Robust Person Identification Across Various Shoe Types Using Footstep-Induced Structural Vibrations

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ABSTRACT

Person identification is important in smart buildings to enable personalized services, such as monitoring individuals' gait health. Existing studies found that the structural vibrations induced by human footsteps provide both identity and gait health information of individuals, such as a person's walking speed, balance, and symmetry, enabling personalized gait health monitoring in smart buildings. However, footstep-induced structural vibrations not only depend on human walking patterns but also on a person's footwear as the footstep force transmits from the foot to the floor. This co-dependency leads to difficulty in identifying the owner of the footsteps when multiple people share the same space and each person has multiple pairs of footwear. In this study, we characterize the effect of footwear on footstep-induced structural vibrations to recognize individuals even when they wear different pairs of shoes (or barefoot). We develop a new metric named *Force Transmissibility (FT)* that measures the proportion of forces transmitting from the foot to the floor through the footwear. This metric unifies the effect of diverse shoe types, and we utilize this metric to enable robust person identification among various shoe types. We evaluated our approach through real-world walking experiments with eight shoe types shared by four participants. Our method achieves a 22% improvement in identifying the owner of the footsteps when compared to a baseline without footwear considerations.

Keywords: shoe type, person identification, gait health, structural vibration

1. INTRODUCTION

Person identification is crucial for various smart building applications, ranging from security and surveillance to occupant health monitoring.[1] In recent years, there has been a growing need for personalized health monitoring in buildings in the face of the emergent challenges of the aging population and climate change. To cater to this need, existing studies have explored camera-based, wearable-based, and acoustic-based approaches,[2–4] which have proven to be effective in tracking people's activity and/or gait. However, many of them have privacy concerns or require individuals to wear devices, causing inconvenience and discomfort in daily life.[5] To overcome these limitations, recent advancements in structural vibration sensing found that the floor vibrations induced by human footsteps provide both identity and gait health information,[6–10] such as a person's walking speed, balance, and symmetry. This approach has the advantages of being low-cost, non-intrusive, and device-free, which has great potential to be widely adopted for personalized services (e.g., health monitoring) in smart buildings.

However, one of the main challenges in vibration-based person identification is the uncertainties in shoe types. Specifically, footstep-induced structural vibrations depend both on the person's walking pattern and the shoe type because the shoe serves as the intermediate layer during the force transmission from the foot to the floor.[11,12] Given that it is unrealistic to ask individuals to wear the same footwear every day, this co-dependency leads to difficulty in identifying the owner of the footsteps when multiple people share the same space and each person has multiple pairs of footwear. While existing studies have achieved promising accuracy in person identification using footstep-induced structural vibrations with participants wearing their own shoes,[6,13,14] the effect of shoes on the results has not been explored. Moreover, the uncertainty in people's shoe types is high due to a large

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number of possible combinations of material, function, and thickness, making it difficult to model their effects on floor vibrations.

In this study, we characterize the effect of footwear on footstep-induced structural vibrations to recognize individuals even when they change shoes (or barefoot). To overcome the high uncertainty challenge in shoe types, we first characterize the structural vibration induced by people wearing multiple shoe types to understand its effect. Then, we develop a new metric named *Force Transmissibility (FT)* to describe the footwear's effect on the floor vibration signals. This metric unifies the type of footwear from diverse categories by quantifying the amount of forces transmitting through the sole based on its hardness and thickness, providing a standard "shoe effect" scale regardless of its materials and functions. We utilize this metric to enable robust person identification among changing footwear types. The person identification algorithm is achieved by a two-stage classification model. In the first stage, we classify the footwear into various levels of FT based on the collected footstep-induced structural vibration signals. In the second stage, we identify the difference in each person's gait pattern by comparing the data within the same FT level. The outputs of the algorithm are the footwear metric FT as well as the owner of the footsteps.

The contributions of the paper are:

- We develop a vibration-based person identification system that is robust to various shoe types, which, to the best of our knowledge, is the first work to achieve this goal.
- We characterize and model the footwear effect by formulating a new metric named Force Transmissibility (FT), which quantifies the proportion of the forces being transmitted from the foot to the floor based on the sole hardness and thickness.
- We evaluate the performance of our method through real-world experiments with participants walking in diverse types of shoes.

