Detecting Foot Strikes during Running with Earbuds

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ABSTRACT

Running is a widely embraced form of aerobic exercise, offering various physical and mental benefits. However, improper running gaits (i.e., the way of foot landing) can pose safety risks and impact running efficiency. As many runners lack the knowledge or continuous attention to manage their foot strikes during running, in this work, we present a portable and non-invasive running gait monitoring system. Specifically, we leverage the in-ear microphone on wireless earbuds to capture the vibrations generated by foot strikes. Landing with different parts of the foot (e.g., forefoot and heel) generates distinct vibration patterns, and thus we utilize machine learning to classify these patterns for running gait detection. With data collected from 25 subjects, our system achieves an accuracy of 87.80% in identifying three gait types. We also demonstrate its robustness under a variety of scenarios and measure its system performance.

1 INTRODUCTION

Aerobic exercise is vital for fitness, improving cardiovascular health, stamina, endurance, mental well-being, and overall fitness. Running is now popular for aerobic exercise due to its simplicity, accessibility, and affordability. According to Statista Research Department's 2022 report, around 50 million Americans (15% of the U.S. population) participate in running or jogging, with this number continuing to grow [2]. Prioritizing safety and efficiency during running is thus crucial to minimize the risk of injuries and maximize performance potential. Most runners, especially untrained beginners, lack knowledge to manage running parameters like pace, cadence, gaits, heart rate (HR), and respiration rate. Therefore, automatic monitoring of these parameters and providing real-time feedback while running are crucial. This enhances the running experience, reduces injury risk, and improves efficiency and performance [10].

Existing studies have primarily measured three groups of running parameters for automatic monitoring and prompt feedback: 1) Location-related factors, including velocity, orientation, position, and stride characteristics, are measured using common sensors such as IMUs and GPS on commercial smartphones and smartwatches [6]. 2) Physiology-related factors like heart rate (HR) and respiration rate (RR) can be monitored with chest-worn straps such as Polar [3] and Zephyr [4] or smartwatches [1]. 3) Strike-related factors such as foot placement and focus, ground reaction force, and force distribution, are mainly measured using multiple IMUs worn on the body [19, 20], sensors in shoes [9, 17], or force platforms on the ground [14]. These approaches are 1) bulky and requiring additional user efforts, resulting in low acceptance rate [9, 17, 19, 20], 2) costly to implement with limited monitoring coverage [14].

In this paper, we focus on the landing posture of runners' feet, a crucial parameter for both running safety and efficiency. Specifically, we aim to detect three types of running gaits, i.e., overstride, forefoot strike, and heel strike, using portable and non-invasive devices to enhance user acceptance and facilitate practical adoption. Thus, we have chosen earbuds, one of the most popular runners' companions during running, as our sensing device. We leverage the in-ear microphone on earbuds to measure the sounds/vibrations generated at the foot, propagated to the ear canal, and amplified by the occlusion effect [7, 13]. Since different parts of the foot have different compositions of tissues and bones, the vibrations generated by different gait types exhibit different patterns (section 2.1). We then devised a signal processing and machine learning pipeline to classify the gait types. We collected data from 25 subjects using our prototype, our system achieved 87.80% classification accuracy. We also demonstrate its robustness against various realistic factors such as ground conditions, shoes, and running speeds. Furthermore, we implemented it as a smartphone application and measured the latency and power consumption. With processing

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BodySys '24, June 3–7, 2024, Minato-ku, Tokyo, Japan
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ACM ISBN 979-8-4007-0581-6/24/06…$15.00
https://doi.org/10.1145/3643832.3661463

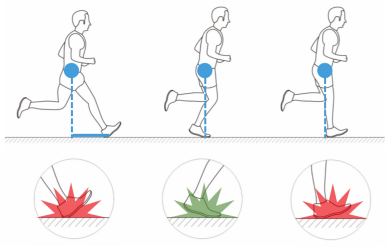


Fig. 1: Illustration of three gaits and their foot close-up.

Table 1: Three running gaits, classified by the stride-strike matrix.

Stride \ Strike	Forefoot	Heel
Over	NA	Overstride
Normal	Forefoot Strike	Heel Strike

one-second data, our system requires 11.01ms and consumes 0.0055mAh on the Xiaomi 13 smartphone, demonstrating the lightweight design of our system. Our system enables portable, accurate, and lightweight running gait monitoring, facilitating safer and more efficient running practices.

