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Sensor commissioning detection in single-pixel thermopile sensing systems

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***Abstract*—We consider the problem of detecting sensor commissioning in the form of determining the sensor layout. We address this problem for single-pixel thermopile sensors, located at the ceiling, that provide remote temperature measurements for people counting applications and HVAC controls. We employ a random forest classifier to determine the deployed layout in an area. For this classifier, we propose spatio-temporal distance features using two-sided cumulative sum recursive least squares (CUSUM RLS) filtering of the thermopile temperature sensor signals. Using sensor data generated with simulated occupancy patterns and a thermopile signal model, we show that the proposed method achieves a true positive rate (determining the correct layout) of 90.2% and false positive rate of 1.3%.**

I. Introduction

Various smart building systems like lighting and HVAC (heating, ventilation and air conditioning) controls and space management applications rely on data from sensor systems [1], [2], [3]. For instance, temperature data and people count estimates from thermopile sensor systems may be used to improve user comfort by adaptively controlling HVAC systems. People counting data may also be used in space management applications to optimize the use of workspaces based on historic trends as well as real-time information. Commissioning information in the form of the sensor plan indicating locations of sensors in an area is critical in these systems for proper functioning. For instance, sensor data aggregation done for space utilization requires knowledge of sensor plans [3].

In this paper, we consider a single-pixel thermopile sensing system delivering temperature data. A single-pixel thermopile sensor remotely measures infrared temperature resulting from objects within its field-of-view (FoV) [4]. We consider a scenario where one of a pre-determined set of sensor plans can be deployed in different areas of a building. The single-pixel thermopile sensors are situated at the ceiling in specific locations according to one of these sensor plans. Two situations may occur involving commissioning detection. One, wherein in an area sensors are situated as per one plan and then moved to a different location as per another design plan. Two, wherein in different areas of a building, sensors are situated according to one of the two sensor plans. The problem in either case is to determine which sensor plan exists in an area. For simplicity, we shall discuss the first scenario in this paper where the sensor plan in an area changes over time.

Given the temperature data collected from the thermopile sensors in an area, the problem under consideration is to determine if the layout has changed over time due to building renovations. Once a commissioning change is detected, a manual inspection may be triggered to ensure that the commissioning change is verified and properly updated. In past work [5], the problem of detecting commissioning changes in lighting areas was considered using binary motion sensor data.

To detect commissioning change, our approach is to use spatial distance features based on temperature level changes. The intuition behind this is as follows. For a given sensor plan, certain workspaces are covered by the FoV of adjacent sensors. Thus, occupancy changes would manifest themselves similarly in the measurements of these sensors. Specifically, using the temperature values over a day from a thermopile sensor, we apply a CUSUM RLS filter [6] to detect abrupt changes in temperature that result due to occupancy changes. We then extract various spatial distance features from this processed signal to capture similarity between detected changes across sensor pairs. These features are then used in a random forest classifier to detect whether a commissioning change had occurred.

We use a thermopile signal model to obtain temperature measurement values under different occupancy levels. Simulated sensor signals are used to create daily sensor signals on which CUSUM RLS processing is performed. Spatial distance features are then obtained for sensor pairs. We show that with the processed signal features, our approach results in a true positive rate of 90.2% and a false positive rate of 1.3% in detecting a sensor plan change.

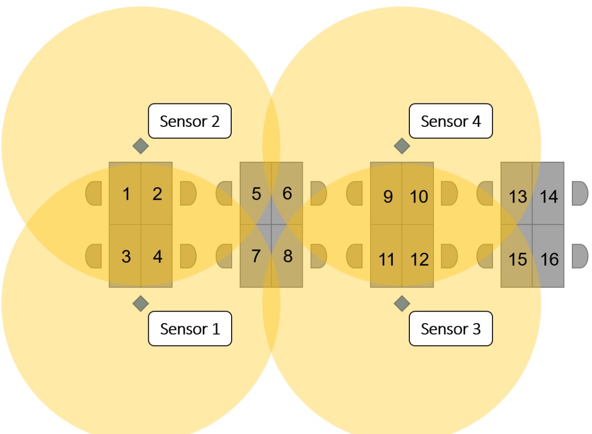
II. Preliminaries

In this section, we first describe sensor commissioning and the general problem addressed in this work. We then consider a thermopile signal model that will be used to emulate temperature data for evaluating the proposed approach.

