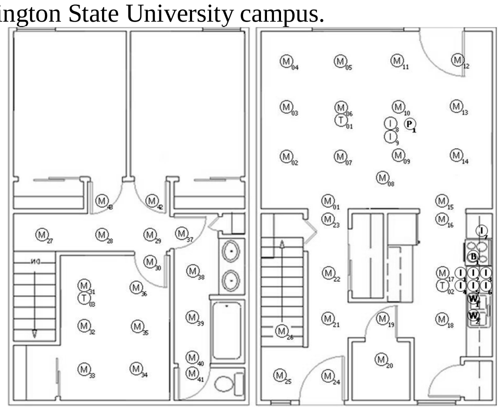

Figure 3. Three-bedroom smart apartment used for our data collection (motion (M), temperature (T), water (W), burner (B), telephone (P),and item (I)).

As shown in Figure 3, to track people's mobility, we use motion sensors placed on the ceilings. The circles in the figure stand for the positions of motion sensors. They facilitate the residents who are moving through the space. A simple power meter records the amount of instantaneous power usage and the total amount of power which is used. An in-house sensor network captures all sensor events. The data from the CASAS smart environment can be assessed for CASASviz in three different ways:

- *PostgreSQL database*
- *Streaming live data over XMPP middleware*
- *Exported data File*

All data is stored in a PostgreSQL database. CASASviz can query, load, and visualize events for a specified time period. Alternatively, the events from the database can be exported into a data file. The data file can also be loaded and played back by CASASviz. To track the resident's mobility in real-time, CASASviz can subscribe to the middleware and play live streaming events in real-time.

After collecting data from the CASAS smart environment, the researchers [5] annotated the sensor events with the corresponding activities that were being performed while the sensor events were generated. The sensor data and activity labels used for our study are expressed by several features summarized in Table 1. These four fields (Date, Time, Sensor ID and Message) are generated by the CASAS data collection system automatically.

TABLE I. SAMPLE OF SENSOR EVENTS AND ACTIVITY LABELS USED FOR OUR STUDY

Date	Time	Sensor ID	Message	Label
2009-07-14	17:10:00	M045	ON	Computer ends
2009-07-14	17:10:06	M046	ON	
2009-07-14	17:10:08	M046	OFF	
2009-07-14	17:12:26	M017	ON	Cooking starts
2009-07-14	17:12:27	D014	OPEN	

B. Data Adapter module

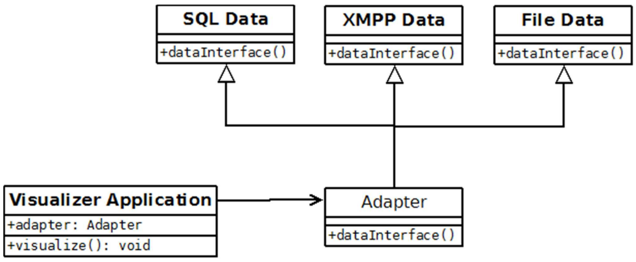

Figure 4. Data Adapter module expressed in UML

Since there are three different data sources assessed to our CASASviz, we develop a Data Adapter module to translate three different original data formats to a compatible interface for various visualization applications. As shown in Figure 4, we use the adapter pattern expressed in UML to implement the Data Adapter module in our CASASviz system.

C. Visualization Application module

1) Main Visualizer

Figure 5. CASASviz main visualizer interface

Figure 5 shows the interface of our CASASviz main visualizer. As shown in the figure, the red circle represents the location of the resident in our CASAS smart environment.

Through XMPP middleware, we can monitor the resident's mobility in real time. We also provide playback mode from a captured file or SQL database storing the sensor readings for reviewing the mobility history of the resident.

