WristConduct: Biometric User Authentication Using Bone Conduction at the Wrist

FENG YI LU*, LEONARD HUSSKE*, and ANTON ROESLER*, Frankfurt University of Applied Sciences, Germany

User authentication is an essential security requirement in all personal electronic devices. While smartphones and laptops can already be unlocked with user biometrics, this is not yet common for smartwatches and other wrist-worn wearables. In this paper, we show that it is possible to identify and thereby authenticate users by analyzing soundwaves that were passed through their wrist bones using bone conduction. In a feasibility study, we took 10 recordings of 24 subjects to create a dataset. Using a deep neural network, our method shows an authentication accuracy of 98.7%.

CCS Concepts: • **Human-centered computing** → **Haptic devices**; • **Computing methodologies** → *Classification and regression trees*; • **Security and privacy** → *Usability in security and privacy*.

Additional Key Words and Phrases: User authentication, Biometric identity, Body reflection, Classification

ACM Reference Format:
Feng Yi Lu, Leonard Husske, and Anton Roesler. 2022. WristConduct: Biometric User Authentication Using Bone Conduction at the Wrist. *Proc. ACM Meas. Anal. Comput. Syst.* 42, 42, Article 0 (2022), 6 pages. https://doi.org/00.0000/0000000.0000000

1 INTRODUCTION

These days, smartwatches are a very common devices used by numerous people. The standard authentication method is to manually enter the pin or by unlocking the connected smartphone. Different research has presented a way of smartwatch authentication by performing specific gestures [6]. These are active methods, which require the user to act. However, there is an increasing number of researches in the field of passive authentication methods. Therefore, we implemented a system that requires no action from the user. With WristConduct, we present a passive method of authentication by using bone conduction at the wrist, to provide fast and reliable authentication. This method of authentication has still not been used for wrist-worn devices that are currently on the market.

Wearable authentication will gain more importance in the near future since it has a wide-reaching use of scenarios. This upcoming trend has also been analyzed and designated as an opportunity by Binachi et al., their research revealed four key themes that will "drive future research" [1]. One of which is the authentication with wearable devices. Schneegass et al. have shown that it is possible to identify different people only by their unique reflected frequencies in the skull [11]. In our research, we want to recreate a similar biometric system that works on the wrist instead of the skull. The fundamentals of this and the common researches are functional biometrics. Liebers and Schneegass explain that the body of a human should be seen as a function that converts a stimulus

*All three authors contributed equally to this research.

Authors' address: Feng Yi Lu, feng.lu@stud.fra-uas.de; Leonard Husske, leonard.husske@stud.fra-uas.de; Anton Roesler, anton.roesler@stud.fra-uas.de, Frankfurt University of Applied Sciences, Nibelungenplatz 1, Frankfurt a. M., Germany, 43017-6221.

2476-1249/2022/0-ART0 $15.00
https://doi.org/00.0000/0000000.0000000

imposed on the body by the authentication system [7]. This means that the underlying function is kept secret, while the stimulus and the measured body reflection creates a pair that can be used for authentication.

We evaluate whether it is possible to identify a specific person by bone conduction at the wrist and to differentiate it from other persons. The final prediction model can distinguish an audio recording of a fixed signal recorded on the wrist of a specific person from the same signal recorded on an extraneous person.

2 RELATED WORK

The field of functional biometrics sees the body of a human as a function f in which a device sends a signal x which is reflected by the body uniquely. This reflection $f(x)$ is read by the device again and can be used for authentication of a user. This novel approach by Liebers et al. results in a higher security compared to active authentication methods [7]. The way such a system appears in reality is not limited. Khorshid et al. show that a high authentication accuracy can be achieved by sending signals from electrodes on the arm through the intra-body communication channels [4]. Other research utilizes vein patterns using thermal imaging [3] and vibration [17]. One more method with high abundance is bone conduction [11, 15].

