A Flexible Framework for Building Occupancy Detection Using Spatiotemporal Pattern Networks

Preprint

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A flexible framework for building occupancy detection using spatiotemporal pattern networks

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Abstract— **This paper presents a reliable, scalable, and transferable framework to predict occupancy in a building utilizing diverse, multi-modal information. We propose a new methodology for learning-driven occupancy detection built on the concepts of probabilistic graphical modeling and observable Markov chain modeling. To capture the relationship between multi-sensor data and occupancy, we propose this Occ-STPN framework that is flexible to support both multivariate and univariate formulations. While the multivariate Occ-STPN performs feature-level fusion of multiple predictors and occupancy time-series data, the univariate Occ-STPN involves decision fusion of occupancy predictions using individual predictors based on a mutual information weighted fusion scheme. We also propose a new metric to evaluate the performance of occupancy prediction algorithms. Two popular datasets are used to validate our approach and demonstrate that our framework is scalable in terms of the number of information sources (e.g., sensors) as well as it is possible to transfer trained models from one building to another without significant reduction in performance. Reliability of the algorithm is also tested by injecting noise into the datasets.**

1. Introduction

Buildings contribute roughly 41% to the world's energy consumption [1]. Due to the increasing need for sustainable energy consumption and reduction of carbon footprint, there has been an increasing focus on the concept of smart building energy systems [2]. One way to optimize performance, or reduce building energy waste, is to leverage information about existing indoor environmental conditions to regulate the HVAC system adaptively in response to prevailing levels of occupancy. Techniques used to detect occupancy in the building will thus play an important role towards this goal.

RELATED WORK: In [3], the authors use online sequential extreme learning machines (ELM) to detect occupancy in a large-scale multi-functional lab. In [4], the authors combined statistical and probabilistic methods to detect whether a building was occupied or not. The authors in [5] use linear regression and decision trees to detect occupancy in a commercial building by collecting data from context rich sources. A point extraction algorithm was used in [6] to detect occupancy inside a building from particulate matter concentration. [7] used particle filters and support vector machines (SVM) to detect occupancy in a non-residential building.

A major limitation in many of these algorithms is the lack of scalability and transferability. When the spatial/temporal aspects of the sensor data get changed, these algorithms may fail to produce correct occupancy result. Different considerations for feature selection or machine learning models may need to be used for different settings, some of which might involve costly computations that may require expensive embedded systems to run on. Hence, we propose a unique framework that is transferable, scalable, and modest in terms of computational cost.

We leverage the concepts used in symbolic dynamic filtering (SDF) [8] and the recently proposed probabilistic finite state automaton (PFSA) based spatiotemporal pattern networks (STPN) [9], [10], [11] built on SDF to construct this framework. There have been several successful applications of this framework in the past, such as wind turbine interactions [10], building energy disaggregation [12], and bridge damage detection [11]. In this paper we will introduce STPN as a robust technique for building occupancy detection. As opposed to other algorithms which conserve only either the temporal or the spatial aspect of the data, this framework conserves both the temporal and spatial aspects of the input data. With our data driven approach, acceptable accuracy is achievable without domain knowledge and with minimal hyperparameter tuning.

CONTRIBUTION:

1) We propose the occupancy detection spatiotemporal pattern network (Occ-STPN) framework for building occupancy prediction.
2) We propose two variants of this framework - multivariate Occ-STPN for feature level fusion to achieve high performance and univariate Occ-STPN for decision level fusion to achieve scalability and flexibility.
3) For the first time we consider transferability aspects of a building occupancy prediction method, i.e., train on one building and evaluate on a different building.
4) We introduce a new causal metric for evaluating performance of building occupancy prediction algorithms

