Poster Abstract: Social Distancing Compliance Monitoring for COVID-19 Recovery Through Footstep-Induced Floor Vibrations

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ABSTRACT

Monitoring the compliance of social distancing is critical for schools and offices to recover in-person operations in indoor spaces from the COVID-19 pandemic. Existing systems focus on vision- and wearable-based sensing approaches, which require direct line-of-sight or device-carrying and may also raise privacy concerns. To overcome these limitations, we introduce a new monitoring system for social distancing compliance based on footstep-induced floor vibration sensing. This system is device-free, non-intrusive, and perceived as more privacy-friendly. Our system leverages the insight that footsteps closer to the sensors generate vibration signals with larger amplitudes. The system first estimates the location of each person relative to the sensors based on signal energy and then infers the distance between two people. We evaluated the system through a real-world experiment with 8 people, and the system achieves an average accuracy of 97.8% for walking scenario classification and 80.4% in social distancing violation detection.

CCS CONCEPTS

• **Human-centered computing → Ubiquitous and mobile computing**; • **Applied computing → Life and medical sciences**.

KEYWORDS

Social Distancing, COVID-19, Footstep-induced Vibration Sensing

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1 INTRODUCTION

Social distancing compliance monitoring is important to advance COVID-19 recovery in public indoor spaces such as schools and offices [4]. To monitor the compliance of social distancing in indoor spaces, existing studies focus on cameras and wearable devices to localize people. However, vision requires direct line-of-sight, which may not work well in indoor spaces with obstructions [1]; wearable sensing requires device-carrying for every occupant, which may be impractical in public settings [2]. They also raise privacy concerns in personal image/location data sharing.

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Therefore, we introduce a new system for social distancing monitoring based on footstep-induced floor vibration sensing. Our system is device-free and perceived as more privacy-friendly. Also, it doesn't require direct line-of-sight. This study explores the walking scenarios with two people in the hallway, which are common in public indoor settings. Our prior work has successfully localized multiple walkers using floor vibration sensing through multilateration [5]. Yet it requires high sampling rates and computational power, which may not be available in large scale public spaces. In addition, there are many possible variations in walking scenarios, including different walking directions, speeds, and the nearest locations where people are closest to each other.

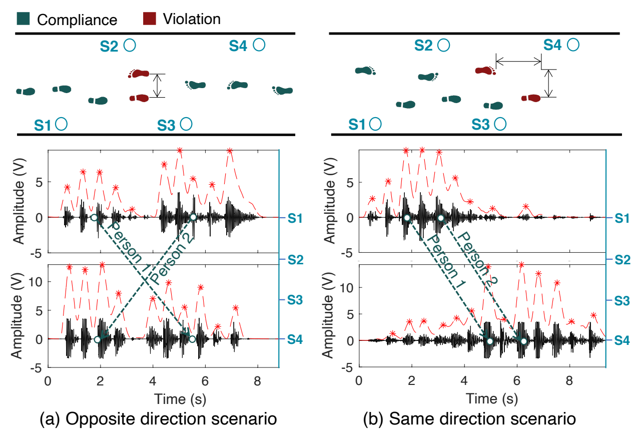


Figure 1: Examples of social distancing monitoring in 2 walking direction scenarios: (a) opposite and (b) same direction. Black lines are vibration signals. Red dashed lines are energy features. Green dotted lines are estimated walking paths between Sensor 1 (S1) and Sensor 4 (S4) over time.

We overcome these challenges through energy-based localization across multiple sensors (see Figure 1). The method is based on the observation that footsteps closer to the sensors typically generate vibration signals with larger amplitudes. Our system first infers the pedestrian location relative to multiple sensors based on the footstep signal energy and then check the social distancing compliance at the nearest location.

We evaluate our system through a field experiment with 4 sensors and 8 people and achieve an average of 80.4% accuracy in social distancing violation detection.

2 FLOOR VIBRATION-BASED SOCIAL DISTANCING COMPLIANCE MONITORING

Our system consists of three steps: 1) footstep detection, 2) walking scenario characterization, and 3) social distancing checking.

2.1 Footstep Detection: The first step is to detect footsteps through energy peak picking over a series of consecutive impulses. We first filter out the sensory and environmental noises and then compute the moving average of signal energy in the dominant frequency band [3]. In this work, 20-50 Hz band is chosen because most signal energy is concentrated within this band. We then pick the energy peaks to obtain the arrival time of the footsteps and the changing trend of the distances between each person and sensor.

