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Characterizing Wave Propagation to Improve Indoor Step-Level Person Localization using Floor Vibration

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ABSTRACT

The objective of this paper is to characterize frequency-dependent wave propagation of footstep induced floor vibration to improve robustness of vibration-based occupant localization. Occupant localization is an essential part of many smart structure applications (e.g., energy management, patient/customer tracking, etc.). Existing techniques include visual (e.g. cameras and IR sensors), acoustic, RF, and load-based approaches. These approaches have many deployment and operational requirements that limits their adaptation. To overcome these limitations, prior work has utilized footstep-induced vibrations to allow sparse sensor configuration and non-intrusive detection. However, frequency dependent propagation characteristics and low signal-to-noise ratio (SNR) of footstep-induced vibrations change the shape of the signal. Furthermore, estimating the wave propagation velocity for forming the multilateration equations and localizing the footsteps is a challenging task. They, in turn, lead to large errors of localization.

In this paper, we present a structural vibration based indoor occupant localization technique using improved time-difference-of-arrival between multiple vibration sensors. In particular we overcome signal distortion by decomposing the signal into frequency components and focusing on high energy components for accurate indoor localization. Such decomposition leverages the frequency-specific propagation characteristics and reduces the effect of low SNR (by choosing the components of highest energy). Furthermore, we develop a velocity calibration method that finds the optimal velocity which minimizes the localization error. We validate our approach through field experiments in a building with human participants. We are able to achieve an average localization error of less than 0.21 meters, which corresponds to a 13X reduction in error when compared to the baseline method using raw data.

Keywords: Occupant Localization, Smart Structures, Footstep-induced Structural Vibration, Human-Structure Interaction, Multilateration, Wave Propagation, Time Difference of Arrival, Wavelet Decomposition

1. INTRODUCTION

Occupant localization is an important component in many smart structure applications including residential, commercial, and health care settings.[1–8] There are several sensing approaches currently used for indoor occupant localization. These sensing approaches are mainly categorized in two classes: device-based and device-free. Device-based approaches[9–14] need the occupants to carry or wear a device and hence are intrusive. Device-free systems, on the other hand, make use of the infrastructure sensors, including cameras,[15–17] RF sensors,[18–21] acoustic sensors,[22–24] passive infrared motion (PIR) sensors[25,26] and vibration sensors.[27–29] Cameras and IR sensors require line of sight. Acoustic sensors, which make use of the occupant's speaking or walking signal to localize them, are often sensitive to high ambient acoustic noise.

To overcome these sensing limitations, we use human footstep induced floor vibration for fine-grained step-level occupant localization. Vibration-based methods allow sparse sensor configuration due to wave propagation mechanism in structures and are non-intrusive.[27,30–34] For localizing the footsteps, we use multilateration technique which is a common approach for source localization in different domains and uses the difference in time of arrival of the excitation signal collected in multiple sensors.[35,36] The main challenges of this approach for localizing footstep induced floor vibrations are: 1) wave propagation is dispersive through building floors(i.e., the propagation velocity is different for different frequency components of the wave.[31,37,38]), 2) the signal-to-noise

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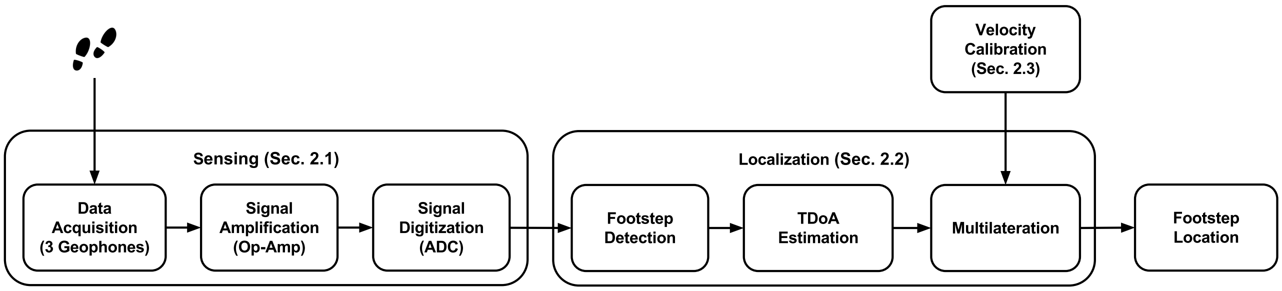


Figure 1: Approach overview

ratio (SNR) of footstep-induced vibration is small, especially when the occupant walks further from the sensor, and 3)to use the multilateration technique, we need to estimate the unknown wave propagation velocity in the building structure. These challenges result in changes in the shape of signal and make it difficult to accurately estimate the time differences of arrival(TDoA) leading to large errors for multilateration.