2 SYSTEM DESIGN

2.1 Gait Type Definition

Stride vs. Strike: Usually, stride and strike are used interchangeably to describe the movement of the human foot during running. However, there are small differences between them. Specifically, stride depicts moving the foot from one location to another (i.e., the swing phase), while strike refers to the part of the foot that contacts the ground first (i.e., the landing phase). As shown in Table 1, the stride type could be normal or over, while the strike pattern could be forefoot or heel. In this work, we define gait type as the combination of different stride and strike types and mainly focus on forefoot strike, heel strike, and overstride, as illustrated in Figure 1. Note that we exclude the combination of overstride with forefoot strike as it is unlikely to happen in practice.

Overstride: Overstride happens when the front leg extends too far forward during running, misaligning with the runner's center of mass. It's often seen as improper and hazardous, potentially causing discomfort or injuries [12]. In addition, overstride might also decrease energy efficiency as it increases the braking force exerted on the body [10].

Forefoot Strike: Forefoot strike occurs when a runner executes a normal stride and lands on the ball of the foot or the toes. It's typically effective for sprinting, but landing too far forward on the toes isn't recommended for longer distances, as it may result in shin splints or other injuries [11].

Heel Strike: Heel strike occurs when a runner lands with the heel during a normal stride. It's a preferred strike pattern for distance runners as it is more energy-efficient at medium

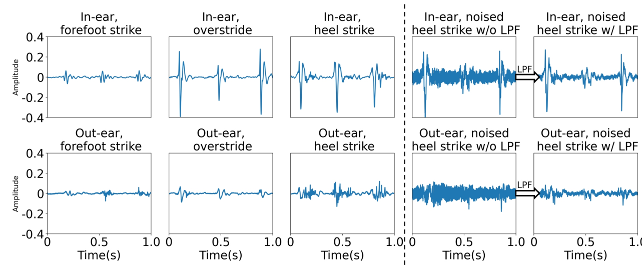


Fig. 2: In-ear (upper row) and Out-ear (lower row) signals of three running gaits and a noisy heel strike gait signal.

speeds. However, heel strikes can exert additional strain on the knees, potentially leading to knee and hip pain.

It's important to note that there's no universally agreed strike pattern for runners, as it depends on factors such as the stage of the run, the runner's proficiency level, and individual preferences. Therefore, continuous monitoring of strike patterns could help runners reduce safety risks and improve running efficiency.

2.2 Sensor Identification on Earbuds

Earbuds have been chosen as the sensing platform as they are a popular accessory for runners. The most common sensor on existing earbuds is the microphone, including the out-ear microphone that captures human voices for communication purposes and the in-ear microphone that measures residual sounds in the ear canal for active noise cancellation. Recent studies also demonstrated that in-ear microphones can capture low-frequency human-generated vibrations/sounds through bone conduction and the occlusion effect [7]. Thus, we simultaneously collected data on different running gaits using both microphones (Figure 2) and explored their feasibility for running gait classification. The left three columns display distinct patterns due to differences in ground contact and propagation paths through the human skeleton for both microphones. However, the in-ear microphone yields stronger gait signals as the bone-conducted signal is further amplified in the ear canal due to the occlusion effect [7]. The right two columns compare the impact of external noise on both microphones. We can see from the raw signals that both microphones are affected. However, after lowpass filtering (<100 Hz), the in-ear signal shows clear gait patterns, while the noise heavily contaminates the out-ear signal. Thus, we select the in-ear microphone for gait signal measurement due to its effectiveness and robustness.

2.3 Signal Processing and Machine Learning Pipeline

Figure 3 depicts the proposed pipeline, consisting of filtering, segmentation, feature extraction, and gait classification.

Envelope-based Cycle Segmentation: To eliminate possible environmental noise (usually higher than 100 Hz), we first apply a low-pass filter (LPF) with a cut-off frequency

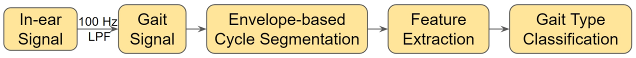


Fig. 3: The signal processing pipeline of our system.

