USING INFRASOUND-BASED INFORMATION FOR NON-DESTRUCTIVE STRUCTURAL HEALTH MONITORING

Z. Jiang¹, Z. Zhang² and A. Maxwell³

ABSTRACT

Natural hazards could be very destructive. One challenge that the society faces is how to rapidly, accurately and cost-effectively evaluate the damage of structures in the aftermath of a disaster. Visual inspection is costly, time-intensive, inherently subjective and only applicable to visible damage. To overcome the limitations of visual inspections, a large body of research has focused on the design and deployment of the structural health monitoring systems. In those systems, various sensors are deployed to obtain the necessary data for the specific health monitoring schemes. These sensors are typically installed with wired and/or wireless networks which the deployment and operation cost largely obstacles their usage. In this study, an attempt has been made to explore the feasibility of using infrasound information obtained from microphones as a cost-effective alternative to identify low-frequency modal properties of structures. Algorithms have been developed to extract the useful information from an array of microphone sensors. Small-scale shake table tests are conducted with a single degree of freedom structure to verify the effectiveness of the proposed algorithms. The study demonstrates the potential of using microphone measurements for non-destructive evaluation.

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Using Infrasound-Based Information for Non-Destructive Structural Health Monitoring

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ABSTRACT

Natural hazards could be very destructive. One challenge that the society faces is how to rapidly, accurately and cost-effectively evaluate the damage of structures in the aftermath of a disaster. Visual inspection is costly, time-intensive, inherently subjective and only applicable to visible damage. To overcome the limitations of visual inspections, a large body of research has focused on the design and deployment of the structural health monitoring systems. In those systems, various sensors are deployed to obtain the necessary data for the specific health monitoring schemes. These sensors are typically installed with wired and/or wireless networks which the deployment and operation cost largely obstacles their usage. In this study, an attempt has been made to explore the feasibility of using infrasound information obtained from microphones as a cost-effective alternative to identify low-frequency modal properties of structures. Algorithms have been developed to extract the useful information from an array of microphone sensors. Small-scale shake table tests are conducted with a single degree of freedom structure to verify the effectiveness of the proposed algorithms. The study demonstrates the potential of using microphone measurements for non-destructive evaluation.

Introduction

History frequently reminds us how destructive natural hazards such as earthquake and hurricanes can be. The 1989 Loma Prieta earthquake (magnitude 6.9) caused an estimated $12 billion in property damage and cost 63 human lives [1]. The Northridge earthquake (magnitude 6.7) in 1994 brought an estimated of $20 billion property damage and claimed the lives of 57 people with more than 5,000 injured [2]. Hurricane Sandy, which hit the United States in 2012, was estimated to cause damage of $75 billion with at least 233 people killed along the path of the storm in eight counties [3, 4]. Hurricane Harvey that just hit Texas is projected to cause damage in excess of $100 billion [5].

Post-hazard safety and functionality assessment of the building structures is crucial to the safety of the occupants and the prosperity of the society as a whole. In current practice, the evaluation process is costly, time consuming and, for many cases, subjective. For instance, the California Governor’s Office of Emergency Services (Cal OES) Safety Assessment Program (SAP) utilizes

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volunteers and mutual aid resources to provide professional engineers and architects and certified building inspectors to assist local governments in safety evaluation of their built environment in the aftermath of a disaster [6]. Cal OES allows people to use safe homes and businesses, and ensures that people are prohibited from entering unsafe structure after a disaster, but the assessment is relatively subjective since it relies on evaluator’s judgment.

Structural health monitoring (SHM) system that is installed in structures can provide a more reliable and accurate assessment in the post-hazard events. Changes in modal properties and responses of structures (e.g. natural frequency, mode shape, flexibility matrix, responses in time-domain or frequency domain, and etc.) during their service life are strongly related to damage in structures. Among the dynamic information, natural frequency reflects the most basic dynamic performance of the structure identifying the global health status of the structure, and it can be identified easily, accurately, robustly, and reliably [7, 8, 9, 10, 11]. Most global health monitoring methods are centered on either finding shifts in natural frequencies or changes in structural mode shapes [12]. To identify the natural frequency, sensors (e.g. strain gauges and accelerometers) are installed in the structure to collect the measurement output. To guarantee that measurement data are reliably collected, SHM traditionally employs coaxial wires for communication between sensors and the repository. While wires provide a very reliable communication, their installation and maintenance can be expensive and labor-intensive [13]. With advancement of technology, wireless sensors and sensor networks attract a lot of interests in recent years as they reduce the cost by removing the wiring between sensors and the data acquisition system. Although wireless sensors provide a promising alternative for sensing, it still requires wires for the data acquisition system and, in current practice, challenges such as fault tolerance and power consumption for the wireless sensor still requires further investigation [14].

