DCount - A Probabilistic Algorithm for Accurately Disaggregating Building Occupant Counts into Room Counts

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***Abstract*—Sensing accurately the number of occupants in the rooms of a building enables many important applications for smart building operation and energy management. A range of sensor technologies has been studied and applied to the problem. However, it is costly to achieve high accuracy by instrumenting all rooms in a building with dedicated occupant sensors. In this paper, we propose a new concept for estimating accurate room-level counts of occupants. The idea is to disaggregate accurate building-level counts via existing common sensors available at the room level. This solution is cost-effective as it scales to large buildings without requiring dedicated sensors in each room. We propose an algorithm named DCount that implements this concept. Our results document that DCount can provide room-level counts with a low normalized root mean squared error of 0.93. This is a major improvement compared to a state-of-the-art algorithm using common sensors and ventilation rate measurements resulting in a normalized root mean squared error of 1.54 on the same data set. Further more, we demonstrate how the results enable occupant-driven analysis of plug-load consumption which is one out of many applications using accurate room-level counts of occupants we hope to enable by proposing DCount.**

1. Introduction

Sensing accurately the number of occupants in the rooms of a building has many applications within data-driven mobile computing. Examples of applications include smart spaces, safety and evacuation, facility management and smart building operation. In terms of building operation accurate people counts can enable applications, such as, adaptive ventilation in rooms, occupant-based energy benchmarking, and model-predictive control of room setpoints. In all these applications the more accurately the number of occupants can be sensed the safer or more energy-efficient a building can become [1], [2].

A range of sensor technologies has been studied and applied to the problem of using sensors to count occupants [3]. These sensing systems have to balance tradeoffs among accuracy, scalability, and cost. One line of work has studied reusing commonly available building sensors for occupant sensing. Studied sensor modalities include CO_2 sensors, PIR sensors, or WiFi access points [4]. However, often these modalities alone only provide information with a high Root Mean Squared Error (RMSE). For instance, Kjærgaard et al. [5] report a RMSE of 21.7 for counting occupants using PIR sensors in a small office building and [6] report an accuracy around 50% for counting occupants in a large hospital complex using WiFi access points. For CO_2 sensors existing work [7], [8] has shown that such sensors are often too error-prone to use for occupant sensing. For instance, Ebadat et al. [9] report only good results given a deep integration with HVAC system components and extensive calibration.

Another line of work has studied lightweight dedicated people counting sensors for occupant counting in all areas of a building. Beltran et al. [10] explore the idea of densely deploying lightweight thermal sensors for occupant counting in all areas of a building. Hnat et al. [11] explore the idea of instrumenting door openings for count sensing. Another option is based on computer vision technology including monocular, stereo, and thermal cameras. These sensors are quite accurate in the short term and long term stability can be obtained by probabilistic modeling [12]. Installing such sensors at a room level can be costly. For instance, the large office building considered in this paper has a size of 8,000 m^2, has eight external entrances and 136 rooms with 164 room entrances. The estimated installation cost for installing dedicated 3D stereo-vision sensors is 328,000$ and room-level vision sensors also raise privacy concerns.

A more cost efficient solution is to install the dedicated 3D stereo vision sensors that count occupants when passing the perimeter of the building. Figure 1 gives an example of such count data over eighteen days for the large office building. However, this solution does not provide accurate counts on a room level needed by the listed applications.

In this paper, we propose a new concept for estimating accurate room-level counts by disaggregating building-level counts. The building-level counts are collected using dedicated high precision people-counting sensors and then disaggregated using less accurate common sensors at the room level. In this paper we focus on 3D stereo-sensors as dedicated people counting sensors. This solution is cost-effective as it scales to large buildings without requiring dedicated people counting sensors in each room. We propose

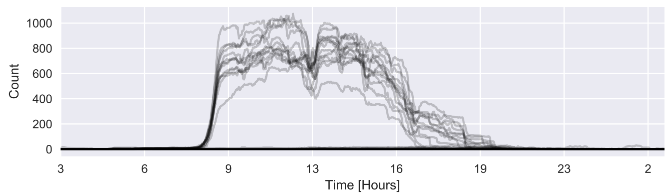


Figure 1: Daily occupant counting profiles for eighteen days in a large office building.

the algorithm DCount that implements this concept. Our results document that this solution can provide room-level counts with a high accuracy.

The main contributions of this paper are as follows:

- Propose a new concept for estimating accurate room-level counts by disaggregating building-level counts collected using dedicated high precision people-counting sensors by less accurate common sensors at the room level and other building information.
- Propose a probabilistic algorithm named DCount for accurately disaggregating building-level occupant counts into room-level counts. The algorithm includes: 1) a method for estimating occupant probabilities based on sensor measurements from common sensor modalities; and 2) a method for disaggregating building-level counts to room-level counts based on occupant probabilities.
- Provide extensive evaluation results for the accuracy of the DCount algorithm based on data from a large office building. Our results document that DCount can provide room-level counts with a low normalized RMSE of 0.93. This is an improvement compared to a state-of-the-art algorithm using common sensors and ventilation rate measurements resulting in a normalized RMSE of 1.54 on the same data set.
- Present an application of using the room-level counts produced by DCount for analysing room-level plug-load consumption.