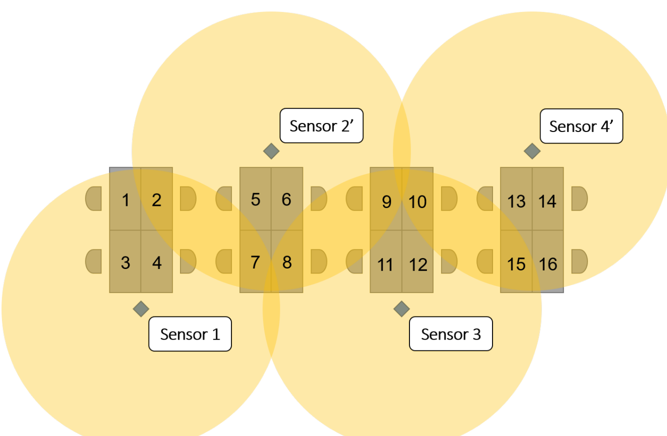
A. Sensor commissioning

We consider a sensor system with thermopile sensors co-located at luminaires. Sensor and lighting plans are respectively designed such that there are no blind areas in the sensor coverage region and the illumination from the luminaires is uniform. Consider a simple illustrative example wherein there are two possible sensor plans, with four sensors in two rows as shown in Figure 1.

In the first sensor plan shown in Figure 1a, sensors 1 and 2 have an FoV that covers five workspaces labeled 1, 2, 3, 4 and 7, and 1, 2, 3, 4 and 5 respectively. It can be expected that occupancy over workspaces 1, 2, 3 or 4 would result in similar temperature measurements at the thermopile sensors 1 and 2. In the second sensor plan shown in Figure 1b, sensors $2^{'}$ and $4^{'}$ are displaced locations compared to sensors 2 and 4 in the previous plan. Sensor $2^{'}$ has an FoV that covers five workspaces labeled 2, 5, 6, 7 and 8. In this sensor plan, the measurements of sensors 1 and $2^{'}$ are influenced by quite different occupancy patterns, given their FoV covers distinct workspaces.



(a) Sensor commissioning of an area with 4 sensors covering 12 workspaces.



(b) Sensor commissioning where the locations of sensors 2 and 4 are displaced after renovation.

Fig. 1: Illustration of commissioning showing sensor coverage of workspaces.

B. Thermopile signal model

A single-pixel thermopile measures the object temperature within its FoV. The measured temperature $T[n]$ at instant n can be modeled as [7],

$$T[n] = T_0[n] + v[n] + \sum_{i=1}^{K_m} \sum_{j=1}^{K_i} f(\theta_{ij}) d_{ij}[n]. \tag{1}$$

There are three components in this signal model: (i) the measured temperature under vacancy, (ii) the effect of sensor FoV, and (iii) the impact of occupancy events.

Under vacancy, the sensor measurement is the temperature of the environment, which can be modeled as a slow varying temperature $T_0[n]$ with additive noise $v[n]$.

The other component in (1) represents the temperature change under occupancy events. At instant n_i, there are K_i people entering or leaving the sensor FoV, with θ_{ij} the angular position of person j with respect to the sensor. There are K_m number of events considered.