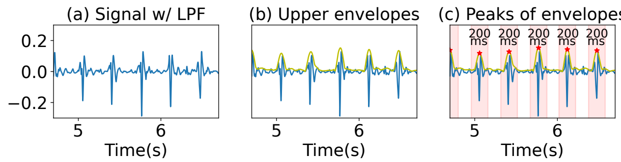
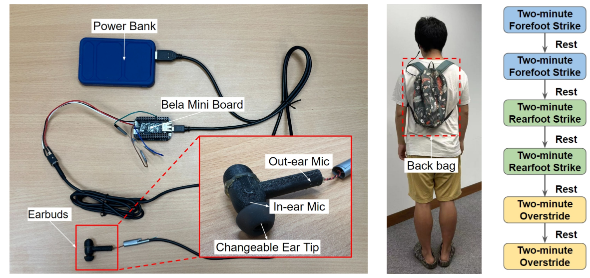


Fig. 4: Envelope-based cycle segmentation of gait signal. (a) low-pass filtered (LPF) heel strike signal, (b) upper envelopes of low-pass filtered heel strike signal, and (c) peaks of upper envelopes and 200 ms samples.



(a) (b) (c)

Fig. 5: (a) The customized earbuds prototype and accompanying data recording device, (b) illustration of a participant wearing the device, and (c) flowcharts of gait data collection.

of 100 Hz to the in-ear signal. The resulting signal refers to the gait signal (Figure 4 (a)). Then, the envelope of the gait signal is extracted using the Hilbert transform. Afterward, a low-pass filter with a cut-off frequency of 5 Hz is applied to smooth the envelope signal (Figure 4(b)). Finally, we perform peak detection on the filtered envelope, where the peaks correspond to the time when the human foot hits the ground. Therefore, the samples that are located 100 ms before and 100 ms after each peak are regarded as the gait signal for a single foot strike (200 ms in total) (Figure 4(c)).

Feature Extraction: MFCC feature is commonly used in speech and audio processing. However, its effectiveness in capturing low-frequency signals like gait sounds (<100Hz) may be limited as it is designed based on human ear sensitivity to higher frequencies. In detail, MFCC decomposes the signal into Mel spectrograms with varying bandwidth, i.e., higher resolution in the human audible frequency range while extremely low resolution for signals below 100 Hz. Thus, we propose to apply Fast Fourier Transform (FFT), which divides the spectrum into bands with equal widths, to the segmented signals to obtain the energy features. Concretely, after removing the DC component, we applied a 65536-point FFT to each 200 ms gait signal, yielding a frequency resolution of 0.12 Hz. The frequencies below 100 Hz are divided into 40 sub-frequency bands, each spanning 2.5 Hz. By calculating the average energy in each sub-frequency band, 40 energy values are obtained as the features.

Model Development and Gait Classification: We opt for an ML-based approach for gait type classification due to its superior performance and relatively low computation. Thus, the extracted features are then fed into an ML model for training. We consider four common machine learning classifiers, namely Support Vector Machine (SVM), K Nearest Neighbors (KNN), Decision Tree (DT), and Random Forest (RF), and select the best one as evaluated in Section 4.1.

In the run-time stage, we follow the same pipeline to process the in-ear signal. The resulting features are passed to the pre-trained ML model for real-time gait-type classification.

3 PROTOTYPING AND DATA COLLECTION

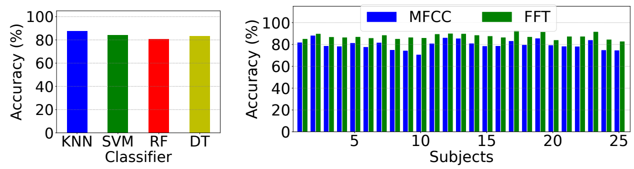
The raw data of in-ear microphones on off-the-shelf earbuds is inaccessible due to the lack of APIs. Thus, we developed a prototype (Figure 5(a)) for data collection and evaluation. This prototype features a 3D-printed earbud shell housing an in-ear microphone positioned at the front of the earbud cavity, facing toward the ear canal. The microphone is connected to a Bela Mini Board via audio jacks. The prototype is powered by a power bank and conveniently enclosed in a small back bag (Figure 5(b)). To ensure participant comfort and achieve a good seal, three different sizes of foam ear tips are provided to accommodate various ear canal sizes.

