

Excerpt of ToothSonic: Eearable Authentication via Acoustic Toothprint

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ABSTRACT

Earables (ear wearable) are rapidly emerging as a new platform to enable a variety of personal applications. The traditional authentication methods thus become less applicable and inconvenient for earables due to their limited input interface. Earables, however, often feature rich around the head sensing capability that can be leveraged to capture new types of biometrics. In this work, we propose ToothSonic that leverages the toothprint-induced sonic effect produced by a user performing teeth gestures for user authentication. In particular, we design several representative teeth gestures that can produce effective sonic waves carrying the information of the toothprint. To reliably capture the acoustic toothprint, it leverages the occlusion effect of the ear canal and the inward-facing microphone of the earables. It then extracts multi-level acoustic features to represent the intrinsic acoustic toothprint for authentication. The key advantages of ToothSonic are that it is suitable for earables and is resistant to various spoofing attacks as the acoustic toothprint is captured via the private teeth-ear channel of the user that is unknown to others. Our preliminary studies with 20 participants show that ToothSonic achieves 97% accuracy with only three teeth gestures.

CCS CONCEPTS

• Security and privacy → Biometrics.

KEYWORDS

Biometrics, Toothprint, User Authentication, Eearable

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1 INTRODUCTION

Earables are rapidly emerging as a new platform to enable a variety of personal applications due to their rich around the head sensing capability. There also have been increasing research efforts to leverage earables to achieve tasks such as understanding our fitness and sleeps, accessing information, identifying contextual information, monitoring or tracking activities [2].

While earables show considerable promise, they also raise new questions in terms of security. This is because much of the value of the services offered by earables depends on the confidential and personal information they capture, process and transmit. However, adapting traditional authentication from other wearables or mobiles can be challenging. Quite simply, earables lack a suitable input interface to support rapid and reliable entry of passwords or most of the traditional biometrics. Voice-based authentication is convenient but has been proven vulnerable to voice spoofing attacks [6, 7]. Despite the issue, earables provide novel opportunities to improve or redesign approaches to authentication due to their rich around the head sensing capability. For example, recent work utilizes earable to sense ear canal and its deformation [5] for authentication. However, emitting acoustic sound to probe the ear canal could be intrusive for those who are sensitive to high-frequency sound.

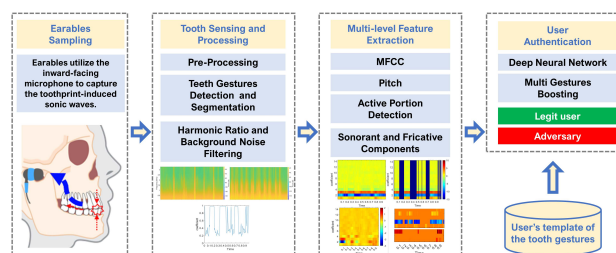


Figure 1: System flow of ToothSonic.

In this work, we propose ToothSonic, a secure earable authentication system that leverages the toothprint-induced sonic effect produced by a user performing teeth gestures for user authentication. In particular, when teeth slide or strike against each other, part of their mechanical energy is released in the form of sonic waves. The harmonics of the friction- and collision- excited sonic wave are

Tooth Gestures	Organ-level			Macro-level										Micro-level		
	Dental Mobility F/B	Dental Mobility U/D	Dental Mobility L/R	Proprietary Channel	Dental arch shape	Depth of bite	Occlusion classes	Dental spacing	Incisor shape and size	Canine shape and size	Molar shape and size	Cusp	Enamel thickness	Enamel patterns	Tooth root	
Occlusion Sliding																
Molar Sliding	✓			✓		✓		✓	✓	✓	✓	✓	✓	✓	✓	✓
Canine Sliding	✓							✓	✓	✓	✓	✓	✓	✓	✓	✓
Incisor Sliding F/B	✓			✓			✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Incisor Sliding U/D		✓		✓				✓	✓	✓	✓	✓	✓	✓	✓	✓
Incisor Sliding L/R			✓	✓			✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Occlusion Tapping		✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Molar Tapping		✓		✓		✓				✓	✓	✓	✓	✓	✓	✓
Canine Tapping		✓		✓					✓	✓	✓	✓	✓	✓	✓	✓
Incisor Tapping		✓		✓			✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Figure 2: Tooth gesture and related biometrics.

dependent on the teeth composition, the dental geometry, and the surface characteristics of each tooth [1]. The key insight is that the sonic waves produce from a teeth gesture carry the information of the toothprint. As every individual has a unique toothprint just like our fingerprint, two users perform the same teeth gesture will result in distinct toothprint-induced sonic waves, which could be sensed by the earables for user authentication. Compared with traditional biometrics, it has several advantages.

Anti-Spoofing. The friction- and collision- excited sonic waves are dependent on the toothprint, which is hidden in the mouth and skull, the head and skull. It is thus more resilient to spoofing attacks compared with traditional biometrics (e.g., fingerprint, face, and voice) that could be exposed to others. In addition, the sonic waves travel through the head tissues and skull channel, which hold the individual uniqueness acting as a hidden and encrypted channel that modulates the sonic waves. ToothSonic is thus resistant to sophisticated adversaries who can acquire the victim's toothprint, for example, via the dentist.