The effect of a limited FoV of the sensor is modeled by an attenuation function $f(\theta)$ and modeled as a raised cosine function,

$$f(\theta) = \begin{cases} 1 & \theta \leq \frac{1-\rho}{2P} \\ \frac{1}{2} + \frac{1}{2}\cos\left(\frac{\pi P}{\rho}\left[\theta - \frac{1-\rho}{2P}\right]\right) & \frac{1-\rho}{2P} < \theta \leq \frac{1+\rho}{2P} \\ 0 & \theta > \frac{1+\rho}{2P} \end{cases} \tag{2}$$

The parameter values $P = 1/90$ and $\rho = 0.4$ are chosen to have an attenuation function close to the specifications of a thermopile sensor with a wide FoV wherein the signal is attenuated by half at an angle of 45° [4].

The function $d_i[n]$ incorporates the temperature change due to an occupancy event,

$$d_i[n] = \Delta T_i \left(1 - e^{-\alpha_i (n - n_i)}\right) u[n - n_i]. \tag{3}$$

Here, the parameter ΔT_i is the temperature difference, α_i is the transition speed, and $u[n]$ is the unit step function. In an occupancy event, the temperature rises faster when people enter and falls slower when people leave; thus, α_i has a higher value for entry events than for leave events.

III. Proposed Method

Given data from the thermopile sensors from an area, we consider a 2-class random forest classifier to determine which of the sensor plans exists in that space. We first describe the signal pre-processing to detect mean temperature changes and then describe the signal features on this processed signal that are inputs to the random forest classifier.

A. CUSUM RLS processing

The temperature signal of a thermopile sensor is a slow varying noisy signal with sudden changes in the event of an occupancy event. In order to detect mean changes, we first obtain the RLS estimate

$$\hat{T}[n] = \beta \hat{T}[n-1] + (1-\beta) T[n] \tag{4}$$

where $0 < \beta < 1$ is a forgetting factor. Define the error term as

$$\epsilon[n] = T[n] - \hat{T}[n].$$

The CUSUM algorithm computes two-sided scores which cumulatively sums this error,

$$g_p[n] = \max\left[g_p[n-1] + \epsilon[n] - \nu, 0\right] \tag{5}$$

$$g_m[n] = \min\left[g_m[n-1] + \epsilon[n] + \nu, 0\right]. \tag{6}$$

This cumulative error is lower bounded by zero for the positive score g_p and upper bounded by zero for the negative score g_m. The drift parameter, ν, is used to suppress noise in the CUSUM, and is chosen such that at least 50% of the score is zero [6].

The CUSUM RLS pre-processing is illustrated in Figure 2. We consider occupancy sequentially over workspaces labeled 1-8 shown in Figure 1 and consider the signals at sensors 1, 2 and $2'$. The top part of the subfigure shows the temperature measurement using the signal model, and the bottom part shows the CUSUM RLS signals g_p (in orange) and g_m (in green). We can observe from the CUSUM RLS signals of sensors 1 and 2 that the occupancy events over workspaces 1-4 result in positive and negative peaks that exhibit correlation. The positive and negative peaks in CUSUM RLS signal of sensor $2'$ result from different occupancy patterns over workspace 5-8, and thus display less correlation with sensor 1.

B. Signal features

We employ different features based on similarity/distance between two signals [8]. Given the temperature signals from two sensors (e.g., over a business day), we collect the respective measurements as signal vectors a and b. The first feature is the Pearson correlation coefficient,

$$\gamma(a, b) = \frac{E[(a-\mu_a)(b-\mu_b)]}{\sigma_a \sigma_b}. \tag{7}$$

The other features are based on spatial distance between signals. These are respectively the City block, Cosine, Euclidean, and the Jensen-Shannon, given by

$$d_{city}(a, b) = \sum |a[n] - b[n]|, \tag{8}$$

$$d_{cosi}(a, b) = 1 - (a \cdot b)/(||a||_2 ||b||_2), \tag{9}$$

$$d_{eucl}(a, b) = ||a - b||_2, \tag{10}$$

$$d_{jens}(a, b) = \frac{1}{2}\sum_{w=1}^{W}\left\{D(A_w||M_w) + D(B_w||M_w)\right\}, \tag{11}$$

where

$$D(A||B) = \sum p(A) \cdot \log \frac{p(A)}{p(B)} \tag{12}$$

in (11) is the Kullback-Leibler divergence and M_w is the point-wise average of A_w and B_w. The Jensen-Shannon divergence is calculated for W windows in a day to limit the number of samples per calculation and then summed up as in (11).