In this paper we present our TDoA based technique for localization footsteps using structural vibrations. In particular we use a multiresolution wavelet approach to decompose the signal into frequency components and focusing on high energy components for accurate indoor localization. Such decomposition leverages the frequency-specific propagation characteristics and reduces the effect of low SNR by choosing the components of highest energy. To estimate wave prorogation velocity in the unknown medium, we minimize the error between estimated locations and a known calibration location.

The core contributions of this paper are threefold:

- We present a novel fine-grained step-level localization technique by measuring the structural vibration using a sparse sensing array which does not need occupants to carry a device.
- We describe a method for reducing wave dispersion, propagation speed, and background noise effects due to complexities of a building structure.
- We validated the accuracy and robustness of the approach using experiments in real structure with human participants.

The rest of this paper has the following order. Section 2 describes an approach to localize occupants using their footstep-induced floor vibrations. Section 3 describes the experiments we conducted in those locations and then discusses the results and performance evaluation of our system. Section 4 provides conclusions of the paper.

2. OCCUPANT LOCALIZATION APPROACH

To localize occupants using footstep-induced vibrations, we develop an approach which has three main components: sensing, localization, and velocity calibration. Figure 1 shows the overview of the proposed approach. The sensing module collects the footstep-induced vibration signal. In the localization module, we first extract the footstep-induced vibrations from the background noise and use it for estimating the TDoA values. Finally, we use the estimated TDoAs for multilateration to localize the footsteps. Wave propagation velocity is necessary for multilateration and is estimated in the velocity calibration stage.

2.1 Sensing

The objective of sensing module is to acquire the footstep-induced structural vibration through sensors mounted on the floor. The sensing module consists of data acquisition using three geophones, signal amplification, and signal digitization using analog/digital converter (ADC). The first step of sensing is to acquire the vibration data using three geophones.[39] Then, to improve the signal resolution, the signal is amplified with an opamp to 1000X.

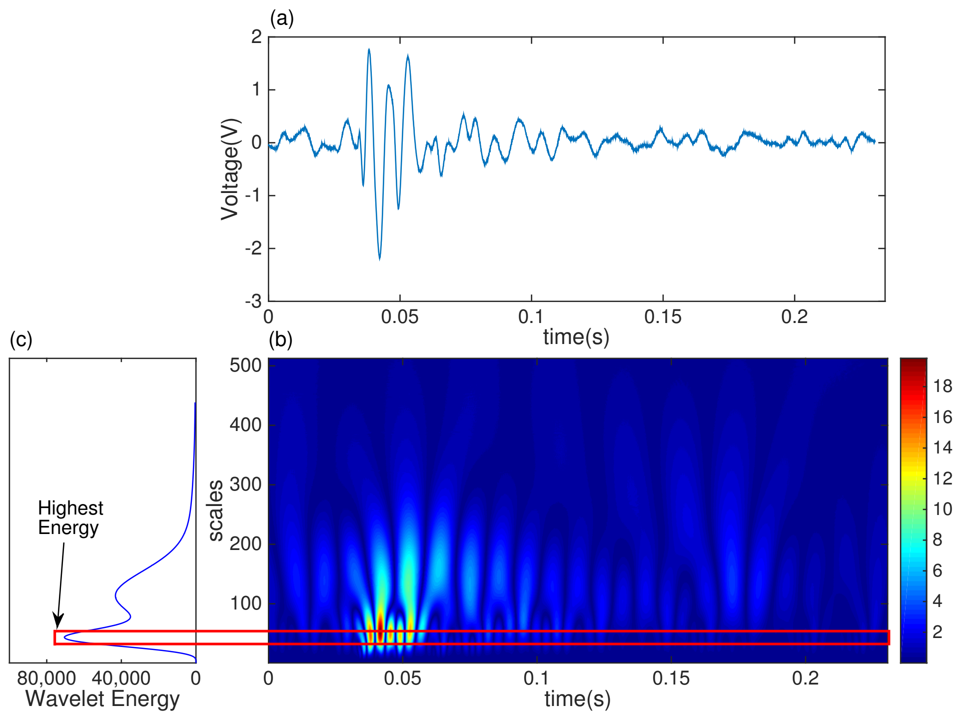


Figure 2: This figure shows an example of how the component of highest energy is chosen. Subfigure (a) is signal of a real footstep excitation. Subfigure (b) is the wavelet transform results of the footstep signal using Mexican hat wavelet. Finally, subfigure (c) shows the total energy for each frequency (scale) component of the signal. Energy of each component is found by squaring the absolute value of the wavelet coefficients and adding the resulting value for each frequency (scale). The red rectangle shows the component with the highest energy which will be used for finding the TDoAs.

