WristConduct: Biometric User Authentication Using Bone Conduction at the Wrist

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ABSTRACT

Biometric user authentication is an important factor to ensure security and privacy for personal devices. While many devices such as smartphones or laptops can be unlocked based on biometric data, smartwatches or other wrist-worn mobile devices still rely on knowledge-based schemes such as PINs or passwords. In a proof-of-concept study with 24 participants, we show that it is possible to identify individuals using sound waves passing through the wrist bones using a bone conduction speaker and a laryngophone (microphone). We tested support vector machines (SVMs) and artificial neural networks (ANNs) for binary classification. Using ANNs our method shows an authentication accuracy of 98.7%. We discuss the implications of integrating our approach into future devices and contribute with our findings in doing the first step for continuous passive user authentication at the wrist.

CCS CONCEPTS

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

KEYWORDS

User authentication, biometrics, wrist-worn device, bone conduction, machine learning

ACM Reference Format:
Jessica Sehrt, Feng Yi Lu, Leonard Husske, Anton Roesler, and Valentin Schwind. 2022. WristConduct: Biometric User Authentication Using Bone Conduction at the Wrist. In *Mensch und Computer 2022 (MuC '22), September 4–7, 2022, Darmstadt, Germany*. ACM, New York, NY, USA, 5 pages. https://doi.org/10.1145/3543758.3547542

MuC '22, September 4–7, 2022, Darmstadt, Germany

ACM ISBN 978-1-4503-9690-5/22/09…$15.00
https://doi.org/10.1145/3543758.3547542

1 INTRODUCTION & BACKGROUND

User authentication for pervasive computing devices is important to secure personal data and access. In addition to knowledge-based schemes such as passwords, gestures [10], and personal identification numbers (PINs), some devices use biometric data such as fingerprints [14], bodily [6] or facial characteristics [5] to authorize access for users. Most of current handheld devices allow access per user session using biometric data with an active input as one-time authentication. Repeatedly or continuous checking the user for device access can massively restrict the device interaction when frequently asking to manually enter the PIN, to perform a gesture, or to constantly keep the face upright to the front camera. However, wrist-worn devices with limited displays for user input, while poorly suited for knowledge-based input, can be worn continuously and passively collect functional biometric data [2, 13, 25].

Functional biometrics considers the human body as a function f in which a device sends a continuous signal x which is reflected by the body in an unique way. The reflection $f(x)$ can be read by a receiver and be used for authentication of the user [15]. Passive functional biometrics can result in a higher security compared to active authentication methods, where the user has e.g., to enter a PIN or password [11]. For example, Khorshid et al. show that a high authentication accuracy can be achieved by sending signals from electrodes on the arm through intrabody communication channels [7]. Other research utilizes vein patterns using thermal imaging [4] or vibration response patterns on the human body such as the system VibID [27]. However, a very promising and easy-to-implement approach with high abundance is the principle of bone conduction [18, 24].

Bones can be characterized using acoustic waves propagating through the bone tissue. Their properties can even be determined by speed-of-sound measurements [23]. Bone conduction can be used, for example, to transmit sound waves to the cochlea causing an improved sound perception for people hard of hearing [12]. Therefore, the use of bone conduction is widely used in technologies for hearing aids, which are placed at the outer or inner part of the ear [21, 22]. Main working principle of those devices is using analog acoustic signals within the audible range. Also the skull transmits a range of sound waves from the outer ear to the inner ear without significantly changing the intrinsic signal [26]. The effectiveness