Sound is measured as the difference in pressure from atmospheric pressure. When an object is vibrating in the presence of air, the air molecules will start to vibrate at the surface of the object, sending the other air molecules nearby into motion. As the vibration propagates through air, pressure will oscillate at frequencies and amplitudes depending on the source. Microphones are designed to transform pressure oscillations into electrical signals. The human hearing range is commonly given as 20 to 20,000 Hz [15]. Infrasound is sound with frequencies below the audibility range of the human ear, typically considered below 20 Hz, which aligns with the frequency range of typical civil structures. In this study, infrasound-based information is proposed to be used for SHM of civil structures. This approach does not required wires as transmit media and it will be a cost-effective alternative to the traditional SHM approaches, given that microphone sensor is nowadays embedded in many devices such as smart phone and tablets that have been part of people’s daily life. However, microphone sensors may pick up any signal within bandwidth from other sources besides source of interest. If the pressure oscillations of the sources of interest can be extracted from the environmental noises (e.g. oscillations from other sources), the acoustic information obtained from a microphone can be used for SHM purposes. To overcome this challenge, Lobo-Aguilar et al. successfully extracted the model frequencies by using direct peak-picking on over two years of infrasound data [16]. Direct peak-picking may work for situation where natural frequency of structure doesn’t overlap with environmental noise or high Signal-to-Noise Ratio (SNR) situation (i.e. large vibration amplitude with regard to environmental noise). However, due to uncertainty and diversity in environmental noise, this direct peak-picking may not be effective and robust in separating structure vibration from other sources in signals received
by acoustic sensors, resulting in incorrect recognition of structure’s natural frequency. The susceptibility of acoustic sensors to surroundings poses great challenge for deployment of this cost-friendly solution for SHM.

In this paper, a novel and more robust feature extraction method to extract useful information from infrasound measurement for non-destructive SHM is discussed. The first part of this paper provides a preliminary study on the comparison of the information obtained from microphone sensor and traditional accelerometers. Next, a newly developed feature extraction method to recognize natural frequency from microphone measurement is introduced and the results produced through the algorithm is compared to direct peak-picking to demonstrate its effectiveness and advantages. Lastly, conclusions from this study are drawn and future work is discussed.

**Preliminary Study**

To evaluate the feasibility of using acoustic sensors to capture the natural frequency of civil structures, a preliminary study with a single-degree-of-freedom (SDOF) structure subjected to ground excitations was performed. The experimental setup is shown in Fig. 1. Sensors used in this study include two PCB 378A07 free field microphones and one PCB 377C20 random incidence microphone. The microphone pointed toward the structure is herein called the main microphone (PCB 378A07) and is meant to capture the motion of the top of the structure, as well as the environmental noise coming from the test room. The microphones (one PCB 378A07 and one PCB 377C20) pointed away from the structure are referred as reference microphone which is meant to only capture the environmental noises in the test room. Two Quanser accelerometers are attached to the shake table and the top of the SDOF structure to serve as a baseline to verify the measurements from the microphone sensors. The ground motion is produced by an earthquake simulator, Quanser Shake Table II, manufactured by Quanser Inc. [17]. The Shake Table II consists of a 46cm×46cm top stage driven by a 400W high-powered 3-phase brushless DC ball-screw motor, allowing it to achieve an operating frequency of 0–20 Hz, a ±7.6cm stroke and a peak acceleration ±1g with a payload of 11.3kg. The microphone measurement was collected using a Data Physics SignalCalc Quattro Dynamic Signal Analyzer (DP240) with four 24-bits input measurement channels, running at 500 Hz sampling frequency. Sensitivities, sensor ranges, and their associated properties are shown in Table 1.

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Sensitivity</th>
<th>Frequency Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Microphone Sensor (PCB 378A07)</td>
<td>5.8 mV/Pa</td>
<td>0.13 Hz – 2000 Hz (±2 dB)</td>
</tr>
<tr>
<td>Microphone Sensor (PCB 337C20)</td>
<td>50 mV/Pa</td>
<td>3.15 Hz – 16000 Hz (±2 dB)</td>
</tr>
<tr>
<td>Accelerometer (Quanser ADXL325)</td>
<td>1V/g</td>
<td>0.15 Hz – 1600 Hz</td>
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</tbody>
</table>
During the preliminary study, tests were conducted by subjecting the SDOF structure to different sine sweep excitation signals produced by the Quanser Shake Table II. Sine sweep excitations had an operating range of 0-10 Hz and duration of 30 seconds. One set of sine sweep excitations had a fixed amplitude of 0.05 cm, while the other set had a fixed amplitude of 0.1 cm. Sine sweep excitation was chosen since it subjected the SDOF to a range of excitation frequencies for system identification purpose.

Figure 1. Experimental setup in preliminary study.

