Residential Occupancy Analysis Using Motion Sensors

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Introduction and Background

- **Various sensors installed in the building exhibit ‘occupancy’ information.**

  light sensors, motion sensors, CO_2 sensors, electric meter, water meter and camera
- **Security and home automation companies instrument motion sensors and provide services related.**

  Alarm.com[6]

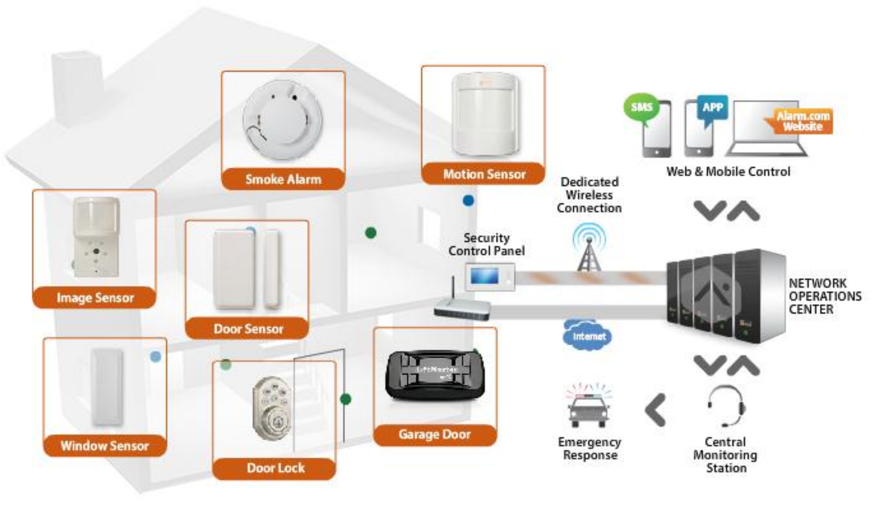

Fig.1 Alarm System from *alarm.com*[6]

- **Utility company may mine the data to make inference about occupants and their behaviors for the purposes that go beyond providing security services.**

  Possibility of privacy concern and additional services
- **Our goal is to seek the possibility of occupancy inference based only on the motion sensors.**

  Infer the number and the identities of the persons in the house

Methodology

Data Collection and Preprocessing

- **Data Collection**

  Data is collected from the *Homeseer* motion sensors, which send out a sequence 0-1-0 to *Xively* when there is a movement.
- **Noise Reduction**

  Ignore isolated motion- when there is no other motion before and after for 30 seconds.
- **Continuous Motion Detection**

  Transform the discrete output of motion sensors into continuous blocks representing successive movements

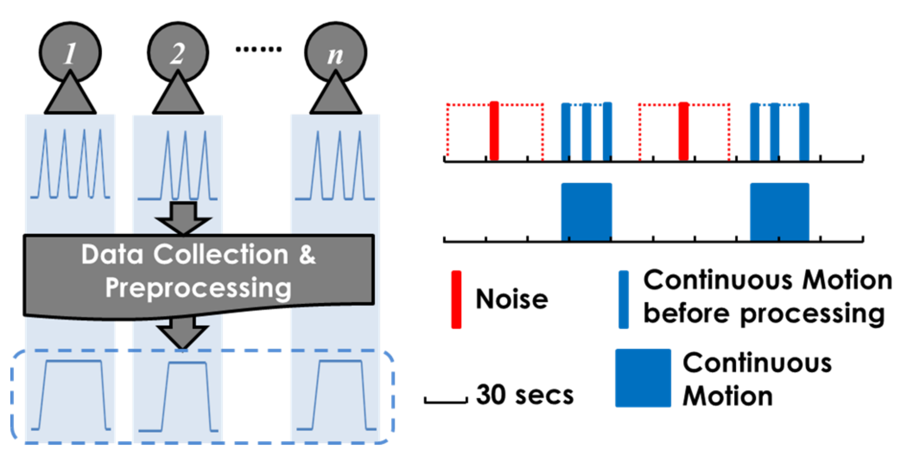

Fig.2 Data Collection and Preprocessing

Inference Model Overview

- **Learning-based Method**

  The model under this category should be re-learned when considering different houses, because a learning process is required when highly-accurate inference is carried out in a specific house.
- **Rule-based Method**

  A rule-based method is more applicable for houses of different settings as no learning is needed. Based on the input features and rules-matching process, we can directly make the inference.

