Occupancy Pattern Modelling Based on a novel Dynamic-HSMM and Streaming Sensor Data

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***Abstract*—Occupancy behaviour has the potential to change indoor condition in buildings and subsequently modify the final energy consumption. It is vital that automatic systems in buildings (BMS) adapt their regulation to actual user behaviour in order to reduce emissions. Recently, mathematical modelling proposals have been introduced consisting in combining sensor data and machine learning techniques with the aim of developing systems that can use occupants and ambient data to create models capable of regulating BMS more efficiently. Models based on hidden Markov (HMM) and hidden semi-Markov models (HSMM) have shown promising results for occupancy pattern detection. These models have the advantages of being able to incorporate data time-series of sequential data from sensors with the objective of being able to infer occupancy states such as presence or user activities from the sensor signals. Despite these advantages and the fact that HSMM overcomes some of the inherent state duration HMM modelling issues, these models still suffer from specific modelling limitations especially when performing real-time classification. In this paper we present a novel Dynamic-HSMM (D-HSMM) algorithm that adresses some of the mentioned limitations by including weighted streaming observations and a continuous duration modelling approach to perform accurate occupancy presence detection using streaming data. In order to evaluate the performance of our model, we compare our results with traditional HMM and HSMM approaches. Our D-HSMM model outperforms the original approaches showing that introducing some modifications to the traditional Markov models, occupancy detection from streaming data can be accurately performed.**

I. Introduction

Buildings are one of the major source of CO_2 emissions, accounting for over 40% of the total; a figure which is expected to increase in the next years[1]. Occupants have a major impact on the final energy consumption performance of buildings both from internal gains and from the interactions with their surroundings. However, that information is not always taken into account when building management systems (BMSs) are automatically regulated. Often, building systems such as lighting or HVAC are regulated based on schedules or peak assumptions that overestimate occupancy and give priority to comfort and functionality over energy efficiency[2]. Therefore, it is crucial to develop strategies to regulate BMSs based on real occupant needs in pursuance of maximising user comfort and building energy efficiency. Furthermore, these models can be adapted to make their predictions in real-time, making them a potential solution for building systems that require 'live' occupancy detection in order to be able to effectively reduce emissions.

A large number of occupant behaviour detection systems have been proposed over the last decades[3][4][5]. With the advance in wireless sensors technologies, researchers have attempted to utilise sensor data in order to create mathematical models capable of capturing occupant/building interaction information[**?**]. These systems will incorporate sensor data into models that will be able to detect user behaviour in the form of presence, number of occupants or activity recognition. Among the most popular approaches, hidden Markov models (HMM) have gained increasing notoriety for their ability to model sensor data as observable discrete temporal sequences and being able to infer occupant (hidden) states based on those observable sensor events combined with Bayesian inference and the Markovian first-order assumption. In spite its notorious advantages, one of the HMM main disadvantages is that state duration is inherently exponentially distributed due to self-state transitions. Real world scenarios demand that state duration can be explicitly model as occupancy states such as presence/absence or activity durations are better captured by using different temporal distributions other than exponential. Hidden semi-Markov models (HSMMs) extended HMM models to include additional state duration parameters. HMMs model state dwelling time by allowing the system to self-transition from state i to i calculating the probability of remaining stationary each timestep, which means multiplying a probability each timestep hence the exponential resulting distribution. HSMMs on the other hand, allow to calculate the most probable dwelling time d based on explicitly modelled duration distributions, during which the state will remain unchanged. More details of previous proposed methods found in literature are given in Section 2.

In spite recent HMM and HSMM success, both approaches present limitations when attempting to make occupancy detection in an online fashion. Markov models traditionally infer probable states based on whole sequences of observable data. In fact, some of the inference algorithms usually associated

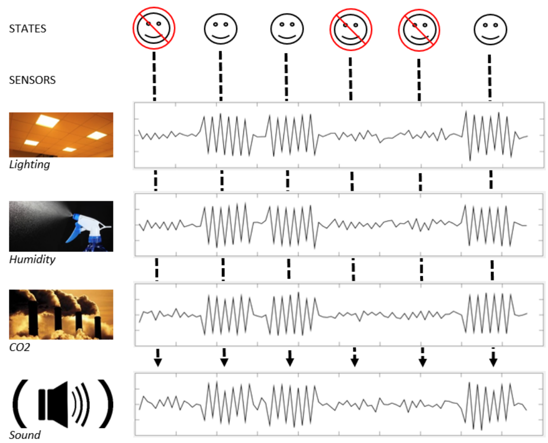

Fig. 1. Example of sensor signals that can be used to detect presence/absence of people in buildings.

