Unsupervised Activity Recognition using Hierarchical Model Clustering

James Howard, William Hoff

Center for Automation, Robotics, and Distributed Intelligence

Colorado School of Mines

Motivation

Using a collection of small anonymous sensors we look to recognize and predict human behavior within a building. Accurate behavior prediction will allow for the creation of building environmental control schemes designed to reduce energy consumption.

Methodology

Using a hierarchical approach allows us to recognize activities at different time scales. First we use local sensor information for 10-20 second length activities. We then use this information as the basis for global activity prediction at the range of 5-10 minutes.

System Design

We designed a sensor network consisting of wireless computer "motes" and passive infrared (PIR) motion sensors [1]. These were mounted in hallways and rooms in a large campus building (Fig 1).

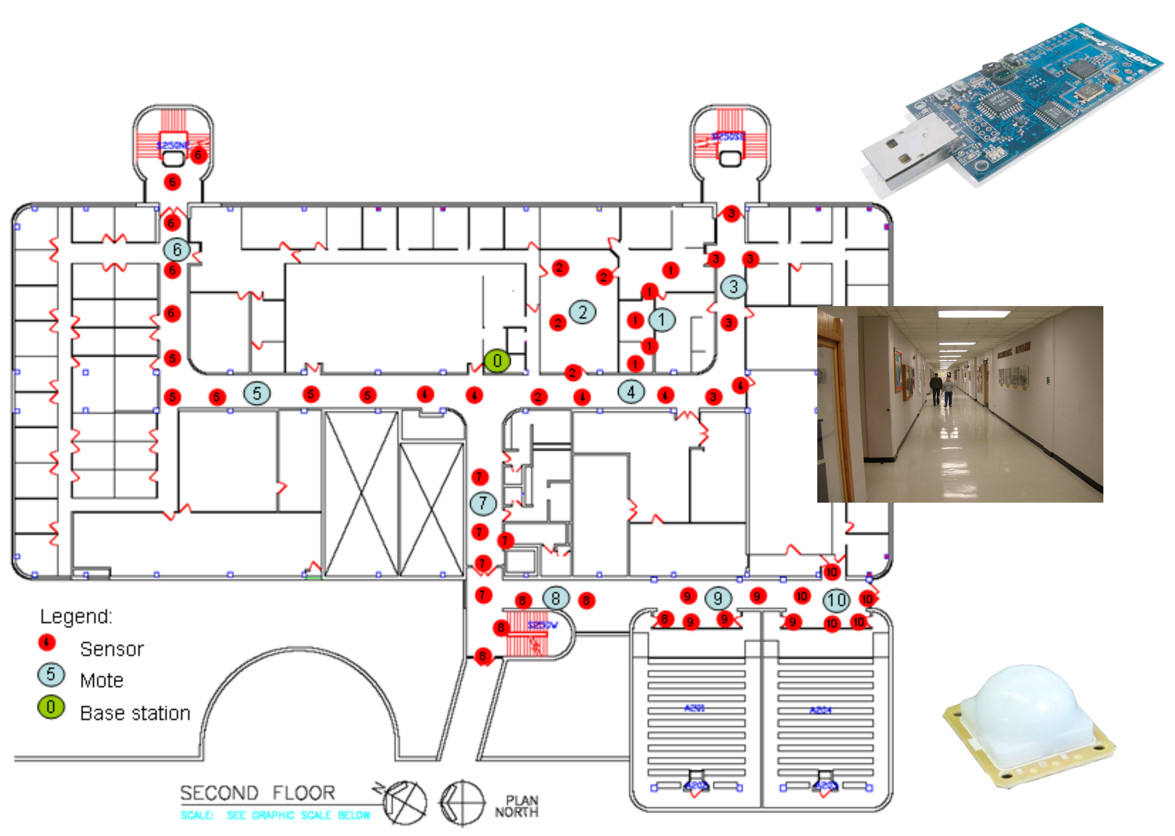

Figure 1. Sensor network; small dots are the PIR sensors; larger dots are motes.