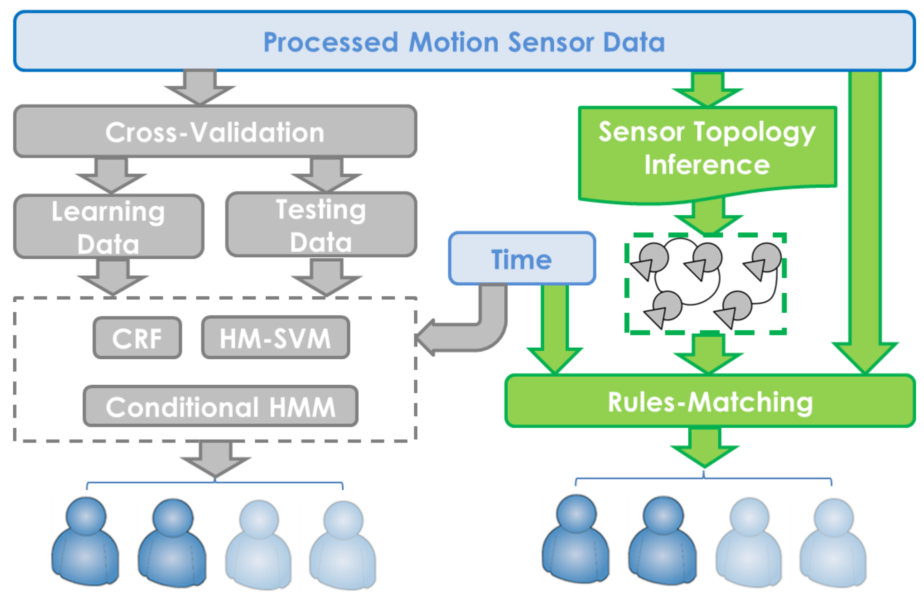

Fig.3 Overview of the inference Model

Learning-based Method

- **Hidden Markov Model(HMM)**

  As a generative model, HMM is chosen for its capacity to model the time series events and describe the relation between input and output. For the HMM we propose, the transition probability is dependent on the time of the day.

  State space(Output):

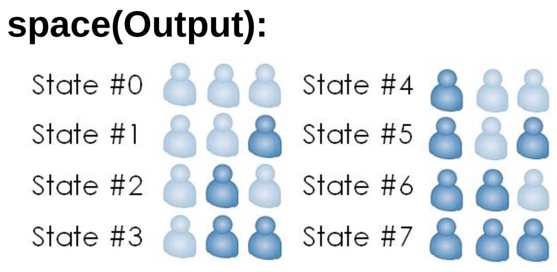

Fig.5 State space of HMM

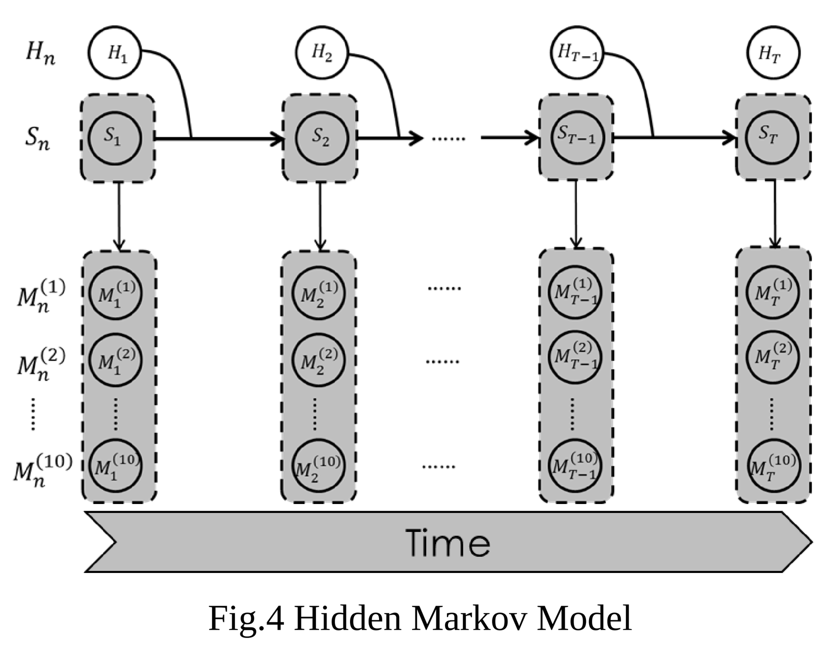

Fig.4 Hidden Markov Model

  Observation(Input): Processed motion sensor data

- **Conditional Random Field(CRF)**

  CRF[1][5] is a discriminative model, which models the posterior probability p(y|x)

$$p(\mathbf{y}|\mathbf{x}) = \frac{1}{Z(\mathbf{x})}\exp\left\{\sum_j \lambda_j F_j(\mathbf{y},\mathbf{x})\right\}$$