with these models including the Forward-Backward or the Viterbi algorithms need a whole batch observable sequences to make their estimations. This poses a real challenge for streaming data state prediction as future observable data is not available when a new state is reached, therefore state prediction has to be decided with the uncertainty of what observable sequence will follows. Furthermore, state duration prediction is made by sampling a number of timesteps from duration distribution and keeping that state monotonically until reaching a transition boundary when the number of timesteps have passed. Finally, these models give each input feature the same relevance whereas in some scenarios certain features (sensors) can have more impact on the final state estimation affecting the overall model performance.

In order to overcome these limitations, we present an Dynamic HSMM (D-HSMM) algorithm, which extends the concept of an explicit HSMM traditional model. Our npvel aproach consists in of modelling each state using different duration distributions using a continuous density function in addition to a minimum and maximum state duration parameter. Also, we model the observations for each sensors signal separately, to later aggregate all the signals in a weighted fashion to calculate a more realistic emission probability. As a result of combining these ideas, we make D-HSMM capable of performing accurate state prediction using just initially partial data and achieving performance results even beyond than other offline Markov approaches. We evaluate our model using a dataset where binary signals from 14 different sensors are used to model presence and absence states in a domestic scenario.

The rest of this paper is organised as follows: Section 2 gives a comprehensive review of the previous related work, Section 3 defines the theoretical concepts of the techniques we have applied, Section 4 describes how our proposal faces the identified issues, Section 5 presents an experimental evaluation of our model and Section 6 concludes with a discussion about the model performance and future work.

II. Previos Work

Hidden Markov and semi-Markov techniques have recently been applied in many pattern recognition problems. Occupancy pattern modelling using Markovian models include the early works of Page et al [3] where an stochastic model based o Markov chains was proposed in order to create occupancy profiles in an office building or the work in [6] where an HMM model was used to create context-aware scenarios to regulate different smart-home systems.

Other models based on HMM extensions also became increasingly popular for occupant behaviour pattern recognition modelling approaches as in [7]. Hongeng et al. [8] proposed a video based event recognition where an adaptation of HMM algorithms was used to detect human activities through video data, as well as the authors in [9] who developed a multi regression hidden semi-Markov model for walking motion modelling though fast video data manually labelled. HSMM models were also presented in [4] introducing an elderly care monitoring system or in Doung et al.'s model[10] which included different duration distribution functions (i.e. Gamma, Poisson or Inverse Gaussian) for activity recognition purposes.

Most of the approaches described so far claimed that HSMM could outperform the classification accuracies from original HMM approaches with manageable increasing in model complexity and computational costs. That encouraged other inspiring works in the human behaviour pattern recognition field as in [11][12][13]. Dong's work [13] presented an HSMM-based occupancy modelling approach for energy savings and comfort management by detecting events extracted from multiple sensor data. Later, in [11] they used HMM and other machine learning approaches to detect occupants in an office building based on multiple ambient sensors, noting that different features (sensors) are potentially more significant for the final state classification decision and that HMM can even be used for predictive purposes. Van Kasteren research [12] provided an interesting activity recognition benchmark work where HMM and HSMM models were evaluated and compared with other state-of-the-art approaches to study modelling issues and performance based on contextual aspects such as time granularity.

In spite all the progresses, little works have been devoted to the development of models for real-time occupancy classification tasks using streaming data. One of the causes probably lies in the fact that using of Markov models for online occupancy detection is subject to specific challenges, particularly because of the need of whole offline data sequences to produce accurate state inference. Few approaches have been studied to address these challenges, mostly based on sliding window approaches [14]. Here we present a DHSMM model that is designed to tackle online limitations by adapting observation and duration models to the specific needs for modelling occupancy behaviour pattern datasets in an streaming fashion.

III. HSMM Model Definition

Here we outline how Markov models are defined and the challenges they usually face for state classification particularly within our domain.

