Footstep-Induced Floor Vibration Dataset: Reusability and Transferability Analysis

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ABSTRACT

Footstep-induced floor vibration sensing has been used in many smart home applications, such as elderly/patient monitoring. These systems often leverage data-driven models to infer human information. Therefore, characterizing datasets is crucial for the generalization of this new modality. This dataset contains 144-minute floor vibration signals from two pedestrians in eight environments. We analyze the reusability of this dataset in three different research areas, including vibration-based information inference, knowledge transferring, and multimodal learning. We further characterize the dataset transferability on the occupant identification task, to provide quantitative insights for the transfer learning problems in the real-world floor vibration sensing applications. The characterization is conducted with three metrics, including distribution distance, information dependency, and influencing factor bias. Analysis results depict that the dataset covers different levels of transferability caused by multiple influencing factors. As a result, there are multiple future directions in which the dataset can be reused.

CCS CONCEPTS

• General and reference → Metrics.

KEYWORDS

Floor vibration, dataset reusability, transferability

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1 INTRODUCTION

Footstep-induced floor vibration sensing has been used for human sensing in recent years. Comparing to other sensing modalities, floor vibration sensing has its non-intrusive and sparse sensing advantage, hence various application scenarios have been explored, including, but not limited to: 1) occupant identification

[4, 32, 36, 40], 2) occupancy estimation [11, 29, 46], 3) occupant localization [9, 12, 26, 31], 4) gait health monitoring [10, 13, 20, 21, 23, 25]. However, in the real-world various influencing factors can affect the footstep-induced vibration signal waveform, including 1) shoe type, 2) structure configuration, e.g., floor material and space layout, 3) distance between the walking trajectory to sensors. In order to understand these influencing factors' impact on application performance, we present this dataset ([Link](#)) [44].

This dataset contains 144-min of floor vibration signals of pedestrian walking by the sensing area. It also contains a 3-axis accelerometer signal using a wearable sensor on the shin as the footstep ground truth. The data is collected with multiple combinations of influencing factors. Hence, we envision this dataset being used for multiple purposes. For example, this dataset can be used to investigate vibration-based information inference (e.g., people, environment, etc.) It can also be reused for benchmarking new knowledge transferring algorithms. Additionally, with the shin acceleration signal, this dataset can be used for multimodal sensing and learning.

We further quantify the level of transferability under the impact of three influencing factors to benchmark new knowledge transferring algorithms. Transferability between two datasets is determined by data distribution shift, which is the difference between distributions of data for model development and inference [18]. To quantitatively understand levels of distribution shift caused by these influencing factors, we analyze the transferability with three metrics: distribution distance, information dependency and influencing factor bias. Results show that three influencing factors impact the dataset transferability at different levels, which could be beneficial for developing algorithms tackling distribution shift.

The contributions of this work are as follows.

- We present a footstep-induced floor vibration signal dataset collected over multiple structural environments with multiple pedestrians.
- We analyze the reusability of the dataset in three different research areas.
- We characterize the dataset transferability with the occupant identification task for benchmarking knowledge transferring algorithms.

2 DATASET DESIGN AND COLLECTION

2.1 Dataset Description

The dataset contains footstep induced floor vibration over different environments and people. When a person's foot strikes on the floor, this excitation causes the floor to deform and induces vibrations. The vibration propagates over the floor surface and then is captured by the vibration sensor. The waveform of the vibration detected by the sensor is, therefore, impacted by three key physical factors:

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Figure 1: Deployment configuration example in the experiment and the vibration sensing node's hardware. Red circles are vibration sensing nodes, the green circle is the additional Raspberry Pi for time synchronization and the blue circle is the accelerometer to capture foot strike motion.

shoe type, structural properties (e.g., floor material and/or layout), and distance between the lane of walking trajectory and the sensor. Wulfmeier et al. describe the factors of influence as physical conditions that cause the distribution shift, which we refer to as **influencing factors** in this paper [41]. Our dataset includes three types of influencing factors: shoe type, structure configuration, and lane-sensor distance.

