A Novel Dynamic Hidden Semi-Markov Model (D-HSMM) for Occupancy Pattern Detection from Sensor Data Stream

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***Abstract*—Occupant presence and behaviour have a large impact on building energy performance. With the availability of low cost and affordable sensors, accurate occupancy detection by combining sensor stream data with machine learning approaches becomes possible. In this paper, we propose a novel dynamical hidden semi-Markov model (D-HSMM) which can accurately detect occupancy pattern from sensor data stream in real time. Our approach extends traditional hidden Markov (HMM) and hidden semi-Markov models (HSMM). The novelty of the proposed approach consists in 1) a new dynamic duration modelling n which the duration is dynamically changing, instead of using fixed duration in traditional HMM and HSMM based models; 2) a new approach to state prediction (i.e. occupant presence or absence in this case) based on a weighted function with partially available observations instead of using the whole set of observations. In order to evaluate the performance of our model, we have compared our results with traditional HMM and HSMM approaches. The experimental evaluation shows that our D-HSMM model outperforms the conventional HMM and HSMM-based approaches with very high accuracy.**

I. Introduction

Buildings are one of the major source of CO_2 emissions, accounting for over 40% of the total [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. The work [2] reported that energy cost savings could be significantly reduced when considering occupancy data in the loop of building energy management systems (BEMS).

Today's building systems such as lighting or HVAC are still regulated based on fixed schedules or peak assumptions that overestimate occupancy which cause the big energy wastage [3]. Therefore, it is crucial to develop strategies to regulate BEMSs based on real occupant needs in pursuance of maximising user comfort and building energy efficiency. To address this, 'Live' occupancy detection is important for energy efficiency and emission reduction.

Much effort has been devoted to occupancy detection and /or occupant behaviour over the last decades [4][5] [6] [7] [8]. Among these models, HMM and HSMM based approaches have gained popularity in modelling occupancy pattern. The early works of Page et al [4] modelled occupancy profiles in an office building based on Markov model. Hongeng et al. [9] proposed a video based event recognition where an adaptation of HMM algorithms was used to detect human activities through video data. Dong's work [8] presented an HSMM-based occupancy modelling approach for energy savings and comfort management by detecting events extracted from multiple sensor data. Later, in [10], 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. The work in [11] 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.

These existing approaches incorporate various sensor data (like CO_2, Humidity, acoustic sensors, camera) into models to detect user behaviour in the form of presence, number of occupants or activity recognition. The example of sensors used for occupancy detection is shown in Fig. 1. Among these methods, hidden Markov models (HMM) and Hidden semi-Markov models (HSMMs) [12] have gained increasing popularity for their ability to model sensor data as observable discrete temporal sequences and being able to infer occupant (hidden) states (e.g. occupant presence/ or absence) based on the combination of all sensor events. The existing HMM-based approaches model state dwelling time by allowing the system to self-transition from state i to i calculating the probability of remaining stationary each time step, which means multiplying a probability each time step, and hence state duration is inherently exponentially distributed. HSMM-based approaches, on the other hand, allow to calculate the most probable dwelling

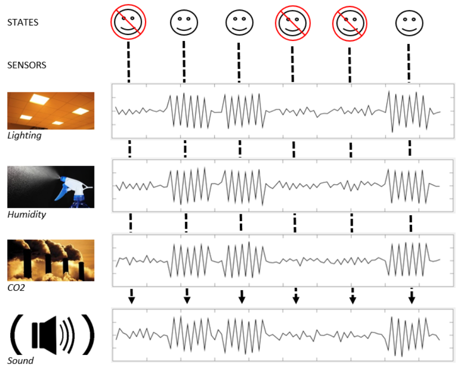

Fig. 1. When sensors signals show fluctuations, it can be expected that the state of the systems moves from absence (crossed-face) to presence (uncrossed-face).

time d based on explicitly modelled duration distributions, during which the state will remain unchanged. However, in real scenarios, the state duration should be better captured by using different temporal distributions other than exponential distribution.

