18 Smart Living & Environment

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Outline

- Smart living
  - Smart home
  - Smart health
  - Hidden Markov model
- Smart environment
  - Waste management
  - Air quality monitoring

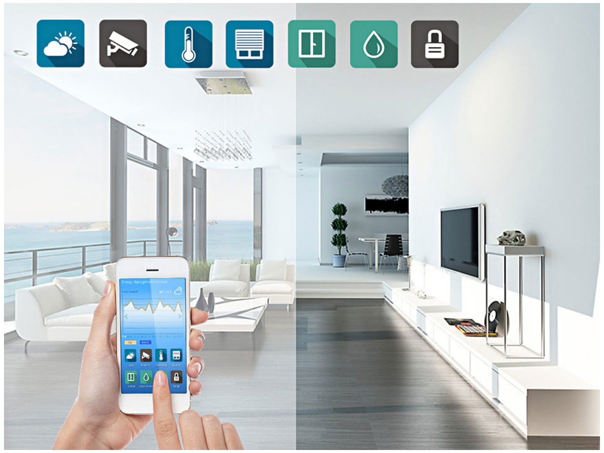
Smart living

- Smart home
- Smart health
- Hidden Markov model

Reference: Rashidi, P., Cook, D. J., Holder, L. B., & Schmitter-Edgecombe, M. (2010). Discovering activities to recognize and track in a smart environment. *IEEE transactions on knowledge and data engineering*, *23*(4), 527-539.

Background

- Nowadays, smartphones are becoming more powerful with reinforced processors, larger storage capabilities, richer entertainment functions and more communication methods.
- Bluetooth, which is mainly used for data exchange, add new features to smartphones.
- Bluetooth technology, created by telecom vendor Ericsson in 1994, shows its advantage by integrating with smartphones.



Bluetooth

- It has changed how people use digital devices at home or office, and has transferred traditional wired digital devices into wireless devices.
- A host Bluetooth device is capable of communicating with up to seven Bluetooth modules at the same time through one link.

Smart home

- Considering its normal working area of within eight meters, it is especially useful in a home environment.
- Thanks to Bluetooth technology and other similar techniques, the concept of Smart Living has offered better opportunity in convenience, comfort and security which
- With dramatic increase in smartphone users, smartphones have gradually turned into an all-purpose portable device and provided people for their daily use

Remote health

- Sensing technology and machine learning can be used for remote health
- The need for the development of such technologies is underscored by the aging of the population, the cost of formal health care, and the importance that individuals place on remaining independent in their own homes.

Activities of Daily Living

- To function independently at home, individuals need to be able to complete Activities of Daily Living (ADLs) such as eating, dressing, cooking, drinking, and taking medicine.
- Automating the recognition of activities is an important step toward monitoring the functional health of a smart home resident.

Activity recognition

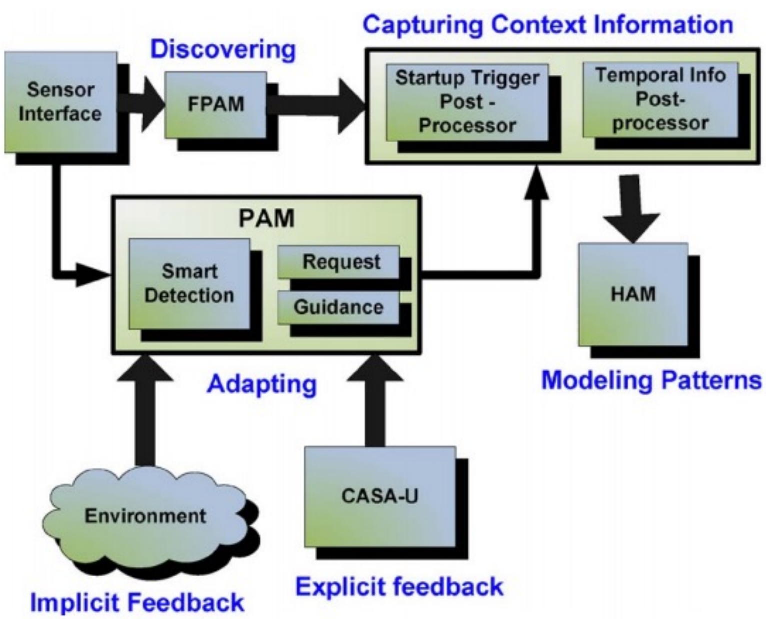
- When surveyed about assistive technologies, family caregivers of Alzheimer’s patients ranked activity identification and tracking at the top of their list of needs
- In response to this recognized need, researchers have designed a variety of approaches to model and recognize activities.

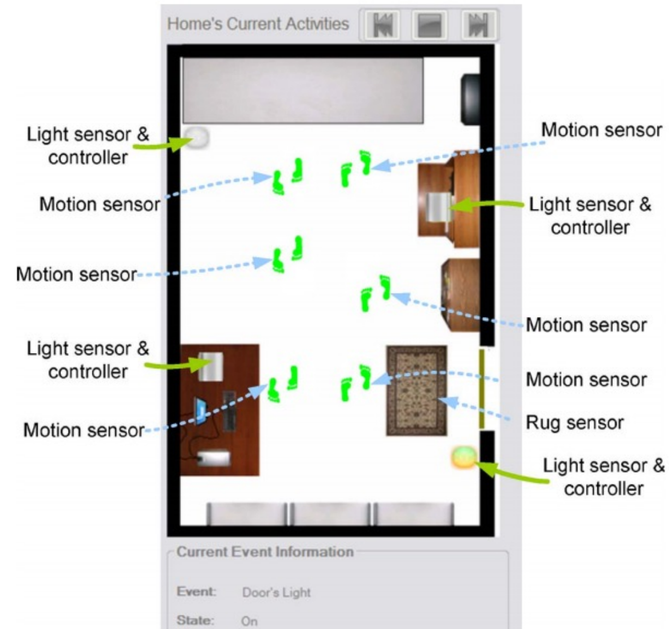
Mapping from activity to health

- The generally accepted approach is to model and recognize those activities that are frequently used to measure the functional health of an individual
- However, a number of difficulties arise with this approach...
  1. Irregular activities may be perfectly normal
  2. Irregular activities may also indicate health condition
  3. Lack of training data

