Human Activity Detection in Smart Home Environment with Self-Adaptive Neural Networks

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Human Activity Detection in Smart Home Environment with Self-Adaptive Neural Networks

Huiru Zheng, *Member, IEEE,* Haiying Wang, and Norman Black, *Member, IEEE*

Abstract— **One of key components in the development of smart home technology is the detection and recognition of activities of daily life. Based on a self-adaptive neural network called *Growing Self-Organizing Maps* (GSOM), this paper presents a new computational approach to cluster analysis of human activities of daily living within smart home environment. It was tested on a dataset collected from a set of simple state-change sensors installed on a one-bedroom apartment during a period of about two weeks. The results obtained indicate that, due to its advanced evolving, self-adaptive properties, the GSOM exhibits several appealing features in the analysis of useful patterns encoded in daily activity data. The approaches described in this paper contribute to the development of a user-friendly and interactive data-mining platform for the analysis of human activities within smart home environment through the improvement of pattern discovery, visualization and interpretation.**

I. Introduction

The desire to improve the quality of life for disabled and the rapid growth of elderly people has prompted a tremendous effort from both academia and industry to develop smart home technology. Currently, a significant number of dedicated smart environment projects are being carried out throughout the world. Examples include MavHome [1], a multi-disciplinary research project at the University of Texas at Arlington focused on the creation of an intelligent home environment; AwareHome [1], aiming to create a living laboratory for research in ubiquitous computing for everyday activities; and HomeLab [3], established by Philips as a testing ground for a better tomorrow with an emphasis on advanced interaction technology.

One of key components in the development of smart home technology is recognition of activities of daily life (ADL) such as eating, dressing, bathing, watching television and toileting [4], [5]. For instance, in an attempt to develop an aware home environment, researchers at the Georgia Institute of Technology introduced several activity recognition techniques to monitor the general activities of the occupants, including low-level tasks such as reading a book or watching television, and higher-level tasks such as preparing a meal, or using a blood glucose monitor [1], [6]. The PlaceLab project [7], a joint initiative between Massachusetts Institute of Technology (MIT) and TIAX, a collaborative product and technology development firm, aims to provide a living laboratory to systematically study human behaviors, the routine activities and interactions of everyday life.

It has been shown that the ability to correctly identify the day-to-day activities of occupants may have significant implications and applications in healthcare. For example it may support independent living as people age at low healthcare costs [8]. Information related to activities of daily living such as anomalous or undesirable patterns found in daily living can be used to develop cost-effective, home-based early warning health system [7]. It is believed that changes in baseline activities of daily living such as eating and sleeping may serve as an important early indicator of emerging physical or mental medical problems, especially for elderly people [4], [9].

However, activity recognition is a non-trivial task. The inherent complexity of human behaviour poses a great challenge for recognition [10]. For example, people often perform several activities simultaneously. Everyday activities are subject to periodic variation. Different activities occur at different time scales.

Recent years have seen a growing trend toward the adoption of diverse data mining techniques to study patterns of human activities from data collected from various sensor systems. For example, Rivera-Illingworth *et al.* [11] used a temporal neural network-based agent to recognize and classify human activities and behavious inside a pervasive living environment. A total of 8 activities including listening to music, working at computer, and sleeping were detected in this study. Based on analysis of data collected from a set of small and simple state-change sensors, Tapia *et al.* [12] applied Navie Bayesian classifier to recognize activities of daily living such as toileting, bathing, dressing and preparing lunch. In a study carried out by Kautz *et al.* [13], a hierarchical hidden semi-Markov model was used to track the daily activities of residents in an assisted living community. The results indicated that different activities may be differentiated solely based on noisy information on the whereabouts of the residents and when they move. More recently, Lühr *et al.* [14] introduced a novel data mining approach for the detection of new and changing behaviour in people living in a smart home. An efficient mining algorithm called intertransaction association rule (IAR) was

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introduced to identify anomalous behavious in smart home environment. To further explore implications of emergent human behaviour found from a real world smart home dataset, a new visual data mining tool was presented.