Let S_T be a set of states that are present in a dataset with a total number of samples T. M would be the total number of different states and each time $t = \{1, 2, ..., T\}$ represents a time step comprising the whole dataset.

As discussed in orevious sections, HMM can only model state duration exponentially. Hidden semi-Markov model was introduced as an extension of the original HMM, where additional parameters were include in order to model durations in a explicit way. HSMM parameters are defined by

$$\lambda = (Q, O, a, b, \delta, \pi).$$

Where, $O = \{o_t | t \in T\}$ and $Q = \{q_t | t \in T\}$ are the observations and the states respectively for each time t. a represents the MxM state transition matrix containing the probability of transitioning from state i to j, $a_{i,j} = p([q_t = s_j | q_{t-1} = i])$ represented by:

$$a_{i,j} = \begin{pmatrix} a_{1,1} & a_{1,2} & \cdots & a_{1,M} \\ a_{2,1} & a_{2,2} & \cdots & a_{2,M} \\ \cdots & \cdots & \cdots & \cdots \\ a_{M,1} & a_{M,2} & \cdots & a_{M,M} \end{pmatrix}$$

Note that, due to the Markovian assumption these models calculate probabilities by looking at the immediate previous state. The emission probability MxN matrix B expresses what is the probability $b_i(v_i) = p([o_t = v_i | q_t = s_i])$ for each state to trigger each of the observations v_i, $i = \{1, 2, ..., k\}$ where k is the number of features. The parameter π represents the Mx1 array which contains the prior probability of each state $\pi_i = p([q_1 = s_i], i = \{1, ..., M\})$.

Finally, duration parameter δ is the (MD) matrix where D_i expresses maximum state duration and $\delta(d) = p(\delta_{s_i} = d)$ is the probability of state s_i lasting for d time steps.

Given the above parameters we can express the joint probability of the observations and the hidden states by:

$$p(O, S) = \prod_{t=1}^{N} p(O_t | S_t) p(S_t | S_{t-1}, d_{t-1}) p(d_t | S_t, d_{t-1})$$

For the maximisation of this joint probability, several dynamic programming algorithms have been proposed which allow to calculate the most likely state sequence for a given $\{O_T, \lambda\}$, the most likely observation sequence for λ, or the most probable parameters that maximise $\{S_T\}$. However, these are out of the scope of this work as we will merely calculate probabilities based on immediate new observation points and remaining state duration probabilities. See Rabiner et al. tutorial for more information about these techniques [15].

IV. Proposed Methodology

In order to make HSMM capable of performing accurate real-time occupancy detection, we present a dynamic hidden semi-Markov approach D-HSMM. Initially, we based our approach in the explicit HMMs which assumes that transitions are independent of the duration of the previous state, self transitions are not allowed ($a_{ii} = 0$) and state duration os only dependent on the current state an independent on

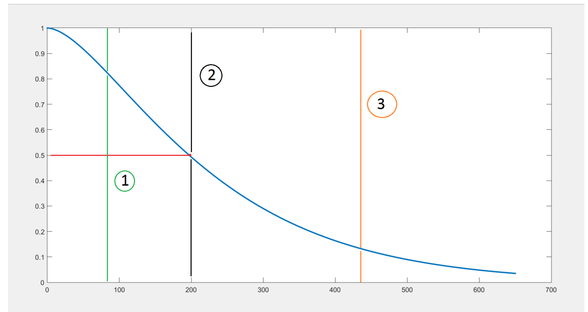

Fig. 2. Probability of remaining in the same state (blue) stays during *Min_Dur*, then decreases based upon the CDF obtained from fitting the data to the duration distribution function that best fits the data. In the unlikely event of reaching *Max_Dur*, the probability of remaining will equal to 0, forcing the system to abandon the state. For example, in 1) it is likely to remain in the state; in 2) it is equal and in 3) the higher probability is to leave. The final transition event will be chosen by combining duration with observation probabilities.

the previous one[16]. Our proposed approach extends these traditional explicit models in two main aspects:

- We do not establish a boundary for state transition when a new state is reached. Instead, we use a remaining state cumulative probability with *Min_Dur* and *Max_Dur* additional parameters.
- We infer the new state based only on one initial observation O_t, therefore we need to maximise the representativeness of that observed values by computing the likelihood of each separated sensor (one feature per sensor) and we assign a data-driven weight parameter.