Technology basis

- Center for Advanced Studies on Adaptive Systems (CASAS)
- Utilizes machine learning techniques to discover patterns in resident's daily activities and to generate automation polices that mimic these patterns





Methodology

- We introduce a state-of-the-art approach in the context of the CASAS Smart Home project by using sensor data that are collected in the CASAS smart apartment testbed.
- Unsupervised learning -> a more automated approach for activity recognition than is offered by previous approaches, which take a supervised approach and annotate the available data for training.
- Algorithmic basis: hidden Markov models (HMMs)
- Two major steps:
    1. Discover activities
    2. Recognize activities

Discover activities

- First step: how to identify the frequent and repeatable sequences of sensor events that comprise our smart environment's notion of an activity.
- How to do this? -> By applying frequent sequential pattern mining techniques, we can identify contiguous, consistent sensor event sequences that might indicate an activity of interest. (Recall smart meters)
- Core idea: frequent sequence mining technique called Varied-Order Sequential Miner (DVSM)
- DVSM can extract the pattern (a, b) from instances $\{b, x, c, a\}$, $\{a, u, b\}$ and $\{a, b, q\}$ despite the fact that the events are discontinuous and have varied orders.

Discovering Frequent Discontinuous Sequences

- DVSM first creates a reduced data set D_r containing the topmost frequent events.
- Next, DVSM slides a window of size 2 across D_r to find patterns of length 2.
- After this first iteration, the whole data set does not need to be scanned again.
- Instead, DVSM extends the patterns discovered in the previous iteration by their prefix and suffix events, and will match the extended pattern against the already discovered patterns (in the same iteration) to see if it is a variation of a previous pattern, or if it is a new pattern.

Similarity measure

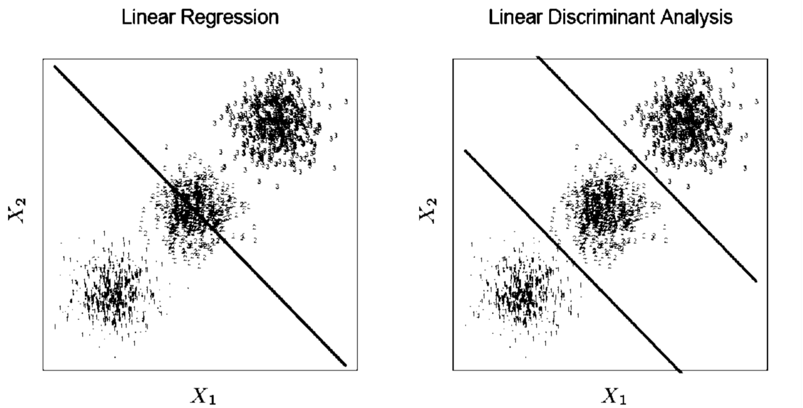
- To see if two patterns should be considered as variations of the same pattern, we use the Levenshtein (edit) distance to define a similarity measure $sim(A, B)$. between the two patterns.
- The edit distance, $e(A, B)$, is the number of edits (insertions, deletions, and substitutions) required to transform an event sequence A into another event sequence B.
- Similarity measure

$$sim(A, B) = 1 - \frac{e(A, B)}{\max\{|A|, |B|\}}$$

- Small $sim(A, B)$ -> variations of same pattern

Clustering Sequences into Groups of Activities

- We need to group the set of discovered patterns into a set of clusters
- The resulting set of clusters centroids represents the activities that we will model, recognize, and track
- Clustering: classify data points close to each other into one category
- Key: measure distance between data points



Clustering Sequences into Groups of Activities

- The patterns discovered by DVSM were composed of sensor events.
- In the clustering algorithm, the pattern is composed of states. (Recall “signatures” in smart meters)
- States correspond to the pattern’s events, but are enhanced to include additional information such as the type and duration of the sensor events.
- In addition, we can combine several states together to form a new state (we call it an extended state).
- For example, if a motion sensor in the kitchen is triggered several times in a row without another sensor event interrupting the sequence, the series of identical motion sensor events will be combined into one event with a longer duration.

Clustering Sequences into Groups of Activities

- How to measure distance between activities? -> Edit distance
- Compute the number of edit operations that are required to make activity X the same as activity Y.
- The edit operations include adding a step or deleting a step (traditional edit distance), reordering a step (order distance), or changing the attributes of a step (for this application, step attributes include the event duration and event frequencies).
- The general edit distance gives us a measure to compare activities and also to define cluster centroids.

Recognize activities

- Once the activities are discovered for a particular individual, we want to build a model that will recognize future executions of the activity.
- This will allow the smart environment to track each activity and determine if an individual's routine is being maintained.

Hidden Markov model

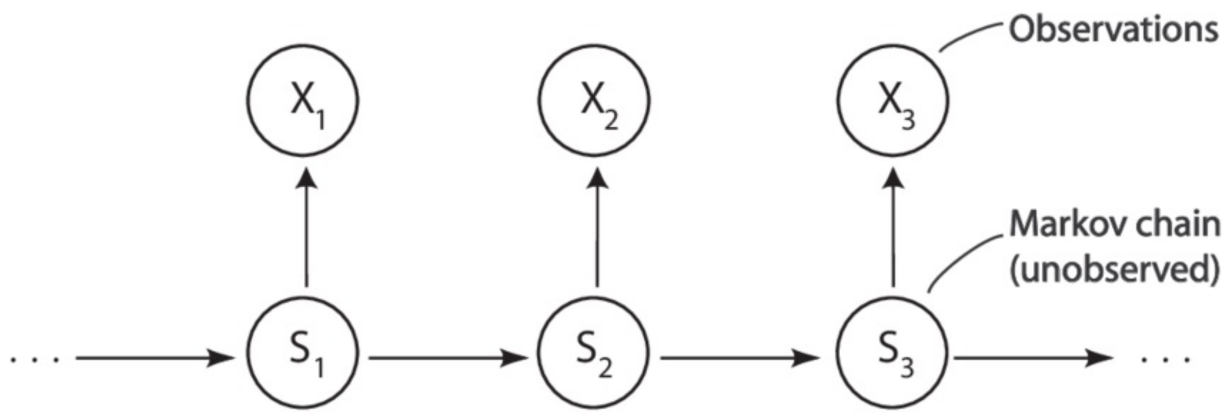
- We use a hidden Markov model (HMM) to recognize activities from sensor data as they are being performed.
- Each model is trained to recognize the patterns that correspond to the cluster representatives found in the previous step.
- A Markov Model is a statistical model of a dynamic system, which models the system using a finite set of states, each of which is associated with a multidimensional probability distribution over a set of parameters.
- The system is assumed to have a Markovian property, such that the current state depends on a finite history of previous states. (Recall queuing model)

