Inferring high-level human behavior from low-cost binary sensors

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***Abstract*—Automatic interpretation and prediction of human behavior using pervasive sensors deployed in the environment has a wide variety of applications ranging from building energy minimization, assisted living systems for elders to surveillance. A lot of focus has been given to using information rich sensors such as cameras for these purposes. However, they are expensive, requires careful planning of deployment, and do not preserve the privacy of the user. For these reasons, we propose the use of low cost binary sensors i.e. simple "on/off" sensors such as motion detectors, status-reporting light switches and so on. Such a system apart from being inexpensive, can be installed easily by end user and is also less invasive. We then show the feasibility of using such sensors for human behavior detection by deploying them in a home, designing an algorithm for modeling the sampled data and then determining human occupancy as well as specific activities.**

I. Introduction

Detecting human behavior has been of interest in the research community for long now. Knowledge of human behavior can be used in a wide variety of applications, ranging from building automation to surveillance. Extensive focus has been placed on using cameras for this purpose. For example, computer vision techniques for behavior detection that uses one or many camera sensors have been proposed in [1]. The authors propose the use of spatio-temporal volumes of force flow to model behavior of crowds. Using this method, they go on to detect and localize abnormal behaviors in crowd videos. [2] provides a survey of vision techniques for human behavior analysis using cameras sensors and computer vision techniques. However, information rich sensors such as cameras, microphones can be expensive. Also they require careful planning during the deployment stage, for example in the case of cameras occlusion can cause the cameras field of view to be blocked due to certain objects and so on. Another major drawback is the fact that they do not maintain the anonymity of the human beings raising huge privacy concerns. Such privacy concerns results in the system not being used at all to begin with.

In order to overcome these drawback, we propose the use of low cost binary sensors i.e. "on/off" sensors such as motion detector, light switches and so on. These kind of sensors are inexpensive and can be easily installed by end users with minimal amount of configuration. Also, they may seem less invasive and protect the privacy of the end users. We believe that systems using such sensors will be adopted more quickly. However, binary sensors only provide two states of information. Hence, it is not clear if it is enough to determine high level human behavior such as abnormal activity and occupancy that can be detected using cameras. In order to demonstrate the feasibility of using binary sensors, we deploy a set of wirelessly connected binary sensors in a home as shown in Figure 1. We collect the sampled data from different types of binary sensors over 7 days. We then provide algorithms to interpret the obtain data using which one can automatically detect the occupancy of the rooms within the home, abnormal human activities and appliance usage information.

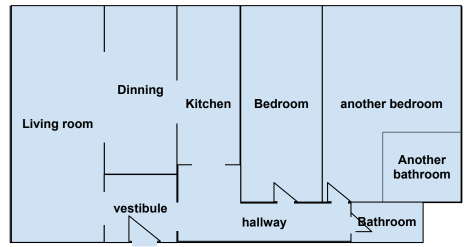

Figure 1: Floor plan of home used for our deployment.

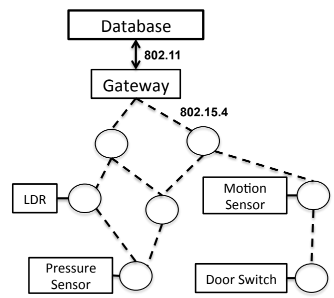

Figure 2: Architecture of the deployed system.

II. System Deployment and Architecture

We will describe the wireless binary sensor network deployment in a home and the architecture of the system used to collect the sampling data. The floor plan of the deployment scene is shown in Figure 1. The system architecture is shown in Figure 2.

We use the following sensors: (1) motion sensors (2) light dependent resistors (LDR) (3) pressure sensors (4) door switch. Each of these sensors are coupled with a micro controller and a IEEE 802.15.4 radio (Arduino and Xbee) which form a multi-hop network. In our deployment we needed only a maximum of two hops for covering the entire house. The sampled data from the sensors is transmitted across the 802.15.4 network to a central gateway which is then connected to a database server over a IEEE 802.11 network link. Additionally, each of the sampled data is time-stamped at the gateway before being entered into the database. Our behavior interpretation algorithm will ideally be running on the machine that the database is hosted. In this manner data is collected over seven days.