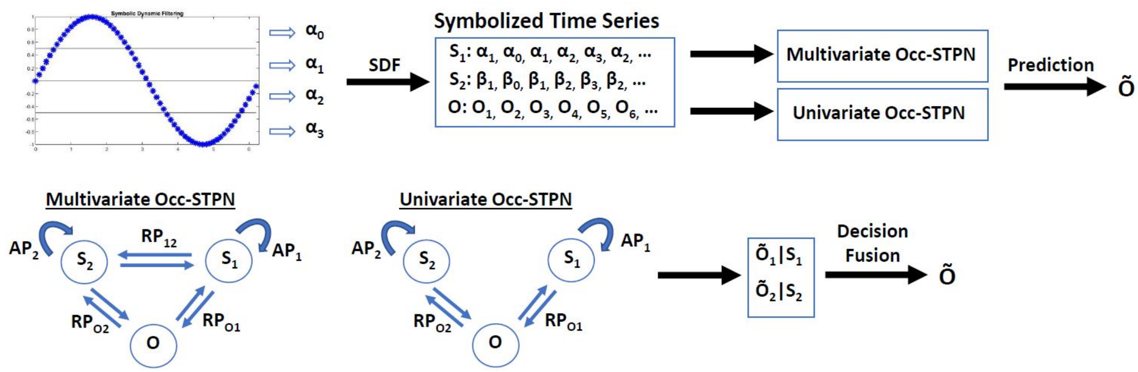

Fig. 1: *Multivariate and univariate Occ-STPN framework for occupancy detection*

that explicitly captures *time delays in prediction*.

OUTLINE: The rest of the paper is presented as follows: Section 2 gives a brief background on the STPN framework, Section 3 explains the detailed flow of operations within STPN framework, Section 4 describes the experimental setup and the data used in this paper, Section 5 presents the results and a detailed discussion of the framework's performance, and finally, Section 6 states the conclusion for this paper and future work for enhancing the framework's performance.

2. Background

A. Discretization

After raw sensor data is collected from indoor sensors, a series of processing steps are performed for efficient data compression and noise filtering through the use of discretization techniques. These wide range of techniques broadly fall into the category of SDF [8] and the D-Markov machine concept [9] is used here as a basis for our technique.

There are many different discretization techniques proposed in the past, such as uniform partitioning (UP), maximum entropy partitioning (MEP), maximally bijective discretization (MBD) [13], and statistically similar discretization (SSD) [14], but for simplicity, in this paper, we use uniform partitioning (UP) in the discretization process.

B. Markov Machines

After discretization of the time-series data, symbolization is implemented subsequently for estimating the D-Markov machines. In SDF, a critical assumption is that we can approximate the symbolized time-series data as a Markov chain of order D, which is a positive integer [9]. This Markov chain is called D-Markov machine, and it can capture temporal aspects in a time-series and cross-correlation aspects (spatial relationships) between different time-series.

3. Methodology and Framework

We now formally define the framework we use for occupancy detection: Occ-STPN. Our framework draws concepts from the closely related spatiotemporal pattern network (STPN) [9].

A. Multivariate Occupancy Detection Spatiotemporal Pattern Network (Occ-STPN)

Definition 3.1 *Let $\{A\}_t = \{a_1, a_2, ...a_n\}_t$ denote discretized symbol sequences at time t, obtained from n variables of interest ($a_1...a_n$). Let $\{B\}_t$ denote the corresponding values of occupancy inside a room denoted as 1 for occupied and 0 for vacant. Then, a probabilistic finite state automaton (PFSA) based occupancy network (Occ-STPN) is a 4-tuple, denoted as $W_d \equiv (Q^A, \Sigma^B, \Pi^{AB}, I^{AB})$*

1) *$Q^A = q_1, q_2, ..., q_{|Q^A|}$ is the state set corresponding to the symbol sequence s_A*
2) *$\Sigma^B = \sigma_1, \sigma_2, ..., \sigma_{|\Sigma^B|-1}$ is the alphabet set of symbol sequences s_B*
3) *Π^{AB} is the state transition matrix of size $|Q^A| \times |\Sigma^B|$ where the ij^{th} element of Π^{AB} denotes the probability of finding symbol σ_j in the symbol string s_B at time $k+1$ while making a transition from state q_i in the state sequence $s_A = s_{a_1}s_{a_2}...s_{a_n}$ at time k. Note that the state transition matrix is time independent since we take the expectation over all time points for all unique transitions.*
4) *I^{AB} denotes a metric that represents the importance of the feature in predicting occupancy. Here it is the mutual information M^{AB} [10].*

B. Univariate Occupancy Detection Spatiotemporal Pattern Network (Occ-STPN)

We propose the univariate Occ-STPN as a special case of multivariate Occ-STPN, when the number of predictors is 1. A major difference lies in the way a prediction for occupancy is performed by both of them. While multivariate Occ-STPN uses a transition matrix that incorporates the joint relationships between n information sources and the true occupancy, univariate STPN uses n transition matrices each considering pairwise relationship from one variable of interest to the true occupancy.