Hidden Markov model

- A hidden Markov model is a statistical model in which the underlying data are generated by a stochastic process that is not observable.
- The process is assumed to be Markovian and can be observed through another set of stochastic processes that produce the sequence of observed features.
- HMMs traditionally perform well in the cases where temporal patterns need to be recognized
- This aligns with our requirement to recognize possibly interleaved activities.

Hidden Markov model

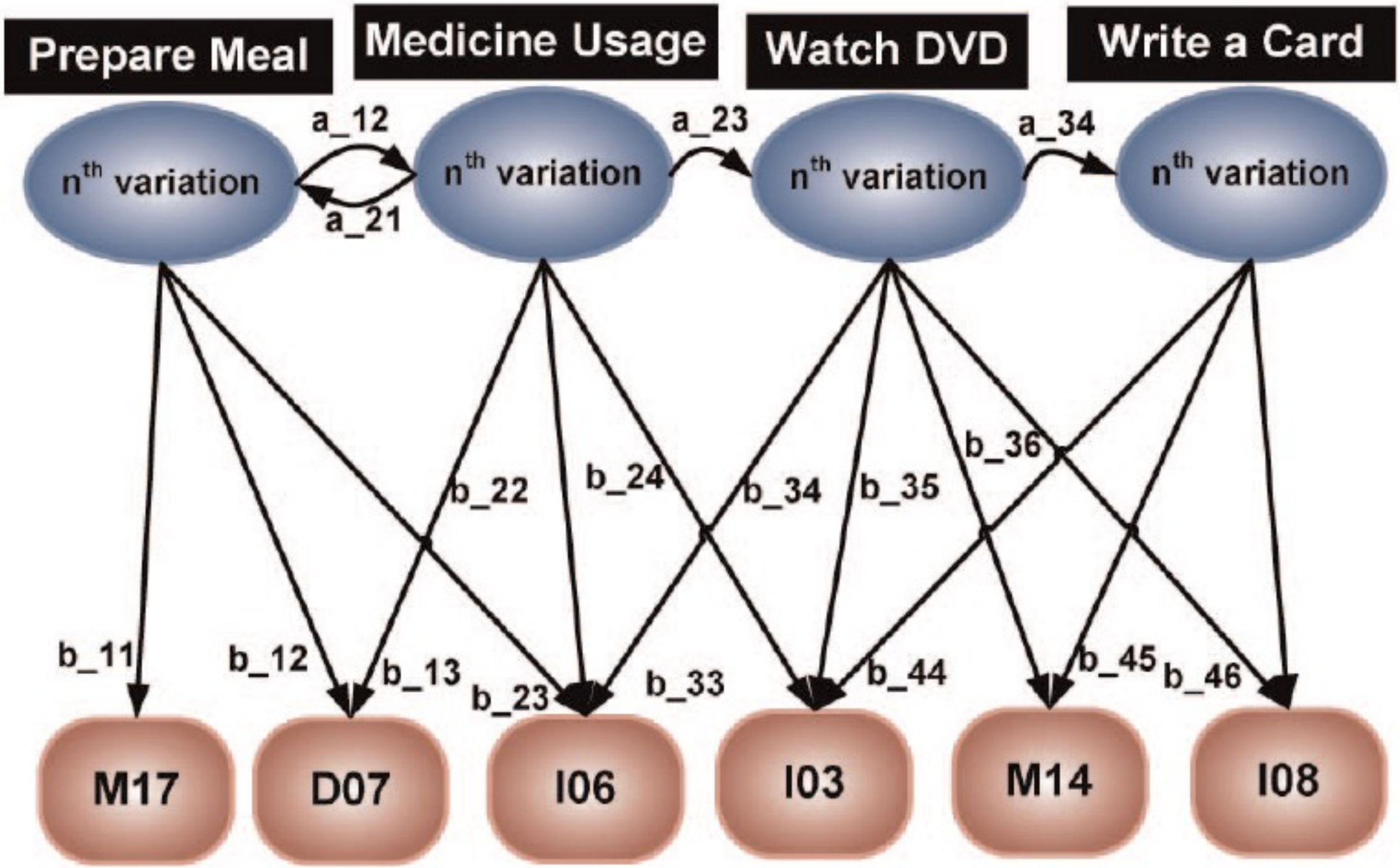
- As with a Markov chain, the conditional probability distribution of any hidden state depends only on the value of a finite number of preceding hidden states.
- The observable variable at time t, namely $x(t)$, depends only on the hidden variable $y(t)$ at that time slice.



