Kalman Filtering Applied to Sensor Fused Data to Deliver Accurate and Rapid Environmental Feedback of an Occupied Space

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Abstract:
Building occupants control the environment of their space or facility based on discomfort or a specific need at the time. In this manner, the correction occurs after the occupant is already uncomfortable or has been adversely impacted. Often, the actions taken by the occupant are seldom recorded or acknowledged for future reference, so that the same uncomfortable conditions perpetuate.

A device to sense environmental conditions at the occupant's height and location was designed so that increased comfort and productivity are achieved before the occupants' discomfort is realized. Additionally, a fast-acting control system will provide the exact heating and cooling necessary resulting in significant energy savings.

The concept to move indoor environmental temperature sensing from the wall to the ceiling and scan the occupied space was investigated. This concept, coupled with machine learning techniques applied to multiple sensors proved capable of providing more accurate, faster and smarter feedback of the conditions of a monitored space. Temperature measurements with a 0.5°C level of accuracy are capable at 1m above the floor with the sensing device mounted at a maximum ceiling height of 5m. This was accomplished by using a combination of integrated thermistors and infrared sensing.

Additionally, a natural requirement is to accommodate and compensate for to the effects of internal heating from the device electronics itself as well as the heating and cooling effects from HVAC equipment in the room.

Keywords:
Temperature, HVAC, sensors, controls, infrared sensing, sensor hub, building automation

1. Introduction

The sensing methodology discussed in this paper makes real-time environmental adjustments possible by providing accurate and immediate feedback to the building automation system. The methods explored track environment changes based on a model synthesized from a large amount of collected data and by using sensors that react to the source of environmental changes.

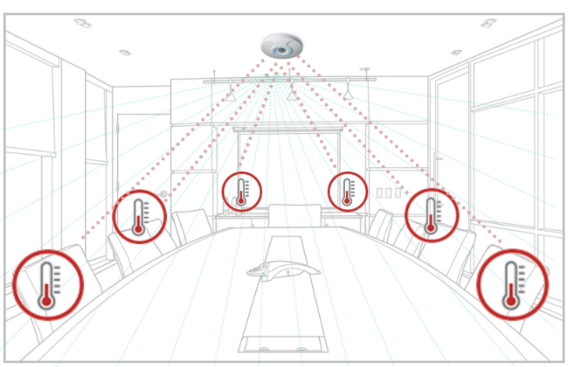

Figure 1. Sensor Hub Mounting

The ceiling-mounted sensing unit as shown in Figure 1 is typically mounted in the center of the room. The IR temperature sensor has a controlled field-of-view pointed downward toward the floor. A model that tracks the air temperature and the temperature detected by the IR sensor based on radiant energy estimates room temperature at occupant-height. [1]

2. Background

The Sensor Hub is typically mounted on the ceiling at a height between 3m to 5m. Despite the Sensor Hub mounted on the ceiling, optimal temperature measurements should be acquired at a height of 1m from the floor as well as closer to the center of the room where people typically occupy the space. Using a combination of local air temperature sensors and infrared temperature sensing, a series of techniques were applied to determine how to reliably calculate temperature 4m away from the device in the surrounding area below the hub.

The effect of internal heating from the device electronics and the effects of heating and cooling from HVAC equipment must also be taken into account. Figure 2 illustrates this the effects of these sources. The red plot shows the internal temperature measured within the device. The plot labeled *0 in 2* shows the temperature measured 10cm away from the device, to demonstrate the localized heating from the electronics. Each plot line below that shows the stratification of the air temperature as you move further down towards 1m from the floor. Lastly, the bottom plotline shows the air temperature of the supply air coming from the HVAC system.