Moreover, 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 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 state prediction of streaming data 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 follows. In addition, for the state prediction of occupant presence or absence, the existing HMM or HSMM based models simply treat all sensor events presenting occupancy state, which affect the overall accuracy performance of prediction. In fact, in real scenarios, individual sensor's contribution to the state prediction is different and should consider weighting factor for each individual sensor event.

To overcome these limitations, we present a novel Dynamic Hidden Semi-Markov Model (D-HSMM) algorithm, which extends the concept of an explicit HSMM traditional model in two ways:

- a dynamic duration distribution modelling, in which, the duration at each time step may dynamically change, this is in contrast to the traditional HMM and HSMM model where the duration is fixed and static.
- a new approach to state prediction based on partial observations where we model observations (i.e. different sensors in this case) separately and then aggregate all sensors using a weighted function to calculate a more realistic emission probability.

We have compared our D-HSMM approach with traditional HMM and HSMM models and evaluated our model with a real dataset to detect presence and absence states in a domestic scenario. As a result, our proposed approach is capable of performing accurate state prediction using just initially partial data and achieving performance results even beyond than traditional HMM and HSMM approaches.

The rest of this paper is organised as follows: Section II describes the background of HSMM and presents our new D-HSMM model, Section III presents an experimental evaluation of our model and Section IV concludes the findings and highlight the future work.

II. The Proposed Approach: A Dynamic Hidden Semi-Markov Model (D-HSMM)

Since our approach is based on hidden semi-Markov model (HSMM), this section will first introduce the definition of HSMM model and then describe our new dynamic HSMM model. For an extensive review of HSMM models and applications, we refer the readers to Yu's work in [13].

A. HSMM Model

As an extension of HMM, HSMM is defined as a semi-Markov chain with a variable duration or sojourn time for each state. The duration of a given state is explicitly defined. Let $S = \{s_1, s_2, ...s_M\}$ be the state of a semi-Markov chain. Let q_t denote the state of the semi-Markov chain at time t, where $t \in T = \{1, 2, ..., T\}$. The HSMM model can be described as follows:

$$\lambda = (Q, O, A, B, \delta, \pi).$$

Where $Q = \{q_t | t \in T\}$ and $O = \{o_t | t \in T\}$ represent the set of states and the set of observations respectively. A represents MxM dimensional state transition matrix representing the probability of transitioning from state i to j, $a_{i,j} = P([q_t = s_j | q_{t-1} = i])$. The emission probability B is a MxN matrix containing 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 initial prior probability of each state $\pi_i = p([q_1 = s_i], i = \{1, ..., M\})$. Duration parameter δ is the $(M$x$D)$ matrix where D_i expresses maximum state (max_dur) duration and $\delta_i(d) = P(\delta = d | s_i)$ is the probability of state s_i lasting for d time steps.

The joint probability of observations and hidden states can be described as follows:

$$P(O, S) = \prod_{t=1}^{N} P(o_t | s_t) P(s_t | s_{t-1}, d_{t-1}) P(d_t | s_t)$$

For the maximisation of this joint probability, several algorithms have been proposed for calculation of 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 $\{s_t\}$, please refer to the work in [14] and [15].

B. The proposed D-HSMM

In our case, the main goal is to predict occupant presence or absence. The states are '*presence*' and '*absence*'. The observations are sensor signals. The state transition matrix defines the likelihood of moving from *presence* to *absence* and vice-versa, and the duration model is built upon the temporal behaviour each presence and absence periods showed in the training set. We assume transitions are independent of the previous state duration, self transitions are not allowed ($a_{ii} = 0$) and state duration is only dependent on the current state an independent on the previous one[12].

We present a dynamic hidden semi-Markov model (D-HSMM) which extends HSMM traditional models in order to overcome specific traditional model issues in two ways: non-stationary duration modelling and state prediction with partially available data based on a weighted function.

