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Video-Based Estimation of Building Occupancy During Emergency Egress

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***Abstract*— Providing real-time estimates of building occupancy to first responders during emergency events can help in search and rescue, and egress management. This paper addresses the estimation of occupancy in each zone of a building, where the building is spatially divided into non-overlapping zones that cover all areas of the building. Each zone contains video cameras located at each portal of the zone, where each camera has a signal processing algorithm that detects number of people passing through the portal in each direction. The technical approach of this paper is to develop a non-linear stochastic state-space model of people traffic during emergency egress, and apply the extended Kalman filter which uses the video signal processing outputs and the people traffic model. The approach is demonstrated on a 16,000 square-foot building that has typical occupancy of 100 people. The estimator is tested on data from an agent-based simulation, and on data from an actual fire alarm. The results show that better estimation accuracy is achieved compared to an estimation approach that uses only the video sensors.**

I. INTRODUCTION

Our interviews with local fire departments revealed the importance of having real-time information on people location in a building during emergencies. Having such information would help in search and rescue, and improve the management of emergency events, thus saving lives. People location estimates could also be used in conjunction with an egress control strategy, where active electronic signs or audible instructions efficiently direct people out of a building.

Having the knowledge of the occupancy of people in a building also has benefits for normal operations, including:

- improving the comfort of the building occupants by controlling lights, temperature, and humidity based on occupancy,
- reducing energy costs by controlling lights and HVAC equipment based on occupancy, and
- improving the convenience of occupants by improved elevator dispatching.

Most buildings today have multiple types of sensors that can be used to help estimate occupancy. Such sensors include video cameras, passive infra-red motion sensors, access control devices, elevator load measurements, and IT-related techniques such as detection of computer key-strokes. Persons sometimes carry active devices, such as active RFID tag or cell phone, which can be detected to indicate their location.

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The purpose of this research is to develop a method for estimating the occupancy of people in areas of a building, based on the available sensor information. This is a challenging problem because of the large number of sensors in a building, the diverse types of sensing, redundant information across sensors (e.g. overlapping fields of view of cameras), and lack of sensor coverage in parts of the building. Another key challenge is that no sensor provides 100% reliable information. This paper does not address tracking of individuals, except to the extent that the output of such tracks can be used as input to estimating occupancy levels.

The state estimator (where "state" is the occupancy of people in various "zones" or areas of a building) takes as input the layout of the building, the location of fixed-position sensors, the capability of sensors (range of detection, probability of detection, false alarm rate, etc), and mode of the building, where mode can relate to normal operations or an egress situation. Knowing the building mode helps the state estimator better understand the traffic patterns of people in the building, and these patterns, represented as a model, helps the estimator estimate people occupancy in areas of the building where there is no sensor coverage and to correct for sensor error. A building's fire alarm control panel can provide the estimator with signals that indicate emergency building modes, such as full emergency evacuation, partial evacuation, etc.

The output of the estimator is a probability distribution over the number of people located in each zone of the building, where the building is spatially divided into non-overlapping zones that completely cover all areas of the building. Ideally, the zones are sized in area to be equivalent to room size. The estimator may also estimate occupancy in larger areas, such as a floor, containing multiple zones.

This paper addresses the estimation problem of a specific building, and can be generalized to other buildings. The floor of this building is 16,000 square feet, has typical occupancy levels up to 100 people, and has 11 video cameras each with real-time video processing to detect movement and direction of people passing beneath the camera.

The technical approach of this paper is to develop a non-linear stochastic state-space model of people traffic during emergency egress, and apply the extended Kalman filter which uses the video sensor outputs and the people traffic model. The approach is demonstrated on the example building described above. The estimator is tested on data from an agent-based simulation, and on data from an actual fire alarm.

The main contribution of this paper is that it presents the first application of people occupancy estimation that makes use of people movement models and outputs from multiple sensors. A key advantage of this approach is that it can estimate occupancy in areas of a building that are not completely covered by video cameras or other sensors. The results show that better accuracy is achieved compared to sensors alone.

