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Abstract—We introduce the sensor-utility-network (SUN) method for occupancy estimation in buildings. Based on inputs from a variety of sensor measurements, along with historical data regarding building utilization, the SUN estimator produces occupancy estimates through the solution of a receding-horizon convex optimization problem. State-of-the-art on-line occupancy algorithms rely on indirect measurements, such as CO\textsubscript{2} levels, or people counting sensors which are subject to significant errors and cost. The newly proposed method was evaluated via experiments in an office building environment. Estimation accuracy is shown to improve significantly when all available data is incorporated in the estimator. In particular, it is found that the average estimation error at the building level is reduced from 70% to 11% using the SUN estimator, when compared to the naive approach that relies solely on flow measurements.

I. INTRODUCTION

The goal of this paper is to introduce a framework and algorithms to analyze and estimate occupancy in buildings using sensor measurements from diverse sources, models of facility use, and historical data. Information regarding occupancy levels and distribution patterns in buildings can be utilized for a number of applications, such as: demand-driven ventilation and lighting controls leading to energy savings [4], security monitoring [9], [15], and to accelerate safe evacuation [2].

The estimation approach proposed in this paper generates occupancy estimates based on a combination of sensors, information regarding prior knowledge of building utilization or utility, and the network structure of the building [7]. An algorithm in the resulting class of algorithms is called the Sensor-Utility-Network (SUN) estimator. Sensors may include CO\textsubscript{2}, passive infrared (PIR), video, sound, badge counters, and even measurements of the number of cars in the parking lot. The utility of the building, or zones within, is estimated based on historical data for the same building or a building of similar characteristics, forecast preferences based on room schedules, typical walking speeds in hallways, and hard constraints on occupancy in each room. Finally, the network structure is specified by decomposing the total building into zones, typically based on individual rooms or groups of rooms. The choice of zones will depend on the primary goal (e.g. ventilation control vs. evacuation), and on the number, location, type and accuracy of the sensors. Estimation is then based on a convex program with hard and soft constraints, taking into account the inherent bias and variance of the various sources of information.

The SUN estimator is motivated in part by the pseudo MAP estimator in statistics [5], and was created as a refinement of the algorithm introduced in [15], which is based on the extended Kalman filter. The SUN estimator is much more adaptable than the algorithm considered in [15], in the sense that it can make use of much greater prior knowledge, constraints, and data sources. On the other hand, the algorithm of [15] is much simpler than the SUN algorithm, and it can be constructed in a decentralized fashion so that estimates are based only on local information. In its simplest form, the convex program that defines the SUN estimator is a type of receding horizon estimation, as described in [3]. Refinements of the algorithm incorporate smoothing as well as prediction to make better use of constraints.

In related research [16], a hidden Markov model (HMM) for occupancy behavior was constructed based on estimated network topology, where the observation equation is based on observed one-bit data streams. Estimation is then performed using the standard Bayes estimator [5]. In general the complexity of the HMM can be extremely high. Fluid and Markovian queueing networks have been used to estimate people movement during evacuation, such as Smith and Towsley [13] (see also [6]), the collection of papers [12], and more recent work reported in [15], [1], [10].

This paper is organized in four sections. In Section II we describe the SUN architecture which can be used for the purpose of occupancy estimation, smoothing and prediction in buildings. Section III describes results from experiments in an office building environment instrumented with digital video cameras, passive infrared motion detectors and CO\textsubscript{2} sensors. Also contained in this section is a detailed discussion on construction of penalty function for these sensors, and utility for capturing building usage patterns. Estimation accuracy using SUN is shown to improve significantly when compared to the naive estimation that relies solely on occupancy flow measurements. Finally, we conclude in Section IV with recommendations for future work.

II. SUN ESTIMATOR

The SUN estimator of occupancy is based on information from sensors, historical data for the same building or a building of similar characteristics, and people’s preferences and patterns of behavior for diverse situations.
A. Technical challenges

Advances in sensing, embedded systems and wireless technology enable unprecedented access to data in today’s commercial buildings though temperature sensors, CO₂ sensors, smoke detectors, CCTV video cameras, water flow sensors, RFID sensors, and other access control devices. Other potential sources of data include phone usage, online calendars and schedule records. The resulting large and heterogeneous data streams contain valuable information that remains largely untapped at present.