After amplification, the effective sensing range for the footstep detection purpose in a commercial building is around 20 meters in diameter. Finally, the signal is digitized using an analog/digital converter and transferred to PC for further analysis.

2.2 Localization

Our approach for estimating location consists of three steps: footstep detection, TDoA estimation, and multilateration. The first step is to separate the footstep-induced vibration from the background noise. For this purpose, we use a threshold-based method[32,33] in which a threshold value is defined using the distribution of the background noise. A footstep event is detected when the energy of signal exceeds the threshold value. The second step is to use these footstep-induced vibrations for estimating the time difference of arrival between different pairs of sensors. For this purpose, a wavelet-based cross-correlation method is used. Finally, the estimated TDoA values are used for forming the multilateration equations and estimating the footstep location. The following sections describe the TDoA estimation and multilateration steps.

2.2.1 TDoA Estimation

Our approach uses the TDoA estimation to perform multilateration. Estimating accurate TDoA is essential for good performance of localization method.[40] However, wave propagation in floors is of dispersive nature which means that different frequency components of wave travel at different velocities.[37,38] Furthermore, footstep-induced vibrations have low SNR values,[32] especially when the footstep occurs far from the sensor. These two factors will result in different shapes of signal received in different sensors for the same excitation, and hence, make estimating TDoA a challenging task.

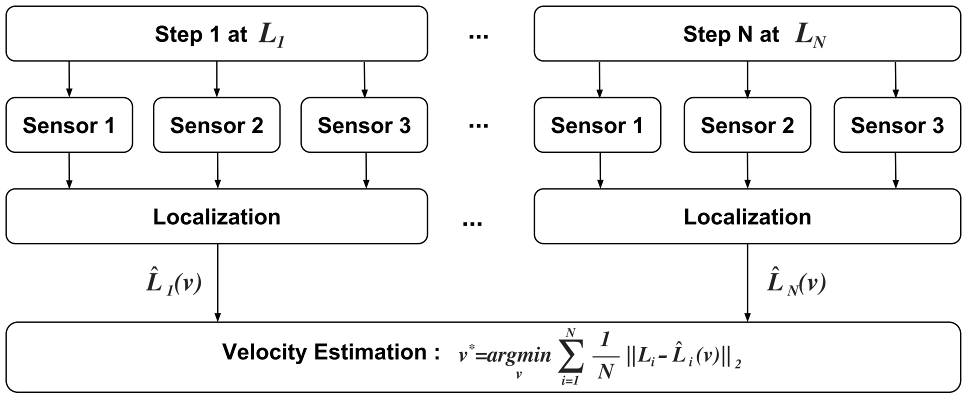


Figure 3: This figure shows the procedure of finding the optimal velocity which minimizes the average localization error over a calibration set comprised of N footsteps.

To overcome these challenges, we decompose the obtained signal into frequency components and focus on the component with the highest energy for estimating TDoA values. We use wavelet transforms because is well suited for non-stationary signals.[41–43]

Mathematically, it can be represented as,

$$T_x\left(b, a; \Psi\right) = w(a) \int_{-\infty}^{+\infty} x(s) \Psi_{b,a}^{*}(s) ds \tag{1}$$

where $w(a)$ is a weighting function to ensure that the wavelets in every scale have the same energy and $\Psi_{b,a}(s)$ is the transformed version of the basis function (mother wavelet $\Psi(s)$) which is translated by b units in time and scaled by the factor of a as