People traffic has been studied extensively in the area of people behavior and movement characteristics. For example, Fruin [3] has provided a comprehensive study on pedestrian movement including the walking speed by gender and age groups, and the speed-density relations. Helbing [5] has observed people behavior such as their preferred path choice and preferred distance from others in different environment. Building occupancy has been studied through agent-based simulation models in which the movement of each individual is tracked. Galea [4] showed that evacuation can be modeled using an agent-based simulation tool EXODUS. Daamen et al. [2] developed a pedestrian model designed for transfer stations. A review is given in Helbing et al. [6] on the work of pedestrian crowd research in normal and evacuation situations. The use of video data in the analysis of people behavior has been mainly limited in the area of individual tracking [7] or the use for manual post-processing. There is little effort in developing methods to estimate people occupancy using video data from multiple sources.

In the next section of this paper, the specific building layout is described and the video processing performance is described. In Section 3, a sensor-only estimator for normal building mode is presented. This estimator provides the initial estimate of people occupancy at the time a fire alarm triggers. Section 4 presents the extended Kalman filter approach, including the model of people traffic. Section 5 provides test results using an agent-based simulation and compares a sensor-only estimator to the extended Kalman filter. Section 6 provides test results on an actual fire alarm where the building was evacuated. Finally, the paper concludes with opportunities for future work.

II. PROBLEM DEFINITION

This paper is focused on developing an estimator for a specific building, and can be generalized to other buildings. This building is two floors, and the second floor is addressed. The layout of this floor is shown in Figure 1. There are three stairwells to the first floor, an elevator to the first floor, and a passageway from an adjacent building. Occupants on the floor are instructed to use the nearest exit during emergency evacuations. Passage to the adjacent building is not a nearest exit for anyone in the example building, and people from the adjacent building egress through the example building. The horizontal hallway in the center of the floor plan is rarely used, as it is a storage and utility area with fire doors on both the left and right side.

The red and blue lines in Figure 2 represent thresholds by which video cameras detect persons crossing. The red lines indicate look-down cameras that are mounted above doors and look perpendicular to the floor. The blue lines indicate oblique cameras, which are mounted on the ceiling in hallways and angle down approximately 30 degress from the ceiling looking length-wise down the hallway.

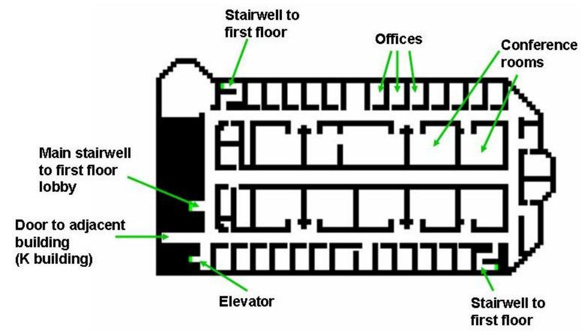

Fig. 1. Layout of test building

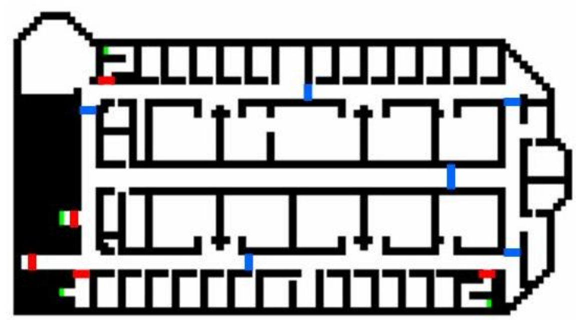

Fig. 2. Location of video cameras for people counting. Red lines indicate look-down cameras, blue indicate oblique cameras.

Each of these digital video cameras send their signals to a central server computer where real-time intelligent video processing is performed to detect persons crossing the threshold and the direction in which they cross. Experimental results yielded a probability of detection of 98% and a false alarm rate of 1 every 4 hours.

The video camera locations were placed in order to divide the floor into reasonably small zones, as shown in Figure 3. Each zone in Figure 3 is bordered by a camera.

The estimation problem is to estimate the number of people, either as a probability distribution function or a mean and variance, in each of the five zones shown in Figure 3.

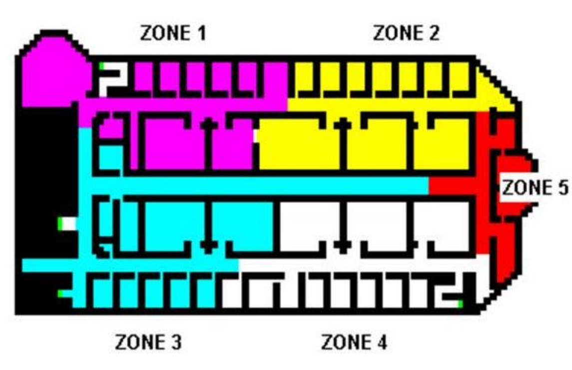

Fig. 3. Floor layout with zones defined by camera locations.