To evaluate our approach, we conducted real-world experiments with four participants wearing eight different types of footwear, including barefoot. Our algorithm achieved a 22% accuracy increase in identifying these people when compared with the baseline which did not account for footwear differences. The results emphasize the significance of footwear in vibration-based person identification and demonstrate the effectiveness of our approach.

2. THE EFFECT OF FOOTWEAR ON FLOOR VIBRATIONS

In this section, we characterize the effect of footwear on footstep-induced floor vibrations and model its influence based on the characterization results. First, we quantify the variability in the resultant vibration signals caused by footwear to understand the significance of the problem. Then, we characterize the effect of shoes on the resultant vibration signals based on empirical data. Finally, we develop a new metric named *Force Transmissibility (FT)* to model the footwear effect on footstep-induced floor vibrations.

2.1 Quantify the Vibration Signal Variability Caused by Footwear

We quantify the signal variability caused by footwear using the data collected in our multi-people, multi-footwear walking experiments (the details will be introduced in Section 4). Existing studies have identified and decomposed multiple sources of variability in footstep-induced floor vibrations, such as the personal walking style and floor heterogeneity across various footstep locations.[14] In this study, we expand the scope to include the variability caused by footwear.

To begin with, we extract the frequency spectrum of each footstep as the representative features for variability comparison. This is because the frequency spectrum summarizes the distribution of various frequency components within a single footstep, which has been found to represent a person's gait effectively.[13] To compare the variability caused by footwear, we regard person and footstep location as a controlled variable and compute the mean variance among footstep samples induced by different shoe types. Similarly, to compute the variability caused by people and floor heterogeneity, we regard footwear as the controlled variable and compute the mean variance

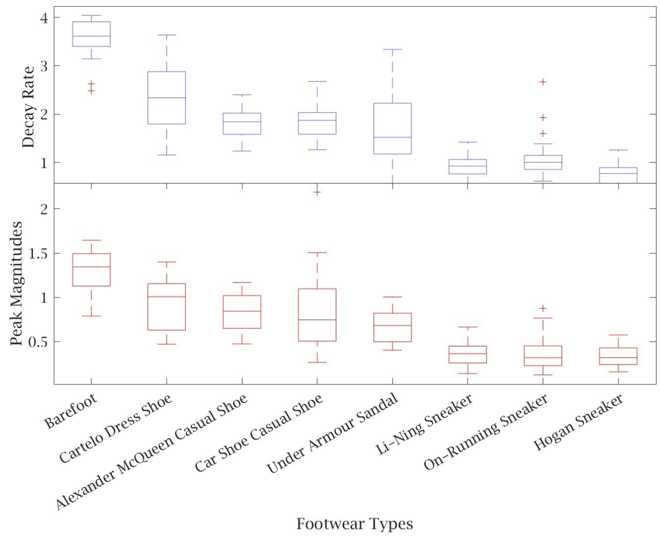

Figure 1. Effect of footwear on footstep-induced floor vibrations in terms of the 1) decay rate (upper) and 2) peak magnitudes (lower) of the individual footstep signals. The value of these two features shows clear trends among various shoe types.

of the frequency spectrum correspondingly. The overall variability is then calculated by summing all of the variances.

Based on the calculation above, we find that the variability percentage caused by footwear, person, and floor are 52.1%, 22.1%, and 25.8%, respectively. This means that footwear makes the greatest contribution to signal variability, which underscores the significant impact it has on footstep-induced floor vibration. Therefore, it is essential to model and reduce the footwear variability for robust and accurate person identification for personalized health monitoring.

2.2 Characterize the Footwear Effect on Floor Vibrations

We characterize the footwear effect on floor vibrations by extracting features that follow a specific trend with respect to shoe types. Specifically, we find that 1) peak magnitudes and 2) decay rate of the floor vibration signal are effective features to represent the footwear's influence on floor vibrations, visualized in Figure 1.