$$\Psi_{b,a}(s) = \Psi\left(\frac{s-t}{a}\right). \tag{2}$$

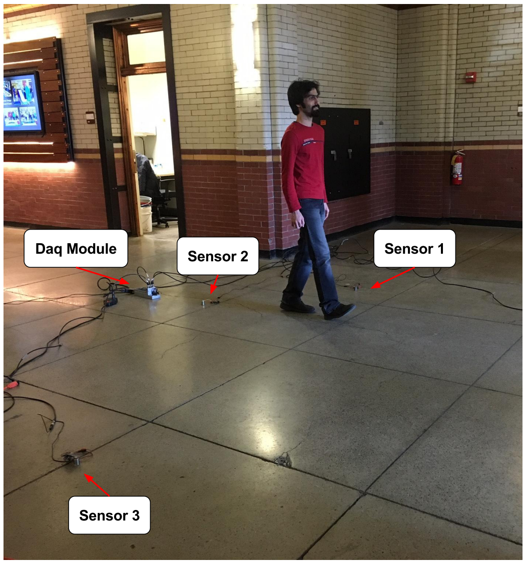
We used the Mexican hat wavelet for $\Psi(s)$ due to its resemblance to footstep-induced signals.[44] The higher scales correspond to more stretched wavelet functions, which in turn relate to lower frequencies present in the signal. Figure 2 shows an example of a footstep-induced vibration signal, its wavelet coefficients, and the diagram of the energy for each frequency. This figure shows an example of how the frequency component with the highest energy is chosen. The energy values are found by squaring the wavelet coefficients and summing them up across time for each scale (or frequency). The frequency component which results in the highest energy is shown by the red rectangle in Figure 2 (b). The absolute value of wavelet coefficients of this frequency component will be used for TDoA estimation.

The TDoA between two sensors is estimated using the cross-correlation of the extracted frequency components of the signals collected from the sensors. Both frequency components are from the same frequency value with high energy. In case those frequencies do not match for the two sensors, their average is used.

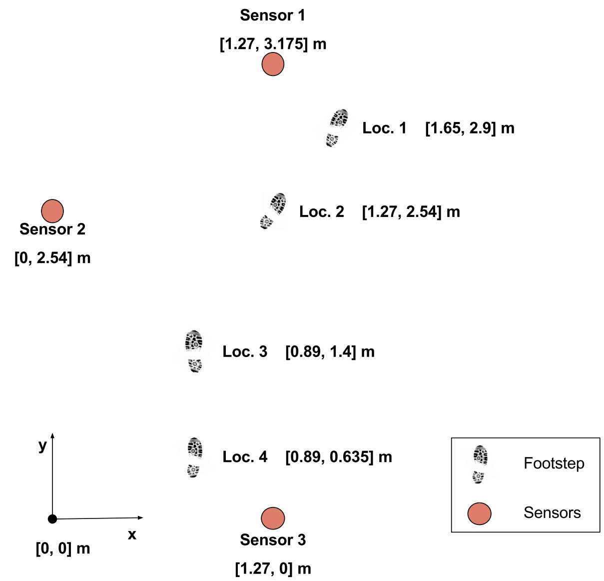
2.3 Multilateration

Multilateration is a common approach for source localization that uses the time difference of arrival(TDoA) between different pairs of sensors.[35,36] Knowing the TDoA between two sensors, the set of possible locations of excitation form one side of a hyperbola. Mathematically, the localization procedure can be described as,

$$\left\|x - p_i\right\|_2 = v\left(t_i - t_c\right) + \left\|x - p_c\right\|_2 \tag{3}$$



(a) Location of the experiments



(b) Sensor configuration

Figure 4: Experimental setup: The experiments are conducted with three sensors in a hallway with concrete floor on the ground which is depicted in (a). The sensor configuration and the location of footstep excitations are depicted in (b).

in which p_c is the location of the first sensor and p_i is the location of the second sensor, x is the location of the excitation (i.e., footstep), and v is wave propagation velocity. For each pair of sensors, we estimate the pairwise TDoA and find one hyperbola. To estimate the source location, we use additional sensors which adds to the number of hyperbolas. The intersection of these hyperbolas is the estimated excitation location. Assuming a constant propagation velocity value, three sensors are necessary to solve the multilateration equations. To find the intersection, the Levenberg–Marquardt algorithm[45] is used. As can be seen in Equation 3, multilateration requires the wave propagation velocity, which is obtained through the velocity calibration module described Section2.4.

2.4 Velocity Calibration

Wave velocity in an unknown structure is difficult to measure. Therefore, a calibration method is needed to estimate this velocity. We make the assumption that the velocity is relatively constant inside the floor. This section estimates wave velocity by minimizing the average location estimation error compared to a known location.

