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Calibration-Free Footstep Frequency Estimation using Structural Vibration

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Abstract

This paper introduces a calibration-free footstep frequency estimation system using footstep-induced structural vibration. Footstep frequency is an important measure for tracking health status in senior/health care and rehabilitation. Using structural vibrations for this estimation can improve intrusiveness commonly associated with long-term monitoring. Because the large number of structure types and the variety of noise they are subjected to, the main challenges of vibration-based approach are: 1) separating footsteps from other impulsive excitations (such as door shutting, cane striking, object droppings, etc.), 2) providing a system which is compatible to different structures and does not require calibration and training for every structure. To combat these challenges, we introduce an online footstep frequency estimation system which uses human walking pattern heuristics to automatically separate and tune the system to distinguish between footstep-induced vibration and other impulsive excitations in different structures. We validate our approach in two different buildings with human participants. The results show that our approach results in F1 score of 0.87, equal to 8X improvement compared to a baseline approach, which classifies the footsteps using a model trained in a different structure.

Keywords: Footstep, Online Learning, Calibration-Free, Structural Vibration, SVM classification

1 Introduction

Detecting gait abnormalities is important for health tracking in many healthcare scenarios. For example, in senior/health care [10, 9]), temporal gait parameters are key indicators of many conditions (e.g. dementia, chronic obstructive pulmonary disease) [6]. Much research has focused on employing mobile devices (e.g., smartphones and wearables) for such step tracking [3, 1]. These approaches are uncomfortable and require direct participant of the patient, which leads to reduced level of cooperation and thus effectiveness.

To combat these limitations, we use footstep-induced floor vibration for counting footsteps and estimating frequency of footsteps. The key intuition behind this sensing system is that footsteps striking on the floor induce vibration waves which propagate through the floor. Such vibration can be measured in a passive manner using vibration sensors mounted on the floor [4, 5, 2]. Main challenges of this approach resides in the fact that 1) impulsive excitation noise whose signal is similar to that of footsteps; and 2) each structure induces unique vibration response to footsteps, which makes the vibration different in different structures. The first challenge results in reduced footstep frequency accuracy by mistakenly considering non-footstep impulsive forces as footsteps, while the second challenge requires training the model for every structure which adds to the deployment difficulty.

In this paper, we introduce an online learning system that learns the footstep induced vibration responses of a specific floor and updates the footstep frequency estimation model on the fly. This system eliminates the need for extensive calibration in different structures. This system consists of three main components: 1) a detection module, 2) a classification module, and 3) an online learning module. The detection module measures the floor vibrations and distinguishes the parts induced by impulsive forces from background noise of harmonic or white nature (such as machinery or measurement noise). Classification module distinguishes footstep-induced vibration signals from other impulsive excitations. Finally, to make the model compatible with new structures, online learning module leverages trace-level heuristic about walking periodicity to update the classifier model. We validate our system performance using field experiments in different structures with human participants.

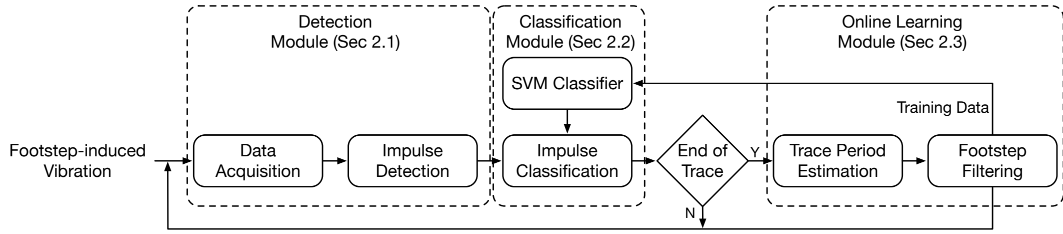


Figure 1: System Overview

2 Online Footstep Frequency Estimation System

Our system for footstep frequency estimation employs an online learning approach to accurately detect footsteps and estimate footstep frequency without extensive calibration using the following three modules: 1) a Detection Module, 2) a Classification Module, and 3) an Online Learning Module. An overview of our system is presented in Figure1.

