Disaggregation Based Occupancy Estimation

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ABSTRACT

Accurate room-level occupancy estimation is essential to different building applications for energy saving, smart building management. However, there is often a trade off between sensor budgets and estimation accuracy. In this paper, we try to find a balance point in those two metrics and propose a new occupancy estimation method by disaggregating accurate floor-level counts via existing common sensors available at room-level. The result shows our method can make the occupancy estimation with a average of 5.16 RMSE, which is lower than widely used method HMM of a average of 7.98 RMSE by using same sensor features on the same data set.

1 INTRODUCTION

Accurately estimating the number of occupants in the rooms of a building has many applications including smart spaces utilization, smart building operation and facility management. In addition, Combining occupancy information with traditional building management system can increase the energy saving in the buildings. A study has been shown that annual energy saving of 10%-42% can be achieved if a proper HVAC strategy that accounts for actual occupancy levels [8]. In all above applications, the more accurate estimation of room occupancy we can get, the greater energy saving or better services a building can supply.

As the growing importance of occupancy information in the energy-efficient and occupant-centered operation of buildings, a variety of sensor technologies have been studied and applied to occupancy count problem. By comparing the result of different approaches, the vision-based occupancy detection systems [13] normally get the highest accuracy and require less manual system calibration. However, in order to get room-level occupancy count information, every target room needs to setup at least one camera, which are usually expensive and could raise privacy concerns. Another type of approaches is to reusing commonly available room-sensors for occupant sensing including PIR sensors [12], wifi access points [5] and different environment sensors like CO_2 sensors, humidity sensors and temperature sensors [6]. Although this type of approaches are less intrusive and require lower cost, the occupancy count results they provide usually have relatively low accuracy. Work [9] has shown that CO_2 measurement errors vary widely and sometimes are too error-prone for occupancy counting.

In this paper, we develop a method for estimating room-level occupancy counts by disaggregating floor-level counts. The floor-level counts are collected from high-precision 3D stereo-sensors [13], and then disaggregated into room-level counts by using measurements from commonly available low-precision sensors in each rooms. This method is more cost effective compared to above vision-based approaches, since it does not require camera installation in each target room. Moreover, by combining low accurate sensor measurements with aggregated floor-level counts, this method can provide a more accurate room-level counts.

The contribution of this paper is showed as follows:

- we propose a new occupancy estimation method by disaggregating accurate floor-level counts via existing common sensors available at room-level. The algorithm includes 1) a method for modeling occupancy probability; 2) a method for modeling the relation between room-level counts and floor-level counts; 3) a disaggregation method.
- we test our method on real-world dataset from a large office building. The result shows our method can make the occupancy estimation with a average of 5.16 RMSE, which is lower than widely used method HMM of a average of 7.98 RMSE.

2 RELATED WORK

A variety of sensing modalities have been studied in occupancy estimation area. Low cost common available sensors are widely used, such as CO2 sensors, temperature sensors [3], PIR sensors [12]. Fisk et. al. evaluate the performance of 44 CO2 sensors located in nine commercial buildings [9], they conclude low precision CO_2 sensors are often too error-prone to use for occupancy estimation. Dong et. al. in [6] have used ambient-sensing system, CO_2 system and indoor air quality sensing-system to discern the room-level occupancy. Some studies also focus on taking advantage of HVAC sensors which already are installed in most commercial buildings [1, 2]. However, those methods often either provide estimation with relatively low accuracy or need extensive calibration.

Another line of work is using high-precision vision-based sensing system. Sangogboye et. al. [10] report a RMSE of 3.3 for a three hours evaluation by using 3D cameras. POEM in [7] utilizes cameras deployed in public hallways along with PIR sensors within rooms to infer occupancy, it shows a 94% accuracy on detecting transitions. However, install such vision-based sensors are costly and may cause privacy issue. The estimated installation cost for installing dedicated 3D stereo-vision sensors is 328,000$ in a size of 8,000m^2 office building [11].

In order to take advantage of low-cost of common available sensors and high precision of vision-based sensors, Dcount [11] install dedicated high precision people-counting sensors that count occupants when passing the perimeter of the building and then utilize existing common sensors to disaggregate the counts to room-level. The work of Dcount inspires us continue to work on this new concept which estimate room-level occupancy by disaggregating building-level counts. The main difference between our work with Dcount is that we use data-driven model to model the occupancy probability $P(M_i^t|N_i^t)$ and we also utilize the occupancy relation pattern between room-level counts and floor-level counts by introducing $P(N_i^t|A^t)$.