Data Representation

Sensor data is represented in the form of a two dimensional matrix H (t,s), where the columns are sensors and the rows are time intervals (Fig 2). Local movement patterns appear as structures in the matrix. For example, a person walking down the hall causes consecutive hits in adjacent sensors, which appears as a diagonal streak.

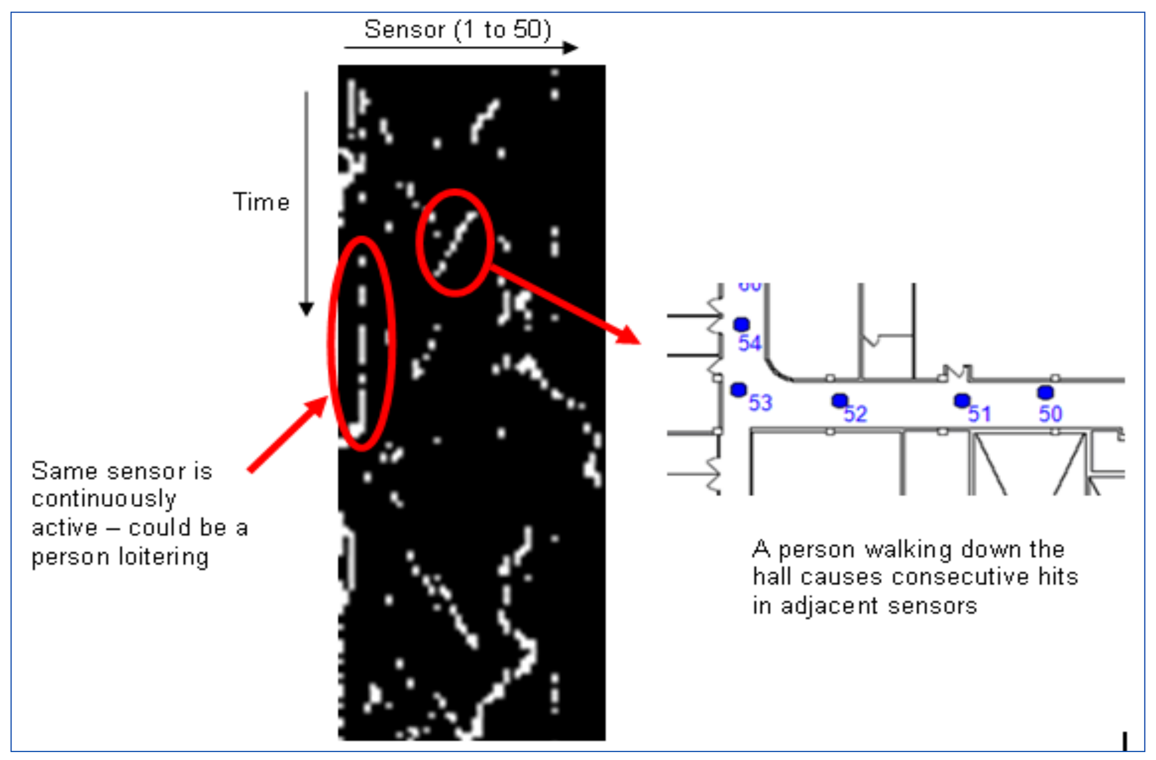

Figure 2. Example of sensor data in the form of a two dimensional matrix.

Local Activities

Network topology is inferred from the sensor data. Strong correlation scores define the local neighborhood for each sensor.

High activity data sensed from local neighborhoods is then clustered using a k-means clustering algorithm. The resulting cluster is then represented by a Hidden Markov Model trained on all data within that cluster. Figure 3 shows some of these trained Hidden Markov Models.