Based on a self-adaptive neural network (SANN) called *Growing Self-Organizing Maps* (GSOM), this paper aims to present a new computational approach to cluster analysis of human activities of daily living. One of the main purposes of this study is to provide a user-friendly data mining environment, which integrates fundamental advantages demonstrated by SANN, for the analysis of human activities within smart home environment through the improvement of pattern discovery, visualization and interpretation. The remainder of the paper is organized as follows. Section II presents a detailed description of the SANN learning algorithm used in this study, followed by a description of the dataset collected from an array of state-change sensors. Results are presented in Section IV. This paper concludes with the discussion of results and future research.

II. Methodologies

A. *The GSOM learning algorithm*

The GSOM [15] is a SANN, which follows the basic principle of the Kohonen self-organising map with a special focus on adaptive architecture. The learning process of the GSOM is started by generating an initial network composed by four neurones on a 2-dimensional grid (Fig.1(a)), followed by iteratively presenting training data samples. Like other SANNs, each input presentation during training involves two basic operations: (a) Determination of the winning neuron for each input data; and (b) adaptation of the weight vectors, w_j, associated with the winning neurons and their neighbourhoods as follows:

$$\Delta w_j(t) = \begin{cases} LR(t) \times (x_i - w_j(t)), & j \in N_c(t) \\ 0 & \text{otherwise} \end{cases} \qquad (1)$$

where $\Delta w_j(t) = w_j(t+1) - w_j(t)$, $w_j(t)$ and $w_j(t+1)$ are the weight values of neuron j before and after the adaptation at iteration t. $LR(t)$ is the learning rate at time t and $N_c(t)$ is the neighborhood of the winning node c.

In the growing phase, the quantization error, E, is accumulated for each winning node at each learning cycle, as illustrated in Fig.1(b). The GSOM keeps track of the highest error value and periodically compares it with a growth threshold, GT, When $E_i > GT$, new nodes are grown in all free neighboring positions of node i, if node i is a boundary node as shown in Fig.1(c) and (d), otherwise the error will be distributed to its neighboring nodes. The reader is referred to [15] and [16] for a detailed description of the learning algorithm of the GSOM.

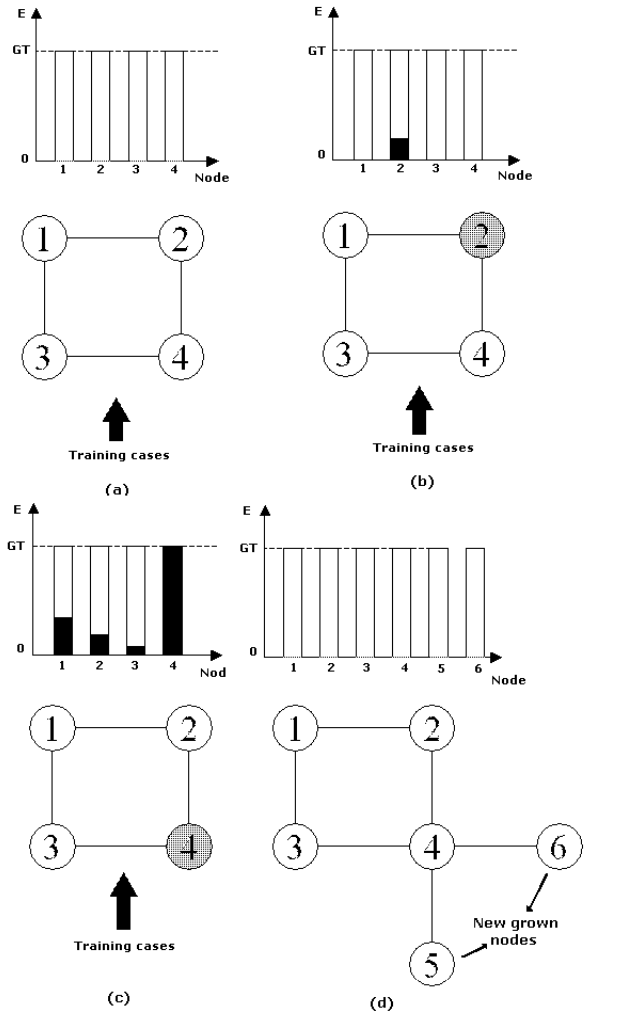


Fig. 1 New neurons generation process for GSOM. (a) The initial topology; (b) Error accumulation. (c) The topology before generation; (d) Neuron growth. The top curves represent the error accumulation during each learning cycle