2.2.1 Footwear Effect on the Peak Magnitude of Vibration Signal

The peak magnitude refers to the maximum value of the vibration signal induced by each individual footstep. While a person's foot exerts forces on the floor during walking, the footwear adds an extra layer that adjusts the peak magnitude by absorbing and re-distributing the force through its cushioning system. This results in a reduced peak magnitude depending on the level of cushioning of the shoe. For example, when people walk barefoot, there is no cushion between the feet and the floor. As a result, the force underneath the foot is directly exerted on the floor, resulting in a large peak magnitude when walking barefoot. Figure 1 (lower) shows the trend of peak magnitude across various shoe types - as the cushioning level (i.e., stiffness) of the shoe becomes higher, the peak value decreases accordingly.

In the context of person identification, we find that the peak magnitude is more sensitive in recognizing people when the shoes they wear are less stiff. This is because the forces a person exerts on the shoes depend highly on people's habits and body weights, and footwear with softer soles (e.g., running shoes) absorb the forces more. The absorption of forces results makes the person's weight and walking style biometrics less significant, leading to less distinguishable peak magnitudes among various individuals. This means that the peak magnitude is an effective feature in person identification when the person is walking barefoot or in stiffer footwear. Conversely, the peak magnitude of the footstep-induced vibration signal may not represent the actual walking characteristics of the person when the footwear is relatively soft (i.e., with lower FT).

2.2.2 Footwear Effect on the Decay Rate of Vibration Signal

The decay rate is defined as the rate of exponential decay in the upper contour of the signal after reaching the maximum amplitude in the time domain, which typically represents the damping effect in the vibration.[15] To extract the decay rate, we pick the first five peaks after the maximum magnitude in the signal and fit them using an exponential function, which gives a relatively consistent decay rate.

We find that the decay rate in footstep-induced floor vibration is affected by both personal walking patterns and shoe types. A healthy adult typically lands on their heels during normal walking, making the force concentrate on the contact area between the heel and the floor in a short duration of time.[16] This effect is particularly significant when people are walking barefoot, the forces of which are impulsive and similar to hammer strikes. However, the force concentration is less significant when people wear shoes because the insole and outsole redistribute the force over a larger contact area and for a longer time. Figure 1 shows decay rate decreases as the shoe gets softer (FT decreases). This means that when people wear footwear, especially sneakers with soft soles, the force between the shoe and the floor is less impulsive but more similar to continuous force with variations over time. In addition, we observe the decay rate is sensitive to people even when they wear the same type of shoes, meaning that it contains personalized gait information in addition to the footwear effect.

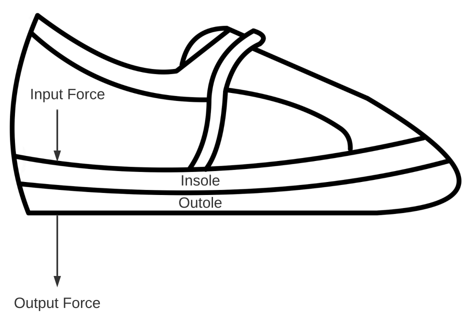

Figure 2. Simplified model of a shoe to demonstrate the force transmission through the inner and outer layer of the sole.

2.3 Model the Footwear Effect on Floor Vibrations

We model the footwear effect on floor vibration signals by formulating a new metric named Force Transmissibility (FT). FT represents the level of force transmission between the foot and the floor due to the footwear effect. Given the positive correlation between hardness and Young's modulus in polymers,[17] polymer materials with higher hardness tend to experience less energy dissipation from deformation, resulting in a higher FT. Hence, the hardness per unit thickness $\frac{h}{t}$ could be an indicator of FT magnitude. Based on a two-layer sole model that is commonly used to describe footwear types (see Figure 2), the FT of the footwear system is then calculated based on the thickness and the hardness of the insole and outsole in Equation 1 below:

$$FT = \frac{h_1}{t_1} \times \frac{t_1}{t_1 + t_2} + \frac{h_2}{t_2} \times \frac{t_2}{t_1 + t_2} = \frac{h_1 + h_2}{t_1 + t_2} \quad (1)$$

