# MD-Vibe: Physics-Informed Analysis of Patient-Induced Structural Vibration Data for Monitoring Gait Health in Individuals with Muscular Dystrophy

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#### **ABSTRACT**

We introduce a footstep-induced floor vibration sensing system that enables us to quantify the gait pattern of individuals with Muscular Dystrophy (MD) in non-clinical settings. MD is a neuromuscular disorder causing progressive loss of muscle, which leads to symptoms in gait patterns such as toe-walking, frequent falls, balance difficulty, etc. Existing systems that are used for progressive tracking include pressure mats, wearable devices, or direct observation by healthcare professionals. However, they are limited by operational requirements including dense deployment, users' device carrying, special training, etc. To overcome these limitations, we introduce a new approach that senses floor vibrations induced by human footsteps. Gait symptoms in these footsteps are reflected by the vibration signals, which enables monitoring of gait health for individuals with MD. Our approach is non-intrusive, unrestricted by line-of-sight, and thus suitable for in-home deployment. To develop our approach, we characterize the gait pattern of individuals with MD using vibration signals, and infer the health state of the patients based on both symptom-based and signal-based features. However, there are two main challenges: 1) different aspects of human gaits are mixed up in footstep-induced floor vibrations; and 2) structural heterogeneity distorts vibration propagation and attenuation through the floor medium. To overcome the first challenge, we characterize the symptom-based gait features of the footstep-induced floor vibration specific to MD. To minimize the performance inconsistency across different sensing locations in the building, we

reduce the structural effects by removing the free-vibration phase due to structural damping. With these two challenges addressed, we evaluate our system performance by conducting a real-world experiment with six patients with MD and seven healthy participants. Our approach achieved 96% accuracy in predicting whether the footstep was from a patient with MD.

### **CCS CONCEPTS**

• Applied computing  $\rightarrow$  Health care information systems; • Computer systems organization  $\rightarrow$  Embedded and cyber-physical systems; • Human-centered computing  $\rightarrow$  Ubiquitous and mobile computing; • Computing methodologies  $\rightarrow$  Machine learning.

### **KEYWORDS**

Gait Health Monitoring, Floor Vibration Sensing, Structural Vibration, Muscular Dystrophy

### **ACM Reference Format:**

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### 1 INTRODUCTION

Muscular Dystrophy (MD) is a genetic neuromuscular disorder influencing 1 in 3500 to 5000 births worldwide [1], causing progressive loss of muscle and early death (average 19 years old) without intervention [2, 3]. This disease is generally first detected during childhood (2-5 years old). Early signs include toe walking and difficulty getting up from the floor [4]. As the disease progresses, muscle

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degeneration impairs cardiac and respiratory functions, leading to a shortened life expectancy. Monitoring of gait health in individuals with MD can help doctors to provide more adaptive and timely treatments. While there is no cure, treatments such as corticosteroid therapy and proactive cardiac and respiratory intervention have been evidenced to delay progression of the disease and can extend a patient's life span by more than 20 years [2, 3].

There are existing clinical approaches and sensing systems to monitor gait health in patients with MD. After clinical diagnosis, the progression of MD is typically tracked by measuring the patients' functional abilities. Those measures include walking speed or ability to do common activities such as climbing stairs, which reflect changes in muscle weakness [5, 6]. The functional assessments and traditional gait analysis, however, are restricted to in-person appointments at healthcare clinics. Since MD is a rare disease this can require the family to travel long distances to see the correct specialist. A system that can monitor a patient in their home would be a useful tool for more frequent and continuous monitoring of MD progression.

There are several existing sensor technologies for continuous gait monitoring, such as pressure-based, wearable-based, and vision-based sensing systems [7, 8]. However, these systems have limitations due to operational requirements; for example, they require an in person visit (direct observation), dense sensor deployment (pressure) or clear lines of sight (vision), and/or requiring the patient to wear a device for a long period of time (wearables). These limitations make such sensors inadequate for continuous monitoring in non-clinical settings.