We recruited 25 participants (16 males, 9 females) for data collection, with IRB approved by the authors' institution. Figure 5(c) illustrates the flow of data collection. Each participant ran on an outdoor rubber track, instructed to perform specific gait types—forefoot strike, heel strike, and overstride, at their comfortable pace. Each gait type was recorded for two two-minute sessions, with a one-minute break between sessions to mitigate potential movement deviations caused by participant fatigue. Each participant completed six sessions, resulting in a total of 49,886 steps recorded for all the subjects.

4 PERFORMANCE EVALUATION

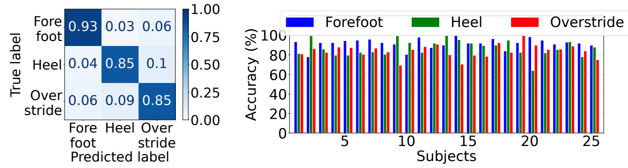
4.1 Comparison of Classifiers

As mentioned in Section 2.3, we utilize conventional ML classifiers for recognizing gait types due to their simplicity and lightweight nature. Data is split into training (75%) and testing (25%) sets for each subject. Four typical classifiers (KNN, SVM, DT, and RF) are employed and compared. Figure 6(a) depicts the average recognition accuracy across 25 subjects. Notably, all classifiers achieve over 80% accuracy, with KNN reaching the highest accuracy of 87.80%. Hence, subsequent analyses utilize KNN as the classifier.



(a) (b)

Fig. 6: (a) Overall performance of four typical classifiers, and (b) individual performance of employing MFCC and FFT.



(a) (b)

Fig. 7: (a) Overall confusion matrix of each gait type, and (b) individual performance of each gait type.

4.2 Comparison of Features: MFCC vs. FFT

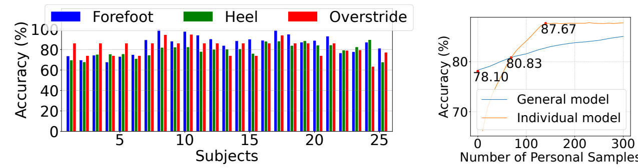
In Section 2.3, we propose using FFT features instead of MFCC features for gait type classification due to the low-frequency nature of gait signals. Figure 6(b) compares the recognition accuracy of both feature types across subjects. We can observe that FFT features consistently outperform MFCC features, achieving an average accuracy of 87.80% compared to 80.01% for MFCC, representing an approximately 8% improvement. Figure 7(a) displays the confusion matrix for the three gait types using KNN and FFT features. Forefoot strike shows the highest accuracy, while the model struggles with distinguishing heel strike and overstride due to their similar landing patterns.

4.3 Individual Performance

In Figure 7(b), we further plot the accuracy of each gait type for each subject. First, we can see there is no significant performance variation across different subjects, indicating that our approach can be applied to different individuals. Second, interestingly, we observe that forefoot strike does not always achieve the highest accuracy as analyzed above, while heel strike and overstride are recognized more accurately for some subjects (e.g., subjects 2, 9, 13 for heel strike, and subjects 19 for overstride). We found that the recognition performance is also related to the preferred running gait type of the user. For instance, subject 2 usually runs with heel strike. Therefore, during data collection, she can perform more consistent heel strikes compared to the other two gait types, resulting in higher-quality heel strike data for model training and in turn higher accuracy during testing.

4.4 Performance of Leave-one-out Test

Individual models require the users to collect personal data for training. To assess whether a pre-trained model can be applied to unseen users, we conducted the leave-one-out



(a) (b)

Fig. 8: (a) Individual performance for leave-one-out test, and (b) performance comparison between employing general model and individual model.

Table 2: Classification performance of different shoes.