A. D-HSMM duration modelling

D-HSMM duration model is similar to the work in [17] in which a non stationary time dependant duration HSMM was introduced. Our approach is designed to keep track of the highest state probability each timestep, therefore a transition boundary is not agreed initially by sampling a likely duration when a new state is reached. Instead, we define a CDF function based on different statistical probabilistic functions. The probability of remaining in the same state will remain 1 the number of timesteps specified in the parameter *Min_Dur*. Consequently, during that period of time, the state will remain unchanged regardless what observations occur. Once *Min_Dur* has ended, the CDF will decrease according to the probabilistic function and parameters of choice until reaching *Max_Dur*. During this interval, the combined probability of remaining (extracted from the CDF) and the observation probability ($b_t(O_t)$) will dynamically determine whether to stay in the same state or transition to the next one. Once decided to leave the state, the next observation and the transition probability will be used to determine the most likely new state to enter.

The example in figure 2 shows a CDF generated from fitting the data with a gamma distribution. The function has a value of one for the number of timesteps corresponding to the minimum duration parameter (30) and it gradually descends until it reaches a value of zero when $d = D$. This approach also allows the use of the statistical function that better represents the data for each state. In our experiments, we have used a mixture of histogram visual inspection and a MSE error function to choose the best probabilistic function fit for each class (see figure 3).

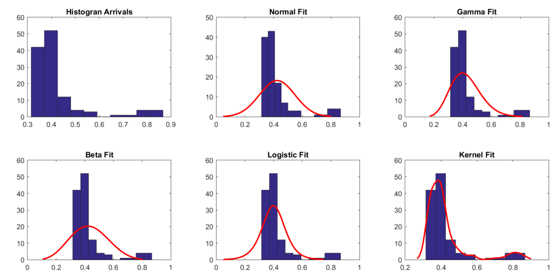

Fig. 3. Functions fitted for Arrival and Departure times.

B. D-HSMM weighted emission parameters

In the original HSMMs and HMMs, the observation model can be estimated following two approaches: 1) all sensor inputs at a time t can be considered as a unique observation O_t consisting of an array of sensor signals at a determined time, or 2) each sensor signal is assumed to be a different observation but happening at the same time. Therefore, to compute the emission probability in the first case we have the probability of occurring a certain combination of sensor signals whereas in the latter we need to calculate the probability of each of the sensors for a given state. For example, if we want to compute the probability of 3 binary sensors being $Z1 = 1$, $Z2 = 1$ and $Z3 = 0$ at time t given a system with two states S_i, i={1,2}, the two options would be:

1) The probability of the sequence [Z1,Z2,Z3] to be [1,1,0]

$$b_{S_i}(Z1, Z2, Z3) =$$
$$P(Z1, Z2, Z3|S_i) = \frac{p(sequence = [1, 1, 0]|S_i)}{\sum_i p(S_i)}; \qquad or$$

2) A different probability for each sensor

$$b_{S_i}(Z1, Z2, Z3) = P(Z1, Z2, Z3|S_i) =$$
$$\frac{p(Z1 = 1|S_i) + p(Z2 = 1|S_i) + p(Z3 = 0|S_i)}{R_t}$$

where R_t is the normalising factor, subject to $\sum_i b_{S_i} = 1$[1].

The first approach presents an immediate drawback from the point of view of sensor data modelling: if the number of sensors is high and the different discrete possible values they can adopt is also big, the different possible sequences would be dangerously high. For example, in a system with 20 binary (2 possible discrete values) sensors the number of possible different sequences would be $20^2 = 400$. For the same number of sensors and 4 possible sensor values, $20^4 = 160000$. This means that each sequence will be likely to happen a very small number running the risk of encountering many new values that never appeared in the training set.

The 2nd approach do not suffer from this. However, this approach unnaturally evens the importance of each sensor when in many applications has been noted that this is not the right modelling approach and some sensors contribute more to the model outputs [13]. To overcome this limitation, we have included a weighted factor cR that is applied to each sensor reading:

$$b_{S_i}(Z1, Z2, Z3) = P(Z1, Z2, Z3|S_i) =$$
$$\frac{cR_1 p(Z1 = 1|S_i) + cR_2 p(Z2 = 1|S_i) + cR_3 p(Z3 = 0|S_i)}{R_t}.$$

For the weights parametrisation, we have used a MSE correlation function applied to the different sensor signals to find which sensors are more correlated to the training labels. We then use these values to a assign a weight to each sensor probability automatically. By doing this, we ensure the emission modelling will adapt realistically to different scenarios with various sensor topologies and sensors of diverse nature.

