Sensor-Utility-Network (SUN) Method for Estimating Occupancy in Buildings

Presented by: Amit Surana*

Joint Work With:

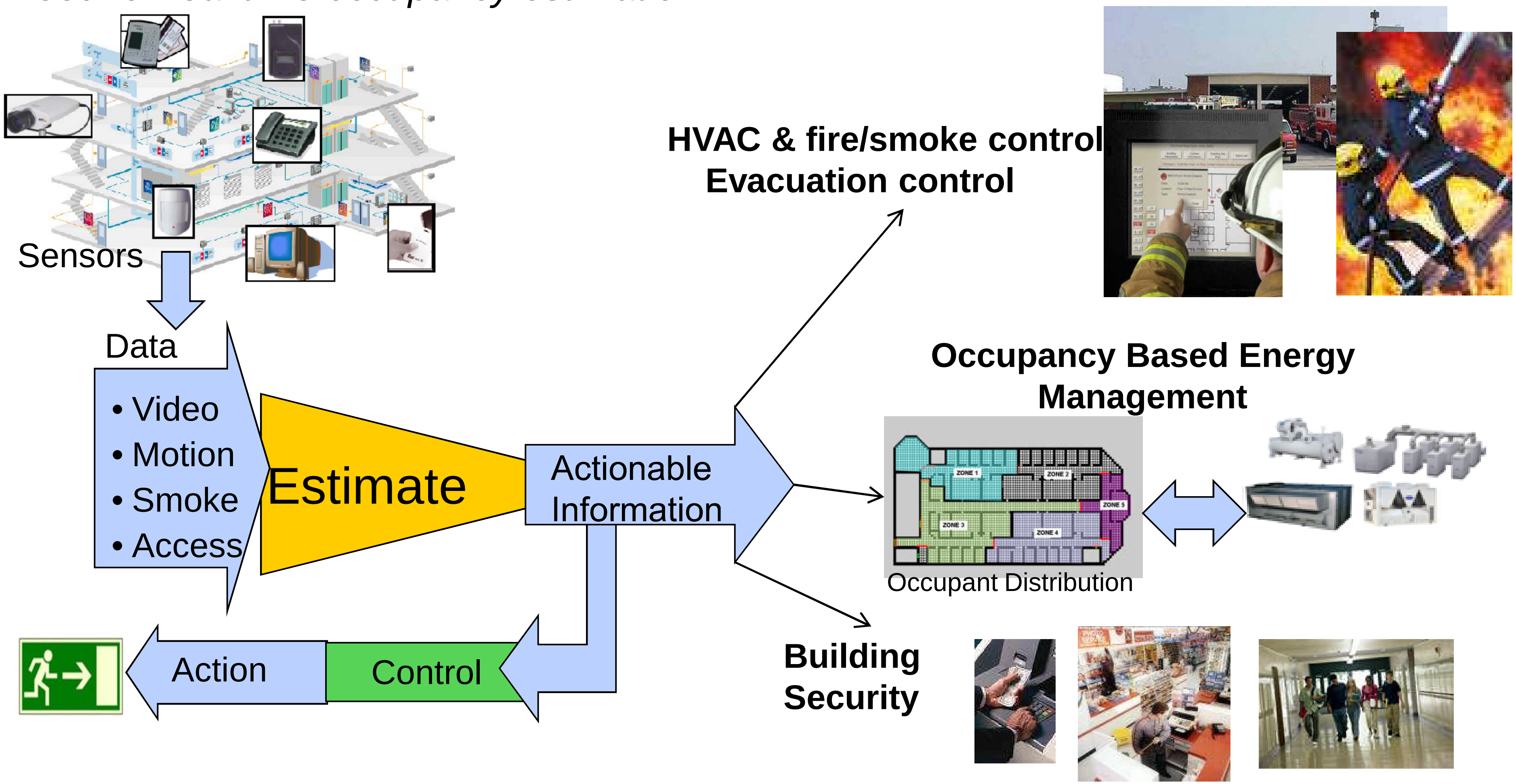
S.P. Meyn (University of Illinois, Urbana-Champaign, IL, U.S.)

Y. Lin, S. M. Oggianu, T. A. Frewen, S. Narayanan, I. Fedchenia

(*United Technologies Research Center (UTRC), E. Hartford, CT 06108, U.S.)