We first collect footstep induced floor vibration signals with known locations of multiple footsteps. Then we find a velocity value which minimizes the average location estimation error. The location of each footstep for a given velocity is estimated using the localization method described in Section 2.2. The location estimation error is defined as the euclidean distance between the estimated location and the true location of the footstep excitation.Thus, the optimal velocity v^* is defined as

$$v^* = argmin_v \sum_{i=1}^{N} \frac{1}{N} \left\| L_i - \hat{L}_i(v) \right\|_2 \tag{4}$$

where L_i is the actual location of the i^{th} footstep, $\hat{L}_i$ is the estimated location of the i^{th} footstep, and N is the total number of footsteps in the calibration set. This procedure is summarized in Figure 3. The estimated velocities are used in Equation 3 for multilateration.

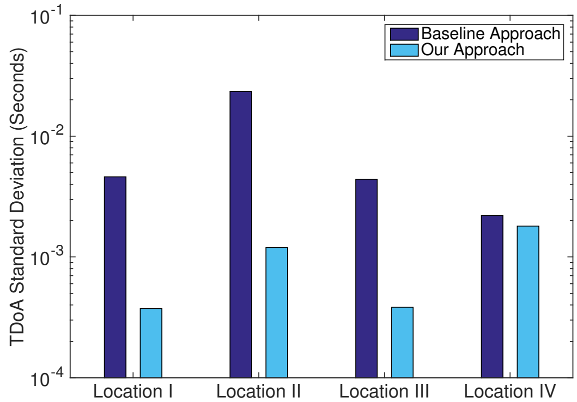


Figure 5: The standard deviations of estimated TDoA values between sensor 1 and sensor 3 for steps occurred in different locations. To better represent the TDoA values, the vertical axis is in logarithmic scale.

3. EVALUATION

To evaluate the accuracy of our localization algorithm, we conducted a set of human walking experiments in a building. The objective is to evaluate the performance of our TDoA estimation procedure and localization approach compared to a baseline approach. The baseline approach uses 1) the cross-correlation of raw signals in time domain for TDoA estimation and 2) average velocity obtained from calibration with a known footstep location. The variance of estimated TDoA values is used to assess the precision of TDoA estimation method, while the location estimation error measured in Euclidean distance is used for localization evaluation. Localization accuracy is assessed using the experimental data from one footstep location, and localization robustness is obtained from multiple footstep locations.

3.1 Experimental Setup

We conducted the experiments for footsteps at four different locations in a hallway with concrete floor. The hallway is on the first floor of an campus building in Carnegie Mellon University in Pittsburgh, PA. Three geophones are used for measuring the velocity of footstep-induced vibrations. To improve the signal resolution, we amplified the signal by 1000X. Finally the data is digitized and transmitted to PC using a NI 9234 data acquisition module, which is a 24 bit A/D converter. As the distances in indoor applications are small, the system requires a high sampling frequency to capture the small values of TDoA. Thus, all the vibrations were captured at high sampling frequency of 25 KHz. Figure 4a shows the hallway with our system set up, and Figure 4b presents the sensor configuration and footstep locations.

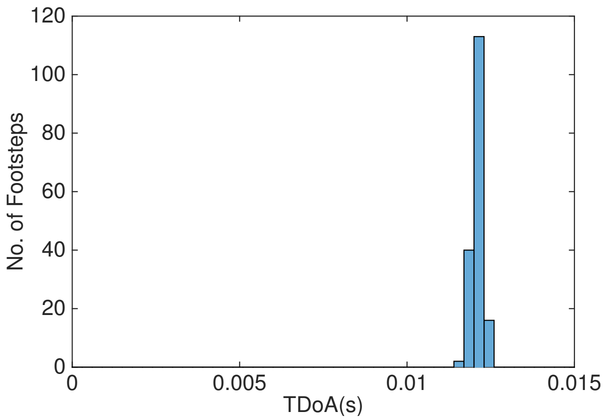
3.2 TDoA Estimation Evaluation

We evaluate the precision of TDoA estimation using the standard deviation. We focus on the uncertainties related to TDoAs between sensors 1 and 2 (T_{12}) and between sensors 1 and 3 (T_{13}) and compare our results with the baseline method. Furthermore, we evaluate the TDoA values for footsteps occurred in four different locations. The standard deviations of estimated TDoA values for different location and the reduction rates using our approach are presented in table 1. In this table, we see that using our approach results in reduction of up to 7.6X and 19.5X for T_{12} and T_{13}, respectively. Furthermore, other than one case, T_{12} in location 1, it consistently results in lower standard deviation and higher precision. This shows that our method is able to reduce the wave prorogation variations in the floor.

