Monitoring Hand-Washing Practices using Structural Vibrations

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ABSTRACT

In this paper, we present a novel system for monitoring hand-washing activities using vibration sensing of the sink structure. In the United States alone, more than 1.7 million patients each year are subjected to preventable infections in the hospital. Proper hand-washing practices are essential for reducing these hospital-acquired infections. Existing approaches for monitoring hand-washing practices include visual observation, wearable sensing, and cameras. These approaches have been limited due to logistical challenges, deployment cost, and intrusiveness. Our system detects and monitors hand-washing activities by measuring the vibration response of the sink structure due to the hand-washing activities. We utilize the key insight that each activity associated with hand-washing (e.g. water running, soap dispenser actuating, hands rinsing with water, etc.) generates unique structural vibration responses in the sink structure. Our approach has the advantage of passively monitoring hand-washing activities through minimal cost-effective sensors with no requirements for additional staff or intrusive wearable sensors. The main research question is how to identify governing features that can distinguish the structural vibration responses due to each hand-washing activity. Our approach investigates the energy distribution of the vibration signal response from each hand-washing activity in the frequency domain. This approach uses the insight that each hand-washing activity generates different responses in the natural frequencies of the sink structure. Our method achieves an average classification accuracy of 95.4% with real-world experiments.

INTRODUCTION

Hand-washing is a critical component of maintaining a clean environment in health-care settings. Millions of patients each year are affected by health care-associated infections (HCAIs), with an estimated incidence rate of 4.5% (1.7 million patients) annually in the United States of America [1]. In an attempt to minimize these HCAI rates, the World Health Organization (WHO) issued a "call to action" in May 2015 to strengthen

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hand-washing monitoring and feedback in healthcare settings [2, 3]. In order to help reduce the HCAI rates in healthcare settings, a comprehensive hand-washing detection and monitoring system is necessary.

A number of approaches to improve monitoring of hand-washing activities have been utilized, but have limitations. Visual observation-based approaches are limited by the fact that the specialized observation staff cannot feasibly observe all instances of required hand-washing [4]. Camera-based methods, including motion-tracking and disinfectant detection systems [5, 6], are limited by line of sight requirements and deployment costs. Wearable-based techniques (e.g. smartwatches, RFID chips) [7–10] are limited by being intrusive for the healthcare providers: each provider must have a device and then wear it during all instances of hand-washing activities.

Our system detects and monitors hand-washing activities by sensing the vibration response of the sink structure. These vibrations contain information about the excitations that generated them (the hand-washing activities) that we use to classify the hand-washing activity type and occurrence. By measuring the vibration response of the sink structure, we are able to monitor hand-washing activities passively with as few as one inexpensive geophone sensor without additional specialized staff, line-of-sight limitations, and without intrusive wearable sensors. Our system detects hand-washing activities (defined as walking to the sink, water running, using the soap dispenser, and rinsing hands in water), then classifies each activity while retaining its sequence in time.

The primary research challenge addressed in this paper is that the relationship between the vibration responses of the sink structure and each hand-washing activity is ambiguous and has high uncertainty; for example, rinsing hands may have a similar response to water running and footsteps of a person approaching the sink may have a similar response as a soap dispenser actuating. To address this challenge, we consider the energy distribution of each activity in the frequency domain. Each hand-washing activity has a varying excitation frequency, and will, therefore, generate different responses in the natural frequencies of the sink structure.

The core contributions of this paper are as follows:

1. We introduce sink structural vibrations as a means to detect and monitor hand-washing activity sequences in a non-intrusive way.

2. We investigate distinct energy distribution features in the frequency domain for each hand-washing activity identification, utilizing the modal properties of the sink structure extracted from ambient vibration noise.

3. We evaluate our approach using real-world hand-washing experiments.

In the paper that follows, we present the physical intuition enabling our system, our approach to detect and identify hand-washing activities, and our evaluation technique, results and observations. Finally, we provide conclusions and discuss future work.