Building Security and Energy Management

Need for real time occupancy estimation



Challenges/Barriers

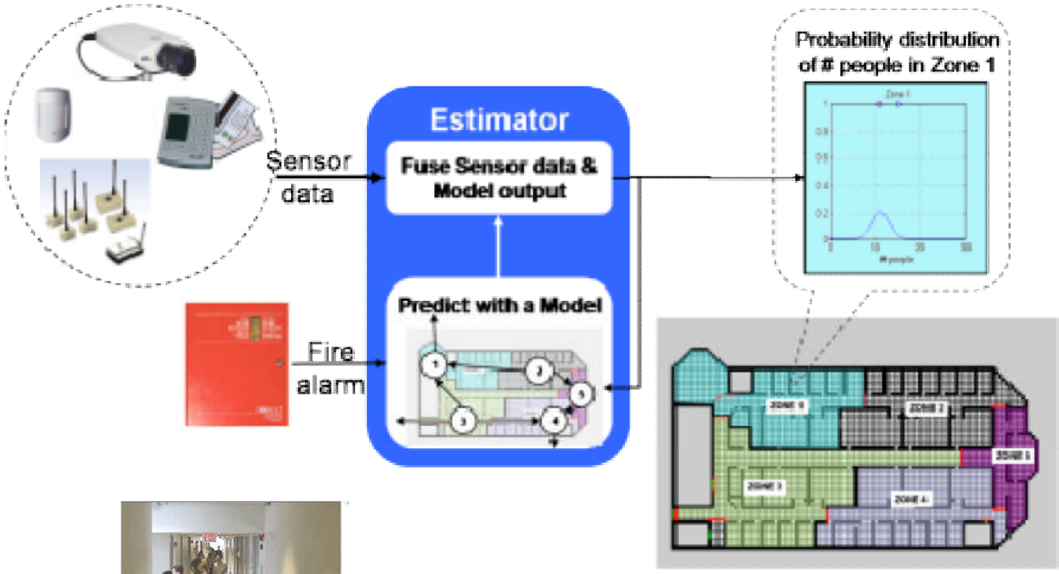
•Information volume (100's of heterogeneous sensors, 1000's of agents)
•Dynamically evolving situation (threat& response time scale overlap)
•Uncertainty (inaccurate, missing sensor data)

Enablers

•Models for occupancy
•Emerging inexpensive sensors with embedded intelligence and communication capability

Related Work: Real time Occupancy Estimation

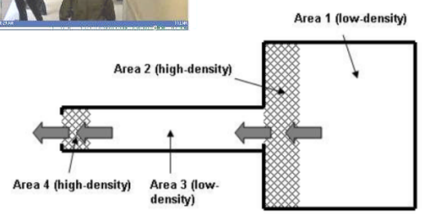
Utilizes Sensors and Models in Real-Time



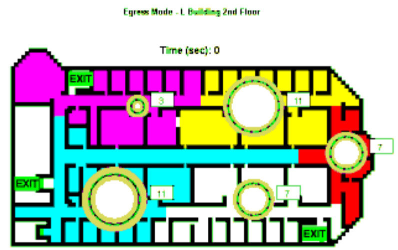
Egress in Buildings

Tomastik et al. 08 (UTRC)

•Kinetic Model for evacuation dynamics (Models vacancies in congested regions and agents in “rarified” regions)



\+ •Extended Kalman Filter



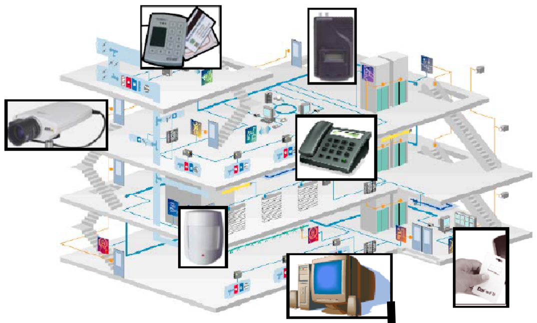
Normal Building Operation: Machine Learning Approaches, CBPD (CMU)

•Use of SVM, ANN, HMM (Lam et al. 09)

•Episode discovery and semi-Markov models for occupancy based ventilation control (Dong and Andrewes 09)

Occupancy Modeling Framework (UTRC)

Building Layout, Prior knowledge on usage



Heterogeneous People traffic Sensor data
Video, PIR, CO2, Access

SUN Estimator

Real Time Zonal Occupancy

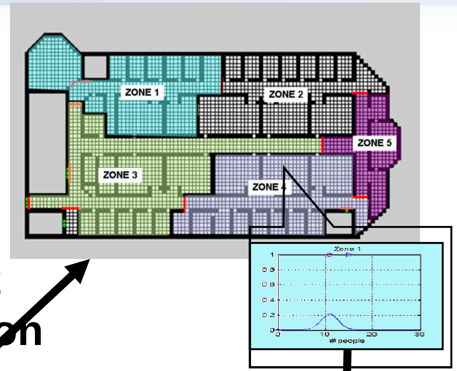
Markov Models

Statistical Patterns in People Traffic

Occupant Movement Model

Calibrated high resolution model for simulating People Traffic

Occupant Distribution



Occupancy Based Energy Management

Anomaly Detection

ThB13.6 (15:50-16:10)
Invited Session 5A
(Learning and Control II)
Anomaly Detection Using Projected Markov Models in Distributed Sensor Network→ **S. P. Meyn**

