EarWalk: Towards Walking Posture Identification using Earables

Nan Jiang
jiangnan@u.nus.edu
National University of Singapore
Singapore

Terence Sim
terence.sim@nus.edu.sg
National University of Singapore
Singapore

Jun Han*
jun.han@yonsei.ac.kr
Yonsei University
South Korea

ABSTRACT

Stress on the knee – caused by various factors including injuries, high-impact activities, and overweight – is a major contributor to orthopedic disorders such as knee osteoarthritis (OA), a severe illness that can even lead to decreased ability to walk. One possible treatment for this problem is to have patients conduct gait modification, getting them to intentionally walk *toe-in* or *toe-out*, thereby reducing the stress on their knees. In this paper, we propose *EarWalk*, a novel solution that utilizes commodity wireless earables to provide constant and real-time feedback on the patients' gait modification. *EarWalk* leverages the built-in accelerometer in earables to sense and ultimately differentiate *normal*, *toe-in*, and *toe-out* gait postures due to the minute differences in their vibrations. As a proof-of-concept, we evaluate *EarWalk* with real-world data by inviting participants to walk while wearing a pair of earables, and demonstrate an average accuracy of over 95% in identifying the gait postures.

CCS CONCEPTS

• **Human-centered computing** → **Mobile devices**.

KEYWORDS

Earables; Walking Posture; Foot Orientation; Ground Reaction Force

1 INTRODUCTION

Excessive *Medial knee loading* is a common orthopedic problem that exerts significant stress on an individual's knees [1]. Prolonged stress often leads to severe illnesses including knee osteoarthritis (OA), also known as "wear-and-tear arthritis", which can reduce the ability to walk [15]. Such knee loading can be attributed to a variety of factors, including high-impact activities, injuries, and being overweight [9, 10].
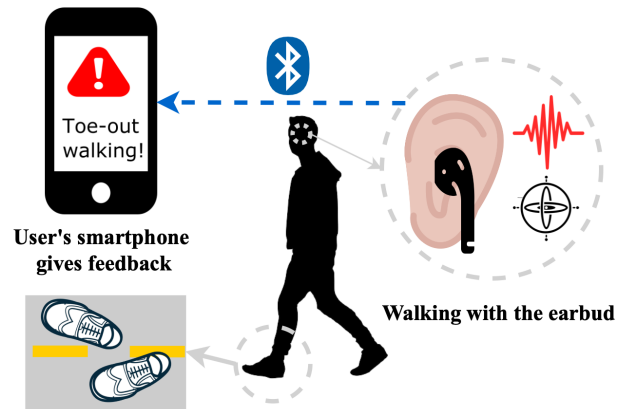
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*Corresponding author.

Figure 1: Overview of *EarWalk*: A knee osteoarthritis patient wears a wireless earable that estimates his walking posture and provides real-time feedback about his gait modification.

One treatment for this problem is to modify one's gait to change the *foot progression angle (FPA)*, namely the angle between the direction of walking and the long axis of the foot. In other words, by intentionally walking with *toe-in* or *toe-out*, one can reduce the stress on the knee. One of the most popular gait modification methods is based on camera feeds to provide visual feedback on the FPA. Such feedback helps patients adjust their gait accordingly [5]. However, the main drawback of this approach is that patients cannot receive constant and real-time feedback on a daily basis because the treatment can only take place in a clinical setting as it requires a motion capture system or pressure mat, and be attended to by a trained professional. Moreover, such solutions are also costly.

To overcome this, we wonder if it is possible to re-purpose commercial off-the-shelf (COTS) smart devices to provide real-time feedback on one's gait modification in a non-clinical setting. Our answer is *EarWalk*, a novel sensing technique that uses the Inertial Measurement Unit (IMU) in modern earables to differentiate *normal*, *toe-in*, and *toe-out* walking postures. *EarWalk* exploits the physical phenomenon in which *toe-in* and *toe-out* walking postures change the *ground reaction force (GRF)* – the force exerted by the ground on the foot during contact [6] – which propagates from the leg to the head, where it is sensed by the earble IMU. Figure 1 illustrates the use case of *EarWalk*. We choose earbuds over other wearable devices based on the following reasons:(1) head remains relatively stable compared to the trunk and upper limbs, making the head motion more representative of the body movement [3], which can be captured using ear-worn sensors; (2) earbuds are already widely available in the electronic markets and the demand for earbuds is

still growing [21]; and (3) earbuds have high user acceptance, as more users are willing to wear earbuds for music while performing everyday activities such as walking and exercising, given their small and light-weighted nature.