Bones can be well characterized using acoustic waves propagating in bone tissue. Their properties are determined through speed-of-sound measurements [14]. Bone conduction is mainly used on the skull to transmit sound waves to the cochlea causing a sound perception. Therefore, the use of bone conduction is widely used in technologies for hearing aids, which are placed at the outer ear [13]. The main system that is implemented in these devices uses analog acoustic signals within the audible range. The skull will then transmit the sound waves from the outer ear to the inner ear without changing the intrinsic signal [16]. The effectiveness of bone conduction depends strongly on the bone that is used, e.g. the skull will behave like a rigid body at low frequencies, at higher frequencies it will incorporate different types of wave transmissions [13].

Previous work shows successful utilization of bone conduction with different wearables on different body parts [5, 10, 11, 19]. ViBand [5] and OsteoConduct [19] are two inventions that both use bone conduction on the wrist, the difference is that OsteoConduct measures the reflected frequency on the elbow joint and ViBand measures it directly on the wrist. However, neither study uses bone conduction to authenticate or identify persons.

Roy and Choudhury have managed to implement a system called "Ripple II" that allows the user of a smartphone to communicate with their device with a ring/watch by using bone conduction [10]. Schneegass et al. have invented "SkullConduct" which uses bone conduction on the skull that is performed by an eyewear [11]. This device has an integrated bone conduction speaker on one side that sends white noise in a specific frequency that gets recorded by a microphone in the front of the eyewear. Velasco took up Schneegass' research, without committing to an eyewear device [15]. As it is the most related work to ours, we leveraged a similar technique, using bone conduction on the wrist to authenticate a user.

The research that has been done in this field shows that signals that are sent though the body can have a high authentication accuracy because of the uniqueness of the body [4, 7]. In our work, we rely on bone conduction, as this has proven as a viable method of authenticating people with different wearables [5, 10, 11, 19].

3 METHOD

Audio recordings of 24 subjects were made for our study. A 3 seconds long white noise sequence was generated as an audio signal. A laryngophone was used as signal receiver to filter out external noise. The laryngophone was placed on top of the radius at the right wrist of the subject. The bone conduction speaker was placed on the bottom side of the wrist at the ulna. The physical arrangement is shown in Fig. 1.

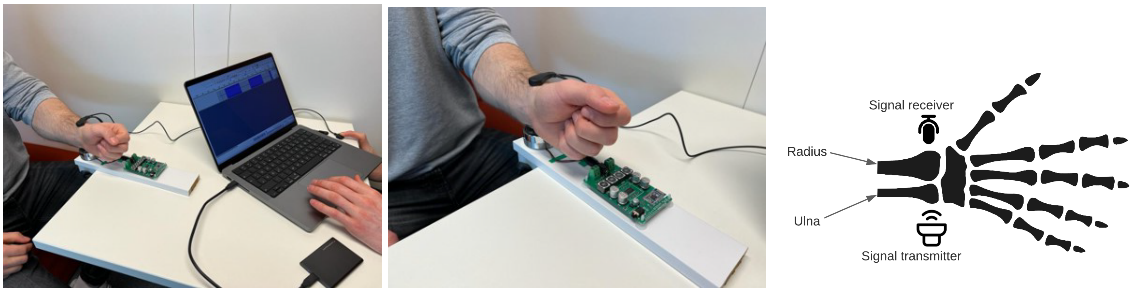

Fig. 1. Physical arrangement.

The experiment took place in an office environment with low background noise. Ten recordings were taken for each subject. In between the recordings, the position of the receiver were slightly changed after each recording to avoid bias. The SUBJECTS' WRISTS serve as the independent variable of our study. The dependent variable is the accuracy of the prediction model.

In total, we recorded 240 labeled recordings. The Mel Frequency Cepstral Coefficient was used to extract features from the recordings and create a numerical data set.