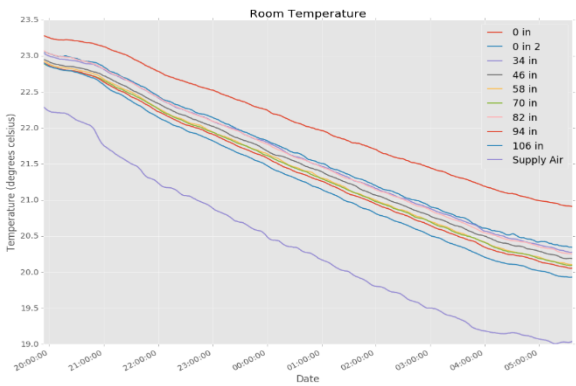

Figure 2. Temperature Influences in an Occupied Space

3. Kalman Filter Solution

A number of different techniques were investigated including simple averaging of the ambient temperature at the ceiling and IR temperature sensors as well as using a Complementary Filter where relative weightings are applied to the sensors. [2] This model did not account for changes in the environment such as ceiling height, cooling or heating rates as well as air circulation.

Linear quadratic estimation, also known as Kalman filtering [3] was investigated to model temperature readings over the area of influence. Kalman filtering is an algorithm that uses a series of measurements observed over time, containing statistical noise and other inaccuracies to produce estimates of unknown variables that are typically more accurate than those based on a single measurement alone, by estimating a joint probability distribution over the variables for each timeframe. [4] In a typical thermostat, the temperature is sampled and reported as the most recent measurement. In the next iteration, the previous result is discarded, and the new sensor measurement is reported. Instead of discarding the previous sample, the Kalman filter incorporates the historical information to improve the next temperature estimate.

For example, suppose the previous output of the Kalman filter was 23 °C. Since sensors are subject to noise the next reading could be far from the current value, say 27°C. Since the Kalman filter has learned the dynamics of the system, it would recognize that the current measurement is likely an outlier and would down-weight its effect. This would cause the output to be between 23°C and 27°C much like a simple moving average.

However, the difference is that the Kalman filter adjusts its parameters every time step in order to produce an optimal estimate. In addition to using historical data, the Kalman filter tracks the correlation between every signal (sensor) in the system and incorporates this into the estimate. Once the correlation between multiple sensors has been learned (the filter has converged) then the weighting given to any new measurement will be determined by looking at measurements from the other sensors in comparison to the newly sampled sensor. The Kalman filter tries to extract as much information from each signal as possible in order to produce an optimal state estimate.

Prediction Step

Predict using (noisy) process model: [3,5]

$$\hat{\mathbf{x}}_{k|k-1} = \mathbf{F}_k \, \hat{\mathbf{x}}_{k-1|k-1}$$

Update covariance (correlation): [3,5]

$$\mathbf{P}_{k|k-1} = \mathbf{F}_k \mathbf{P}_{k-1|k-1} \mathbf{F}_k^{\mathrm{T}} + \mathbf{Q}_k$$

Table 1. Update Step [3]

Name	Equation
Residual	$\tilde{\mathbf{y}}_k = \mathbf{z}_k - \mathbf{H}_k \, \hat{\mathbf{x}}_{k\|k-1}$
Residual covariance	$\mathbf{S}_k = \mathbf{R}_k + \mathbf{H}_k \mathbf{P}_{k\|k-1} \mathbf{H}_k^{\mathrm{T}}$
Kalman gain	$\mathbf{K}_k = \mathbf{P}_{k\|k-1} \mathbf{H}_k^{\mathrm{T}} \mathbf{S}_k^{-1}$
Updated state estimate	$\hat{\mathbf{x}}_{k\|k} = \hat{\mathbf{x}}_{k\|k-1} + \mathbf{K}_k$
Updated estimate covariance	$\mathbf{P}_{k\|k} = (\mathbf{I} - \mathbf{K}_k \mathbf{H}_k) \mathbf{P}_{k\|k-1} (\mathbf{I} - \mathbf{K}_k \mathbf{H}_k)^T + \mathbf{K}_k \mathbf{R}_k \mathbf{K}_k^T$
Measurement post-fit	$\tilde{\mathbf{y}}_{k\|k} = \mathbf{z}_k - \mathbf{H}_k \, \hat{\mathbf{x}}_{k\|k} \, \tilde{\mathbf{y}}_{k\|k} = \mathbf{z}_k - \mathbf{H}_k \, \hat{\mathbf{x}}_{k\|k}$

Where **F** is the state-transition model, **H** is the observation model, **Q** is the covariance of the process noise and **R** is the covariance of the observation noise.

