Preventive Maintenance of Centralized HVAC Systems: Use of Acoustic Sensors, Feature Extraction, and Unsupervised Learning

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Abstract

In this paper, we propose a predictive maintenance scheme for centralized HVAC systems by autonomous monitoring and analyzing their acoustic emissions. Our proposed solution allows a building to be retrofitted to monitor its HVAC without having to modify the existing infrastructure. Our approach is to employ an energy-efficient, low-cost, and distributed acoustic sensing platform to capture and process audio signals from HVAC systems. As part of this project, we develop audio models of a running HVAC system using a combination of unsupervised and supervised machine learning techniques with a human-in-the-loop for fault identification and prediction.

Introduction

Centralized HVAC systems are the primary means to control the indoor climate and to maintain its occupants' comfort in over 88% of the commercial buildings in the USA [4]. HVACs are also one of the most expensive systems in commercial buildings in terms of both installation or replacement cost, and energy consumption. Failure of an HVAC system is, therefore, detrimental to our well-being as well as to the finances. A notable consequence of faulty HVAC systems is the *sick building syndrome*, which leads to respiratory problems attributed to poor ventilation, low or high humidity, and unfiltered airborne particles and chemical pollutants in the buildings. With adults spending over 40% of their average daytime at workplaces, a proactive prognosis of HVAC system performance cannot be overlooked.

Most HVAC failures are fixable but are extremely costly [20]. A number of HVAC problems if not repaired early, lead to costlier repairs, or even the need to replace the system entirely. For instance, if the blower motors are left running at a compromised state, they strain other heating and cooling components. Likewise, continued running of a faulty condenser fan stresses the system, and causes compressor failures [7]. Identifying and repairing such problems early can save building owners a considerable amount of money. However, due to the lack of an effective, low-cost, and continuous assessment and prognosis mechanism for detecting under-performing HVAC units, it is extremely difficult to determine whether a repair, retrofit, or permanent retirement of an HVAC system is warranted. For a systematic prognosis and life-cycle management of centralized HVAC systems, what we need is a robust, inexpensive, and easily deployable system, so that impending failures can be detected early. Such a system will save money, and help us breathe healthy. It will also reduce negative environmental impacts of HVAC systems as it will help decreasing the number of retired units that find their ways to the landfills, which in turn, will reduce escaped contaminants that have been shown to deplete the ozone layer [14]. Keeping an HVAC system functioning properly also keeps it energy efficient.

A key to repairing HVAC systems before a total failure is early identification of problems. Similar to many other mechanical systems, noise is a key indicator of impending failures in HVAC systems. For instance, squealing or screeching could indicate a bad belt or motor bearing problem [2]. InspectAPedia [9], the free encyclopedia of building and environmental inspection, testing, diagnosis, and repair, has a detailed classification of HVAC noises. We hypothesize that *by employing a smart, low cost distributed acoustic sensor system that uses machine learning algorithms to learn and classify these noises in real-time, we will be able to detect faulty HVAC components, predict HVAC failures, and help building owners predictively maintain their HVAC systems in a cost-effective manner.*

The proposed *Smart Audio SEnsing-based HVAC Maintenance* (*SASEM*) system has a single unifying intellectual focus, i.e., enabling predictive maintenance of building equipment by autonomous monitoring and analyzing their acoustic emissions. Using audio signatures to predict equipment failure requires more than simply connecting a microphone to a dig-

Table 1: Typical Faults in HVAC Systems.

Category	Device	Typical Faults	Acoustic Detections
Equipment	Fan	Pressure drop is increased	Subject to Test
		Overall failures of supply and return fans	Yes
		Decrease in the motor efficiency	Yes
		Belt slippage	Yes
	Duct	Air leakage	Subject to Test
	Heating coil	Fouling (fin and tube) leads to reduced capacity	Subject to Test
	Cooling coil	Fouling (fin and tube) leads to reduced capacity	Subject to Test
	Preheating coil	Fouling and reduced capacity	Subject to Test
Actuator	OA, RA and,EA dampers	A damper is stuck or a faulty position	Yes
		Air leakage at fully open and closed positions	Yes
	Heating coolingcoil, preheating coil valve	A valve is stuck broken or wrong position	Yes
		Leakage occurs at fully open and closed valve	Yes
Sensor	SA, MA, OA, RA temp	Failures of a sensor are offset, discrete or drift	No/Causal
	MA, OA, RA humidity	Failures of a sensor are offset, discrete or drift	No/Causal
	OA, SA, RA flow rate	Failures of a sensor are offset, discrete or drift	No/Causal
	SA and zone pressure	Failures of a sensor are offset, discrete or drift	No/Causal
Controller	Motor modulation	Unstable response	Yes
	Heating/cooling valve	Unstable response	No/Causal
	Flow difference	The system sticks at a fixed speed	Subject to Test
	Static pressure	Unstable response	Subject to Test
	Zone temperature	Unstable response	No/Causal