The goal of the estimation procedure presented here is to use all these potential information sources, and to address the following issues: (i) Cost-benefit trade-offs involved in the selection of sensors and their placement; (ii) Complement sensor measurements with models of building usage; (iii) Selection of sensors and their placement; (ii) Complement

Occupancy estimation would appear to be a matter of simple book-keeping based on all of this data. However, there are several barriers to reliable estimation, such as:

(i) Sensor noise. The selection of the type and quality of sensors will impact the reliability, bias and type of noise of the variables that are in the measurements.

(ii) Lack of observability. If available sensors provide only measurements of the number of individuals that pass from one region to another, then the system is not observable (in the linear system theory sense). This means that a linear filter cannot be used to obtain reliable estimates.

(iii) Lack of reliable models. Databases are available that provide insight into occupant behavior in special cases, such as during egress. However, in normal situations this behavior is highly unpredictable, and is sensitive to culture and environment.

Although any one data source may be unreliable when taken alone, we argue that the data taken together is significantly more informative. This is in fact the motivation for the SUN estimation procedure that combines data from all available sources for estimation.

B. Estimator architecture

We begin with a basic stochastic model, in discrete-time. Let \( x(t) \) denote the vector of occupancy in each zone, and \( r(t) \) the vector of the number of persons moving from one zone to another during time-slot \( t \). The state process \( \phi(t) \) is defined as the joint process,

\[
\phi(t) = \begin{pmatrix} x(t) \\ r(t) \end{pmatrix}
\]

(1)

It is subject to the simple mass-balance constraints

\[
x_i(t+1) - x_i(t) = \sum_j r_{ji}(t) - \sum_r r_{ri}(t).
\]

(2)

Throughout most of the paper it is assumed that for each time \( t \) the vector representing the sequence of observations consists of noisy measurements of a subset of the variables \( \{x_i(t), r_{kl}(t)\} \). With (2) taken as a linear state space model with state \( \phi(t) \), it can be shown that the state process is not observable based on observations of the flow \( r(t) \) alone. In fact, observability requires that measurements of each \( x_i(t) \) be made available. Fortunately, observability is a purely linear concept. There is a great deal of information relative to building usage that can be used to reduce estimation error. For example, it may be known that a building is empty at 4:00 a.m.

To understand the role of prior information, and to motivate the SUN estimator we turn to a Bayesian setting. Consider the general nonlinear model in discrete time,

\[
\begin{align*}
\phi(t+1) &= f_t(\phi(t)) + W(t + 1) \\
y(t) &= h_t(\phi(t)) + V(t + 1)
\end{align*}
\]

(3)

where \( y(t) \) represents the sequence of observations. If the noise in (3) and the initial condition \( \phi(0) \) are jointly Gaussian and mutually independent, and the noise is i.i.d., then it is possible to construct a closed form expression for the a posteriori probability \( p(\phi | y) \). The maximum a posteriori probability (MAP) estimate is then \( \hat{\phi}(t) = \arg \max_{\phi} p(\phi | y(0), \ldots, y(t-1)) \).

Under these assumptions the negative of the log of the probability of observations, \(-\log(p(\phi_0, \ldots, \phi_T | y_0, \ldots, y_{T-1}))\), is proportional to

\[
||\phi_0 - \bar{\phi}_0||^2_{\Sigma_0} + \sum_{t=0}^{T-1} \left( ||y(t) - h_t(\phi(t))||^2_{\Sigma_{yt}} \right)
\]

\[
+ ||\phi(t + 1) - f_t(\phi(t))||^2_{\Sigma_{tt}} \}
\]

(4)

where \( (\Sigma_{dt}, \Sigma_{yt}) \) are the covariance matrices for \( (W(t), V(t)) \), \( \Sigma_0 \) is the covariance of the initial condition, and \( \phi_0 \) is its mean. It is useful that the application of variance information on sensors and dynamics arises so naturally in the estimator.

