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Soft Wearable Patch for Continuous Cardiac Biometric Security †

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Abstract: Recent studies show the possibility of using the sound information of an individual as the basis of a biometric security system. This paper introduces a soft wearable system that includes a miniaturized microphone and a wireless circuit for real-time, continuous detection and transmission of sounds measured on the chest. The skin-wearable patch that is non-invasive, flexible, and skin-friendly measures high-quality cardiac sounds to gather personalized biometric data. Convolutional neural network-based machine learning provides a real-time classification of detected sounds for biometric-based recognition of specific people. Creating such an identification key particular to an individual is markedly easier and more effective than the existing biometric systems currently in use because of its consistency and ability to be used continuously.

Keywords: cardiac monitoring; biometric security; soft; wearable patch

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1. Introduction

The cardiovascular system supervises a large number of the major body systems and provides crucial signals for body medicine. The heart provides sound data: the first heart sound (S1), indicating the closure of mitral and tricuspid valves, and the second heart sound (S2), representing the closure of the aortic and pulmonary valves [1]. These sounds reflect important information, especially the mechanical activities of the heart. When heart valves open and close, due to the blood turbulence in the valves, there are not only sounds coming from the heart itself, but also mechanical vibrations on the chest wall. Collecting such sounds and analyzing them are well-practiced techniques conducted by medical professionals for monitoring these body systems, called auscultation [2], using the collecting chest wall vibrations in what is called phonocardiography (PCG).

The idea of heart sound as a source of biometric information was first introduced by Beritelli and Spadaccini, who use chirp-z transform (CZT) to extract various features, as well as the Euclidean distance (ED), for the biometric classification of heart sounds [3]. The overall security level depends on using various feature extraction techniques and classification networks, and will result in collecting information that includes the speed of the recognition, correct recognition rate (CRR), which is the accuracy of the classification, and finally, the kappa coefficient, which measures inter-rater reliability for qualitative items, such as the biometric system, in this application [4]. Other biometrics have been used in the past in their biometric locking system with a good amount of success, but each of them has its flaws. These biometrics include facial recognition, iris scanning, retina scanning, fingerprint identification, voice recognition, hand geometry detection, and others [5]. The cons of these biometric keys can be assessed according to the following categories: susceptibility, replicability, danger in use, and the invasiveness of continuous scanning. Table 1 shows the approximate error rate, replicability, permanence, and the sensor types of the various biometrics used, as well as the cost for each sensor [6]. As shown in the table, heart biometric information has the lowest cost with the highest permanence and, most importantly, it is the only biometric that enables continuous verification for the users, offering a reliable biometric for human identification based on vulnerability, acceptability, usability, and uniqueness [7].

Table 1. Summary of various biometrics with their error rates [6], permanence, sensor type, and cost of each sensor.

Biometric	Continuous Verification	Estimated Error Rate	Replicability	Permanence *	Sensor Type	Cost
This Work (Heart)	Yes	1.7%	No	4	MEMS microphone	Low (<USD 5)
Fingerprint	No	5.0%	Yes	3	Optical, ultrasound, and multispectral image	Medium (>USD 50)
Signature Recognition	No	2.0%	Yes	1	Digitizing tablets using electromagnetic transduction	Medium (>USD 100)
Hand Geometry	No	0.2%	Yes	3	CCD (charge-coupled device) camera	High (>USD 1000)
Face Geometry	No	Not Specified	Yes	3	High-resolution cameras, thermal sensors	High (>1000)
Voice Recognition	No	2.0%	Yes	2	Acoustic sensors (microphones), non-acoustic sensors (electromagnetic motion sensor)	Medium (>USD 50)
Ear Shape	No	Not Specified	Yes	3	High-resolution camera and 3D imaging	Not Specified
Retina	No	0.00001%	Yes	4	Scanner using infrared light	High (>USD 1000)
Iris	No	0.0008%	Yes	4	Basic camera using infrared light	Medium (>USD 100)
Palm Veins	No	0.88%	Yes	3	Infrared light	Medium (>USD 200)

* 5—Does not change for a lifetime, 4—Could be changed due to environment, disease, or uncontrollable factors, 3—Could be changed manually, 2—High possibility of change, 1—Could be changed frequently.