Training	Shoe1		Shoe2		Shoe1+Shoe2	
Testing	Shoe1	Shoe2	Shoe1	Shoe2	Shoe1	Shoe2
S1	90.83%	85.27%	85.74%	87.91%	89.30%	86.82%
S2	87.29%	83.1%	81.40%	84.67%	85.50%	84.33%
S3	90.08%	82.98%	82.47%	86.32%	86.78%	84.83%

test, where only one user is iteratively selected for testing while the remaining subjects are for training. Figure 8(a) indicates the average accuracy drop from 87.70% to 78.10%, which may be attributed to: 1) gait signals captured inside the ear canal are propagated through bone conduction across the whole body, while different people might have distinct skeletons, leading to a unique modulation on the gait signals; 2) different subjects might perform the three gait types in slightly different ways, resulting in pattern variations.

To solve this issue, the user needs to provide some personal samples for model training. Here, we investigate two different strategies: 1) individual model training with different numbers of personal samples and 2) model fine-tuning with personal data. From Figure 8(b), with only 10 samples, the individual model yields even poorer performance compared to the general model. This is because the general model can benefit from a larger volume of training data. By increasing the number of personal samples, the accuracy gradually increases until it saturates at 87.67% with 140 samples. For model fine-tuning, the accuracy consistently increases with more personal samples. In specific, with 70 samples, it achieves the same performance as the individual models. While with more samples, the performance is lower because the variations from other subjects might interfere with the current subject. Thus, we conclude that 1) Without personal data, our approach offers 78.1% recognition accuracy; 2) With limited samples (<70), train the model alongside others' data; 3) With more samples (>70), train solely with personal data.

4.5 Impact of Different Shoes

Our approach relies on the sounds/vibrations produced during foot-ground contact to distinguish gait types. One factor affecting these sounds is the type of running shoes, which may vary in sole materials or air cushioning thicknesses. To investigate this, we conducted a small-scale study with three subjects. Each subject wore two different shoes and

Table 3: Performance of different ground conditions.

Training	Rubber		Cement		Rubber+Cement	
Testing	Rubber	Cement	Rubber	Cement	Rubber	Cement
S1	90.83%	85.35%	83.61%	93.40%	86.47%	90.74%
S2	87.29%	82.06%	81.53%	89.77%	84.19%	87.13%
S3	90.08%	84.17%	84.49%	92.46%	87.46%	90.13%

Table 4: Performance at different running speeds.

Training / Testing	Slow	Normal	Fast	Slow+Normal+Fast
Slow	87.81%	83.32%	81.08%	87.58%
Normal	84.55%	89.15%	80.52%	87.36%
Fast	83.54%	80.74%	86.13%	86.02%

performed three gait types. Table 2 show that: 1) Training and testing on the same shoes yield the best performance; 2) Testing with an unseen shoe leads to a 4% accuracy drop due to material and geometry variations affecting the signals; 3) Using data from both shoes for training improves individual accuracy compared to testing with unseen shoes. However, our leave-one-out test already accounts for individual shoe differences, the impact of running shoes is therefore limited.

4.6 Impact of Ground Conditions

Runners encounter various ground materials, such as rubber tracks or cement roads, each with unique properties influencing foot-ground contact sounds. For instance, rubber tracks offer greater shock absorption and longer contact times, affecting foot strike sounds and classification performance. To assess this impact, we had three subjects run on both rubber tracks and cement roads, representing soft and hard ground materials. Table 3 shows that: 1) Cement roads showed better performance due to their harder surface, which minimizes vibration absorption during foot strikes; 2) Testing on unseen ground conditions resulted in a 7% accuracy drop, attributed to signal pattern changes; 3) Combining data from both ground conditions for training improved recognition accuracies. Given the limited ground conditions, users can collect data from each for training. Moreover, since runners often prefer specific ground conditions, models tailored to these conditions can optimize performance.

4.7 Impact of Running Speeds

Runners may vary in speed, adjusting stride length while maintaining a consistent cadence [15]. However, speed adjustment involves altering foot-ground contact force, potentially increasing gait signal magnitude. To assess speed's impact on gait type recognition, we recruited one subject to run at three speeds (slow: 7.5 km/h, normal: 10 km/h, fast: 12 km/h) and conducted the gait type recognition. Table 4 shows recognition performance with different training and testing data. When training and testing with different speeds, there's an average 5% accuracy drop, indicating slight differences in gait patterns at various speeds, likely due to biomechanical and muscle activation variations. Combining data from all speeds for training significantly improves accuracy, yielding performance akin to when training and testing data are sourced from the same speed.