The objective is a model that can authenticate a single specific person and reject all extraneous persons. The data set consists of a total of 240 items, ten of which belong to each of the 24 subjects. To obtain representative results, we created a separate data set for each of the 24 test persons by applying a positive label to the respective person and a negative label to all other persons. The resulting 24 data sets are unbalanced, with 10 positive to 230 negative elements each. In order to balance the datasets slightly more and at the same time not make them too small, we turned each dataset into five datasets, each with the identical 10 positive elements, but with a random selection of 92 of the negative elements inserted. We divided each of the 120 data sets stratified into training (.65) and test (.35) data, each of which were used to train and evaluate a dedicated model.

We tested two classifiers with different complexity. [1]

(1) Low complexity: Support vector machine (SVM) with stochastic gradient descent (SGD) using weighted classes
(2) High complexity: Deep artificial neural network (NN); six dense layers, binary cross entropy loss and adam optimizer; 200 epochs

In our results, we put the main focus on the NN due to better performance, and mention SVM results for comparison. Both methods, SVM [8] and NN [12] have proven viable as biometric user authentication classifiers.

4 RESULT

Fig. 2 shows the model accuracies per subject that were achieved with the NN. To consider the total 120 NN models as one, we can regard the summed confusion matrix, shown in Table 1. All key figures mentioned below refer to that sum, which corresponds to the respective mean of all models. With the NN models, we were able to achieve an average accuracy of .987, a F1-Score of .944 and a Matthew Correlation Coefficient (MCC), a superior metric in binary classification evaluation [2], of .937. The accuracy of the SVM initially appears to be similar at .971, but the F1 .870 of score and MCC of .854 reveal that this is caused by the unbalanced data set.

[1] github.com/antonroesler/Wrist-Conduct

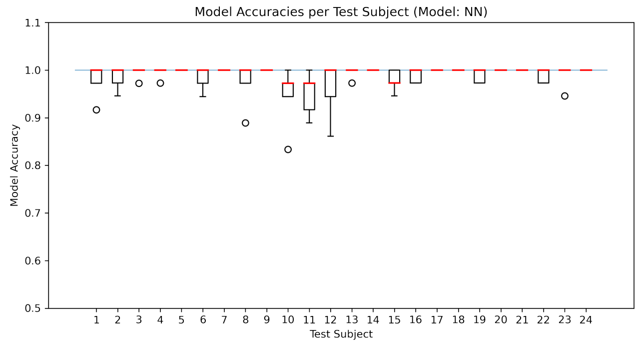

Fig. 2. The accuracies of each of the five NN models that were trained for each subject

Table 1. Confusion Matrices of the sum of all test outcomes for the NN and SVM models

Neural Networks

Predicted	True Class: Negative	True Class: Positive
Negative	3858	19
Positive	37	471

Support Vector Machines

Predicted	True Class: Negative	True Class: Positive
Negative	3829	62
Positive	66	428

The main task of an authentication device is to positively identify the person to be identified. Our NN model achieves a sensitivity of .961. Thus, the false negative rate is .039. Even more important in such a system, however, is that extraneous persons are classified as negative. Our NN model achieves a specificity of .991. Thus, the false positive rate is less than one percent.

The Receiver Operating Characteristic (ROC) (Fig. 3) confirms these results. It shows that for different threshold values, a high true positive rate can be achieved, while the false positive rate remains low. The area under the ROC curve (ROC-AUC) is .99 (±.07) for the NN.

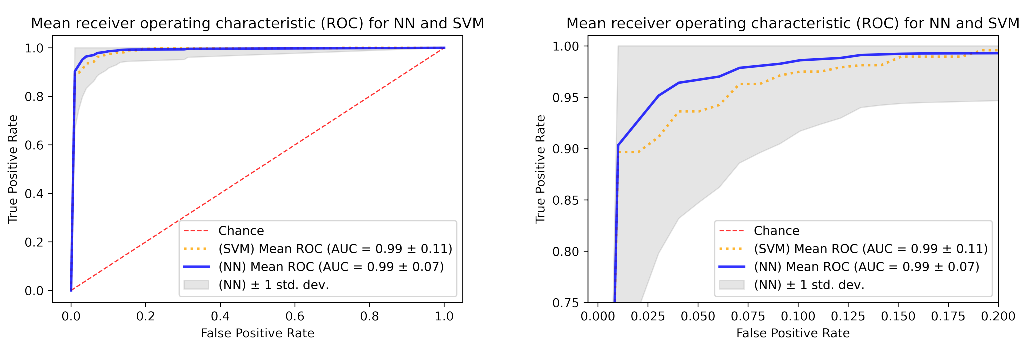

Fig. 3. ROC curve for both models (the lines represent the mean of the 120 models respectively)