Due to its dynamic, self-evolving nature, the GSOM exhibits several appealing features for patterns recognition and visualization. For example, after completing a learning process, the GSOM can reveal patterns hidden in the data by its shape and attract attention to such areas by branching out. A *spread factor*, *SF*, which is independent of the data dimensionality, is introduced in the GSOM. The user can provide a $SF \in [0,1]$ to specify the spread amount of the GSOM. This provides a straightforward way to measure and control the expansion of the network. Meanwhile, it allows the data analyst to identify interesting clusters based on a small map at the beginning and to perform a finer analysis of the areas of interest later. This can be significantly advantageous in handling larger data sets. Based on the selection of different values of *SF*, hierarchical and high resolution clustering may be implemented.

B. *The sensor dataset under study*

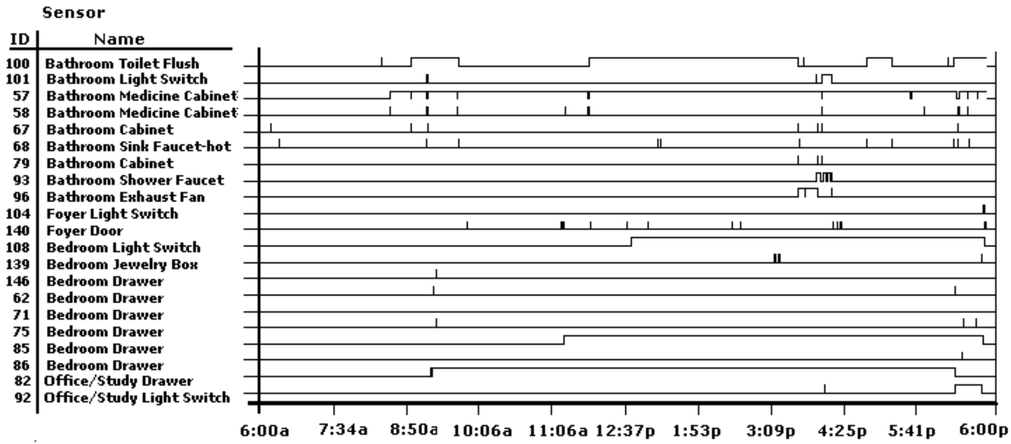
Different approaches have been used to gather information related to people's daily activities. For example, Vallejo [17] proposed a monitoring system to detect human activities based on acoustic evidence collected from distributed audio sensors installed at home environments. By use of multiple smart cameras, Wolf and Burak Ozer described a real time human activity recognition system [18]. One of problems of these approaches is that sensors such as microphones and cameras are commonly used as recording devices, thus they can be perceived as invasive and threatening by some people [12].

Activities recognition and detection carried out in this research was based on analysis of data collected by using a set of small and simple state-change sensors installed on everyday objects such as doors, drawers, refrigerators, stoves, sink, light switchs and containers and electronic appliances, e.g. DVDs, stereos, washing machines, dish washers and coffee machines. It has been shown that such a simple, low-cost sensing system represents an important alternative to analyse human activities at home environment [10], [12].

The dataset under study was generated by a 30-year-old woman who spent free time at a one-bedroom apartment for about two weeks (from 27 March 2003 to 11 April 2003). A total of 76 sensors installed on 28 daily objects were distributed all around the apartment: 11 in bathroom, 3 in foyer, 46 in kitchen, l4 in living room, 9 in bedroom, 1 in porch and 2 in study room. During the 16-day period, activation and deactivation time of each sensor was recorded as illustrated in Fig. 2(a). As these sensors sense when and where everyday objects are operated, activities of daily living such as toileting, bathing, and doing laundry were decomposed as a sequence of binary activation and deactivation events as illustrated in Fig.2(b). A total of 295 activities were recorded. The distribution of activities over each class is shown in Table 1. A full detailed description of the dataset can be found in [12].