Computation of the estimates \( \{\hat{\phi}(0), \ldots, \hat{\phi}(T)\} \), given the observations \( \{y(0), \ldots, y(T-1)\} \), reduces to a quadratic program (QP) when \( h_t \) and \( f_t \) are linear, and there are no hard constraints on \( \phi \). In this special case, the MAP estimator coincides with the Kalman filter. Since the model is constrained, it makes little sense to assume that any of these random variables are Gaussian. Regardless, the resulting estimation algorithm defined as the optimization (4) subject to state space constraints, is very appealing and flexible.

The estimator introduced in this paper generalizes these ideas through the introduction of utility and penalty functions that model behavior. These functions are denoted as follows:

\( U_z \): Occupancy utility function defined for each room or connections between rooms, such as corridors.

\( P_0 \): Penalty function that models confidence in the initial estimate \( \phi_0 \).

\( P_g \): Penalty function based on sensor information

\( P_d \): Penalty function based on temporal dynamics.

Each of these is a function of \( \phi = (x, r) \), and the specific form of the penalty and utility functions will be determined based on various factors. Some suggestions are provided later.
The convex program that defines the SUN estimator is given as the minimization,
\[
\arg \min_{\phi_0, \ldots, \phi_T} \left\{ \mathcal{P}_0(\phi_0) + \sum_{t=0}^{T-1} [\mathcal{P}_y(\phi(t), y(t)) + \mathcal{P}_d(\phi(t+1), \phi(t)) - \mathcal{U}_e(\phi(t))] \right\}
\]
(5)
The minimizer in (5), subject to given hard constraints, is taken as the estimates \(\{\hat{\phi}(0), \ldots, \hat{\phi}(T)\}\), given the observations \(\{y(0), \ldots, y(T-1)\}\).

Interpretation of the results of the estimator requires special considerations. At time \(T\) the SUN estimator gives the \(T+1\) estimates \(\{\hat{\phi}(0; T), \ldots, \hat{\phi}(T; T)\}\) after solving the optimization problem (5). \(\hat{\phi}(T; T)\) is the current estimate of the state. For \(t < T\), \(\hat{\phi}(t; T)\) is interpreted as the smoothed estimate of \(\phi(t)\). We can also obtain predictions of future state values. Define \(\hat{\phi}(t; T)\) for \(t > T\) through a second optimization procedure after \(\hat{\phi}(T) = \hat{\phi}(T; T)\) is obtained. Fix \(T_1 > T\) and consider,
\[
\arg \min_{\phi_Tr, \ldots, \phi_T1} \left\{ \sum_{t=T}^{T_1-1} \left[ \mathcal{P}_d(\phi(t+1), \phi(t)) - \mathcal{U}_e(\phi(t)) \right] \right\}
\]
(6)
and subject to \(\hat{\phi}_T = \hat{\phi}(T)\). In some situations smoothing and prediction should be performed simultaneously. For example, if it is known that a very large meeting is scheduled at 3:00 p.m., then this information should be made available at time 2:30 p.m. In this case, at time \(T\) we solve the optimization problem,
\[
\arg \min_{\phi_0, \ldots, \phi_T, \ldots, \phi_T1} \left[ \mathcal{P}_{\text{smooth}} + \mathcal{P}_{\text{pred}} \right]
\]
(7)
where \(\mathcal{P}_{\text{smooth}}\) is the summand in (5), and \(\mathcal{P}_{\text{pred}}\) is the summand in (6). Thus, the SUN estimator can be employed in different modes: smoothing, estimation and prediction.

C. Construction of Utility and Penalty Functions

This section describes the mathematical construction of a utility function for occupancy and flow rate; and a penalty function for initial estimates, temporal dynamics and sensors.

1) Penalty functions: The construction of the penalty function \(\mathcal{P}_y\) is based on a linear observation model, \(y(t) = C\phi(t) + N(t)\) for some matrix \(C\), where \(N\) denotes an i.i.d. sensor noise process. The discussion leading to (4) motivates the general form,
\[
\mathcal{P}_y(\phi(t), y(t)) = \mathcal{P}_y(y(t) - C\phi(t))
\]
(8)
If \(N\) is a zero-mean sequence, then \(\mathcal{P}_y: \mathbb{R}^n \rightarrow \mathbb{R}_+\) vanishes only at the origin.