III. Sensor Processing

We use a number of sensors deployed across the house. Note that there can be more than one sensor of the same type covering the same area. For example, there can be more than one motion sensor with the same room. We simultaneously need to current location of the human within the house as well as determine his activity i.e. the *events* occurring within the house need to be determined. For this, we first need to "fuse" the information from orthogonal binary sensors such as motion sensors and light sensors across time as well as space to *detect* an event. Then, once the sensor data is fused then an interpretation algorithm will determine the *type* of event.

A. Sensor Fusion

The sensor fusion is used to detect an event. For example, motion sensors along with light sensors and door sensors can determine if a person walked in to a room and so on. The fusion of multiple sensors is required to reduce the false positives arising in event detection using binary sensors if only one type of sensor is used. In order to perform fusion, we use correlation filters. We expect sensors that are placed within close proximity of each other to exhibit strong correlation (positive or negative) in time when an event occurs.

B. Interpretation

After an event is detected then the type of event needs to be detected. For this purpose, both the time as well as location information is used. For example, the presence of a person in bed room can be detected using motion sensors and information whether the lights are switched on or not can be obtained using the light sensors. Then, combining it with the time-stamp information of the sampled data, one can predict if the person is sleeping or not. Such an event classification is probabilistic in nature. Bayes' filters offer a well known way to estimate the state of a dynamic system from noisy sensor data in real work domains. The *state* represents occupant location and activity, while sensors provide information about the state. A probability distribution, called the *belief*. describes the probability that the occupant is in each state $p(X_t = x_t)$. A Bayes filter updates the belief at each time step, conditioned on the data. Modeling systems over time is made tractable by the Markov assumption that the current state depends only on the previous state.

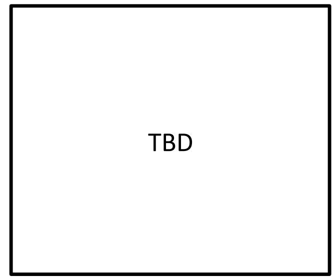

Figure 3: Sampled data over 24 hours.

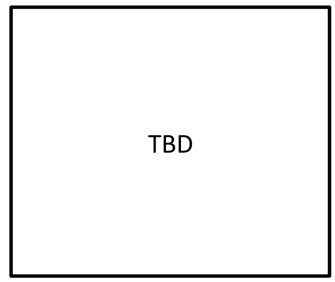

Figure 4: Correlation of sensor data across time and space.

We estimate the state $x_t = \{x_{1t}, x_{2t}, ..., x_{Mt}\}$ of M occupants at time using the sensor measurements collected so far, $z_{1:t}$. At each time step we receive the status of many binary sensors. The measurement $z_t = \{e_{1t}, e_{2t}, ..., e_{Et}\}$ is a string of E binary digits representing which sensors have triggered during time step t. We choose a non-metric (i.e., discrete) state representation due to low sensor granularity and limited computational resources. Rooms provide a natural and intuitive discretization of possible occupant locations. Moving or not moving are the initial categories of possible activity. The update equation is analogous to the forward portion of the forward-backward algorithm used in Hidden Markov Models (HMMs). Please see [3] for detailed description of how HMMs work. Having multiple occupants complicates the problem further requiring data association to each occupant. In this work, we assume that there is only one occupant.

IV. Evaluation

We evaluate the performance of our system in this section. Figure 3 shows the collected data over a 24 hour period. It shows the data for four different types of sensors collected in the living room. The correlation of sensors across time can be observed. The correlation of sensors across time and location within the house over 7 days is show in Figure 4. The circles show the clustering of sensors based on the correlation information. We then compare the accuracy of our event classification for various types of events obtained by comparing against ground truth information which is shown in Figure 5.

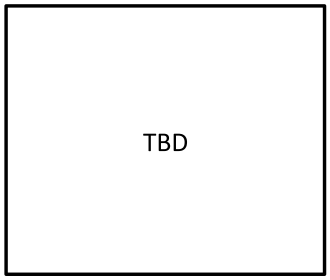

Figure 5: Detection accuracy for different types of events.

V. Conclusion and Future Work

In this work, we propose the use of binary sensors for detecting and classifying events related to human behaviors. This has a wide variety of applications and using binary sensors has the following advantages: inexpensive, ease of deployment and privacy protection. We deploy out system and show that behavior detection can be feasibly performed using our HMM based algorithm. In this work, we assumed that there is only one occupant and also the deployment duration was only for a week. As future work, we will collect data over longer durations and consider multiple occupant scenarios.

VI. Acknowledgements

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