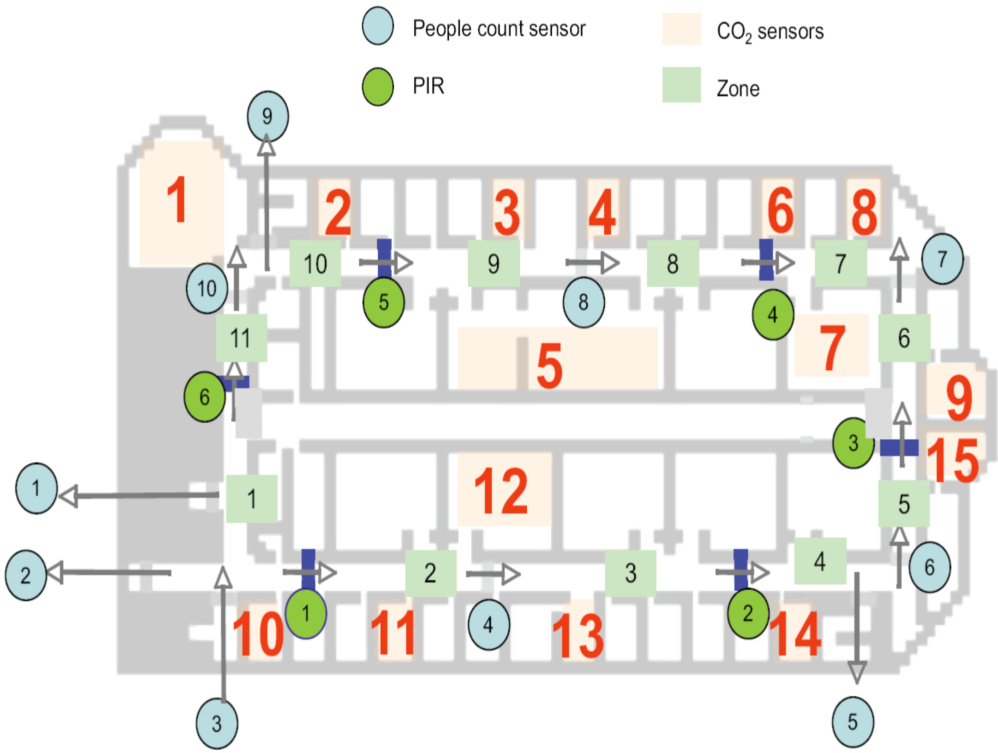
Sensor Architecture

Develop Offline Energy Management Options

Egress/Normal Operations

UTRC L Building Test Bed

Video (People Count), PIR (Passive Infra Red), Co2 Sensors



Video (People Count)

Exhibit significant variance & bias:

- Overcount: Poor lighting condition (during early & late hours), Turning light switch on/off, Several crossings due to occupants loitering.
- Undercount: Multiple people crossing

PIR (Motion Detection)

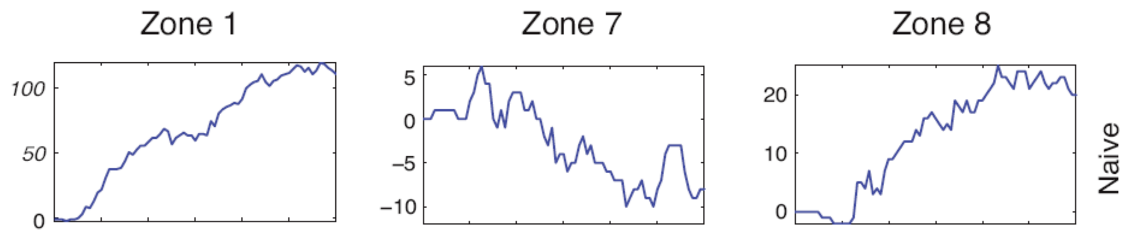
- Do not give people count information

$C0_2$ Sensors (Occupancy)

- High variability due to fluctuations in ambient $C0_2$ levels, HVAC system settings, and door open/close status
- Suffer from slow response time (about 10-20 minutes in this study)

Naive Estimator : People Count

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



United Technologies Research Center

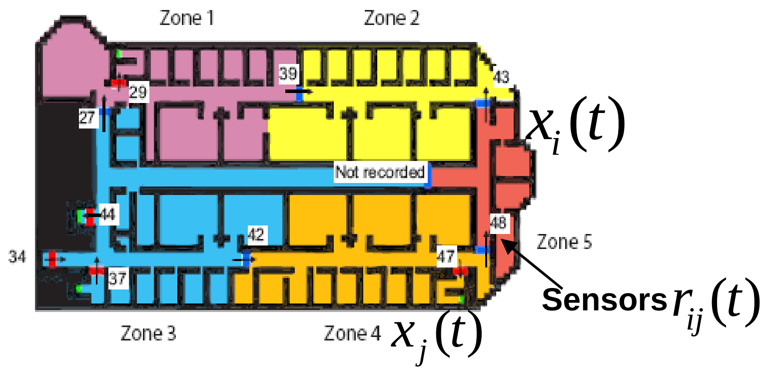
Motivation for SUN Estimation Framework

Role of Constraints and Prior Knowledge in Estimation

$$\phi(t) = \begin{pmatrix} x(t) \\ r(t) \end{pmatrix}$$ **Occupancy** **Flow rate**

$$x_i(t+1) - x_i(t) = \sum_j r_{ji}(t) - \sum_l r_{il}(t)$$

$$y(t) = C\phi(t) = \begin{bmatrix} C^x & 0 \\ 0 & C^r \end{bmatrix} \phi(t)$$



- **Message from Linear Systems theory**

$$\phi(t+1) = A\phi(t) + W(t+1)$$
$$y(t) = C\phi(t) + V(t+1)$$

Any linear model of occupancy is not observable based on flow measurements (Rule out construction of an asymptotically stable estimator without further structure on behavior)