C. Random Forest Classifier

A random forest classifier is a collection of decision trees which all make a separate classification decision based on the input features [9]. There are two key parameters - number of trees and their depth, in the random forest classifier. The proposed classifier uses the five features defined in (7-11) for a pair of sensors computed for both the two-sided CUSUM RLS signals in (5-6). Thus for each sensor pair, ten features are used as input to the 2-class classifier to determine which plan the sensors belong to. The final decision on commissioning change is then determined by majority voting within the classifier.

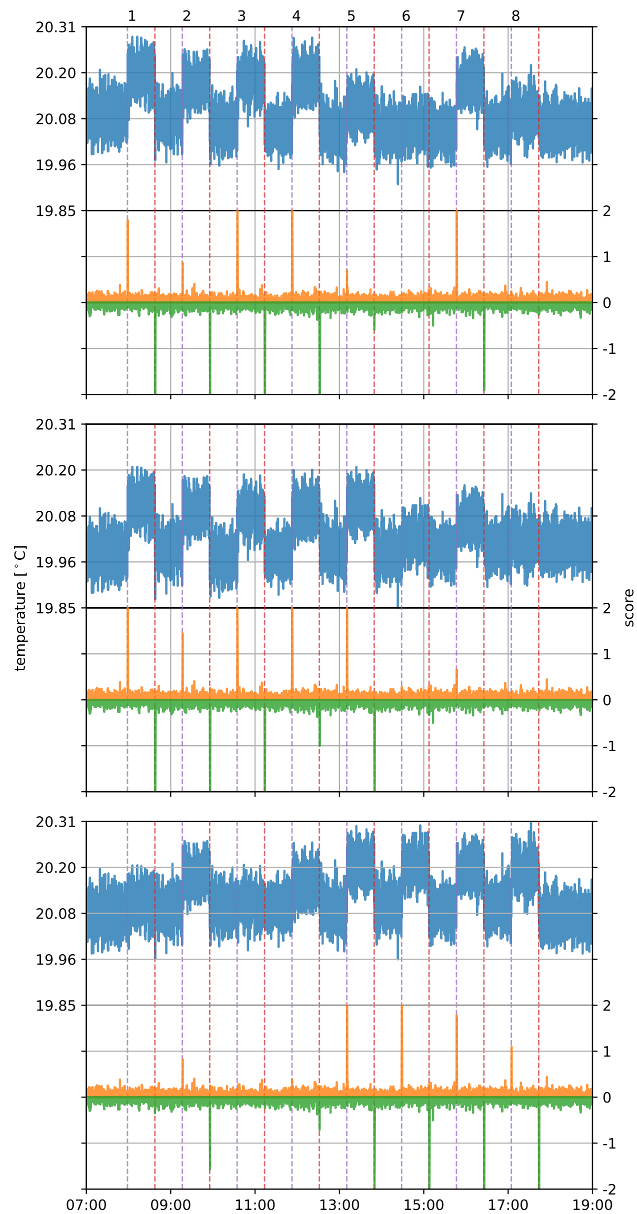


Fig. 2: Simulated temperature measurements and CUSUM RLS signals (g_p in orange and g_m in green) from sensors 1, 2 and $2'$ (top to bottom).

IV. Performance evaluation

In order to evaluate the performance of the proposed approach, we consider a commissioning change scenario wherein the commissioning plan changes from the one depicted in

Figure 1a to Figure 1b. For this commissioning plan detection scenario, we shall use the true positive rate (TPR) - ratio of the number of detected plan changes to the number of actual plan changes, and false positive rate (FPR) - ratio of the number of detected plan changes to the total number of no plan changes, as performance metrics.