OA, RA, EA, SA, and MA stands for outside, return, exhaust, supply, and mixed air.

ital signal processor; it requires the development of novel hardware and software that are low cost, low maintenance, easy to deploy, and take into consideration the variations in noises produced by different equipment, acoustically hostile building environments, and false positives and negatives during classification. We create novel hardware and middle-ware for audio data gathering using wireless acoustic sensor networks and cloud computing. We also develop effective machine learning-based classifiers to identify acoustic characteristics of building equipment. The three specific aims of this research are:

- **Unsupervised Acoustic Modeling:** We devise unsupervised clustering methods to automatically identify the states and transitions of a running HVAC system under normal/healthy condition. Deviations from the 'ideal state' (which is dynamic and an outcome of a continuous learning process) is identified using this model to discover 'potential' faults and failures.
- **Human-in-the-loop Fault Learning:** We use the concept of human-in-the-loop to verify the state of an HVAC system to retrain our data for supervised learning. A knowledgeable human operator is notified with the location of the seemingly faulty component and asked to make the final identification. Both in cases of an actual fault or a false alarm, the acoustic models will be retrained to include this new knowledge, as labeled by a human.
- **Engineering a Low-Cost Sensor System:** We develop a low-cost acoustic sensing platform for audio data collection and on-board processing. The platform is built using off-the-shelf hardware components, and costs around \$100-\$200 per typical air handling room of an HVAC system, which is less than \$0.10 per square foot in commercial buildings.

Background: HVAC Faults and Their Relations to Acoustics

Acoustic sensing methods rely on the rich information provided by sound, where small shifts and changes in its spectro-temporal characteristic reliably indicate differences in the behavior, performance or content of a system. Examples include acoustic pulse reflectometry [22, 19] and acoustic emission analysis [21]. Soundscape capture and analysis [18] has been used to learn about the diversity of sound sources including sounds generated by the environment [13] and biological organisms [12]. Over the past few decades, microphones and microphone arrays have been implemented in order to monitor the propagation of sound in urban environments and to detect acoustic events [15, 10]. More recently, the same principles have been used in monitoring factory machinery and the maintenance and detection of faults in engines using their noise signatures [5, 1]. Because of the reliability of sound behavior, sound emission analysis serves as a dependable alternative to other sensing modes for predictive maintenance. Typical faults in the air handling room of an HVAC system are discussed in [6], and we summarize them in Table 1.

Table 1 shows four major types of HVAC components, devices for each category, typical faults for each type of device, and the potential for using acoustic sensors in detection a fault. All actuator faults and some of the equipment faults are detectable from their sounds. These are labeled 'Yes' in the last column to indicate so. These devices produce mechanical noises that change as they wear out. On the other hand, sensors and controllers are digital, and because they do

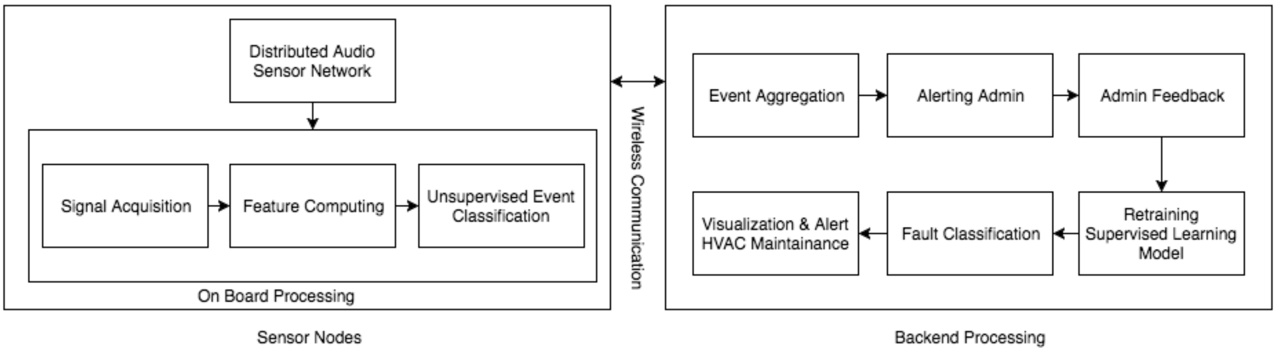


Figure 1: System Architecture of SASEM.

not produce any sounds their failures are not directly detectable. However, many of these faults are interrelated. For example, failure of a temperature sensor will have an effect on the fan, heating- and cooling-coil, and to some extent, on the duct. Hence, these failures can be inferred by learning the causal relationship between different components. These are labeled as 'No/Causal' in the table. Finally, some of the devices make noises that are too generic that human hearing is not capable of distinguishing them. However, by carefully training machine learning classifiers, these sounds can be distinguished from one another.