As for \(\mathcal{P}_d\), the mass-balance constraint (2) is imposed as a hard constraint in the optimization (5), so that
\[
\tilde{x}_i(t+1) = \tilde{x}_i(t) + \sum_j \tilde{r}_{ji}(t) - \sum_k \tilde{r}_{ik}(t).
\]
(9)
Soft constraints on \(\tilde{r}(t)\) can be imposed via,
\[
\mathcal{P}_d(\phi(t+1), \phi(t)) = \mathcal{P}_d(r(t+1) - Ar(t))
\]
(10)
with \(A\) a square matrix, and \(\mathcal{P}_r\) similar to \(\mathcal{P}_y\). For example, \(\mathcal{P}_r\) is interpreted as a continuity constraint if \(A = I\).

2) Utility functions: Utility functions in the SUN estimator can be constructed based on historical data, or prior knowledge regarding occupancy and people flow. The optimization procedure to obtain the estimates \(\{\hat{\phi}(t)\}\) will impose hard constraints on occupancy levels: non-negativity, upper limits, and the mass-balance constraints in equation (9). Hence the utility function can be designed without regard to state space constraints.

The following is a non-exclusive list of possible factors included in the utility function:

- **Occupancy**: Prior knowledge takes on various forms, depending on context. In an office building there are scheduled meetings; in a park a music event may be scheduled in advance. Figure 1 illustrates a typical piecewise linear utility function that could represent these priors. The particular shape depends upon the uncertainty on the a-priori expected occupancy.

- **Rates**: In a building, the utility of a hallway is low from the point of view of occupation, while the utility for the same hallway from the point of view of transportation is high.

Since traffic can go in one of two directions, the utility function for a given rate would appear as shown in Figure 2. To obtain a convex program based on this function of rates, it is necessary to expand the dimension of the state space, treating \(r_i\{r_i \geq 0\}\) and \(-r_i\{r_i < 0\}\) as separate variables.

- **Patterns**: In applications over a large region with limited information a utility function that favors certain patterns of behavior might be considered, including clustering and lane formation.

- **Seasons or times of the day**: The utility functions may vary seasonally, with time of the day or even days of the weeks and holidays. For example, a park utility function is usually higher during the day than over night. This changes on a 4th of July, when crowds gather to watch fireworks in U.S. cities.

III. EXPERIMENTAL RESULTS: ARCHITECTURE

In this section we describe the estimation architecture constructed for experiments in an office building.
\textbf{A. Sensor and sensor layout}

Figure 3 shows the building floor layout as well as locations of the sensors. Three classes of sensors were used in the experiments: (i) Digital Video Cameras, (ii) Passive Infrared (PIR) Detectors, and (iii) CO$_2$ sensors. Ten video cameras were installed across pre-defined lines located at the 5 entrances of the floor and in the middle of the hallways. Twelve non-directional PIR sensors were located in pairs between the video cameras. Additionally, 15 CO$_2$ sensors were distributed in different rooms.

1) Video Cameras and PIR Detectors: Video cameras can provide information regarding people count and the direction of flow. These cameras if not properly installed and configured can exhibit significant errors, arising from three main factors. Firstly, during early and late hours, when the lighting condition is poor, a single person crossing may be counted multiple times. Also, turning a light switch on or off may trigger a sensor count. Secondly, multiple people crossing at the same time may be undercounted. Lastly, the video system may count several crossings during a time interval in which there are occupants loitering close to the camera. Such events lead to a significant positive bias. Figure 7 (subplots in first row) illustrates the consequence of this bias for a naive estimator based on simple flow-counts (see (15)).

PIR detectors provide indication of motion within sensor range. The detectors employed in this study were non-directional. By using them in pairs, they were rendered directional to obtain a convex program.

2) CO$_2$ Sensors: CO$_2$ sensors provide concentration readings in parts per million (ppm), which is indicative of the occupancy. However, reliably correlating CO$_2$ levels with the actual occupancy is difficult due to the high variability and slow response time of CO$_2$ sensors: Variability arises due to fluctuations in ambient CO$_2$ levels, HVAC system settings, and door status (open/close). In addition, there are dynamics: CO$_2$ measurements suffer from slow response time. For example, the inevitable delay in CO$_2$ concentration increase following an increase in occupancy (about 10-20 minutes in this study).