- **Message from Statistics**

$$\phi(t+1) = f_t(\phi(t)) + W(t+1)$$
$$Y(t) = h_t(\phi(t)) + V(t+1)$$

MAP (Maximum a posteriori)

$$\hat{\phi}(t) = \arg\max_\phi p(\phi \mid Y_0^t).$$

$$-\log(p(\phi_0, \ldots, \phi_T \mid y_0, \ldots, y_{T-1})) \propto$$

$$\xrightarrow{\text{Gaussian Assumptions}} \quad \|\phi_0 - \bar{\phi}_0\|^2_{\Sigma_0^{-1}} + \sum_{t=0}^{T-1} (\|y(t) - h_t(\phi(t))\|^2_{\Sigma_{yt}^{-1}}$$
$$+ \|\phi(t+1) - f_t(\phi(t))\|^2_{\Sigma_{dt}^{-1}})$$

Information on sensor and dynamics naturally arise

Model is constrained (Gaussian assumption invalid) , regardless estimation algorithm defined as an optimization, subject to state space constraints is attractive

United Technologies Research Center

SUN: Receding Horizon Estimation

SUN :Sensor, Utility & Network Structure combined through Constrained Optimization

Constrained Optimization

$$\min \quad P_0(\phi_0) + \sum_{t=0}^{T} P_y(\phi(t), y(t)) + \sum_{t=0}^{T-1} P_d(\phi(t+1), \phi(t)) + \sum_{t=0}^{T} U_x(\phi(t))$$

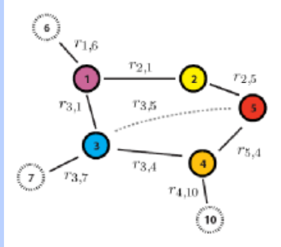
Flow Balance

$$x_i\,(t+1) = x_i\,(t) + \sum_j r_{ji}(t) - \sum_j r_{ij}\,(t)$$

Bounds on Occupancy & Flow rates

$$XLB\,(t) \le x(t) \le XUB\,(t), \forall t$$

$$RLB\,(t) \le r(t) \le RUB\,(t), \forall t$$



Initial state penalty function

$$P_0(\phi_0) = \left\|\phi_0 - \hat{\phi}_0\right\|^2_{\Sigma_0^{-1}}$$

Model dynamics penalty function, e.g.: continuity

$$P_d(\phi(t+1), \phi(t)) = \|x(t+1) - x(t)\|^2_{\Sigma_x^{-1}} + \|r(t+1) - r(t)\|^2_{\Sigma_r^{-1}}$$

Model and sensor consistency penalty function

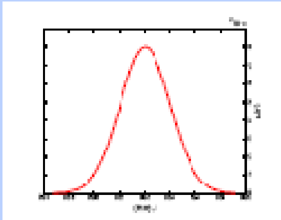
Sensor Measurements

$$P_y(\phi(t), y(t)) = \|r(t) - y(t)\|^2_{\Sigma_{y_t}^{-1}}$$

Occupancy Utility Function

$$U_x(x(t)) = \| x(t) - m(t) \|^2{}_{\Sigma xt}^{-1}$$

Prior Knowledge



- Building space usage pattern
- Preferences for walking speed, proximity, path
- Clustering, Lane formation
- Behavior dependence on age, mobility, aggressiveness…

