Device-free Multiple People Localization through Floor Vibration

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ABSTRACT

Structural vibration-based human sensing provides an alternative approach for device-free human monitoring, which is used for healthcare, space and energy usage management, etc. Prior work on this approach mainly focused on one person walking scenarios, which limits their widespread application. The challenge with multiple walkers is that the observed vibration response is a mixture of each walker's footstep-induced response, and it is difficult to identify 1) how many concurrent walkers are present, and 2) the timing of their footstep impacts on the floor. As a result, the extraction of detailed location information for each walker is erroneous. To address this challenge, we propose a structure-informed vibration signal characterization method to enable the detection and localization of overlapping vibration signals induced by multiple concurrent walkers. The intuition is that, due to the randomness in people's behavior, their footsteps do not impact the floor exactly at the same time and overlap partially. We decompose the signal to a non-fundamental frequency band which contains the heel strike onset information. With this decomposed signal, we can identify the number of walkers and use the initial peak information to localize each person independently. We conducted real-world experiments with up to three concurrent walkers and our system achieved a detection rate of up to 90% and an average localization error of 0.65m (2.9X baseline improvement).

CCS CONCEPTS

• **Human-centered computing** → *Ubiquitous and mobile computing*.

KEYWORDS

Ambient vibration sensing, multiple pedestrian localization, indoor localization, overlapping signal, TDOA

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1 INTRODUCTION

Indoor occupants localization enables various smart building applications such as building energy management and elderly/child monitoring. Various approaches have been explored for device-free localization, including vision [1, 3, 10], pressure [22], infrared [8, 14], and radio [2, 21]. These methods often rely on dense deployment or particular sensing requirements (e.g., line-of-sight). Researchers have been explored an alternative sensing modality through footstep-induced floor vibrations [5, 12, 13, 16, 18, 19]. They demonstrate sub-meter level localization when *a single* person walks through the sensing area, or when at most two people walks in a small scope without considering the situation vibration signals overlap severely [16]. However, these works do not handle the situation when multiple people walk simultaneously and their footstep-induced floor vibration signals overlap and are difficult to detect and distinguish. Furthermore, the physical characteristics (e.g., structural natural frequency) of the propagation medium (i.e., the floor) make the structural vibration signal structure-dependent [7], thus making separating overlapping signals by traditional methods such as blind source separation (BSS) inapplicable [11]. Since we are focusing on the detection and localization with overlapping signals instead of localization refinement through sequential information, we will not discuss this aspect owing to space limitation.

In this paper, we present a system to enable multiple people localization using the following intuition: 1) the randomness of people's behavior will make their footstep-induced vibrations partially overlap even when they walk simultaneously, and 2) the footstep-induced signal onset shows high SNR and high damping rates in non-fundamental frequency bands (*target scale band*), which minimizes interference between multiple people's signals. Within this *target scale band*, our system conducts multiple footstep-induced signal onset detection and applies multi-dimensional scaling (MDS) on the extracted onsets to estimate footstep locations by minimizing a loss function. The major contributions of this work include:

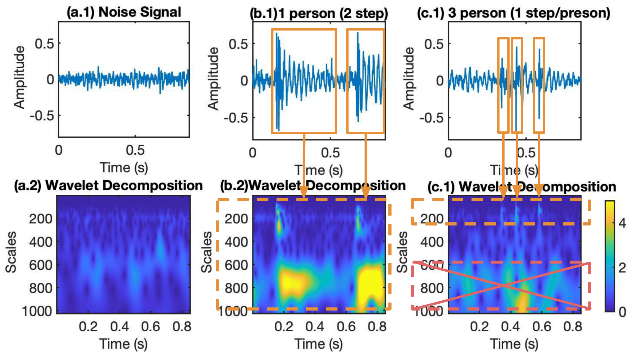

Figure 1: The first row shows the raw signal of ambient structural vibration signal (a.1), one person walking footstep-induced vibration signal (b.1) and three persons walking footstep-induced vibration signals that are partially overlapping (c.1). The second row shows their corresponding wavelet transforms.In (c.2), scales between 50 and 125 demonstrate three distinguishable footstep signal onsets, while the scales beyond 600 lose such time resolution.

- We present a device-free system to localize multiple people through floor vibrations.
- We utilize the intuition and domain knowledge on human behavior and structural response properties to detect the onsets of the partially overlapping footstep signals for localization.
- We evaluate the system through a series of real-world experiments and compare to baseline methods.

2 PHYSICAL KNOWLEDGE

We discuss the two intuitions – human behavior randomness and onset signal response in non-fundamental frequency band.