C. Implementation Protocol

In this study, each activity is represented by the status of each sensor (on or off), objects activated and rooms activated. Those classes with the number of activities less than 5 were excluded in this analysis. *SF* is the spread factor as introduced above; N_0, and α_0 stand for the initial neighborhood and the initial learning rate respectively. Unless indicated otherwise, the parameters for the GSOM-based results reported in this paper are as follows: $SF = 0.9$, $N_0 = 4$, and $\alpha_0 = 0.1$. The numbers shown on the resulting



(a)

Activity				Sensor				
Class	Date	Starting time	Ending time	ID	Object	Room	Activation time	Deactivation time
Toileting	01/04/2003	17:30:36	17:46:41	100	Toilet flush	Bathroom	17:39:37	18:10:57
				68	Sink faucet-hot	Bathroom	17:39:46	17:39:52
Preparing a snack	01/04/2003	23:10:42	23:11:21	88	Sink faucet-cold	Bathroom	23:10:26	23:10:31
				68	Sink faucet-hot	Bathroom	23:10:28	23:10:33
				84	Drawer	Kitchen	23:10:44	23:10:47
				72	Cabinet	Kitchen	23:10:53	23:11:08

(b)

Fig. 2 (a) An example of reading recording activation and deactivation time of each sensor during the period from 27 March 2003 to 11 April. (b) An example of activities in a form of a sequence of binary activation and deactivation events map nodes of a GSOM represent the order in which they were created during the growth phase.

TABLE 1 THE DISTRIBUTION OF ACTIVITIES OVER EACH CLASS

Class of Activity	Number of Activities
Washing dishes	8
Toileting	84
Preparing lunch	17
Preparing dinner	8
Preparing breakfast	14
Preparing a snack	15
Preparing a beverage	15
Grooming	37
Going out to work	12
Going out for shopping	3
Going out for entertainment	1
Dressing	24
Doing laundry	19
Cleaning	9
Bathing	18
Washing TV	3
Washing hands	1
Putting away laundry	2
Putting away groceries	2
Putting away dishes	2
Lawnwork	1
Other	1
Total	295

III. RESULTS

A representative GSOM output map is shown in Fig. 3. It has branched out in two directions (Branch A and Branch B), suggesting that there are two main classes in the dataset. An analysis of activity distribution over each branch (see the distribution shown below the Fig. 3) indicates that all the activities assigned to each branch share something in common. For example, out of 52 activities found in Branch A, 48 are strongly related to kitchen type of activities such as *Preparing Lunch*, *Preparing dinner*, *Preparing Breakfast* and *Preparing Berverage*. Similar observation can be found in Branch B. Most of activities assigned to Branch B have a direct link to Bathroom. For example, out of 99 activities located in Branch B, 44.4% are *Toileting* and 35.4% are *Grooming*. Based on these figures, one may confidently assume that during this 16-day period, most of activities occurred in kitchen and bathroom. While Branch A is linked to kitchen activity, Branch B is associated with daily activities occurring at bathroom.

An important advantage of GSOM-based data analysis is that it provides several facilities to allow users to perform a multi-resolution and hierarchical clustering on areas of interest. For example, it allows users to perform a finer cluster analysis on selected areas of interest by incorporating additional information. Fig. 4 is a finer GSOM map based on cluster analysis of the activities found in Branch A of Fig. 3 by incorporating the knowledge of starting and ending time of each activity. The groups of activities can be seen more clearly in this spread-out map, which has been dispersed in three directions (Sub-Branches A, B and C). Most of events happening in the morning such as *Preparing Breakfast* were found in Sub-Branch C, while evening related activities such as *Preparing Dinner* were assigned to Sub-Branch A. Sub-Branch B includes those events that occurs around noon, for example, *Preparing Lunch*. Thus, a more understandable map is obtained.

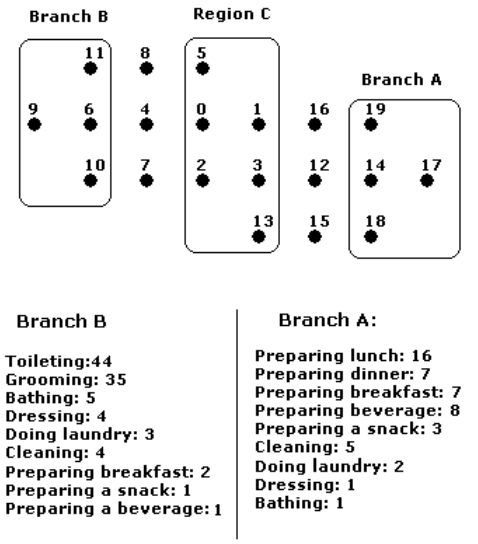


Fig. 3 A representative GSOM map generated for the dataset.