C. Occupancy Detection using Occ-STPN

An overview of both frameworks are shown in Figure 1, where it could take in single or multiple time-series data and output the corresponding predicted occupancy at each point in time. The detailed operations within the framework are shown below:

1) Training data is collected in the form of a table where each column represents the time-series sensor data and the last column denotes the status of occupancy at each time point along the rows of the table.
2) Time-series discretization using SDF [8] and assign unique states to sensor values at each time point.
3) A transition matrix representing the state space and transition properties of the dynamic system is learned using a recent technique based on cross-markov machines of depth parameter D [15].
4) **Multivariate case:** The joint transition probabilities from $\{A\}$ to B are estimated.
   Univariate case: The n transition probabilities from $a_i \in A$ to B are estimated.
5) Retaining important information in the matrix and eliminates potentially redundant states in transition matrix by performing *state merging* [9] as shown in Algorithm 1.
6) The merged transition probabilities are used to predict the state of occupancy inside a building.
   Multivariate case: We use Equation 3 to predict occupancy directly.
   Univariate case: If n is our total number of informative sources, then we obtain n predictions for probability of a room being occupied at the next time instant. We call each of the predictions, a decision. We assign weights w_i to each probability based on calculated mutual information value $M^{a_d B}, d = 1, ..., n$. The final probability of occupancy is calculated as below:

$$w_i = \frac{M^{a_i B}}{\sum_{d=1}^{n} M^{a_d B}} \tag{1}$$

$$Pr(\text{Occupancy}_{t+1}) = \sum_{i}^{n} w_i Pr_i(s_t) \tag{2}$$

$$E(\text{Occupancy}_{t+1}) = \sum_{i}^{n} Pr_i(s_t) E[\text{Occ}|_{s_{t+1}}] \tag{3}$$

Here, t is the point in time or instance, s_t is the unique state at time t found in the transition matrix $\Pi^{a_i B}$, and n is the number of decisions in consideration. To obtain a binary prediction of occupancy at time $t+1$, we apply a threshold of 0.5 on the probability value obtained in Eqs. 2 and 3.

Remark 3.1 *Multivariate Occ-STPN and Univariate Occ-STPN behave the same when there are only 1 predictor or input to the framework since weights w_1 is always 1.*

D. State Merging

State merging operation eliminates less informative states in transition matrix $\Pi^{a_i B}$. A detailed mathematical consideration of state merging for STPN is provided in [16]. Here, we provide a simple pseudocode in Algorithm 1. The threshold is a small arbitrary value, which we set it to be 0.001.

Algorithm 1 State Merging Algorithm

1. **Input**: Transition matrix from Step (5) in Section 3A
2. **Output**: Merged transition matrix
3. **for each** unique state, s in transition matrix:
4.   Compute standard deviation, σ
5.   **if** $\sigma \geq$ threshold:
6.   Keep s
7.   **else**
8.   Merge s to closest state
9. **return** Merged transition matrix

E. Performance Evaluation

1) Accuracy: Accuracy is a common performance metric for occupancy detection algorithms and it is computed as the ratio of the sum of correct predictions to the total number of predictions.

2) Fading Memory Mean Squared Error (FMMSE): Comparing accuracies can be tricky for prediction algorithms as they may have varying time-delays in prediction. In other words, given an observed state at time instant t, the desirable prediction may be obtained at a later time instance $t+q$, where q is a variable delay. This is often a result of failing to completely model latent variables of the system or ill-conditioning of obtained transition matrices due to fewer observed data for a particular state.