3 PROBLEM DEFINITION

We assume there are R rooms in the floor. At each timestamp t, given the aggregated floor-level count A_t and the sensor measurements in each room $\{M_t^1, M_t^2, ..., M_t^R\}$, our disaggregation algorithm produces the room-level count N_t^i for each room i. The main idea of our algorithm is to estimate more accurate room-level counts by disaggregating floor-level count using data from inaccurate sensor measurements. The sensor measurements can be any measurements from common available sensors in each room like CO_2 sensors, temperature sensors and humidity sensors which are normally already exist in commercial buildings. The aggregated floor-level count are collecting by high-precision vision-based sensor which are installed around the floor. For example, we can install cameras in each enter gateway of the floor to count the entering and exiting people, then combine these counts or using more powerful post-processing algorithm [13] to continuously get the aggregated floor-level count.

4 DISAGGREGATION METHODOLOGY

In order to get the room-level counts, in each timestamp t, our algorithm computes $P(N_t^1, N_t^2, ..., N_t^R|A_t, M_t^1, M_t^2, ..., M_t^R)$,where N_t^i is the room-level count of room i, A_t is the aggregated floor-level count and M_t^i is the sensor measurements in room i. Each M_t^i is a vector of length k, which contains measurements from k sensors in room i. We assume the room-level count of each room is independent with other rooms. So we can get the equation (2) base on this assumption. According to the relation graphical model shows on figure (2), we can decompose the $P(N_t^i, A_t, M_t^i)$ into two separate probabilities $P(M_t^i|N_t^i)$ and $P(N_t^i|A_t)$, then we can get equation (3).

$$
\begin{aligned}
&P(N_t^1, N_t^2, ..., N_t^R|A_t, M_t^1, M_t^2, ..., M_t^R) &(1)\\
&= \prod_{i=1}^{R} P(N_t^i|A_t, M_t^i) &(2)\\
&= \prod_{i=1}^{R} \frac{P(N_t^i, A_t, M_t^i)}{P(A_t, M_t^i)}\\
&= \prod_{i=1}^{R} \frac{P(N_t^i, A_t, M_t^i)}{\sum_{n=0}^{A_t} P(M_t^i, N_t^i = n, A_t)}\\
&= \prod_{i=1}^{R} \frac{P(N_t^i, M_t^i|A_t)P(A_t)}{\sum_{n=0}^{A_t} P(M_t^i, N_t^i = n|A_t)P(A_t)}\\
&= \prod_{i=1}^{R} \frac{P(M_t^i|N_t^i, A_t)P(N_t^i|A_t)}{\sum_{n=0}^{A_t} P(M_t^i|N_t^i = n, A_t)P(N_t^i = n|A_t)}\\
&= \prod_{i=1}^{R} \frac{P(M_t^i|N_t^i)P(N_t^i|A_t)}{\sum_{n=0}^{A_t} P(M_t^i|N_t^i = n)P(N_t^i = n|A_t)} &(3)
\end{aligned}
$$

The main goal of our disaggregation algorithm is to find the room-level counts $\{N_t^1, N_t^2, ..., N_t^R\}$ which maximize the $P(N_t^1, N_t^2, ..., N_t^R|A_t, M_t^1, M_t^2, ..., M_t^R)$. Therefore, the next step is to model $P(N_t^i|A_t)$ and $P(M_t^i|N_t^i)$. In our dataset, we have around one year's sensor measurements and occupant counts of each room, so data-driven model is chosen to model these two probabilities. We use Hidden Markov Model (HMM) for modeling $P(M_t^i|N_t^i)$ since HMM has been well studied and shows relatively high accuracy in room occupancy estimation [6] and Artificial Neural Network (NN) for modeling $P(N_t^i|A_t)$. Our method for estimating room-level counts based on sensor measurements and aggregated floor-level counts are illustrated in figure (1).

