EarPass: Continuous User Authentication with In-ear PPG

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ABSTRACT

In the rapidly expanding universe of smart IoT, earable devices, such as smart headphones and hearing aids, are gaining remarkable popularity. As we anticipate a future where a myriad of sophisticated applications—interaction, communication, health monitoring, and fitness guidance—migrate to earable devices handling sensitive and private information, the need for a robust, continuous authentication system for these devices becomes more critical than ever. Yet, current earable-based solutions, which rely predominantly on audio signals, are marred by inherent drawbacks such as privacy concerns, high costs, and noise interference. In light of these challenges, we investigate the potential of leveraging photoplethysmogram (PPG) sensors, which monitor key cardiac activities and reflect the uniqueness of an individual's cardiac system, for earable authentication. Our study presents *EarPass*, an innovative ear-worn system that introduces a novel pipeline for the extraction and classification of in-ear PPG features to enable continuous user authentication. Initially, we preprocess the input in-ear PPG signals to facilitate this feature extraction and classification. Additionally, we present a method for detecting and eliminating motion artifacts (MAs) caused by head motions. Through extensive experiments, we not only demonstrate the effectiveness of our proposed design, but also establish the feasibility of using in-ear PPG for continuous user authentication—a significant stride towards more secure and efficient earable technologies.

CCS CONCEPTS

• **Human-centered computing → Ubiquitous and mobile computing**.

KEYWORDS

earable authentication, PPG sensing, wearable security, machine learning

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1 INTRODUCTION

With the advancements in artificial intelligence and the Internet of Things, a variety of wearable devices, including smartwatches and ear-worn devices, have become integral to daily life. Notably, ear-worn devices, or earables, owing to their brain proximity and portability, are well-positioned to capture valuable information [14]. Nowadays, they promise more than just music and call facilitation, which could evolve into standalone devices as powerful as current smartphones in the near future. For example, equipped with multiple sensors, earables are able to track head motions [18], identify on-the-face gesture interactions [30], monitor health conditions [6]. However, with the growing capabilities of earables, they may access personal data continuously, raising significant security and privacy concerns. Therefore, a robust continuous authentication system for earables becomes essential, which could also provide an additional security layer for the paired devices like smartphones, eliminating unnecessary user-device interactions.

Most of recent studies on earable-based user authentication leveraged in-ear microphones [7, 17, 20, 38, 43]. For example, [38] proposed a user authentication mechanism when the user performs tooth gestures using in-ear microphones. [17] developed a system that enables continuous user authentication via an in-ear microphone while the user is walking. However, it's important to note that these approaches both require active user participation. [43] employed in-ear microphones to record both behavioral characteristics and physiological features, when the user begins the act of wearing earphones and secures the wearing, which thus cannot offer continuous authentication. [20] enables continuous user authentication through active acoustic sensing using an in-ear speaker and microphone by recording the echos from the user's ear canal. Nevertheless, this system leads to high cost due to continuous sound playing, and it could potentially interfere with the primary functions of earphones. [7] is a recent study leverages in-ear microphones for continuous user authentication by exploring unique intracorporal biometrics, which combine heart motion, bone conduction, and body asymmetry, using deep learning techniques.

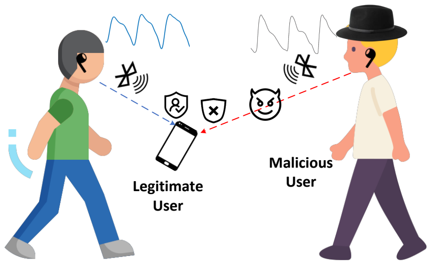

Figure 1: Continuous authentication with in-ear PPG. Since the blood volume variations caused by the legitimate user's cardiac system is unique, the malicious user can not attack successfully.

Despite their potential, audio-based solutions still face challenges. While audio-based solutions offer numerous advantages, they still present challenges that need addressing. These include privacy issues arising from the use of always-on microphones, the significant processing costs incurred due to high sampling rates, and interference from environmental noise.