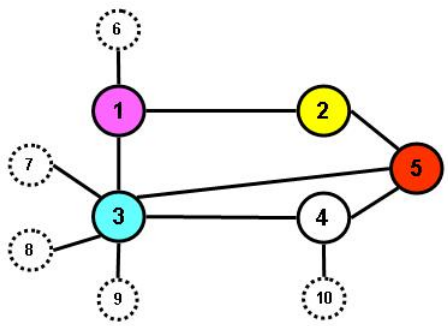

Fig. 4. Graph of zones of building, with large nodes representing zones, small nodes representing exits, and arcs representing passages.

The estimation occurs for both normal building operations, and in emergency egress mode. The occupancy estimate from normal building operations provides the initial conditions to the egress estimation at the time of a fire alarm.

In this paper, the estimator for normal operations uses the sensor readings only, and does not use a model of people traffic. This is an opportunity for future enhancement. The egress estimator does use a people traffic model.

III. ESTIMATOR FOR NORMAL BUILDING MODE

The estimator for normal building mode basically adds and subtracts the people-counting outputs from each camera and for each zone according to direction of flow, while also keeping track of the probability distribution corresponding to each sensor output. It makes no use of people movement models, although use of such a model would improve the estimation as will be shown for egress mode.

The zones of the building form a graph as in Figure 4. Each node with a solid line on the graph is a zone, a node with a dashed line indicates an exit, and each arc represents a physical path between zones or between a zone and exit. The variables $x_i(t)$ for $i = 1, 2, ..., 5$ represent the occupancy level in zone i at time t, and $y_{ij}(t)$ represents the number of people that move from node i to j at time t (where $y_{ij}(t) = -y_{ji}(t)$). Note that the people flow on each arc is measured by a video camera.

With node 1 as an example, the occupancy dynamic equation is:

$$x_1(t+1) = x_1(t) + y_{21}(t) + y_{31}(t) + y_{61}(t). \qquad (1)$$

Each of the variables $x_i(t+1)$ for $i = 1, 2, ..., 5$ represent the variables to estimate, based on the prior belief of $x_i(t)$ and current sensor readings $y_{ij}(t)$. The estimation problem is to compute the probability

$$p[x_i(t+1) = n \mid \phi_{ij}(t),\ p(x_j(t) = m) \quad \forall j, m], \qquad (2)$$

where $\phi_{ij}(t)$ is the sensor reading for number of people moving from node i to j at time t, and $p(x_j(t) = m)$ is the prior estimate at time t. This estimation problem is to compute the probability distribution function of $x_i(t+1)$.

With node 1 as an example, the right hand side of Equation 1 is a sum of random variables. Therefore, the probability distribution function (pdf) of the estimate of $x_1(t+1)$ is the convolution of the pdf's of the variables on the right hand side:

$$f_{x_1(t+1)} = f_{x_1(t)} * f_{y_{21}(t)} * f_{y_{31}(t)} * f_{y_{61}(t)}, \qquad (3)$$

where $*$ is the convolution operator, and f_x is the pdf of random variable x.

The pdf of $x_1(t)$ is provided by the prior iteration of the estimation. At some initial time $t = 0$, the estimate of $x_i(t)$ is initialized. In practice, it is initialized to equal zero with very high probability at a time where it is known that no persons are in the building, such as at 3am.

The pdf of $y_{ij}(t)$ is based on the sensor reading $\phi_{ij}(t)$. Formally, the pdf of $y_{ij}(t)$ is defined as

$$p[y_{ij}(t) = n \mid \phi_{ij}(t) = m]. \qquad (4)$$

This quantity is computed by using Bayes rule:

$$p[y_{ij}(t) = n \mid \phi_{ij}(t) = m] = p[\phi_{ij}(t) = m \mid y_{ij}(t) = n] \cdot p[y_{ij}(t) = n]. \qquad (5)$$

The term $p[\phi_{ij}(t) = m \mid y_{ij}(t) = n]$ corresponds to the sensor performance, which is based on probability of detection P_d and probability of false alarm P_f. Table 1 provides the probabilities for the above term.

