Methods and Tools for Real-time Occupancy Estimation

Issues

A barrier to efficient building operation is lack of information. This section concerns one aspect of this problem: Occupancy estimation in a large building. Effective occupancy estimation is a critical part of the Merced project to investigate the impact of demand-based heating and cooling.

There are many uses for occupancy measurements beyond HVAC. In particular, occupancy estimates are of tremendous value to first responders arriving to a building on fire.[1]

Among the barriers to be overcome are:

1) Lack of "observability". Can we expect to know the distribution of people in Golden Gate Park based on observations at the gates? Even if a very popular event is located in the middle, there will be some in the park who prefer a quiet picnic. Similar uncertainty arises when attempting to estimate the distribution of occupants in a building based on measurements of their movement through hallways.
2) Uncertainty. The lack of observability is typically combated by introducing prior knowledge. However, it is not likely that we can obtain a detailed and accurate model of the behavior of individuals in a building.
3) Noise. For example, sensor accuracy may be diminished in a crowded hallway or in low light conditions.
4) Prediction. A demand-based HVAC system will incorporate predictions of occupancy. These forecasts combined with a dynamic model for the building can be used to maintain a comfortable environment. Forecasting is also important with the introduction of dynamic prices for electric power.
5) Complexity and distribution of information. A centralized estimation approach may provide an optimal solution in an ideal environment. However, distributed estimation is valuable as a means to complexity reduction, and to avoid global failure in case of emergency.

Approaches

Members of the team have investigated these questions using several different approaches. Linear systems approaches are introduced in [tomnarbanmey08] for the purposes of occupancy estimation during egress.[2]

The issue of observability is addressed through the introduction of projections to take into account prior knowledge. An estimator based on a projected Kalman filter is found to be effective in most cases for egress, but errors can accumulate when the algorithm is used in normal operation where the behavior of occupants is less structured.

A decentralized Kalman filter is introduced in [meyogg08]. To make use of greater prior knowledge regarding the anticipated use of the building, the paper [meyogg08] adapts ideas from model predictive control and the *pseudo MAP estimator* in statistics to create a model predictive estimator. The SUN estimator is introduced, based on the existence of a set of sensors (S), utility functions (U) that model preferences for subzones in a building, and the network structure (N) of the building and sensors. Estimation error is reduced significantly in experiments.

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[1] Rethinking Egress Workshop, Gaithersburg, MD, April 1-3, 2008. http://www.fire.nist.gov

[2] See the 1981 paper by Smith and Towsley [smitow81], and the collection of papers [schsha02].

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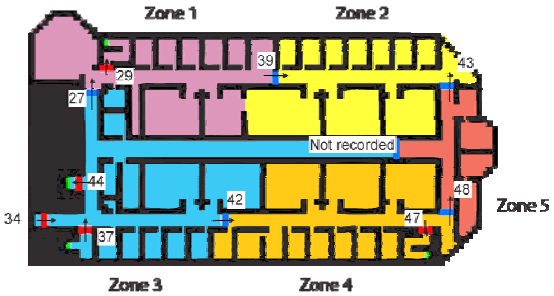
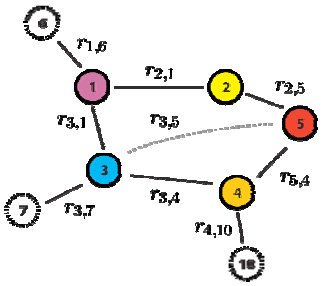
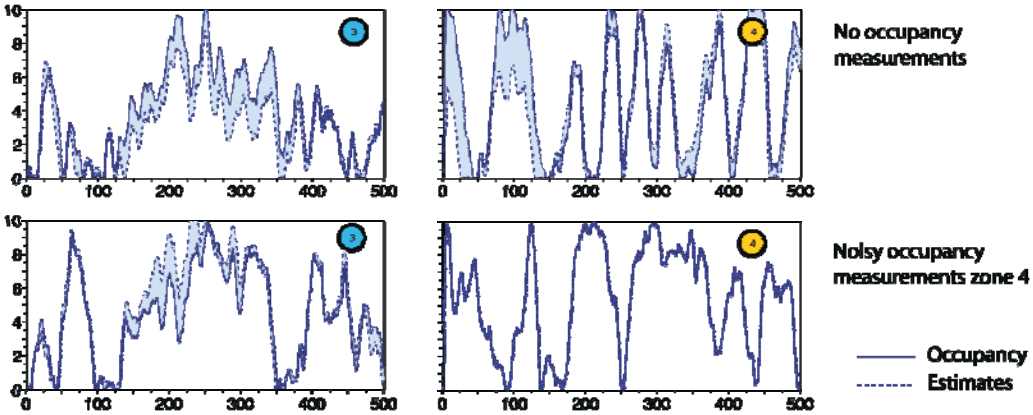




Typical performance of the projected Kalman filter is illustrated in Figure ?? for the building shown on the left in Figure ??.