Although we get slightly better results with the NN Model, it is important to mention the SVM results. The quality of the NN model is better, but the calculation is much more computationally expensive. In a wearable device, with little computing resources, a model with less complexity, such as an SVM, may be a suitable option.

5 DISCUSSION

In our user study, we tested the general feasibility of using bone conduction at the wrist to authenticate users. The evaluation of our system proves that bone conduction is suitable for reliable authentication at the wrist. However, our user study took place in a controlled environment with low background noise and a static apparatus. For the use of bone conduction in a realistic environment, it will be required to build a wearable bone conduction authentication apparatus with a much smaller bone conduction speaker. Such bone conduction speakers are already in use for communication systems, language development approaches, mitigation of stuttering, audiometric investigations and medical applications [9]. There are possibilities to miniaturize the speakers while improving efficiency [18]. In our study, we did not have access to such devices and therefore had to rely on an accessible, significantly larger, alternative. We assume that a smaller device is sufficient for authentication, since we did not come close to using the maximum volume of our large speaker. Additional variables whose influence on the quality of the authentication should be assessed are the position of the bone conduction speaker at the wrist and its volume. These and more factors could impact, and may further increase, the accuracy of the system and need to be evaluated in future research.

REFERENCES

[1] Andrea Bianchi and Ian Oakley. 2016. Wearable authentication: Trends and opportunities. *it-Information Technology* 58, 5 (2016), 255–262. https://doi.org/10.1515/itit-2016-0010

[2] Davide Chicco and Giuseppe Jurman. 2020. The advantages of the Matthews correlation coefficient (MCC) over F1 score and accuracy in binary classification evaluation. *BMC genomics* 21, 1 (2020), 1–13. https://doi.org/10.1186/s12864-019-6413-7

[3] Sarah Faltaous, Jonathan Liebers, Yomna Abdelrahman, Florian Alt, and Stefan Schneegass. 2019. VPID: Towards Vein Pattern Identification Using Thermal Imaging. *i-com* 18, 3 (2019), 259–270. https://doi.org/10.1515/icom-2019-0009

[4] Ahmed E. Khorshid, Ibrahim N. Alquaydheb, Fadi Kurdahi, Roger Piqueras Jover, and Ahmed Eltawil. 2020. Biometric Identity Based on Intra-Body Communication Channel Characteristics and Machine Learning. *Sensors* 20, 5 (2020). https://doi.org/10.3390/s20051421

[5] Gierad Laput, Robert Xiao, and Chris Harrison. 2016. ViBand: High-Fidelity Bio-Acoustic Sensing Using Commodity Smartwatch Accelerometers. In *Proceedings of the 29th Annual Symposium on User Interface Software and Technology* (Tokyo, Japan) *(UIST '16)*. Association for Computing Machinery, New York, NY, USA, 321–333. https://doi.org/10.1145/2984511.2984582

[6] Antwane Lewis, Yanyan Li, and Mengjun Xie. 2016. Real time motion-based authentication for smartwatch. In *2016 IEEE Conference on Communications and Network Security (CNS)*. 380–381. https://doi.org/10.1109/CNS.2016.7860521

[7] Jonathan Liebers and Stefan Schneegass. 2020. Introducing Functional Biometrics: Using Body-Reflections as a Novel Class of Biometric Authentication Systems. *Extended Abstracts of the 2020 CHI Conference on Human Factors in Computing Systems* (2020), 1–7. https://doi.org/10.1145/3334480.3383059