2. DCount: an Algorithm for Disaggregating Building-level Counts

We propose the DCount algorithm to implement the concept of estimating room level counts by disaggregating building-level counts. The DCount algorithm estimates room-level counts based on the inputs and algorithmic steps illustrated in Figure 2. By (X) we refer to the labels on the figure. Three types of configuration inputs (A) is assumed by DCount: 1) a count B for the building from accurate dedicated people counting sensors that monitor the building perimeter; 2) a list C of maximal room capacities, e.g., as specified on a fire evacuation map; 3) optionally, a list A of the spatial layouts of rooms represented by polygons. Furthermore, the algorithm takes as input for each room inaccurate measurements M measured by common sensors for each time step (e.g., Boolean presence measurements from PIR sensors or readings from CO_2 sensors) (B). The DCount algorithm estimates room counts based on a probability distribution where each element represent a spatial area in a building, e.g., a distribution over a regular grid of points spanning all floors in a building based on the room layouts in A. The probability distribution might be initialized with a uniform distribution or be derived from a posterior distribution of a temporally preceding execution of the algorithm (C). The algorithm follows a Bayesian estimation approach to update the probability distribution with the given inaccurate room-level measurements (D). To produce room-level counts the algorithm runs a disaggregation method that given the building-level count B, the probability distribution and the room capacities C estimate room-level counts R. Finally, the room-level estimates R are provided as outputs of the algorithm.

3. Problem Formalisation

Given a building with n rooms, the goal of DCount is to output a vector R of length n where element R_i is the count estimate for the room number i. DCount can run continuously outputting a reading every time step to produce a time-series of room counts. The core idea of the algorithm is to disaggregate a building-level count B using data from inaccurate common sensors and building information. The building-level count can among others be measured using dedicated people counting sensors monitoring the perimeter of the building. The counts can then be combined or even better processed by an algorithm such as PLCount to remove biases and apply error correction techniques [12]. We here assume that B is available for every time step t where we want to run DCount.

DCount takes several types of information into account about the building. We formulate five versions of the algorithm depending on the sensor data and amount of information available about a particular building. We explore the five different versions to demonstrate that DCount can work in different settings. For some buildings all the listed information is available via information services for calendar bookings or indoor map services (e.g. [13]). Else, these data can be collected with a bit more effort manually either via fire evacuation plans or building drawings. We consider the following five versions in this paper:

DCount-S: uses data from common sensors for the rooms in R. The part of a building that is not part of R, e.g., hallways are modeled as a single area named "common area".

DCount-SA: assumes that in addition to the sensor data for each room we also have information about the spatial layout of rooms. In particular that a vector A of room layout polygons where A_i is the polygon representing the layout of room i. The polygon is represented in a common Cartesian coordinate system for the whole building including information of the floor level the polygon is placed on. This information enables DCount-SA to take the size of the room into account. This is based on an assumption that larger

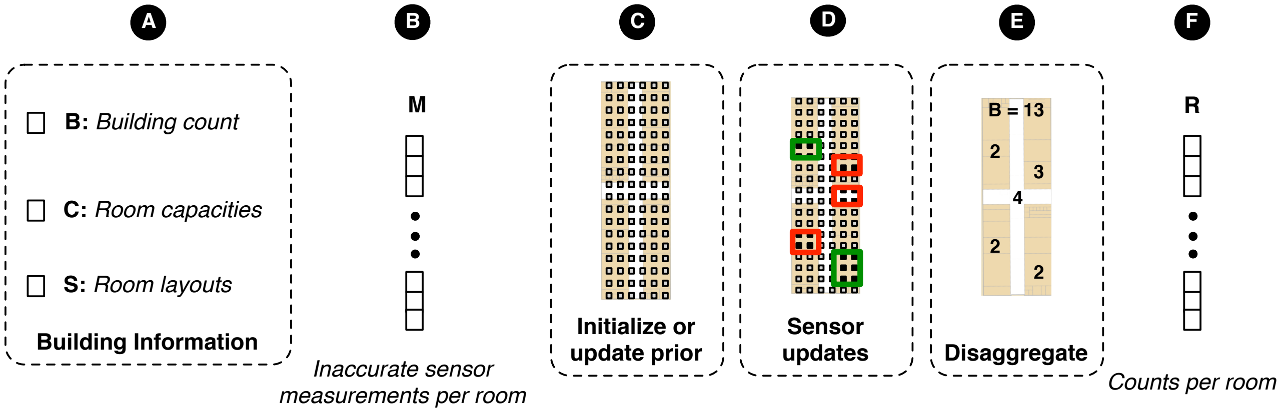


Figure 2: Overview of inputs, algorithmic steps, and outputs of the DCount algorithm.

rooms will often have a higher number of occupants than smaller ones.

DCount-C, DCount-SC and DCount-SAC: assume the availability of a vector C of maximum room capacities of occupants where C_i is the maximum capacity of room i. The capacity can among others be used by the algorithm as an upper limit on occupation. The room capacity is often available either via fire evacuation plans or building drawings. For common areas we put the capacity at a lower limit than what is allowed for fire safety. This is to reflect that prolonged occupation of these areas are uncommon as they are only used as people move through the building. DCount-C only uses capacities and is included as a reference for the other methods. DCount-SC combines sensor data and capacity information and DCount-SAC combines sensor data, spatial layout information and capacity information.

3.1. Measurements

When DCount uses common sensor data it takes as input any sensor measurements available at the room level. The sensor measurements might be CO_2 or PIR measurements. However, other measurements could also be used, such as, door openings, power consumption or wireless network usage. Let M be a vector of length n where each entry M_i is a list of measurements available for room i. The list of measurements contains tuples of T x v where T is the type of measurement and v is the value of the reading. As the sample times and frequencies might differ among sensors we assume that M contains the most recent reading from any sensor. There might be rooms in a building with no sensors, however, based on our own observations these are often rooms not designed for prolonged occupation, e.g., storage, technical or cleaning facility rooms. The algorithm takes such rooms into account but does not update occupation probabilities based on any measurements.