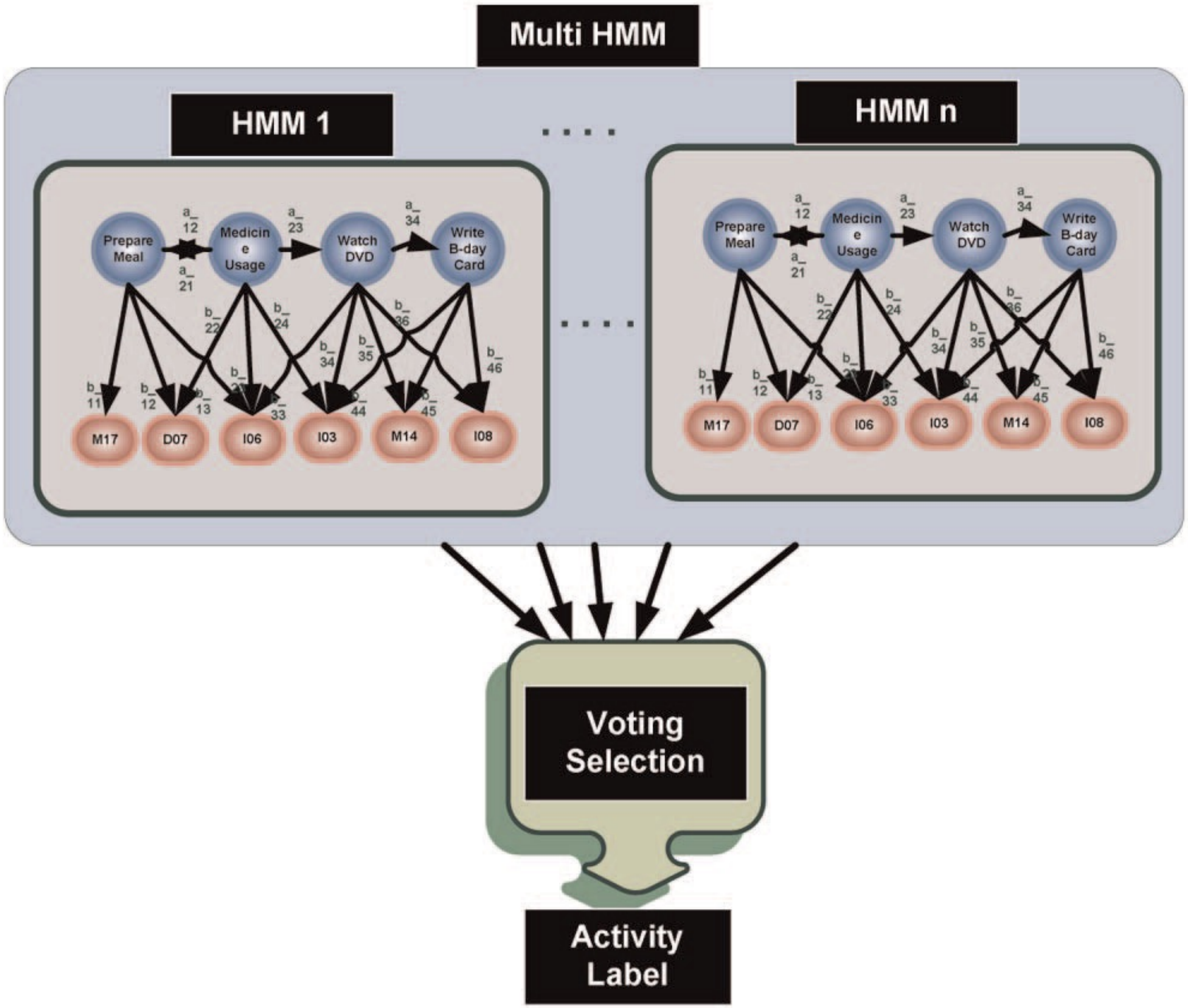
Hidden Markov model

- We can specify an HMM using three probability distributions:
  1. the distribution over initial states $\Pi = \{\pi_k\}$
  2. the state transition probability distribution $A = \{a_{kl}\}$, where
  $$a_{kl} = \Pr\{Y(t+1) = l|Y(t) = k\}$$
  is the probability of transitioning from state k to state l; and
  3. the observation distribution $B = \{b_{il}\}$, with
  $$b_{il} = \Pr\{X(t) = i|Y(t) = l\}$$
  indicating the probability that the state l would generate observation $X(t) = i$.
- The HMM can be trained using the maximum likelihood method