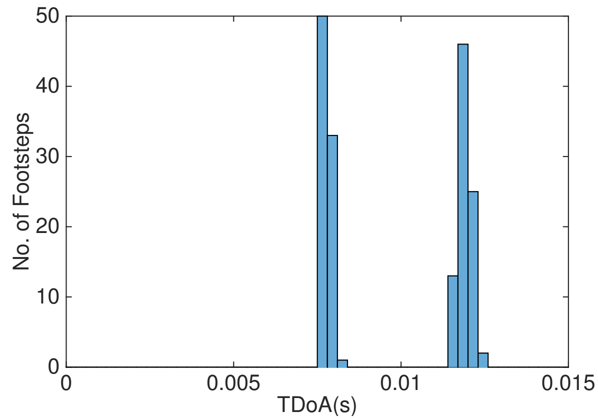
To better see this reduction, the standard deviation of estimated T_{13} values for the baseline approach and our approach are presented in Figure 5. The standard deviations of the estimated TDoAs are smaller using our approach which means that our TDoA estimation is more precise. Furthermore, the histogram of estimated T_{13} values for Location 1 is presented in Figure 6b. In this figure, as the footstep excitations are all in the same location, we expect the estimated TDoA values to be close and in one cluster. However, the estimated values

Table 1: Standard Deviations of Estimated Pairwise TDoA

	T_{12}			T_{13}		
	Our Approach	Baseline	Reduction	Our Approach	Baseline	Reduction
Location 1	1.43×10^{-4}	4.64×10^{-5}	0.32X	3.74×10^{-4}	4.6×10^{-3}	12.2X
Location 2	1×10^{-4}	1×10^{-4}	1X	1.2×10^{-3}	2.34×10^{-2}	19.5X
Location 3	2.8×10^{-5}	1×10^{-4}	3.6X	3.8×10^{-4}	4.4×10^{-3}	11.5X
Location 4	5×10^{-4}	3.8×10^{-3}	7.6X	1.8×10^{-3}	2.2×10^{-3}	1.2X



(a) Using our approach



(b) Using the baseline approach

Figure 6: Distribution of pairwise TDoA(T_{13}) for location 1. Knowing that the footsteps are in the same location, we expect that the estimated TDoA values are similar for all the footsteps. However, the baseline approach results in two distinct clusters of estimated values.

using the baseline approach have two clusters, i.e., half in the range of [0.0113, 0.0125] seconds and another half in the range of [0.0074, 0.0083] seconds. The clusters are the effect of peak miss-alignment due to signal deformation when looking at the entire waveform. This inconsistency results in lower velocity estimation and localization accuracy. In comparison, the estimated values using our approach are in one cluster. In summary, the standard deviation of estimated T_{12} and T_{13} values, on average, is decreased by the factor of 3X and 11X, accordingly. Considering all the TDoAs together, the standard deviation of estimated TDoA values is decreased by factor of 7X.

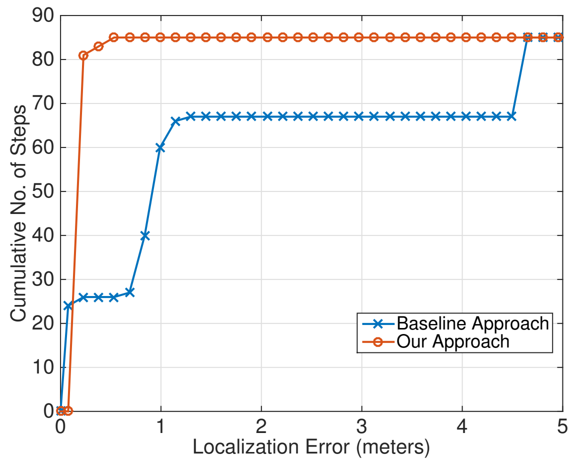
3.3 Localization Evaluation

We evaluate the localization technique in two scenarios: 1) to evaluate localization when only one location is available for velocity calibration, we evaluate the localization accuracy using 170 footsteps only at Location 2; and 2) to see the robustness of the velocity calibration, we further evaluate the localization approach by considering 280 footsteps in four locations. The results are compared to the baseline method that utilizes the waveform as a whole.