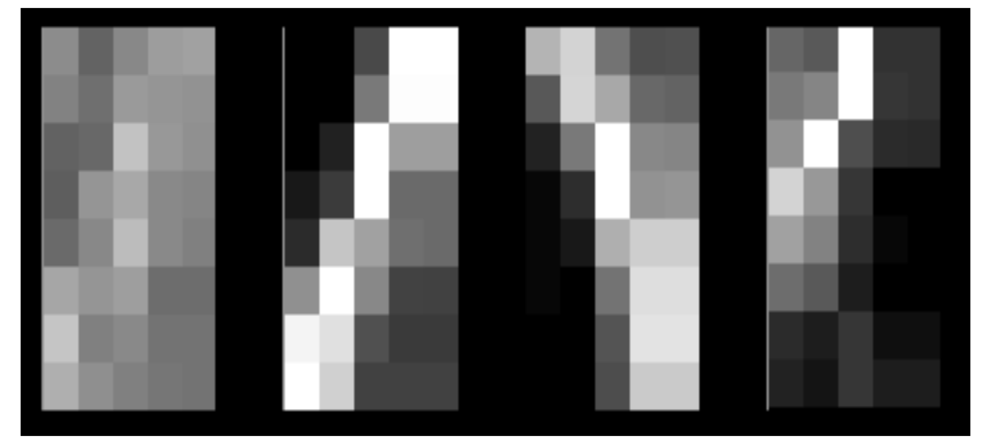

Figure 3. Representative Hidden Markov Models trained from local neighborhood data

Global Activities

We analyze the large scale distribution of local patterns over time using the method of probabilistic latent semantic analysis [2]. The method discovers a small number of latent or "hidden" classes in the distribution of detected local events.

We divide the local patterns into fixed length time periods, and find latent classes in the distributions. For any new period of time, we can represent it as a combination of latent classes. Applying k-means clustering on this latent class space allows us to assign a class label to any new activity (Fig 4).

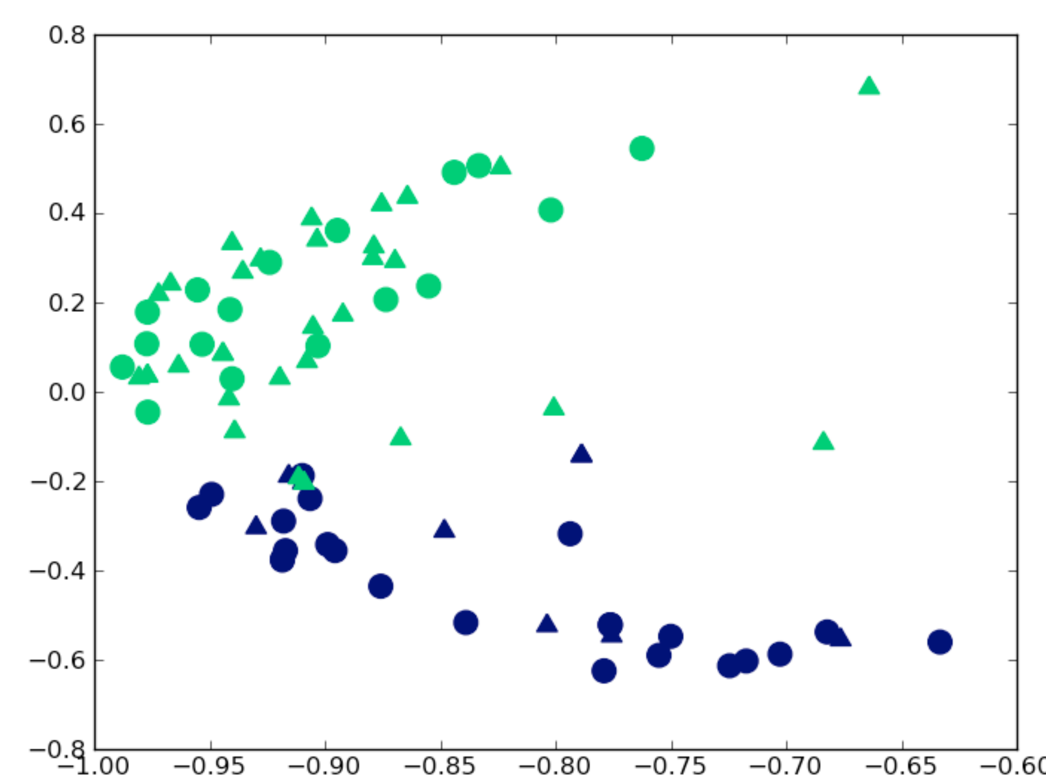

Figure 4. Clustering of latent class projected data. Early Morning (o) and evening (triangle)