3.2. Initialization

As the basis for DCount we have chosen to apply a Bayesian estimator. The goal for DCount is an algorithm that works without training data from the sensors of the particular building in target. Therefore, this goal constraints us from applying learning-based algorithms. Bayesian estimation is a well-known and robust framework. The Bayesian estimator uses general models to avoid being dependent on training data. To scale the algorithm to very large building complexes, particle filters might be an option to consider to avoid the state space explosion with a Bayesian estimator. However, in this paper we presents results for a 8000 m^2 building where the algorithm runs instantly and, therefore, we leave particle filters as a possible future extension.

For modeling the estimation problem we define π as a probability vector over the space of the building in question. For DCount-S, DCount-C and DCount-SC the length of π matches the number of rooms and each entry π_i is the probability for occupation in room i. For DCount-SA and DCount-SAC we use the spatial layout for each room to generate an equal distanced grid of points over all rooms. A separate grid is generated for each floor in the building. Thereby, each entry π_i is the probability of occupation for the grid point number i. Figure 3 visualises such a grid on the case building for all three floors. The grid is constructed with a point-to-point distance of approx. 2.5m in north-south directions and approx. 1.25m in east-west directions. This sizing result in 2,247 gridpoints in total and at least one gridpoint per room. Using a finer grid will result in longer run times of the algorithm but will not increase accuracy as the measurements of each common sensor is used to update all points in a room. This grid is also used in the presented results.

Before each run of the algorithm we initialize π using an uniform distribution. We have also tested the option of using the occupant probabilities from the preceding time step to initialize π with. However, this option did not lead to improved performance. The main reason being that each CO_2 reading in a room is not independent of the last reading. Therefore, over time the occupation probabilities quickly accumulates in a few rooms resulting in highly erroneous estimates. DCount-C only initializes π and skips the sensor update step.

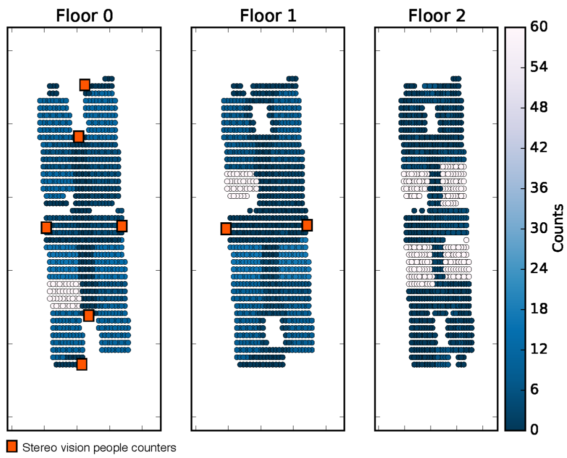


Figure 3: Gridpoints over three floors colored by estimated disaggregated counts including placement of stereo vision people counters.

3.3. Sensor Updates

Using Bayesian estimation we update the probability vector π with sensor measurements M for each time step. Assuming that the sensor measurements for each room are independent we update using:

$$\overrightarrow{\pi}'_i = \frac{P(M_i|i) * \overrightarrow{\pi}_i}{\eta} \tag{1}$$

where

$$\eta = \sum_{i=1}^{n} P(M_i|i) * \overrightarrow{\pi}_i \tag{2}$$

The parameter η is a normalizer to make sure that π is a valid probability vector.

The occupation probability for each measurement $P(M_i|i)$ is calculated by the following model. The model at present incorporate the sensor modalities CO_2 and PIR but can be extended to include other sensor modalities as relevant. The motivation behind the model is that CO_2 and PIR measurements are inaccurate proxies for occupation. In particular CO_2 sensors are inaccurate because of the following reasons: Firstly, if ventilation is present CO_2 will only increase until a set-point for ventilation is reached, however, in most buildings the set-point is the same through out the building. This means that equal likelihood for occupation can be assigned to different rooms in a building based on CO_2. Secondly, CO_2 is reacting slowly to changes in occupation. Thirdly, opening and closing of windows and doors will lower the CO_2 content compared to the occupation level. Given these error sources we have designed a probability model that include CO_2 as a relative indication of occupation for disaggregating counts and PIR as a Boolean indication of occupation. DCount has the advantage that by combining CO_2 with building-level counts it can upscale small changes in CO_2 which might address the slow reaction in the measurements.

The model is defined as follows:

$$P(M_i|i) = \frac{Z(M_i) + \beta}{\lambda} \tag{3}$$

where β is a balancing constant, $Z(M_i)$ is the occupation factor given the sensor readings, and λ is a normalization factor. The role of β is to keep the probabilities above a certain threshold so a room or gridpoint never becomes extremely unlikely which will limit the system in reacting to changes in number of occupants. In our experimental results we used a value for β of 0.1.