Table 1: Conditional probability of sensor performance

Actual flow (n)	Sensor output of # of people flow (m)			
	0	1	2	...
0	$1-P_f$	P_f	0	
1	$(1-P_d)\cdot(1-P_f)$	$P_d(1-P_f)+(1-P_d)P_f$	P_dP_f	
2	0	$(1-P_d)(1-P_f)$	$P_d(1-P_f)+(1-P_d)P_f$	
...				

The last term in Equation 5, $p[y_{ij}(t) = n]$, is based on the prior knowledge of how many people walk below the sensor. During normal business hours at this building, approximately 25 people per hour cross under each sensor. Thus, with a time sample of 1 second, the probability that a person crosses a sensor during a one second interval is 0.007. With the assumption that at most 3 people can cross under the sensor at one time, and the probability of people crossing is independent among/between people, Table 2 provides the probabilities for $p[y_{ij}(t) = n]$.

Table 2: Probability of correct sensor reading

n	$p[y_{ij}(t) = n]$
0	$(1-0.007)^3$
1	$0.007 \cdot (1-0.007)^2$
2	$0.007^2 \cdot (1-0.007)$
3	0.007^3

The estimation for normal building mode is thus the iteration of Equation 3 at each time sample. This estimator provides the pdf for all zones.

IV. ESTIMATOR FOR EGRESS BUILDING MODE

The chosen approach for state estimation of people occupancy is to use the well-proven extended Kalman filter [1]. In this approach, a nonlinear dynamic stochastic state-space model is used:

$$x(t+1) = f(t, x(t)) + v(t), \quad (6)$$

where x is the vector of state variables (people occupancy in each zone), f is some non-linear function of time t and states $x(t)$, and $v(t)$ is process noise, representing the uncertainty in how people move in a building. The form of f for people traffic during emergency egress is presented later in this section.

The extended Kalman filter also requires a sensor model:

$$z(t) = h(t, x(t)) + w(t), \quad (7)$$

where z is the vector of sensor outputs, h is some function of t and state vector x, and w is sensor noise.

The extended Kalman filter approach is to use the Taylor series expansion of f and h and form a linear system about the current state estimate, and then use the standard linear Kalman filter to estimate the mean and variance of the states. The details of the approach can be found in [1]. For a linear system, the Kalman filter is optimal in minimizing the mean-square error of the estimate compared to the actual state.

The next sub-sections describe the process model and sensor model.

A. Egress Process Model

The first element of the egress model is the function $f(t, x(t))$ from Equation 6. The structure of this model is shown for node 1 of the graph:

$$x_1(t+1) = x_1(t) + y_{21}(t) + y_{31}(t) - y_{16}(t). \quad (8)$$

The term $y_{16}(t)$ is the flow out of the zone through the exit, which is a positive term during egress, and is defined as

$$y_{16}(t) = min[x_1(t), \alpha \cdot C_{16}], \quad (9)$$

where C_{16} is the capacity of the link from node 1 to 6, and α is a tuning parameter found experimentally.

The flow from node 2 to 1 is modeled as

$$y_{21}(t) = min[a_{21}x_2(t) \cdot \beta / C_2 \cdot (C_1 - x_1(t))/C_1, C_{21}], \quad (10)$$

where a_{21} is the percent of people in node 2 who have the exit in node 1 as the nearest exit, the term β / C_2 represents the delay for people moving across zone 2, β is a tuning parameter, C_2 is the maximum occupancy of node 2 which is proportional to the area of the corresponding zone, the term $(C_1 - x_1(t))/C_1$ represents congestion in zone 1 that slows people from moving into the zone, and finally C_{21} is the link capacity from node 2 to 1.

The flow between other nodes are modeled in the same manner.

The model uses the assumption that people use the nearest exit. Figure 5 shows the exits and the corresponding areas which would use that exit as the nearest exit. Using this

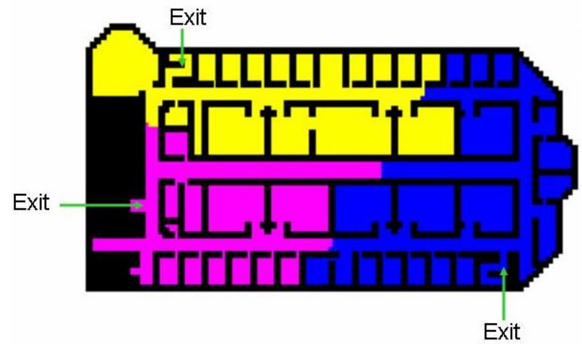

Fig. 5. Colors indicate common closest exit.

