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Demo Abstract: Active Structural Occupant Detector

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ABSTRACT

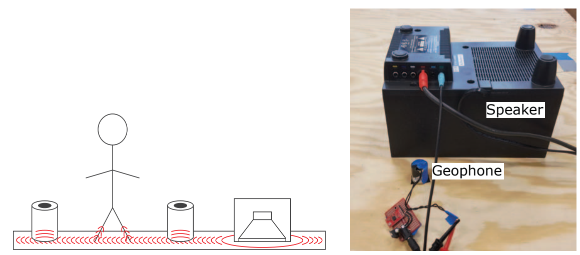
This paper presents the Active Structural Occupant Detector, an active vibration sensing system that detects stationary occupants through injection of vibration signals into the floor. Many smart buildings require occupant detection in order to provide personalized services. Some examples include optimized energy usage and security. Several methods currently exist for occupant detection, each with their own drawbacks, such as installation requirements. Structural vibration sensing overcomes many of these drawbacks by measuring impulses created by occupants to infer their movements, but cannot detect stationary occupants. The ASOD utilizes active vibration sources, which inject acoustic waves into the structure then measure how the structure responds to them. Any occupants present interact with these waves, causing changes to the measured signal. By characterizing the changes in how the waves travel, we can predict the presence or lack of an occupant with up to a 97.7% accuracy, as demonstrated by experiments in a real-world environment.

KEYWORDS

Sensors, Smart Buildings, Structural Vibrations, Active Structural Vibration Sensors

1 INTRODUCTION

Emerging smart-building applications require means to accurately detect occupant presence in order to provide services. Some examples include security [9] and optimal energy management [1, 7]. Various sensing modalities have been proposed to meet this demand, such as vision [2, 6], wearable devices [5], radio [10], pressure [7], and acoustics [2]. Each one of these approaches suffers from drawbacks which limits its usage in real-life applications. Vision-based methods, for example, can be impaired by occluding objects and raise privacy concerns [11]. Wearables, on the other hand, are dependent on the person carrying the device, which cannot always be guaranteed. Structural vibration sensors overcome many of the pitfalls common to other sensing modalities, such as occlusion for vision or the sensor density requirements of pressure plates [4, 7–9]. Despite these desirable qualities, this system tracks only walking targets, who produce particular impulsive excitations in the floor. Stationary targets, or those rolling or sliding on the floor, produce different kinds of vibration and thus are filtered out with background noise. We propose the addition of a vibration signal source to the sensing device in order to provide a known input signal to measure against. These waves are then be observed as they interact with the structure and any obstacles present, revealing the presence of the impeding occupant.



(a) Illustration of the operating principle: a person affects vibrations (shown in red) as they pass through the floor between sensors

(b) A photograph of the testing environment, with key components labeled

Figure 1: Depictions of the experiment setup

2 SYSTEM DESIGN

The Active Structural Object Detector is an array of geophone sensors (see [8]) and signal injectors placed around a room. The injectors induce acoustic waves in the floor which propagate between the geophones. We observe how those vibration waves change as they pass through the structure using the sensors. An occupant or object disturbs the signal path, which alters the signal detected by geophones past it. These changes manifest as amplitude differences at particular frequencies in the geophones' output signals. We use a classifier to infer the presence or lack of an obstacle based on these measured signals.

2.1 Hardware

For initial experiments, two geophones are used with a separate speaker acting as injector. The speaker is oriented to maximize acoustic coupling, with the diaphragm approximately parallel to the surface, and produces sinusoidal tones. Although a lone sensor could be used with the speaker, using a sensor at both the start and end reduces unknowns and ambient noise in the measured signals. Common parts of the signals between the two sensors are removed by taking the ratio of signal spectra at the two geophones. Figure 2 shows an example of the frequency spectrum ratios that result from this data collection.

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2.2 Inference Method

We predict the presence or lack of an occupant between the sensors using a classifier model, with frequency spectrum ratios as the input data. Only a few frequencies are significantly affected by an obstacle, so other frequencies only add noise to the measurement. We identify a few frequencies of interest, where the magnitude change in structural response is greatest, by sweeping across the full detection range of the sensors, producing a plot like Figure 2. Then, we select the two or three frequencies of largest magnitude difference, and excite the structure with only those frequencies for later measurements. This has the added benefit of significantly reducing the measurement burden. The classifier is trained on these later measurements, where only the interesting frequencies are excited.

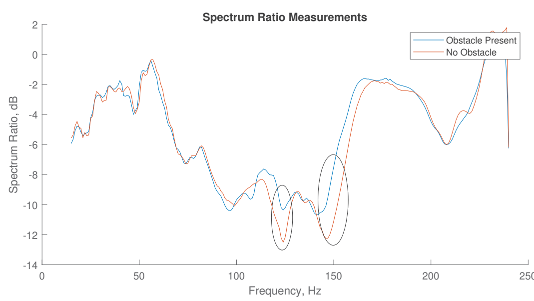

Figure 2: Two measured spectrum ratios, one with an obstacle present, one without. Frequencies of interest, where the two differ the most, are circled for emphasis.

3 PRELIMINARY RESULTS

Initial experiments resulted in a 97.7% accuracy when predicting the presence or lack of an occupant between the geophones. The data for these measurements was taken at Carnegie Mellon University using excitation frequencies 125 Hz and 150 Hz (identified using Figure 2) and a Support Vector Machine classifier [3]. Two obstacles were used for testing, an 80 kg researcher and a 16 kg bucket of sand. 300 samples of training data were taken, 100 each with no obstacle present, with the researcher, and with the bucket. Accuracy estimates are obtained by 10-fold cross-validation on the full training set.

4 DEMONSTRATION

The demonstration will use a table as the structure and a stack of books as an example obstruction for training data. Once the model is trained, the sensing system will use that model to provide real-time predictions. The audience can interact with the system, providing alternative obstacles for live detection.

5 FUTURE WORK

We have presented a preliminary system design capable of binary determination as to the presence or lack of occupants between sensors. To determine the capabilities of this sensing approach, further testing is needed to assess the effect of environmental variables such as structural stiffness and ambient vibration. Mass and position of the detected object may also affect both the frequencies and amplitude changes of features. Once the system is better understood, we plan to expand to identifying multiple target occupants with a larger array of sensors covering more area at once.

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