V. Experimental evaluation

We have used sensor data information from a real life scenario for the evaluation of our D-HSMM. From the datasets published in [12], we have adapted the data to represent events of people coming in and out from a built environment, therefore the classification task consists of differentiating when the space is occupied or empty. The objective is to prove that D-HSMM is able to perform real-time occupancy classification with high standards of accuracy compared to other state-of-the-art approaches.

A. Data description

The final data is composed of 2 classes representing presence and absence as our target labels. The observation data consists of 14 different binary sensors (motion, pressure, contact and flush detector). There are a total of approximately 12k labelled samples, each representing an observation sequence of 14 features for each timestep which have been discretised into slices of 60 seconds.

B. Experimental setup

We have performed a 3-fold cross validation of the results and we used different metrics to validate our results including accuracy, recall, precision and F-score. Each new data point has been processed by our system in a streaming fashion, where predictions have been made without having the whole test sequences. To asses model performance, we have compared our D-HSMM against traditional HMM and HSMM approaches.

[1]Note that each sensor probability should be multiplied. However, we use addition instead as we can normalise probabilities for each state to add to 1. By doing this, we can later assign weights to each sensor.

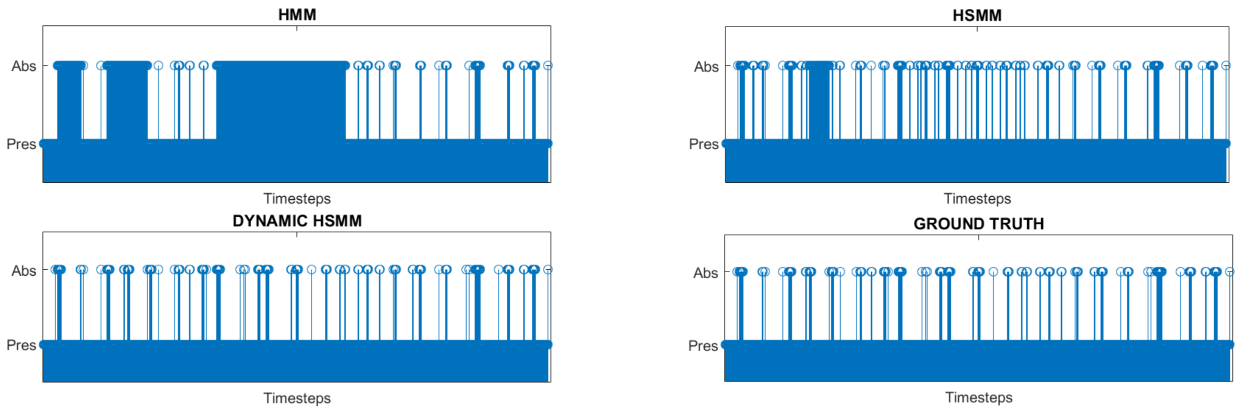

Fig. 4. Predicted states from HMM, HSMM, D-HSMM against the ground truth.

HMM

Accuracy: 65.6%		Ground Truth		
		Presence	Absence	Precision
Predicted	Presence	6795	4034	62.75%
	Absence	77	1036	93.08%
	Recall	98.88%	20.43%	

HSMM

Accuracy: 91.7%		Ground Truth		
		Presence	Absence	Precision
Predicted	Presence	9975	854	92.11%
	Absence	139	974	87.51%
	Recall	98.63%	53.28%	

D-HSMM

Accuracy: 98.6%		Ground Truth		
		Presence	Absence	Precision
Predicted	Presence	10738	91	99.16%
	Absence	78	1035	92.99%
	Recall	99.28%	91.92%	

Fig. 5. Confusion matrices, accuracy, precision and recall.