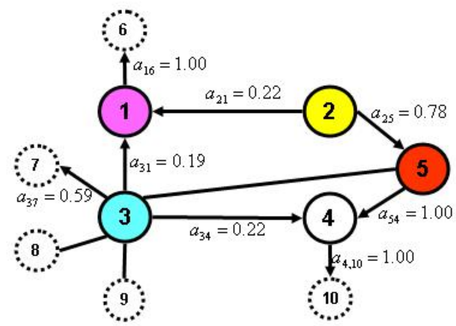

Fig. 6. Graph of zones of building, with percentage of flow according to nearest exit.

result, the parameter a_{21} is defined as the percentage of floor area in zone 2 which has its nearest exit in zone 1. Figure 6 shows all parameters a_{ij}.

The second component of the egress process model is the process noise. The process noise model accounts for the uncertainty in how people move between zones. A straightforward and simplistic approach is to assume that the process noise $v(t)$ in Equation 1 is zero-mean and Gaussian with variance proportional to $x(t)$ and independent among zones. In the implementation of the extended Kalman filter, the covariance matrix for the process noise is set equal to a diagonal matrix with elements corresponding to the state variance of the current estimate.

B. Tuning of Egress Model

There are two parameters, α and β, in the egress model that must be tuned. Since actual fire alarm data is difficult to obtain, the authors developed an inexpensive method to tune these parameters without actual egress data. The method is an agent-based simulation of people movement. In this simulation, each person in the building is modeled as an individual agent, and this agent moves toward the nearest exit, with some probability of deviating from the shortest path at each discrete time step. The agents move on a floor plan that is discretized into 2-feet by 2-feet squares. Only one agent can occupy a 2x2 cell at a time, so that congestion is modeled.

The values of α and β were found through simple trial and error, comparing the curve of number of people in the

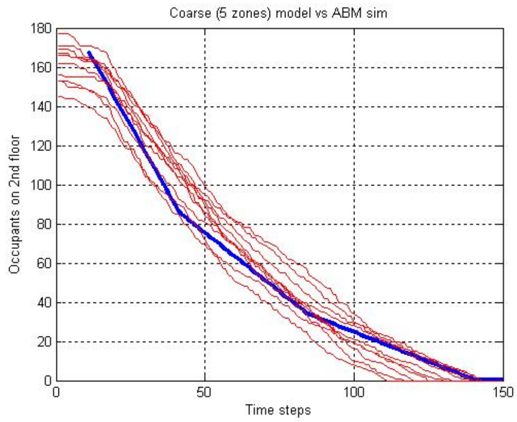

Fig. 7. Calibrated 5-zone model (blue) compared to agent-based model (ABM) simulation runs (red).

building (using model in Equation 6) versus time against the agent-based simulation curve. The best values found are:

$$\alpha = 0.3 \qquad (11)$$
$$\beta = 30$$

The corresponding plots are shown in Figure 7.

C. Sensor Model

The sensor model of Equation 7 is represented by the function h and the sensor noise w.

The output vector $z(t)$ represents the occupancy measurement in each of the five zones. It is derived by appropriately summing the sensor outputs bordering each zone. For example, for node 1,

$$z_1(t) = z_1(t-1) + \phi_{21}(t) + \phi_{31}(t) - \phi_{16}(t). \qquad (12)$$

A key characteristic of the means of sensing occupancy is that the errors of the sensors ϕ_{ij} build up over time. The sensor readings z_i themselves are not "noisey," but instead are biased based on errors in detection and false alarms. Also, the more sensors that border a zone, the higher the error.

Despite these characteristics, the sensor noise is modeled as zero mean and white, with variance equal to the variance of the estimate of the sensor-only estimator used for normal building mode at the time of the fire alarm. This variance increases only slightly during an evacuation, which lasts only several minutes or less.

D. Initialization of Kalman Filter

The extended Kalman filter at the beginning time of an evacuation needs an initial mean and covariance of the state estimate. This comes from the normal operations estimation described in Section 3.