For the desired application, the room temperature and its time derivative (rate of change) are tracked. The time derivative is included so that the filter will track temperature trends correctly. If the rate of change is not included, then long temperature trends would be treated as process and/or measurement noise in the filter, causing noticeable lag.

$$\mathbf{x} = \begin{bmatrix} T \\ \dot{T} \end{bmatrix}$$

A simple kinematic model is used to track changes in temperature: $T_{k+1} = T_k + \Delta t * \dot{T}_k$

The process model, $\mathbf{F}$ describes this in matrix form with respect to the chosen state variables $\mathbf{x}$.

$$\mathbf{F} = \begin{bmatrix} 1 & \Delta t \\ 0 & 1 \end{bmatrix}$$

$$\mathbf{P} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

$$\boldsymbol{Q} = \begin{bmatrix} \frac{\Delta t^3}{3} & \frac{\Delta t^2}{2} \\ \frac{\Delta t^2}{2} & \Delta t \end{bmatrix} \Phi_s$$

Since temperature is measured directly, the coefficients for the $\dot{T}$ terms are set to zero.

$$\mathbf{H} = \begin{bmatrix} 1 & 0 \\ 1 & 0 \end{bmatrix}$$

$$\mathbf{R} = \begin{bmatrix} \sigma_m^2 & 0 \\ 0 & \sigma_m^2 \end{bmatrix}$$

The initial state estimate, T (room temperature) and $\dot{T}$, are set to the mean of the temperature signals and the initial sample-to-sample difference respectively. Filter performance is highly dependent on parameters listed in Table 1; parameters were selected through experimentation.

Once the filter reliably converged, the Kalman filter was plotted against a high precision temperature reference as well as the simple average as shown in Figure 3

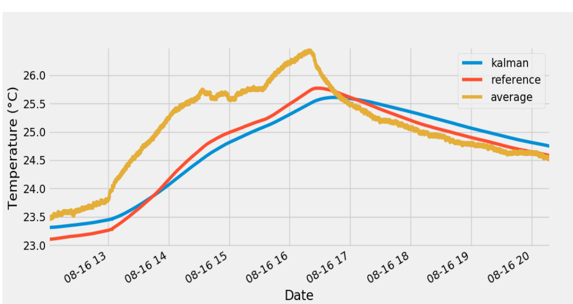

Figure 3. Kalman filter performance

Calibration

A single calibration point is required to tune the temperature sensor to measure 1m from the ground as well as to negate effects of airflow, floor material and other temperature influencing room parameters.

A simple mechanism to calibrate the sensor hub was created using a Smartphone app as shown in Figure 4. and calibrated thermometer or other temperature sensing device. The user simply needs to sample temperature at the appropriate height under the sensor hub and input the data into the app. The app then synchronizes this data over a direct Bluetooth connection to the Sensor Hub and applies the calibration value to the equation.

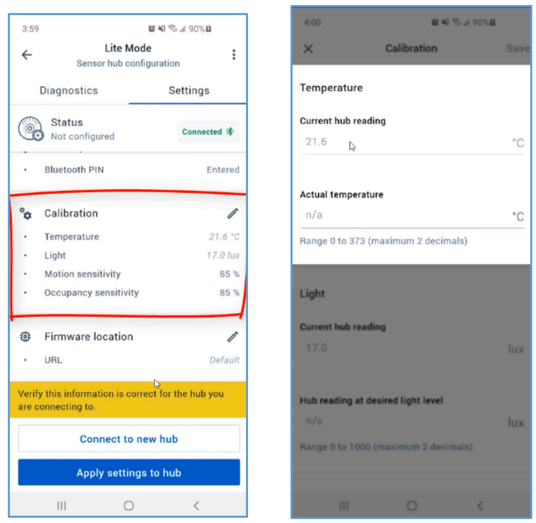

Figure 4. Calibration Tool

4. Results and discussions

Lab testing and field deployments have proven the Sensor Hubs temperature sensing method to function superior to any traditional thermostat. Results are shown in Figure 5.