The results shown in the first row of Figure ?? who occupancy evolution and occupancy estimates with flow measurements, but no direct occupancy measurements. One can see how information is gained when occupancy at one location hits a boundary so that the projection is enforced.

The introduction of a noisy occupancy estimator at room 4 results in dramatic reduction in estimation error - This is shown in the two plots in the second row. Note that estimation error is significantly reduced in zone 3 even though the measurement noise is over 25% at zone 4, and there is no direct occupancy sensor at zone 3. Similar results are observed in the other zones.



Recently occupancy estimation has been addressed through more fine-grained modeling of occupancy behavior, notably through Markov or hidden Markov models [dodhentilguo06,hutihlsmy07,denchemehmey08,niedenmehmey08]. The *Nature* article [helfarvic00] and *Science* article [gonhidbar08] describe distinct approaches to modeling occupant behavior.

We do not expect perfect models, or perfect estimation. Fortunately we can expect significant benefits from estimation even in a non-ideal environment in which estimation errors are more than 10%. Moreover, the SUN estimator and its variants can be used to obtain *absolute bounds* on estimation error. For given bounds on occupancy, rates, and sensor error, it is possible to obtain strict bounds on the resulting error as the solution to a convex program.

Several methods will be developed to combat complexity.

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i. Multi-scale models will be used to construct decentralized estimation algorithms. Some preliminary work based on Markov chain decomposition is described in [niedenmehmey08].

ii. Model reduction techniques based on Markov spectral theory are expected to be of value in the application of Bayesian techniques, where complexity can make direct application prohibitive.

iii. The *workload relaxation* technique of [CTCN] can be regarded as a variant of the singular perturbation technique for nonlinear systems, albeit highly specialized to network models. This technique is adapted to application to building systems in [denchemehmey08]. This paper concerns egress, but similar techniques are expected to be of great value for model reduction in estimation.

Using these model reduction techniques we can obtain tools for constructing estimation algorithms, and there are many other side benefits. In particular, each of methods (ii) and (iii) provides methods for visualizing evolution of occupancy in a large building.

In addition we must address the following topics.

Adaptation. Any algorithm will be based on prior assumptions that must be updated as the building is put to differing uses and occupant behavior changes. For example, the SUN algorithm is based on a set of utility functions to model preference for rooms in the building. These can be updated using least squares. Or, model updates for a hidden Markov, the Baum-Welch algorithm can be used to compute maximum likelihood estimates for the parameters in the HMM model based on observations [capmoubyd05].

Integration. Occupancy estimation is an enabler for demand based ventilation systems. Do we anticipate difficulties with integration here?

Validation. Merced project here

TO BE REFERENCED:
Use Of Whole Building Simulation In On-Line Performance Assessment: Modeling And Implementation Issues. Haves, P., Salsbury, T., Claridge, D., and Liu, M., Proc. of International Building Performance and Simulation Conference, Rio De Janeiro, Brazil, 2001.

REFERENCES TO BE PUT IN CONTEXT
[clacullliudenturhab00, frihaagil04,milfripowbouclahaapie04,milboupie04]

[liusoncla02]

Methods and Tools for Diagnostics and Prognostics

Estimation, inference, and diagnostics are required in the majority of tasks in this proposal:

- Once commissioned and shown to operate at expected levels of performance, a building can quickly fall out of tune and degrade in performance. Building performance monitoring requires estimation since energy performance is not directly measured. Utility bills and building management systems provide data on how much energy a building consumes or has consumed in the past at the whole building level, but rarely provide actionable

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information about relative performance - comparison to design intent, comparison to what could be achieved through optimization and adaptation.

- Similarly, POD modes change with occupancy, building state, and weather. The best model at a given time must be chosen based on available information.
- If HVAC is to be occupancy based, then occupancy estimates are required.
- As much as 20% of the energy consumed by commercial building HVAC and lighting systems could be wasted due to unobserved or unattended faults [rotwesfenllaqua05].

The importance of reliable information will increase with the introduction of greater automation. This information will be obtained through monitoring, estimation, and inference.

