Model-based Real-Time Estimation of Building Occupancy During Emergency Egress

PED 2008 Presentation

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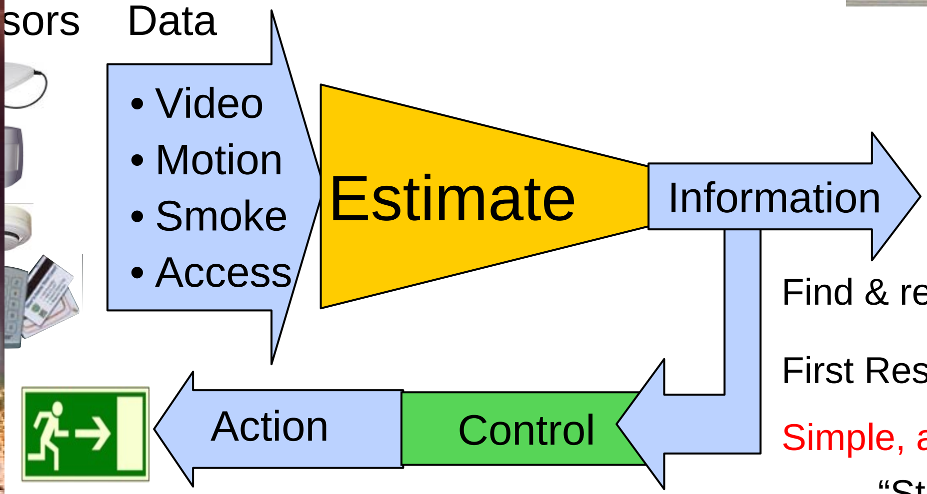
Real-time Situational Awareness for Building Safety

Issues: Complexity, real-time information synthesis, uncertainty

Drivers



Find & rescue people, find & suppress fire

First Responders need

Simple, actionable, real time insight

“Static” pre-plan information

Occupant and threat information

- & fire/smoke control
- Evacuation control

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)

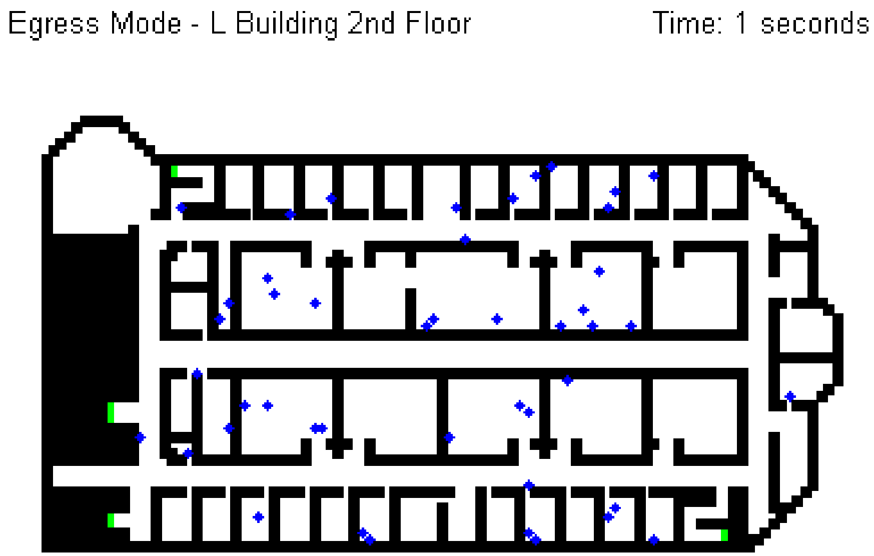
Needs

Reduced-order models for real time applications
Scalable and robust decision support algorithms
Approaches for sensor network configuration optimization

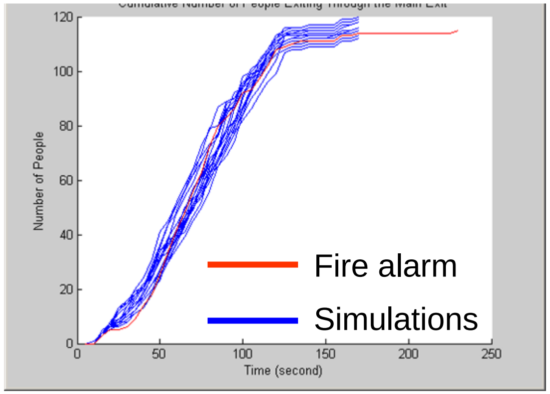
State-of-the-Art in Evacuation Dynamics Modeling

Agent-Based Simulations

- Trajectories of individuals on fine grid simulated using parameters associated with speed and behavior
- Unsuitable for real-time applications or optimization in large-scale buildings (***need estimates in secs for response***)



UTRC ABM validation with fire drill experimental data*

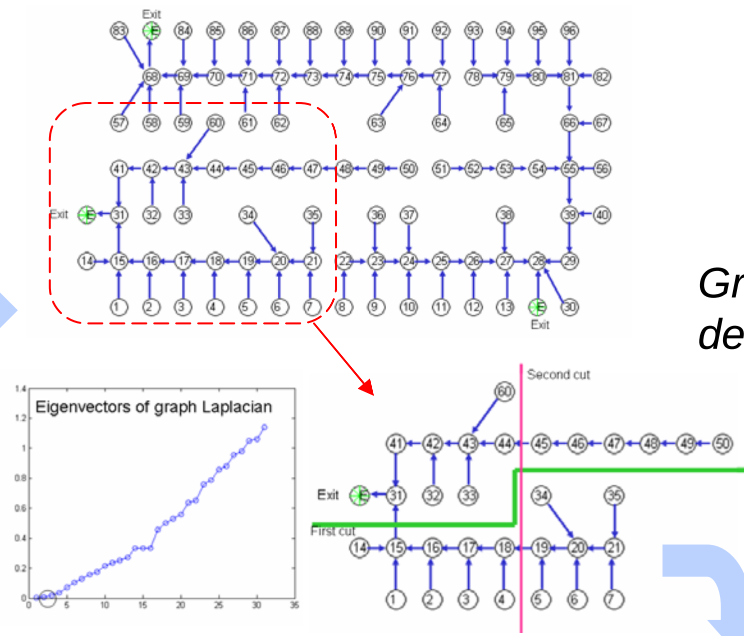


- 100+ occupants undertaking unannounced fire drill in 2-storey building
- 3 available exits