4.1 $P(M_t^i|N_t^i)$ Modeling

In this section, we explain how to infer $P(M_t^i|N_t^i)$ by trained HMM. From [6], a Hidden Markov Model is "a statistical model in which the system being modeled is assumed to be a Markov process with unobserved hidden states". The objective of the model is to determine the hidden states from the observable parameters. In our work, the room-level count is considered to be hidden state and the selected features from sensor measurements are observations. The HMM structure shows on fig.(1). N_t represents occupant count at time t and $\{M_t^1, M_t^2, ..., M_t^k\}$ are the sensor measurement features at time

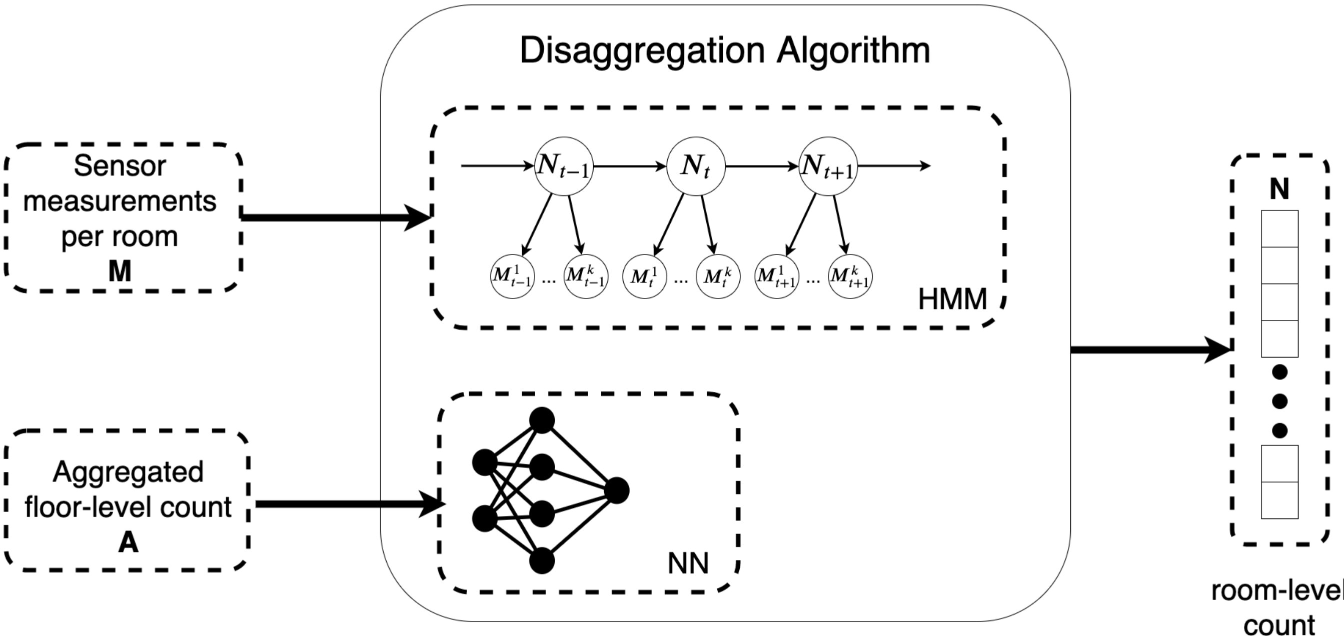

Figure 1: Overview of the method.

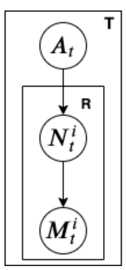

Figure 2: Relation graph model.

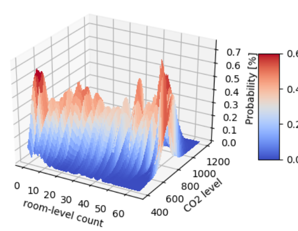

Figure 3: $P(M_t^i|N_t^i)$ for CO_2 readings at different room-level counts in time t

t. The objective is determine the probability of sensor measurements at time t given room-level count at same time point.

In our dataset, there are 5 sensors installed in each room to measure different environmental factors, which are CO_2, humidity, illuminance, temperature, Variable air volume (VAV). After comparing the results from different studies [4, 6] and several experiments implemented by ourselves, we choose to use CO_2 and humidity as our observation features in HMM. Other sensor modalities also can be included in features.

The Python package ODToolkit [16] is used for training HMM from the observable sensor measurements and to obtain $P(M_t^i|N_t^i)$ parameter. In ODToolKit, the model parameters are estimated using maximum likelihood estimation (MLE). Since the ground truth of maximum occupant counts in each room is unknown, we use maximal room capacity as the largest occupant counts for specifying the number of hidden states. We train one HMM per room. Figure (3) shows the probabilities $P(M_t^i|N_t^i)$ for different CO_2 readings over different room-level counts in one specific room.