Given the ubiquity of earables, such as AirPods and Galaxy Buds, we expect *EarWalk* to be a practical and cost-effective solution that supplements state-of-the-art feedback systems by providing continuous feedback to the population with mild knee OA to prevent the exacerbation of the disease.

Designing *EarWalk*, however, comes with challenges. We design *EarWalk* by extracting and processing signals from multiple steps within a gait. However, each step may be inherently minutely different, resulting in signals of varying lengths and numerical values despite similar patterns. Hence, our first challenge is to extract common patterns from differing step signals. We overcome this challenge by computing the average of signals – that we call *walking profile* – to remove the variations utilizing Dynamic Time Warping Barycenter Averaging (DBA). The second challenge is to perform pattern matching of the extracted step signal with the pre-collected gait profiles to determine the walking postures, namely *normal*, *toe-in*, or *toe-out*. We solve this challenge by utilizing Dynamic Time Warping (DTW) to compute the DTW distances and determine the walking posture.

To demonstrate the feasibility of *EarWalk*, we evaluate *EarWalk* with real-world data by inviting eight participants to wear Nokia eSense earables while walking on a treadmill with different walking postures. From our preliminary evaluation, *EarWalk* is able to distinguish the three types of walks, namely, *normal*, *toe-in*, and *toe-out* with an accuracy of 95%.

Overall, we make the following contributions:

- We propose EarWalk, which is – to the best of our knowledge – a first system that identifies minute differences in *toe-in*, *toe-out*, and *normal* walking postures only with an earbud.
- We overcome the inherent challenges with *EarWalk*'s system design, using DTW and DBA algorithms.
- We demonstrate through our real-world experiments that *EarWalk* is capable of distinguishing *toe-in*, *toe-out*, and *normal* walking postures with high accuracy.

2 BACKGROUND

We present background information on *toe-in* and *toe-out* walking postures and the corresponding feasibility study of *EarWalk*.

2.1 Toe-in and Toe-out Walking Postures

Toe-in and *toe-out* walking postures represent types of walk where a person would point her foot inwards or outwards, instead of pointing forward. Furthermore, the interaction of the foot with the ground induces a *ground reaction force (GRF)*, which is applied to the inner (or *medial*) knee. GRF has a tendency to cause the shinbone to rotate anti-clockwise about the knee joint, producing more compression of the inner knee joint and thus exerting more stress. *Toe-in* and *toe-out* are demonstrated to be effective to reduce such stress on the inner knee (i.e., medial knee loading) as they shift the applied GRF closer to the knee center [4]. *Toe-in* and *toe-out* change direction of GRF applied to the knee by altering the area of foot in contact with the ground. Such shift decreases the stress on
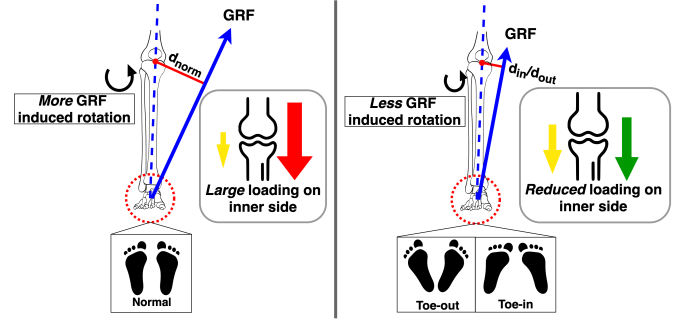

Figure 2: Figure illustrates how *toe-in* and *toe-out* postures can reduce the stress on the inner knee. When a person walks with *toe-in* or *toe-out*, the ground reaction force (GRF) applied to the knee is shifted closer to the knee joint (as the d_{norm} reduces to d_{in} (or d_{out})), reducing the tendency for shinbone to rotate around the knee. As a result, the stress applied on the inner knee reduces compared to normal posture
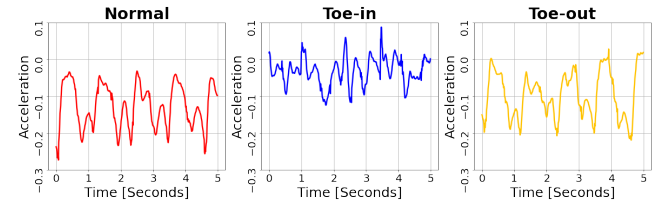