Figure 4 shows an example of latent class projected data that has been clustered into two clusters, green and blue. The green cluster consists of data that primarily came from late afternoon periods (triangles), and the blue cluster consists of data that primarily came from early morning periods (circles). Thus, the algorithm has distinguished morning activities (i.e. many building entrance events) from afternoon activities (i.e. exit events).

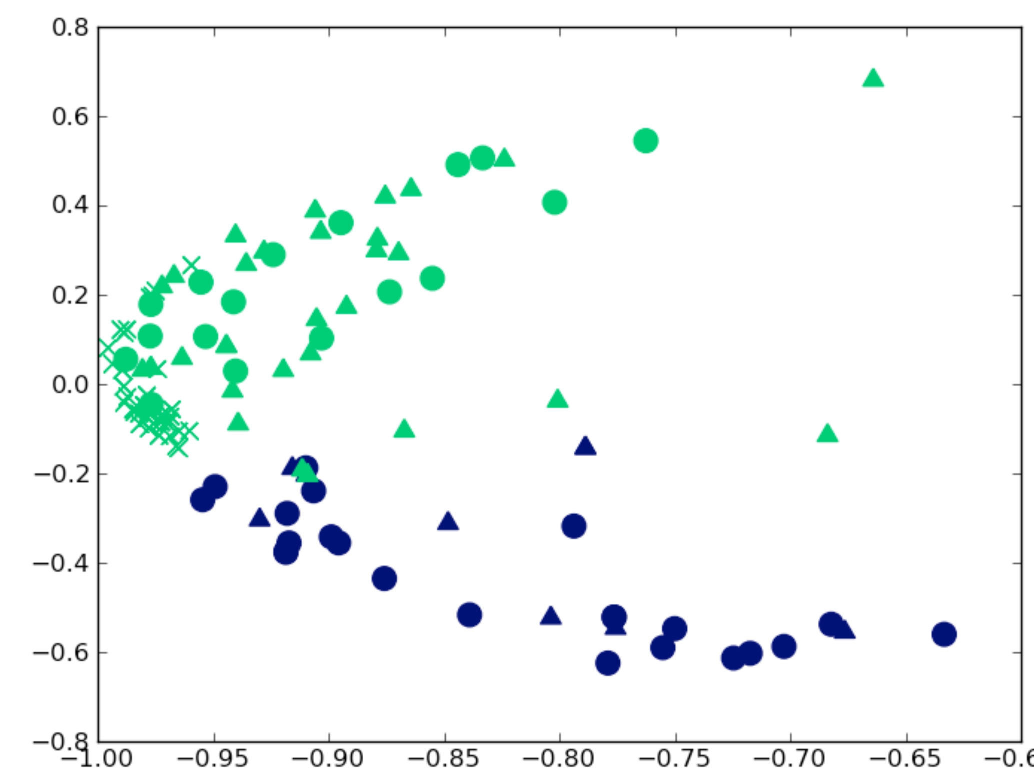

Figure 5. Classifying lunch time (x) data onto early/late split

Projecting data extracted from the beginning of typical lunch times (12:05 pm - 12:20pm), we see in figure 5 that all data is projected to our cluster associated with building exit.

Acknowledgments

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References

[1] W. Hoff, J. Howard, "Activity recognition in a dense sensor network," 1st Int'l Conf on Sensor Networks & Applications, 2009

[2] T. Hofmann, "Probabilistic Latent Semantic Indexing", Int'l SIGIR Conf on Research & Development in Information Retrieval, 1999