Figure 2. Spectrum of sensor signal from main microphone and accelerometer during excitation.
The frequency spectra of the sensor signal from the main microphone and accelerometer during excitation amplitude of 0.05 cm are shown in Fig. 2. This SDOF structure has natural frequency of 3.8 Hz. Signals from these two sensors were scaled properly to have comparable magnitude of natural frequency. As can be seen from Fig. 2, the microphone sensor can pick up the natural frequency of the SDOF structure exactly as from accelerometer. However, it also picked up other sources with noticeable intensity (e.g. 14.28 Hz, 19.38 Hz, and 36.56 Hz). That is, microphone can provide exact model information as traditional accelerometer, but with a lot of “noises”. How to extract the desired information is crucial in utilizing microphone as an economical and convenience alternative for SHM purpose.

**Information Extraction**

Typically, as in direct peak-picking, the maximum magnitude of the sensor spectrum is used to identify the intensity of certain frequency component. Microphone sensor, as shown in the preliminary study, will pick up any vibration signals within its bandwidth including those from other sources in addition to the source of interest (i.e. SDOF structure vibration in this application). The direct peak-picking may work for high SNR situation, but it is not effective and robust in separating useful information from noises, especially with low SNR, due to uncertainty and diversity in environmental noises. The susceptibility of acoustic sensors to surroundings poses great challenge for deployment of this cost-friendly solution for SHM.

To remove noises and extract natural frequency information from microphone sensor signals, a methodology named Peak Index is proposed in this study. For simplicity of notation, direct peak-picking is denoted herein as $DP$. $DP$ value for certain frequency ($\omega$) is denoted as $DP(\omega)$, which is magnitude of that frequency component in sensor spectrum. The newly proposed Peak Index is denoted as $PI$ and its value for certain frequency ($\omega$) is denoted as $PI(\omega)$. $PI$ needs to be properly designed to identify natural frequency by separating it from other frequency components. Several techniques of signal processing are employed to extract structural natural frequency, $\omega_n$, from microphone sensor measurement. Signals from main microphone sensor is first pre-processed by subtracting the reference microphone sensor signals in frequency domain. Later on, a non-causal peak filter is applied to take into account the shape of the peak and calculate $PI$ value from pre-processed frequency domain data. For better visualization of peak filter, a peak shape is defined by height of center frequency and width at 50% of its height. Fig. 3 shows three peak shapes with same height (height = 1) but different width, which is 2, 4 and 8, respectively, as indicated by the arrows. In Fig. 3, ‘0’ corresponds to frequency peak and the width represents $n^{th}$ adjacent point with regard to center frequency (frequency of peak). Height is equivalent to magnitude in sensor spectrum. For these three peak shapes, $DP$ would treat them equally since they possess the same value in height whereas the proposed $PI$ method will differentiate them with a different $PI$ value.
The proposed $PI$ is defined as a peak feature extraction function which is formulated in Eq. 1 as,

$$PI(\omega) = \sum_{n=1}^{N_g} (2g(\omega, 0) - c(n)g(\omega, n) - c(-n)g(\omega, -n))$$

where $PI(\omega)$ is Peak Index for center frequency, $\omega$. $n$ refers to $n^{th}$ adjacent frequency of $\omega$. Positive $n$ refers to the right side of $\omega$ while negative means the left side of $\omega$. $g(\omega, n)$ refers to the magnitude of corresponding frequency. $c(n)$ is the discount factor for $n^{th}$ adjacent frequency of $\omega$ ($0 < c(n) < 1$), indicating the importance of corresponding frequency in describing the geometry of the peak shape. Larger $c(n)$ implies more importance of $n^{th}$ frequency in shaping the peak shape. $N_g$ is the maximum of the left and right adjacent points ($n$) and it is chosen as 10 in this study. Larger $N_g$ in peak feature extraction function enables representation of a more complicated peak geometry.

Each frequency $\omega$ can be evaluated through Eq. 1 for its own $PI$ value. For better generalization, discount factor $c(n) = 1$ (i.e. equally weight for adjacent frequencies) is selected in the feature extraction function for $\omega_n$ recognition. By applying Eq. 1 at $c(n) = 1$, relationship between $PI$ value and two peak parameters (i.e. height and width) can be obtained as shown in Fig. 4. As can be seen from the figure, larger height and narrower width results in larger $PI$ value. Also, $PI$ value tends to become more sensitive to width at higher height. These further confirmed that $PI$ value from Eq. 1 is the indicator of mean sharpness of peak, which can be used to characterize the geometry of peak, and width plays an important role in $PI$ value to distinguish $\omega_n$ from other...
sources with strong magnitude. One intuitive interpretation of the proposed PI method is that vibration energy tends to be concentrated when structure is being excited at its natural frequency, whereas other acoustic sources tend to present broader band components.