2) Mobility Heat Map

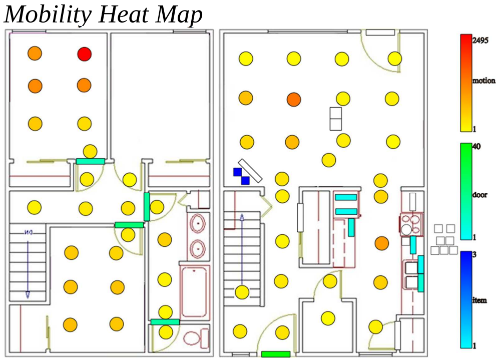

Figure 6. CASASviz Mobility Heat Map

Figure 6 illustrates the mobility heat map of our CASASviz visualization, which describes the frequency of the sensor events triggered by the residents by incremental colors. The heat map uses three different color sets (yellow, green, blue), which represent the frequency of motion sensors, door sensors, item sensors respectively, in the specified time window. Higher frequencies are represented by dark colors and lower frequencies are represented by lighter colors.

3) Activity Graph

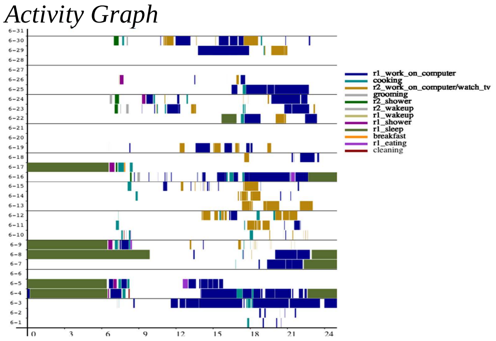

Figure 7. CASASviz Activity Graph

As seen in Figure 7, a graph of annotated activities can be generated from a single or multiple annotated data files and each color stands for a monitored activity. With the help of an activity map, researchers can identify changes of behavior patterns in the habit of an inhabitant and look for anomalies in this data. Visually comparing differences between human-generated and AI-generated annotations has also been done using Activity Graphs.

4) Power Usage Visualizer

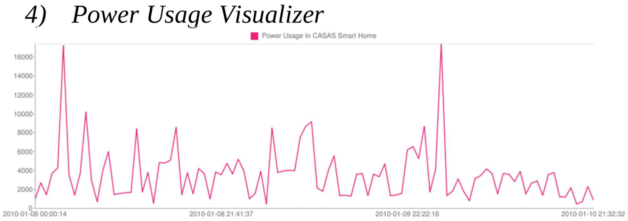

Figure 8. CASASviz Mobility Heat Map

In smart environments, power usage is also an important factor to represent behavior patterns of the residents. As shown in Figure 8, CASASviz provides an energy usage visualizer to express energy fluctuations that occurred during the time the user defined. This graph can be used to identify trends and abnormalities of power consumption.

5) Long-term and Abnormal Patterns Visualizer

To discover long-term and abnormal behavior patterns of the residents, we extend a data structure of suffix tree [6] as an efficient sensor event representation to analyze the global structural patterns of sensor events. Intuitively, for a sensor stream S, we consider a sensor pattern p in S to be an anomaly, if the frequency of this pattern does not satisfy a pre-specified threshold. If the frequency of the pattern is one of the highest in all the patterns, we define this pattern will be a long-term behavior pattern for the resident.

6) Activity Feature Extraction

In smart environments, we need to make use of machine learning techniques to do some predictions, such as activity recognition and energy prediction. Before making use of these learning algorithms, another important step is to extract useful features or attributes from the raw annotated data. We have considered some features that would be helpful in prediction and recognition. These features have been generated from the sensor data by our feature extraction module. The following is a listing of the resulting features that we used in our ongoing prediction experiments.

- *Activity length in time (in seconds)*
- *Time of day (morning, noon, afternoon, evening, night, late night)*
- *Day of week*
- *Weekday / weekend*
- *Previous activity*
- *Next activity*
- *Number of kinds of motion sensors involved*
- *Total Number of times of motion sensor events triggered*
- *Energy consumption for an activity (in Watt)*
- *Motion sensor M1…M51 (On/Off)*

III. Conclusions

In this work, we develop a web-based visualization system for our CASAS smart environment. This visualization system can monitor the mobility of the residents in real time, review the history of the mobility of the people, and discover long-term and abnormal patterns during a defined time period. Moreover, CASASviz also provide power consumption graph in smart environment for detecting the overall current and abnormalities during a specific time period. To be helpful to apply machine learning technique, CASASviz can extract relevant features, which can be used to recognize activities and predict energy consumption.

References

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