
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**

- Sensors
  - Data
    - Video
    - Motion
    - Smoke
    - Access

**Estimate**

- Actionable Information

**HVAC & fire/smoke control**

**Evacuation control**

**Occupancy Based Energy Management**

**Occupant Distribution**

**Building Security**

**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)

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)

- **SUN Estimator**
  - Real Time Zonal Occupancy

- **Markov Models**
  - Statistical Patterns in People Traffic

- **Occupant Movement Model**
  - Calibrated high resolution model for simulating People Traffic

- **Sensor Architecture**

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

- **Build Layout, Prior knowledge on usage**

- **Occupant Distribution**

- **Occupancy Based Energy Management**

- **Anomaly Detection**

- **Develop Offline Energy Management Options**

- **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

- **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

CO2 Sensors (Occupancy)
• High variability due to fluctuations in ambient CO2 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

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

Zone 1

Zone 7

Zone 8

Naive
Motivation for SUN Estimation Framework

Role of Constraints and Prior Knowledge in Estimation

\[
\begin{align*}
\phi(t) &= \begin{pmatrix} x(t) \\ r(t) \end{pmatrix} \\
\phi(t+1) &= A\phi(t) + W(t+1) \\
y(t) &= C\phi(t) + V(t+1)
\end{align*}
\]

- Occupancy
- Flow rate

\[
x_{ij}(t+1) - x_{ij}(t) = \sum_i r_{ji}(t) - \sum_l r_{il}(t)
\]

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

• Message from Linear Systems theory

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

\[
\begin{align*}
\hat{\phi}(t) &= \arg\max_{\phi} p(\phi \mid Y^t_0) \\
-\log(p(\phi_0, \ldots, \phi_T \mid y_0, \ldots, y_{T-1})) &\propto \\
\|\phi_0 - \bar{\phi}_0\|_{\Sigma_0}^2 &+ \sum_{t=0}^{T-1} (\|y(t) - h_t(\phi(t))\|_{\Sigma^{-1}_{u,t}}^2) \\
&\quad + \|\phi(t+1) - f_t(\phi(t))\|_{\Sigma^{-1}_{\phi,t}}^2
\end{align*}
\]

Gaussian Assumptions

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
SUN: Receding Horizon Estimation

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

\[
\begin{align*}
\min & P_0(\phi_0) + \sum_{t=0}^{T} P_y(\phi(t), y(t)) + \sum_{t=0}^{T-1} P_d(\phi(t+1), \phi(t)) + \sum_{t=0}^{T} U_x(\phi(t)) \\
\text{Flow Balance} & \quad x_i(t+1) = x_i(t) + \sum_j r_{ji}(t) - \sum_j r_{ij}(t) \\
\text{Bounds on Occupancy} \quad & \quad XLB(t) \leq x(t) \leq XUB(t), \forall t \\
\quad & \quad RLB(t) \leq r(t) \leq RUB(t), \forall t \\
\end{align*}
\]

Initial state penalty function

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

Model dynamics penalty function, e.g.: continuity

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

Sensor Measurements

\[
P_y(\phi(t), y(t)) = \left\| r(t) - y(t) \right\|_{\Sigma_y^{-1}}^2
\]

Prior Knowledge

Occupancy Utility Function

\[
U_x(x(t)) = \left\| x(t) - m(t) \right\|_{\Sigma_{xt}}^{-1}^2
\]

- Building space usage pattern
- Preferences for walking speed, proximity, path
- Clustering, Lane formation
- Behavior dependence on age, mobility, aggressiveness…
Soft Sensor Penalty for Video and PIR Sensors

Composed (in time) sensor utility admits a quadratic approximation

Soft Penalty / Utility for Sensor

\[ p_i(r) = e^{-P_i(r)} \]

Quadratic Soft Penalty

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

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

Bias

Variance

Composition of Soft Penalty

\[ p = e^{-P} \]