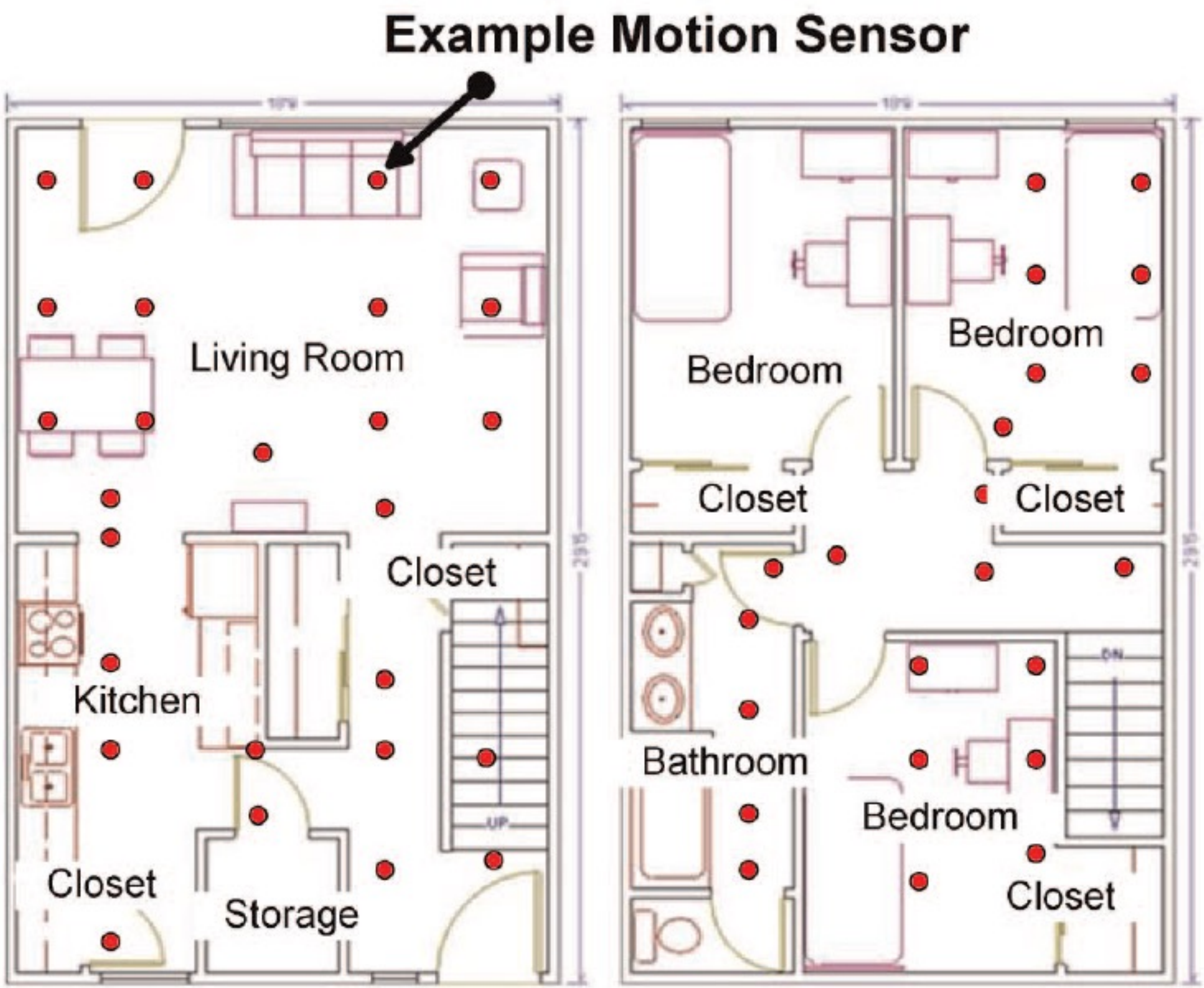
Hidden Markov model



Implementation



Implementation



Implementation

- The smart apartment testbed includes three bedrooms, one bathroom, a kitchen, and a living/dining room.
- The apartment is equipped with motion sensors positioned on the ceiling approximately 1 meter apart throughout the space.
- In addition, we have installed sensors to provide ambient temperature readings, and custom-built analog sensors to provide readings for hot water, cold water, and stove burner use.

motion sensor

Implementation

- Voice over IP using the Asterisk software captures phone usage, contact switch sensors monitoring the open/closed status of doors and cabinets, and pressure sensors monitor usage of key items such as the medicine container, cooking pot, and phone book.
- Sensor data are captured using a sensor network that was designed in house and is stored in an SQL database.

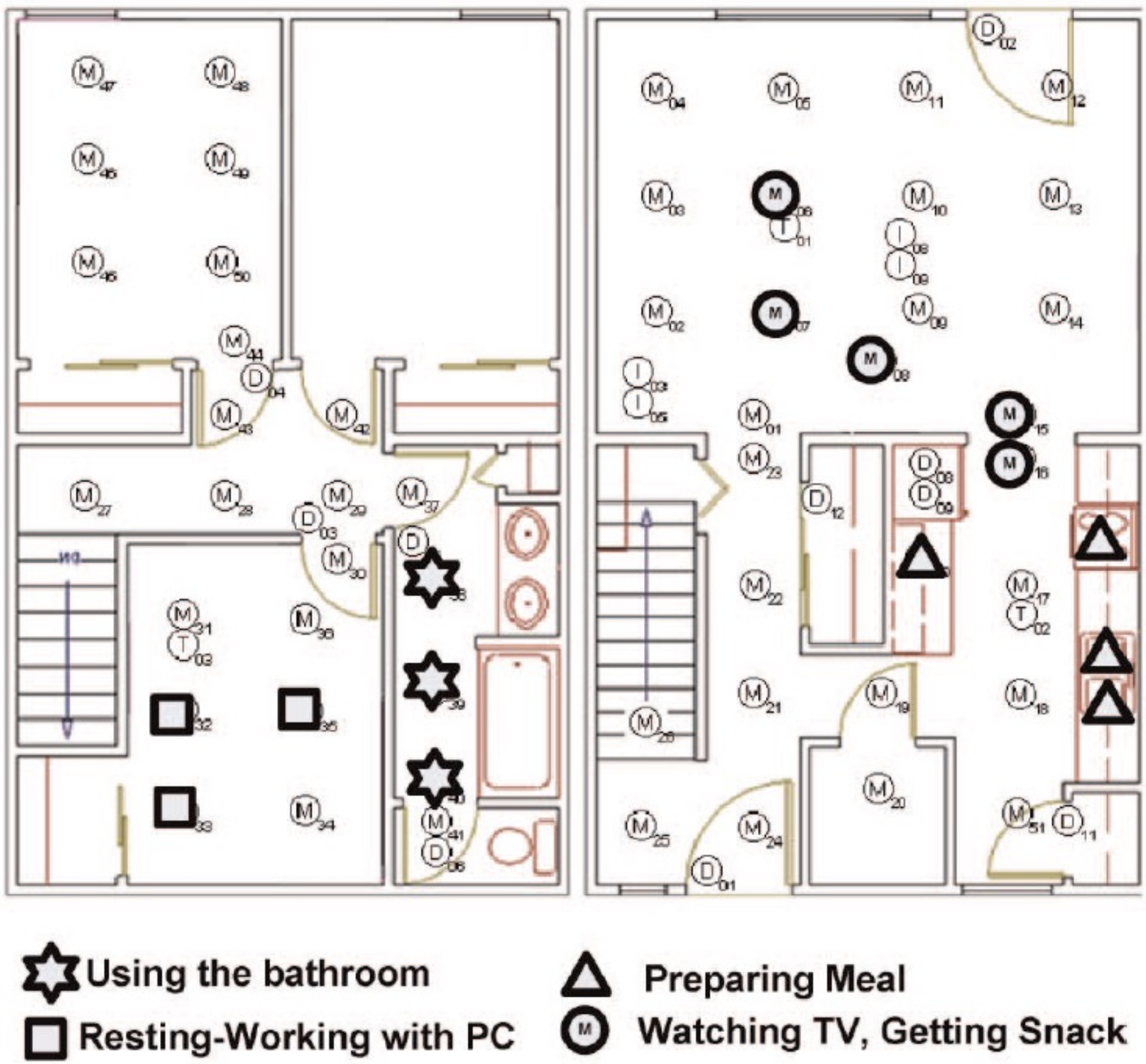
Sensor ID	time	value
8146000000B	12 10:50:45.673225	ON
E460000000D	12 10:50:48.903745	ON
A360000000F	12 12:30:09.56483	1.98

Resident performing “hand washing” activity. This activity triggers motion sensor ON/OFF events as well as water flow sensor values.