To overcome these limitations, we introduce a footstep-induced floor vibration-based system that can monitor gait health in a patient's home. The primary intuition is: when humans are walking in the building, each footstep serves as an excitation to the floor to generate a vibration response. By analyzing these footstep-induced floor vibrations, we characterize the patients' gait using vibration-based features to identify disease-related gait impairments. Compared to other gait analysis approaches, footstep-induced floor vibration sensing is non-intrusive and can be sparsely deployed (up to 20m distance [9, 10]). More importantly, it allows monitoring in a non-clinical setting with fewer privacy concerns. By interpreting vibration characteristics as an indicator of disease progression, we suggest our system to be a useful monitoring tool for gait-related disease progression.

Through prior studies, footstep induced vibration-based methods have been successful in multiple walker identification, step localization, and gait parameter estimation [11–15]. However, it remains a challenge to address the problem of monitoring individuals with MD for the following reasons: 1) the floor vibration signals contain other aspects of the footstep that are not related directly to the gait disorder; 2) when the vibration waves propagate through the floor, detected gait patterns are sensitive to variability in structural properties of the floor medium. Therefore, it is necessary to reduce the structural effects captured in the vibration signal to improve the robustness of our system.

To address these challenges, we leverage a physics-informed approach to extract gait information and reduce structural influences. To address the first challenge of separating the mixture of gait information, we convert vibration signals into temporal gait parameters,

stability scores, and toe-walking likelihood to quantify physical symptoms which have been demonstrated to characterize MD, such as low step frequency, poor balance, and toe-walking gait [6]. This conversion of the vibration signal into the aforementioned features known to be related to MD improves the interpretability of our system. To address the second challenge of confoundment in the vibration signal from structural effects, we leverage the insight that one footstep can be assumed as an impulse to the floor that results in two primary vibration response phases: 1) forced-vibration phase, and 2) free-vibration phase [16]. The free-vibration phase occurs after the forced-vibration phase caused by the footstep impulse. In the free-vibration phase, the floor vibrates under structural damping, primarily governed by structural properties rather than footstep impacts. Thus, we detect and exclude the free-vibration phase. This truncation of the vibration signal serves to increase the effective gait information input to our model, which improves the efficiency of our system performance.

To evaluate our method, we conducted real-world walking experiments at Nationwide Children's Hospital with thirteen human subjects, six of which are patients with MD. Our system achieved an average accuracy of 96% for detecting the presence of MD ( $4\times$  error reduction over a naive baseline that uses signal-based features only).

The contributions of this paper are:

- We develop a footstep-induced floor vibration system for monitoring gait health in individuals with MD.
- We characterize the footstep-induced floor vibrations to extract physical symptoms of MD and to reduce the structural effects. This improves the interpretability and robustness of our system.
- We evaluate the performance of our method using real-world walking experiments with MD patients.

The remainder of the paper covers the physical insights, our physics-informed approach in MD monitoring, and the field evaluation of our approach, followed by conclusions and future work.

# 2 PHYSICAL INSIGHTS FOR FOOTSTEP-INDUCED FLOOR VIBRATION SENSING

Footstep-induced floor vibrations are generated by footstep impact forces. Similar to hammer strikes, each footstep can be regarded as a short-duration force applied to the floor, which causes a small deformation in the underlying floor slab [16]. Although the displacement is unobservable to the human eye, it can change the internal stress of the slabs with an increase in shear force and bending moment around the impact location, resulting in dynamic structural response to retain equilibrium. As the ensuing structural response waves propagate through the floor, they can be measured by vibration sensors deployed on the ground, which transform the vertical displacements into electrical voltage series. Variation in the footstep forces due to gait anomalies results in variance in the floor vibration response, which we use to infer physical characteristics of human gaits in individuals with MD.

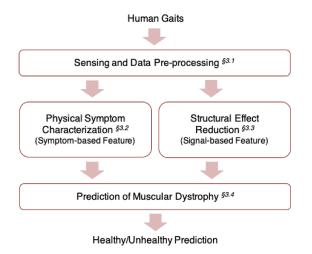


Figure 1: The Framework of Our Method

Many types of gait symptoms of MD are reflected in footstep-induced floor vibrations. First, slow walking and unbalanced footsteps due to weakness in leg muscles are characterized by spatiotemporal parameters in gait analysis [17]. Previous research showed that temporal gait parameters such as step time or stride time, left-right gait balance, and footstep forces can be estimated from footstep-induced floor vibrations [13, 18]. Secondly, at the clinical gait analysis scale, toe-walking gait - in which a subject makes contact with the floor using only the ball of their foot/toes (i.e., no heel strike) - is a frequent characteristic [3, 4]. Previous research suggests that transitions in heel-to-toe contact with the floor can be reflected by the low frequency bands in footstep-induced vibrations, which allows us to detect toe-walking behavior using features in the frequency domain [19]. Details of this implementation are described in Section 3.2.