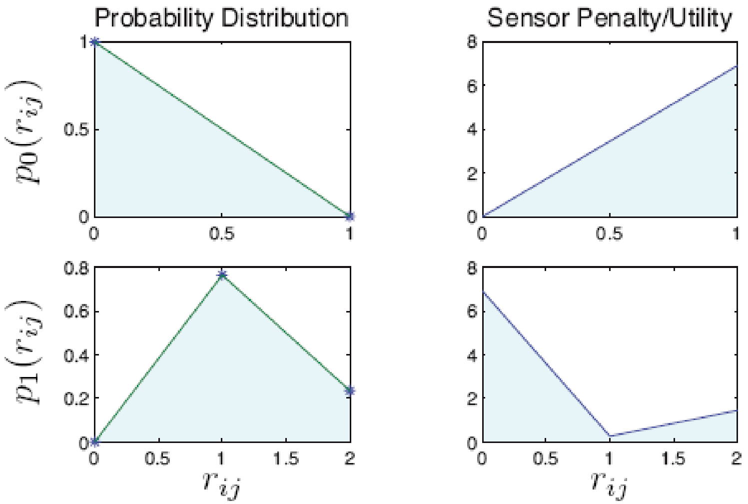
United Technologies Research Center

Soft Sensor Penalty for Video and PIR Sensors

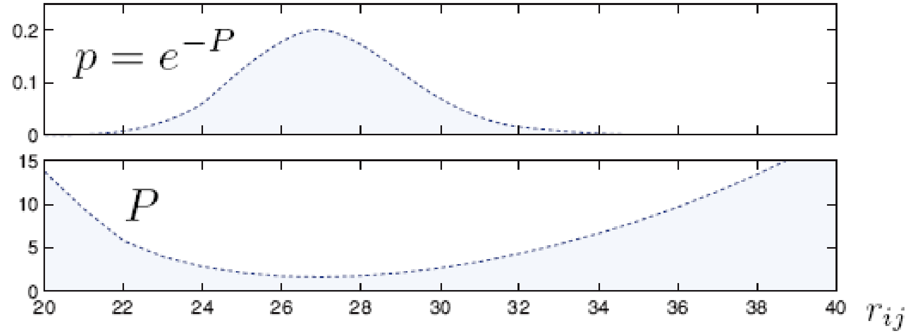
Composed (in time) sensor utility admits a quadratic approximation

Soft Penalty /Utility for Sensor

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



Composition of Soft Penalty



Quadratic Soft Penalty

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

$$P_{y_{ij}}(r_{ij}, y_{ij}) = \tfrac{1}{2}(y_{ij} - b_{ij}(y_{ij})))^2/\sigma_{ij}^2$$

Bias **Variance**

Y_{ij}	$8\text{am} < t < 5\text{pm}$	$t < 8\text{am}$ or $t > 5$ pm
0	$b_{ij} = 0, \quad \sigma_{ij}^2 = 10^{-5}$	$b_{ij} = 0, \quad \sigma_{ij}^2 = 10^{-5}$
1	$b_{ij} = 0, \quad \sigma_{ij}^2 = 0.5$	$b_{ij} = 0, \quad \sigma_{ij}^2 = 1$
2	$b_{ij} = -0.25, \quad \sigma_{ij}^2 = 1.2$	$b_{ij} = -1, \quad \sigma_{ij}^2 = 2.4$
> 3	$b_{ij} + Y_{ij} = 1, \quad \sigma_{ij}^2 = 2$	$b_{ij} + Y_{ij} = 1, \sigma_{ij}^2 = 4.5$

Table 1
Soft penalty/utility parameters for People Count Sensors

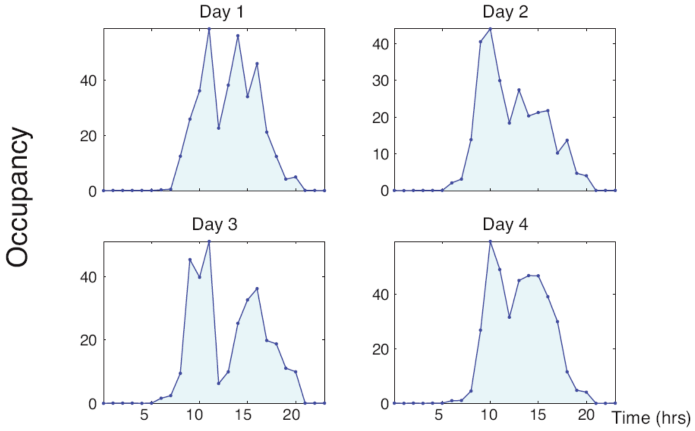
Y_{ij}	$8\text{am} < t < 5\text{pm}$	$t < 8\text{am}$ or $t > 5$ pm
0	$b_{ij} = 0, \quad \sigma_{ij}^2 = 10^{-2}$	$b_{ij} = 0, \quad \sigma_{ij}^2 = 10^{-4}$
1	$b_{ij} = 0, \quad \sigma_{ij}^2 = 100$	$b_{ij} = 0, \quad \sigma_{ij}^2 = 1$

Table 2
Soft penalty/utility parameters for PIR Sensors

Occupancy Utility via Smoothing

Smoothing using historical data

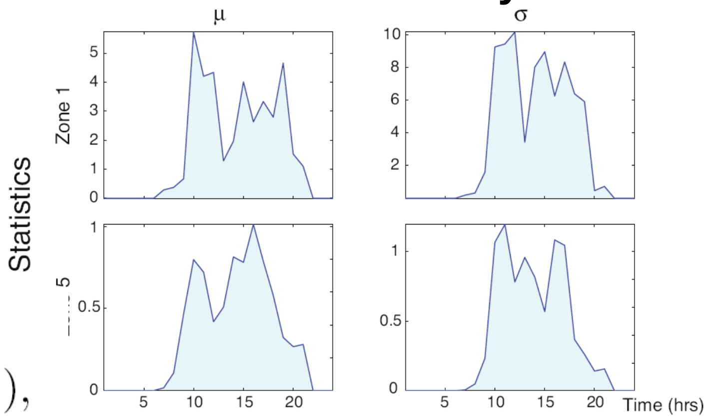
SUN for whole day
enforcing zero occupancy at
boundaries & using Sensor Utility
(hourly time scale)



$$\mu_i = N^{-1}\sum_{k=1}^{N}\widehat{x}_i^k, \qquad \sigma_i^2 = N^{-1}\sum_{k=1}^{N}(\widehat{x}_i^k - \mu_i)^2$$