Figure 3: Figure depicts the an example of raw acceleration readings as a person is walking in three different walking postures, namely *normal, toe-in,* and *toe-out*. The plots clearly depict the differences in both the value and shape of the signal which can be attributed to the differences in the induced GRF from different walking postures.

the inner knee as it reduces the GRF-induced rotation by shortening the distance between the GRF and shinbone. Figure 2 illustrates this effect.

2.2 Feasibility Study

We present a preliminary study on how the acceleration values measured by earable IMU differ in the walking postures, namely *normal*, *toe-in*, and *toe-out* as depicted in Figure 3. We observe clear differences in both the value and shape of the signal among three postures, which can be attributed to the differences in the induced GRF from different walking postures that get propagated from the foot through the body ultimately to the ear. However, we observe that there is no clear pattern in signal values *across different people*, as gait is inherently unique and often used as a type of biometrics [7, 11, 12]

3 SYSTEM DESIGN

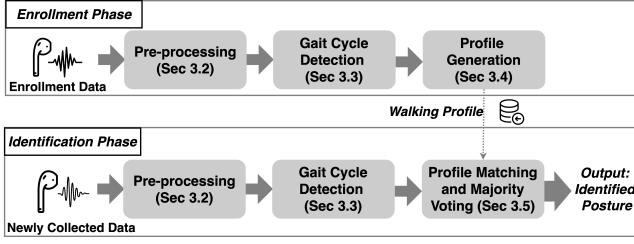We now present our system design and describe details of each module.

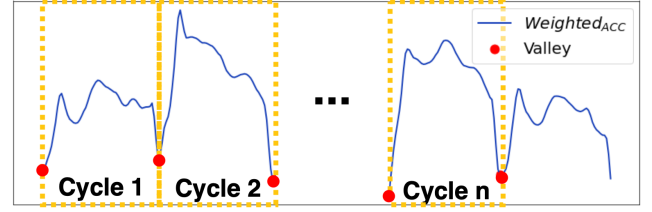**Figure 4: Figure depicts the overview of *EarWalk*'s system design.**

Figure 5: A person's walk is constituted of different steps, or *gait cycles*, depicted in dotted boxes. Furthermore, red solid dots indicate the local minima, or *valleys*. The signal between each valley forms a gait cycle.

3.1 *EarWalk* Overview

EarWalk's goal is to utilize IMU sensors on wireless earables to differentiate walking postures with different foot progression angle (FPA). *EarWalk* consists of two phases, namely *Enrollment* and *Identification Phases*. First, during the *Enrollment Phase*, *EarWalk* utilizes collected sensor data to generate a walking profile for each of the target walking postures we aim to differentiate – specifically, *normal*, *toe-in*, and *toe-out* postures. Subsequently, in the *Identification Phase*, *EarWalk* compares the newly collected sensor data to finally identify the walking posture.

Figure 4 illustrates the overall design of *EarWalk*. Specifically, for the enrollment data, *EarWalk* first processes the data in the *Pre-processing Module* (§3.2) to remove noise and then splits the processed data into segments corresponding to each walking step in *Gait Cycle Detection Module* (§3.3). Finally, to mitigate variation in the extracted step segments, *EarWalk* generates a walking profile constituted of all the steps of the person by taking an average across the steps in the *Profile Generation Module* (§3.4). Similarly, for the newly collected sensor data in the *Identification Phase*, *EarWalk* feeds the data to the *Pre-processing* and *Gait Cycle Detection Modules* sequentially. Finally, the *Profile Matching Module* (§3.5) compares each data segment with each of the walking profiles and outputs the *identified walking posture* based on the majority voting strategy.