2.2 Walking Scenario Characterization: In this step, we characterize walking scenarios by estimating people's walking paths based on the time sequence of their nearest footsteps to the sensors. Before selecting the nearest footsteps for each sensor, we first cluster the energy peaks for each sensor to group consecutive footsteps occurring near each sensor. As Figure 1 shows, there can be either one or two clusters of peaks depending on walking scenarios.

Next, we identify the nearest footsteps in each cluster. When there is only one cluster, we pick the first and the second highest peaks to represent the two nearest footsteps because the cluster includes two people's footsteps. On the other hand, if there are two clusters, we compute the centroid of each cluster to represent the nearest footstep for each person. In both cases, two nearest footsteps are identified for each sensor signal, representing the arrival time of the two people at the sensor location.

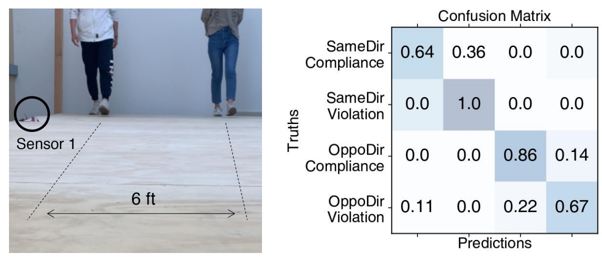
After that, we estimate the walking paths of each person based on the sensor locations and the arrival time of the nearest footsteps. Since one of the two outermost sensors (i.e., either S1 or S4) detect a person's presence first among all the sensors, we sort the nearest footsteps from all the outermost sensors by their arrival time and assign the first occurring footstep to person 1. Assuming both pedestrians walk without changing directions, each of their next nearest footstep occurs at the next sensor in their walking direction at a later timing. Thus, the walking path of person 1 can be extended by connecting the nearest footsteps between adjacent sensors. Each time person 1 proceeds from one sensor to the next one, we check if any of the outermost sensors has detected a nearest footstep during the same time interval. If it does, that outermost sensor is determined as the starting location of person 2. This means that at least one more sensor (e.g., S2 or S3) is required between the outermost sensors in order to determine the starting location of person 2. After both people are detected, we match the first nearest footstep of each sensor to the person who arrives first. This results in two complete paths connecting the two outermost sensor locations. In scenarios when there is an intersection in the walking paths, the nearest location is at the intersection (e.g., see the intersection of the green lines in Figure 1a). If there is no intersection, the location with the minimum time difference along the walking paths is determined as the nearest location. Furthermore, the walking speed of the person between sensors can be estimated based on the slope of the walking path, where a steeper slope indicates faster walking.

2.3 Social Distancing Checking: We check social distancing compliance at the nearest locations determined in Section 2.2. When people walk in the opposite directions, we use an energy threshold to determine the compliance because people need to step closer to the walls (i.e., closer to the sensors which leads to higher signal energy) in order to keep social distancing. The energy threshold is chosen based on the trade-offs between false positives and negatives during training. The social distancing result is predicted as compliant if the signal energies from the nearest sensors for the two persons are both greater than the threshold.

When people walk in the same direction, we first check the time difference between person 1 and person 2 at the nearest location. The larger the time difference, the farther away the two people are. The time threshold is chosen based on the required distance divided by the walking speed. If one person surpasses the other, we then check the social distancing using the energy threshold at the nearest location. A failure in any of these two cases means violation of social distancing.

3 EVALUATION RESULTS

We evaluate the system through a real-world experiment with 8 people (i.e., 4 walking pairs) using 4 sensors along a 7.3-meter long corridor. Our system achieved 97.8% accuracy for walking scenario characterization and 80.4% overall accuracy for violation detection. Experiments were conducted according to the approved IRB-54912.



(a) Field Experiment (b) Evaluation Results

Figure 2: Evaluation for our system: (a) field experiment, (b) evaluation results with 80.4% violation detection accuracy

4 CONCLUSIONS

In this paper, we introduce a social distancing monitoring system based on footstep-induced floor vibration sensing. To address the challenge of large uncertainties in walking scenarios and scalability, we introduce a new energy-based method that estimates two people's walking paths through cross-sensor peak energy fusion. Our system achieved 97.8% and 80.4% accuracy for walking scenario characterization and compliance checking in field experiments. For future work, we will explore scenarios with three or more people.

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