Table 1

<table>
<thead>
<tr>
<th>Y_{ij}</th>
<th>8am &lt; t &lt; 5pm</th>
<th>t &lt; 8am or t &gt; 5 pm</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>b_{ij} = 0,  \sigma_{ij}^2 = 10^{-5}</td>
<td>b_{ij} = 0,  \sigma_{ij}^2 = 10^{-5}</td>
</tr>
<tr>
<td>1</td>
<td>b_{ij} = 0,  \sigma_{ij}^2 = 0.5</td>
<td>b_{ij} = 0,  \sigma_{ij}^2 = 1</td>
</tr>
<tr>
<td>2</td>
<td>b_{ij} = -0.25,  \sigma_{ij}^2 = 1.2</td>
<td>b_{ij} = -1,  \sigma_{ij}^2 = 2.4</td>
</tr>
<tr>
<td>&gt; 3</td>
<td>b_{ij} + Y_{ij} = 1,  \sigma_{ij}^2 = 2</td>
<td>b_{ij} + Y_{ij} = 1,  \sigma_{ij}^2 = 4.5</td>
</tr>
</tbody>
</table>

Table 2

<table>
<thead>
<tr>
<th>Y_{ij}</th>
<th>8am &lt; t &lt; 5pm</th>
<th>t &lt; 8am or t &gt; 5 pm</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>b_{ij} = 0,  \sigma_{ij}^2 = 10^{-2}</td>
<td>b_{ij} = 0,  \sigma_{ij}^2 = 10^{-4}</td>
</tr>
<tr>
<td>1</td>
<td>b_{ij} = 0,  \sigma_{ij}^2 = 100</td>
<td>b_{ij} = 0,  \sigma_{ij}^2 = 1</td>
</tr>
</tbody>
</table>

Soft penalty/utility parameters for People Count Sensors

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)

\[
\mu_i = N^{-1} \sum_{k=1}^{N} x_i^k, \quad \sigma_i^2 = N^{-1} \sum_{k=1}^{N} (x_i^k - \mu_i)^2
\]

\[k = 1, \ldots, N \text{ Days}\]

\[
\mathcal{U}_i(x_i) = -\frac{1}{2}(x_i - \mu_i)^2 / \sigma_i^2
\]

**Occupancy Utility**

\[
\mathcal{U}_x(x) = \sum_{i=1}^{N} \mathcal{U}_i(x_i)
\]

**Prediction**

\[
\arg \min_{\phi_T, \ldots, \phi_T} \left\{ \sum_{i=1}^{T-1} \left( \mathcal{U}_x(\phi(t | i), \phi(t)) \right) \right\}
\]

**Smoothing & Prediction**

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

Based on 16 Days
Follow smoothing procedure (like for occupancy) to obtain $\text{CO}_2$ Utility

Reformulation to account for partial $\text{CO}_2$ measurement in each zone

$$\phi(t) = \begin{pmatrix} x(t) \\ x^c(t) \\ r(t) \end{pmatrix} + \sum_{j=1}^{N_{\text{ex}}} \hat{x}_j(t) + \sum_{j=1}^{N_{\text{ex}}} \tilde{x}_j(t)$$

$y_i(t+1) = \alpha y_i(t) + \beta \hat{x}_i^c(t)$
Occupancy Estimation using SUN

Assessing impact of different sources of information

Naive: People Count

SUN A (Soft Sensor Penalty for People Count & PIR, $C\text{O}_2$ to refine occupancy bounds)

SUN B (Soft Sensor Penalty for People Count & PIR+Occupancy Utility, $C\text{O}_2$ to refine occupancy bounds)

SUN B (Soft Sensor Penalty for People Count & PIR+Occupancy Utility+$C\text{O}_2$ Utility)

Zonal Bounds Based on Typical Room Usage Pattern
Summary: Occupancy Estimation Error

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

<table>
<thead>
<tr>
<th>Method</th>
<th>Building Level Error</th>
<th>Zonal Level Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Naive</td>
<td>70%</td>
<td>30%</td>
</tr>
<tr>
<td>SUN A</td>
<td>21%</td>
<td>20%</td>
</tr>
<tr>
<td>SUN B</td>
<td>8%</td>
<td>21%</td>
</tr>
<tr>
<td>SUN C</td>
<td>11%</td>
<td>22%</td>
</tr>
</tbody>
</table>

**Ground Truth:** Manually by sifting through video data

6pm

\[
E = \frac{1}{T_f - T_0} \sum_{t = T_0, x(t) \neq 0}^{T_f} \frac{|x(t) - \hat{x}(t)|}{x(t)},
\]
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 & CO₂), 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