Overview of SASEM

Our proposed design of SASEM comprises of a microphone, a microcontroller, and a WiFi module for audio signal capturing, on-board processing, and information communication. First, audio signals are captured with microphone and features are extracted from audio frames. After signal acquisition and feature extraction, we perform unsupervised clustering to detect a deviation of the machine from its ideal state. If the deviation is above an empirically learned threshold, we send an alert to the admin to verify the fault. Using this verification, a supervised learning method is trained for failure detection. Moreover, our system provides a visual interface for advanced warning of failures to owners and property managers. Figure 1 shows the system architecture of SASEM, which consists of two major high-level blocks: sensor nodes and back-end processing. The sensor nodes are responsible for signal acquisition and on-board acoustic processing to identify and communicate potential faults. The back-end server is responsible for both classifying actual faults and alerting the human operator.

Figure 2: Acoustic Modeling.

The three major tasks corresponding to acoustic modeling, fault labeling, and development of the SASEM system are described next.

Task 1 – Unsupervised Acoustic Modeling

We employ an unsupervised approach in order 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. We use an unsupervised clustering-based machine learning approach [23] as opposed to a supervised algorithm [11] in order to make sure that our technique does not require training for every type of acoustic components, or components made by different manufacturers, or components running in different environments. A clustering algorithm does not require labeling of the data. Instead, it creates *clusters* of similar data points without labels. For different types of HVAC components and different environments, the number and size of clusters may be different, but the proposed algorithm automatically learns and models this for a given HVAC system, e.g., during the first week after the installation of the system. Besides identifying the clusters, our system also models the *transitions among clusters over time* so that it captures the temporal dynamics of the HVAC system. The overall process is shown in Figure 2, and the steps of modeling the HVAC's temporal acoustical dynamics are as follows.

- **Step 1:** The audio stream is converted to a stream of 50ms frames and passed through a frame-level feature extraction stage where Mel-Frequency Cepstral Coefficients (MFCC) [24] are computed for each frame. As part of the preprocessing step, we apply standard filtering [3] and noise compensation technique [17] to reduce background noise from the signals.
- **Step 2:** The *k-means* clustering algorithm is used to cluster similar audio frames. Cluster assignment is used as an encoding for each frame. This step maps acoustic frames to 1 of k clusters $\{C_1, C_2, C_3, \cdots, C_k\}$ and produces a sequence of clusters.
- **Step 3:** Transition probabilities, $P(C_n | C_{n-1}, C_{n-2}, \cdots, C_{n-l})$ to one cluster

given l previous clusters is estimated over time. The exact value of l (look-back states) is estimated empirically.

Once the transition probabilities are in steady state, a sequence of unlikely transitions would mean that the HVAC's behavior is unusual with respect to the currently learned model. Note that, modeling the normal HVAC is a continuous learning task, which is susceptible to high false positive rates at the early stage. To mitigate this, we employ a human-in-the-loop approach that is described next.

Task 2 – Human-in-the-Loop Fault Learning

If an HVAC system deviates from the ideal state beyond a tolerance value, an alert is sent to the system administrator with the location of the seemingly faulty component. The location of a fault is determined by solving by using blind source separation techniques. The admin verifies the condition to label the true or false positive case. Both in cases of an actual fault or a false alarm, the acoustic models will be retrained to include this new knowledge, as labeled. It is expected that as time goes by, the number of required human interventions will be decreased.

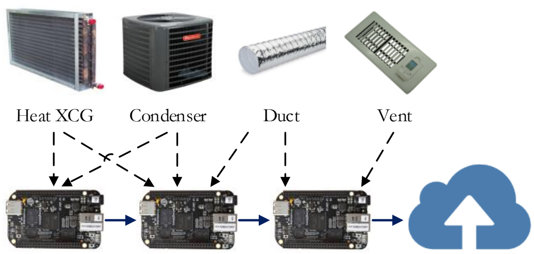


Figure 3: Distributed Acoustic Sensing in SASEM.