where t_1 and t_2 represent the insole and outsole thickness, and h_1 and h_2 represent the hardness of insole and outsole, respectively. In this equation, the terms $\frac{h_1}{t_1}$ and $\frac{h_2}{t_2}$ represent insole and outsole hardness per unit thickness, and $\frac{t_1}{t_1+t_2}$ and $\frac{t_2}{t_1+t_2}$ describes the proportion of insole and outsole out of the entire thickness. By multiplying the mean hardness with the thickness proportion, we first obtain the FT of the insole and outsole, respectively. Then, by summing up the FT of both soles, we obtain the overall FT of a given footwear. Equation 1 signifies that the FT of the footwear increases with sole hardness and decreases with sole thickness, which aligns with the physical intuition that stiffer soles make the force easier to transmit while softer soles absorb more forces and energy.

To validate the effectiveness of our FT formulation, we plot the distribution of samples for different types of shoes (dots with different colors) in the axis defined by $\frac{h_1}{t_1+t_2}$ and $\frac{h_2}{t_1+t_2}$ in Equation 1 as Figure 3. We observe a clear separation among various shoe types, indicating that FT is effective in describing the distinctive properties among various shoe types.

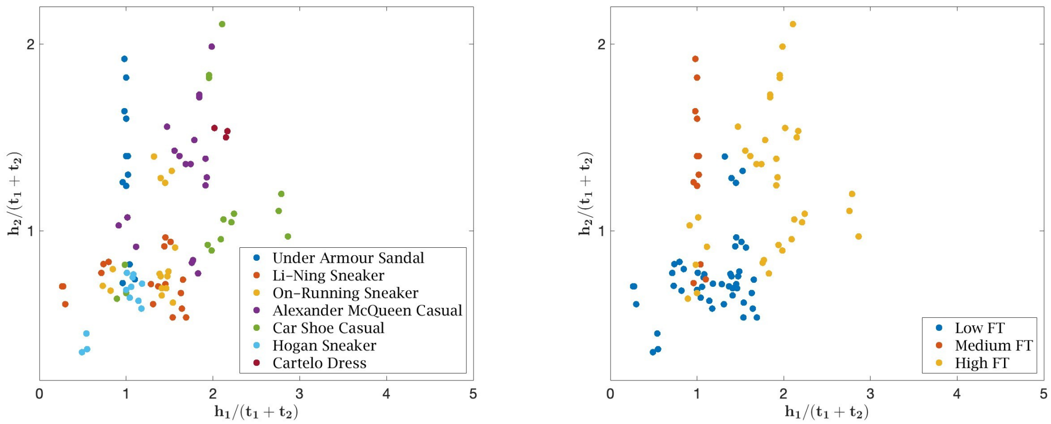

Figure 3. Visualization of various shoe types with respect to FT and its sub-components. The clear separation in dots validates FT's effectiveness in describing the difference among various shoe types.

3. FOOTWEAR-INFORMED PERSON IDENTIFICATION SYSTEM

We develop a robust person identification system that is aware of footwear types, described in Figure 4. The main idea of our system is to recognize people when they wear shoes with similar physical properties (i.e., FT level). Our system consists of three modules: 1) data pre-processing, 2) footwear FT classification, and 3) footwear-specific person identification. In order to recognize the walker, we first estimate the footwear FT level based on the resultant vibration signals, and then compare the walker's vibration pattern with the data collected at the same FT level to determine the walker's identity. The details of each module are introduced in the following subsections.