3.2 Pre-processing

3.2.1 Smoothing. We first smooth the signals to increase the signal-to-noise ratio and the subsequent identification performance. We utilizes Savitzky–Golay filter [24], which is extensively used in filtering noise of digital signals, to smooth the raw signals while preserving the signal characteristics. Savitzky–Golay filter works by fitting adjacent data points within a moving window with a low-degree polynomial. We empirically set the window length of 5 and the polynomial degree of 2.

3.2.2 Feature Selection. EarWalk subsequently performs feature extraction on the pre-processed signal. We combine the accelerations from the three axes (i.e., ACC_x, ACC_y, and ACC_z) to generate a new signal sequence $Weighted_{ACC} = w_1 * ACC_x + w_2 * ACC_y + w_3 * ACC_z$, that is more robust to the changes of the earables' orientation (where w_1, w_2, and w_3 are weightage assigned to each axis). We generate $Weighted_{ACC}$ as different axes may contain parts of the useful signal that contain the information due to the vibrations induced by the GRF to differentiate the walking postures. Specifically, the direction perpendicular to the walking direction contains

more distinguishable information [6]. Based on our observations, we set $w_1 = 0.25$, $w_2 = 0.25$, and $w_3 = 0.5$ because we find that the z-axis of eSense is almost aligned to this direction when wearing comfortably. Besides, using weighted sum could also accommodate the earbuds position change due to wearing variability and body motion.

3.3 Gait Cycle Detection

This module aims at extracting the periodic patterns from $Weighted_{ACC}$, as walking is composed of multiple repetitive steps. We define the periodic pattern as the *gait cycle* and the local minima as *valleys*. Figure 5 depicts an example of $Weighted_{ACC}$ containing n gait cycles. *Gait Cycle Detection Module* extracts the cycles representing each step.

EarWalk detects the gait cycle by detecting all the valleys in $Weighted_{ACC}$. Specifically, this module takes as input the $Weighted_{ACC}$ and searches for the local minima using a sliding window of 0.6 seconds with a 0.3-second overlap. Then, *EarWalk* obtains a collection of gait cycles $\mathcal{S} = \{S_1, S_2, \ldots, S_n\}$ by splitting the $Weighted_{ACC}$ based on the detected valleys. Instead of outputting $\mathcal{S}$ directly, *EarWalk* evaluates each $S_i \in \mathcal{S}$ for $i = 1, 2, \ldots, n$ to only output the gait cycles such that $Range(S_i) \geq 0.15$. This rule filters out gait cycles during unsteady walking (i.e. the beginning and end of a walking session) and outputs gait cycles $\mathcal{S}' = \{S'_1, S'_2, \ldots, S'_m\}$ of steady walking.

The length of the sliding window is set according to our empirical observation that most gait cycles last for no more than 0.6 seconds. Hence, setting a window of length 0.6 must involve at least one and at most two valleys. When two valleys are in the same window, the larger valley is missed as we only take the minimum. To avoid such missing detection, we set an overlap of the sliding window. The choice of overlap duration is based on the consideration that shorter overlap makes the valley searching less efficient, whereas larger overlap may still lead to missing valleys. Thus, we set an empirical value of 0.3 seconds as the overlap duration.

3.4 Profile Generation

Although gait cycles contain information related to a repetitive step in walking, the cycle patterns present a relatively large variation, as depicted in Figure 5. Hence, this module aims at mitigating such variation by computing the average of gait cycles $\bar{S}$ from
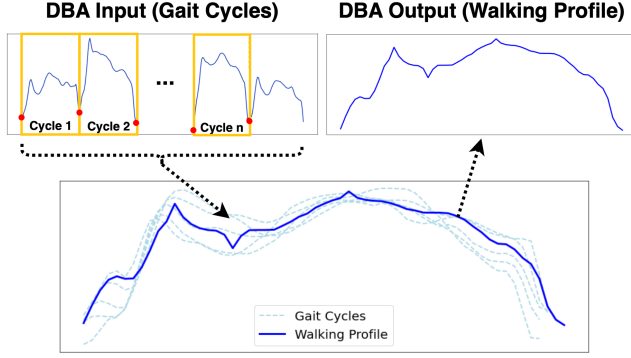
Figure 6: Figure depicts the *Profile Generation Module* utilizes the *Dynamic Time Warping Barycenter Averaging* (DBA) to output a walking profile. The dashed curves are the input gait cycles, and the solid curve is the output walking profile.