While structural vibrations capture gait-related characteristics, they are confounded by the structural response of the floor slab, resulting in inconsistent system performance across different sensing locations. When vibration waves travel through the floor, heterogeneity in structural properties, such as mass, stiffness, and natural frequency, will alter patterns of wave dispersion through the floor and force transfer through joints and connecting walls [12, 14, 20]. As a result, sensors at different locations and in different buildings receive dissimilar wave forms despite the same input force. In certain cases, different footstep impacts can even generate very similar vibration signals, resulting from distortion due to structural effects. This impairs the system performance in characterizing the footstep inputs using sensor records. To address this issue, we develop an approach to reduce structural effects, which we discuss further in Section 3.3.

# 3 PHYSICS-INFORMED ANALYSIS FOR MUSCULAR DYSTROPHY MONITORING

Our method uses physics-informed analysis to achieve the goal of monitoring the gait patterns of individuals with MD. Figure 1 shows the framework of our method. Firstly, we record and pre-process the

footstep-induced floor vibrations generated by human gaits. Then we address our two challenges by identifying the following features of the vibration: 1) symptom-based: we characterize physical gait symptoms of MD by extracting different aspects of gait patterns from footstep-induced floor vibrations; and 2) signal-based: we reduce the structural effect on vibration signals by excluding the free-vibration phase and then extract signal-based features from the truncated signals in both time and frequency domains. Among symptom-based features, we also consider gender as a feature in addition to the gait characteristics since gender difference leads to different gait patterns [21]. In addition, MD almost exclusively affects males due to the dystrophin gene mutation occurring on the X-chromosome [2, 22], so using gender as a feature incorporates this sampling bias factor. To test our ability to differentiate between MD gaits and normal ones, we extract both signal- and symptom-based features from each footstep and learn a label of either "Healthy" or "Unhealthy".

## 3.1 Sensing and Data Pre-processing

To capture the footstep-induced floor vibrations, we use an array of geophone sensors to measure the vertical velocity of floor vibrations and then process the signals into isolated footstep traces. The recorded signals are first detrended to zero mean and de-noised with a 200 Hz lowpass filter and Wiener Filter. We then apply an anomaly detection algorithm which identifies significant signal amplitude changes by detecting the deviation of the mean signal from ambient noise levels [11]. The algorithm consists of two passes: in the first pass, individual footsteps are identified using anomaly detection; in the second pass, a group of consecutive footsteps are segmented as one footstep trace. Detected and segmented footsteps are then analyzed in the following sections.

### 3.2 Physical Symptom Characterization

With extracted footstep traces and associated individual steps, we characterize the physical symptoms of MD, including 1) slow walking, 2) balance difficulty, and 3) toe-walking gait. In this section, we describe each of these features and how they relate to MD classification.

Slow Walking: As demonstrated in past research, muscle loss from MD results in a slower walking speed and irregularity in footstep pace [6]. As presented in Figure 2, the footstep traces contain temporal information of the beginning and end of each footstep, which can be used for characterizing "slow walking". In this way, we estimate step time (time to transition from the left to right foot, or vice versa) and stride time (time between consecutive steps by the same foot, for one complete stride) by extracting the onset of each detected footstep in a trace. Once estimated, step time and stride time are used as features which characterize temporal aspects of a person's gait.

Balance Difficulty: Difficulty in maintaining balance between left and right footsteps is an important clinical indicator used in MD assessment [6]. When patients have difficulty maintaining gait balance, their footsteps tend to induce less consistent floor vibrations than those induced by healthy gaits. This symptom is reflected in the power spectrum because differences in footstep impact forces lead to changes in power across frequency bands.