[8] Isao Nakanishi and Yuuta Sodani. 2010. SVM-Based Biometric Authentication Using Intra-Body Propagation Signals. In *2010 7th IEEE International Conference on Advanced Video and Signal Based Surveillance*. 561–566. https://doi.org/10.1109/AVSS.2010.12

[9] Sabine Reinfeldt, Bo Håkansson, Hamidreza Taghavi, and Måns Eeg-Olofsson. 2015. New developments in bone-conduction hearing implants: a review. *Medical Devices (Auckland, NZ)* 8 (2015), 79. https://doi.org/10.2147%2FMDER.S39691

[10] Nirupam Roy and Romit Roy Choudhury. 2016. Ripple II: Faster Communication through Physical Vibration. In *13th USENIX Symposium on Networked Systems Design and Implementation (NSDI 16)*. USENIX Association, Santa Clara, CA, 671–684. https://dl.acm.org/doi/10.5555/2930611.2930655

[11] Stefan Schneegass, Youssef Oualil, and Andreas Bulling. 2016. SkullConduct. *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems* (2016), 1379–1384. https://doi.org/10.1145/2858036.2858152

[12] Sandeep Singh Sengar, U. Hariharan, and K. Rajkumar. 2020. Multimodal Biometric Authentication System using Deep Learning Method. In *2020 International Conference on Emerging Smart Computing and Informatics (ESCI)*. 309–312. https://doi.org/10.1109/ESCI48226.2020.9167512

[13] Stefan Stenfelt. 2011. Acoustic and physiologic aspects of bone conduction hearing. *Implantable bone conduction hearing aids* 71 (2011), 10–21. https://doi.org/10.1159/000323574

[14] J Tonndorf. 1976. Bone conduction. In *Auditory system*. Springer, 37–84. https://doi.org/10.1007/978-3-642-66082-5_2

[15] Jessica Velasco, Edmon Fernandez, Gerald Joseph Adiao, Ericka Bianca Alarilla, Patrick Charles Luwell Cano, Ma De Lara, Joseph Christian Grande, Jermaine Nuevo, Ira Valenzuela, Lean Karlo Tolentino, et al. 2019. User Authentication for Computer Security Based on Sound-to-Feature Algorithm and Artificial Neural Network Using Bone Conduction. *Lecture Notes on Research and Innovation in Computer Engineering and Computer Sciences* (2019). https://doi.org/10.2139/ssrn.3626988

[16] Dan Yang, Bin Xu, Xu Wang, and Xueqin Jia. 2006. The study of digital ultrasonic bone conduction hearing device. In *2005 IEEE Engineering in Medicine and Biology 27th Annual Conference*. IEEE, 1893–1896. https://doi.org/10.4028/www.scientific.net/AMR.1030-1032.2330

[17] Lin Yang, Wei Wang, and Qian Zhang. 2016. VibID: User identification through bio-vibrometry. In *2016 15th ACM/IEEE International Conference on Information Processing in Sensor Networks (IPSN)*. IEEE, 1–12. https://doi.org/10.1109/IPSN.2016.7460725

[18] Koya Yoshikawa, Wataru Kitagawa, Takaharu Takeshita, Akihiro masuda, Masahiro Nakashima, Akiko Nakatani, and Hidenori Nakatani. 2015. Improvement Efficiency and Miniaturization of Bone Conduction Speaker. *Journal of the Japan Society of Applied Electromagnetics and Mechanics* 23, 3 (2015), 474–479. https://doi.org/10.14243/jsaem.23.474

[19] Lin Zhong, Dania El-Daye, Brett Kaufman, Nick Tobaoda, Tamer Mohamed, and Michael Liebschner. 2007. OsteoConduct: Wireless body-area communication based on bone conduction. In *Proceedings of the ICST 2nd international conference on Body area networks*. 1–8. https://doi.org/10.4108/bodynets.2007.181