Let $\{G\} = \{g_1, g_2, ...g_f\}$ denote the ground truth occupancy data for time points 1 to f. Let $\{P\} = \{p_1, p_2, ...p_f\}$ denote prediction probabilities of a room being occupied from time instants 1 to f. We let γ denote the parameter that controls the penalty value due to time-delay detection that is used to evaluate the effectiveness of the algorithm. With this setup, our new proposed metric is given by:

$$T = \sum_{i=1}^{f} (g_i - p_i)^2 \times (1 - \gamma^c) \tag{4}$$

$$\text{where } c = i - x \tag{5}$$

$$x = \{\text{argmin}(i - x) | \text{abs}(G(x) - G(x+1)) \geq 1\} \tag{6}$$

Ideally, the best algorithm would have the lowest value possible for T. In parallel we also calculate T for the same ground truth for a model that randomly guesses occupancy for time $t+1$ with probability p_{rand}. By varying the probability p_{rand}, we can judge the sensitivity of our algorithm. Without loss of generality, we can extend this method to compare sensitivities between any two occupancy prediction algorithms.

4. Experiments

A. Occupancy Datasets

In this paper, two open source datasets are used to demonstrate our framework's performance on occupancy detection.

The first dataset we used is the University of California, Irvine's building occupancy detection dataset [17] (UCI) which consists of data collected from indoor environmental sensors such as temperature (°C), relative humidity (%), illuminance level (lux), CO_2 (ppm) and humidity ratio (kg-water-vapor/kg-air).

The second dataset is the ECO dataset [18]. The dataset contained electrical consumption data such as power, current, and voltage in different phases for many appliances as well as the ground truth occupancy. For the ECO dataset, we mainly focus on the raw data obtained from the sum of real power over all phases for selected appliances. The appliances that we selected are the tablet, dishwasher, air exhaust, fridge, entertainment, freezer, kettle, television, and stereo. At this point, the appliances selection is purely based on its completeness or amount of missing data.

B. Sensor Scalability and Feature Transferability

In order to demonstrate the scalability and transferability of this framework, in the following section, we present some interesting occupancy prediction results for household 1, 3, 4 and 5 in ECO dataset using training data from household 2 and our univariate Occ-STPN framework. Note some households may not include all the appliances as we only took the common appliances from both households for prediction. This is possible because our framework is not strictly dependent on the number of predictors.

5. Results and Discussion

A. Multivariate Occ-STPN

In the first part of our experiment, we use only one time-series data from ECO dataset on on our multivariate Occ-STPN, and our framework could achieve a best accuracy of 92% and FMMSE value of 0.0039 (stereo power consumption) on occupancy detection as shown in Table I.

From Figure 2, our multivariate framework detected an unoccupied event around the 2000 minute mark, but there was some time lag, and maybe due to the short unoccupied period, the framework was not able to detect the unoccupied status around the 550 minute mark. To improve performance, we combined multiple appliances' power consumption data as the framework input for the following experiments.

Table I showcase our framework's robustness to changing size and modality, where we have number of predictors ranging from 1 to 6. The prediction accuracy was around 92% with only single time-series input and will slightly increase as the number of time-series input increases. In the last row of the table, we challenged the reliability of the framework by replacing one of the time-series inputs with random noise, but even with the disturbance of this noise, we could still achieve an accuracy of 91.28% and an FMMSE value of 0.00397.

Furthermore, Figure 3 shows the results of multivariate Occ-STPN on UCI dataset, which have a prediction accuracy

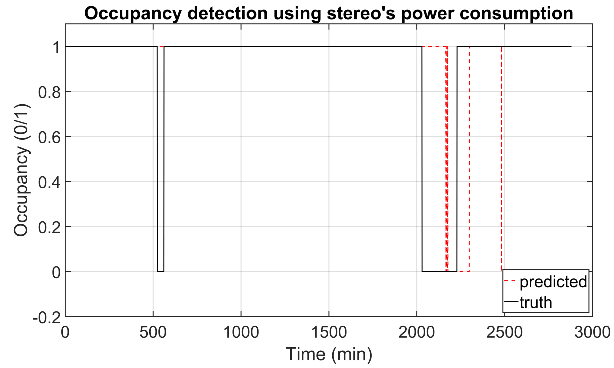

Fig. 2: *Occupancy detection using ECO household 2 stereo's power consumption data on **multivariate** Occ-STPN*

of 94%. The framework predicted the first half of the unoccupied status almost perfectly, though the transition from unoccupied to occupied is slightly late, it is still around the 950 minute mark. In the second half, our framework detected the occupied status very well, and it also detected one of the unoccupied status spikes in the ground truth occupancy as well. Besides that, in Figure 4, we show the prediction results using UCI dataset data, each injected with 10% of white Gaussian noise. Compared to Figure 3, this result is almost identical, but there are some fluctuations around the 900 minute mark and 1200 minute mark. Nevertheless, we're still able to achieve an accuracy of 89.44%.