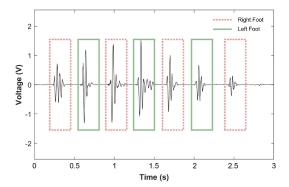


Figure 2: Sample footstep trace. Detected footsteps are shown in boxes

Therefore, we characterize the gait balance by a stability score that compares the similarity of the power spectrum between footsteps. To measure the pair-wise step stability, we use the cosine similarity  $(S_{i,j})$  defined as [23]:

$$S_{i,j} = \frac{X_i(\omega) \cdot X_j(\omega)}{\|X_i(\omega)\| \|X_j(\omega)\|} \quad \forall i \neq j$$
 (1)

where  $X_i$ ,  $X_j$  represent the power spectral density of vibrations induced by two randomly selected footsteps of a given person. Unlike Euclidean and Mahalanobis distance, cosine similarity quantifies the difference between two vectors in orientation instead of in magnitude, so that this metric is less affected by different sensing distances and amplification rates.

Toe-walking Gait: Toe-walking gait, an early sign of Duchenne and Becker Muscular Dystrophy, is commonly considered as a physical criterion for diagnosis of these diseases [3, 4]. It is characterized by the absence of heel strikes and occurs as a compensation for muscle weakness when walking. Therefore, we determine the "likelihood of toe-walking" as the confidence in classifying a footstep for displaying toe-walking behavior. The classification is conducted using a support vector machine (SVM) with Gaussian kernels, because it has larger model capacity than the rest of the nonlinear classifiers using the kernels, and empirically it performed the best in accuracy for toe-walking prediction. In addition, SVM can provide a measure of confidence in predictions based on the distance of sample points from the decision boundary. Since previous studies suggest that different footstep impact forces lead to discrepancies in frequency bands of the vibration signals [11], and power spectral density around 40Hz indicates heel strike and toe push-off behaviors [19], we incorporate dominant frequency and power spectral density around 40Hz as features. In addition, we include step time and stride time as features since individuals who toe-walk can have slower walking pace than normal walking in order to maintain left-right balance. Using this model, we compute the confidence of toe-walking for each footstep. The confidence is then converted into the probability of the footstep made by a person with toe-walking gait using a probabilistic model on top of the SVM [24], where high confidence results in a large probability. The resulting probability of toe-walking is then used as a feature in our main system, where

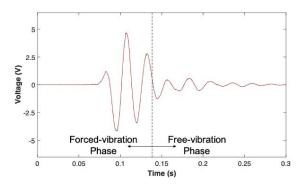


Figure 3: Forced-vibration phase and free-vibration phase of a sample footstep signal

the classification task is to predict whether the footstep was made by a person with MD.

### 3.3 Structural Effect Reduction

As discussed in Section 2, footstep-induced floor vibrations can be influenced by structural properties when the waves are transmitted between the excitation source and sensors [20]. While it is impossible to completely remove this effect, we are able to minimize its influence through footstep phase separation. In general, structural vibrations induced by the impact of each footstep are divided into two phases: 1) the forced-vibration phase when the gait force is impacting the floor, and 2) the free-vibration phase when the structure is vibrating without excitation forces [25]. While the former contains physical information of the gait patterns, the latter mainly involves the structure behavior itself. Figure 3 presents a sample footstep-induced floor vibration signal containing these two phases. We can observe that the vibration damped out under the structural effect during the free-vibration phase.

To achieve our goal of structural effect reduction, we detect and remove the free-vibration phase of the signal. However, as the separation point of the two phases is unclear, we use a grid search to find the optimal separation point. The process for this phase separation is as follows: 1) given an assumed separation point, we conduct training to predict whether the footstep was made by a person with MD on the signal-based features without the freevibration phase with 5-fold cross validation; then, 2) we calculate the corresponding prediction accuracy to infer the effectiveness of the chosen point. By repeating the process using a grid search over the time-domain, we obtain the separation point where the highest prediction accuracy occurs. Once we find this point, we remove the free-vibration phase of footstep-induced floor vibration signals. After that, characterization as a MD footstep is performed using only the forced-vibration phase, from which we extract signalbased features. Since it was previously observed that the frequencydomain characteristics infer how the foot impacts the floor [19], we select the dominant frequency, mean power spectral density, and signal energy as our features. With these signal-based features extracted from the isolated forced-vibration phase, we improve the robustness of our system performance across different sensing locations.