2.1 Human Behavior Analysis

The randomness of human behavior dictates that people walking in the same area are usually do not walking in perfect synchrony, (i.e., unlike military marching). As a result, their footstep-induced vibration signals may be partially overlapping instead of completely overlapping all the time [17]. Therefore, extraction *signal onsets* of partially overlapping signal is usually applicable.

In addition to the inference above, we also note that different people walk at different stepping frequencies [15] and with varying walking patterns [9]. Therefore, we infer that the heel strike timing for multiple pedestrians may not be completely overlapping, which enables us to identify a signal onset corresponding to each individual walker in the sensing area.

2.2 Structural Response Characteristics

To achieve multiple people detection and localization in overlapping vibration signals, we require an appropriate spectral subspace (*target scale band*) which provides high time resolution and SNR. Thus, the spectral properties of the instrumented floor are in demand.

To characterize the structural properties of the instrumented floor and identify an appropriate spectral subspace, we use a variation of a common structural identification approach, known as the Basic Frequency Domain (BFD) or "peak-picking" technique [4]. In our work, we use the continuous wavelet transform (CWT) to decompose the spectral components of the vibration responses in place of the traditional Fourier transform or Power Spectral Density estimation due to the fact that wavelet decomposition provides high time resolution in addition to frequency resolution. This high time-frequency resolution is advantageous over traditional frequency-only approaches because footstep-induced responses are time-varying (i.e., their spectral content may vary with time).

We placed a sensing node on the floor to record the ambient structural vibrations as well as the footstep-induced structural vibrations and compare their time and frequency components in Figure 1. Figure 1 shows the raw signal for structure vibrations in different scenarios and their corresponding wavelet decomposition. The wavelet decomposition is illustrated in the second row of Figure 1, where the x-axis is time, the y-axis is the wavelet scale, and the colors represent the wavelet coefficient magnitude.

We observe in Figure 1 (b.2) that the footstep induced vibration signals have a concentration of energy between scales 700 to 1000 with a duration of 0.2s and another energy concentration with a significantly shorter duration between scales 200 and 400. These two spectral bands of energy concentration correspond to natural frequencies of the structure. Due to the concentrated energy and high SNR of the signals on the natural frequencies, prior work on human sensing utilized it for one person walking footstep detection.

However, when there are multiple impulsive signals overlapping, such selection criteria is inapplicable. Since the damped free vibration of natural frequency (usually < 30Hz) decays slowly, multiple peoples' signals at these frequencies have a high probability of overlapping. For instance, the three impulses from (c.1) and (c.2) overlap significantly on the scales corresponding to the structural natural frequency (i.e., beyond 600), making the detection on that scale difficult, if not impossible. Therefore, **we select the scale range between 50 and 125 as our *target scale band*** through the observation. For the three persons walking signal shown in Figure 1 (c.1) and (c.2), the three footstep-induced signal onsets have distinguishable time resolution between scales 50 and 125, as marked out with the orange dash-line box in Figure 1 (c.2).

3 SYSTEM ARCHITECTURE

Our structural vibration localization system consists of three modules as shown in Figure 2: vibration sensing, footstep event detection and onsets extraction, and multiple pedestrian step-level localization. In this section we describe each module in detail.

Structural Vibration Sensing: The vibration sensing module obtains floor vibration through multiple vibration sensing nodes placed at different locations. The system mainly consists of three parts: 1) a geophone sensor (which converts the surface vibration velocity into voltage signals); 2) an amplification board (to amplify the sensor output voltage signal so that the digitized signals will have sufficient resolution for analysis); and 3) analog-to-digital converter (ADC) and data collection module.

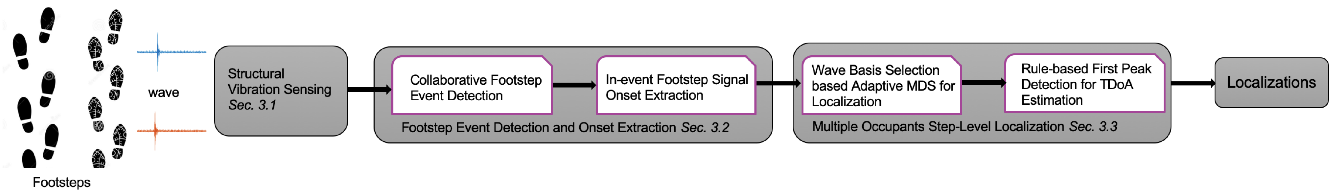

Figure 2: System Overview.