HAND-WASHING MONITORING PHYSICAL INTUITION

The physical intuitions that enable our approach incorporate principles in human-structure interactions and structural dynamics. Each hand-washing activity excites the sink structure, causing structural vibrations. For example, when water is used in the sink, the continuous impact of the water with the sink basin generates a small displacement in

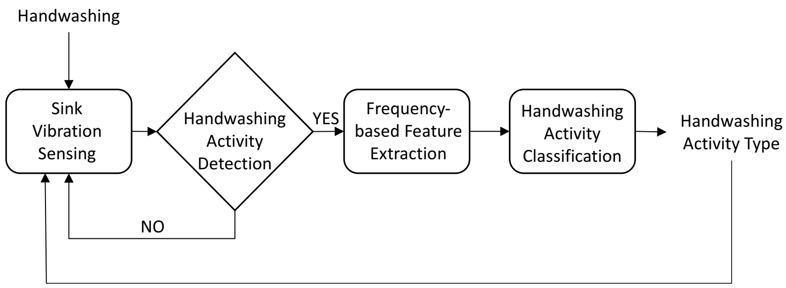


Figure 1: Hand-Washing Monitoring System Approach Overview

the sink structure. Because of its elasticity, the sink partially restores to its original state, causing an oscillation (vibration) in the sink structure. By measuring these vibrations, we can infer the nature of the excitations (hand-washing activities).

To uniquely identify each hand-washing activity, we utilize the intuition that different types of excitations generate different responses in the natural frequencies of a structure. With the four hand-washing activities, we observe that they represent different types of excitations. For example, footsteps and soap have similar characteristics as "impulse" excitations, while water and rinsing are typically more continuous in nature. As a result, we infer that the varying excitations generated by each hand-washing activity will generate different responses in the natural frequencies of the sink structure. Our approach utilizes this physical inference in the signal feature extraction and classification methods described below.

HAND-WASHING ACTIVITY IDENTIFICATION APPROACH

Our method of identifying and monitoring the sequence of hand-washing activities contains four distinct steps: 1) our system senses the vibrations in the sink structure, 2) it detects hand-washing activity-generated signals and isolates them from the overall vibration signal, 3) the system uses the isolated signal to calculate the Power Spectral Density (PSD) function amplitudes in predefined frequency bands as features, and 4) the detected hand-washing activity is classified using a support vector machine algorithm. Figure 1 provides a summary of our approach. For our system, we define "hand-washing activities" based on the WHO Hand Hygiene guidelines [3]: water running, using a soap dispenser, and rinsing hands in the water. In addition, we consider the footsteps of a person approaching the sink as a "hand-washing activity" to help reduce the risk of falsely detecting a hand-washing event (i.e. if footsteps are detected in sequence with other hand-washing activities, the likelihood of a true hand-washing event is greater).

Sink Vibration Sensing

The first step in our hand-washing activity monitoring method involves recording the raw structural vibration signal due to each hand-washing activity (excitation source). For our method, a geophone [11] is mounted to the surface of the sink structure, and is used for collecting these raw vibration signals. To increase the signal resolution, the raw signal from the geophone is amplified with an operational amplifier between 200-2000X, and then calibrated to the specific sink structure to obtain a higher signal amplitude

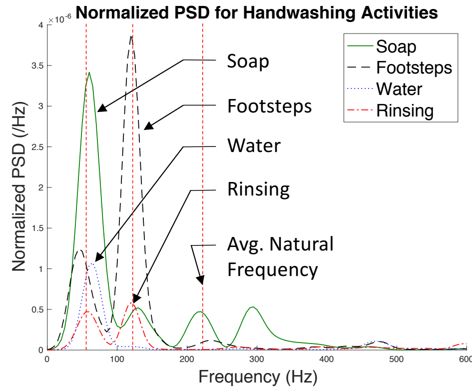


Figure 2: Power Spectral Density Functions for different hand-washing activities. Note differences in peak values between each activity type. Vertical dashed lines represent empirical natural frequencies of the sink structure.

while reducing the risk for clipping of the signal with higher energy excitations [12]. Following amplification, the vibration signal is converted to a digital signal using an analog-to-digital converter (ADC) and transmitted to a PC for processing.