To investigate structural configuration factors, we select eight different environments. These environments have varying floor materials (e.g., concrete, carpet, epoxy) and/or structural layout (e.g. hallways, rooms, and open space) from both office and residential buildings. Table 1 lists the characteristics of each environment. In each environment, we select a sensing area and place the sensors in the same layout to keep consistency. To characterize the lane-sensor distance factor, we define three lanes in each sensing area. We select three types of shoes with different outsole hardness: sneaker, skate shoe and hiking boot. The sneaker has the softest outsole and the hiking boot has the stiffest one.

Table 1: Deployment environment details.

Environment ID	Floor Material	Layout
1	Epoxy	Room
2	Low Pile Carpet	Aisle
3	Epoxy	Bridge
4	Epoxy	Hallway
5	Epoxy	Aisle
6	Deep Pile Carpet	Room
7	Deep Pile Carpet	Aisle
8	Concrete	Open space

2.2 Sensing Hardware Setup

The data collection system consists of two sensing modalities: 1) distributed vibration sensing nodes to capture the floor vibration; and 2) a wearable sensing node to capture pedestrian's shin motion

Figure 2: Sensing deployment configurations.

as the ground-truth of footfalls. Figure 1 (a) shows the configuration example of the system, and (b) illustrates details of the vibration sensing node.

The vibration sensing node consists of a geophone SM-24 [24], an operational amplifier LVM385 [38], an Arduino zero board with a 32-bit ARM Cortex-M0+ processor and a 10-12 bit ADC module [2], and a Raspberry Pi 4 model B [14]. The Arduino zero samples the vibration sensor at a rate of 6500 Hz. We setup an additional Raspberry Pi 4 model B to synchronize the sensing nodes. For the wearable sensing node, we adopt an accelerometer module ADXL 337 [3] to capture the shin motion, and an Arduino Feather M0 board [1] to digitize the signal at 800 Hz for each axes. The data is then send to a Raspberry Pi 4 model B via serial port for storage. All sensors are powered by batteries.

2.3 Data Collection Protocol

Figure 2 shows the configuration of sensing system deployed at each environment with a defined sensing area of 14×4 sq.ft. In order to study the fine-grained structural variance within an environment and its impact to the system, we place four identical vibration sensing nodes (S1, S2, S3, S4) and design three lanes (Lane 1, 2, 3) for pedestrians to follow, whose locations are marked in the figure. We collect floor vibration signals when the pedestrian walks along the lane through the sensing area. Both two pedestrians are 25-year-old males. They are required to walk naturally along the marked lane one person at a time. The data collection process follows the guideline of IRB UCM2019-115. In each environment, there are 18 influencing factors combinations of signal: 2 pedestrians $\times$ 3 lanes $\times$ 3 shoe types. For each combination, a 1-minute vibration signal is collected. For instance, data *P1-E1-S1-L1-Sh1* is the data collected with person 1 in the environment NO.1, from sensor 1. And the pedestrian walks in the lane 1 with shoe type 1. In total, we collect 144 minutes worth of footstep-induced floor vibration data.

3 REUSABILITY ANALYSIS

The footstep-induced floor vibration data has been used for multiple areas of research, such as vibration-based information inference, knowledge transferring, and multimodal sensing and learning.

3.1 Vibration-based Information Inference

For floor vibration sensing systems, prior works have explored multiple types of information inference, including and not limited to occupant footstep detection [34], occupant identification [36], sensing quality assessment [45], and sensor placement recommendation [42]. Figure 3 depicts exemplary results of this dataset used for different purposes. It is a critical basis for all footstep-induced

Figure 3: Examples of dataset applications.

floor vibration applications to accurately detect footsteps in the signal. Figure 3 (a) illustrates the floor vibration signal from a sensor and its corresponding footstep detection result. However, the footstep excitations can be challenging for an accurate detection in low SNR signals. In this dataset, there are environments with strong background noise, which it's suitable for developing and bench-marking footstep detection algorithms.