The CO_2 readings in M are preprocessed from absolute readings to relative CO_2 readings by subtracting the natural CO_2 level. The natural CO_2 level is estimated as the minimum CO_2 level that a sensor has recorded in the preceding fourteen days. If M_i contains a relative CO_2 reading (v_{CO_2}) and a PIR reading (v_{PIR}) then

$$Z(M_i) = \begin{cases} v_{CO_2} & \text{if } v_{PIR} \text{ is true} \\ 0 & \text{if } v_{PIR} \text{ is false} \end{cases}$$

if M_i only contains a CO_2 reading then $Z(M_i) = v_{CO_2}$. If M_i only contains a PIR reading we put $Z(M_i) = 100$ to represent the ppm increase of CO_2 in a lightly occupied room compared to the natural CO_2 level. The argumentation is that CO_2 sensors are most often present in highly occupied rooms where as PIR sensors are used in less occupied rooms. The parameter λ is defined as follows:

$$\lambda = \sum_{j=1}^{v_{\max CO_2}} j \tag{4}$$

Here $v_{\max CO_2}$ is the maximum among all CO_2 measurements in M for each time step. Thereby, the factors are relative to the room with the highest CO_2 concentration. Figure 4 shows the probabilities $P(M_i|i)$ for different CO_2 readings over a day as $v_{\max CO_2}$ changes.

3.4. Disaggregation

The disaggregation is performed to compute a vector R of room counts from the occupation probabilities π and the building-level count B. In the following we will focus on the disaggregation algorithm for DCount-C, DCount-SC and DCount-SAC, however, DCount-S and DCount-SA are similar except for not applying the room capacity to balance probabilities and limiting room counts based on the room's maximum capacity. The pseudocode in Algorithm 1 lists the steps of the disaggregation algorithm. The algorithm first sums probabilities at a room level. To balance probabilities in regards to the capacity of the rooms, we multiply with the room capacities and normalize the probabilities. The assignment procedure assigns counts starting with the room with the highest probability for occupation. The reason for this is that we would rather assign a person counted to a

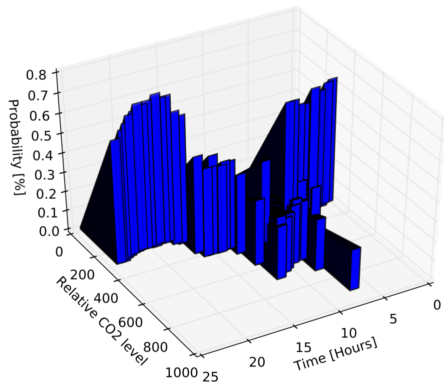


Figure 4: Occupation probabilities $P(M_i|i)$ for relative CO_2 readings with $v_{\max CO_2}$ changing at different times a day.

room with a high probability than spread them out in rooms with a low probability. The algorithm then continues until all counts have been assigned to rooms.

Algorithm 1: Capacity-based disaggregation algorithm

Data: Probability vector π and building-level count B
Result: Disaggregated room counts R
Fill a vector Π with an entry for each room by summing π entries for each room;
Multiply each Π_i with the room capacity C_i and normalize;
Initialize A := 0;
while A *less than* B **do**
  Select room R_i with the highest probability Π_i;
  Calculate the percentage s of Π_i out of the sum of Π;
  Assign the share s of $B - A$ to R_i;
  Π_i := Π_i modulo s;
  if R_i *more than* C_i **then**
    R_i := C_i;
  end
  A := A + R_i;
end

4. Implementation

The DCount algorithm has been implemented in Python for our evaluation study. The DCount algorithm uses the pandas framework for processing time series data. The PLCount algorithm was implemented in Python and used to clean count data [12]. All sensor data queries and storage of time-series sensor data is handled using the sMAP [14] software platform.

To evaluate the DCount algorithm sensor measurements, and building information data were obtained from a large office building. The large office building is a 8,000 m^2 building, it records an average of 1,000 occupants on normal weekdays and it facilitates several types of staff and student activities. Room types in this building comprises mainly of offices, classrooms, and study areas. Eight PC2 3D stereo-vision cameras from the company Xovis are installed along the perimeter of the building to cover the transitions through the entrances and exits of the building. This includes six ground-level entries and two walkways connecting the building to neighboring buildings. Measurements are collected from KNX connected PIR and CO_2 sensors in 81 and 89 rooms, respectively. The eight rooms without PIR sensor data are parts of hallways. The measurements are collected per minute on the sMAP software platform for building data [14]. The 47 rooms in the building without any sensor data consists of technical rooms, hallway areas, and storage rooms. For the evaluation we use a dataset spanning 30 days from September to October 2016 which are busy months in the building. This dataset contains 345,600 people counts, 3,499,200 PIR readings and 3,844,000 CO2 readings. Room capacities were extracted from building plans for the 136 rooms. The room layouts are available as open data from an indoor map service API provided by [13]. The API provides the room layouts as polygons represented in geojson including floor information.

5. Results

This section presents accuracy evaluation results for applying the disaggregation concept and the DCount algorithm in particular. The results cover an evaluation with room-based ground-truth data for four rooms and visual inspection of results for a larger set of rooms in the building.

5.1. Evaluation Setup

To quantify and compare the accuracy of the algorithms we use the Normalized Root Mean Squared Error (NRMSE). We favor the use of NRMSE over RMSE because RMSE can only be interpreted with a prior knowledge of the duration and the particular occupant-level of each room. In the following results we compute NRMSE for each day and each room normalized by the average number of occupants computed via ground truth data. This respects the changes in occupant-levels on different weekdays and in different rooms and at the same time normalize the values by the occupant-level so they are comparable.