Hand-washing Activity Detection

We utilize an anomaly-based detection algorithm to detect each hand-washing activity and record its sequence in the time domain. Our detection algorithm is an adaptation of similar anomaly detection techniques that detect events of interest through signal anomalies which exceed levels of ambient noise as presented in [13–15]. We use a 0.2s sliding window to detect when the mean of the signal amplitude in the window exceeds the typical ambient noise level. We choose this type of detection algorithm based on the observation that hand-washing activities generate signal amplitudes that are larger than typical ambient noise amplitudes. The window size is based on observed signal durations for each hand-washing activity in the time domain; we note the shortest duration is 0.2s, and select this as our window size so that each activity can be captured without being influenced by environmental noise. When an activity is detected, the system records its timestamp and isolates the signal from the overall vibration signal for feature extraction and hand-washing activity classification.

Feature Extraction

Our system next computes the feature values of the isolated activity signal. We observe that each hand-washing activity excites the natural frequencies of the sink structure in different ways. As a result, we consider the PSD of each detected activity to identify signal energy distribution as a function of frequency [16]. Figure 2 shows a typical example of the PSD plots obtained from each type of activity; as can be seen each activity has distinctive peaks at different frequencies, and thus their energy distributions can be used to uniquely identify each activity. For our feature values, we normalize the PSD values by the total energy of the isolated signal, then compute their sum across frequency bands centered on the natural frequencies of the sink structure. We select these features because there is a clear distinction in the PSD values for the hand-washing activities at the locations of the natural frequencies (see Figure 2).

To determine the natural frequency bands for the sink structure, we calibrate using a measured ambient noise vibration signal. We assume that the ambient noise is similar to a white noise excitation and generates a broad bandwidth response. We use this ambient noise vibration signal to estimate the natural frequencies of the sink structure using the Basic Frequency Domain or "Peak Picking" technique by finding the peaks of its PSD function [17]. To account for minor variations in the natural frequency estimations, we consider the natural frequency to be the mean estimation across several ambient noise vibration signals and define the PSD frequency bands for feature extraction to consist of the frequencies one standard deviation above and below this mean. In our approach, we estimate the first three natural frequencies and their frequency bands for the sink structure. We choose the first three frequency bands by observing with our training data that considering only the first two frequency bands does not contain sufficient information for uniquely identifying each hand-washing activity.

Hand-washing Activity Classification

Using the computed feature values for the detected activity, we classify it with a Support Vector Machine (SVM) algorithm. For our analysis, we choose a SVM algorithm for its ability to classify non-separable classes in multidimensional space. For computational efficiency, we utilize the L-1 norm formulation of the SVM training algorithm as presented by [18]. Based on our observations of preliminary data, we note that the feature values for each activity are not linearly separable, and therefore utilize a Gaussian radial basis function (RBF) kernel to transform the feature space. The RBF kernel has fewer training parameters and achieves comparable accuracy to higher-order kernels [19]. To classify each of the four hand-washing activities of interest, we adopt a technique similar to the "one-against-one" method presented in [20]. For the four hand-washing activities, we obtain a total of six SVM classification models. In order to reduce the possibility of misclassification and to avoid unintended labeling of other events as hand-washing events, we classify only when three of the six models provide the same label for an activity (note that when using our "one-against-one" method three is the maximum number an event can achieve and a 3-3 tie is not possible). In the event that an activity is not classified, the system marks it as "unclassified" (a non-hand-washing activity) and does not use it to indicate the presence of hand-washing. Once the detected activity has been classified, our system records the occurrence and the timestamp of the activity to establish the sequence of hand-washing events.

EVALUATION

To evaluate our method, we conducted real-world experiments at Carnegie Mellon University in the restroom on the ground floor of the Porter Hall building. Our evaluation assesses the accuracy of our system in identifying hand-washing activities and validates our feature selection and classification approach. We compared our system accuracy with a "baseline" approach that only considers the PSD values in the first natural frequency range, based on the intuition that the strongest structural response is typically represented by the first natural frequency, so the responses from each excitation in that frequency should contain the most information about that excitation.