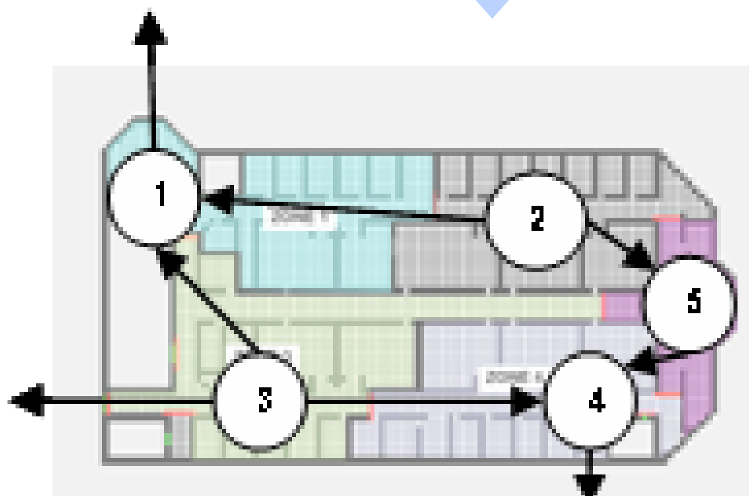
*Lin et al. "Agent-based Simulation and Reduced-Order Modeling of Evacuation: An Office Building Case Study" PED2008 paper

Reduced-order Models of Evacuation Dynamics

“Coarse” Modeling*



*Graph decomposition**

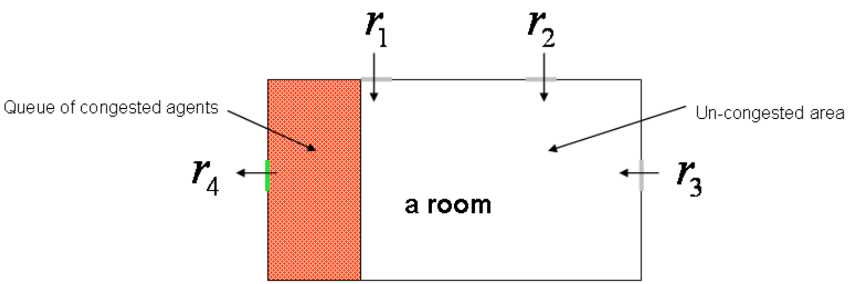


- Traffic dynamics represented on a graph
- Spatial resolution reduced
- Model accuracy deteriorates

*Lin et al. “Agent-based Simulation and Reduced-Order Modeling of Evacuation: An Office Building Case Study” PED2008 paper

Reduced-order Models of Evacuation Dynamics

Kinetic Model+



(α selected based on room size & agent walking speed – not tuned or empirical)

$$x_{1q}(t+1) = x_{1q}(t) + \alpha_1 x_1(t) - r_4(t)$$

$$x_1(t+1) = (1-\alpha_1)\cdot x_1(t) + r_1(t) + r_2(t) + r_3(t)$$

$$r_4(t) = f(x(t))$$ f models congestion and is a function mainly of x_q

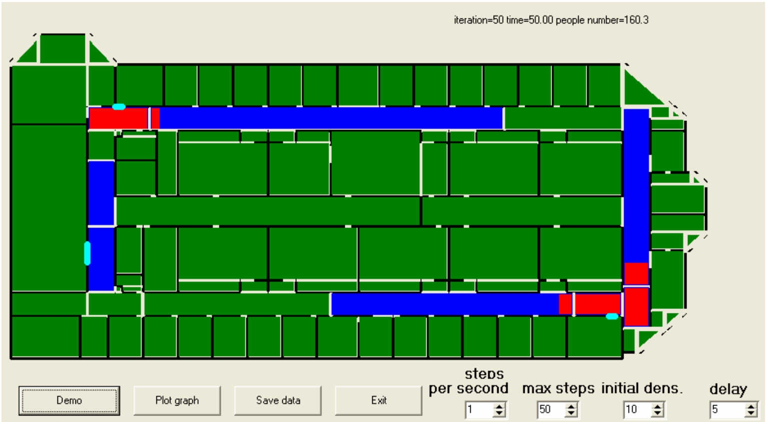
x_{1q} = # of agents in queue

x_1 = # of agents in un-congested area

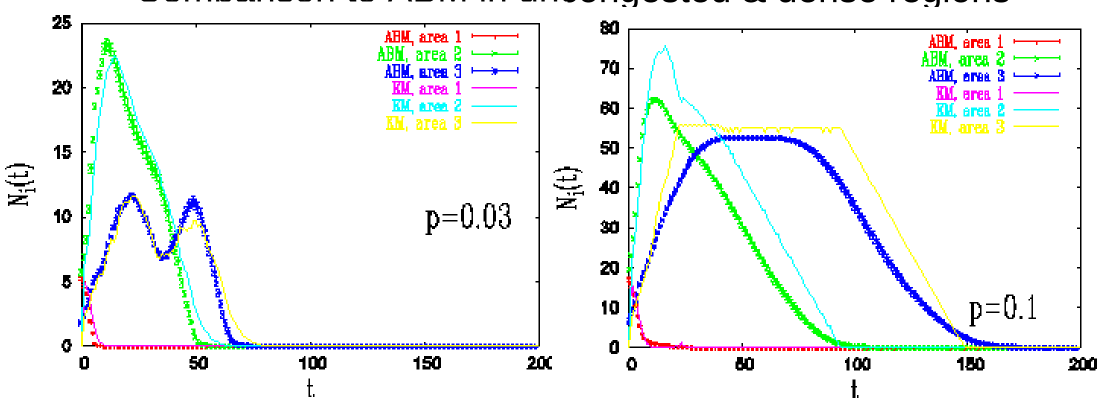
r_i = # of agents moving through a door

$$\frac{dx_{\text{int}}}{dt} = J_{ag} - J_{vac}$$ Interface movement is balance of agents & vacancy flux

- Models vacancies in congested regions and agents in "rarified" regions
- Enables real-time estimation (3 orders of magnitude faster than ABM)
- Loss of accuracy minimal