A. Simulated data for commissioning change

We consider the setup shown in Figure 1b with occupancy generated over workspaces 1-8 over 10000 days, and a working time between 07:00 and 19:00. Sensor data was generated for sensors 1, 2 and $2^{'}$ according to the model in (1), with a sampling frequency of 10 Hz. Daily temperature data thus generated between 07:00 and 19:00 is used as the raw signal. Signal vectors a and b used to compute the features (7-11) have 432000 measurements. The noise was assumed to be AWGN with zero mean and a standard deviation of 0.04. The attenuation due to sensor FoV is determined based on physical locations of user workspaces with respect to the sensors. Values for the transition speed α and effective temperature change were chosen according to a normal distribution with a respective mean of 0.08 and 0.12, and a respective standard deviation of 0.02 and 0.015. These values were determined based on experimental data collection. We use a simple occupancy model to emulate workspace occupancy over a day by generating a number of enter/leave events, where the duration between events was chosen to be at least 5 minutes. The reader is referred to [10] for occupancy modeling in office buildings.

B. Random forest classifier parameters

Signal features were computed on daily datasets. Out of the 10000 days simulated, 8000 were used for the training set and 2000 for the test set.

In Figure 3, we show the distribution and scatter plot for the features (7-11) computed on the CUSUM RLS signal g_m. The plot shows that each feature is able to discriminate between the no change (class 0)/change (class 1) commissioning scenarios to different extents.

The number of trees in the random forest classifier was set to 20 and the maximum number of nodes set to 9. The performance of the random forest classifier was tested using k-cross validation [11] to limit any bias to the training and test set.

C. Performance results

To evaluate the effectiveness of the proposed features, we shall use certain baseline features as benchmark. It is common to employ statistical features to characterize a signal by considering measures of central tendency, variability, shape and impurity, using the mean, variance, minimum value, maximum value, skewness, kurtosis and entropy [12]. Given the thermopile signals from two sensors, we use the difference of features in the random forest classifier, and will be used as a benchmark.

We first consider the performance of the random forest classifier with the baseline features applied to the raw temperature signal and the CUSUM RLS signal. The resulting confusion matrix is shown in Figure 4. We obtain a TPR of 54.50% and 53.20% for the raw signal and CUSUM signals respectively with an FPR respectively at 29.70% and 25.30% respectively. The accuracy with CUSUM RLS is moderately better than when using the raw signal. These results suggest that the baseline features are not effective.

We next consider the performance of the random forest classifier with the proposed features using the raw temperature signal and the CUSUM RLS signal. The confusion matrix for change detection is shown in Figure 5. In this case, we obtain a TPR of 74.0% and 90.2% for the raw signal and CUSUM signals respectively, with an FPR of 8.6% and 1.3% respectively. Improvements with the proposed features are observed in both the raw and processed signals, with the latter combination most effective in line with the intuition of using distance features in combination with mean changes in the temperature signal.

V. Conclusions

We considered a random forest classifier to determine changes in thermopile sensor location plan. The classifier used various signal distance features for pairs of sensors. We proposed these features using CUSUM RLS processed temperature signals from the thermopile sensors. Using simulated occupancy conditions and an analytical thermopile signal model, daily datasets were generated for evaluating the proposed approach. We obtained a TPR of 90.2% and an FPR of 1.3% using the proposed distance features computed using the CUSUM RLS signal, and showed improvements over using basic statistical features. While we considered a specific commissioning detection scenario in this work, the proposed methods can be extended more generally to topology change detection using similarity/distance features of CUSUM signals.

