Poster Abstract: Smart Earpieces that Know Who You Are Quietly

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ABSTRACT

User authentication and identification on smart devices has great significance in keeping data privacy and recommending personalized services. Existing few research works propose active sensing systems that emit and receive inaudible acoustic signals to authenticate users. But they share shortcomings of intrusiveness to users, high power consumption, and purely focusing on authentication. Instead, in this paper, we propose a passive sensing system called EarID with low-cost customized earpieces which attains user authentication and identification simultaneously. It makes use of a embedded microphone to sense body sounds spread out through ear canals and extract 'fingerprints' as a novel biometric feature. With self-designed earpieces, we design a deep learning-based real-time data processing pipeline. Extensive experiments under different real-world settings show that EarID can achieve a rather low false acceptance rate less than 5% for user authentication and a high $F1$ score of 96% for user identification.

CCS CONCEPTS

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

KEYWORDS

Smart earphones; Biometric authentication

ACM Reference Format:
Haibo Lei, Jinyuan Liu, Yongpan Zou, Kaishun Wu. 2020. Poster Abstract: Smart Earpieces that Know Who You Are Quietly. In *The 18th ACM Conference on Embedded Networked Sensor Systems (SenSys'20), November 16–19, 2020, Virtual Event, Japan.* ACM, New York, NY, USA, 2 pages. https://doi.org/10.1145/3384419.3431254

1 INTRODUCTION

Biometric authentication is a key technique to keep data privacy and security on smart devices. Fingerprinting is currently the most widely-adopted authentication scheme in commercial smart devices, especially smartphones and tablets. However, it requires to equip specialized fingerprinting sensors on devices which either occupy large spaces or cost too much. Due to this, it is not suitable for some wearable smart devices such as smartwatches, smart glasses and smart earpieces. Moreover, fingerprinting requires a user to consciously participate in the authentication process and is not suitable for continuous authentication scenarios. Within the scope of biometric authentication, researchers have also proposed some novel methods based on other biological features or physiological activities differing from the above, such as breathing [1], dental occlusion [4], heartbeat [3] and ear canal shape [2]. However, the works [1, 3, 4] require users to put devices close to noses, mouths or chests, which degrades the user experience especially in continuous authentication cases. EarEcho [2] is the most similar work to ours which makes use of ear canal structure as biometric feature. But it follows a active sensing approach which utilizes a microphone-speaker pair equipped in earpieces to transmit and receive inaudible acoustic signals.

In this work, we pay attention to the user authentication and recognition problem with smart earpieces, considering their increasing popularity in our daily life. Different from the traditional problem, we not only care about whether a user is legitimate or not, but also intend to know exactly who he/she is if identified as legitimate. The rationale of our consideration is due to the characteristics of smart earpieces. On one hand, since earpieces are a kind of private items, people are not willing to share them with others except for family members. Thus checking the legitimacy of a user is necessary for guaranteeing their private property. On the other hand, people sometimes share their earpieces with closest friends or families. By identifying who the present user is, the smart earpieces can switch to corresponding personal settings and provide personalized services. Considering the shortcomings of existing approaches as mentioned above, we propose a truly passive sensing system by making use of low-cost microphone sensor embedded in earpieces to collect human body sounds spread out through ear canal. The underlying rationale of our method are two fold. For one thing, the collected body sounds through ear canal are mostly produced by heart beating which is a unique feature for different people. For another thing, human body sounds propagate through body structures including ear canal which act as a series of signal transformation systems. Due to the differences of these structures, their transfer functions are different which exert different impacts on body sound signals.

2 IMPLEMENTATION AND EXPERIMENTS

2.1 System Implementation

The EarID system consists of two parts, one is the earpieces hardware and the other is a mobile application on a smartphone, tablet or any other smart devices. In the following, we shall give details about these two parts.