To this end, this paper proposes to use PPG sensors to capture in-ear PPG signals, developing a continuous user authentication system, *EarPass*, on earables as shown in Figure 1, which is more privacy-protective, noise-resistant, and lightweight compared to existing microphone-based solutions. Due to their non-intrusive nature, capacity for biometric sensing, and affordability, PPG sensors are being increasingly incorporated into current ear-worn devices to conduct heart rate monitoring [12], blood oxygen saturation monitoring [37], blood pressure monitoring [5, 9], and sleep staging [26]. Moreover, a PPG sensor relies on two components, an LED that emits light and a photodetector that captures the reflected light. The changes in the intensity of reflected light are attributed to variations in blood volume. Recent researchers have found that such variations caused by individual's cardiac system is unique and can be utilized as a reliable biometric method for continuous user authentication [10, 42].

Developing this system presents two key challenges. Firstly, existing user authentication systems utilizing PPG sensors have been primarily focused on the wrist [10, 42]. The exploration of in-ear PPG signals for user authentication, however, remains a significantly under-researched area. Consequently, the feasibility of using in-ear PPG signals for authentication is yet to be determined. Secondly, users wearing earphones inevitably perform various head movements, leading to MAs that can significantly undermine the authentication performance. Therefore, designing a method to eliminate these MAs is a critical challenge. In response to these issues, we propose an innovative pipeline for the extraction and classification of in-ear PPG features to enable continuous user authentication. Initially, we preprocess the input in-ear PPG signals to facilitate this feature extraction and classification. In addition, we introduce an approach for the detection and removal of MAs, specifically designed to address the challenge posed by head movements.

In summary, this paper has made the following contributions:

- To the best of our knowledge, this paper is the first work which proposes to use in-ear PPG sensors for continuous user authentication on earables.
- We verify the feasibility of in-ear PPG for continuous user authentication on earables through identifying and addressing two unique challenges.
- Through extensive experiments, our results demonstrate consistent, high-quality authentication accuracy across diverse scenarios.

2 RELATED WORK

PPG Sensing. Due to their non-intrusive nature, capacity for biometric sensing, and affordability, PPG sensors are widely used in various smart health applications, such as heart rate or heart rate variability monitoring [4, 32, 36], blood oxygen monitoring [37], blood pressure monitoring [5, 9], respiration rate monitoring [1, 3, 22], sleep monitoring [21, 31], motion tracking [28, 34, 35, 41], and gluecose monitoring [24, 40]. In these PPG-based applications, multiple wear positions are involved, including forehead, wrist, fingertip, earlobe, and ankle. Because of the rich physiological information can be sensed in the ear, many researchers have worked on the application of ear-worn devices [8, 13, 15, 25, 39]. According to the previous works, the in-ear PPG applications mainly focus on measuring the key physiological indicators [2, 19, 33]. In particular, the researchers in [33] designed a prototype to conduct cardiovascular monitoring such as heart rate monitoring. Another work [19] leveraged the in-ear PPG sensor to measure the vital signs such as heart rate, heart rate variability, blood oxygen saturation and respiration rate. Besides, the researchers in [2] utilized a commercial in-ear wearable device to conduct remote vital signs monitoring of COVID-19 risk patients in home isolation. These studies demonstrate the broad range of applications for PPG sensors in the field of smart health, suggesting that in the near future, earables equipped with PPG sensors will become a popular trend. Consequently, ensuring the safety and privacy of these earables will become a crucial concern. Therefore, a robust continuous authentication system becomes essential. To the best of our knowledge, this paper is the first work to verify the feasibility of using in-ear PPG signals to enable continuous user authentication on earables.