Task 3 – Engineering a Low-Cost Acoustic Sensor System

Robust and efficient integration of recent developments in wireless sensor networks and cloud computing technologies for the purpose of acoustic anomaly detection of HVAC systems has not been previously attempted. A critical challenge is developing a low-cost hardware platform with a sufficiently small form factor that can capture the necessary audio signatures at the required fidelity. To overcome the challenges and to develop a novel technology for soundscaping centralized HVAC systems, we propose an embedded audio monitoring device that includes a microphone, a microcontroller, and a WiFi module. These embedded devices are capable of continuously recording audio data at an appropriate sampling rate, as well as of performing real-time on-board data processing and classification. These devices will be placed at different locations throughout the building as part of a network and will coordinate with one another to process audio data and transmit events to a base station as shown in Figure 3.

Our choice of sensors and the computing platform is based on the system's requirement in terms of accuracy as well as the cost of deployment. We record audio at maximum of 44.1 kHz as the system considers only the audible frequency range. For this, a low-cost, omnidirectional microphone that supports 44.1 kHz sampling rate and does not attenuate signals at low frequencies is sufficient. For on-board data processing, an ARM-based microcontroller unit is sufficient to process audio in real-time [16]. For communication purpose, we choose to use WiFi as opposed to low-power Bluetooth LE, as WiFi offers sufficient bandwidth and the device is powered using wall-power.

Experimental Evaluation

Testbed and Datasets

We conduct a long-term experiment where we monitor the air handling unit (AHU) room of *Harn Museum* of UFL in real-time using a smartphone network. We use smartphones as opposed to the proposed custom platform to quickly setup a 3-node acoustic sensor network that captures acoustic signals and seven other types of on-board sensor readings (accelerometer, gyroscope, humidity, light, temperature, magnetometer, and pressure) from three AHUs of the HVAC. The deployment is shown in Figure 4. Although this setup is not low cost (each Samsung Galaxy S4 costs around \$500 in the consumer market), for a quick deployment and to initiate the data collection as early as possible while we are building the final sensing platform, this was a suitable option.

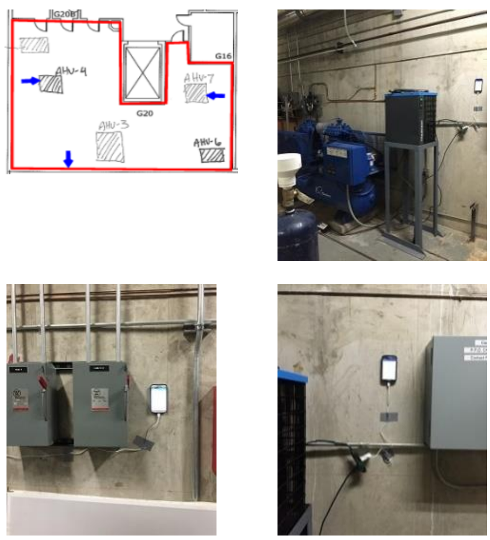


Figure 4: Smartphone based deployment.

We have been collecting these data since May 1, 2016. A custom smartphone application is developed to capture audio signals at 44.1 kHz and all other sensors at 100 ms internal. After capturing, we perform basic data cleaning operations, including detection and removal of human voice, and ship them to a secure server maintained by the University of Florida. From the server, these data are periodically downloaded and analyzed in Matlab.

In order to validate our algorithm's performance on audio data recorded from unknown HVAC systems that are not part of our testbed, we use another online data set [8]. The data set contains 49 recordings (1.65 GB, 61 minutes, 24bit/96kHz quality) of fans, heaters, and coolers of various HVAC systems.

Result 1 – Acoustic Pattern Estimation

	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

Figure 5: The similarity between transition matrices computed on two different time spans are noteworthy. This phenomenon provides an empirical validity of our acoustic modeling strategy.

In Figure 5, two transition probability matrices (using 3 clusters) computed on two completely disjoint and independent time spans (524,280 frames each) are shown. The similarity between corresponding cell-values tells us that our proposed acoustic-based HVAC state modeling strategy is fairly stable. With more data and larger number of clusters, these two matrices will converge to steady-state values– which are used to discover potential faults in HVAC systems.

Result 2 – Spectral Analysis

Figure 6 shows example spectrogram plots of eight audio clips recorded near a pump, two fans, four boilers, and between two AHUs inside these three buildings. One of the clips also contain human voices in the background. The horizontal axis of each of the spectrograms denotes time (up to 60s), the vertical axis denotes the frequency (up to 22.05 kHz), and the color/shade denotes the power/frequency (dB/Hz), from -30dB (yellow/lighter shades) to -150dB (blue/darker shades).