2.1.1 Hardware. As present commercial earpieces do not have in-ear microphones and output raw data, we design a pair of smart earpieces with low-cost electret microphones which can be bought

SenSys'20, November 16–19, 2020, Virtual Event, Japan

ACM ISBN 978-1-4503-7590-0/20/11…$15.00
https://doi.org/10.1145/3384419.3431254

Table 1: The performances of different models

Perf. / Model	Params (Mb)	Training time (s)	FAR±std (%)	FRR±std (%)	Precision (%)	Recall (%)	F1 score±std (%)
MPL	0.24	63.5	19.8±7.1	23.5±5.3	76.0±5.7	74.3±5.4	74.9±5.5
LSTM	0.25	65.5	7.8±3.1	4.0±0.9	93.2±2.7	94.7±1.3	93.9±1.8
Bi-LSTM	0.63	135	7.5±2.7	4.2±1.0	93.2±2.0	94.6±1.3	93.8±1.7
LSTM+DCGAN	0.25+0.35+7.23	899	7.2±2.8	3.9±0.8	93.6±2.0	94.9±1.2	94.2±1.7
MobileNet	2.23	514	5.7±1.8	4.0±1.4	94.6±1.3	95.4±1.1	94.9±1.0
ResNet18	11.17	1275.5	5.0±1.9	3.2±1.0	95.4±1.2	95.7±0.9	95.7±1.0

Figure 1: Application scenarios of EarID

by about 10 CNY online. We connect the microphone with an acoustic signal amplifier MAX9814 which is a low-cost, high-quality microphone amplifier with automatic gain control (AGC) and low-noise microphone bias. The device features a low-noise preamplifier, variable gain amplifier (VGA), output amplifier, microphone-bias-voltage generator and AGC control circuitry. The micro-controller unit we used is an ESP32, a low-cost and low-power system on a chip with integrated Wi-Fi and dual-mode Bluetooth. We print a plastic case with 3D printer and integrate all the hardware components together as shown in Fig. 1.

2.1.2 Software. We develop a mobile application on Android platform which is responsible for transferring data with earpieces via Bluetooth and executing data processing pipeline. Although we select a relatively lightweight deep learning model, the training process still incurs excessive computing burden for a smartphone. As a result, we shift this part of work to a server. Specifically, the training data are uploaded to a cloud server and model parameters are transmitted back to the smartphone when the training process is finished. In our experiments, we make use of a Huawei Mate 9 smartphone with a Hisilicon Kirin 960 CPU, 6GB RAM, 128GB ROM and Android 9 operating system.

2.2 Data Collection

We conduct comprehensive experiments with different settings to evaluate EarID's performance. We first recruit a total number of 50 participants with 15 females and 35 males (denoted by $P_1 \sim P_{50}$) from our university aged from 18 to 35 years old, including students, staffs and faculties. Each participant is paid by 60 CNY per hour after experiments. Before starting up, we tell participants about the details of experiments to make sure that they clearly know what they should do during experiments. And we also instruct them to use the EarID system like charging the hardware when batteries run out, installing applications on smartphones and using them for data collection, and *etc.*. On the whole, our experimental settings are determined according to four impact factors, including noise level, user's movement, wearing angle of earpieces and emotional state of a user. These influence factors cover different aspects of potential interference in real-world usage scenarios. In the following, we shall demonstrate the details of each experimental setting.

3 EARID PERFORMANCE

In order to select an appropriate model, we implement EarID with different models including multilayer perceptron (MLP), LSTM, Bi-LSTM, LSTM combining with DCGAN (denoted by LSTM+DCGAN), MobileNet and ResNet18. In LSTM-based models, the input data is the acoustic signal sequence after preprocessing. But in the LSTM+DCGAN, we first make use of a deep convolutional generative adversarial network (*i.e.*, DCGAN) to enhance the training dataset. In both MobileNet and ResNet18, we need to transform the time series into spectrograms by the short-time Fourier transform (STFT) before feeding them into the networks.

We evaluate these models from different aspects besides authentication and recognition performance. Table 1 shows the evaluation results. We can see that except for MPL, all the other models can achieve high performance with FAR and FRR lower than 8% and 4.5% respectively, and F1 score higher than 93.5%. Among them, MobileNet and ResNet perform the best in terms of these three metrics, with lower FARs and FRRs by about 2%, yet at the cost of large parameter size and overlong model training time. As a result, taking the trade-off between system performance and complexity, we finally select LSTM as the learning model in EarID, with which the following evaluation is conducted.

ACKNOWLEDGMENTS

This research was supported in part by the China NSFC Grant 61802264, Shenzhen Science and Technology Foundation (No. JCYJ 20180305124807337), Natural Science Foundation of SZU (No. 860-000002110537).

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