Implementation

- 20 Washington State University undergraduate students recruited from the psychology subject pool perform the following five activities:
  - Telephone Use: Look up a specified number in a phone book, call the number, and write down the cooking directions given on the recorded message.
  - Hand Washing: Wash hands in the kitchen sink.
  - Meal Preparation: Cook oatmeal on the stove according to the recorded directions, adding brown sugar and raisins (from the kitchen cabinet) once done.
  - Eating and Medication Use: Eat the oatmeal together with a glass of water and medicine (a piece of candy).
  - Cleaning: Clean and put away the dishes and ingredients.

Implementation



Smart environment

- Waste management system
- Air quality monitoring

- Chowdhury, B., & Chowdhury, M. U. (2007, December). RFID-based real-time smart waste management system. In *2007 Australasian telecommunication networks and applications conference* (pp. 175-180). IEEE.
- Postolache, O. A., Pereira, J. D., & Girao, P. S. (2009). Smart sensors network for air quality monitoring applications. *IEEE transactions on instrumentation and measurement*, *58*(9), 3253-3262.

Waste management

Waste (e.g., garbage) collection and disposal is a major environmental problem, especially now in urban centers.

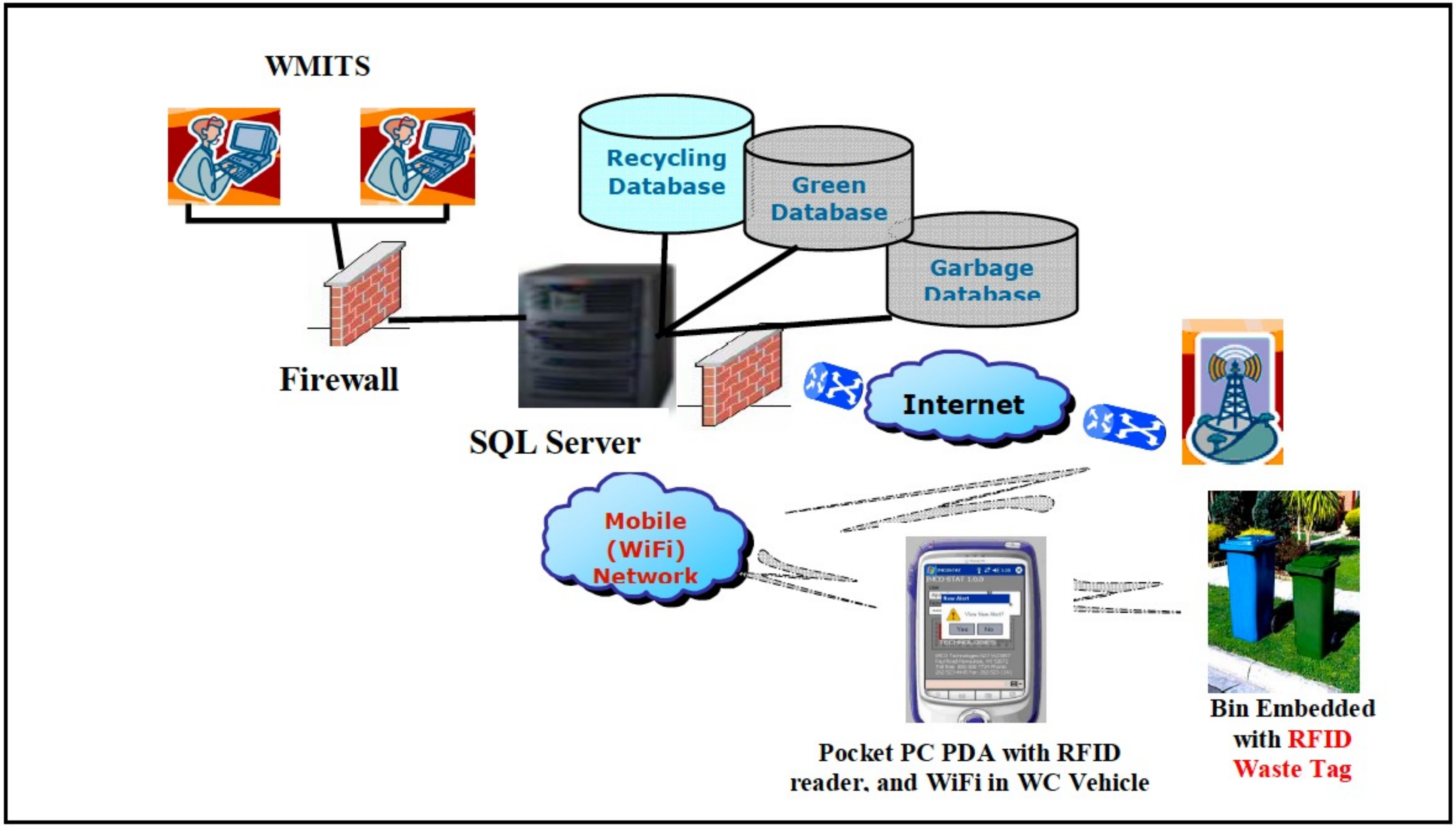
Waste management

In recent years, waste management services have made a concerted effort to use information technology to reduce waste management costs and to identify missing/stolen bins.