We observe that, different units have different spectral characteristics that can be leveraged to identify a unit. For example, maximum acoustic power exerted by a pump, a fan, and a boiler at any time is in the ranges of -53.4 ± 13.6 dB/Hz, -62.3 ± 7.4 dB/Hz, -28.3 ± 5.24 dB/Hz, respectively. Furthermore, some of these units have special acoustic signatures identifiable by detecting a special acoustic event, e.g., the pump in H2 occasionally makes a sound that excites all frequencies.

The presence of voice is identifiable by observing the change in human voice frequency range in the spectrograms. For example, the same fan in H3 and H4 show slightly different spectral plots due to the presence of voice. Therefore, by using spectral subtraction, voice can be removed from the audio signals to preserve privacy. However, since the AHU rooms are in general not accessible to people other than the admins, privacy is not a major concern in such places.

The location also has an effect on the acoustic characteristics. For example, boilers in Phillips Center (P1 and P2) are similar in spectral characteristics, boilers in SW Rec Center (R1 and R2) are also similar to each other, but there is a significant difference between boilers from these two places. Hence, by modeling the spectral characteristics of each unit, it is possible to identify the unit's type and location, remove background noise and, if necessary, human speech, and detect expected/unexpected events.

Result 3 – HVAC Component Recognition

In this experiment, we evaluate the performance of the proposed audio-based HVAC component recognition algorithm. We divide and categorize the data set [8] into eight classes. The first column in Figure 7 shows the types of HVAC components which includes two kinds of fans, two kinds of cooler components, two exhausts, a pressure meter, and a ventilation motor. For each sound file, we take 25 ms of audio samples and extract MFCC audio features. We use a support vector machine (SVM) classifier to classify these frames. Figure 7 shows an 8×8 matrix where each entry shows the accuracy of classifying one type of sound in presence of another one. For example, the first row shows that the proposed algorithm has $97\% - 99.7\%$ accuracy when it tries to recognize an unstable fan in presence of a cooling fan, an exhaust door, a pressure meter, or a ventilation motor. But the accuracy drops to $92.7\% - 93.1\%$ when there is a cooling cooling compressure or an industrial-grade exhaust fan is present. The accuracy of the algorithm can be further improved if we consider additional information such as the location of the component and/or when we combine classification results from multiple acoustic sensors.

Conclusion and Future Work

Through SASEM, we aim to develop and mature the science of using acoustic signals for system assessment prognosis of centralized HVAC systems. Our next step is to build the energy-efficient low-cost sensing platform comprising of a network of embedded devices. Moreover, we will develop a decision support system with an optimization model and a visualization platform. The optimization model will help decision makers choose the optimal timeframe for retiring centralized HVAC systems with a short-term and long-term decision horizon. The visualization platform will allow acoustic-based system assessment and prognosis through simulation and learning, and enable interactive user functionalities for data analysis

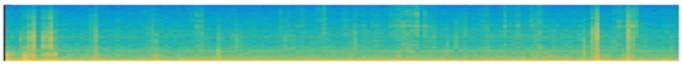
Location	Equipment	Spectrogram Plot (x axis: time 60s, y axis: Freq. [-30dB, -150dB])
H1: Harn Museum	Between AHUs	
H2: Harn Museum	Pump	
H3: Harn Museum	Fan	
H4: Harn Museum	Fan + Voice	
P1: Phillips Center	Boiler	
P2: Phillips Center	Boiler	
R1: SW Rec Center	Boiler	
R2: SW Rec Center	Boiler	

Figure 6: Spectrogram plots of different AHU units within the three buildings.

		F1	F2	C1	C2	E1	P1	E2	V1
Fan Unstable	**F1**	-	99.7	93.1	97.0	99.3	98.8	**92.7**	99.1
Cooler Fan	**F2**	99.7	-	**93.9**	97.5	99.0	97.6	96.4	99.1
Cooling Compressor	**C1**	93.1	93.9	-	94.0	**91.2**	93.6	93.4	92.7
Cooling Unit	**C2**	97.0	97.5	94.0	-	92.7	94.1	97.1	**91.2**
Exhaust Outdoor	**E1**	99.3	99.0	**91.2**	92.7	-	93.3	93.7	96.9
Pressure Meter	**P1**	98.8	97.6	93.6	94.1	93.3	-	**92.9**	96.5
Exhaust Industrial	**E2**	**92.7**	96.4	93.4	97.1	93.7	92.9	-	95.7
Vent Motor	**V1**	99.1	99.1	92.7	**91.2**	96.9	96.5	95.7	-

Figure 7: Accuracy of HVAC component recognition from audio signals.

and control.

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