# CPS EAGER Collaborative

# Smart Audio Sensing-based HVAC Maintenance (SASEM)

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Source codes are available at https://github.com/uncmobile/HvacAudioService

**This work will radically reduce energy waste of centralized HVAC systems. In the U.S., centralized HVAC systems are used in 88.7% of all commercial buildings. In terms of energy, over 42.8% of commercial building energy usage is due to HVAC systems.**

**In future, the proposed research can be applied to industrial systems such as commercial washing machines in laundromats where the total annual repair cost for all multi-load washers in the U.S. exceeds $2B.**

## 1. Identify

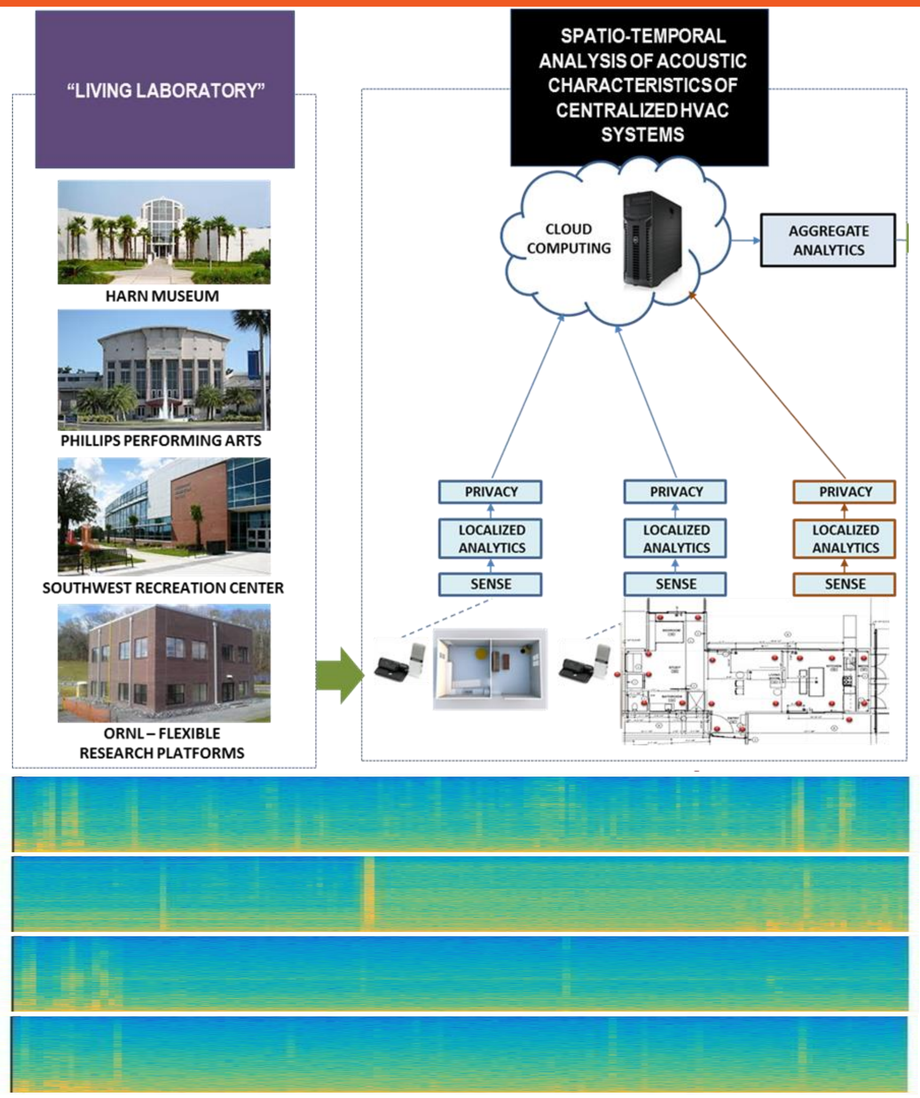
For air handling units (AHU), faults that can be classified into two groups – the mechanical faults and the digital faults (i.e. sensor and controller faults).

## 2. Detect

Detection is based on the hypothesis that the operation sound and noise maintain stable or in a certain pattern when there is no fault occurs.

## 3. Diagnose

This process is conducted based on the hypothesis that different types of system faults should cause different change in system operation sound and noise.




**Spectrogram Plot (x axis: time 60s, y axis: Freq. [-30dB, -150dB])**

**We employ an unsupervised learning approach to model and encode the regular pattern in the acoustic time-series data, and to discover if a running HVAC system has deviated from its regular pattern of operation at any point in time. At first, the audio stream is converted to a stream of 50$_{ms}$ frames and passed through a frame-level feature extraction stage where Mel-Frequency Cepstral Coefficients (MFCC) are computed for each frame. Then k-means algorithm is used to cluster similar audio frames. Cluster assignment is used as an encoding for each frame. This step maps acoustic frames to k clusters. Finally, we compute the transition probabilities between each pair of clusters. Once the transition probabilities are in steady state, a sequence of unlikely transitions would mean that the HVACs behavior is unusual with respect to the currently learned model.**

Two transition matrices computed on two completely disjoint and independent time spans (524,280 frames each) are shown.

| | C1 | C2 | C3 |
|---|---|---|---|
| C1 | 0.076 | 0.017 | 0.013 |
| C2 | 0.017 | 0.759 | 0.004 |
| C3 | 0.013 | 0.004 | 0.097 |

(a) Transition Matrix 1

| | C1 | C2 | C3 |
|---|---|---|---|
| C1 | 0.066 | 0.01 | 0.008 |
| C2 | 0.01 | 0.814 | 0.002 |
| C3 | 0.008 | 0.002 | 0.08 |

(b) Transition Matrix 2

The similarity between corresponding cell-values tells us that our proposed acoustic-based HVAC state modeling strategy is fairly stable. With larger number of clusters, these two matrices will converge to steady-state values and can be used to discover potential faults in HVAC.