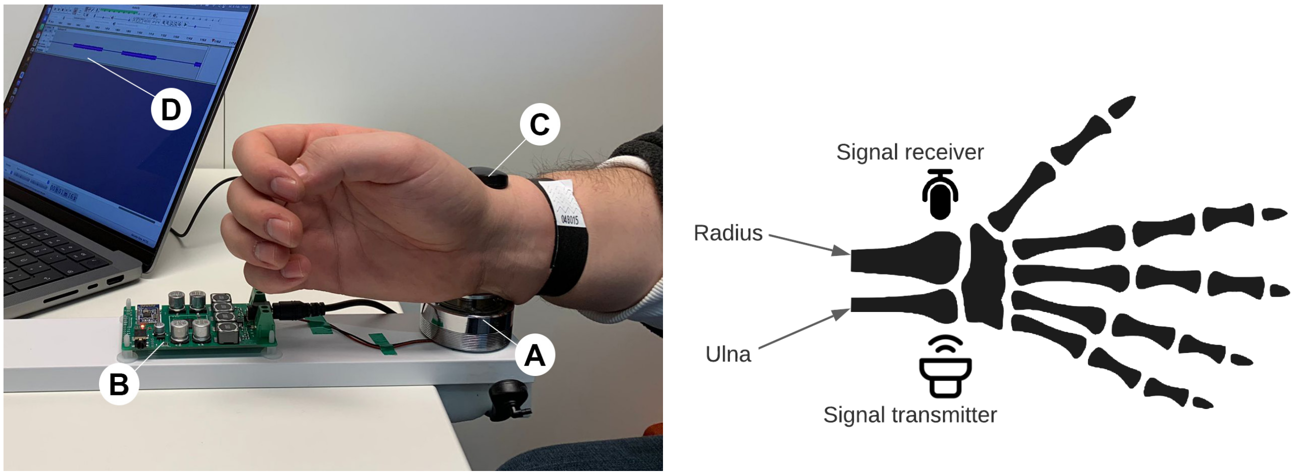

Figure 1: Photo and concept illustration of *WristConduct*. The vibration speaker (A) is transmitting sound waves from an amplifier (B) into the bone tissue of the ulna bone. A laryngophone (C) was used as signal receiver and placed on the top of the radius bone. Sound waves have been recorded and later classified using a personal computer (D).

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 [22].

Previous work successfully demonstrates the utilization of bone conduction with wearable mobile devices on different body parts [8, 17, 18, 29]. For example, ViBand [8] and OsteoConduct [29] are two systems that use bone conduction for communication between devices. While OsteoConduct measures the reflected frequency on the elbow joint, ViBand measures sound directly on the wrist for passive object and activity recognition. Based on these paradigms, Roy and Choudhury, for example, implemented a system that allows users of smartphones to communicate with a ring or a watch by using bone conduction [17]. More related to our research, Schneegass et al. developed "SkullConduct" that authenticates users based on the biometric properties of their skull [18]. The device uses the integrated bone conduction speaker of a Google glass device near the ear that sends white noise in a specific frequency that gets recorded by a microphone in the front of the eyewear. Velasco et al. took up the idea and suggest a general machine-learning based user authentication algorithm for sound classification of bone conduction without committing to a specific device [24]. However, it is currently unknown if bone conduction directly at the wrist (between ulna and radius, see Figure 1) is able to authenticate or identify individual persons.

In line with previous research suggesting that sound signals sent through bone tissue can have a high authentication accuracy because of the uniqueness of the human body structure [7, 11], we investigated the general feasibility of a proof-of-concept bone conduction system placed at the wrist to identify and authenticate individual subjects. Similar to previous work that uses unique reflected frequencies and the principle of bone conduction at the skull for unlocking head-mounted displays [18], we use bone conduction at the wrist to provide fast and reliable biometric authentication for potential wrist-worn devices such as smartwatches and fitness bands. Using machine learning trained classification we are able to 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. Thus, we conducted a pilot study with 24 subjects and our prototype to test the robustness of the approach. With neural networks, we were able to achieve an average model accuracy of overall 99.1 % and a false negative rate of 0.07 %. We contribute with our findings and discuss further approaches that can also be used for passive and continuous user authentication for wrist-worn mobile devices.