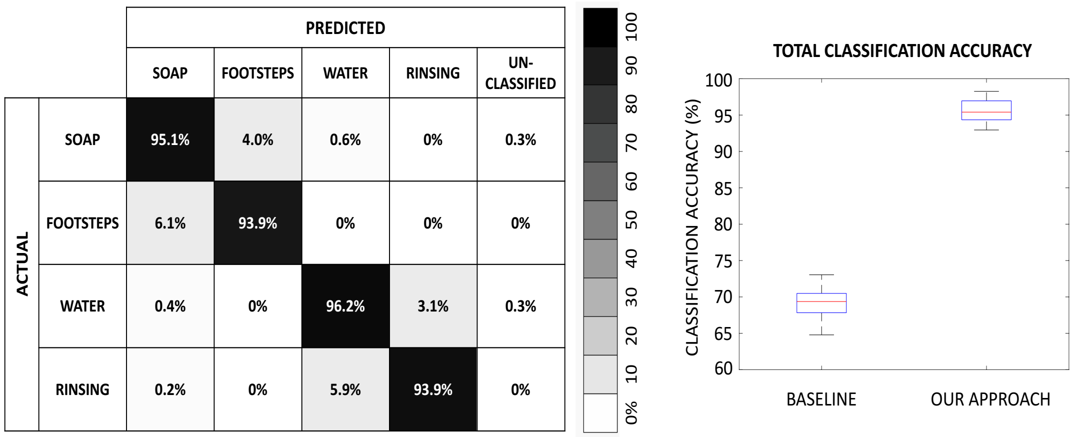
Figure 3: Experimental Setting

Experimental Setup

We instrumented a wall-mounted ceramic sink with one geophone sensors on either side of the faucet (two total) and collected the sink vibration responses with a sampling frequency of 25.6 kHz. Figure 3 shows the experimental setting. We collected 326 soap dispenser, 230 footsteps, 1306 water, and 426 rinsing samples across two participants. To account for potential sources of environmental noise, we monitored hand-washing activities with and without sources of noise (e.g. toilet flushing, hand dryer). For ground truth we gave verbal cues to the participants to start each activity at a predefined time. We calibrated the natural frequency bands of the experimental setting with two noise samples; each of two second duration with multiple 0.2 second windows extracted for computing the PSD functions. We determined the average natural frequencies to be at 46.6, 119.5, and 222.6 Hz, with maximum standard deviations of 8.0, 7.2, and 33.7 Hz, respectively.

Hand-washing Activity Identification Results and Discussion

To evaluate the performance of our method, we conducted a 10-fold cross validation of our recorded hand-washing activities. For each iteration, a value of 13 was used for the slack variable coefficent, C, based on optimization of the test accuracy over multiple values of C. To remove sample number bias, we updated the SVM training model weighting parameter to reflect equal distribution. To evaluate, we consider three metrics: overall accuracy (correctly predicted/total), precision (correctly predicted/total for that activity), and recall (correctly predicted/total predicted for that activity). The cross validation results are presented in Figure 4a. As can be seen in this confusion matrix, our method identifies each of the hand-washing activities with a high level of accuracy. Furthermore, our system achieves average precision rates of 93.9%, 94.3%, 97.9%, and 90.7% for soap, footsteps, water, and rinsing, respectively, and recall rates of 95.1%, 93.9%, 96.2%, and 93.9% for the same activities. Across the 2288 samples, 5 were labeled as "unclassified" using the our voting approach (at least 3 models with the same label in order to classify). In Figure 4b, we compare the accuracy results of our method with those from the "baseline" approach. We observe that our system achieves an average accuracy of 95.4%, which is a 1.4X improvement over the baseline (69.1%).



(a) Classification Confusion Matrix

(b) Classification Accuracy

Figure 4: Experimental Results: (a) shows the confusion matrix for the 10-fold cross-validation and (b) shows the total accuracy distribution of the "baseline" vs. our approach. The blue boxes represent the 25th and 75th quantiles, the small red line represents the median accuracy, and the whiskers represent the maximum and minimum accuracy values. Outliers are represented by red crosses.

CONCLUSION

In this paper we present our method for identifying and monitoring the sequence of hand-washing activities using structural vibrations of the sink. Our system accomplishes this passively without the need for direct observation by healthcare staff or intrusive wearable devices. To successfully monitor hand-washing, we identified governing frequency-band features to distinguish each activity. With our method, we are able to identify each of the four hand-washing activities with an average accuracy of 95.4%, which is a 1.4X improvement over the baseline approach.

In our future work, we will further explore the performance of our method in different structures and with different sink types. Additionally, we will consider the effects of different participants with varying hand-washing techniques.

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