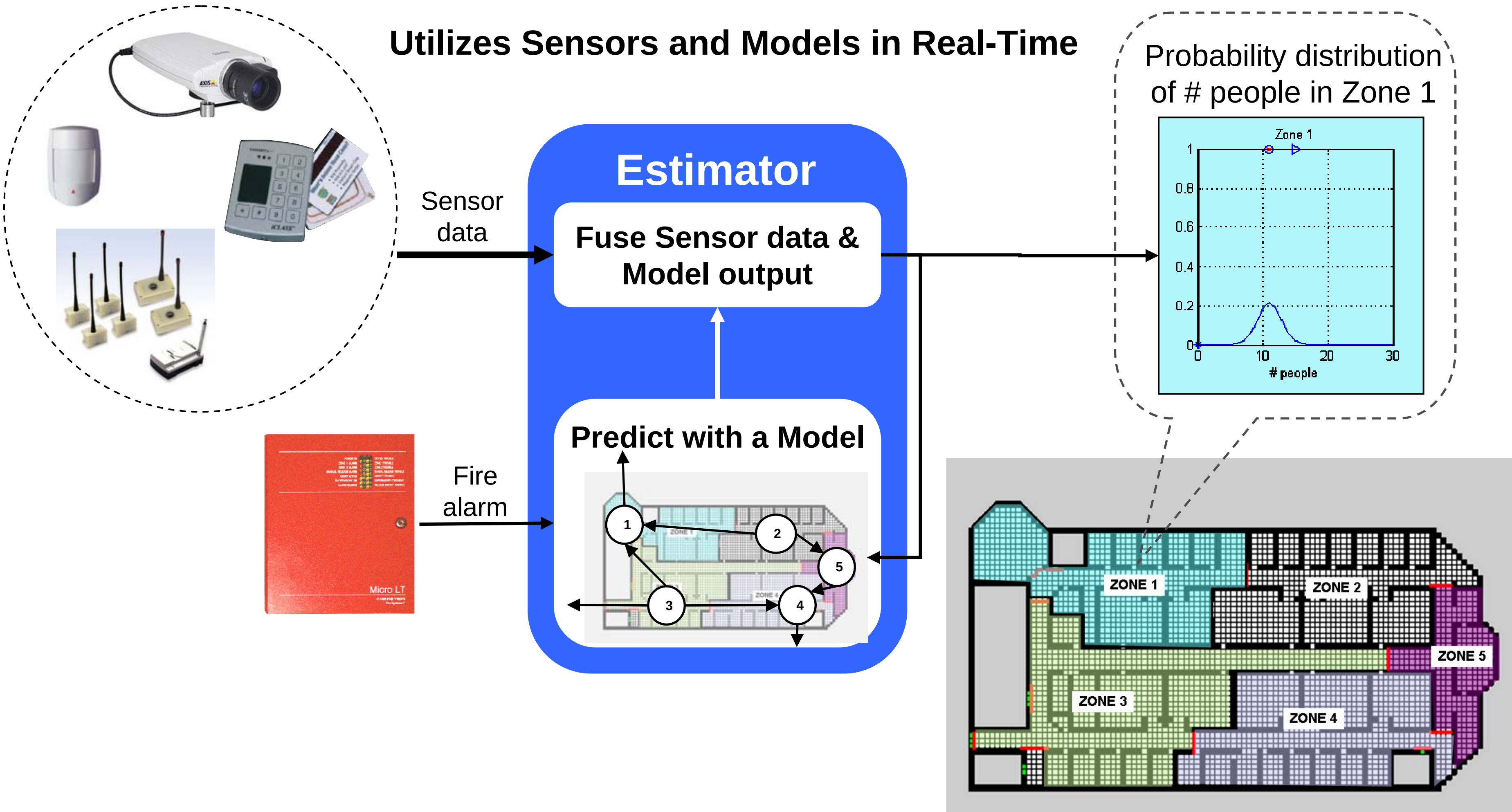


Comparison to ABM in uncongested & dense regions



+Burlatsky et al. "A Novel Kinetic Model to Simulate Evacuation Dynamics" PED2008 poster

Concept for Real-Time Occupancy Estimation



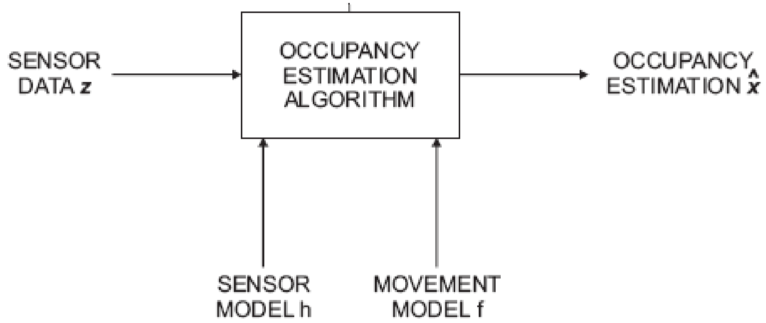
L-Building coarse zones

Occupancy Estimator Using Extended Kalman Filter (EKF)

- People-movement model: state variable model

$$x(k+1) = f(k, x(k)) + v(k)$$

  - k = time index
  - x(k) = vector of people occupancy in each site / zone
  - v(k) = process noise
  - f = a general non-linear function, traffic model in state space form

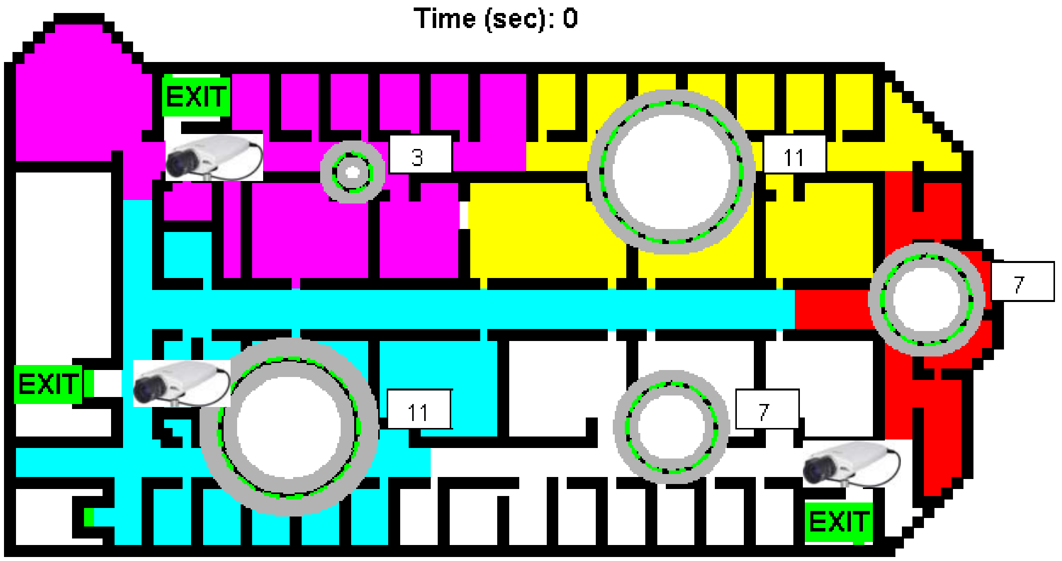


- Linearize state model at each time step around current state estimate, and use standard Kalman filter, which is optimal for linear systems
- EKF provides estimate of mean value and the state covariance
- Initialization of EKF at time of alarm: use sensor-only estimate