2 SYSTEM & EVALUATION

To investigate the feasibility of sound propagation using bone conduction at the wrist, we developed a proof-of-concept hardware prototype and a software classification system using neural networks. Hardware prototype and concept are shown in Figure 1. As current devices off-the-shelf mobile devices (e.g., smartwatch or fitness tracker) only use air and no bone conducting speaker or contact microphones (c.f. [18]). Thus, our hardware consisted of an AIYIMA 2 inch 25W resonance vibration speaker (TPA3118) with a 12V/5A power amplifier and a laryngophone – a contact microphone for Yaesu Vertex VX and throat-based push-to-talk devices. The laryngophone was used as signal receiver and placed on top of the radius bone at the right wrist of the subject's arm. The bone conduction speaker was placed on the bottom side of the wrist at the ulna bone. Sound has been recorded with a personal computer. A three seconds uncompressed white noise sound sequence ranging from 0 to 44100 Hz with 16 bit/s was used as audio signal for the transmitter.

Sound propagation of 24 computer science students (19 m, 5 f) within our institution were recruited in the context of our course and compensated with credit points for the lecture. The participant's age ranged from 20 to 27 (M = 23.15 SD = 2.83). The experiment took place in our laboratory (a closed office environment)

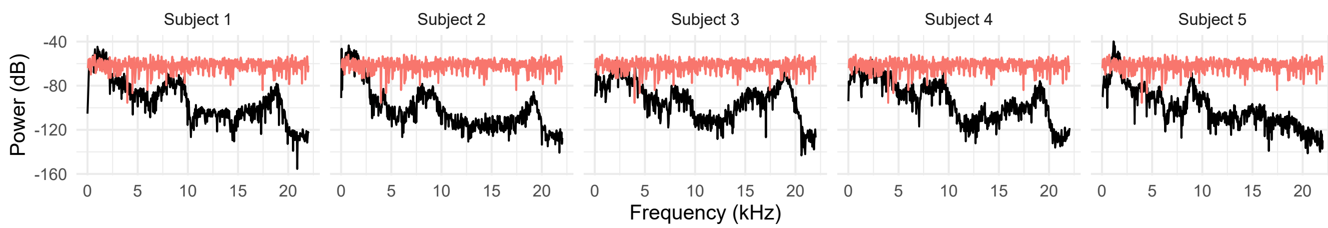

Figure 2: The power density (in dB) indicating the sound damping between the wrist bones for one of the ten recordings among 5 random subjects in the range of 0 kHz to 25 kHz (black line). White noise sound between resonance speaker and contact microphone (without wrist) is indicated by the red line.

with low background noise. After providing informed consent participants were asked to rest their right hand on the speaker (see Figure 1, A) to ensure body contact with the device and to keep their hand in a relaxed state. The position of the receiver was slightly changed after each recording to avoid any bias or over-optimization for one specific location at the wrist. Ten recordings were taken for each subject. One of the recordings of each subject compared to the original white noise are shown in Figure 2. In total, we recorded 240 labeled audio files. Acoustic recordings had a 41,000 Hz sample rate and 16 bit/s without any file compression.

Main objective is a model that can authenticate a single specific person and reject all extraneous persons. 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 were 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, however with a random selection of 92 of the negative elements inserted. We divided each of the 120 data sets stratified into training (65%, N=78) and test (35%, N=42) data, each of which were used to train and evaluate a dedicated model. The Mel Frequency Cepstral Coefficient was used to extract features from the recordings and create a numerical data set.

In a first step, we tested two common types of binary classifiers provided by the Keras API by Google's TensorFlow with different levels of complexity: (1) low classification complexity: A support vector machine (SVM) with stochastic gradient descent (SGD) using weighted classes with and with a higher complexity (2) an artificial neural network (ANN) with six dense layers, binary cross entropy loss, and adam optimizer (200 epochs).