Table 5: System performance of our system executed on Xiaomi 13 to process one-second data.

	Pre-processing	Feature extraction	Gait prediction	Overall
CPU (%)	3.4	4.8	6	-
Latency (ms)	0.38	5.91	4.72	11.01
Energy (mAh)	0.0001	0.0030	0.0024	0.0055
Battery Usage (%/hour)	3	4	4	1.10

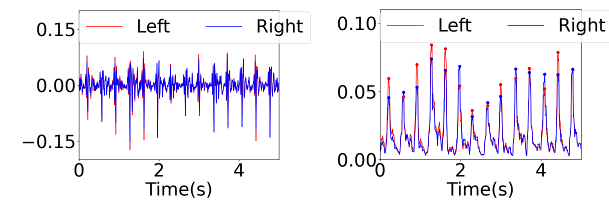
4.8 System Performance

We implement our system as an Android application and evaluate its performance on Xiaomi 13, featuring a Snapdragon 8 Gen 2 processor and a 4500mAh battery. The gait type classification process involves three stages: pre-processing (low-pass filtering and peak segmentation), feature extraction, and gait prediction.

To gauge system performance, we measure CPU load and latency by running a specific code segment 1000 times, averaging over five iterations. Battery usage is assessed during one hour of background processing with the screen off, subtracting idle standby consumption. Table 5 summarizes the performance based on processing one-second data. Gait type recognition completes within 11.01 ms, ensuring real-time detection. CPU load remains low at around 5%. Power consumption is approximately 1.1% battery capacity per hour, comparable to typical smartphone applications like music players (2%/hour). These results highlight the lightweight design of our classification pipelines, ensuring minimal burden on the mobile device and prolonged operation without excessive battery drain.

5 RELATED WORK

Extensive research has delved into running assistant systems, focusing on three key factors: location-related, strike-related, and physiology-related aspects. The first category revolves around factors such as velocity, step counts, stride frequency, and stride length. For instance, Seethi et al. [16] showcased a precise running speed detection algorithm using accelerometer data and deep convolutional neural networks. The second category covers physiology-related factors like heart rate (HR) and respiratory rate (RR). hEARt [5] proposed monitoring HR during running using an in-ear microphone, while RunBuddy [8] and ER-Rhythm [18] developed methods for monitoring RR using smartphone IMUs and RFID, respectively. The third category involves strike-related factors, including foot placement, ground reaction force, and force distribution. These factors are typically measured using multiple IMUs worn on the body, sensors integrated into shoes, and force platforms on the ground. For example, Hassan et al. [9] introduced a wearable running assistant that detects heel striking and controls foot angle before landing



(a) (b)

Fig. 9: (a) Left and right ear signal during a forefoot strike running, and (b) The RMSE of left and right ear signals.

to reduce knee-related injuries. Similarly, Zhang et al. [19] used multiple body-worn IMUs to detect common running patterns. Despite their effectiveness, these methods can be bulky, uncomfortable, or expensive. We delve deeper by developing portable and lightweight solutions for continuous, high-fidelity monitoring across various gait types.

6 DISCUSSION AND FUTURE WORK

Symmetry: earbuds & feet. We utilize a single earbud to detect the user's gait type, defining each gait cycle as a foot strike. However, it cannot distinguish whether detected gait is from the left or right foot. However, if both earbuds are utilized, the amplitude of the signals alternate, as shown in Figure 9(b). This attributes to the small difference of propagation distance between the two years. Specifically, left foot strike results in higher amplitude on signals from left ear, and vice versa. Thus, we can leverage both earbuds to identify the left and right foot strikes.

Real-time feedback/guidance. Currently, our pipeline ends after detecting the gait type, without making user of the detection results to provide real-time feedback or guidance. In the future, we plan to apply the domain knowledge of running, such as the optimal gait type of different speeds, stages of the run, etc., and design an coaching system. For instance, the runners can specify the running distance and duration before the run, and the coaching system can suggest what is the gait type to be used at different stages. During running, the system can provide audio guidance to the runners and correct them if improper gaits are detected.

7 ACKNOWLEDGMENTS

This research was supported by the Singapore Ministry of Education (MOE) Academic Research Fund (AcRF) Tier 1 grant (Fund Code: MSS23C006).

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