1) D-HSMM duration modelling: In traditional HMM and HSMM based approaches, duration was obtained by sampling a random duration τ from the distribution model and kept constant for a number of timesteps until a new state is entered as shown in Fig. 2. In our model, we we obtain the duration distribution based on the training dataset, the duration is modelled as the probability of remaining in a state by using a complementary cumulative distribution function CCDF (1-CDF) to calculate the probability of remaining $P(Rem)$ in the same state each time step. Initially, $P(Rem)$ will be forced to1 for the number of timesteps specified in the minimum duration parameter *min_dur*. During that initial period of time, the state will remain unchanged regardless of what observations occur. Once *min_dur* is ended, the system decides whether to remain or leave the current state based onII-B1:

Algorithm 1 Dynamic transition detection

1: **if** $b_i \cdot P(Rem) > b_j \cdot (1 - P(Rem))$ **then** $S_t \leftarrow s_i$ ▷ No transition. State remains
2: **else** $S_t \leftarrow s_j$ ▷ Transition occurs. State changes

If no transition is reached previously, $P(Rem)$ will decrease according to the CCDF until reaching maximum duration *max_dur*, where $P(Rem)$ will be set to 0, forcing the system to transition to other state. Fig. 3 shows the working principle of our approach.

The example in Fig. 4 shows a CCDF generated from fitting the data with a gamma distribution. $P(Rem)$ is set to 1 until min_dur. After that, at each time step D-HSMM calculates the joint probability of remaining and the observations $P(Rem, o_t|s_i)$ for all possible states. $P(Rem)$ will decrease over time and the transition will happen when the joint probability of leaving will be higher than to remain ($P(1 - Rem, b_j|Leave) > P(Rem, b_i|Remain)$); setting $P(Rem) = 0$ when max_dur is reached. 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 (as show in Fig. 5), from which we will construct our CCDF. Our approach also allows to use several different statistical functions for each state duration model.

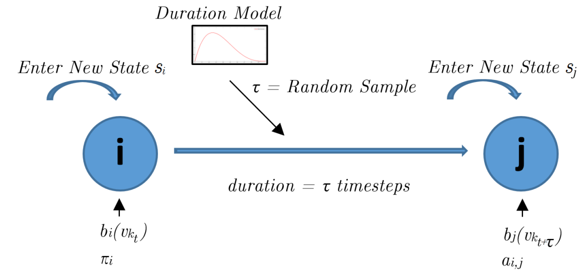

Fig. 2. State prediction with fixed duration in traditional HMM and HSMM based approaches

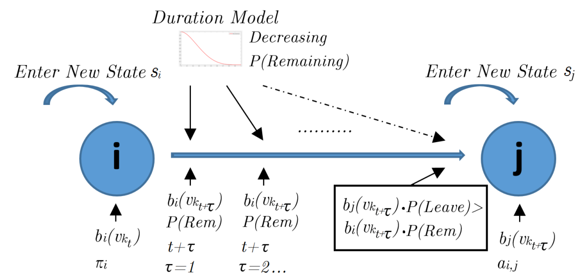

Fig. 3. State prediction with D-HSMM duration model, dynamically detecting duration.

2) State prediction using a weighted function: In traditional HSMMs and HMMs based approaches, 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 feature, consisting of an array of sensor signals at a determined time, or 2) each sensor signal is assumed to be a different observation feature but happening at the same time. Therefore, to compute the emission probability in the first case, we have the probability of occurring a combination of sensor signals whereas in the latter we need to calculate the aggregated probability of each of the sensors for a given state. For example, for 3 binary sensors signals $z_1 = 1$, $z_2 = 1$ and $z_3 = 0$ at time t, given a system with two possible states s_i, i={1,2}, the two options would be:

1) Probability of one unique sequence $[z_1, z_2, z_3]$ to be $[1, 1, 0]$.

$$b_i(z_1, z_2, z_3) =$$
$$P(z_1, z_2, z_3|s_i) = \frac{P(sequence = [1, 1, 0]|s_i)}{\sum_i P(s_i)}; \quad or$$

2) A different probability for each sensor

$$b_i(z_1, z_2, z_3) = P(z_1, z_2, z_3|s_i) =$$
$$\frac{P(z_1 = 1|s_i) + P(z_2 = 1|s_i) + P(z_3 = 0|s_i)}{R_t}$$

where R_t is the normalising factor, subject to $\sum_i b_i = 1$.