$k = 1, \ldots, N$ Days

Based on 16 Days



$$\mathcal{U}_i(x_i) = -\tfrac{1}{2}(x_i - \mu_i)^2/\sigma_i^2$$

Occupancy Utility $\mathcal{U}_x(x) = \sum_{i=1}^{N_z}\mathcal{U}_i(x_i),$

Prediction

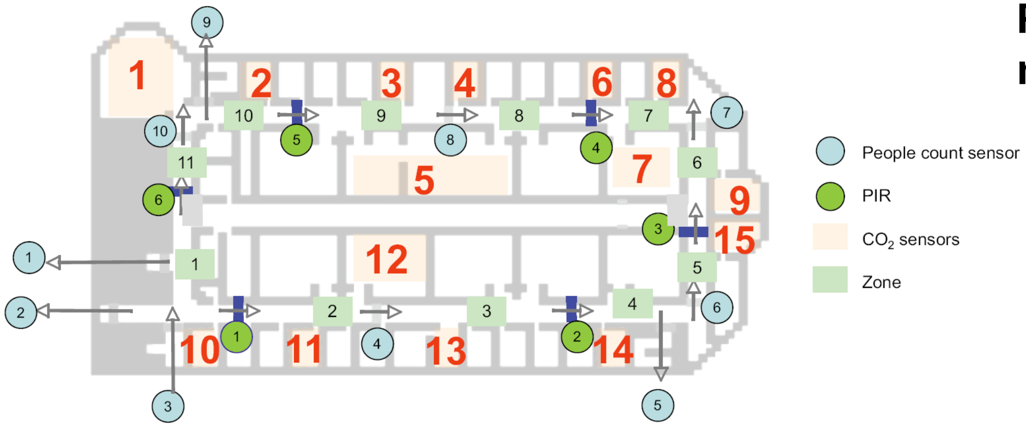
$$\arg\min_{\phi_T,\ldots,\phi_{T_1}}\left\{\sum_{t=T}^{T_1-1}\left(\mathcal{P}_d(\phi(t+1),\phi(t)) - \mathcal{U}_x(\phi(t))\right)\right\}$$

Smoothing & Prediction

$$\arg\min_{\phi_0,\ldots,\phi_T,\ldots,\phi_{T_1}}\left[\mathcal{P}_{\text{smooth}} + \mathcal{P}_{\text{predict}}\right]$$

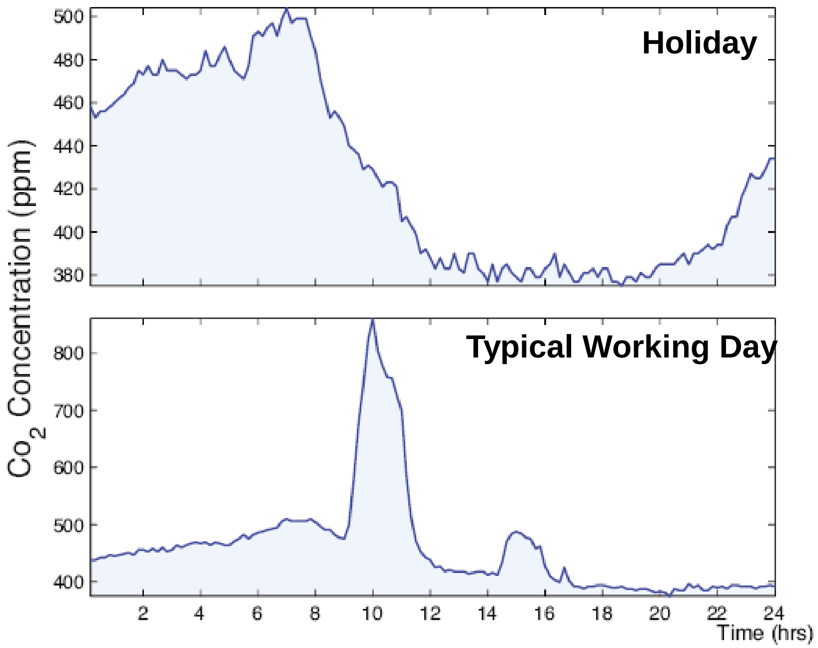
$C0_2$ Utility

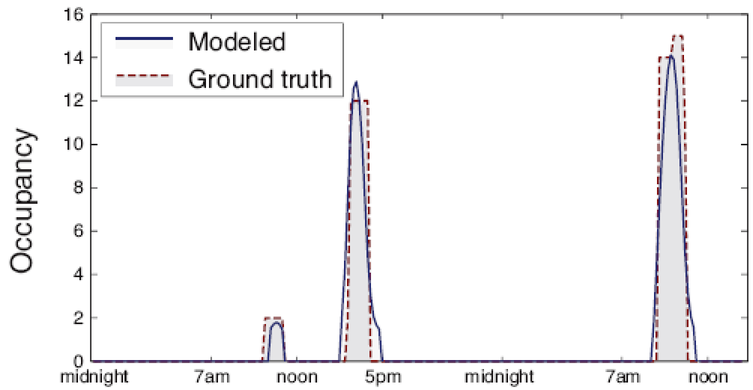
Follow smoothing procedure (like for occupancy) to obtain $C0_2$ Utility