# 3.4 Prediction of Footsteps from Individuals with Muscular Dystrophy

Our final feature set for prediction consists of both signal- and symptom-based features. For model training and testing, we selected Support Vector Machine (SVM) with a Gaussian Radial Basis Function (RBF) kernel because the flexible nature of the RBF kernel captures a high degree of non-linearity between features. The model classifies each footstep signal with one of two labels: "Healthy", indicating the footstep originates from a healthy subject, or "Unhealthy", indicating it comes from a subject with MD. Through this framework, we provide insights into the characteristics of abnormal gait patterns seen in individuals with MD.

### 4 FIELD EVALUATION

To evaluate our method, we conducted an experiment at Nationwide Children's Hospital in Columbus, Ohio with six patients with MD and seven healthy participants.

### 4.1 Experimental Setup

For the experiment, eight SM-24 geophone sensors recording at a sampling frequency of 25.6 kHz were mounted to the floor along one edge of a 26-meter long, 2-meter wide hallway, spaced apart by 2 meters. To accommodate variations in deployment conditions including differences in geophone sensors, distance between sensor and footsteps, etc., we incorporate records from all the sensors for latter analysis. To improve the signal-to-noise ratio (SNR), the raw signal was amplified by connecting each geophone to a 100-1000× variable gain operational-amplifier to aid in capturing footstep signals and increasing the sensing range to up to 20 meters in diameter [26]. The amplification rate is selected empirically by conducting preliminary walking experiments and maximizing response amplitude while avoiding clipping of the signal. A National Instruments NI DAQ is used to acquire and convert the analog signal to the digital signal. In addition to vibration sensors, three cameras are installed at the designated locations to provide visual references of gait behavior. During the experiments, we hammer the floor to indicate the start and end of each experimental run. As presented in Figure 4, the participants are requested to walk/run with their most comfortable gaits. Each of them walked along the hallway on the left lane and turned around to return back on the right lane, then repeated the same path to make a total of two full loops (i.e., 104 meters in total). All experiments were conducted in accordance with our approved IRBs (CMU: STUDY2017-00000498, NCH: IRB12-00001, and Stanford: IRB-55372).

The raw signals contain multiple sources of noises from the sensing system. These noises are from noise sources such as: the sensors, ADC, amplifiers, and power outlets. In order to de-noise the raw signals and extract gait information, we applied the method described in Section 3.1 and compiled a dataset of footstep features from the recorded time series.

After data pre-processing, a total of 1448 footsteps are in our dataset. The labels of the dataset are collected from the clinical diagnosis of MD, where the footsteps from the six patients are labeled as "Unhealthy" and the remaining footsteps in the control group were labeled as "Healthy". Overall, the ratio of healthy:unhealthy footsteps is 750:698 in the final dataset, which is relatively balanced.

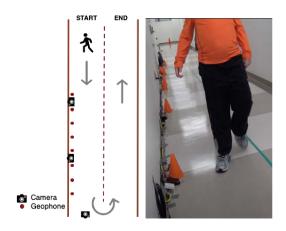


Figure 4: Experimental setup

In addition, the subject's gender is used as a feature, in order to account for potential gait differences. To get the ground truth for toe-walking, we also visually identified whether patients exhibit toe-walking gaits from the camera video recordings. Among all subjects in the healthy control group, only one adult demonstrated toe-walking gait, while in the unhealthy group, everyone except one child showed toe-walking gait.

### 4.2 Results

With the dataset obtained from the field experiments, our system achieves an overall cross-validation accuracy of 96% for classifying whether the footstep was from a healthy subject or one with MD. In the following sections, we address the aforementioned challenges and demonstrate improvements to the model first through the addition of physical symptom-based features, then through the structural effect reduction.

### 4.2.1 Evaluation of Physical Symptom-based Features.

In order to extract information from the signals related to MD, we characterize the gaits for each participant by estimating the temporal parameters, stability scores, and their toe-walking probability for each footstep. As shown in Figure 5, the first three bars represent the prediction performance using only singular aspects of gait symptoms of MD. The fourth bar considers all three symptom-based features in the box and the fifth bar includes all signal-based features. Then the last two bars evaluate the effectiveness of structural effect reduction, which is discussed in Section 4.2.2. The last bar in dark red, in particular, shows our system performance with both symptom-based and signal-based features.