The room-based ground-truth evaluation is based on ground-truth data for four rooms where two are regular teaching rooms and two are student zones with mixed use for student activities, such as, project work or solving exercises. The ground truth is collected by eight highly accurate PC2 3D stereo vision cameras from the company Xovis mounted over the two room entrances to each of the four rooms. The implementation of the PLCount algorithm was used to clean the data. Previous results with this type of sensor and the

PLCount algorithm has demonstrated an accuracy of 0.075 RMSE compared to a manual ground truth [12]. Therefore, the accuracy of this setup is several times more accurate than DCount and can therefore be used as ground truth to evaluate the accuracy of DCount.

We evaluate the five different variants of the DCount algorithm using different amounts of sensor data and building information: DCount-C, DCount-S, DCount-SC, DCount-SA, and DCount-SAC and for different combinations of measurements from common sensors: CO2+PIR, CO2 and PIR.

To highlight the improvements of using the disaggregation concept for room-level count estimation and the implementation in DCount we compare to a state-of-the-art algorithm based on common sensors and ventilation rate measurements named Ref-HVAC. The contribution of this paper is the idea to combine building-level counts and common sensors to estimate room counts and the implementation of this idea with DCount. Therefore, we do not in the following compare to rudimentary approaches that use the building-level counts or common sensor values as these have much worse accuracies. For instance, we tested an algorithm combining PIR and room capacities which had an NRMSE of above 3.5 on our dataset.

Ref-HVAC is a state-of-the-art method for estimating occupants using common CO_2 sensors and ventilation rate measurements similar to Gruber et al. [8]. Compared to DCount this method requires integration with the BMS to access ventilation rate measurements and it also requires calibration of a number of method parameters. The method is based on step-wise error minimization in the following transient balance equation:

$$V_r \frac{dc_r}{dt} = \frac{p\dot{V}_{cp} + (\dot{V}_{ve} + N_{inf}V_r)(c_n - c_r)}{3600}, \qquad (5)$$

where V_r [m^3] is the room volume, c_r is the room CO_2 concentration [ppm], p is the number of occupants (estimated), $\dot{V}_{cp}$ is the CO_2 generation per person [m^3 per hour], $\dot{V}_{ve}$ is the ventilation airflow [m^3 per hour], N_{inf} is the infiltration airflow expressed in air changes per hour [h^{-1}], c_n is the neutral CO_2 level [ppm] and t is time [s]. Since the CO_2 concentration is very low, it is assumed that it does not affect the air mass balance. Hence, Eq. (5) is formulated using volumetric quantities. This assumption has been tested by Gruber et al. [8]. The ventilation rate is calculated from the VAV box damper position which is measured by the BMS. The infiltration rate N_{inf} and CO_2 generation per person $\dot{V}_{cp}$ depend on the building type and occupant activity level. In this evaluation the parameters were tuned based on 24 hours ground-truth occupant numbers (survey) for one of the rooms. Finally, $N_{inf} = 0.33$ and $\dot{V}_{cp} = 0.04$ were assumed. The model is implemented in Python and Brent's method from the SciPy package is used for error minimization.

5.2. Groundtruth-based Accuracy

Figure 5 plots NRMSE results for the five variants of the DCount algorithm and the reference algorithm by their

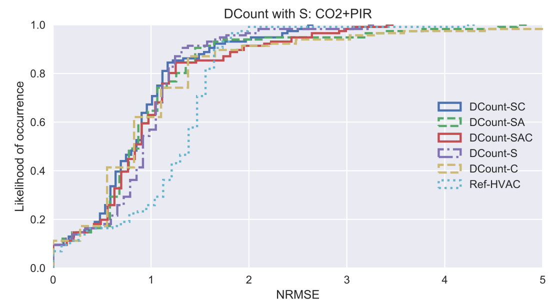


Figure 5: DCount NRMSE results as a CDF over individual days with both CO_2 and PIR measurements.

Cumulative Distribution Function (CDF). The results are computed using both CO_2 and PIR measurements. From the figure we can observe that the different formulations of the DCount algorithm provide a comparable performance. However, DCount-SC has the best overall performance and DCount-C and DCount-SA the worst as they in several cases produces a NRMSE above 2.5. The NRMSE of Ref-HVAC is consistently worse providing evidence for the benefits of DCount.

To evaluate the individual sensor modalities' contribution to accuracy, Figure 6 and 7 show results with only CO_2 and PIR measurements, respectively. The results for CO_2 show the same picture as with both measurement types with DCount-SC as the best performer. The results for PIR is substantially worse than combined with CO_2 in particular there is a higher level of large errors. This is also supported by that DCount-C which does not use the sensor measurements has the best performance. Overall the DCount algorithm is still better than Ref-HVAC. These statements are confirmed by Figure 8 which directly compare the performance of DCount-SC with different sensor combinations.

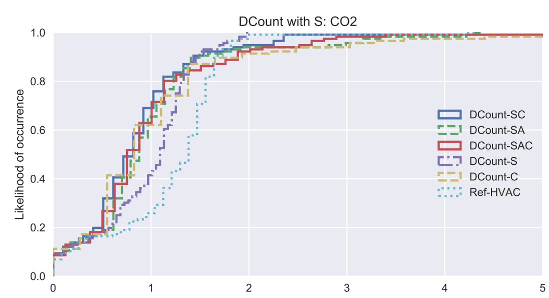


Figure 6: DCount NRMSE results as a CDF over individual days with CO_2 measurements.