4.2 $P(N_t^i|A_t)$ Modeling

In this section, we use a simple neural network to model the probabilities of room-level count given aggregated floor-level count in time t. We assume both room-level counts and floor-level counts data in each timestamp t are available in training stage. Neural Network is a computational approach that mimics the functioning of biological neural networks. NN is a non-linear statistical data modeling tool and has been successfully used in different area including pattern recognition [16]. In this paper, we adopt a simple one-hidden-layer fully connected neural network. We use floor-level count A_t with the *hour* of day denoted by $\mathbf{h}$ as the input features. In training stage, instead of using one-hot encoding vector of room-level count N_t^i as ground truth label, we use a probability vector $\mathbf{O}$. The length of vector $\mathbf{O}$ is $C_i + 1$, where C_i is the maximal capacity of the room i. Each entry $O[i]$ is the relative likelihood that variable i is equal to ground truth N_t^i. In other words, $O[i] = f(i)$, where function f is the probability density function of $Normal(\mu = N_t^i, \sigma = 1)$. We use Kullback-Leibler divergence loss for loss function to measure the distance between two probability distribution. The reason we choose to use probability vector O rather than one-hot encoding vector of N_t^i as target output is because one-hot vector usually are used for classification problems.

4.3 Disaggregation

The disaggregation algorithm is to get vector of disaggregated room-level counts by using trained HMM, trained NN and the aggregated floor-level count A_t in each timestamp t. The pseudocode in Algorithm (1) lists the steps of the disaggregation algorithm. The algorithm first find all possible room-level counts combinations from A_t and the number of rooms R. Then in every room-level counts combination, it computes the joint probability shows in equation (1) using our trained HMM and NN. The algorithm keep recording the best combination which has the highest joint probability until go through all combinations. Once the number of rooms R increases linearly, the number of possible combinations will exponentially increase, which will significantly slow down the algorithm. However, in this paper, our dataset only includes three rooms where algorithm runs in a reasonable time. We will explore some evolution strategies [15] for speeding up the algorithm in our future work.

Algorithm 1: disaggregation algorithm

```
Input: trainedHMM, trainedNN and floor-level
       count A
Result: Disaggregated room-level counts
maxP := 0.0;
maxCombination := None;
combinations := findAllPossibleCombinations(A, R);
for (N_1, N_2, ..., N_R) in combinations do
    P := computeJointProb((N_1, N_2, ..., N_R),
      trainedHMM, trainedNN);
    if P > maxP then
        maxP := P;
        maxCombination := (N_1, N_2, ..., N_R);
    end
end
return maxCombination
```

5 EXPERIMENT

5.1 Dataset

To evaluate the occupancy estimation approach, we use the dataset collected in a large office building via sensors on room-level occupant counts together with related data on indoor environmental quality [14]. The office building is approximately $8500m^2$, which has 1000 occupants on normal weekdays and it facilitates several types of student and staff activities. The data is collected from three rooms, two of them are study zones and one is a lecture room. Six PC2 3D stereo vision cameras from company Xovis have been installed to collect the occupant counts entering and leaving the rooms. Except having vision cameras for counting occupancy, each room contains several sensors to measure the indoor environmental quality factors including CO_2 level, relative humidity, illuminates, temperature, and the in-room airflow estimated by the damper position (VAV). The filled version dataset includes measurements from March 1_{st}, 2018 to April 30_{th}, 2019, which has around 63360 sensor readings for each sensor. We use 90% of data to train our HMM and NN model, and 10% for evaluation. The evaluation data is spanning from Jan., 2019 to Apr., 2019.

5.2 Result

We run the proposed method on our evaluation dataset to estimate room-level occupants in each room. We use the Root Mean Squared Error (RMSE) to quantify and compare the accuracy of different algorithms. In order to highlight the improvements of our proposed method, we compare our method with widely used HMM occupancy estimation model [4]. Table (1) shows the performance of proposed method and HMM. Room1 is the lecture room, and Room 2,3 are the study zones. The evaluation result shows that our proposed method outperforms the HMM method in all 3 rooms.