Footstep signals are sensitive to the aforementioned physical factors, it is important to design signal processing and feature extraction techniques based on these factors' condition. Otherwise, the application performance can be negatively affected. For instance, Figure 3 (b) shows ROC curves of footstep floor vibration-based occupant identification in environment NO.5 and NO.8, with the same signal feature extraction and classification model. It is clear that there is a performance difference. In order to realize a comparable performance, it is critical for the signal from the environment with inferior performance to have more advanced signal processing and feature extraction techniques. The proposed dataset can provide different combinations of influencing factors for investigating and testing the application-oriented signal processing and feature extraction techniques.

In order to achieve high scalability and robustness in complicated physical world, it is important to understand the impact from the physical environment on the sensing system. Therefore, a quantitative deployment characterization metric is necessary. We leverage the physical knowledge to characterize environment NO.5 and NO.8's assessment factors (AF) [45] and show the measurements in Figure 3 (c). We can find these two environments have different deployment properties, which could be the reason why the model performs differently in Figure 3 (b). This dataset covers 8 different environments, which makes it a good fit for developing environment characterization metrics.

Not only the environment factor, the sensor placement location is also crucial for optimizing the application performance. Even in the same environment, for example, the structure homogeneity and the beam in the wave propagation route can affect the vibration waveform. On the other hand, if the target sensing area is large, it's costly to test the vibration sensor placement everywhere then find the optimal location. Therefore, how to optimize the placement with minimum effort is another critical problem to be delved in. Figure 3 (d) illustrates the performance of single sensor at different locations. From the figure, it is clear that different sensor placements can achieve different performances. The proposed dataset has sensors located at four different locations, hence it can be leveraged to develop and test new sensor placement recommendation algorithms.

3.2 Knowledge Transferring

To allow accurate information inference that is robust to different influencing factors, it is important to develop algorithms that can generalize well over these changes, that is. Therefore, transferring the knowledge across different settings is critical for real-world applications. This dataset consists of multiple influencing factors and can be used to benchmark knowledge transfer and domain adaptation algorithms across these factors. For instance, efforts have been done to minimize the structure effect via physics-driven knowledge transfer approaches [30]. Even in the same structure, different shoe types and the distance between footstep and sensors would result in signal waveform differences. To have an in-depth understanding of these different influencing factors and providing a quantitative insight for knowledge transfer research, we further characterize the impact of influencing factors on transferability in Section 4.

3.3 Multimodal Sensing and Learning

Different sensing modality has its advantages and limits, multimodal sensing and learning aim to let multiple sensing modality complement to each other. Sensor fusion algorithms are one of the keys to efficiently combine and utilize the advantages of different sensing modalities. In this dataset, there are vibration sensing signal and the corresponding wearable (shin motion) signal. Prior work has shown that infrastructural sensing is rich in spatial information, while wearable sensing is continually sensing the motion with rich temporal information [22, 35]. This dataset can be used for benchmarking sensor fusion algorithms that efficiently utilize wearable and infrastructural signals' complementary spatial-temporal information.

4 TRANSFERABILITY ANALYSIS

In real-world floor vibration-based occupant monitoring applications, the data distribution shift between the model developments and inference is one of the most critical challenges. A big distribution shift indicates a low transferability, which leads to either a weak application performance or costly requirements for labels. Therefore, we conduct a transferability analysis to provide quantitative insights for designing knowledge transferring algorithms.

In this section, we take the occupant identification as the exemplary task to understand the impact of different influencing factors

Figure 4: Occupant identification accuracy, PAD and IDSS over datasets with different influencing factors. (a) and (b) are generated from sub-dataset pairs within the same environment but different lane factor (a) or shoe type (b). (c) is generated from one sub-dataset from the environment NO.4 as the reference and one sub-dataset from other environments as listed in x-axis.

on transferability. We conduct the analysis with three different metrics: 1) signal feature distribution distance, 2) information dependency between features and the label, and 3) influencing factor bias. The first metric quantifies the signal distribution shift, which is useful for However, it does not reflect the impact of distribution change on the application task – pedestrian identification. As a result, we adopt the second metric, given it not only considers the signal distribution but also the corresponding task labels. In addition to these two, identifying the bias of each class in dataset is important for designing knowledge transfer algorithms [28]. Therefore, we further present the third metric, which characterizes the influencing factor bias.