S'. *EarWalk* then uses $\overline{S}$ as the walking profile to identify newly collected accelerometer signals.

However, it is impossible to compute the mean directly due to the fact that most gait cycles have unequal lengths. To overcome this challenge, we apply the *Dynamic Time Warping Barycenter Averaging* (DBA) algorithm [20], which iteratively applies *Dynamic Time Wrapping* (DTW) [18] to update $\overline{S}$ to minimize the sum of squared DTW distance between each S'_i and $\overline{S}$: $\underset{\overline{S}}{\mathrm{argmin}} \sum_{i=1}^{m} DTW(\overline{S}, S'_i)$. DTW measures the distance between two time series with varying speed [18].

To compute the $\overline{S}$, DBA iteratively applies DTW to find the optimal mapping between each gait cycle S'_i and the $\overline{S}$, which is generally set as the medoid of S' at the beginning of the algorithm. DBA then updates $\overline{S}$ by computing the average of the optimal mappings and continue updating $\overline{S}$. DBA is proved to have convergence after a certain number of iterations. We implement DBA to compute the $\overline{S}$ for each walking posture we want to identify and store it as the walking profile. Figure 6 illustrates an example of using DBA to generate the walking profile.

3.5 Profile Matching and Majority Voting

This module aims at identifying the walking posture for newly collected accelerometer signals in the *Identification Phase*. This module takes as input the following: (1) the extracted gait cycles, S' (output from *Gait Cycle Detection Module*); and (2) the walking profile, $\overline{S}$ (output from *Profile Generation Module*). Subsequently, this module computes the DTW distance, $dist_{ij}$, between each gait cycle, $S'_i \in S'$, with the candidate walking profiles, $\overline{S}_j \in \overline{S}$, to find the most likely candidate walking profile $\overline{S}_j$ such that $dist_{ij} = DTW(\overline{S}_j, S'_i)$ is minimized.

However, there may be outliers in some subjects' gait cycles due to abrupt changes in speed or pattern. Hence, the accuracy of identification based on single gait cycle can be degraded. To overcome this problem, we conduct a *majority voting* within a sliding window.

4 PRELIMINARY EVALUATION

We now present our preliminary evaluation setup and the corresponding results.

4.1 Experiment Setup

Apparatus. We implement *EarWalk* using Nokia eSense earables [17], with a six-axis IMU on the left side. The IMU samples at its highest configurable sampling rate of 100Hz. We retrieve the IMU data using *eSense Client*[19] installed on iPhone XR.

Data Collection. We recruit eight healthy participants (four male and four female with an average age, height, and weight of 27.9±8.7 years, 169±6 cm, and 61.5±10.7 kg, respectively), adhering to the approval of our university's Institutional Review Board (IRB). Figure 7a depicts our experimental setup. We instruct participants to wear eSense and to walk barefoot on the treadmill. We make sure participants wear eSense in a fixed manner without additional calibration such that the z-axis of IMU is perpendicular to the walking direction. We configure the treadmill such that each participant walks at a constant speed of 3.5km/h. We ask each participant to conduct ten trials of the walks, where each trial consist of two minutes of walk for each of the three postures – i.e., *normal*, *toe-in*, and *toe-out*. Prior to collecting the data, we ask the participant to practice the three postures such that the walks are as stable and comfortable natural as possible. To collect the ground truth information, we record the walks using an overhead camera (DJI Pocket 2 camera recorded at 60 fps) and perform image processing to calculate the foot progression angle (FPA) of all the walks. Figure 7b demonstrates how we measure the FPA to determine the walking postures.