Reformulation to account for partial $C0_2$ measurement in each zone

$$\phi(t) = \begin{pmatrix} x(t) \\ x^c(t) \\ r(t) \end{pmatrix} \quad \widehat{x}_i(t+1) + \sum_{j=1}^{N_{ci}} \widehat{x}_j^c(t+1) = \widehat{x}_i(t) + \sum_{j=1}^{N_{ci}} \widehat{x}_j^c(t) + \sum_j \hat{r}_{ji}(t) - \sum_l \hat{r}_{il}(t),$$





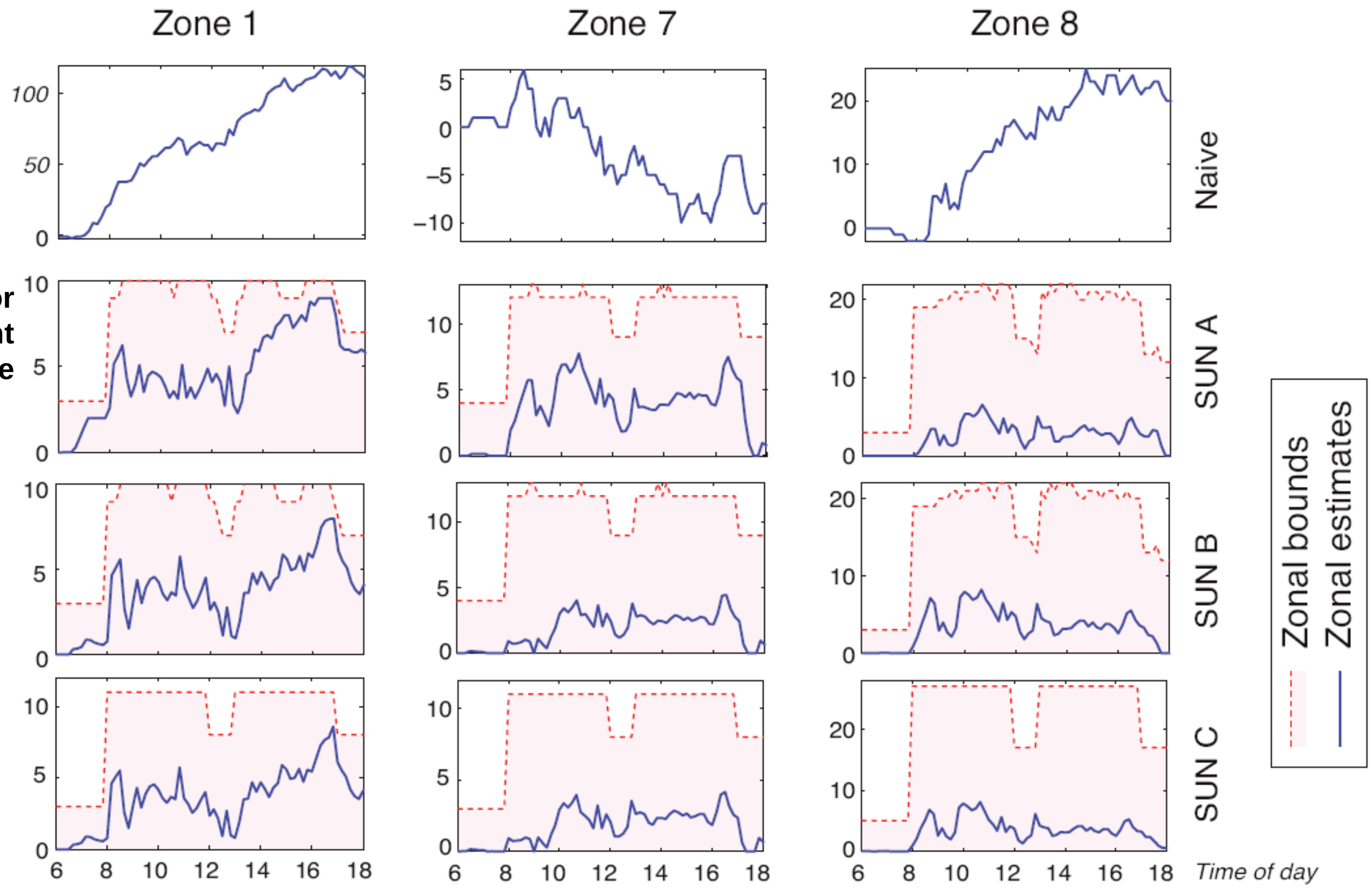
$$y_i(t+1) = \alpha y_i(t) + \beta \widehat{x}_i^c(t),$$

$C0_2$ Data **Occupancy**

United Technologies Research Center

Occupancy Estimation using SUN

Assessing impact of different sources of information



Naive: People Count

SUN A (Soft Sensor Penalty for People Count & PIR, $C0_2$ to refine occupancy bounds)

SUN B (Soft Sensor Penalty for People Count & PIR+Occupancy Utility, $C0_2$ to refine occupancy bounds)