For those areas where it is difficult to differentiate between clusters such as Region C in Fig. 3, a high-resolution can be carried out using GSOM with different learning parameter settings e.g. a lower *SF* value. Fig. 5 is a high-resolution map of Region C in Fig. 3 with *SF*=0.1 and α = 0.05. A close examination of the distribution of activities over regions reveals that the relevant activity patterns were highlighted in this spread-out map in a more meaningful way. For instance, all the activities included in region A are labeled as *Going Out to Work*. More than 92% activities assigned to Regions C and D belong to *Dressing* and *Doing Laundry* respectively. Region B mainly includes *Toileting* activities. Interestingly, the results show that the GSOM not only can develop into different shapes to reveal patterns hidden into the data, but also it can attraction attention to interesting groups by isolating relevant areas using dummy nodes (accumulating "0" hits at the end of the training phase). For example, in Fig. 5, Region A associated with *Going Out to Work* activity was situated at very end of one of branches and well separated by the area covered by dummy nodes such as 68, 50, and 44 from other regions. Such a shape easily attracts user's attention.

The GSOM-based activity recognition not only can detect relevant activity patterns of human daily life but also it can be used to identify error and abnormalities in the data. As discussed, Sub-Branch A in Fig. 4 is linked to evening events. Surprisingly, two activities labeled as Preparing Lunch happening on March 31 2003 and April 09 2003 respectively were unexpectedly found in this sub-branch, suggesting that the occupant was preparing the lunch at abnormal time on these two days. However, by carefully checking the original record published on http://courses.media.mit.edu/2004fall/mas622j/04.projects/home/, we found that one of activities could be mistakenly labeled. There were two *Preparing Lunch* activities recorded on April 09 2003: One started at 12:53:52 and finished at 13:29:05. The other started at 18:46:34 and finished at 19:36:01. Together with the observation found in Fig. 4 and the knowledge that there was no *Preparing Dinner* recorded on that day, we may conclude that the activities recorded on 18:46:34 April 9 2003 was mistakenly labeled as *Preparing Lunch*.

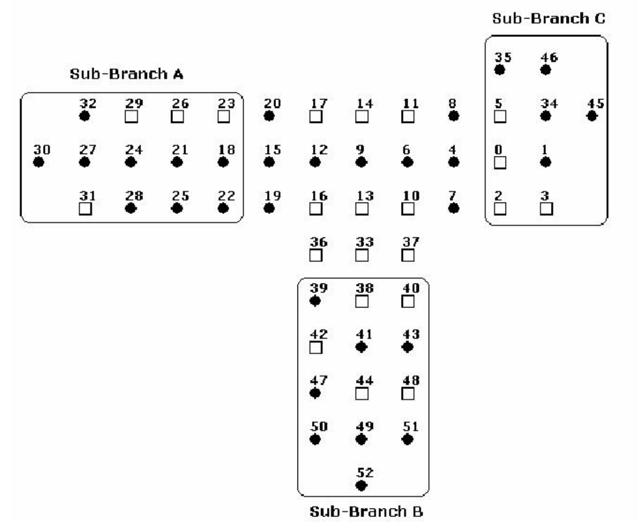


Fig. 4 A finer analysis of activities found in Branch A in Fig. 3 with GSOM by incorporating information about starting and ending time of each activity. α_0=0.01.

Interestingly, the GSOM can also be used to reveal multitask activities. For instance, in Fig. 5, most of activities fallen in Region C belong to *Doing Laundry* activity with the exception that node 34 represents a *Preparing a Snack* activity. It hints that the occupant may do something related to *Doing Laundry* while she was preparing a snack. A close examination of the original record during the period between 19:58:42 and 20:01:10 on April 10 2003 confirms this observation: while she started to prepare the snack, she ran the laundry dryer in the kitchen. A similar observation was also made in Fig. 3. As pointed out, Branch A in Fig. 3 is associated with kitchen type activities such as *Preparing Meals*. Unexpectedly, an event labeled as *Bathing* was also found in this branch, strongly indicating that the occupant may perform several tasks at the same time. This is consistent with her activity record: Just before she took a bath around 4:00 o'clock in the afternoon on March 29, 2003, she did some work in the kitchen. For example, she used the burner to do some cooking from 15:54:01 to 15:54:12 and disposed garbage at 15:54:50. After that she turned on the shower faucet at 15:56:09 to have a bath.