C. Results

As shown in 4 and 5, D-HSMM clearly outperforms the HMM which in most cases fails to reproduce the dynamics of the fast paced short absence periods. Traditional HSMM greatly improves the representation of short periods compared to HMM, however it fails to reproduce sequences with accuracy. Finally, our D-HSMM reaches high accuracy values of over 98%.

Other metrics also show D-HSMM performance standards for example recall values for the absence class where HMM and HSMM only reach 20% and 53% respectively whereas D-HSMM achieves 92%. Clearly, results show that D-HSMM significantly outperform original Markov models, both HMM and HSMM and is able to process streaming data with high degrees of accuracy for this dataset.

VI. Discussion

From the experimental results we can conclude that our D-HSMM algorithm achieves the highest levels of classification performance. Our approach improves the HMM and HSMM results using the same data and under the same conditions for all the metrics evaluated.

Based on these results, it is interesting to discuss why the use of our approach might be beneficial beyond the accuracy figures. Following, we discuss reasons as to why our model is a sound option to better reproduce the real underlying process that theoretically generated the data and why is beneficial when used with real-time data scenarios; frequent in occupancy models.

A. Generative occupancy models

Generative models such as HSMMs, can be used to infer states based on new input data and also to create new synthetic data sequences, to retrain model parameters (i.e. the Baum-Welchmann algorithm for Markov models) or to to give further information like the most likely observations given the parameters λ. Contrarily to the case of the discriminative models, generative ones are intended to approximate the true process that originated the data. Hence their performance tend to suffer when trying to generalise for new data and scenarios. However, D-HSMM not only is capable of modelling occupnacy process but it is also able to perform operation in real time.

B. Incremental learning

Another advantage of HSMMs as well as other Bayesian networks approaches is that they can be adapted to perform incremental online learning; understanding this concept as the update of model parameters alongside the arrival of new data points. These methods usually involve establishing a way of penalising when the model fails to predict a state through a cost function and subsequently. When the system prediction fails, the necessary adjustments in the model parameters are made in order to incorporate the new information without retraining the model from scratch while reducing the rate of failures.

So far, little researchers have devoted their efforts to the use of semi-Markov models either for streaming data processing or incremental learning. However, current applications increasingly demand these 'live' approaches, therefore it is crucial find ways of adapting our models according to these requirements.

VII. Conclussions

In this paper we have outlined what special requirements a real-time occupancy detection model based upon hidden Markov and semi-Markov approaches need to address in order to accurately detect occupancy behaviour in a variety of scenarios and contextual factors. We have introduced the previous approaches existing and how the traditional methodologies did not take into account the issues to model streaming data using HSMM models. We presented a novel dynamic hidden semi-Markov model D-HSMM algorithm designed to tackle the main issues related to the use of HSMM for 'real-time' occupancy prediction. We have showed how our proposed methodology is able to achieve the highest classification standards compared to previous hidden Markov and semi-Markov models.

A. Future work

We expect to include this algorithm as the final stage of system capable of detecting a whole workday of occupant presence by combining the study of times of arrival/departure though stochastic functions, a change event prediction stage based on a SVM classifier and the final D-HSMM stage which will be in charge of modelling the small periods of absence during a typical working day.

Furthermore, having being able to use a semi-Markov model to perform real-time classification, we can now include an online learning function that will update the model parameters to adapt the system to new unexpected data without having to retrain the model from scratch. Some approaches for the incremental learning of Markov models have already been proposed and the next step would be to include these ideas to further improve our D-HSMM model.

References

[1] P. Nejat, F. Jomehzadeh, M. M. Taheri, M. Gohari, and M. Z. Muhd, "A global review of energy consumption, CO2 emissions and policy in the residential sector (with an overview of the top ten CO2 emitting countries)," *Renewable and Sustainable Energy Reviews*, vol. 43, pp. 843–862, 2015. [Online]. Available: http://dx.doi.org/10.1016/j.rser.2014.11.066

[2] E. Azar and C. C. Menassa, "A comprehensive analysis of the impact of occupancy parameters in energy simulation of office buildings," *Energy and Buildings*, vol. 55, pp. 841–853, dec 2012. [Online]. Available: http://linkinghub.elsevier.com/retrieve/pii/S0378778812005117

[3] J. Page, D. Robinson, N. Morel, and J.-L. Scartezzini, "A generalised stochastic model for the simulation of occupant presence," *Energy and Buildings*, vol. 40, no. 2, pp. 83–98, jan 2008. [Online]. Available: http://www.mendeley.com/catalog/generalised-stochastic-model-simulation-occupant-presence/

[4] M. Pavel, T. L. Hayes, A. Adami, H. Jimison, and J. Kaye, "Unobtrusive assessment of mobility," *Annual International Conference of the IEEE Engineering in Medicine and Biology - Proceedings*, vol. 97239, pp. 6277–6280, 2006.