Evaluation Metrics. We define the metrics to evaluate *EarWalk*'s performance. For each participant, we define $Accuracy_{normal}$, $Accuracy_{toein}$, and $Accuracy_{toeout}$ as the ratio of correct predictions to total predictions for *normal*, *toe-in*, and *toe-out* posture, respectively. *Accuracy* refers to the average of $Accuracy_{normal}$, $Accuracy_{toein}$, and $Accuracy_{toeout}$ (i.e. $Accuracy = (Accuracy_{normal} + Accuracy_{toein} + Accuracy_{toeout})/3$)

4.2 Preliminary Results

For each trial, we generate a new walking profile (§3.4) for each walking postures using 20 randomly selected gait cycles (Section 3.3) from the participants. We perform walking posture identification (Section 3.5) on the remaining gait cycles. Hence, we have ten evaluation results for each participant. Figure 8a depicts the confusion matrix for the classification of *normal*, *toe-in* and *toe-out* walking postures. We achieve an average accuracy of 95% across all postures. This result is significantly higher than a random guessing of 33.3%. However, we observe that *toe-in* walking has relatively low classification accuracy compared to *normal* and *toe-out* walking. We attribute this to the difficulty of maintaining *toe-in* posture throughout the entire walking duration. Figure 8b demonstrates the average identification accuracy for individual participants. We can achieve an accuracy above 96% for most of the participants except for P_4. This is because the angle difference between P_4's *toe-in* and *normal* posture is not significant compared to that of other participants. The averaged *toe-in* angle of P_4 is 11.04 degrees less than that of the *normal* posture, which is significantly lower
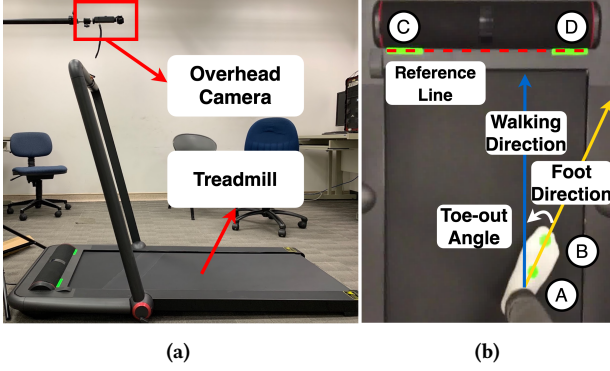
(a) **(b)**

Figure 7: (a) depicts the experimental setup. We collect the data as the participants are walking on the treadmill. We also collect the ground truth information with an overhead camera capturing participant's foot during walking. (b) demonstrates the view of the overhead camera and how we compute the foot progression angle (FPA) using markers attached on the foot. We put two green markers A and B on the participant's foot. The line connecting A and B is defined as the foot direction. As the reference, we put two additional markers C and D on the treadmill. Then we define the line perpendicular to CD as the walking direction. The FPA can be calculated as the angle between the foot direction and walking direction, which in turn can help us to determine the ground truth walking postures.

than the average difference of 17.873 for all participants. Therefore, the gait cycles of S4 are less distinguishable than those of the rest.

5 DISCUSSION

We now discuss *EarWalk*'s deployment considerations, limitations of *EarWalk* and future directions.

Deployment Considerations. We discuss two deployment considerations. (1) Recall that each user must first go through an enrollment phase before (s)he can use our system. Although having a generic reference template can reduce the effort for enrollment, the user still needs to learn the modified walking posture under the instruction of experts. We argue that the enrollment can be done in this phase, which will not pose extra burden to the user. Besides, researchers have demonstrated that subject-specific gait modification programs reduce knee load more than uniformly assigned modifications and have the potential to slow the progression of knee osteoarthritis[25]. (2) Recall that all participants wear earbuds in a fixed manner (Section 4.1). However, this is for our implementation so that we can use a set of predefined parameters (i.e. w_1, w_2, w_3) introduced in Section 3.2.2. We design it in this manner to accommodate the earbud position changes and wearing variability. In practice, the parameters can be determined according to the patient's earbud model and wearing habit in the enrollment phase.

Limitations and Future Directions While we demonstrate *EarWalk*'s ability to identify different walking postures – i.e., *normal*, *toe-in*, and *toe-out*, it would be more beneficial to obtain a more fine-grained information about the walking postures for gait

modification purposes. Specifically, it would be more useful to obtain specific foot progression angles (FPA) to provide more specific guidance regarding the patients' gait modifications. Furthermore, we plan to conduct a more comprehensive experiments to evaluate *EarWalk* as we controlled several conditions including having the participant walk at a constant speed or walking barefoot on a treadmill. In addition, we plan to evaluate *EarWalk*'s energy consumption, as continuous usage of the accelerometer could affect earbuds' battery life. In addition to identifying the walking postures, we also envision extending *EarWalk* to assist in other types of physical activities including detecting abnormal postures in walking, running and fitness program to prevent injury.