Real-Time Occupancy Estimation Demonstration

Proof-of-concept of real-time estimation demonstrated during fire drill

Egress Mode - L Building 2nd Floor



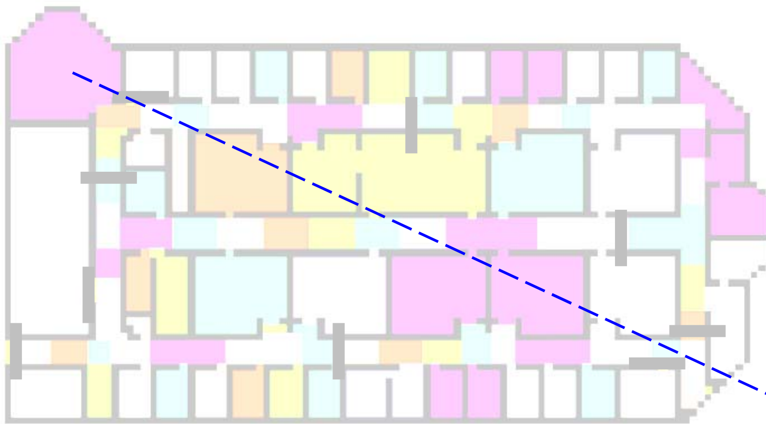
- Occupancy estimator tracks measured data well
- Occupancy estimates from combining models & sensor data superior to & robust when compared to using sensors only
- Computational complexity scales with $N_{sensors}^3$, not with N_{people}, N_{rooms}, Building size

Mean Error in no. of people per zone

Estimator	9 Cameras	3 Cameras
Sensor only	1.5	5.3
Model+Sensor (EKF)	1.0	1.4

Simulation of Room-Level Occupancy Estimation

Layout of Building 2nd floor



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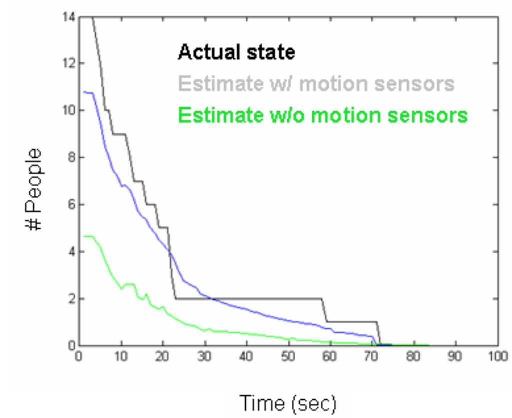
Look-down camera

Motion sensors in all rooms

Estimator	Mean Error avg per **room** over all time and sim runs	Mean Error avg per **zone** over all time and sim runs
Sensor only (3 cameras)	0.35	4.9
EKF w/ KM, 3 cameras	0.14	1.1
EKF w/ KM, 3 cameras, motion sensors in each office/conference room	0.08	0.9



Concluding Remarks

- Reduced-order models of evacuation in combination with data can provide substantially higher accuracy and robust estimates of occupancy for real-time use
- Computational complexity scales with $N_{sensors}^3$, not with N_{people}, N_{rooms}, Building size
- Even use of relatively inexpensive and inaccurate sensors (e.g. motion sensors) when used with traffic models can be effective (40% estimation error reduction)
  - Challenge is to enable information exchange among disparate systems cost effectively: fire/safety, security and lighting
- Other advances made leading to estimation performance improvement:
  – Utilizing constraints (such as door/exit width) in estimate variance computation
  – Use of people flow as state variable (eliminate bias error)
  – Projection of EKF estimate onto the feasible space ($0 \leq$ occupancy $\leq$ room size, and people flow $\leq$ max flow), enforcing constraints such as positivity of state variable and conservation of number of people in building
- Need approach for occupancy estimate at time of fire alarm (initial conditions)
  – Estimator that uses a *model of traffic during normal building operations*

Back up

Simulation Results Using Motion Sensors

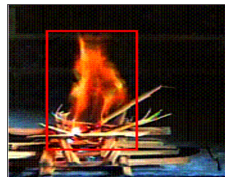
Estimator	Mean Error avg per **room** over all time and sim runs	Mean Error avg per **zone** over all time and sim runs
Sensor only (3 cameras, no motion sensors)	0.29	2.8
EKF w/KM, 3 cameras, no motion sensors	0.18	1.9
EKF w/KM, 3 cameras, and a motion sensor in every office and conference room	0.10	1.0

Building Emergency Response Problem

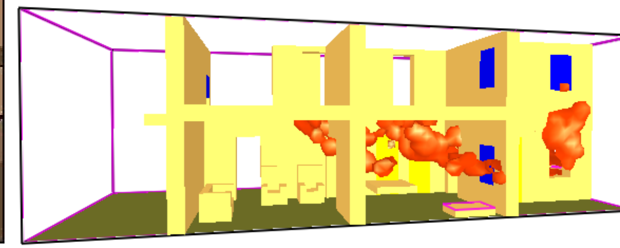
Enablers:

Analytical methods





Data processing and fusion

Dynamic models of traffic and fire/smoke propagation

Sensors: Data:

- Video
- Motion
- Smoke
- Access

People Threat

Simplify

Information

Action

Control

Drivers

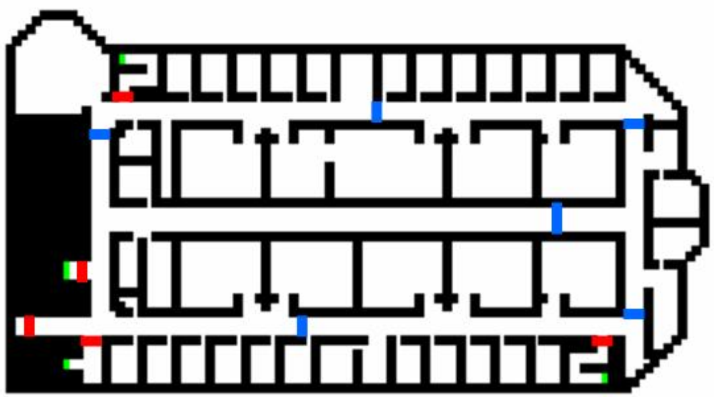
First Responders need

- Simple, actionable information about occupant, threat situation & building

- HVAC & fire/smoke control
- Evacuation control

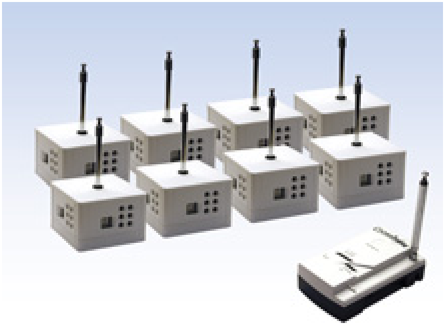
People Estimation Problem Definition

- Sensors: video cameras with Lenel intelligent video for directional people counting