The first approach is not the best option for occupancy datasets as many sensors can be involved, therefore a lot of potential combination might not occur in the training set but be present in the new incorporated data. The second approach overcomes this by aggregating the likelihood of each sensor

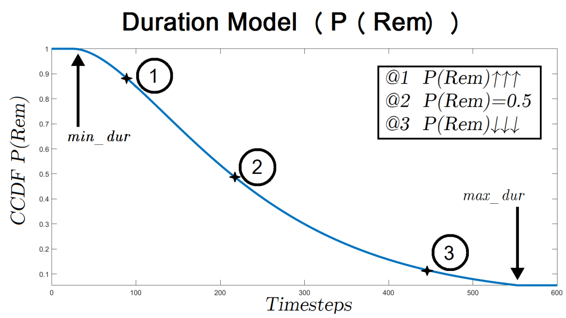

Fig. 4. DHSMM duration model. In this example, P(Rem) @1 will be close to 1 (unlikely transition); @2 P(Rem)=0.5, so transition will be determined by the observations only; @3 as P(Rem) reaches 0, the system will be pushed to enter a new state.

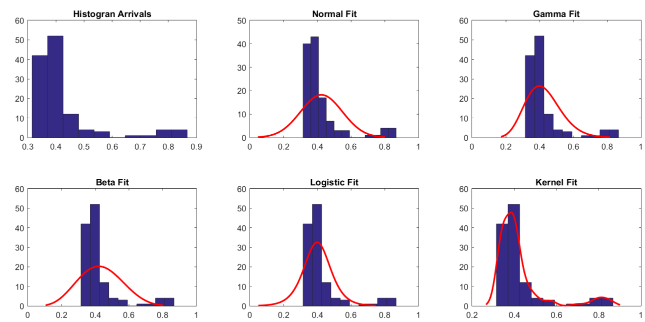

Fig. 5. Example of different statistical functions fitted for Arrival times.

separately. However, this approach evens the significance of each sensor, yet in many applications has been noted that this is not the right modelling approach as some sensors contribute more to the model outputs [8][16]. To improve the observation model further, we propose to include a weighted factor cR for the relevance of each sensor signal as follows:

$$b_i(z1, z2, z3) = P(z1, z2, z3|s_i) = \frac{cR_1 \cdot P(z1 = 1|s_i) + cR_2 \cdot P(z2 = 1|s_i) + cR_3 \cdot P(z3 = 0|s_i)}{R_t}.$$

To calculate the weight parameters, we use a MSE (mean square error) correlation function applied to each sensor signals during the training phase to find the more significant sensors. We then use the correlation values to a assign the weights. This ensures the emission modelling will adapt more realistically to different scenarios that include various sensor topologies and sensors of diverse nature.

III. Experimental Evaluation and Discussion

We have used publicly available real sensor dataset [11] and compared our approach with the existing HMM and HSMM-based approaches for real time occupancy detection and performance evaluation.

A. Data description

The data is composed of 2 classes representing occupant presence and absence. The observation data consists of 14 different binary sensors (such as motion, pressure, contact and flush detector). There are a total of approximately 12,000 labelled samples, each representing an observation sequence of 14 features for each time step which have been discretised into slices of 60 seconds.

B. Evaluation metrics

To asses model performance, we have compared our D-HSMM against traditional HMM and HSMM approaches. We have performed n-fold cross validation and used various standard metrics in [17] including: **Accuracy** = $(TP + TN)/(P + N)$, **Precision** = $(TP/TP + FP)$, and **Recall** – $TP/(TP + FN)$. where P represents positive samples; N represents negative samples; TP represents true positive; TN represents true negative; FP represents false positive; FN represents false negative. Each new data point has been processed by our system in a streaming fashion.