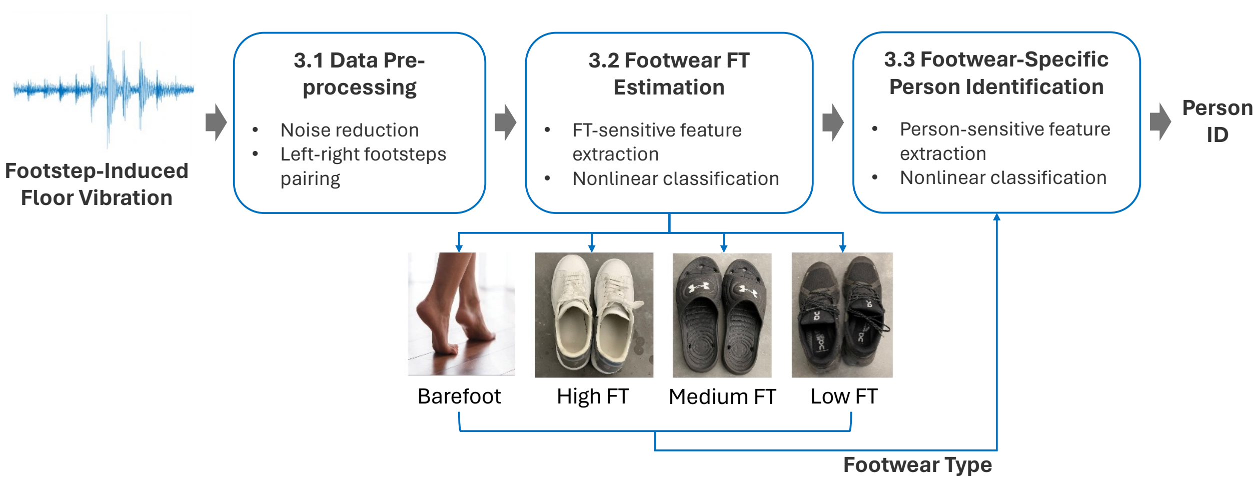

Figure 4. System overview

3.1 Data Pre-processing

The data pre-processing module aims to reduce the noises in the raw signals and segment the signal into groups of footsteps. For noise reduction, a low-pass filter and a Wiener filter are applied to reduce the high-frequency electrical noises and background noises in the environment.

After noise filtering, we detect individual footsteps through a peak detection algorithm to separate continuous walking signals into individual footsteps.[7] This method helps us to extract the two consecutive steps that are closest to the sensor, which not only has the best signal-to-noise ratio but also reduces the variability caused by floor heterogeneity among various footstep locations.

Next, we group left and right footsteps into pairs to incorporate potential left-right asymmetry during walking, which is a commonly observed gait abnormality in medical practices. The grouping adds additional gait health information through the combination of features from both feet, making it easier to distinguish between people who walk normally and asymmetrically.

3.2 Footwear Force Transmissibility (FT) Estimation

This module aims to estimate footwear FT level based on the resultant vibration signals. In order to identify people who wear shoes with similar physical properties, we divide FT values into four levels: 1) barefoot, 2) high FT, 3) medium FT, and 4) low FT. The discretization is conducted based on the empirical observation of significant shoe type shifts as the FT value changes. Specifically, the low FT level includes soft shoes such as running shoes and sneakers, the medium FT level shifts towards sandals, while the high FT level includes stiffer footwear such as dress shoes and boots. The FT levels are determined through a non-linear classifier (i.e., support vector machine) using the peak magnitude and decay rate as FT-sensitive features. Details on how these features reflect the shoe types are discussed in Section 2.2.

3.3 Footwear-Specific Person Identification

Once the FT level is determined to represent the footwear category, we extract person-sensitive features for person identification. These features include continuous wavelet transform (CWT) coefficients, power spectrum density (PSD) spectrum, as well as the decay rate and peak magnitudes. These features have been shown to be effective in representing the unique walking patterns of individuals.[13,14] The decay rate and peak magnitudes are included here because they are sensitive to both footwear and people, as discussed in Section 2.2. In addition, we develop a footwear-specific feature selection algorithm to reduce the feature dimension for more efficient model training. This step is important because the feature importance varies among various footwear due to the shift in frequency components. In order to search for the most sensitive frequency under the current footwear, we use the efficient forward feature selection method to reduce the PSD and CWT feature dimension.[18] After that, we use a support vector machine (SVM) model with a radial basis function kernel to train the person identification classifier. The model is chosen based on empirical performance comparison among multiple commonly used non-linear classifiers. The output of our method is the identity of the walker.