Footstep Event Detection and Onset Extraction: To localize multiple people's footstep through structural vibrations, our system first detects footstep events with the raw signal from a group of sensors. Then within a detected event, our system applies the CWT using Morlet wavelet as the mother wavelet. The selected wavelet has high waveform similarity with our target signal [12], which reduces dispersion effects and signal distortion. Lastly, with the *target scale band*, our system extracts footstep signal onsets from the partially overlapping signals and transmits the onset information to the localization module.

Multiple Occupant Step-Level Localization: Once the footstep onsets within a detected event are extracted, our system utilizes the wavelet decomposition of the extracted onsets signal for TDoA estimation. We conduct a rule-based peak detection to detect the first peak of the onset signals and estimate the TDoA between all pairwise sensors. Then, we utilize the TDoA values for the selected scales (*target scale band* on a range of wavelet scales) to further conduct adaptive multi-dimensional scaling (MDS) [6, 20] on these scales to estimate the localization of the footsteps.

4 EXPERIMENTAL EVALUATION

To evaluate our system, we conducted experiments in a school building hallway as shown in Figure 3.

Experimental Settings: We deployed our system with a group of four sensing nodes in a hallway to conduct experiments for evaluating our system. The experimental structure is a concrete slab on grade with a first observed natural frequency of 23.83 Hz. Figure 3 shows the sensor deployment. Light blue circles indicate the sensor locations and the solid dash lines are the trajectories that pedestrian will step on during the real-world experiments. The target sensing area is approximately $3 \times 4m$, where a pedestrian usually crosses through with six to seven steps. We use a camera placed in the hallway as the ground truth and marked the step location to guide occupants.

Metrics for System Performance: The evaluation metrics to measure the system performance are twofold: localization rate and localization accuracy. We calculate the Euclidean distance between the detected locations and the corresponding ground truth locations to measure the localization accuracy. When multiple footsteps occur simultaneously and the system fails to detect all of them, we compare the estimated locations to their closest ground truth location and calculate the error. We further evaluate the localization performance with the localization rate calculated as:

$$Localization\_Rate = \frac{\#onsets\ localized\ in\ the\ sensing\ area}{\#onsets\ detected}$$

Pedestrian Walking Scenarios: We designed different pedestrian walking scenarios to demonstrate the robustness of the system.

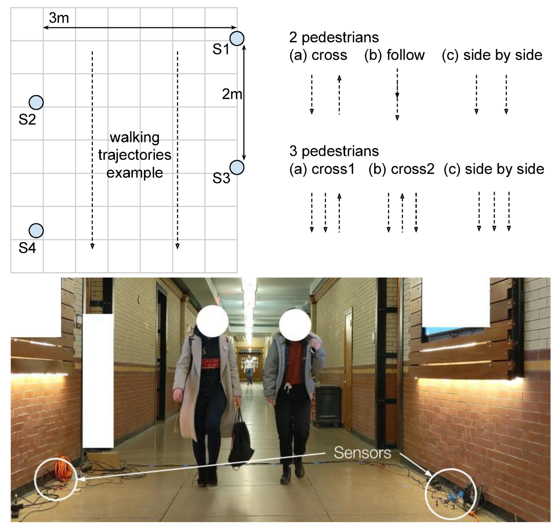

Figure 3: Experimental settings. Top left figure shows the sensor placement. Top right figure shows the walking scenarios investigated when multiple people walk through the sensing area simultaneously. The bottom figure shows a photo taken during the experiments.

Each scenario is evaluated with five repetitions. We investigate different walking direction combinations (Figure 3), including:

- Cross: people walk towards each other from two sides of the area at the same time
- Side by Side: people walk through the area side by side
- Follow: one person walks through the sensing area while another follows him/her three steps away.

4.1 Baseline Methods

To evaluate how well our algorithm that takes into account the vibration physical properties, we compare our localization algorithm to two baseline methods as follows:

- *NoFilter*: applying the MDS on the TDoA estimated from the raw signal without adapting the scales;
- *NoAdaptive*: using the MDS on TDoAs estimated from a randomly selected wavelet scale signal.

5 RESULTS AND ANALYSIS

The goals of the experiments include 1) understanding system performance under different signal overlapping conditions, and 2) evaluating system's ability to handle different number of occupants and different walking scenarios.