Red Lines   Blue Lines

- Sensors: PIR motion sensors on motes, located in each office and conference room



(motes installed at UTRC are a different model than shown)

Extended Kalman Filtering Algorithm

State estimate at time t

$$\hat{x}(t|t)$$

State prediction

$$\hat{x}(t+1|t) = f(t, \hat{x}(t|t))$$

Measurement prediction

$$\hat{z}(t+1|t) = H \cdot \hat{x}(t+1|t)$$

Innovation

$$v(t+1) = z(t+1) - \hat{z}(t+1|t)$$

Update state estimate

$$\hat{x}(t+1|t+1) = \hat{x}(t+1|t) + W(t+1) \cdot v(t+1)$$

State covariance

$$P(t|t)$$

Evaluate Jacobian of f

$$F(t) = \left.\frac{\partial f(t)}{\partial x}\right|_{x=\hat{x}(t|t)}$$

State prediction covariance

$$P(t+1|t) = F(t) \cdot P(t|t) \cdot F(t)' + Q(t)$$

Innovation covariance

$$S(t+1) = H \cdot P(t+1|t) \cdot H' + R(t)$$

Filter gain

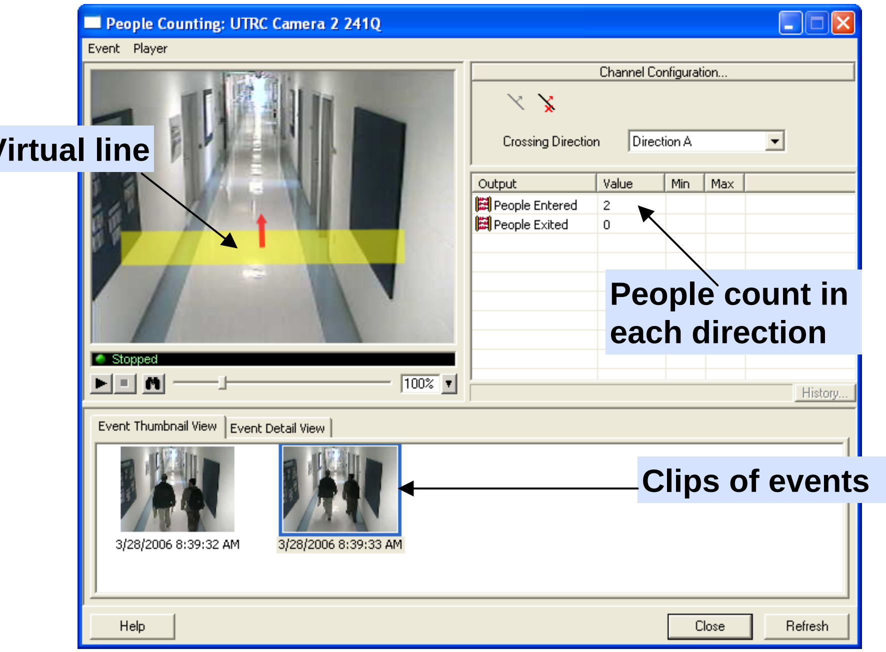
$$W(t+1) = P(t+1|t) \cdot H' \cdot S(t+1)^{-1}$$

Update state covariance

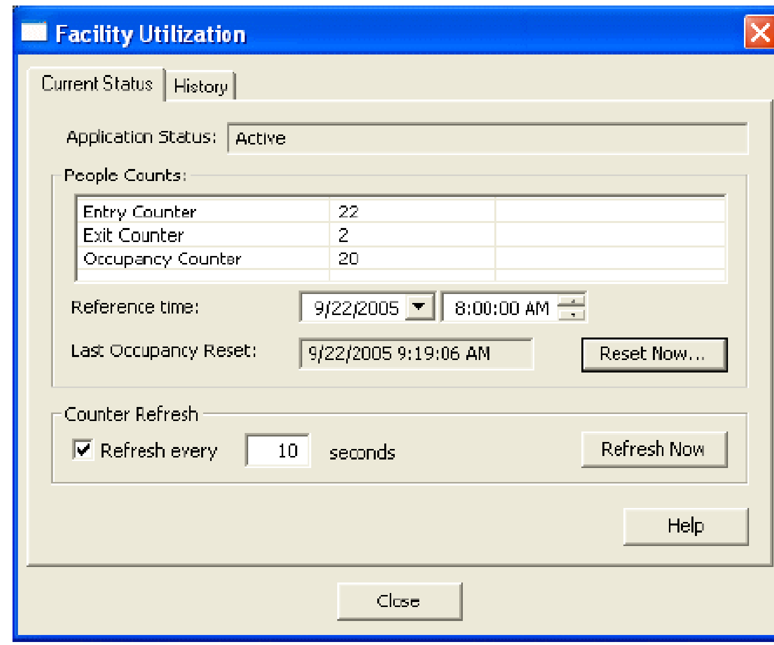
$$P(t+1|t+1) = P(t+1|t) - W(t+1) \cdot S(t+1) \cdot W(t+1)'$$

UTC Lenel Intelligent Video (IV) Products

People Counting Algorithm



Facility Utilization Application

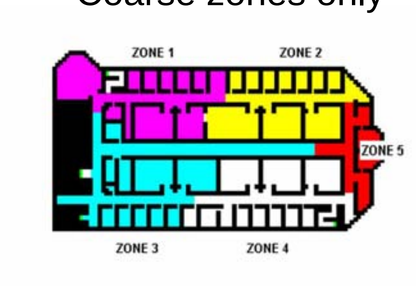


Counts people, using IV on look-down cameras at various “gates,” and adds / subtracts people as they pass through gates. Useful when order of magnitude of in/out flow is comparable to the occupancy.