4. REAL-WORLD EVALUATION

To evaluate our approach, we conducted a real-world walking experiment with 4 healthy participants with similar shoe sizes to share the same set of footwear. During the experiment, each participant walked with 8 types of footwear (including barefoot) to create 32 different combinations of footwear and person. Our results show promising accuracy in estimating FT levels and recognizing people when they wear randomly chosen shoes.

4.1 Experiment Setup

The experiment involves two steps: 1) footwear property measurement and 2) floor vibration sensing during walking. We repeated the two-step experiment for each of the 32 person-footwear combinations.

To measure the footwear properties and determine the FT levels, we measured the thickness (mm) and hardness (HA) of the shoes using tape and a Durometer for both the footwear's insole and outsole. Note that all the insole thicknesses were rounded to 5 mm for efficiency of measurement. Then, we compute the FT of each

Figure 5. Footwear types and their FT levels measured in the experiment

Table 1. Footwear properties

Shoe types	Insole properties		Outsole properties		Footwear Transmissibility (FT)
	Hardness (HA)	Thickness (mm)	Hardness (HA)	Thickness (mm)	
Under Armour Sandal	31.7	5	24.8	10	7.56
Li-Ning Sneaker	23.2	5	25	37	3.31
On-Running Sneaker	28.3	5	35	34	5.81
Car Shoe Casual Shoe	51.2	5	54.2	30	17.32
Alexander McQueen Casual Shoe	63.3	5	66.2	45	27.31
Hogan Sneaker	23.3	5	31.7	55	2.85
Cartelo Dress Shoe	45.8	5	63.3	25	20.85

shoe type using Equation 1. The average measured footwear properties and their corresponding FT levels are summarized in Table 1 and Figure 5.

During the walking trials, each participant walked on a 7.31-meter-long wooden walkway. While the participants share the same shoe size, their weights and heights are different to incorporate personal variations. Each person walked along the walkway 5 times in each type of shoe, and each trial consisted of around 10 footsteps. The experiment was conducted in a quiet room to mitigate environmental disturbances. To capture the floor vibration generated by people's walking, we deployed four geophone sensors (SM-24) on the surface of the floor slab to measure the vertical floor vibration. Each geophone sensor was connected to an operational amplifier (LVM385) and then a National Instrument DAQ device to amplify the signal and convert the analog signals into digital time series data. The geophone sensors have a sampling frequency of 25.6 kHz, and the layout of the sensors is illustrated in Figure 6.

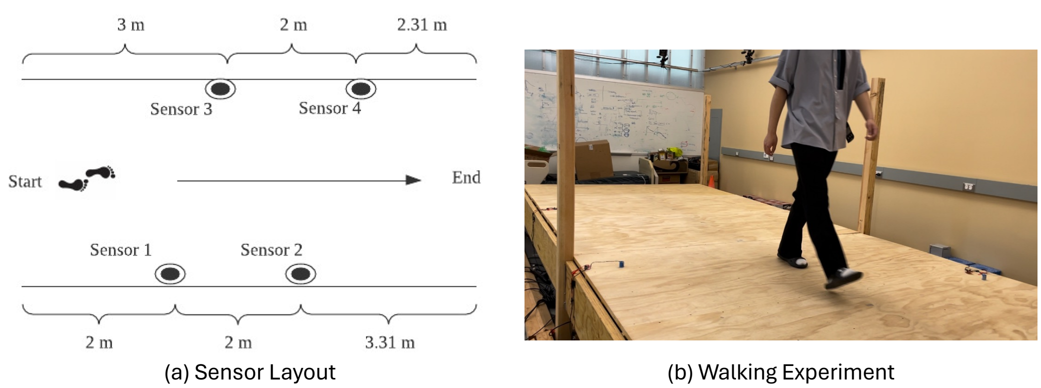

Figure 6. Experiment setup for real-world walking with various footwear: (a) sensor layout, (b) walking experiment