B. Univariate Occ-STPN

In this subsection, we demonstrate our framework transferability using univariate Occ-STPN. As mentioned in previous section, for this experiment, multiple instances of the framework were pre-trained using each time-series data from household 2 and the mutual information weighted probability was used to predict the occupancy in another household.

A graphical representation of occupancy prediction is shown in Figure 5. From the figure, our framework accurately predicted the exact number of unoccupied events in household 1,3, and 5 with only multiple "false alarms" in household 4. Besides that, in household 3, the prediction is able to uncover the transition from occupied to unoccupied

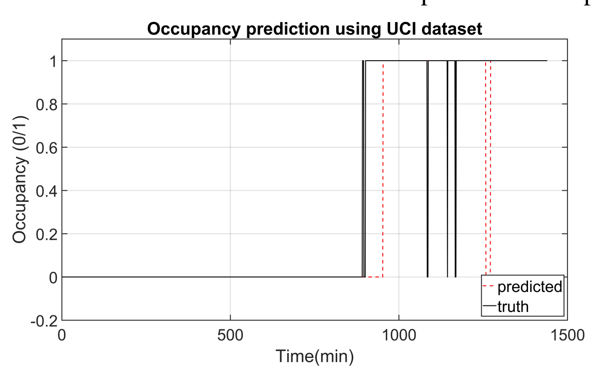

Fig. 3: *Occupancy prediction with UCI dataset on **multivariate** Occ-STPN*

TABLE I: *Occupancy detection accuracy with different number of predictors using ECO household 2 dataset on **multivariate** Occ-STPN, **univariate** Occ-STPN, and LDA method*

Number of predictors	Appliances power data	Multivariate		Univariate		LDA	
		Accuracy(%)	FMMSE	Accuracy(%)	FMMSE	Accuracy(%)	FMMSE
1	Stereo	92.01	0.003941	91.46	0.0139594	91.11	0.013981
3	Dishwasher, Entertainment, Stereo	92.67	0.003156	92.01	0.0139577	91.77	0.01396
6	Dishwasher, Entertainment, Stereo, Fridge, Freezer, Kettle	93.09	0.003375	91.42	0.0139624	92.25	0.013983
6	Entertainment, Stereo, Fridge, Freezer, Kettle, ***Random Noise***	91.28	0.00397	91.04	0.0139624	91.07	0.013983

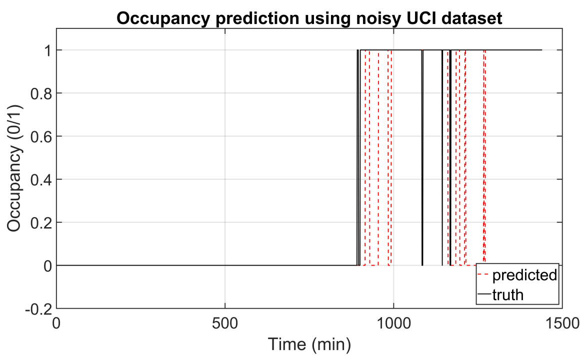

Fig. 4: *Occupancy prediction using UCI dataset with 10% white gaussian noise on **multivariate** Occ-STPN*

in both events very accurately, and in household 5, though there is delay in the prediction, our framework is able to predict a certain period of unoccupied status fairly well.

Table II shows both the accuracy metric and FMMSE metric. It shows that we could obtain decent prediction accuracy, but we think the accuracy metric does not fully reflect the prediction performance due to the existence of a time lag. Hence, we analyze the prediction performance for transferability using FMMSE as suggested in Section 3-E. By using random probabilities, we obtained an FMMSE of 0.2724, which is twice the highest FMMSE among the households (household 4). Notice for household 4, it has a huge error due to multiple false alarms in the predictions, followed by household 1 which was slightly penalized as it predicts the events but not the time period of the events. Similarly, for household 3, it was able to predict the events, but with the correct prediction on the transition, the FMMSE value is slightly lower than household 1. Lastly, household 5 performs really well by having the good predicted number and period of unoccupied events as reflected in the lowest FMMSE value among other household. All in all, household 5 is probably the most transferable option based on the FMMSE value, and we believe with some tuning of the framework, we could reduce the delay and enhance the performance on these transferred framework predictions.