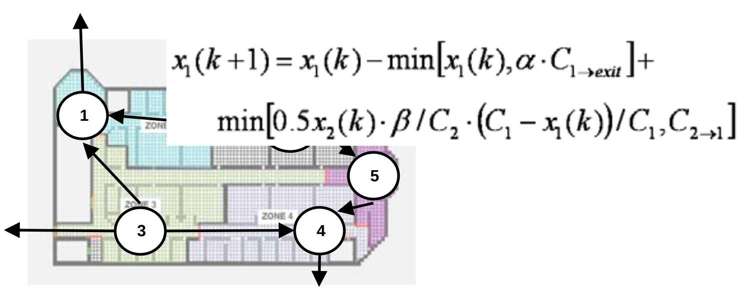
Summary of Real-time Occupancy Estimation Schemes

"Coarse" Model-based Estimation

Coarse zones only

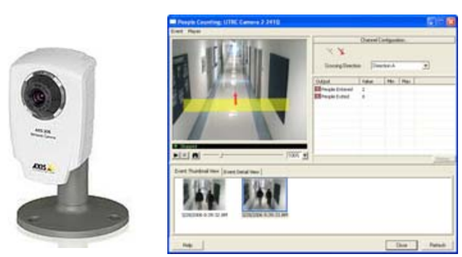


Simplified Model of People Movement



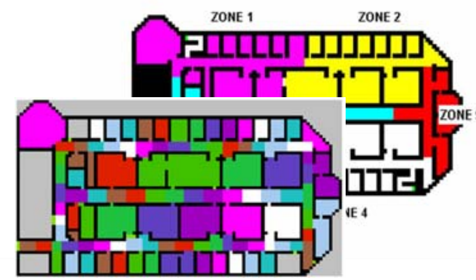
$$x_1(k+1) = x_1(k) - \min[x_1(k), \alpha \cdot C_{1\to exit}] + \min[0.5x_2(k) \cdot \beta / C_2 \cdot (C_1 - x_1(k))/C_1, C_{2\to 1}]$$

Sensors for Directional People-Counting

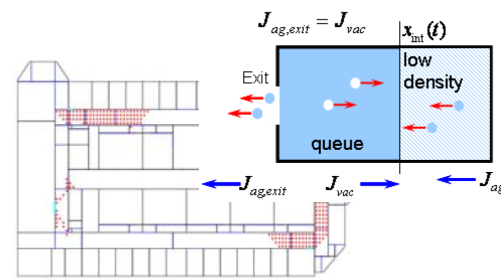


Kinetic Model-based Estimation

Hierarchical: room, zone, floor, building



Kinetic Model of People Movement

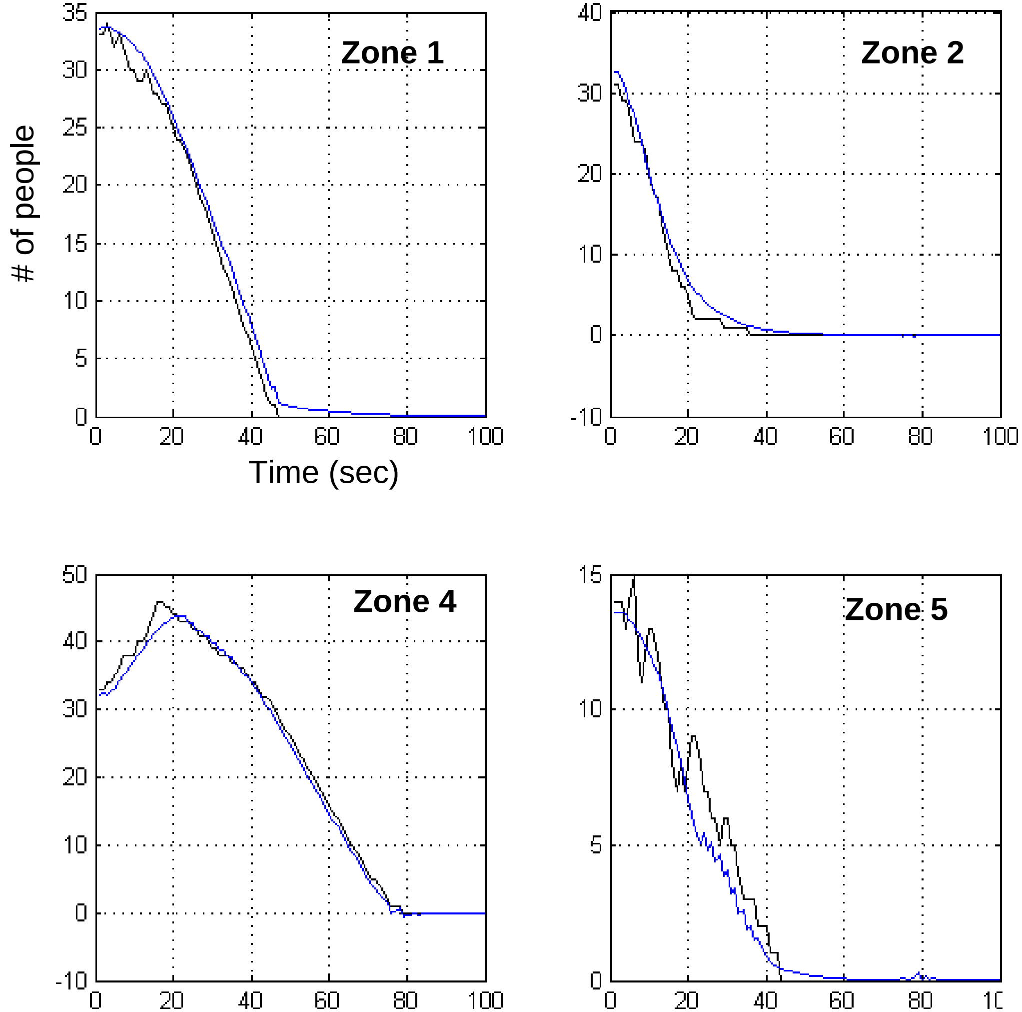


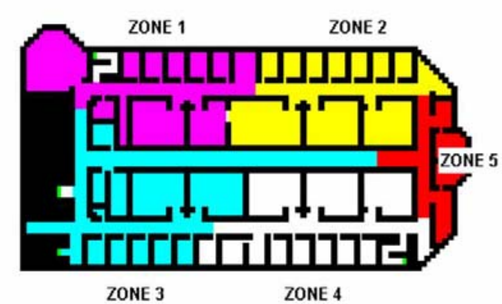
Sensors for Occupancy Level

Example Simulation Run (3 cameras)