Earable-based authentication. Current earable-based authentication systems are mainly based on audio signals, *i.e.,* leveraging the in-ear microphones [7, 17, 20, 38, 43]. Specifically, the system proposed in [20] leveraged the uniqueness of ear canal geometry and utilized the in-ear microphone to capture the echo sound. Another work proposed in [38] leveraged the inward-facing microphone to record the toothprint-induced sonic when a user performs teeth gestures. In addition, EarGate [17] leveraged the uniqueness of the human gait to identify the user. However, above systems either needs the active transmission of sound pulses or requires the user involvement such as performing teeth gestures and walking. The study [43] employed in-ear microphones to record both behavioral characteristics and physiological features when the user begins wearing earphones and secures their placement. However, this method does not offer continuous authentication. [7] conducted a recent study that leverages in-ear microphones for continuous user authentication by exploring unique intracorporal biometrics. This approach combines heart motion, bone conduction, and body asymmetry, utilizing deep learning techniques. Despite the potential of audio-based solutions, they still face challenges. These challenges include privacy concerns arising from the use of always-on microphones, significant processing costs due to high sampling rates, and potential interference from environmental noise. In contrast, this paper introduces an approach that utilizes PPG sensors to capture in-ear PPG signals, aiming to develop a continuous user authentication system using earables, offering several advantages over existing audio-based solutions, including enhanced privacy protection, resistance to noise interference, and a lightweight design.

PPG-based authentication. Previous research has also explored the use of PPG sensors for authentication purposes. For instance, TrueHeart [42] utilized fiducial features extracted from the wrist PPG signal for user authentication, while PPGPass [10] proposed a set of geometric features to enable two-factor authentication systems. However, it is important to note that these systems predominantly rely on PPG signals acquired from the wrist, which are susceptible to interference from frequent hand motions in daily activities. Moreover, it also indicates the feasibility of utilizing in-ear PPG signals for authentication still remains uncertain from existing studies, which will be solved by this paper.

Security of Wearable devices. The rapid advancement of the intelligent Internet of Things has significantly propelled the growth of wearable applications. However, the extensive capabilities of wearable devices also render them susceptible to attacks. For instance, in [29], the authors discovered that smartwatches can potentially compromise our typing privacy. Additionally, as outlined in [27], the sensors integrated into wearable devices may be susceptible to adversarial attacks. Consequently, ensuring the security of wearable devices becomes a paramount concern.

3 SYSTEM DESIGN

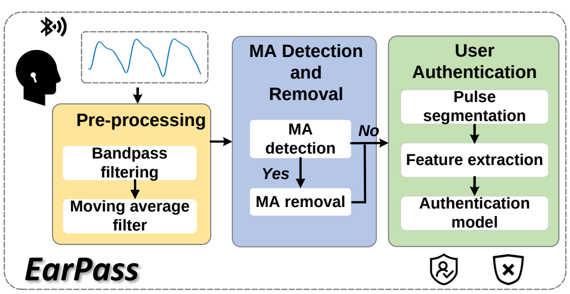

Figure 2: Overview of *EarPass*.

This section introduces the system design of *EarPass*, including **Preprocesssing**: the methods for noise reduction and smoothing; **MA Detection and Removal**: the proposed approach for the detection and removal of MAs caused by head motions; **User Authentication**: the proposed pipeline for the extraction and classification of PPG feature from in-ear PPG signals for continuous user authentication, as illustrated in Fig. 2.

3.1 Preprocessing

After obtaining the raw PPG data from the ear canal, our first step is to remove noise in order to filter out powerline interference and eliminate baseline drift. To achieve this, we employ a two-step process. Initially, we utilize a moving average filter to smooth the raw signal. Subsequently, we implement a second-order Butterworth bandpass filter, with a passband of 0.5-4Hz, to eliminate high-frequency noise.

3.2 MA Detection and Removal

Figure 3 displays a collected sample of in-ear PPG signals. It is evident that when the user remains stationary, the gathered pulse wave signals unveil dependable variations linked to the individual's cardiac system. This information proves sufficient for authenticating the user. However, it is inevitable for users to move their heads while wearing earphones, which introduces MAs, as represented by the red box in Fig. 3. Such head movements can result in a relative displacement between the PPG sensor and the skin, provoking fluctuations in the PPG signal tied to motion and potentially diminishing the authentication performance. Consequently, *EarPass* exploits this inherent feature to implement MA detection.