To consider the impact of the types of room we have studied the individual results for classrooms and study zones. The classrooms have the highest occupation with a maximum of 84 people and the study zones have a lower maximum occupation of 32. The median of the NRMSE for DCount-SC with CO2+PIR in the two classrooms are 0.6 and 0.83, and in the study zones 0.85 and 0.94. In all rooms

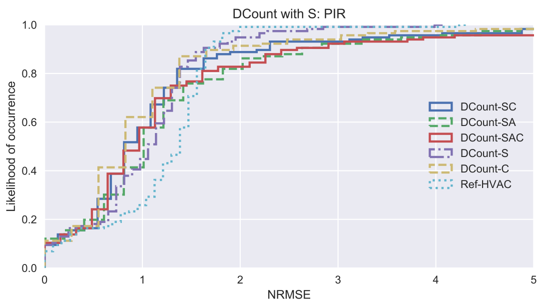


Figure 7: DCount NRMSE results as a CDF over individual days with PIR measurements.

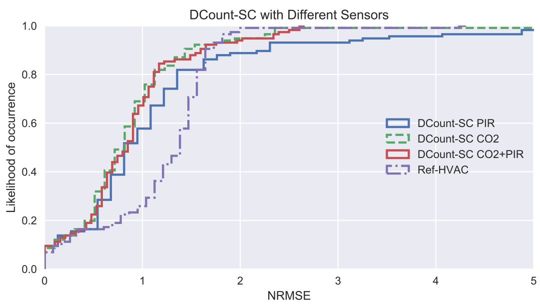


Figure 8: DCount-SC NRMSE results as a CDF over individual days for different sensors.

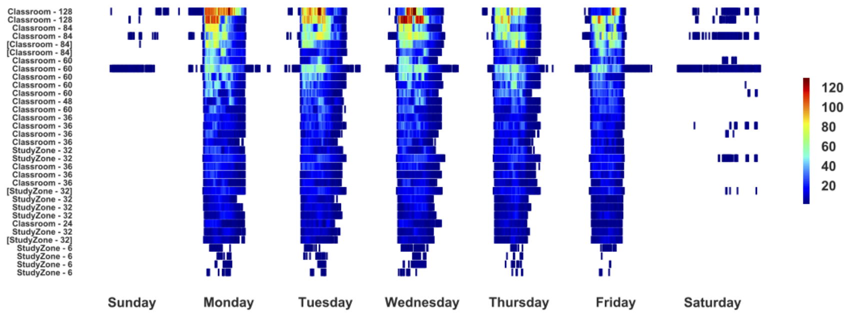
this is an improvement over Ref-HVAC with medians for the NRMSE of 1.56 and 1.1 in the classrooms, and 1.41 and 1.44 in the study zones, respectively.

5.3. Visual Analysis

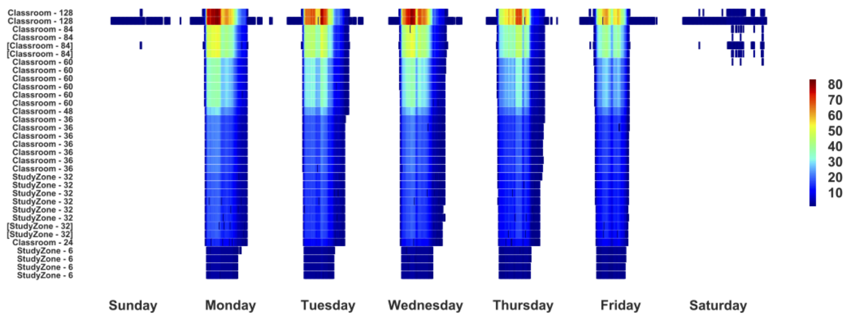
To evaluate the results from all the rooms we are limited to apply visual inspection as it is infeasible to collect ground-truth data in all rooms of the building. However, it is still relevant to check the correctness of the estimates for the rest of the rooms in terms of overall expected patterns. To visually inspect the correctness of the estimates we have visualised the results for rooms designed for occupation of more than six persons. The reason we leave out individual offices is to protect the privacy of individuals. Figure 9 shows the estimates over a week in the middle of September with the four rooms analysed with ground-truth data highlighted with brackets. The two subplots show the estimates for DCount-SC and DCount-C, respectively. What we hope to observe is that patterns we expect to find is reflected in the data. In terms of expected occupant patterns both staff and students have access to the building 24/7. Classes are scheduled primarily between 8-16 on weekdays. If we focus on DCount-SC, firstly, we can observe the difference between day and night, and weekdays and weekend. Secondly, we can observe the high occupation in the classrooms as they are designed for. For study zones we can observe less structured start and end times than in the scheduled class rooms. We can also notice that students use the building in weekends. We expect that the occupation outliers in the evening, night and morning can be attributed to cleaning, technical and security staff visiting the rooms outside normal office hours. Therefore, the data for DCount-SC based on a visual inspection provides the patterns we would expect. DCount-C which does not use any room-level sensor data provides a median accuracy of 1.12 in the presented results but with the highest deviation. However, from the visual inspection we can notify that the produced estimates are unusable in practice as all rooms of similar sizes get the same counts. This might be a good estimate on average, however, this does not enable applications such as adaptive ventilation control. The issue is that the adaptive system can only save power for ventilation when the system can detect that it can go into a low power consuming operation. Therefore, DCount-SC provides much better estimates for this application than the difference in accuracy indicates.