Black = actual
Blue = estimate

Zone-level estimates





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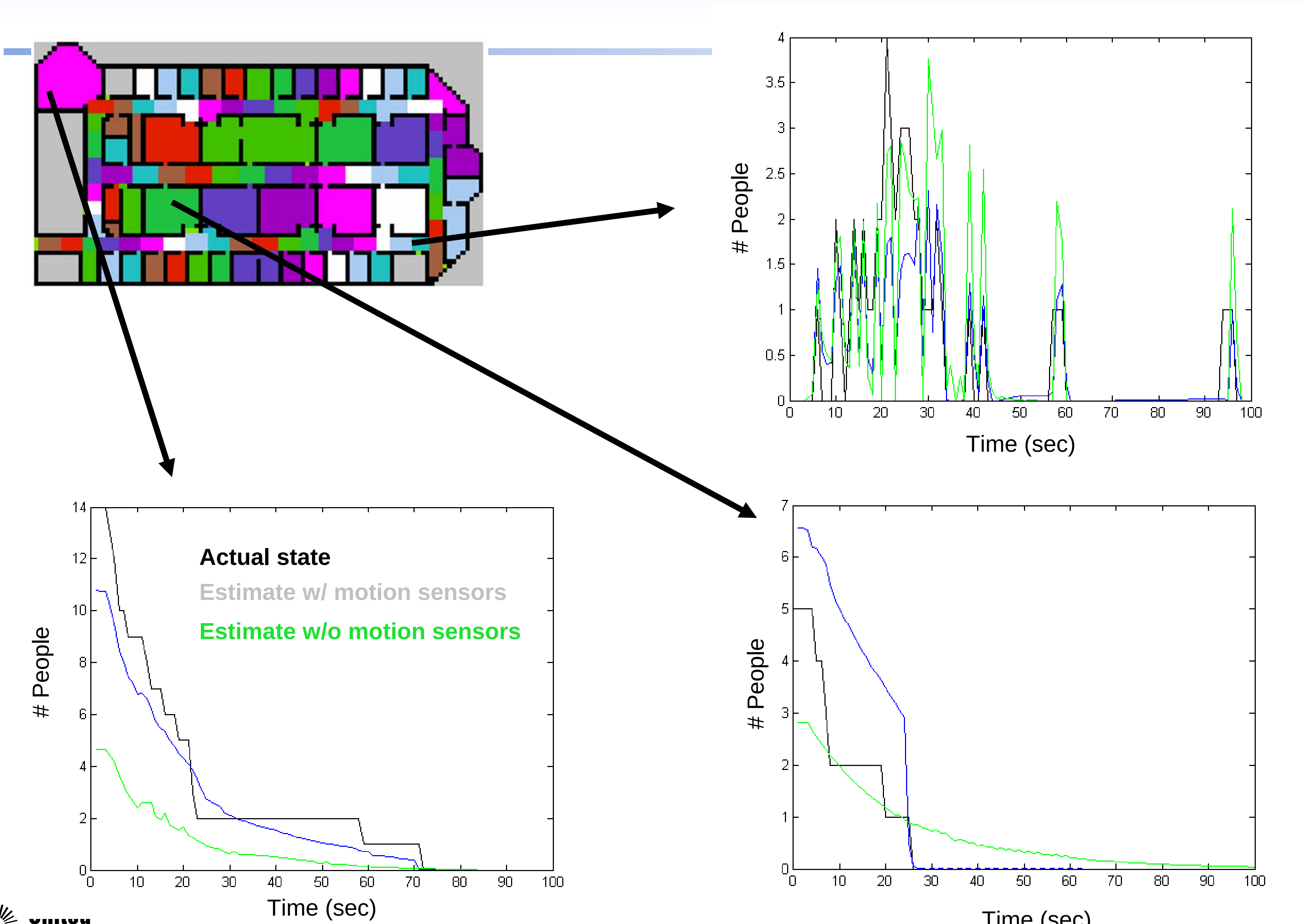
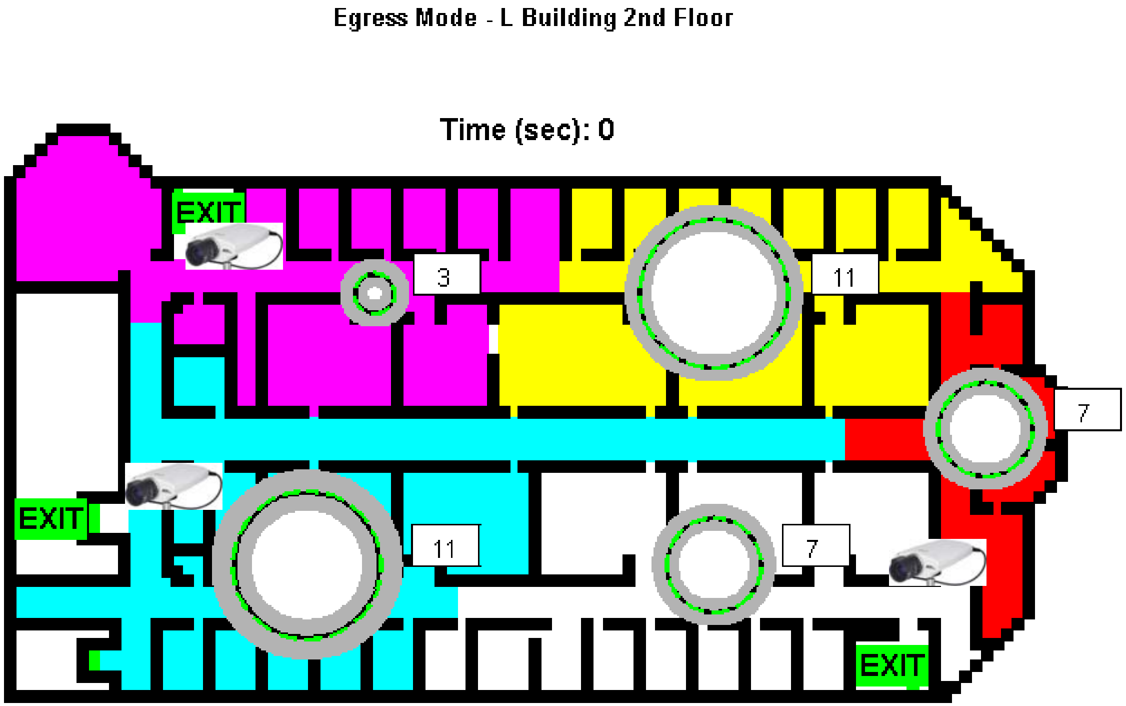
Example Simulation Run