For each metric, we conduct a controlled analysis: keeping 2 influencing factors the same, analyze the result from the target factor’s change. The identification accuracy from a Gaussian kernel SVM classifier [7] is adopted as the reference of distribution shift. The classifier is trained with one sub-dataset and tested on another sub-dataset, both are sampled from sensor node 1’s data in the proposed dataset. The two sub-datasets are different in one influencing factor and consistent in other factors. The signal feature for occupant identification is the vibration signal’s frequency amplitude between 11Hz to 400Hz [36]. The test identification accuracy under different influencing factors is shown in Figure 4 with light blue bars. Details of each analysis are elaborated as follows.

4.1 Distribution Distance

To quantify the impact of each influencing factor on the data distribution, we utilize the *Proxy – $\mathcal{A}$ – distance* (PAD) as the distance metric. $\mathcal{A}$ – distance has been proven an effective metric to evaluate the distance between two distributions: a low PAD indicates a close distance [6, 15, 16, 27]. Given computing the exact $\mathcal{A}$ – distance is generally hard, we adopt the approximation method by calculating its proxy via running a learning algorithm to classify data sampled from two distributions, where the labels are the dataset IDs [16]. If the learning algorithm can accurately distinguish the data from two distributions, it implies the two distributions are different, i.e., the distance between two distributions are far, hence the transferability between two data distribution is low [6, 17]. In this paper, we measure ϵ , the error of dataset ID classification, with

a linear support vector machine (SVM) classifier. The proxy for the $\mathcal{A}$ – distance is then defined as $\hat{d}_A = 1 - 2\epsilon$ [6] to reach a unified 0-1 scale as other two metrics. We calculated the pair-wise PAD for each train and test pair, and the distribution of the PAD value is depicted in Figure 4. It is depicted in the figure that different influencing factors introduce a different level of the distribution shift. The environment factor has the biggest overall PAD in 3 factors. The mean PAD value of the environment factor is 0.919 (STD: 0.176), while that for the shoe type factor and lane factor is 0.152 (STD: 0.294) and 0.136 (STD: 0.222). The high distribution distances indicate low transferability. The mean test identification accuracy across different environments is 0.636 (STD: 0.114), while that for across different shoes and different lanes are 0.667 (STD: 0.134) and 0.764 (STD: 0.135). This result reveals that the transferability between different environments is lowest. And the transferability across different shoe is lower than different lane.

4.2 Information Dependency

When used for real-world applications data transferability quantification, PAD is not sufficient since it is task-invariant and does not reflect the transferability for specific sensing tasks. Test accuracy can reflect this impact, but it pertains to specific models. Therefore, we leverage the information-theoretic approach and provide a task-specific and model-invariant metric. We adopt the mutual information (MI) [8] to quantify the information dependency between frequency domain features and the task label. MI is one of the widely used measures of dependency between two variables. It quantifies the obtained information of one random variable, through the other random variable. The mutual information between two random variables is defined as follows:

$$MI(X; Y) = \sum_{x \in X} \sum_{y \in Y} p(x, y) \frac{p(x, y)}{p(x)p(y)} \quad (1)$$

where X is one individual feature space, Y is the task label space, $p(x, y)$ is the joint distribution of elements in X and Y . A high value of mutual information between two random variables means that the two variables are highly dependent [5]. Given a dataset with m samples and features of length n , we calculate the MI between each feature X_i , ($i \in n$, $X_i \in \mathbb{R}^m$) and the label Y as

Figure 5: Distribution of t -test result of influencing factor bias at different levels.

$MI(X_i; Y)$ [37]. In this way, for each sub-dataset, we can have a vector of MI values. The MI vector of one sub-dataset is denoted as $V = [MI(X_1; Y), \dots, MI(X_n; Y)]$, $V \in \mathbb{R}^n$. We propose the metric Information Dependence Similarity Score (IDSS), which is defined as the cosine similarity [33] between two MI vectors from two sub-datasets. IDSS measures the similarity of signal-label information dependency between two sub-datasets, hence indicates the transferability between two sub-datasets. For two MI vectors, V_1 and V_2 , IDSS is defined as

$$IDSS(V_1; V_2) = \frac{V_1 \cdot V_2}{\|V_1\| \|V_2\|}, \quad (2)$$

where $V_1 \in \mathbb{R}^n$, $V_2 \in \mathbb{R}^n$. A high IDSS indicates that two sub-datasets have similar high-dependency individual features. In other words, the classifier is more likely puts similar weight to features if the IDSS is high.