3 RESULTS

To consider the performance of the total 120 ANN models, we determined the confusion matrix for the tests. Aggregated results are shown in Table 1. More scores of classification refer to the sum or to the respective means of the model classes. The accuracy of the SVM initially appears to be similar fashioned with at 97.1 %, but the F1 score of 87.0 % and a MCC of 85.4 % revealed a small drawback of using SVMs with unbalanced data sets. With the ANN models, we were able to achieve an average accuracy of 98.7 %, a F1-Score of 94.4 % and a Matthew Correlation Coefficient (MCC) – a superior metric in binary classification evaluation [3] – of 94.6 %.

The ANN models achieved a sensitivity of 96.1 %. Consequently, the false negative rate is 3.9 %. Figure 3 shows the accuracy rates for each of the models. Even more important in such a system, however, is that extraneous persons are classified as negative. The ANN model achieves a specificity of 99.3 %. Thus, the false positive rate is 0.7 % and less than one percent.
The receiver operating characteristic (ROC) as shown in Figure 4 confirms these results. It indicates 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 99.0 % (±.07) for the ANN.

Although we get slightly better results using the ANN model, it is important to mention the efficacy of the SVM classification. Though the quality of the ANN model is better, but the calculation of ANNs can be computationally much more expensive. Using a wearable device with small computing powers, a model with less complexity, such as an SVM can be a suitable option, in particular for passive and even continuous authentication with limited options for energy consumption.

4 DISCUSSION

In a proof-of-concept study with 24 subjects, we tested the general feasibility of using bone conduction at the wrist to authenticate users with our *WristConduct* system prototype. We tested SVMs and ANNs as binary classifiers and found the best accuracy using

Table 1: Confusion matrices of the test outcomes of *WristConduct* for the support vector machines (SVM) and artificial neural networks (ANNs) with the corresponding false negative and false positive rate (FNR/FPR) and other performance measures.

		SVMs			ANNs		
		True	False	FNR/FPR	True	False	FNR/FPR
Predicted	Neg.	3841	42	8.57 %	3867	19	3.88 %
	Pos.	448	54	1.39 %	471	28	0.72 %
Sensitivity			91.4 %			96.1 %	
Specificity			98.6 %			99.3 %	
Accuracy			97.8 %			98.9 %	
F1-Score			90.3 %			95.2 %	
MCC			89.1 %			94.6 %	

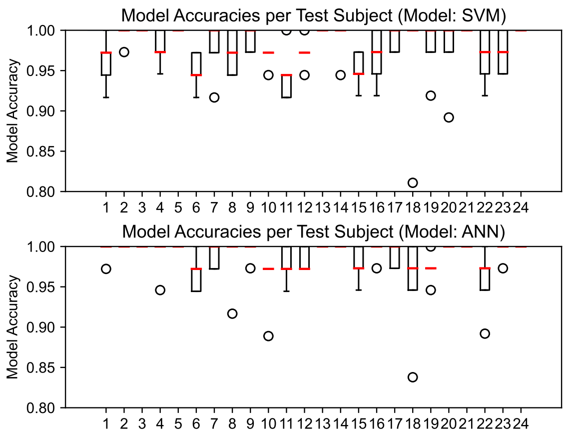

Figure 3: Average SVM and ANN accuracy rates for each of the models (5) that were trained for each subject.

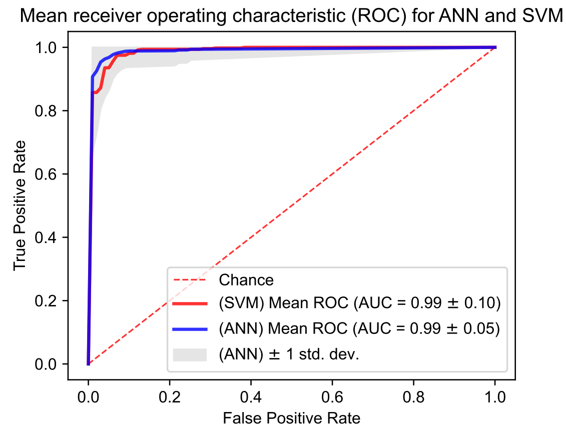

Figure 4: ROC curve for both model types (SVMs and ANNs). The lines represent the mean of the 120 models respectively.