Wide acceptability. ToothSonic provides eye-free and hands-free authentication when hands and eyes are occupied (e.g., carrying objects or driving). It is also more socially acceptable than voice-based authentication in public places (e.g., offices and libraries) as the sonic waves of teeth gestures are much less perceptible and unobtrusive to others.

Implicit authentication. ToothSonic can also be exploited as an implicit authentication method when teeth gestures are used as a hands-free computer interface, for example potentially in "Switch Access" services, and for people with motor impairments.

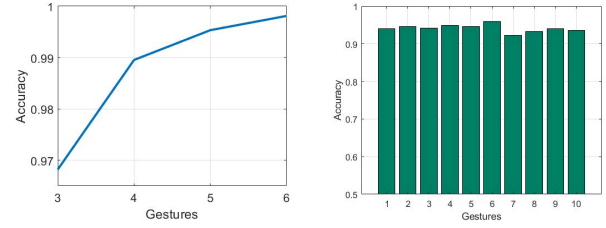
2 SYSTEM DESIGN

Our system comprises four major components, as shown in Fig. 1. The system uses energy-based event detection to locate the gestures. Next, our system segments the recorded signals into a sequence of gestures by utilizing the Munich Automatic Segmentation system [3]. To enhance the SNR, we apply the harmonic ratio to filter our background noise when no gestures are performing.

As shown in Fig. 2, we design 10 teeth gestures including 6 sliding gestures and 4 tapping gestures. The sliding gestures contain occlusion sliding, molar sliding, canine sliding, incisor sliding front/back, incisor sliding up/down, and incisor sliding left/right. And the tapping gestures are occlusion tapping, molar tapping, canine tapping, and incisor tapping. These gestures cover the major factors that affect the sonic waves of the toothprint when performing gestures.

3 PERFORMANCE EVALUATION

Fig. 3 (a) shows the accuracy that leverages multiple gestures. In sum, we could see that ToothSonic achieves high accuracy over 99% by combining a few gestures. In particular, our system could



(a) Multiple gestures

(b) Different gestures

Figure 3: Authentication accuracy.

achieve authentication accuracy of 99.81%, 99.53%, 98.95%, 96.82% by with 6, 5, 4, 3 gestures, respectively.

Fig. 3 (b) shows the accuracy across 10 different gestures when using only one gesture for authentication. No.1 to No.6 stand for the six different sliding gestures and the left 4 gestures are tapping gestures. We observed that the performance of the sliding gesture is better than the tapping gestures. This is because sliding gestures have a longer duration and contain more tooth participants with different dimensions of information. Therefore, sliding gestures contain more features than tapping gestures, and thus could provide more accurate authentication. We could also find that the accuracy of canine gestures is the lowest. This is due to canine gestures only involve one side canine with less information, and such gestures are harder for users to perform in our experiments.

4 CONCLUSIONS

This paper proposed the excerpt of ToothSonic [4], a secure earable authentication system that leverages the toothprint-induced sonic effect produced by teeth gestures for user authentication. ToothSonic has several advantages over traditional biometric authentication including anti-spoofing, wide acceptability, and conditionally implicit authentication. We investigate representative teeth gestures that produce effective sonic waves carrying the information of the toothprint. Multi-level acoustic features are also extracted to represent intrinsic toothprint information. Our preliminary results demonstrate the effectiveness of ToothSonic in authenticating earable users.

REFERENCES

- [1] Jean-François Augoyard. 2006. *Sonic experience: a guide to everyday sounds*. McGill-Queen's Press-MQUP.
- [2] Romit Roy Choudhury. 2021. Earable computing: A new area to think about. In *Proceedings of the 22nd International Workshop on Mobile Computing Systems and Applications*. 147–153.
- [3] Florian Schiel, Christoph Draxler, and Jonathan Harrington. 2011. Phonemic segmentation and labelling using the MAUS technique. (2011).
- [4] Zi Wang, Yili Ren, Yingying Chen, and Jie Yang. 2022. ToothSonic: Earable Authentication via Acoustic Toothprint. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 6, 2 (2022), 1–24.
- [5] Zi Wang, Sheng Tan, Linghan Zhang, Yili Ren, Zhi Wang, and Jie Yang. 2021. EarDynamic: An Ear Canal Deformation Based Continuous User Authentication Using In-Ear Wearables. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 5, 1 (2021), 1–27.
- [6] Linghan Zhang, Sheng Tan, Zi Wang, Yili Ren, Zhi Wang, and Jie Yang. 2020. VibLive: A Continuous Liveness Detection for Secure Voice User Interface in IoT Environment. In *Annual Computer Security Applications Conference*. 884–896.
- [7] Linghan Zhang, Sheng Tan, Jie Yang, and Yingying Chen. 2016. Voicelive: A phoneme localization based liveness detection for voice authentication on smart-phones. In *Proceedings of the 2016 ACM SIGSAC Conference on CCS*. 1080–1091.