E. Comments

Although the comparison of the state space model against the agent-based simulation showed good correlation, there are still several opportunities to improve the state space model. One is that the model does not conserve the number of people in the building from one time step to another, because of the process noise model is independent for each zone. Ideally, the process noise should be used to model the number of people who transition between zones, and use this noise value in adding / subtracting the occupancy in each zone accordingly. The second area for improvement is with the sensor noise model, which is zero-mean white noise. In reality, the video sensors are not white noise but have some bias error which slowly changes over time as detection errors and false alarms accumulate. The third modeling opportunity is that the current model assumes every person moves to the nearest exit during egress. As will be shown later in this paper, this is not the case, as some people use the exit that they entered the building, some use a familiar exit, etc. Finally, the model assumes that no persons enter the example building from the adjacent building, which is not the case – during a fire drill, 16 people entered.

V. TESTING ON AGENT-BASED SIMULATION

With an agent-based simulation, extensive tests can be run on simulated emergency egress. The simulation also models each sensor's probability of detection and probability of false alarm, so that an estimator can be tested on simulated data.

The purpose of the testing is to determine experimentally how accurate the extended Kalman filter (EKF) is in providing occupancy estimates, both mean and variance. A second purpose is to compare its accuracy to the sensor-only estimator (used for normal operations and described in Section 3), to show that the EKF's combined use of sensors and a model provides significant accuracy improvement over a sensor-only estimator.

The key metric to measure estimation accuracy is mean-square error. For the extended Kalman filter, a second metric is the percent of occurrences (for each zone and time step) where the actual occupancy falls within the 90% confidence interval of the estimate – this gives an indicates of how good is the variance estimate.

The agent-based simulation used for testing in this section assumes that: no people enter from the adjacent building during emergency egress; each person uses nearest exit (without using the horizontal center hallway, which is a storage and utility area); the sensors have a P_d and P_f as specified previously; and there is a period of normal operations prior to a fire alarm, and the sensor-only estimator is used to estimate occupancy during this time.

A. Normal Operations Test Results

This testing is used to gain an understanding of the variance of the estimate at the end of some period of normal operations, after which begins the period of emergency egress.

The agent-based simulation for normal operations simulates both floors of the test building. It creates a unique movement profile of each agent. In this particular test set-up, there are 10 agents that arrive every minute, and their arrival time is spread randomly over the duration of the simulation run (while maintaining 10 agents per minute). Each agent

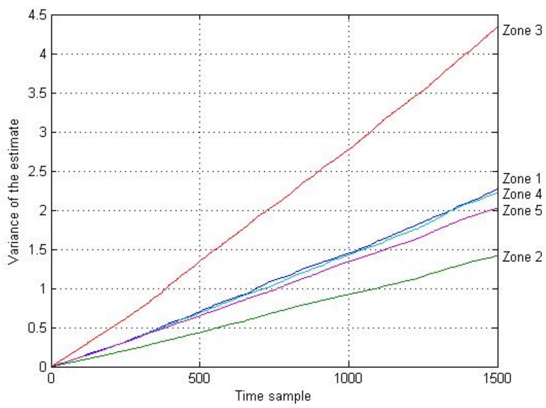

Fig. 8. Variance of the estimate for normal building mode.

arrives at a random entrance on the first floor. The agent then proceeds using shortest path to a random office location on the first floor, and stays in that office between 1 and 150 time steps (randomly generated with uniform probability distribution). The agent then moves to a stairwell or elevator (randomly selected) to move to the second floor, and moves to a random office on that floor, where the agent stays with duration randomly selected between 1 and 1500. Then the agent leaves the office and heads to one of the stairs to the first floor, and exits out of the building using the same door that the agent entered the building. Each time sample represents 0.4 seconds.

Figure 8 shows the results of one simulation run of duration 10 minutes (1500 time samples), and plots the variance of the estimate over simulation time. The figure clearly shows that variance increases as the errors in the sensor readings accumulate. It also shows that some zones have higher variances because there are more entrances/exits, and thus more cameras surrounding it. More cameras result in a higher probability of false alarms, thus the higher estimation variance for these zones.

B. Test Results for Estimation During Egress

In this section, test results of two methods of estimation during egress are provided: sensor-only and extended Kalman filter. The sensor-only model is exactly the same as the estimator used for normal operations.