  State space(Output) : Same with HMM

  Observation(Input): Processed motion sensor data and present hour value

  Feature function F:

$$F_j(\mathbf{y},\mathbf{x}) = \sum_{i=1}^{T} f_j(y_{i-1}, y_i, x_i, i)$$

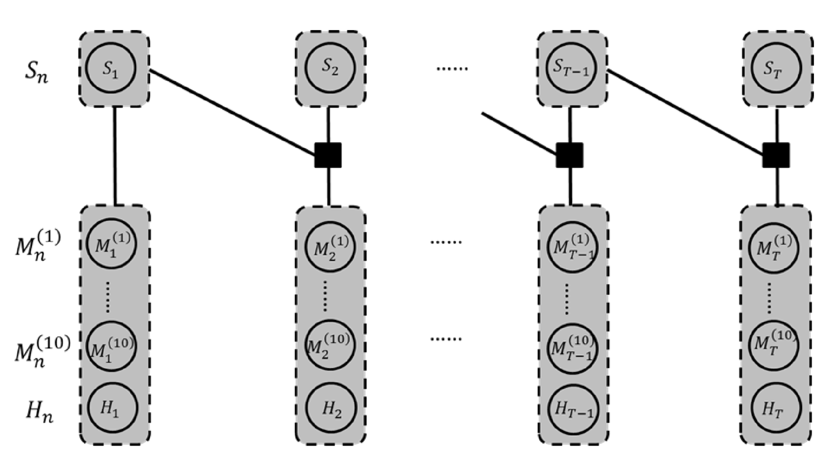

Fig.6 Conditional Random Field

- **Hidden Markov-Support Vector Machine(HM-SVM)**

  Hidden Markov-SVM[3][4] is employed for its nature of combining the characteristics of the Hidden Markov Model and the Support Vector Machine. It models a discriminant function **F** over input **x** and output **y**. The prediction is based on the maximization of this function over the output **y**. When doing the learning process, the criteria of ‘maximum margin’ is adopted.

$$f(\mathbf{x}) = \mathrm{argmax}_{\mathbf{y}} F(\mathbf{x},\mathbf{y};\boldsymbol{\omega}) \qquad F(\mathbf{x},\mathbf{y};\boldsymbol{\omega}) = \langle \boldsymbol{\omega}, \Phi(\mathbf{x},\mathbf{y})\rangle$$

  State space(Output) : Same with HMM/CRF **Observation(Input):** Same with CRF

  Feature Selection: First-Order transition and Zero-Order emission $\Phi(y_{i-1}, y_i)/\Phi(y_i, \mathbf{x}_i)$

  Definition of ‘margin’: $\gamma_j = F(\mathbf{x}^j, \mathbf{y}^j) - \max_{\mathbf{y}\neq\mathbf{y}^j} F(\mathbf{x}^j, \mathbf{y})$

Rule-based Method

Step 1: Sensor Topology Inference[2] : If sensor **i** and sensor **j** are always triggered successively in 30 seconds, then we define these sensors as ‘Adjacent sensors’, otherwise the pair of sensors are denoted as ‘remote sensors.’

Fig.7 Inference of Sensor Topology

Step 2: NUM Calculation: Maximum number of Remote Sensors triggered simultaneously

Step 3: Inference for the number of occupants in the building

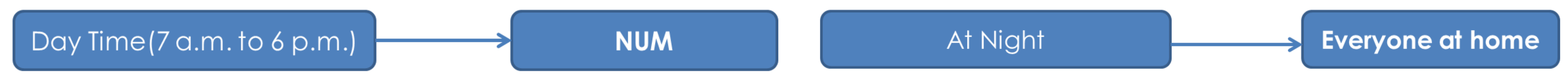

Fig.8 Inference of Occupants’ number

Step 4: Identity Inference: Randomly choose a person when occupancy changes

Experiment and Results

- **Experiment**

  -**Three-person house**(outfitted with **10 motion sensors** - one in each room)

  -Raw data from the motion sensors are collected for **9 days**.

  -Ground truth is manually recorded by using the camera installed.

  Two scenarios: 10 motion sensors/3 motion sensors(Master bedroom/Study/Foyer)

  7 different methods:

  HMM/CRF/HM-SVM/Rule-based Method/Naïve Strategy/Biased Guess/Random Guess

  Performance Evaluation: Symmetric Difference
- **Results**

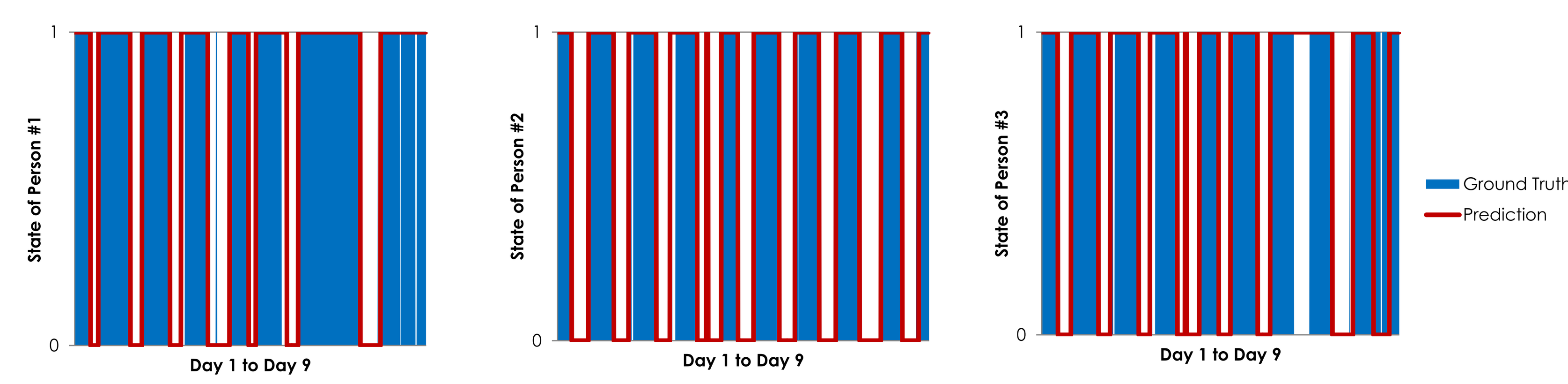

Fig.9 Identity Inference Using Conditional Random Field+10 Sensors

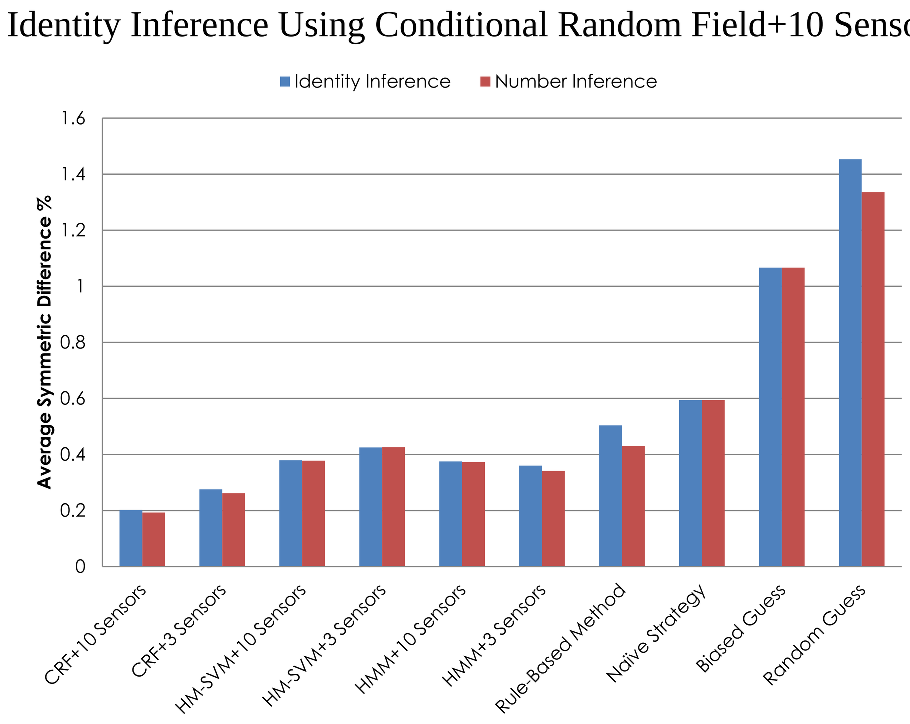

Fig.10 Performance comparison of different Methods used in the inference problem

Conclusions

- By combining the anonymous motion sensors and publicly available information, we can make good non-anonymous inferences about the specific residents. The best result we can get right now has a symmetric difference value one-third of the naïve strategy’s value.
- Even in the limited sensor scenario, the inference is quite accurate, which further demonstrates the possibility of occupancy inference under the motion sensor-based only condition.
- The rules-based method, which is applicable for houses of different settings without the learning process, is also an effective method to extract occupancy information from the motion sensors.

Reference

[1] Sutton, Charles, and Andrew McCallum. "An introduction to conditional random fields for relational learning." *Introduction to statistical relational learning* 93 (2007): 142-146.

[2] Ellis, Carl, et al. "Creating a room connectivity graph of a building from per-room sensor units." *Proceedings of the Fourth ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Buildings*. ACM, 2012.

[3] *Altun, Yasemin, Ioannis Tsochantaridis, and Thomas Hofmann. "Hidden markov support vector machines." ICML. Vol. 3. 2003.*

[4] SVMHMM Version V3.10 http://www.cs.cornell.edu/people/tj/svm_light/svm_hmm.html

[5] CRF++ http://crfpp.googlecode.com/svn/trunk/doc/index.html#download

[6] http://www.alarm.com/

NESL Networked & Embedded Systems Laboratory http://nesl.ee.ucla.edu