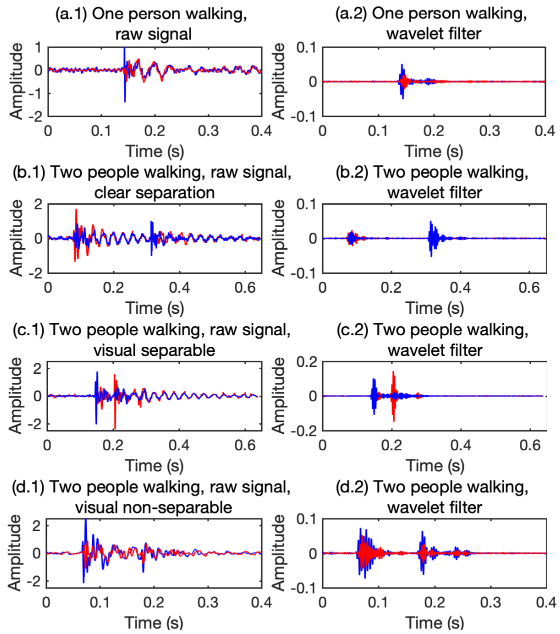

Figure 4: Example signals detected by two sensors when overlap conditions vary.

5.1 Overlapping Status Analysis

We evaluate the system in three categories of signal overlap. Figure 4 demonstrates examples of these possible signal overlaps: 1) **clear separation**, where the offset between signals is no less than 1/4 of the interval of two consecutive footsteps from the same person (e.g., Figure 4 (b.1)); **2) visually separable**, where we can visually separate the signal onsets, but the offset is less than 1/4 interval of two consecutive footsteps from the same person (e.g., Figure 4 (c.1)); **3) visually non-separable** (e.g., Figure 4 (d.1)).

In figure 4 we observe that the filtered signal is clearer and contains less noise than the unfiltered signal, making footstep detection in overlapping signals easier. Figure 4(x.1) shows the raw footstep-induced vibration signals when people walk by the sensing area, captured by two sensors. The corresponding filtered signals are shown in Figure 4(x.2).

5.2 System Characterization

Figure 5 shows the distribution[1] of the localization error when two people walk through the sensing area with varying levels of footstep overlap. When multiple pedestrians are walking in the target sensing area, we calculate the localization rate and localization error to evaluate our system. For all the investigated walking scenarios with different numbers of pedestrians, Figure 6 shows the localization rate (6(a)) and localization error (6(b)). Our system achieved 100% localization rate for all the cases, which demonstrates the localization robustness. Our system achieves an average localization error of just 0.65m, which represents 2.9× and 2.4× improvement over baseline approaches *NoFilter* (1.91m) and *NoAdaptive* (1.56m). From these results, we conclude that our approach accurately localizes multiple concurrent walkers with submeter accuracy, which enables robust indoor occupant monitoring in a variety of real-world walking scenarios.

[1]Note that in this paper, the boxplot presents the mean as the circle marker and the median as the center line, the box upper and lower edges indicate the 75 percentile and 25 percentile respectively.

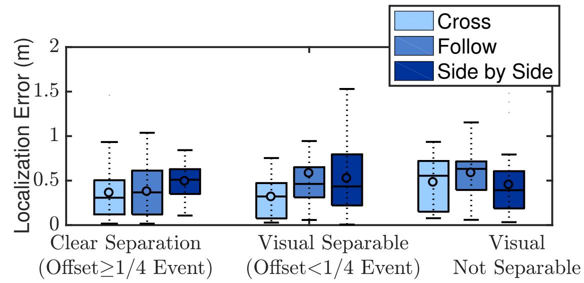

Figure 5: Footstep localization error when two people walk in the sensing area in different scenarios.

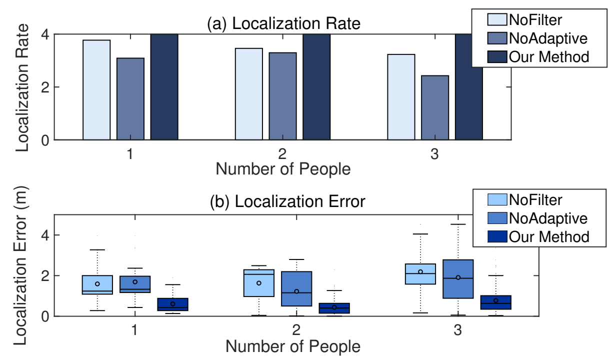

Figure 6: Footstep localization error when different numbers of people walk in the sensing area at the same time.

6 CONCLUSION

In this paper, we present a device-free system that localizes multiple occupants through footstep-induced structural vibrations. Our system utilizes physical knowledge on structural frequency excitation response to select non-fundamental frequency bands that have high SNR and high damping rate for heel strikes induced vibration signal. The signal filtering on these selected frequency band enables separation of footstep onsets from the partially overlapping signals for detection and localization. We evaluate our system and achieve sub-meter level localization accuracy through a series of real-world experiments, which enables various indoor application scenarios.

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