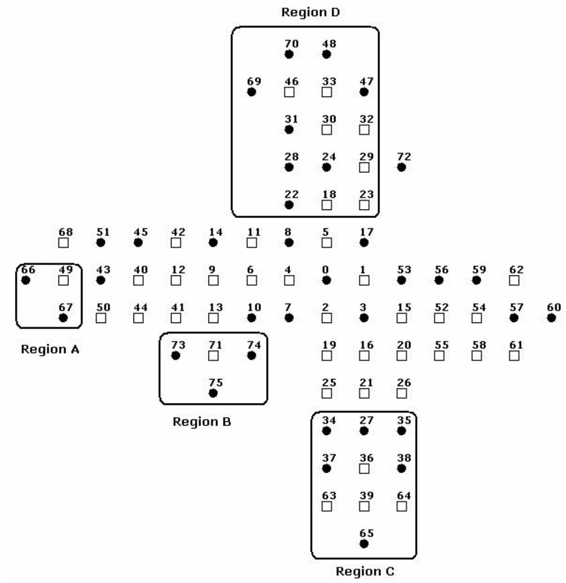


Fig. 5 A high-resolution map of Region C using GSOM with *SF*=0.1 and α = 0.05.

IV. Discussion and Conclusions

This paper presented a GSOM-based data mining approach to cluster analysis of human activities within smart home environment. The results obtained have demonstrated several appealing features exhibited by the GSOM-based approach in the analysis of useful patterns encoded in daily activity data. For example, due to its advanced evolving, self-adaptive properties, the GSOM can reveal relevant activity patterns in the data by its shape and attract attention to such areas by branching out [16]. Thus, the relevant patterns, together with data collection errors and unusual, abnormal behaviors can be readily detected and understood. Moreover, the resulting network has a structure that is directly linked to the underlying data set. This may provide a basis for developing a personalized data-mining platform to study activity patterns of each individual person. In addition, the GSOM-based approach provides several methods to allow a finer analysis on selected areas of interest. Therefore, multi-resolution and hierarchical clustering analysis of human activities may be implemented. Once trained, the GSOM can also be used for classification of the new activity into existing clusters. The whole clustering process does not have to be repeated [18]. Hence, the classification of new data can be completed in almost real time. This may be particularly useful in some environments, which require real-time monitoring tasks.

Like other neural network-based techniques, the GSOM requires users to determine several learning parameters in advance such as initial learning rate and the size of the initial neighborhood. Currently there is not a standard way to define a priori the optimal learning parameters. The selection of learning parameters such as the spread factor *SF* and the intial learning rate α_0 was mainly achieved by using trial-and-error approach. Integrating other machine learning techniques within the GSOM learning process to determine the best combination of learning parameters would be part of our future work.

It is worth noting that features used in this study are by no means to be the best representation of each activity. There are several other ways to describe people activity from the sensor activations. For example, Munguia Tapia *et al.* [12] employed a large number of low-order binary temporal relationships to represent each activity such as whether activation of a particular sensor exists during some time period and whether a particular sensor fires before another particular sensor. Encoding other feature sets especially temporal information between sensors into the GSOM model deserves further investigation.

REFERENCES

[1] D. J. Cook, M. Youngblood, III E. O. Heierman, K. Gopalratnam, S. Rao, A. Litvin, and F. Khawaja, "*MavHome: An agent-based smart home*," in *Proc. of First IEEE International Conference on Pervasive Computing and Communications* (PerCom'03), pp. 521--524. IEEE Computer Society Press, March 2003.

[2] C. D. Kidd, R. J. Orr, G. D. Abowd, C. G. Atkeson, I. A. Essa, B. MacIntyre, E. Mynatt, T. E. Starner and W. Newstetter. "The Aware Home: A Living Laboratory for Ubiquitous Computing Research," in *the Proc. of the Second International Workshop on Cooperative Buildings*, 1999.