Figure 4. Influence of width and height to PI value.

To evaluate different feature extraction methods (i.e., DP and PI methods), probabilities of correct $\omega_n$ recognition is utilized as the metric. It can be formulated via the Softmax function as in Eq. 2,

$$P_{\text{correct}} = \frac{e^{x_0}}{e^{x_0} + e^{\bar{x}}}$$

where for DP method, $x_0$ is $DP(\omega_n)$ and $\bar{x}$ is the mean of first $N$ largest $DP$ values. Similarly, for PI method, $x_0$ is $PI(\omega_n)$ and $\bar{x}$ is the mean of first $N$ largest $PI$ values. Larger $x_0$ relative to other frequency components implies higher probabilities for recognizing $\omega_n$ correctly. Here, complement of $\omega_n$ is denoted as $\omega_n^c$.

For simpler notation, maximum amplitude of the shake table excitation is denoted as $A_{ex}$. Fig. 5 shows the comparison between the $DP$ and $PI$ methods for $A_{ex} = 0.05$ cm based on one experimental trial. Result is normalized to maximum value which is taken as 100. For $DP$ method, $DP(\omega = 2.31) = 100$ and $DP(\omega = \omega_n) = 46$, meaning that $\omega = 2.31$ Hz has higher probabilities to be selected as $\omega_n$ and the probability of picking the correct $\omega_n$, $P_{\text{correct}} = 25\%$ as calculated from Eq. 2. In contrast, for the proposed $PI$ method, $PI(\omega = \omega_n) = 100$ and $P_{\text{correct}} = 87\%$. Therefore, the $PI$ method correctly identified $\omega_n$ and improved recognition accuracy with significantly higher confidence.
Fig. 5 shows comparison of the DP and PI methods for $A_{ex} = 0.05$ cm.

Again, for DP method, $DP(\omega = 30) = 100$ and $DP(\omega = \omega_n) = 78$, meaning that $\omega = 30$ Hz has larger probabilities to be selected as $\omega_n$ and $P_{correct} = 53\%$. In contrast, the PI method gives $PI(\omega = \omega_n) = 100$ and $P_{correct} = 82\%$. Larger excitation signal improves probabilities of correct $\omega_n$ recognition (from 25% to 53%) if the DP method is used, however DP method still fails to recognize $\omega_n$ correct in this example.

Fig. 6 shows comparison of the DP and PI methods for $A_{ex} = 0.1$ cm in one experimental trial.

Figure 5. Comparison of DP and PI methods for $A_{ex} = 0.05$ cm.

Figure 6. Comparison of DP and PI methods for $A_{ex} = 0.1$ cm.
One data point may not be representative. Therefore, 120 data sets in total are collected with excitation amplitude of 0.05 cm and 0.1 cm (each with 60 data sets). Fig. 7 shows the cumulative density function of $P_{\text{correct}}$ for DP and PI methods under different excitation amplitudes. The red dashed line in Fig. 7 indicates $P_{\text{correct}} = 50\%$. As can be seen from the results, DP method can detect 9\% and 84\% of trials which achieved $P_{\text{correct}} > 50\%$ for $A_{\text{ex}} = 0.05$ cm and $A_{\text{ex}} = 0.1$ cm, respectively. PI method is able to detect 89\% and 98\% of trials which achieve $P_{\text{correct}} > 50\%$ for $A_{\text{ex}} = 0.05$ cm and $A_{\text{ex}} = 0.1$ cm, respectively. In conclusion, PI method improves correct detection rate significantly for $A_{\text{ex}} = 0.05$ cm, and slightly for $A_{\text{ex}} = 0.1$ cm since DP method is also able to achieve a reasonable $P_{\text{correct}}$ due to high SNR (i.e. large excitation amplitude).

![Cumulative density function of $P_{\text{correct}}$.](image)

**Conclusions**

In this study, an attempt is made to explore the feasibility of using infrasound information obtained from microphone sensors to identify low-frequency modal properties of structure. In order to overcome the challenges of low SNR and environmental noises presented in the microphone measurements, a newly developed feature extraction method called Peak Index method, is proposed to identify natural frequency from microphone measurement. Experiments on a SDOF structure subjected to ground excitations were conducted to verify the effectiveness and robustness of the proposed method. The results demonstrate the potential of using microphone measurements for non-destructive evaluation by showing that the proposed PI method correctly identified $\omega_n$ and improved recognition accuracy with significantly higher confidence even under low SNR cases (9\% for DP method vs 89\% for PI method under $P_{\text{correct}} > 50\%$ assumption). The PI method introduced in this study serves as one feature to extract useful information. More features are under development to constitute a more robust and accurate identifier of natural frequency. Also, preprocessing methods and their theoretical proofs are being worked on to improve SNR before feeding into feature extraction functions.
Acknowledgments

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References