6 RELATED WORK

Feedback System for Gait Modification. Many studies have explored the use of real-time feedback to increase the reduction in stress on the knee during gait modification retraining program. *Visual* feedback is a widely-used method. It provides real-time video of the patients' posture, or directly calculating the foot progression angle (FPA) using costly three-dimensional motion capture system and force plates [13, 22, 23]. However, to film or measure the patients' walking parameters, the training process is limited in clinical settings and most likely on a treadmill. To overcome these issues, researchers also explored wireless motion sensors to measure the FPA. These works utilize multiple sensors attached to the leg or shoes of the patients [26–28]. *EarWalk* overcomes the limitations of the existing feedback systems in terms of flexibility, portability, and low cost. Unlike vision-based feedback system, we use wearable devices which allows patients to carry out gait training anywhere anytime instead of going to the clinics in a fixed time. Using wireless sensor networks can address this drawback. Furthermore, installing sensors on the foot or leg could hinder patients' daily activities which is not a big problem for our system since more and more people are wearing earables while working out.

Earable Sensing in Gait Analysis. Gait parameters, such as step length, stride time, and swing time help to diagnose certain diseases and assess a patient's rehabilitation process. Earables are shown to be effective in *gait parameter measurement* [8, 14, 16]. However, how *toe-in* and *toe-out* gait affect these parameters is unknown. Hence, *EarWalk* aims at finding features that are unique across *normal*, *toe-in* and *toe-out* postures. Earables are also used in *abnormal gait identification*, as the head is the least affected part by movement, yielding signals that are better for human gait classification. Identifying abnormal gait plays an important role in health monitoring and injury prevention. However, research is limited to injured gait detection[2, 3]. *EarWalk* aims to identify walking postures whose differences are more subtle.

7 CONCLUSION

We present *EarWalk*, a novel earable-based walking posture identification system that is capable of providing constant and real-time feedback to patients conducting gait modifications to reduce stress on their knees. *EarWalk* leverages the physical phenomenon that the walking postures, namely *normal*, *toe-in*, and *toe-out*, induce minute differences in the vibrations caused by the walks that propagate through the body to the earable, to sufficiently identify the
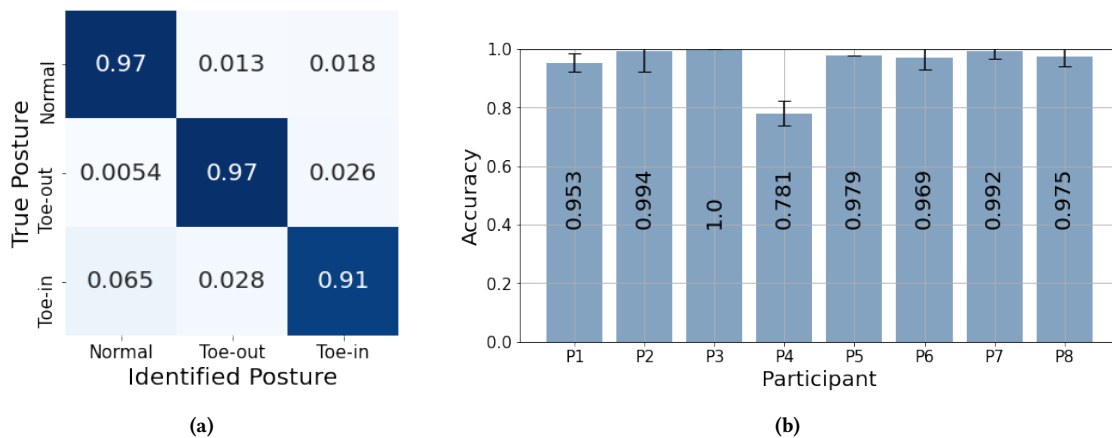
(a)

(b)

Figure 8: (a) demonstrates the confusion matrix depicting the overall performance of *EarWalk* in identifying the walking postures for all participants. (b) depicts the posture identification accuracy of individual participants.

postures. We present a preliminary evaluation to verify that *Ear-Walk* is able to succeed at identifying the postures with an average accuracy of over 95%.

ACKNOWLEDGMENTS

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