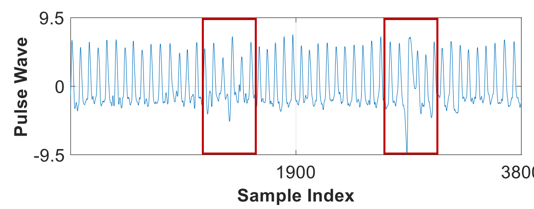

Figure 3: A sample of in-ear PPG signals with head motions.

3.2.1 *MA detection.*

We leverage the fluctuations of the PPG signals to conduct the MA detection. As shown in Fig. 3, we can observe that motions can cause abrupt changes in signal amplitude. Therefore, we employ the Kullback–Leibler (KL) divergence [23] to calculate the similarity of amplitude distribution between two adjacent windows. Specifically, we take N data points as the length of each sliding window to calculate the KL divergence of the amplitudes distribution of two adjacent windows $Q = W_n$ and $P = W_{n+1}$, which can be formulated as follows:

$$D_{KL}(P||Q) = \sum_{i=1}^{N} p_i \log_2 \frac{p_i}{q_i} \quad (1)$$

where W_n and W_{n+1} represent the nth and the $n+1$th sliding windows, respectively. Utilizing this metric, *EarPass* can discern whether the current sliding window encompasses any motion-related segment. Specifically, we observe that the absolute value of D_{KL} between two adjacent sliding windows that include the motion segment is greater than a certain threshold, denoted as δ. Conversely, the absolute value of D_{KL} between two sliding windows devoid of any motion part is less than this threshold. Empirically, this threshold is set at 10. Thus, after *EarPass* acquires the preprocessed PPG signal, it initially segments it into multiple sliding windows. Subsequently, it computes the D_{KL} between each pair of adjacent windows sequentially. Any sliding window with a D_{KL} absolute value exceeding δ signifies the presence of motions.

3.2.2 *MA Removal.*

Since the head motion is occasional and potentially diminish the authentication performance (validated in Section 5), *EarPass* mitigates this issue by disregarding the corresponding sliding windows associated with detected head motions.

3.3 User Authentication

3.3.1 Pulse Segmentation. Following the preprocessing and the MA detection and removal processes, the resulting signal consists solely of pulsatile components. The subsequent step involves the segmentation of these pulses based on the local minima and maxima of the signal. Post-segmentation, the signal is partitioned into numerous segments of the pulse wave cycle. Fig. 4(a) shows one segment, each of which encompasses one systolic and one diastolic peak.

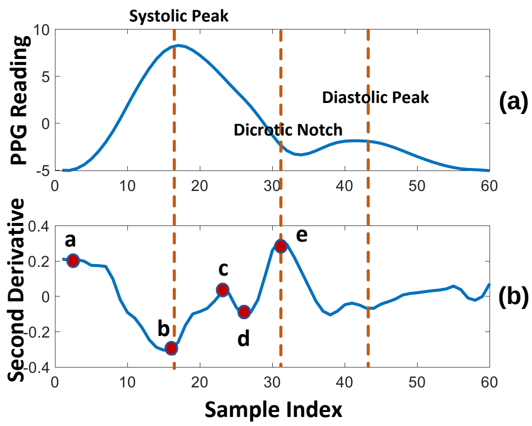

Figure 4: Fiducial points of (a) one PPG segment and (b) its second derivatives.

3.3.2 In-ear PPG Feature Extraction. Subsequently, *EarPass* conducts feature extraction based on the fiducial points of each PPG segment and its second derivatives as used in [16, 42]. Specifically, Fig. 4(a) illustrates one PPG segment and three fiducial points: *systolic peak*, *diastolic peak* and *dicrotic notch*. Fig. 4(b) displays the second derivatives of this PPG segment, as well as the waves denoted as *a*, *b*, *c*, *d*, and *e*. Utilizing these fiducial points, *EarPass* extracts five features, the physiological meanings of which are provided in Table 1.