Detection Module: Detection module measures the floor vibration and detects signal induced by impulsive forces. Ambient floor vibration is measured using sensors mounted on the floor. Using a geophone, ambient vibration consists of parts resulted from impulsive excitations (induced by footsteps, door shutting, walkers, etc.) and parts resulted from harmonic or white background noise (e.g., machinery or measurement noise). We separate the impulsive excitation parts which contains the footstep-induced vibration from the background noise using an energy-based threshold method [7]. This method, assumes a Gaussian distribution for background noise and three standard deviations above the mean ($\mu + 3\sigma$) of the signal energy is set to be the threshold to detect impulses.

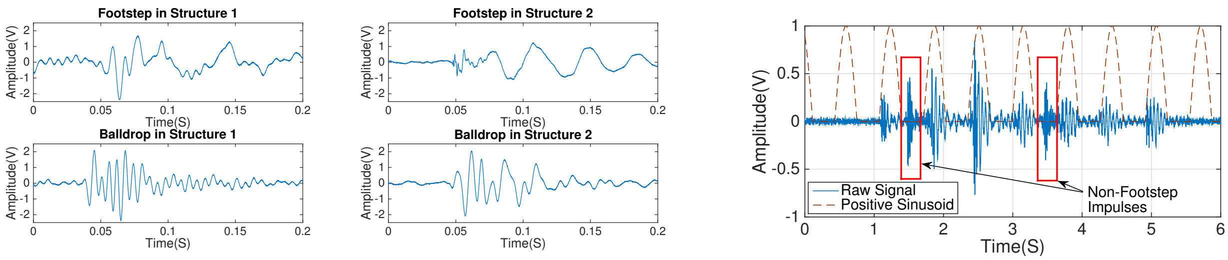
Classification Module: To accurately estimate footstep frequency, we need to accurately distinguish the footsteps from other impulsive excitations. To this end, our system leverages a one-class SVM classifier using features based on frequency-domain representation of the signal. One-class SVM [8], trains the classifier using data related to one cluster (e.g., footsteps) and considers the rest of data points as outliers. This classifier is suitable for our purpose as in real-world application the source of all impulsive non-footstep excitations is not known. Hence, we train the one-class SVM classifier using only the footstep-induced vibrations. However, the waveform of a footstep is different in different structures as shown in Figure 2a. Therefore, trained classifier will be dependent on the structure and is not compatible with different structures. To eliminate extensive calibration for each structure, we introduce an online learning module.

Online Learning Module: Our system employs trace-level heuristics about walking patterns (i.e. periodicity) to detect potential footstep-induced signals on the fly and leverage such footsteps as training data to update the model to accurately represent footstep-induced vibration in each structure. The main intuition is that traces resulted from footsteps are periodic with a specific range of frequencies, whereas other impulses are not generally periodic.

To leverage such periodicity, we find impulse signals that have similar periods as footsteps. The period of potential footsteps is estimated using the dominant frequency component of the auto-correlation function. Next, we separate the parts of the vibration signal which are induced by periodic footsteps in a specific range of frequencies from other non-periodic impulsive excitations. To this end, we find the inner product of the positive sinusoidal signal of the determined frequency with the energy of trace signal. The resulting signal only includes the walking trace and does not contain the impulses of different periodicity. An example of this procedure is presented in Figure 2b.

3 Evaluation

In order to validate our system, we conducted field experiments with human participants in two structures: a campus building which has a non-carpeted concrete floor with an observed first natural frequency of 23.83 Hz and a nursing home facility which has a carpeted concrete metal deck floor with an observed first natural frequency of 14.84 Hz. The experiments consist of two different people walking in their natural gait and several types of impulses (i.e., object drops, walkers, canes, and door closing). We first train the system in one of the structures. The accuracy of classification in the other structure is then compared for two cases: before and after updating the classifier using our approach. The results show that our approach results in as much as 8X improvement in the accuracy of classification.



(a) (b)

Figure 2: (a) Footstep and ball-drop induced vibrations are different in two structures (left and right). (b) A raw signal is plotted with the positive sinusoid with the period of the estimated footsteps. Red boxes mark impulses identified as non-footsteps.

4 Conclusions

In this paper, we introduce a non-intrusive system based on footstep-induced floor vibration. We focus on addressing the main challenges of this sensing system: 1) distinguishing footstep-induced vibrations from other impulsive excitations; and 2) providing an algorithm which is compatible to different structures. To address these challenges, we utilize a calibration-free online learning technique that leverages trace-level heuristics to extract footstep-induced vibration in different structures. We validated our approach through field experiments in two structures with human participants. The results show 8X improvement in F1 score compared to a static learning approach.

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