Waste management

RFID is a modern and fast growing mobile technology that uniquely and accurately identifies a RFID tag (waste tag) attached to, or embedded in, a waste bin (e.g., garbage)

Waste management



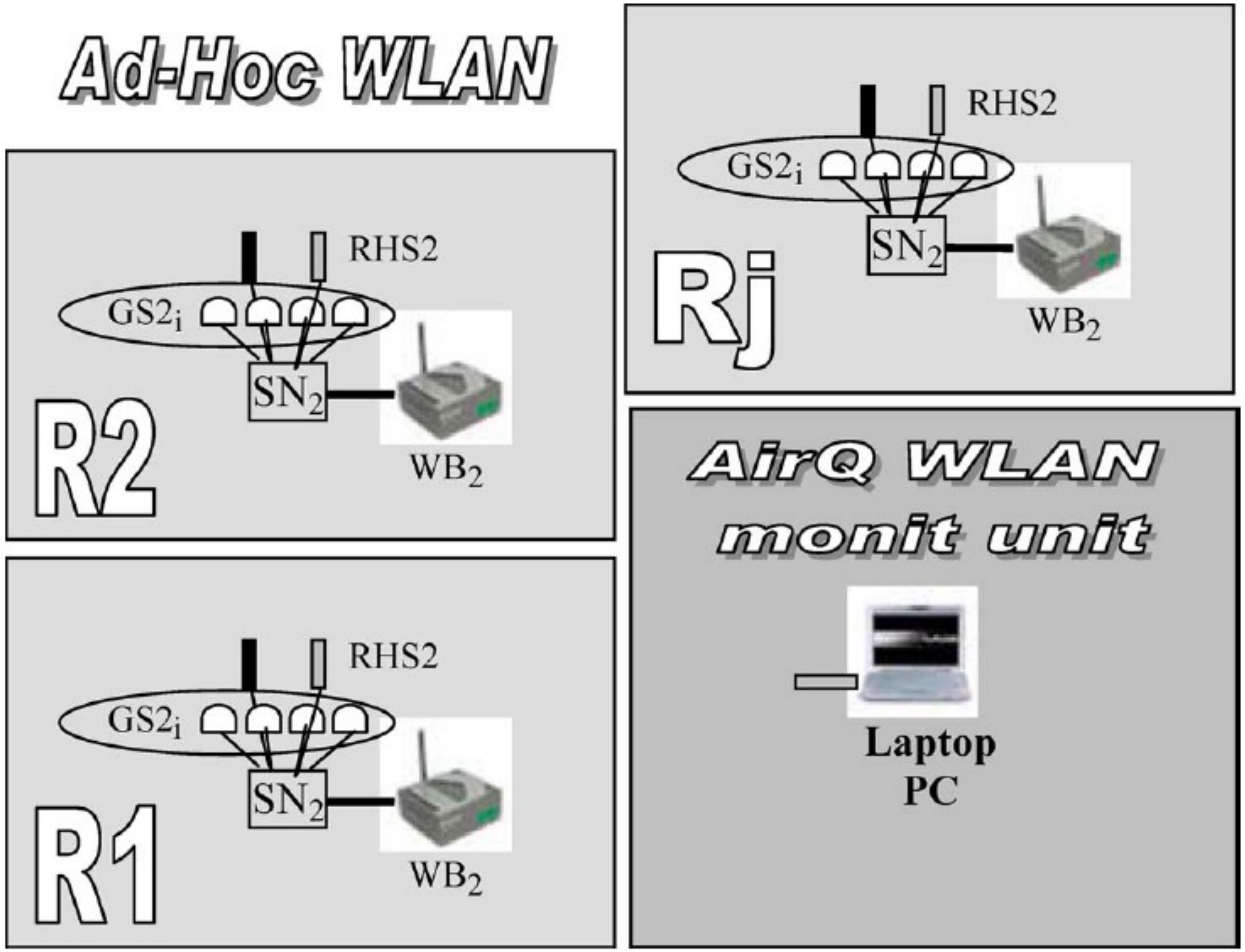
Air quality monitoring

- Air supplies us with oxygen that is essential for our bodies to live.
- Air is 99.9% nitrogen, oxygen, water vapor, and inert gases.
- Human activities can release substances into the air, some of which can cause problems for humans, plants, and animals.