In this paper, we use pedestrian identification as the task and quantify the information dependency between the labels and features. We use the frequency band energy of normalized signals as features, from 11Hz to 400Hz, each 10Hz is a band. We calculated the pair-wise IDSS for each train and test sub-dataset pair, and the distribution of the IDSS value is depicted in Figure 4 with dark blue bars. We observe that the environment variance leads to the lowest IDSS and indicates the lowest transferability when conducting pedestrian identification tasks. The mean IDSS for different environments is 0.396 (STD: 0.133). For distribution shifts introduced by different shoes and different lanes, the mean IDSS is 0.553 (STD: 0.184) and 0.650 (STD: 0.202). This is consistent with our observation on PAD in Section 4.1.

4.3 Influencing Factor Bias

A dataset is considered biased if certain outcomes are more frequent than others [28]. Many factors could cause influencing factor bias

at different levels. We characterize the significance of bias induced by the three influencing factors in the dataset.

Here we utilize "Equality of odds" [19] as the metric to quantify this influencing factor bias. Different from the previous two metrics, this metric is task-specific and model-specific. To calculate the "Equality of odds", we first define a supervised learning model $\hat{Y} = f(X)$, which is learned from a training set of (input, output, 'biasing') tuples (X, Y, Z) . Y is the occupant identification label space, X is the frequency feature space, Z is the 'biasing' variable space. For the discrete output variable Y , if $\hat{Y}$ and Z are independent conditioned on $Y = y$, the model $f(X)$ satisfies equality of odds. This means that, for a particular value of the true label y , $P(\hat{Y} = \hat{y})$ is the same for *all values* of the 'biasing' variable: $P(\hat{Y} = \hat{y}|Y = y) = P(\hat{Y} = \hat{y}|Z = z, Y = y)$ [19, 43].

To quantify the significance of the bias at three influencing factors, we first conduct a 5-fold supervised occupant identification task and log the true-positive rate (TPR) for each class in each fold. In each task, we sample a sub-dataset from sensor 1's dataset. Each sub-dataset has its unique combination of three influencing factors. For instance, a sub-dataset is footstep signals collected in environment 1's lane 1 with shoe type 1. Then we conduct a pair-wise two-sample t -test between TPRs of sub-datasets. For each t -test pair, we keep one biasing variable different and the other two the same. We depict the p -value [39] from t -test to investigate the statistic significance of the bias [43].

The distribution of the p -value for each biasing variable are show in Figure 5. In this figure, if the total counts of bins of $p < 0.05$ is large, it means there is a high bias. Since the total number of tests is different for each influencing factor, we compare the ratio of test counts whose p -value is less than 0.05 to the total test counts. From the figure, the bias level between shoe type difference and lane difference are identical, which is both 0.113 (9/80) for $Y = 0$ and 0.075 (6/80) for $Y = 1$. For environment factor difference, the ratio is 0.234 (59/252) and 0.306 (77/252), for $Y = 0$ and $Y = 1$, respectively. This indicates that for this dataset, the environment introduces the most significant influencing factor bias for knowledge transfer.

5 CONCLUSION

In this paper, we present a footstep-induced floor vibration signal dataset. This dataset contains 144-minute floor vibration data collected from two pedestrians in eight different environments. To study the major influencing factors that impact the data distribution of floor vibration signals, we collect the dataset with controlled physical factors, including shoe type, structure configuration, and lane-sensor distance. We further discuss three directions to reuse the dataset, including vibration-based information inference, knowledge transferring, and multimodal sensing and learning. We then conduct a transferability analysis with three different metrics: distribution distance, information dependency and influencing factor bias. The analysis reveals aligned results. The environment factor introduces the highest reduction in transferability, while the lane type factor has the least impact on transferability.

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