Lastly, Table I provides a complete comparison of univariate Occ-STPN, multivariate Occ-STPN and a common method linear discriminant analysis (LDA) method. Comparing both tables, in the transfered univariate Occ-STPN prediction setting, the accuracy will generally be lower and the FMMSE value will be higher as well. However, in Table I itself, both multivariate and univariate Occ-STPN are providing better accuracy and FMMSE values than the LDA method. In other words, by using only household 2 for training and predicting, both methods are still comparatively better than the incumbent method.

TABLE II: *Performance metrics for occupancy prediction transferability using ECO household 1,3,4 and 5 dataset on **univariate** Occ-STPN*

Household	Appliances power data	Accuracy(%)	FMMSE
1	Fridge, Kettle, Freezer	83.99	0.0246
3	Tablet, Freezer	90.66	0.0195
4	Entertainment, Fridge, Freezer, Tablet	88.92	0.1417
5	Entertainment, Fridge, Tablet	70.73	0.0141

6. Conclusion

Occ-STPN is a scalable, transferable, and reliable framework for occupancy detection. We proposed two variants of the framework, multivariate Occ-STPN and univariate Occ-STPN. Multivariate Occ-STPN considers the relationships between the predictors in predictions and offers high accuracy, while univariate Occ-STPN does not consider and does not require the relation between predictors and offers good flexibility and scalability. Besides that, we proposed a new metric, fading memory mean square error (FMMSE), which takes into account the time delay in making predictions. Some noticeable shortcomings from the result can be seen that the prediction was fluctuating at some part especially when predicting unoccupied status, and there could potentially be a slight time lag in prediction as well. Another drawback of Occ-STPN is that the time and space complexity grows exponentially with increasing number of partitions. This issue was solved by state merging operation as it accelerates the performance by merging uninformative states and tremendously reduces the size of transition matrix. For future work, we will extend our framework into a forecasting algorithm by considering longer training sequences, and develop new approaches that enhances Occ-STPN flexibility without completely removing the relational patterns between the predictors.

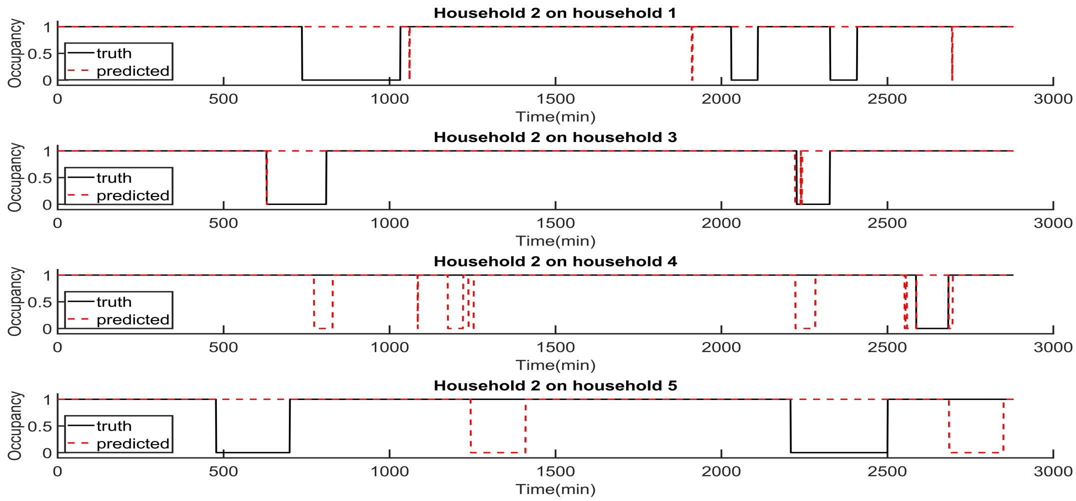

Fig. 5: *Occupancy prediction of ECO dataset household 1,3,4 and 5 using framework trained on household 2 on* ***univariate*** *Occ-STPN*

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