In the next section we show how the bias, variance and dynamics in the occupancy and flow measurements, can be systematically handled in the SUN framework.

\textbf{B. SUN Implementation}

The estimation algorithm used in the experiments was a special case of the convex program (5), with the objective function,

$$
\begin{align*}
\sum_{t=0}^{T-1} \left\{ P_y(\phi(t), y(t)) + \| \phi(t+1) - A_t \phi(t) \|^2_{\Sigma_t^{-1}} - U_x(\phi(t)) \right\} + \| \phi_0 - \bar{\phi}_0 \|^2_{\Sigma_0^{-1}}
\end{align*}
$$

where, $P_y$ and $U_x$ are quadratic functions of $\phi = (x, r)$. In addition bound constraints were imposed on occupancy and flow. As a result, the convex program simplifies to a quadratic optimization problem.

The building floor was divided into 11 zones, dictated by the location of video and PIR sensors (see Figure 3 for specifications). The matrix $A_t$ in the dynamics penalty term in the objective (11) was taken to be the identity matrix. Incorporating CO$_2$ measurements in the above framework requires additional modifications. This is described in detail below, along with the construction of $P_y$, $U_x$, and the choice of bounds.

1) Penalty function for Video Cameras and PIR Motion Detectors: It was pointed out in Section III-A that video sensors suffer from large accumulated bias and variance. The PIR detectors used in our study provide much coarser data — these sensors completely miss people-count information. Statistical models are required in order to adaptively correct for such missing data.

Assume that we have a prior probability distribution $p_{ij}(r)$, that the flow from zone $i$ to zone $j$ is $r_{ij} = r$, given that the PIR indicates movement. To simplify notation in this discussion, consider just two such prior distributions $\{p_i : i = 0, 1\}$, where $p_0$ is the probability distribution when the PIR sensor does not indicate any activity and $p_1$ is the distribution when it is activated (see top two panels of Figure 4). Assume that these probabilities are log-concave:

$$
p_i(r) = e^{-p_i(r)}
$$

That is, $P_i = -\log(p_i)$ is a convex function of its argument. By convolving the $\{p_i\}$ we can obtain a probabilistic model at any time scale desired for occupancy estimation. The convolved function is not convex in general. In numerical experiments we found that convolutions preserve convexity when $p_i$ has small support. Moreover, the Central Limit Theorem justifies this approximation: Letting $p = e^{-P}$ denote the convolution, this may be approximated by a Gaussian distribution with mean equal to the sum of the means, and variance equal to the sum of the variances. This approximation is illustrated in the two bottommost panels in Figure 4.

Motivated by this, we take the sensor penalty term $P_y$ in (11) to be of the form

$$
P_y(\phi, y) = \sum_{i=1}^{N_f} \sum_{j>i} P_{y_{ij}},
$$

\textbf{Fig. 3. Sensor layout for people traffic estimation.}
where \( N_f \) is the total number of flow sensors (video and PIR), and the terms \( \{ P_{y_{ij}} \} \) are soft penalty for each sensor,

\[
P_{y_{ij}}(r_{ij}, y_{ij}) = \frac{1}{2}(r_{ij} - b_{ij}(y_{ij}))^2 / \sigma_{ij}^2,
\]

with \( b_{ij} \) the bias (that depends on the measurement \( y_{ij} \)), and \( \sigma_{ij}^2 \) is the variance. These parameters defining the soft penalty functions for video count and PIR sensors were obtained by an extensive statistical analysis of the ground truth occupancy flow data.