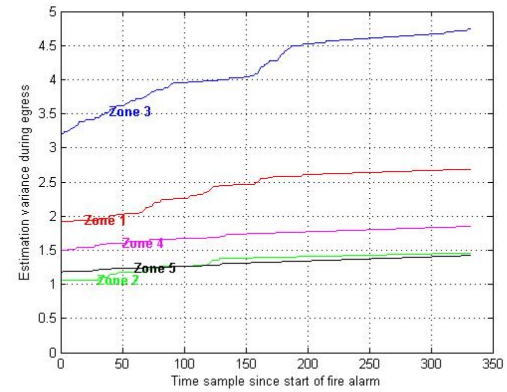


Real-Time Occupancy Estimation Demonstration

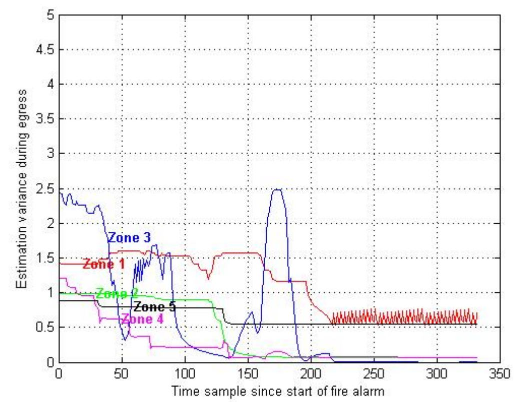
Proof-of-concept of real-time estimation demonstrated during fire drill



Sensor-only estimate variance



Model-based estimate variance



- Occupancy estimator tracks measured data well
- Occupancy estimates from combining models and sensor data superior to and robust when compared to using sensors only
- Computational complexity scales with (# of sensors)^3, not with # rooms, square feet, # people

Mean Error in no. of people per zone

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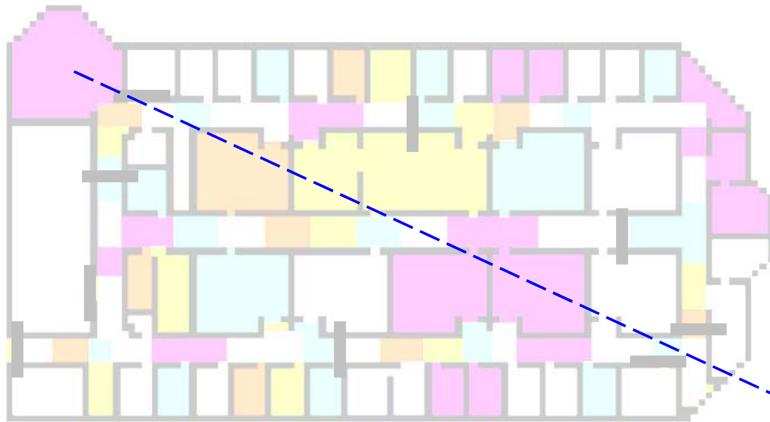
Sensor only	1.5	5.3
Model+Sensor (EKF)	1.0	1.4

Simulation of Room-Level Occupancy Estimation

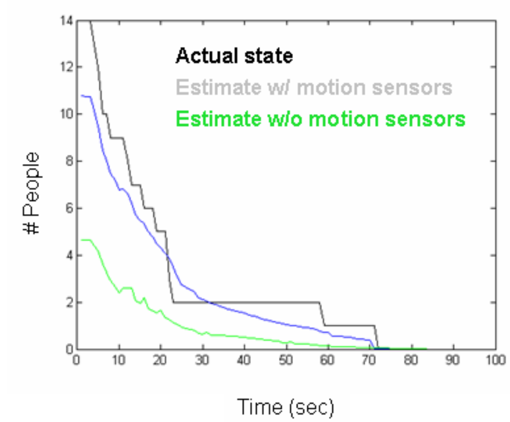
Layout of Building
2nd floor



Look-down camera

Motion sensors in all rooms

Estimator	# Cameras	Mean Error, # of people (avg per zone over all time and 500 sim runs)
Sensor only	9	1.5
EKF w/ “coarse” model	9	1.0
EKF w/ KM	9	0.8
Sensor only	3	5.3
EKF w/ “coarse” model	3	1.4
EKF w/ KM	3	0.9



Role of Constraints in Estimation

Any linear model of occupancy is not observable based on flow measurements

- Missing information can be recovered by including 1. Prior knowledge of occupancy preferences, and 2. Hard constraints on occupancy
- Kalman filter can be posed as a quadratic program. The introduction of constraints and preferences leads to an effective algorithm:

$$\arg\min\left\{\mathcal{P}_0(\phi_0) + \sum_{t=0}^{T-1}\left(\mathcal{P}_y(\phi_t, y_t) + \mathcal{P}_x(\phi_{t+1}, \phi_t) - \mathcal{U}_x(\phi_t)\right)\right\}$$

Subject to Network constraints

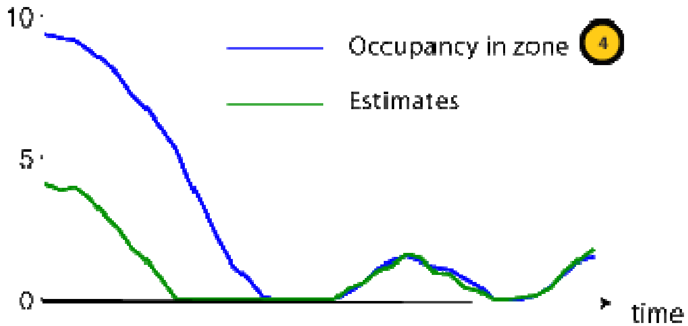
Initial condition

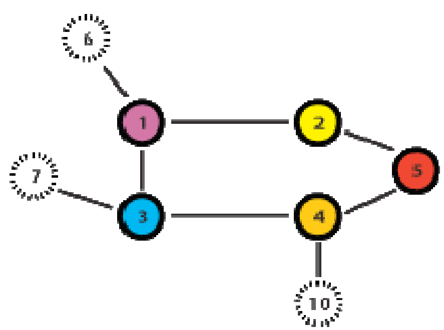
Sensor confidence

Dynamics

Utility

- During egress: “preference for movement to exit”
- Preferences for walking speed, proximity, path
- Clustering, Lane formation
- Continuity: Avoid drastic direction change
- *Behavior dependence on* age, mobility, aggressiveness…





Initial occupancy error of 200% corrected using projection (non-negativity constraints)

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