Feature A_s signifies the amplitude of the pulsatile signal. Due to hardware imperfections, the amplitude of the signal collected from the same user at two different times may vary. As a result, *EarPass* initially standardizes each user's feature A_s, formulating the new feature A_s' as $A_s' = \frac{A_s - \mu}{\sigma}$, where μ and σ represent the mean and standard deviation of the feature set, respectively. Subsequently, in order to lessen the impact of differing feature scales on classification, *EarPass* performs normalization on all five features for all users. This is formulated as $feature_j' = \frac{feature_j - MIN}{MAX - MIN}$ $(1 \leq j \leq 5)$, where MAX and MIN denote the maximum and minimum of $feature_j$ across all users, respectively.

3.3.3 User Authentication using SVM. Once the features are extracted, *EarPass* proceeds with user authentication, leveraging machine learning models. We experimented with classifiers like the Support Vector Machine (SVM) and the Gradient Boosting Decision Tree (GBDT), and discovered that the binary SVM classifier outperforms the others. The libsvm library [11] was employed to implement the machine learning models. During the training phase, we opted for the Radial Basis Function (RBF) kernel.

Feature Name	Feature Description
A_s	Systolic amplitude
P_w	Pulse width
P_i/A_s	Ratio of pulse interval to systolic amplitude
T_c	Crest time
$A_{b-w}/A_{a-w})$	Ratio of amplitude of b-wave and a-wave

Table 1: Name and description of five features.

4 IMPLEMENTATION

4.1 Earable prototype

We have developed a prototype of an earable device, each containing one PPG sensor. As depicted in Fig. 5, each PPG sensor comprises a green light-emitting diode (LED) and an ambient light sensor. These sensors are incorporated into the earbud that fits comfortably within the user's ear canal. An amplifier circuit board connects the sensor and an Arduino microprocessor, serving the dual purpose of amplifying and performing initial filtering of the PPG signal. The data is captured at a sampling rate of 100Hz.

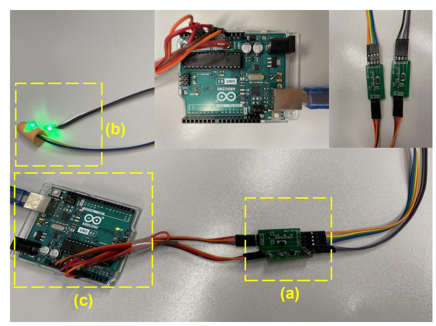

Figure 5: The prototype consists of three parts: (a) an amplifier circuit (b) the green light PPG sensor (c) the Arduino microprocessor

4.2 Software setup

We use Matlab to implement the algorithms for pre-processing, MA detection and removal, and user authentication modules.

5 EVALUATION

5.1 Data Collection

We recruit 10 participants to collect PPG raw data from the ear canal using our earable prototype. During the data collection process, participants are required to wear our earable prototype on their ears. During the data collection process, there are two scenarios taken into consideration. First is the static scenario, 10 participants are asked to sit still wearing our earable prototype on their ears for 10 mins. The second scenario is the head motion scenario, where 5 participants perform the motion "nodding" and "shaking left and right" repeatedly for 2 mins and still for 3 mins.

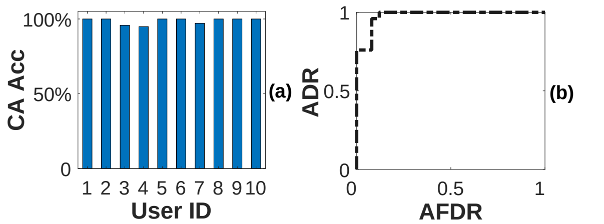

Figure 6: (a) CA Acc across different users and (b) ROC curve under attack.

5.2 Evaluation Metrics

We utilize the evaluation metrics as used in paper [42], which are shown as follows:

- **CA Accuracy** (CA Acc): The number of sliding windows that are correctly labeled as the legal user over the total number of sliding windows.
- **Attack Detection Rate** (ADR): The number of sliding windows that are correctly labeled as the attacker over the total number of sliding windows.
- **Attack False Detection Rate** (AFDR): The number of sliding windows that are incorrectly labeled as the attacker over the total number of sliding windows.
- **Receiver Operating Characteristic (ROC) Curve**: The trade-off between ADR and AFDR.