6. Occupancy-driven Energy Analysis

Given the positive results we in this section illustrate the use of the DCount produced room-level counts. This is just one of the many use cases for room-level occupant counts. The case we consider is occupant-driven energy consumption analysis. The case is motivated by a wish of the technical staff in the large office building to analyse the consumption of students' plug-loads. In the building a rich metering infrastructure is installed among others electricity metering of plug-loads on a room-level. In total the building consumed 18,397 kWh in September 2016 where 27% is plug-loads, 23% is ventilation, 15% is room lightning, 12% is lighting for decoration plants, and the remaining is split among networking equipment, elevators and pumps. DCount enables an analysis of these meter readings versus occupants. It is here important that the occupant data is as accurate as possible as else the technical staff will not trust the analysis. Figure 10 plots an example from this analysis. The figure shows the relation between daily plug-load consumption and total daily occupation time for two different room types. The total occupation time is computed from the DCount room-level estimates by summing over a day the total occupation of each room for each time step. From the two figures one can observe a great variation in consumption and occupation for each day. The variation has the greatest variation for the study zones. This might be due to a greater variation in consumption between solving exercises on paper and collaborative work with laptops and other equipment. For the class rooms, we also observe a large variation, but for days with prolonged occupation, we see a clear increase in consumption. Looking at the general trends of consumption versus occupation, it is approximately 12 Wh per occupation hour in the class rooms and 24 Wh per occupation hour in the study zones. However, with a substantial variation for any particular day. These numbers might look small but with hundreds of students in the building they sum up. The sum is actually a large percentage of the overall consumption of the building as all other systems in the building have been designed to be extremely energy



(a) DCount-SC



(b) DCount-C

Figure 9: Estimated counts over seven days for rooms designed for occupation of more than 6 persons.

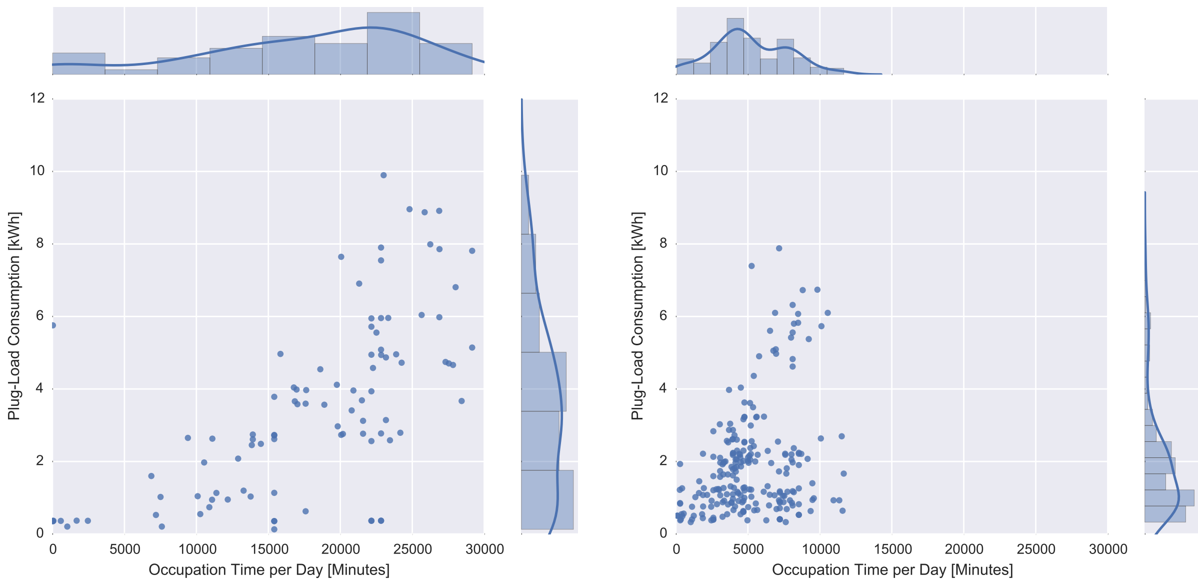
efficient. This analysis is an important input to designing, for instance, nudging campaigns for powering off unused laptops with the screen on and doing energy budgets based on knowledge of student behavior as numbers grows and drops over the years. This case illustrates how the counts produced by DCount can be applied to analyse electricity consumption over a wide range of rooms which is one out of many applications of room-level count data [1], [2].

7. Related Work

Many sensing modalities have been considered for counting room occupants. A commonly used sensor for controlling ventilation rates is a CO_2 sensor. Several studies have considered sensing occupants using CO_2 sensors [7], [8], potentially, in combination with other sensors [15]. An obvious challenge for utilizing CO_2 sensors is the long response time resulting in detection delays. Fisk et. al. in [7] analyse the accuracy of CO_2 based occupant counts using 44 CO_2 sensors deployed in nine commercial buildings. The study concludes that the sensors are very prone to failures and calibration errors. Only a deep integration with the HVAC system (which is rarely possible) combined with door and window sensors enables a highly accurate system using these sensors [9].

Another occupant detection method is Wi-Fi measurements [4], [6], [16], [17]. Christensen et. al. identified a partial correlation between Wi-Fi enabled devices connected to existing network infrastructure and electricity consumption in commercial buildings. They concluded from these results that connected devices can be a fair metric for estimating occupants in a building. Schauer et. al. [16] proposed a method based on Wi-Fi management frames in which typical devices (smartphones, laptops) without additional software can reliably be detected. Ruiz et. al. extracted spatio-temporal features from similar measurements of Wi-Fi management frames in order to determine occupants density and flow, and to classify behavioral roles within an hospital building. A challenge with these methods is that occupants are required to carry personal devices. Kleiminger et al. [17] explored using similar data in a residential setting. Similar challenges could be noticed in [18] which utilizes Bluetooth beacons for occupant detection in buildings. The system proposed in [18] requires active connection to installed Bluetooth beacons and all gathered location data from monitored devices are sent to a server for additional processing. The accuracy recorded was only based on connected devices not on ground-truth occupant counts of people in the detected location. Kjærgaard et. al. [5], compared count data obtained from PIR sensors in a building with ground-truth data. The results highlight that PIR sensors are not fit for occupant counting because of a RMSE of 21.7. Thermal cameras and 3D counting cameras [12] can both provide highly accurate counts but are costly to install in many rooms.