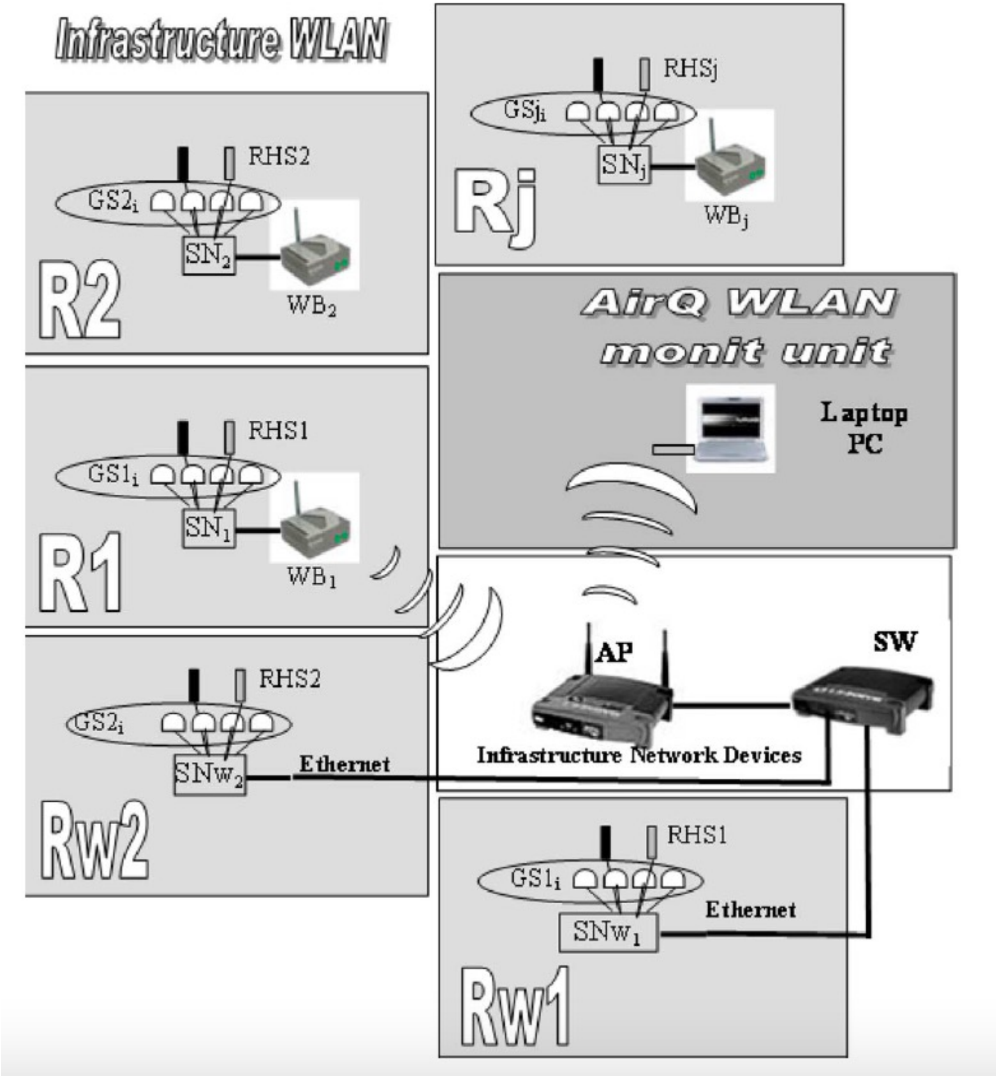
Air quality monitoring

- Air quality can be expressed by the concentration of several pollutants such as carbon monoxide (CO), sulphur dioxide, nitrogen dioxide, and ozone.
- Good air quality = below threshold values for pollutants.
- Pollution also needs to be considered inside our homes, offices, and schools.
- Some of these pollutants can be created by indoor activities such as smoking and cooking.

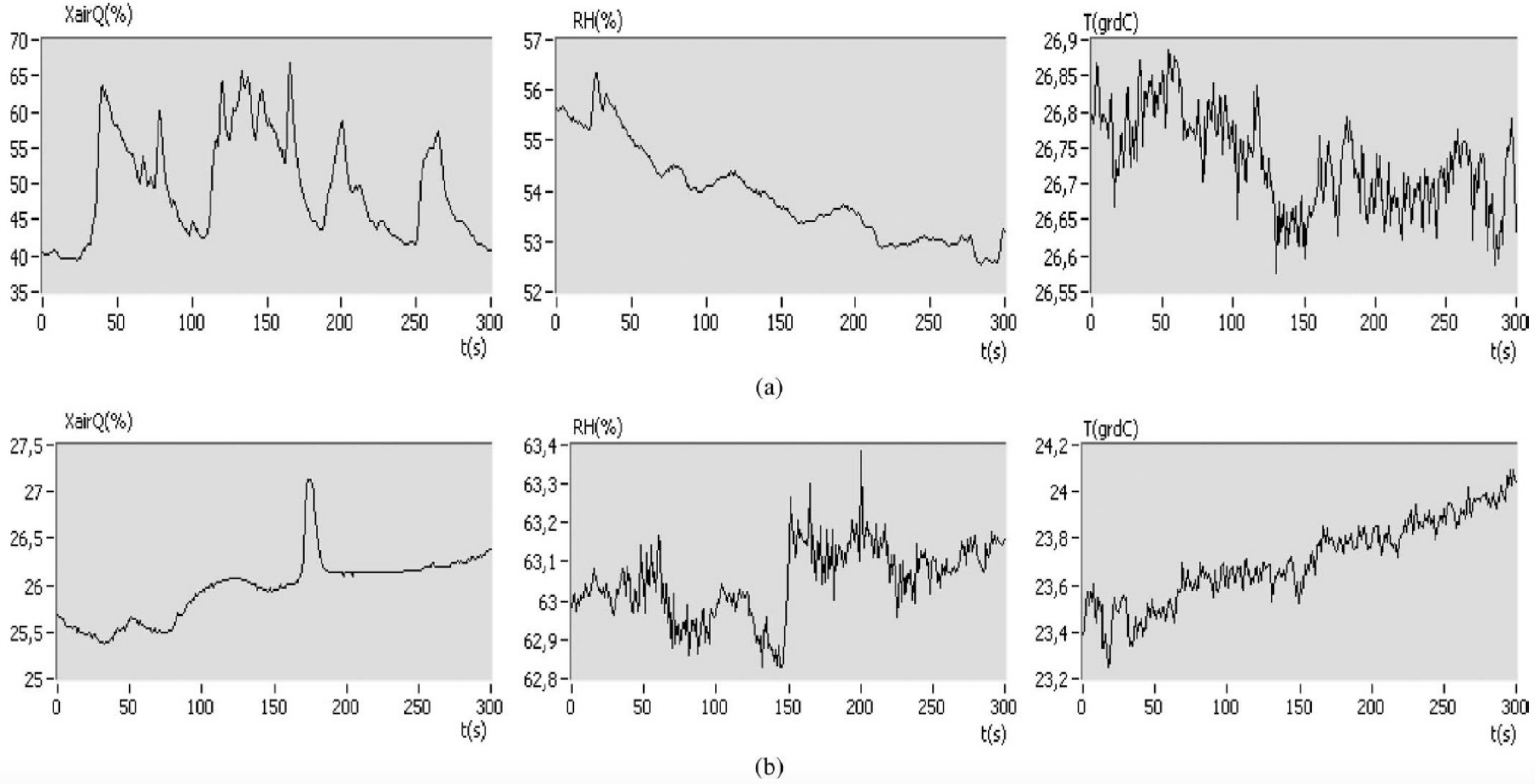
Air quality monitoring



Air quality monitoring



Air quality monitoring



Summary

- Smart living
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  - Hidden Markov model
- Smart environment
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Next time

- Smart economy
- Smart governance
- Project presentation & report instructions