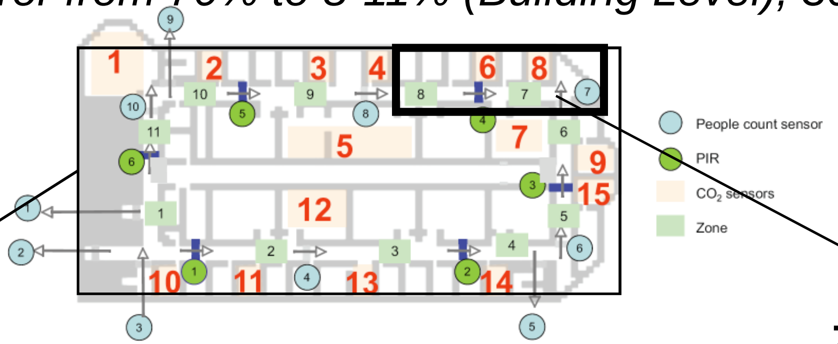
SUN B (Soft Sensor Penalty for People Count & PIR+Occupancy Utility+$C0_2$ Utility)

Zonal Bounds Based on Typical Room Usage Pattern

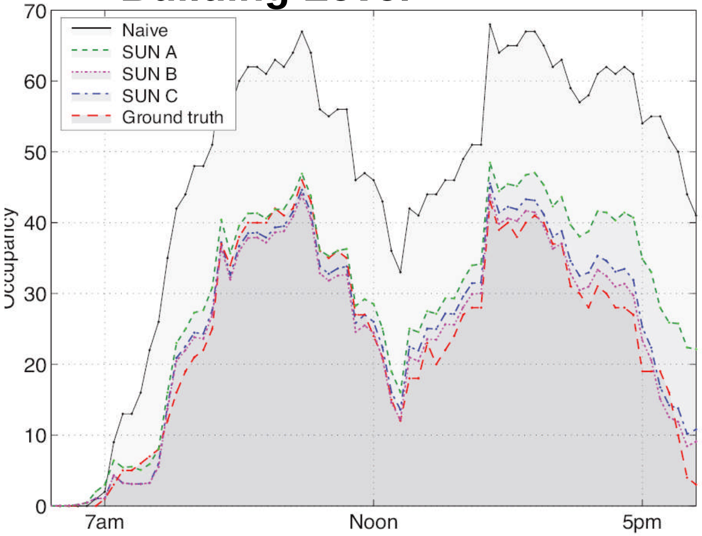
United Technologies Research Center

Summary : Occupancy Estimation Error

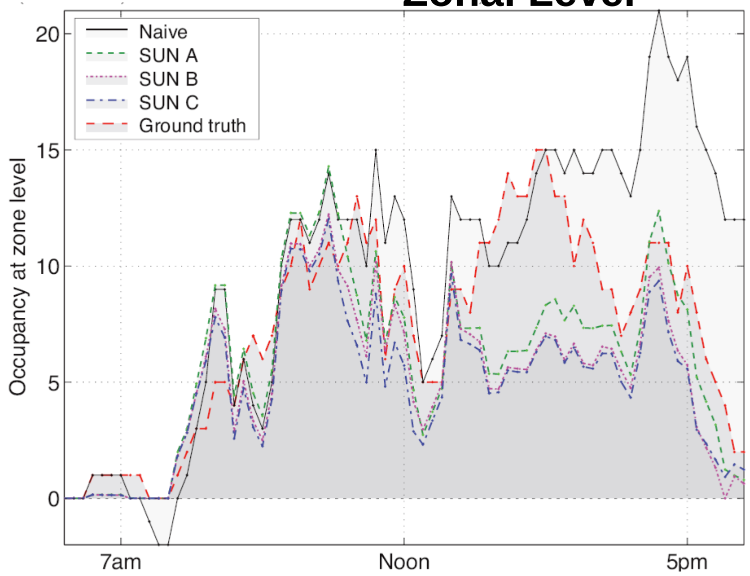
SUN reduces estimation error from 70% to 8-11% (Building Level), 30% to 22% Zonal Level



Building Level



Zonal Level



Ground Truth: Manually by sifting through video data

6pm

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

	Building Level Error	Zonal Level Error
Naive	70%	30%
SUN A	21%	20%
SUN B	8%	21%
SUN C	11%	22%

Conclusions

Contributions:

SUN (Sensor-Utility-Network)

- Occupancy estimation via solution of a receding-horizon convex optimization problem
- Gives a systematic framework for suitably combining inputs from distributed sensor measurements (e.g. video, PIR, access & $C0_2$), along with historical data regarding building utilization in estimation
- Demonstrated feasibility and superior performance of SUN in a Test Bed

Current Research:

- Evaluation of performance of SUN estimator in predictive applications (e.g. for occupancy based ventilation control)
- Adaptive techniques for learning building usage and associated utility functions
- Sensitivity of utility functions for spaces and buildings of similar type
- Optimal sensor architecture (numbers, types and locations) for SUN performance/cost tradeoff.
- Decentralized SUN