2) Utility for Occupancy: A smoothing procedure was used to construct occupancy utility functions at zonal levels by using historical data of the building usage pattern. In smoothing, at the end of each day, say at 11pm, the algorithm (11) was run over the period \([0, T] = [12am ... 11pm]\), with the constraint that occupancy is near zero at the beginning and end of the period. The SUN estimator returns estimates \( \{ \hat{\phi}^k(t : T) : t = 0, \ldots, T \} \) of occupancy and flow for each day \( k = 1, \ldots, N \). Based on these occupancy estimates over several weeks, we obtained the mean and variance of occupancy in various zones, for each hour

\[
\mu_i = N^{-1} \sum_{k=1}^{N} \bar{x}_{ik}, \quad \sigma_i^2 = N^{-1} \sum_{k=1}^{N} (\bar{x}_{ik} - \mu_i)^2
\]

where, \( i = 1, \ldots, N_z \), with \( N_z = 11 \) equal to the total number of zones. This information was translated to occupancy utility in the SUN estimator, as

\[
U_i(x) = \sum_{i=1}^{N_z} U_i(x_i),
\]

where, the zonal occupancy utility function is the quadratic

\[
U_i(x_i) = -\frac{1}{2}(x_i - \mu_i)^2 / \sigma_i^2.
\]

The minus sign comes from the fact that utility is to be maximized. We applied this smoothing procedure on sensor data from 16 days to obtain the mean and variance of occupancy for the different zones. Figure 5 shows hourly occupancy estimates at building level obtained for 4 (among 16) days, and also the mean and variance of occupancy as a function of time for two different zones.

3) Incorporating Partial Information from \( \text{CO}_2 \) Sensors:
Recall that \( \text{CO}_2 \) sensors were installed only in some rooms (see Figure 3). The simplest way to incorporate such partial information into the existing formulation (11) is to augment the vector of decision variables with the estimated occupancies of rooms equipped with a \( \text{CO}_2 \) sensor. To simplify the description of the refined algorithm we extend the definition of the state variable via \( \phi(t) = (x(t), x^c(t), r(t))^T \), where, at time \( t \), the vector \( x(t) \) consists of occupancy levels for all zones that do not have \( \text{CO}_2 \) sensor-equipped rooms, and \( x^c(t) \) is the vector of occupancy levels for rooms with \( \text{CO}_2 \) sensors. The mass balance constraint for each zone takes the form,

\[
\bar{x}_i(t + 1) - \bar{x}_i(t) = -\sum_{j=1}^{N_{c,z}} \bar{x}_{ij}^c(t + 1) + \sum_{j=1}^{N_{c,z}} \bar{x}_{ij}^c(t) + \sum_j \hat{r}_{ji}(t) - \sum_l \hat{r}_{il}(t),
\]

where \( N_{c,z} \) is the number of rooms equipped with \( \text{CO}_2 \) sensors in \( i^{th} \) zone. The mean and variances required for the \( \text{CO}_2 \) utility functions are computed empirically using 16 days of \( \text{CO}_2 \) sensor measurement data, similar to as described in the Section III-B.2.

However, before extracting the mean and variance for \( \text{CO}_2 \) utility functions, preprocessing of \( \text{CO}_2 \) measurements is required. First, in order to eliminate the day to day variations, the \( \text{CO}_2 \) readings of a typical day is subtracted by \( \text{CO}_2 \) data on a day without any occupancy (such as a weekend or a holiday). The top and middle panels in Figure 6 shows \( \text{CO}_2 \) profile in an unoccupied and occupied room,
The CO₂ measurements are then denoised using a 4th order low-pass FIR digital filter. The model used to relate the filtered CO₂ measurements $y_i(t)$ (with background CO₂ level subtraction) to the underlying occupancy estimates $x_i(t)$ (accounting for a single step 10 minute time lag) is given by

$$y_i(t + 1) = \alpha y_i(t) + \beta \tilde{x}_i(t),$$

where the coefficients $\alpha$ and $\beta$ are fitted using the ground truth occupancy data and corresponding CO₂ measurement data available, as shown by a red curve in bottom panel in Figure 6. The modeled occupancy is set to zero when the CO₂ level is below a “tolerance” of 50ppm, since the observed variability in CO₂ measurements for zero occupancy is approximately 50ppm. The bottom panel in Figure 6 shows the comparison between the actual occupancy and modeled occupancy using this approach.

4) Bounds on Occupancy and Flow Rates: The lower bound on occupancy level in any zone is set to be zero, while the upper bounds imposed on each rooms in the zone.