Five simulation runs are executed, each with 10 minutes of normal operations followed by egress. For each run, the exact same data set of people movement and sensor outputs is used for both estimators. For different runs, a different random number seed is used, and the number of agents arriving per minute is varied. Table 3 shows for each run the mean-square error (MSE) for both the sensor-only estimator and extended Kalman filter (EKF). Table 4 shows for each of the same runs the percent of occurrences (over each zone and time step) where the actual occupancy falls within the 90% confidence interval of the estimate.

For Run 3, Figure 9 shows the plot of the estimate for each zone during egress mode, the 90% confidence interval,

Table 3: Mean-square error (MSE) of sensor-only estimator compared to EKF estimator, for five simulation runs

Run	MSE Sensor-only estimator	MSE EKF estimator
1	1.33	1.39
2	1.32	0.98
3	2.38	2.10
4	8.73	5.19
5	4.30	2.72

Table 4: Percent of occurrences (over each zone and time step) where the actual occupancy falls within the 90% confidence interval of the estimate

Run	Normal mode with sensor-only estimator	Egress mode with EKF estimator
1	83.4%	85.7%
2	98.7%	98.8%
3	88.6%	89.8%
4	90.0%	81.9%
5	82.6%	94.0%

and the actual number of occupants. Figure 10 shows the variance produced by the EKF during Run 3 egress mode.

The results in Table 3 show that the EKF MSE is better in 4 out of 5 runs, and only slightly worse on the other run. The results in Table 4 provide a good indication that the EKF variance is reasonable. Figures 9 and 10 show how the variance of the estimate decreases over time, thus reducing the uncertainty of the estimate, which has practical value to first responders. The EKF's improvement in MSE and the reduction in variance is a direct result of the use of people movement model in the estimation algorithm.

VI. TEST ON FIRE ALARM DATA

This section describes a test of the two estimators on data from an actual fire alarm. Video from all cameras in the building was recorded, and manually post-processed to determine the initial position of all people in the building at the time of the fire alarm, each person's trajectory out of the floor, and the trajectory of each person who entered from the adjacent building. Also, the same video recordings were processed by the intelligent video algorithms, and these serve as the sensor outputs used in estimation.

The initial conditions are shown in Figure 11 (the exact location of people within each room is unknown).

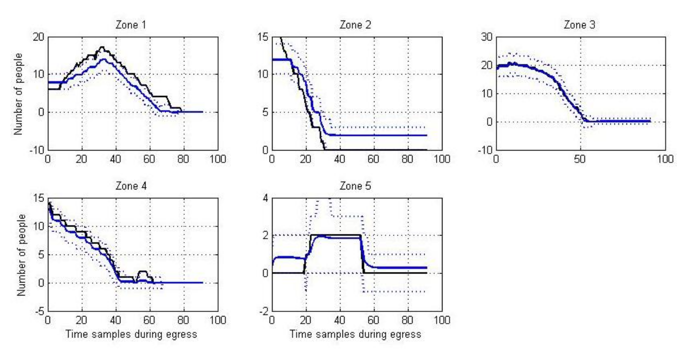

Fig. 9. Run 3, plot of EKF estimate (solid blue), 90% confidence interval (dashed blue), and actual occupancy (black).

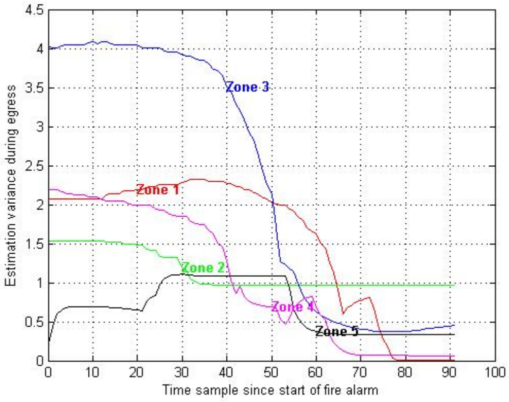

Fig. 10. Run 3, variance of the EKF estimate for egress mode.

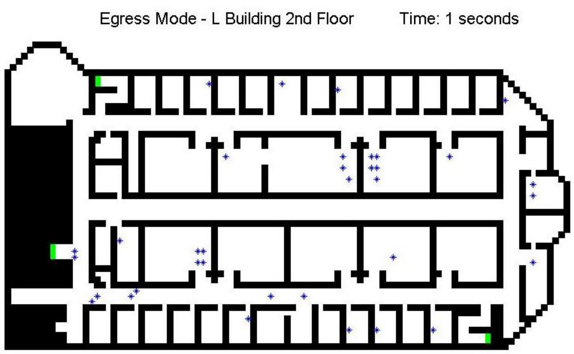

Fig. 11. Location of people at beginning of fire alarm.