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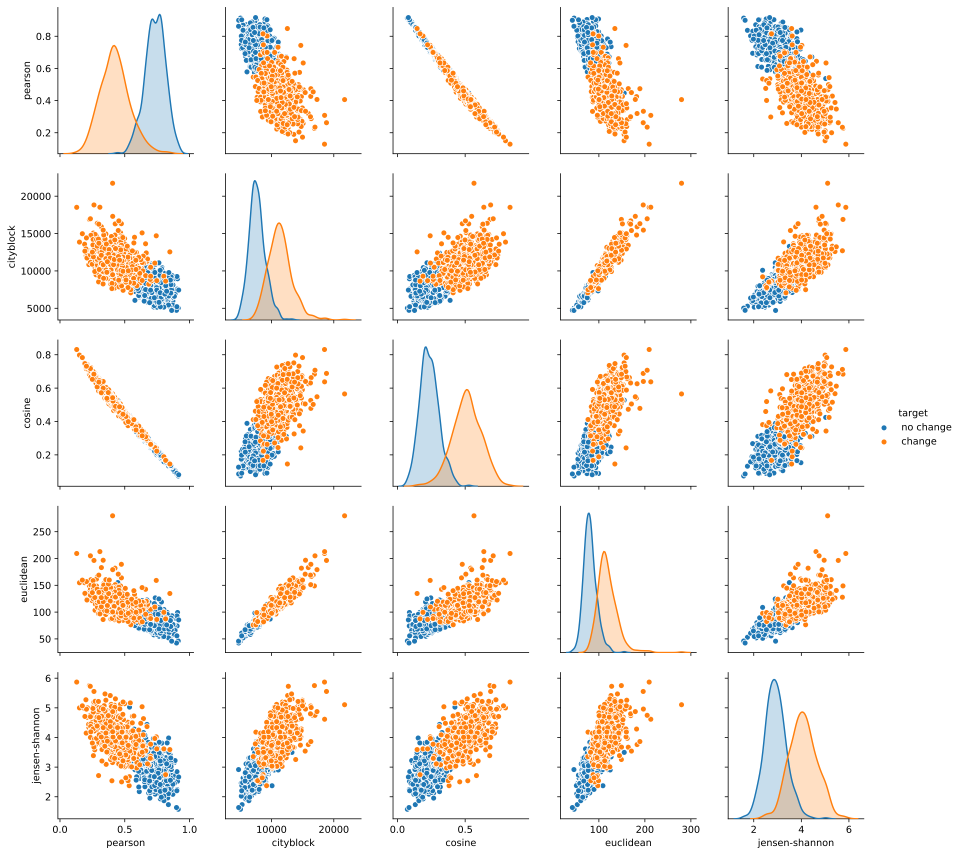

Fig. 3: Distribution and scatter plot of CUSUM RLS signal features for test set.

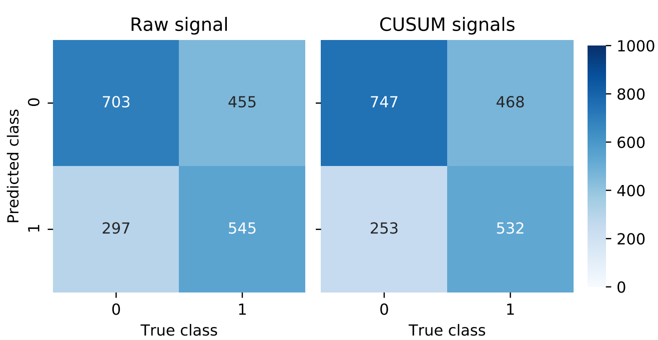

Fig. 4: Confusion matrices when using baseline features.

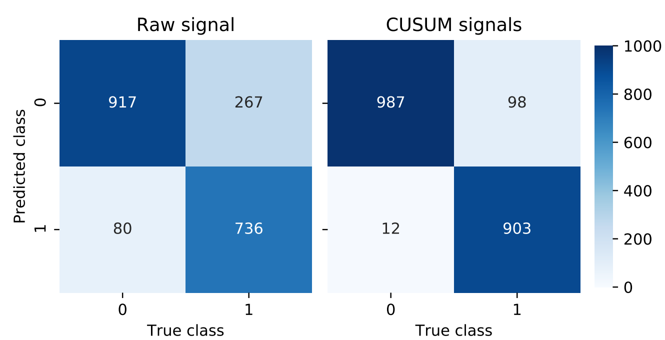

Fig. 5: Confusion matrices when using proposed features.

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