In the remainder of this section we describe some tools for estimation and inference, many of them recent, that we believe are ideally suited to these problems.

Modeling. Different modeling techniques will be used in different applications. For HVAC operations, a model must capture complex interactions between occupants and environment. Coarser models are needed to aid in the construction of diagnostics algorithms, or to obtain bounds on the limits of performance. Models are required to predict energy performance potential at commissioning relative to design intent and benchmarks, and to estimate the error in these predictions due to inevitable model mismatch.

Markov models arise naturally within the context of detection and diagnostics. Complexity may rule out direct application of standard detection techniques when applied to a detailed model of a building. To combat this complexity, projective Markovian models can be created and tuned on-line in a non-homogeneous setting [sha48,cho03,chohalkup00,matmey07].

MPC for estimation. Model predictive control (MPC) is favored for many of the control problems encountered in this research because of the existence of hard constraints – Detailed discussion can be found in Section ??.

Constraints are also evident in the estimation problems encountered here. In particular, occupancy cannot be negative, and air flows are tightly constrained. Section ?? contains details on our prior work on the application of estimation techniques based on MPC principles for occupancy estimation.

In the text above I refer to the essays on the SUN estimator.

Statistical learning. Many machine-learning techniques have reached a level of maturity on par with favored linear systems techniques, such as the Kalman filter.

In particular, adaptive model selection will be developed based on temporal difference learning, which is similar to the use of Galerkin projection to obtain POD models for airflow modeling [bertsi96a,tsiroy97a,bormey00a,mac03a,CTCN]. Actor-critic algorithms can be used for on-line tuning [bertsi96a]. This approach is based on a Markov model, using Schweitzer's perturbation theory of sch68. We believe the technique can be applied in the complex models envisioned here by using the simpler projective models.

All of these methods are based on variants of Monte-Carlo estimation, and hence large variances can create barriers to implementation. Variance reduction techniques such as importance

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sampling, control variates will be adapted for simulation, adaptation, and learning [asmgly07,henmeytad03a,CTCN,konmey07a].

Information theory. Information theory can be regarded as a sister to systems theory. A goal of the latter is to construct models to describe a physical system, such as airflow in a room, or evolution of occupancy in a building. A major goal of information theory is to understand what inputs and outputs are *typical*. Model reduction or signal discrimination is made possible if the space of typical signals is much smaller than the set of all possible signals.

For example, demand for energy is not completely predictable, but the range of possible demand profiles is far smaller than the space of all functions of time. The quantitative measure of typicality is *entropy*.

An information theoretic viewpoint may be valuable on many levels in this project, but these techniques are most obviously suited to fault detection. We will adapt techniques from robust decision theory that have been successfully applied for anomaly detection in buildings [banfedlinmatmeynarsur08]. The robust hypothesis testing frameworks built over the past decade and applied in [banfedlinmatmeynarsur08] are naturally adaptive, and can be designed to include prior knowledge regarding anomalous behavior if that is available [zeigut91b,zeigut91a,panmeyven04b,panmey06a,abbmedmeyzhe07a]. This is in contrast to classical approaches that require exact models of normal and anomalous behavior.

Support vector machine (SVM). This is a highly flexible approach to data clustering.

There are similarities with Vapnik's SVM approach and robust hypothesis testing. Important differences are i) in this application, the choice of an SVM basis or kernel is not clear (e.g., in the application [liadu07] the choice is essentially arbitrary), while these tests incorporate detailed structure of dynamics; ii) Statistical error analysis is simplified since it is part of the FDD construction; iii) Multiple faults can be discriminated without resorting to complex voronoi cells.

Lasso, regularization, and compressive sensing. A more recent quantification of typicality is through the notion of *sparseness*. For example, the low entropy associated with energy usage in a building can be expressed using language from linear algebra, and this context suggests new approaches to analysis and construction of algorithms. With an appropriate choice of basis, energy usage profiles will be restricted to a very low dimensional subspace within the set of all signals.

The LASSO algorithm is designed to find a sparse representation (one with a small number of coefficients with respect to the basis) using a technique known as l_1 *regularization* [hastibfri01]. Compressive sensing is a more recent application of l_1 regularization for estimating high-dimensional variables based on relatively low dimensional measurements [don06a,trowakduabarbar06].

For example, suppose that over the course of many months, POD modes have been constructed for a collection of rooms in a building. Different days and different environments will require the use of different modes. An application of LASSO would take *all of the modes together* to obtain an over-complete representation of airflow. The algorithm would find the best subset of modes to explain current building behavior.

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