Table 1: The RMSE of Our approach and HMM

Method	Room1	Room2	Room3
Our Approach	6.34	3.04	6.11
HMM	11.14	3.16	9.65

Figures (4), (5), (6) show the our approach and HMM predictions, and ground truth room-level occupancy in 3 rooms at a specific day. In figure (4), we can observe the prediction error becomes high when the ground truth occupancy level is low. The reason for this observation maybe due to fact that our method is highly dependent on the accuracy of $P(M_t^i|N_t^i)$ model and $P(N_t^i|A_t)$ model. In our work, we use same HMM model for modeling $P(M_t^i|N_t^i)$ and we can see

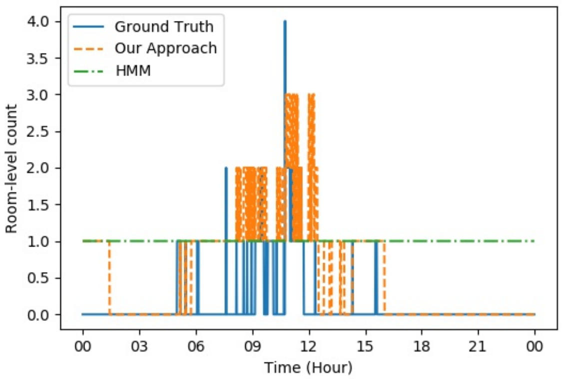

Figure 4: Estimated room-level counts in room1

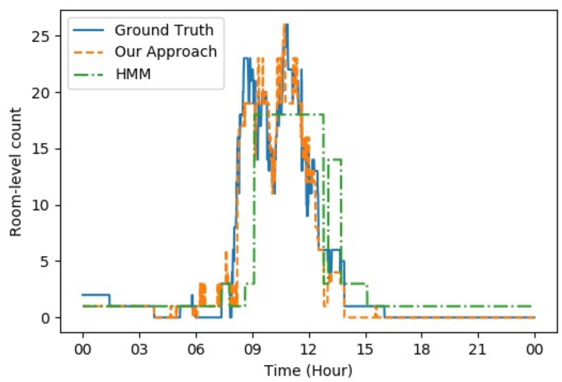

Figure 5: Estimated room-level counts in room2

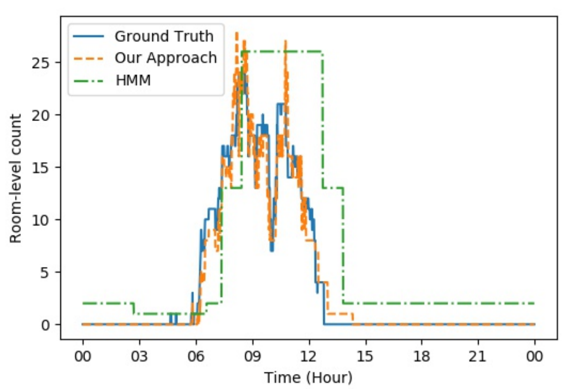

Figure 6: Estimated room-level counts in room3

HMM shows bad prediction performance during that specific day in room 1. In future work, we will explore more robust methods to model these two probabilities. There is a another observation can be seen is that high prediction errors in three rooms generally occur in same time period. It is because the room-level counts are assigned using aggregated floor-level count in same timestamp. If wrong prediction happens in one room, the error will accumulate in other rooms' prediction.

6 DISCUSSION

In this paper, we estimate room-level occupancy by disaggregating floor-level counts collected using high-precision people counting sensors with less accurate common sensors at room-level. This method can take advantage of low cost of common sensors and high precision of dedicated people counting sensors without raising privacy issue. The result of experiments shows our disaggregation method improves the performance compared to data-driven method HMM.

Despite of the novelty of our disaggregation technique, it has several limitations. First, we assume the three rooms in dataset are located in same floor. However due to fact that the room identity is anonymized, we have no evidence for this assumption. And the number of rooms we test is too small to make strong conclusion on performance improvement. In the future work, we plan to create our own dataset for testing our approach. Second, in our experiments, we only compare our method with one widely used method. Therefore, it could be relevant in future work to evaluate our work with other state-of-art methods studied in occupancy estimation. Last but not least, the occupancy relation pattern between room-level counts and floor-level counts, $P(N_t^i|A_t)$, is very specific to one floor, which can not be generalized to other floors. What's more, the room-level ground truth data is only available in training stage for $P(N_t^i|A_t)$ modeling. However, in testing stage, as the time goes by, the occupancy relation pattern may significantly changes and these changes will not be captured by our trained model. Thus, the most important work in our future is to find ways to avoid using the occupancy relation pattern between room-level counts and floor-level counts.

7 CONCLUSION

In this paper, we propose a new occupancy estimation method by disaggregating accurate floor-level counts via existing common sensors available at room-level. This method can take advantage of low cost of common sensors and high precision of dedicated people counting sensors without raising privacy issue and it is cost-effective as it scales to large buildings without requiring high precision people counting sensors in each rooms. The result shows our method can make the occupancy estimation with a average of 5.16 RMSE, which is lower than widely used method HMM of a average of 7.98 RMSE.

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