[5] D. Cook, A. Crandall, B. Thomas, and N. Krishnan, "CASAS: A smart home in a box," *Computer*, 2013. [Online]. Available: http://www.ncbi.nlm.nih.gov/pmc/articles/PMC3886862/

[6] H. Si, Y. Kawahara, H. Morikawa, and T. Aoyama, "A stochastic approach for creating context-aware services based on context histories in smart home," *Histories in Smart Home, Proceeding of the 3rd International Conference on Pervasive Computing*, 2005.

[7] J. Yamagishi, K. Ogata, Y. Nakano, J. Isogai, and T. Kobayashi, "HSMM-Based Model Adaption Algorithms for Average-Voice-Based Speech Synthesis," *Acoustics, Speech and Signal Processing, 2006. ICASSP 2006 Proceedings. 2006 IEEE International Conference on*, vol. 1, no. 3, pp. 77 – 80, 2006.

[8] S. Hongeng, R. Nevatia, and F. Bremond, "Video-based event recognition: Activity representation and probabilistic recognition methods," *Computer Vision and Image Understanding*, vol. 96, no. 2 SPEC. ISS., pp. 129–162, 2004.

[9] T. Yamazaki, N. Niwase, J. Yamagishi, and T. Kobayashi, "Human walking motion synthesis based on multiple regression hidden semi-Markov model," *Proceedings - 2005 International Conference on Cyberworlds, CW 2005*, vol. 2005, pp. 445–452, 2005.

[10] T. V. Duong, D. Q. Phung, H. H. Bui, and S. Venkatesh, "Human behavior recognition with generic exponential family duration modeling in the hidden semi-Markov model," *Proceedings - International Conference on Pattern Recognition*, vol. 3, pp. 202–207, 2006.

[11] B. Dong, B. Andrews, K. P. Lam, M. Höynck, R. Zhang, Y.-S. Chiou, and D. Benitez, "An information technology enabled sustainability test-bed (ITEST) for occupancy detection through an environmental sensing network," *Energy and Buildings*, vol. 42, no. 7, pp. 1038–1046, jul 2010. [Online]. Available: http://linkinghub.elsevier.com/retrieve/pii/S037877881000023X

[12] T. van Kasteren and T. L. M. van Kasteren, "Human activity recognition from wireless sensor network data: Benchmark and software," *Activity Recognition in Pervasive Intelligent Environments Atlantis Ambient and Pervasive Intelligence*, vol. 4, pp. 165–186, 2011.

[13] B. Dong and B. Andrews, "Sensor-based occupancy behavioral pattern recognition for energy and comfort management in intelligent buildings," *Proceedings of building simulation*, pp. 1444–1451, 2009. [Online]. Available: http://ibpsa.org/proceedings/BS2009/BS09_1444_1451.pdf

[14] N. Krishnan and D. Cook, "Activity recognition on streaming sensor data," *Pervasive and Mobile Computing*, 2014. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S1574119212000776

[15] L. R. Rabiner, "A tutorial on hidden Markov models and selected applications in speech recognition," *Proceedings of the IEEE*, vol. 77, no. 2, pp. 257–286, 1989. [Online]. Available: http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=18626

[16] T. Yu, "Modeling Occupancy Behavior for Energy Efficiency and Occupants Comfort Management in Intelligent Buildings," in *2010 Ninth International Conference on Machine Learning and Applications*. IEEE, dec 2010, pp. 726–731. [Online]. Available: http://www.mendeley.com/catalog/modeling-occupancy-behavior-energy-efficiency-occupants-comfort-management-intelligent-buildings/

[17] E. Marhasev, M. Hadad, and G. A. Kaminka, "Non-stationary hidden semi markov models in activity recognition," *Signal Processing*, no. Rabiner 1989, 2006.