5.3 Overall Performance

We assess the overall performance using the authentication results from three continuous windows through voting. As depicted in Fig. 6 (a), the average CA Acc among the 10 users is 98.7%. This suggests that our system, *EarPass*, can achieve high authentication accuracy when the user is in a static scenario. The overall performance indicates the feasibility of using PPG sensors for continuous authentication in earables.

Moreover, Fig. 6 (b) illustrates the ROC curve. In particular, the ADR is 96% while the AFDR is 8%. The experimental results demonstrate that *EarPass* can accurately identify unauthorized users with a high detection rate, while simultaneously maintaining a low error rate in misidentifying legitimate users as unauthorized. This shows the effectiveness of our system.

5.4 Performance with MA Removal

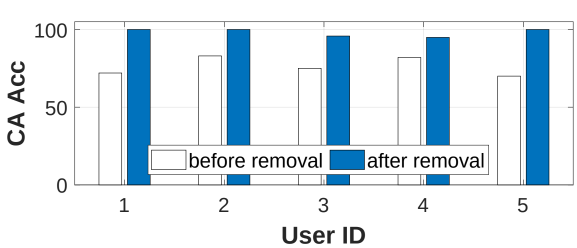

Figure 7: CA Acc of different users before and after MA removal

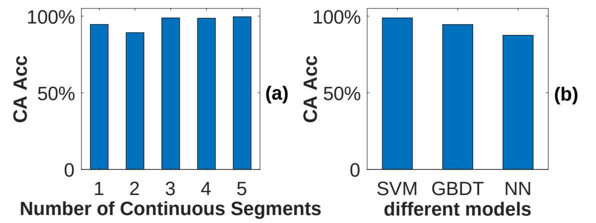

Figure 8: CA Acc with (a) different number of continuous segments. (b) different models

Fig. 7 illustrates the CA Acc across different users before and after MA detection and removal. In particular, the CA Acc before MA detection and removal is between 70% to 83% and the average CA Acc is 76.4%. The results suggest that *EarPass* remains effective even when head motions is present. On the other hand, after the removal of the head motions, the average CA Acc can achieve around 98%. The results indicate the efficacy of our MA detection and removal design, leading to improved authentication performance.

5.5 Micro-Benchmarks

5.5.1 Impact of the number of windows for voting. Fig. 8 (a) illustrates the CA Accuracy with different number of continuous windows, *i.e.*,, 1, 2, 3, 4, 5. As shown in Fig. 8 (a), CA Accuracy increases with the increase of the number of continuous windows. When it reaches 3, the CA Accuracy starts to stabilize. To strike a balance between runtime latency and accuracy, we choose 3 as the number of continuous windows for our baseline model.

5.5.2 Impact of Machine Learning Methods. In order to test the performance of different models under the static scenario, we input the same features into the binary-SVM, binary-GBDT (Gradient Boosting Decision Tree) and MLP (Multilayer Perceptron). As shown in Fig. 8 (b), SVM works best, *i.e.*,, the CA Accuracy for 10 users is 98%. Followed by GBDT, the CA Accuracy is 94.5%. MLP performed the worst with an CA Accuracy of 87.5%. Therefore, we choose SVM model as the final authentication model.

6 CONCLUSION

This paper introduces a portable and cost-effective PPG-based earable continuous authentication system. We conducted an investigation of the PPG signal from the ear canal and validated its feasibility for use in earable authentication. Specifically, we propose a pipeline that contains three modules, the preprocessing module, the MA detection and removal module and the user authentication module. In addition, we develop a PPG-based earable prototype and conduct comprehensive experiments. Our experimental results demonstrate consistent, high-quality authentication accuracy across diverse scenarios, providing a security solution for ear-worn devices and offers unlimited opportunities for future applications of ear-worn devices.

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