C. Occupancy Estimation Results

In this section we compare the SUN estimator with a naive estimator that relies solely on flow measurements. The naive estimator is based on simple counting,

$$\tilde{x}_i(t + 1) - \tilde{x}_i(t) = \sum_j \hat{r}_{ji}(t) - \sum_l \hat{r}_{il}(t),$$

where, $\hat{r}_{ji}(t)$ are the estimates of people flow from video cameras and PIR detectors rendered directional (see section III-A for details).

The accuracy of each method was evaluated based on comparison with the ground truth occupancy evolution —

This was obtained manually by analyzing individual video frames and correcting them for under counts, over counts, and missed detections. In order to obtain building level occupancy ground truth, five peripheral video cameras (labeled as 1,2,3,5, and 9 in Figure 3) which monitor people traffic at entrance and exit locations were chosen. In addition two video people count sensors (7 and 8 in Figure 3) were used in the interior of building to assess the accuracy of occupancy estimates at zonal levels. This pair of zones was chosen since they comprise one of the high traffic areas, and shows wide variability in occupancy levels during the course of the day. The estimation error was computed as the average % error,

$$E = \frac{1}{T_f - T_0} \sum_{t=T_0, x(t) \neq 0}^{T_f} \frac{|x(t) - \hat{x}(t)|}{x(t)},$$

where, $x(t)$ is the ground truth occupancy and, $\hat{x}(t)$ is its estimate, with $T_0 = 6$ hrs corresponding to 6am and $T_f = 18$hrs corresponding to 6pm.

In applying the naive estimator (15), the recursion is initialized to zero occupancy at 12am. Figure 7 shows occupancy estimates in the three zones based on this estimator over a typical weekday. The occupancy levels are either unexpectedly high at the end of the workday or have non physical negative values. The lack of observability is evident from these plots: the video cameras providing flow measurements have a small positive bias that is integrated over the course of the day resulting in a massive error at 6:00 p.m. At building level (see Figure 8), the occupancy variation is more reasonable due to cancelation of mutual errors, although high occupancy at the end of the day is again
unrealistic. The average estimation error based on this naive estimator is around 70%. Figure 9 shows a similar plot at the zonal level, where the estimation error is approximately 30%.

In the SUN implementation we studied in detail the importance of different terms in the objective function (11). Not surprisingly, it was found that the best estimates are obtained by a suitable combination of the different terms, each of which model different source of information: we only report the final results (details can be found in [8]). The zone level SUN estimates are shown in Figure 7, while Figure 8 shows the estimates at the building level. These estimates were obtained for 10 minute intervals by using a backward receding horizon of 1 hour, i.e. $T = 60$ minutes in objective (11). The initial occupancy estimates at 12am were taken to be zero both for the occupancy and the flow rate with a low error covariance $\Sigma_0$.

The estimation error at building level was approximately 11%, while that at zonal level it was around 21% (see Figure 9). Inspite of the large bias and variance in the occupancy and flow measurements, the SUN estimator yields occupancy estimates that are in good agreement with the ground truth, especially at the building level.

IV. CONCLUSIONS

We introduced a sensor-utility-network (SUN) method for accurate estimation of occupancy levels and distribution in buildings. Based on inputs from a variety of distributed sensor measurements (video, PIR, access control, and CO2), along with historical data regarding building utilization, the SUN estimator produces occupancy estimates through the solution of a receding-horizon convex optimization problem. In our experiments we found that this approach reduced average occupancy estimation errors at building level from 70% obtained using a naive estimator, to 11%. Moreover, being a convex program, SUN admits a computationally efficient implementation, making it ideal for real time applications.

There are several challenges that remain to be addressed. These include: 1) evaluation of performance of SUN estimator in predictive applications (e.g. for occupancy based ventilation control); 2) adaptive techniques for learning building usage and associated utility functions; 3) sensitivity of utility functions for spaces and buildings of similar type, and 4) impact of sensor placement (numbers, types and locations) on SUN performance. Finally, decentralized algorithms are required to make these algorithms scalable and reliable in large buildings. Decentralized versions of the SUN algorithm based on message passing via consensus [11], and Lagrangian decomposition [14] are being explored currently.

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