[3] Philips Research- Technology. Avaliable: http://www.research.philips.com/technologies/misc/homelab/ [August 2007].

[4] M. Philipose, K. P. Fishkin, D. Fox, H. Kautz, D. Patterson, and M. Perkowitz, "Guide: Towards understanding daily life via auto-identification and statistical analysis," in *Proc. of the Int. Workshop on Ubiquitous Computing for Pervasive Healthcare Applications* (Ubihealth), 2003.

[5] T. V. Duong, H. H. Bui, D. Q. Phung, and S. Venkatesh, "Activity recognition and abnormality detection with the switching hidden semi-markov model," in *Proc. of the 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition* (CVPR'05), 2005.

[6] The Aware Home Research Initiative. Available at http://www.awarehome.gatech.edu/projects/index.html [August 2007].

[7] S. S. Intille, K. Larson , J. S. Beaudin , J. Nawyn , E. Munguia Tapia , and P. Kaushik, "A living laboratory for the design and evaluation of ubiquitous computing technologies," in *Proc. of Conference of Human Factors in Computing Systems*, April 02-07, 2005, Portland, OR, USA, pp.1941-1944.

[8] B. Logan, J. Healey, Matthai Philipose, E. Munguia Tapia, and S. Intille, "A long-term evaluation of sensing modalities for activity recognition," in *Proceedings of the International Conference on Ubiquitious Computing*, vol. LNCS 4717. Berlin Heidelberg: Springer-Verlag, 2007, pp. 483–500.

[9] E. Munguia Tapia, S. S. Intille, K. Larson, R. Rockinson, and J. Beaudin, "Tools for Ubiquitous Computing Research," in *Proceedings of the International Symposium for the Realization of Ubiquitous - City*. Seoul, Korea, 2006.

[10] E. Munguia Tapia, E. Activity Recognition in the Home Setting Using Simple and Ubiquitous Sensors. M.S. Thesis Media Arts and Sciences, Massachusetts Institute of Technology, September 2003.

[11] F. Rivera-Illingworth, V. Callaghan, and H. Hagras, " Automated Discovery of Human Activities inside Pervasive Living Spaces," in *Proc. of 1st International Symposium on Pervasive Computing and Applications*, 2006, pp. 77 – 82.

[12] E. Munguia Tapia, S. S. Intille, and K. Larson, "Activity recognition in the home setting using simple and ubiquitous sensors," in *Proceedings of PERVASIVE 2004*, vol. LNCS 3001, A. Ferscha and F. Mattern, Eds. Berlin Heidelberg: Springer-Verlag, 2004, pp. 158-175

[13] H. Kautz, O. Etzioni, D. Fox, and D. Weld, "Foundations of assisted cognition systems," University of Washington, Computer Science Department, Technical Report, Tech. Rep., 2003.

[14] S. Lühr, G. West, and S. Venkatesh, "Recognition of emergent human behaviour in a smart home: A data mining approach," *Pervasive Mob. Comput.* 3, 2, pp.95-116, 2007.

[15] D. Alahakoon, S. K. Halgamuge, and B. Srinivasan, "Dynamic self-organising maps with controlled growth for knowledge discovery," *IEEE Trans. Neural Networks*, vol.11, no.3, pp.601-614, 2000.

[16] H. Wang, F. Azuaje, and N. Black, "An integrated and interactive framework for improving biomedical pattern discovery and visualization," *IEEE Trans. Information Technology in Biomedicine*, vol., 8, no. 1, pp. 16-27, 2004.

[17] G. Vallejo. Listenin: Ambient auditory awareness at remote places. MS thesis, MIT Media Laboratory, Massachusetts Insitute of Technology, September 2003.

[18] W. Wolf and I. Burak Ozer, "A smart camera for real-time human activity recognition," in *Proc. of 2001 IEEE Workshop on Signal Processing Systems*, 2001, pp. 217-224.

[19] M.Y. Kiang, U. R. Kulkarni, and K.Y.Tam, "Self-organizing map network as an interactive clustering tool – an application to group technology," *Decision Support Systems*, vol. 15, pp. 351-374, 1995.