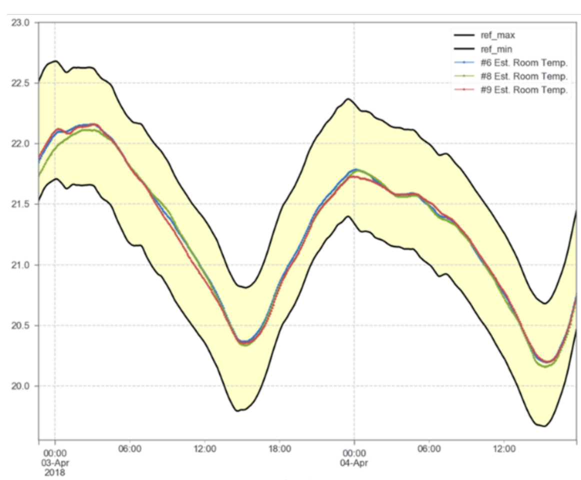

Figure 5. Temperature Measurement Results

Measurements from six high precision temperature sensors recorded temperature in the field of view of the

Sensor Hub. The variance of these measurements is indicated by the yellow shaded area in Figure 5.

After calibration, three Sensors Hubs recorded temperature over time, measurements were recorded in the middle of the variance recorded by the high precision sensors. All three Sensor Hubs tracked each other very well.

Energy Savings

Sensor Hub Mounting Height is 4.6m

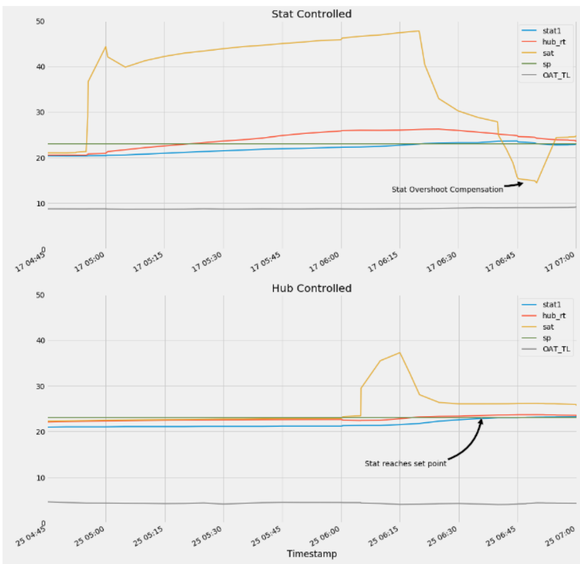

Figure 6. Energy Savings

As shown in Figure 6 the yellow plot shows the supply air temperature used to control the temperature in a large open office space. The red plot is the temperature measured by the sensor hub in the space. The blue plot is the temperature measured by a traditional thermostat in the same space.

Both graphs show a pre-heat in the early morning and how the system responds. The top graph is controlled by the thermostat, the bottom by the sensor hub.

As you can see, the system is active for much less time using the sensor hub, and the total energy savings are significant.

5. Conclusions and outlook

The Sensor Hub has been accepted by building control integrators, engineers and architects as a more aesthetic and functional device due to its diverse sensor suite and optimal installation location on the ceiling directly above the space that is actually being utilized. The integration of various sensors in a single device and ability to provide visual and audible interaction with the building occupants has positioned the device as a conduit for sensor data for every space throughout an entire building.

The accurate and fast temperature response using the Kalman filter design achieves the requirement for both occupant comfort and energy savings.

Using a high-resolution thermal IR sensor an even more accurate representation of the occupied space can be achieved. Additional value-added features can be incorporated such as people counting and equipment failure detection.

Acknowledgements

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