Overall, our system achieves the highest accuracy among all other models. The accuracy of the first three bars are all larger than 50% (i.e., random guessing), which indicates that the estimated gait parameters improve the accuracy of prediction. By comparing these bars, we observe that toe-walking probability has the greatest predictive ability since the third bar (model with only toe-walking probability as a feature) has higher accuracy than the other two (models with only footstep stability or only temporal parameters as features). Temporal parameters have significantly more influence than footstep stability. In addition to the three physical symptoms,

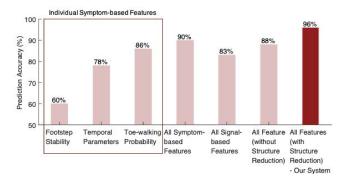


Figure 5: System performance on predicting whether the footstep was made by a person with MD. Demonstrate the 1) effectiveness of symptom-based features and signal-based features and the 2) effectiveness of structural effect reduction. The boxed bars represent individual symptoms of MD. The dark red bar represents our system.

we also compared the prediction accuracy with and without the biological sex feature. We have a  $2\times$  improvement in error rate reduction (error reduced from 8% to 4%) by adding biological sex to our feature set. In summary, our system achieves a 96% of accuracy in prediction of whether the footstep was made by a person with MD.

By comparing the fourth and fifth bars, it is observed that the symptom-based features are more influential than the signal-based features in prediction as the model with the former has higher accuracy than that with the latter. In addition, since both of these two bars have lower accuracy than the last bar (the model performance by all features - our system), it is shown that both symptom-based and signal-based features are necessary in our system to boost up the overall performance. Among the signal-based features, we selected 20-50Hz and 60-80Hz frequency bands in the power spectrum based on the empirical observation of the healthy/unhealthy label versus the mean power spectral density (PSD) plot. We observed that "Unhealthy" subjects have lower mean PSD magnitude than "Healthy" subjects in 20-50Hz, while the mean PSD magnitude of "Unhealthy" subjects in 60-80Hz are higher than "Healthy" subjects. The choice of these two bands is influenced by the structural properties, deployment conditions, etc. that distort the vibration signals in the frequency domain.

### 4.2.2 Effectiveness of Structural Effect Reduction.

We compare the accuracy of predicting whether the footstep was made by a person with MD with and without the structural effect reduction in order to evaluate its effectiveness. Prior to applying the structural effect reduction (the second-to-last bar), signal-based features are computed using the full footstep time signal. After the structural effect is reduced by eliminating the free-vibration phase of the signal (the last bar), those features are computed using the truncated footstep time signal.

When comparing the fourth and sixth bars in Figure 5, we notice that when signal-based features without structural effect reduction are added to the symptom-based features, the prediction accuracy drops by 2%. This is because the structural effect in the the signal-based features leads to model overfitting towards the structure instead of the human gait. In contrast, the last two bars present that model performance improves significantly (by 8%) after reducing the structural effect. It is because the gait information becomes more influential in the input, which reduces the model variance due to the structural effect.

### 5 DISCUSSION AND FUTURE WORK

The performance in evaluation shows promising results for achieving the goal of monitoring the gait patterns of individuals with MD. There are many future directions to expand our method. First, we will explore more physical symptoms of MD in addition to the three symptoms that we evaluated. Since symptom-based features allow us to track symptoms across different stages of MD, we will conduct long-term experiments with a fixed set of subjects to evaluate our system's performance on quantitative assessment of MD progression. Secondly, we will consider discrepancies in walking behavior due to differences in age, gender, body figure, etc. We will also collect additional data from healthy children and unhealthy adults as age is a factor that influences both the human gaits and the prediction results. Furthermore, since our system can lead to in-home applications in MD monitoring and tracking, it is necessary to design robust algorithms and reliable hardware schemes to achieve continuous indoor monitoring.

### 6 CONCLUSION

In this paper, we present a footstep-induced floor vibration sensing system for monitoring the gait patterns of individuals with MD. To separate different aspects of gait information mixed up in vibration signals, we characterize physical symptoms specifically for MD, which improves the reliability and interpretability of our system. To address the challenge of the inconsistent performance at different sensing locations, we introduce structural effect reduction approach to enhance the robustness of our system. Our approach is evaluated in a real-world walking experiment with MD patients. Our system achieves 96% of testing accuracy in the prediction of whether the footstep was from patients with MD, which significantly outperforms the model without any physical insights. These promising results demonstrate the effectiveness of taking a physics-informed approach to improve the performance of MD prediction through footstep-induced floor vibration sensing.

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