4.2 Results

Our method has an 84% accuracy in estimating footwear FT and a 71% accuracy in recognizing four people wearing randomly chosen footwear. Compared with the baseline method without footwear FT estimation, our method achieves a 22% accuracy improvement over the baseline (which only has 49% accuracy in person identification). Figure 7 shows the accuracy comparison between our method and the baseline approach as the number of footwear increases. As observed from the figure, the two methods have the same accuracy for person identification when only one type of footwear is considered. However, as more types of footwear are added, the baseline's accuracy in person identification drops significantly, indicating that the baseline struggles to distinguish if certain signal characteristics are due to the footwear or the person. In comparison, our system showed robustness as the number of shoe types increased - the drop in person identification accuracy is less significant as observed in Figure 7.

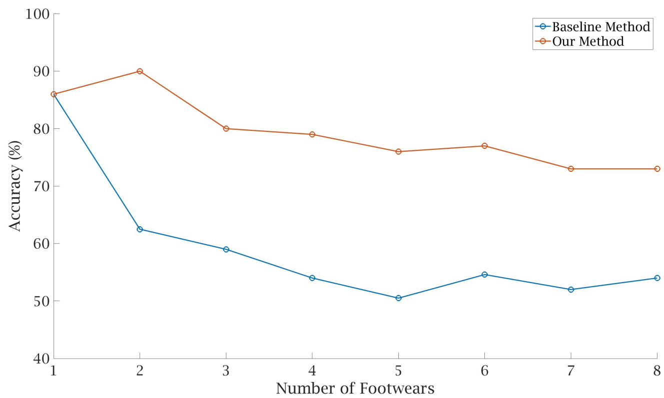

Figure 7. Comparison of person identification accuracy between our method and the baseline without FT estimation. Our method has higher and more consistent accuracy as the number of footwear increases.

In addition, we find that the person identification accuracy differs within each of the FT levels, as shown in Figure 8. Specifically, as the FT level decreases, the person identification accuracy drops significantly. This is because a person's unique gait characteristics may be masked by the footwear as the cushioning system absorbs and re-distributes the force underneath the foot.

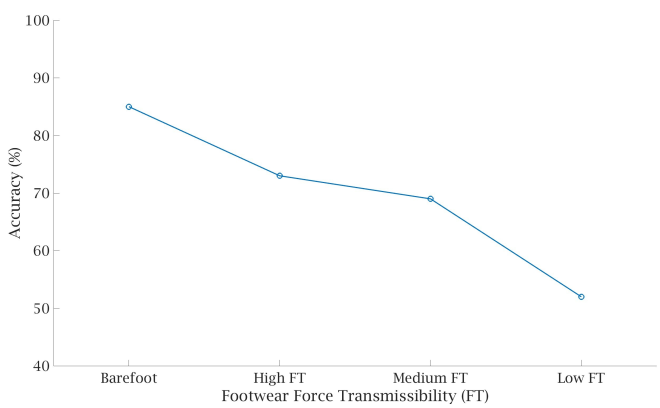

Figure 8. Effect of FT on person identification accuracy. The accuracy drops significantly as the FT decreases, meaning that softer shoes may mask an individual's unique walking patterns.

5. CONCLUSION AND FUTURE WORK

In this study, we develop a robust person identification system across various shoe types through footstep-induced floor vibrations. We characterize the effect of footwear on footstep-induced structural vibrations and develop a new metric named *Force Transmissibility (FT)* to quantify such effect. Through a real-world walking experiment with eight shoe types, our method has an 84% accuracy in footwear FT level estimation, which helps to improve the person identification accuracy by 22% (from 49% to 71%) when people have multiple shoes. We found that footwear with lower FT levels may mask the walking characteristics of individuals, while walking barefoot maintains their walking characteristics, leading to the best accuracy in person identification.

Our future work aims to overcome the challenge in low FT cases when inferring people's identity and gait health. For example, we plan to explore transfer learning to convert the vibration signals from various footwear to barefoot to address this challenge. We also plan to examine the effect of footwear on extracting gait parameters and detecting gait abnormalities. These efforts could ultimately lead to improved accuracy and reliability in personalized gait health monitoring in smart indoor spaces.

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