ANNs (98.9 %), which achieved a specificity of 99.3 %. With a false positive rate of less than one percent (0.7 %), our approach shows one of the highest classification performance rates compared to solutions from the literature. For example, the scores indicate a better classification performance compared to the related work with an ANN (97.0 % accuracy and 3 % false positives) [18] or VibID (91 % accuracy and 9 % false positives) [27]. Thus, the evaluation shows that even with simple and cheap hardware as well as common software classification, bone conduction at the wrist can be a promising method of user classification and authentication.

Our data collection took place in a controlled and calm environment with low background noise and a static apparatus. Using a bone conduction speaker with 25 W, the hardware was likely to be more powerful than it might have been necessary for classifying the audio data. Our research indicates that there is a potential for miniaturization and optimization to integrate the hardware into a portable device. Testing bone conduction with high ecological validity in a more realistic setting requires to build a wearable bone conduction authentication band with a smaller bone conduction speaker and receiver microphone. Such bone conduction speakers are already in use for communication systems, language development approaches, mitigation of stuttering, acoustic investigations and medical applications [16]. We are sure that there are possibilities to further miniaturize the speakers and microphone while improving their efficiency [28].

Another aspect of using bone conduction is the white noise pattern, in which frequencies can be optimized based on the characteristics of the human body. As we covered our device's audio range generously, we highly recommend optimizing the apparatus and white noise for those audio characteristics. It may be possible to develop such as band operating at inaudible frequencies so that bystanders or the wearer do not hear the noise. Related to that factor is that the classification accuracy is based on the duration of the white noise sequence. As the work by Schneegass et al. indicates, more than five seconds do not contribute to a significantly better audio classification performance [18]. Based on their results, we chose a short duration, however, the results may differ with other hardware and can be optimized for continuous and passive usage. Based on the moment when sensing the signal is distracting or unpleasant for the user or potential bystanders the wearable can have a low social acceptability (c.f. [19]). Probably with emitting low-frequency sound waves there is the possibility of conducting sound over the bones without users noticing the sound. We see the greatest potential for improvement here and hope for further research (c.f. [1, 25]).

In our study, we only implemented a stationary device due to lacking hardware alternatives during the fast prototyping process. Further, our approach has only been evaluated in a single experimental session, however, future studies in repeated sessions (e.g., at different days) are required to test and further improve the robustness of the approach and the validity of the classification accuracy. For testing the ecological validity of the approach, we also recommend to test the approach in a smaller device and different in settings with acoustic backgrounds or environmental noise. More factors that can influence the quality of the authentication are the exact location of the speaker and the microphone on the wrist, the audio volume, and pattern frequency.

Based on our results, we highly recommend to consider bone conduction as a biometric measure not only for improved security but also for improved accessibility of wearable devices and multiple factor authentication. We recommend to further test the approach at different sound settings and in multi-session designs (e.g., across multiple days). Of course, we assume that there are potentially more sophisticated deep-learning algorithms to detect sound waves transmitted to bones. Thus, we recommend for future research to investigate and optimize that factors and further increase the accuracy of the system using more sophisticated ANNs and additional input vectors to reduce the classification error (cf. [9, 20]). To allow other researchers to replicate and extend our findings, we published our software and the full dataset at Github[1]

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

5 CONCLUSION

In a proof-of-concept study with 24 participants, we show the feasibility to identify human users using propagating soundwaves passing through bone tissue of the wrist using simple bone conduction speaker and a laryngophone (the receiver microphone) with high accuracy. We tested support vector machines (SVMs) and artificial neural networks (ANNs) as common means for binary classification. Using ANNs our method shows an authentication accuracy of 98.7% and a false positive rate of 0.7 %. We direct future work to further explore the possibilities of wrist-based bone conduction for passive and continuous user authentication for mobile and wearable devices.

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