Another line of work has studied lightweight dedicated people counting sensors for occupant counting in all areas of a building. Beltran et al. [10] explore the idea of densely deploying lightweight thermal sensors for occupant counting in all areas of a building. Hnat et al. [11] explore the idea



(a) Classrooms

(b) Study zones

Figure 10: Relationship between time spent in rooms by occupants and plug-load consumption per day.

TABLE 1: Comparison of cost and accuracy properties of different solutions.

Solution	Cost of Installation	Cost of Configuration	Limitations	Accuracy (NRMSE)
Dedicated 3D stereo vision sensors	Very High	High	Privacy	<0.1
Ref-HVAC [8]	Medium	High	Integration with BMS	1.54
DCount-C	Medium	Low		1.12
DCount-S (CO_2+PIR)	Medium	Low		1.08
DCount-SAC (CO_2+PIR)	Medium	Medium		0.97
DCount-SA (CO_2+PIR)	Medium	Medium		0.97
DCount-SC (CO_2+PIR)	*Medium*	*Low*		*0.93*

of instrumenting door openings for count sensing. Yang et al. [19] consider densely installing LED sensing for counting occupants. As we argue in this paper a more cost efficient solution for large buildings is to 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 a room-level. The results in this paper document that this concept implemented via the DCount algorithm achieves high accuracy and is a substantial improvement over using the Ref-HVAC algorithm based on common sensor and ventilation rate maesurements.

8. Discussion

The results of the paper document the accuracy of the five versions of DCount for sensing room-level occupant counts. Table 1 compares the properties of the five versions with the state-of-the-art HVAC sensor based solution and room-level monitoring with dedicated 3D stereo-vision sensors. The table covers the properties: *cost of installation* including equipment purchase, *cost of configuration* including any parameterisation and training data collection, *limitations* of the approach and *accuracy*. A solution with dedicated 3D stereo vision sensors at the room-level has a very high cost of installation (e.g. 328,000$ for the large office building) and a high configuration cost for configuring several parameters including counting lines, has limitation in terms of privacy implications but also provides a very high accuracy. Using Ref-HVAC has a medium cost of installation to collect both CO_2 and ventilation rate measurements, high cost of installation to collect calibration data and parameterize the method for each room and result in a poor accuracy. Furthermore, some BMSs do not provide APIs to collect ventilation rate measurements. The different versions of DCount have a medium cost of installation as dedicated 3D stereo-vision sensors have to be installed to collect building counts along the perimeter (e.g. 16,000$ for the large office building). The cost of configuration is either medium or low depending on if the spatial layouts are used or not, respectively. The best performing version of DCount following our results is DCount-SC with CO_2+PIR data which also has a low cost of configuration. However, the PIR data only provide a minor improvement compared to only using CO_2 data.

The results of the paper document DCount as a cost-efficient occupant sensing method with a low NRMSE. These results were produced with one specific combination of dedicated people counting sensors (3D stereo vision cameras) and common sensors (CO_2 and PIR). However, other dedicated and common sensors could be applied with the DCount algorithm, e.g., the ones mentioned in related work. In our future work we plan to explore the combination of other sensor modalities of dedicated and common sensors to evaluate the combinations in terms of accuracy, scalability and cost.

In this work, ground-truth data was collected in two types of rooms. However, the results document that the observed accuracy depends to some degree on the occupant patterns of the rooms. Therefore, it could be relevant in future work to evaluate DCount with data from other room types, e.g., as found in public, retail or industrial buildings.

In this paper, we considered maximum room capacities as well as the spatial layout of rooms as inputs to the algorithm. However, there might be opportunities for further improving the accuracy of the algorithm by additional inputs and modeling elements. An example of an input could be scheduled activities in rooms. However, we are hesitating to follow this direction as often occupant sensing systems are used to quantify deviations from schedules. Using schedules would also require an additional integration with the calendar system of all organizations occupying a building. In terms of modeling an opportunity might be to model the movement of occupants among rooms and gridpoints. This would require additional information about the connectivity of the rooms but might further improve accuracy. Another aspect is to consider the privacy of occupants via anonymization methods [20].

9. Conclusion

In this paper, we considered how to sense accurately the number of occupants in each room of a building. Counts at the room-level enables many important smart building applications. We proposed a new concept for estimating room-level counts by disaggregate building-level counts collected using dedicated high precision people-counting sensors via common sensors at the room level. The solution is cost-effective as it scales to large buildings without requiring dedicated people counting sensors in each room. We implemented the concept with the algorithm DCount and tested five different versions of the algorithm. Our results document that DCount and in particular DCount-SC can provide room-level counts with a low NRMSE of 0.93 which is lower than a state-of-the-art algorithm using common sensors and ventilation rate measurements demonstrating a NRMSE of 1.54. Furthermore, we demonstrated how the results enable occupant-driven analysis of plug-load consumption which is one out of many applications using accurate room counts that we enable by proposing DCount.

Acknowledgment

This work is supported by the Innovation Fund Denmark for the project COORDICY (4106-00003B).

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