Sixteen people from the adjacent building enter the test building starting at 7 seconds from the alarm and ending at 156 seconds from the alarm. All of these people use the main stairwell.

Each estimator is initialized with a variance shown in Table 5, and a mean value taken as a random number from a Gaussian distribution with the variance from Table 5 and mean equal to actual number of people. The number of simulation runs is 10, where each run uses a different initial mean for the estimator. Table 6 shows the results, which show that both estimators perform about the same in terms of MSE. The reason that the EKF does not perform better than the sensor-only estimator (as it did in agent-based simulation testing) is that the people movement model used for the EKF during fire alarm had several key differences compared to actual people movement. The first difference is that the model assumes people use the nearest exit, where during the fire alarm 63% (22 people) of the 35 people who started in the test building used the nearest exit. A second significant difference is that the model assumes that no people from the adjacent building egress through the test building, whereas 16 people did during the fire alarm. The last major difference is that the model assumes people egress at the start of the fire alarm, compared to the fire alarm data which shows 10 people waited more than 20 seconds before leaving their office or conference room.

Table 5: Estimation variation at start of fire alarm

Zone	Initial variance
1	1.84
2	0.97
3	3.13
4	1.41
5	1.10

Table 6: Mean-square error (MSE) of sensor-only estimator compared to EKF estimator, for ten different initial conditions of the estimator

Run	MSE Sensor-only estimator	MSE EKF estimator
1	1.17	0.61
2	3.73	3.91
3	0.77	0.75
4	0.68	1.15
5	2.45	2.52
6	1.59	1.00
7	1.35	0.60
8	0.84	0.37
9	2.59	1.03
10	3.61	3.36

For Run 1, Figure 12 shows the plot of the estimate for each zone, the 90% confidence interval, and the actual number of occupants. Figure 13 shows the variance produced by the EKF during Run 1. In Figure 13, the spike in variance of zone 3 at time sample 175 is a result of people egress from the adjacent building into zone 3 (this effect can also be seen in Figure 10).

VII. FUTURE WORK

Several opportunities were already identified in Section IV-F. In addition, a significant area of future work is to extend the approach to handle additional types of sensors. The authors also plan to develop an improved estimator for normal building operations; such an approach would include a model of people movement, versus the sensor-only approach shown in this paper. Finally, the issue of computational scale-ability of the approach to large buildings with 1000's of sensors will be explored.

VIII. ACKNOWLEDGMENTS

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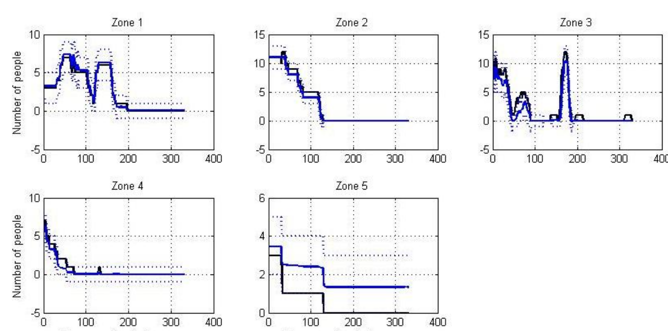

Fig. 12. Run 1, plot of EKF estimate (solid blue line), 90% confidence interval (two dashed blue lines), and actual occupancy (black line).

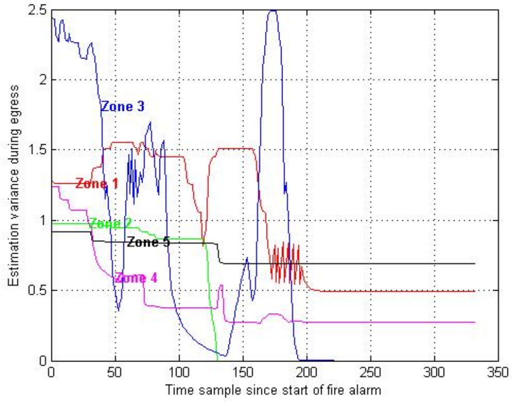

Fig. 13. Run 1, variance of the EKF estimate during egress.

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