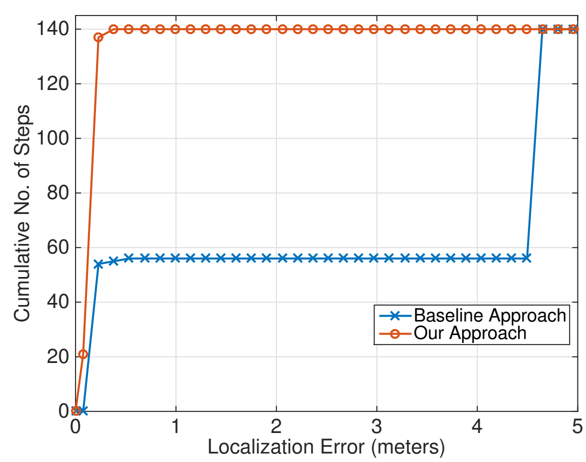
3.3.1 Localization Accuracy Evaluation

To evaluate the accuracy of our localization algorithm, we estimate the localization error for footsteps in the same location and compare it with the baseline method. The experiment consists of 170 footsteps at Location 2. Half of the footstep signals are used for velocity calibration and half of them are used for localization. The average value of velocity using the baseline approach is 265 m/s. On the other hand, in our approach, the velocity of 151.5 m/s is found by minimizing the average localization errors for all the 85 steps in calibration set.

We use the estimated velocities for the multilateration and the error of localization is estimated using the Euclidean distance between the actual location and the estimated location. The errors in TDoA values may result in no solution for multilateration problem, in which case half of the hallway width (mean error) are used as the localization error. The results of evaluation are



(a) Localization accuracy evaluation results



(b) Localization robustness evaluation results

Figure 7: Cumulative number of steps in each error range for time-domain cross-correlation method (the baseline) and wavelet-based cross-correlation method (our approach). For cases with no solution half of the width of the hallway is used as the localization error. This can be seen in the figure by the jump that happens in localization error of 4.5 meters.

- Using the baseline approach, the solution exists for 67 steps (out of 85) with an average error for these cases are 0.635 meters. Assuming half of the hallway width as the error for no solution cases, the average error is 1.4535 meters.
- Using our approach the solution exists for 85 steps (out of 85) and the average error is 0.205 meters.

Figure 7a shows the cumulative number of steps in each error range and compares the difference between the performance of two approaches. In summary, the average localization error using our approach reduces by almost 7X factor compared to the baseline method.

3.3.2 Localization Robustness Evaluation

To evaluate the robustness of our localization algorithm, we estimate the localization error for footsteps in four different locations and compare the results with the baseline approach. We collected signals for 35 footsteps in four different locations (140 in total) which are used as calibration data for estimating the velocity. In this case, for each location and for each pairwise TDoA value, we find one velocity. Averaging these values for the baseline approach leads to velocity value equal to 167.9 m/s. on the other hand, our approach find the velocity which minimizes the average location estimation error for all the steps (140 in total) in the calibration set, resulting in 175 m/s. Consequently, the velocity value is used for multilateration.

The results of evaluation are

- Using the baseline approach, we have a solution for 56 steps (out of 140) and the average error for these cases are 0.235 meters. Assuming half of the room as the error of cases with no solution, the average error is 2.84 meters.
- Using our approach the equations have solution for 140 steps (out of 140) and the average error is 0.21 meters.

Figure 7b shows the cumulative number of steps in each error range and visualizes the difference between the localization error using these two approaches. In summary, the average localization error using our approach reduces the error of localization for different footstep locations by almost 13.5X factor compared to the baseline method. This, in turn, means our approach is more robust to changes in footstep location.

4. CONCLUSION

We have proposed a fine-grained step-level occupant localization algorithm which utilizes the footstep-induced vibration. Our system enables sparse deployment and does not require the occupants to carry a device. By using multiresolution wavelet decomposition to focus on frequency components with the highest energy and using velocity calibration, we address the three main challanges: 1) Wave propagation in floors results in signal distortions; 2) The SNR for footsteps is small, which adds to the signal distortion; and 3) The wave propagation velocity is unknown a priori. This resulted in less than 0.21 meters, which corresponds to a 13X reduction in error when compared to the baseline method using raw data. This accurate, non-invasive localization approach can significantly improve future smart structure applications.

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