C. Results and Discussion

Fig. 6 and 7 demonstrate the proposed D-HSMM clearly outperforms the HMM and HSMM-based approaches. Fig. 6 shows the prediction results. Comparing to the ground truth Fig. 6 d), in most cases the HMM-based approach fails to reproduce the dynamics of the fast paced short absence periods. The HSMM-based approach greatly improves the representation of short periods compared to the HMM-based approach, however it fails to reproduce sequences with accuracy. In Fig. 7, the accuracy, precision and recall have been calculated. Our proposed D-HSMM has high accuracy of over 98% while the HMM based approach has 65.6% accuracy and the accuracy of the HSMM based approach is 91.7%. For precision and recall, the D-HSMM achieves high value for both recall (99.28% and 91.92%) and precision (99.16% and 92.99%). The results show that D-HSMM significantly outperforms both HMM and HSMM and is able to process streaming data with high degrees of accuracy for this dataset.

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. Our model can accurately capture and predict the short periods with partially available data.

IV. Conclusion and Future Work

In this paper, we have proposed a novel dynamic hidden semi-Markov model D-HSMM algorithm, which extends traditional HMM and HSMM by introducing a new dynamic duration distribution modelling and a new approach to state prediction using a weighted function for real-time occupancy detection with partially available data. The proposed model is in contrast to the traditional HMM and HSMM based model where the static duration was used and the state prediction used the whole sequence of the observations.

We have compared our approach with the HMM and HSMM-based approaches with publicly available real datasets. The accuracy performance has been calculated based on

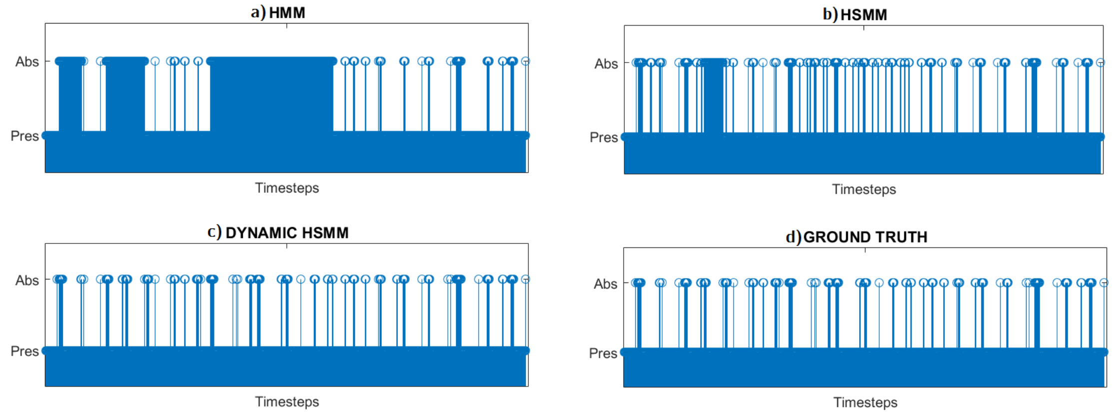

Fig. 6. Predicted states from a) HMM, b) HSMM, c) D-HSMM against the ground truth in d).

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. 7. Confusion matrices, accuracy, precision and recall.

standard metrics including **Accuracy**, **Precision**, and **Recall**. The experiment results show that our method significantly outperforms the existing HMM and HSMM based approaches. The accuracy of DHSMM is 98% while the HMM based approach has 65.6% accuracy and the accuracy of the HSMM based approach has 91.7%.

The future work will be to further improve the proposed model with the more realistic duration modelling and the weighted function.

ACKNOWLEDGEMENT

This work has formed a part of the funded project Occupancy Pattern Detection for Energy Efficiency and Comfort Management in Buildings Based on Environmental Sensing, by Manchester Metropolitan University.

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