This paper focuses on the continuous biometric characteristics of the S1 and S2 peak signals of heart sounds from the auscultation using a microelectromechanical (MEMS) microphone, which uses a small silicon membrane on the backplate inside the chip that converts vibrations from the sound pressure entering the microphone hole to the capacitance or voltage, depending on the interface circuit structure [2]. The device integrated with the microphone chip operates on a flexible printed circuit board (PCB) that is made of flexible polyimide with copper traces in between. The bio-compatible silicone encapsulation on the entire board, in combination with the battery, makes the continuous cardiac biometric (CCB) patch as a continuous biometric security system.

2. Materials and Methods

2.1. Proposed Continuous Cardiac Biometric System

The application of any device begins with the device itself— understanding its mechanics, specifications, fabrication, and its range of abilities will enable a deeper understanding of why the biometric security system application of the CCB patch will function better than other digital microphones in the market. Figure 1a shows the flexible board itself, which is rectangular, with a MEMS microphone hole on the back to gather sound. Nano-circuitry is placed on the top layer of the board, including the microchips, such as the Bluetooth-low-energy (BLE) microcontroller unit, analog-to-digital converter (ADC), pre-amplifier, and the microphone. The analog signal acquired from the MEMS microphone travels through the pre-amplifier to increase the gain and filter out in the first-stage lower and higher cut-off frequencies. It then moves to the ADC, becoming converted to a digital signal to feed the BLE microcontroller and send data wirelessly via Bluetooth to mobile devices.

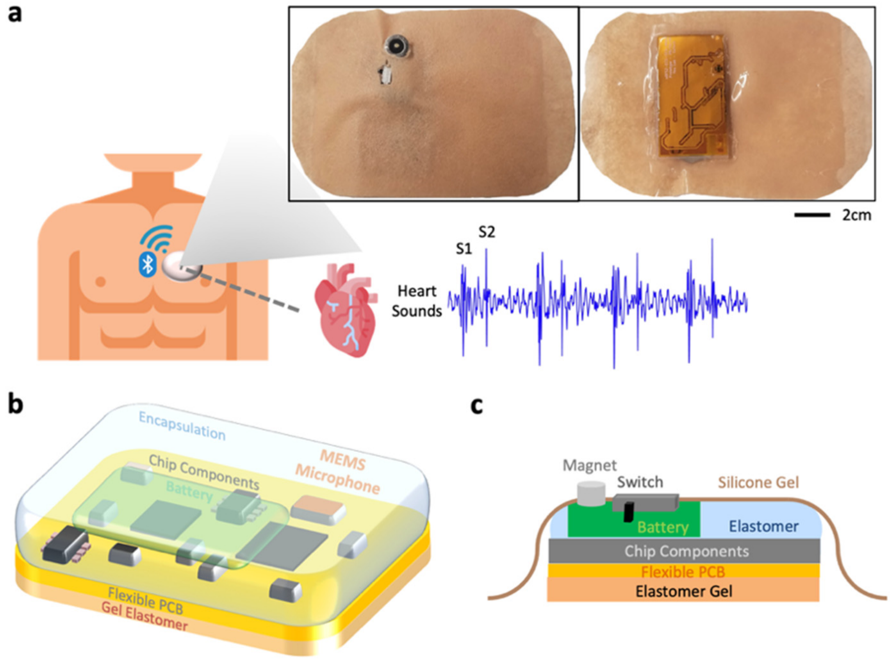

Figure 1. System Overview. (**a**) Summary of a wearable patch on the chest collecting heart sounds, (**b**) 3D view of the device with components, and (**c**) 2D side-view representation of the device.

Beyond the actual circuitry of the device, there are other aspects of it that aid in data collection and purity. The silicone elastomer encasement plays a massive role in deflecting unwanted sound waves. The base layer of silicone is a sticky, cohesive layer on the underside of the board that keeps the entire body of the board attached to the skin. The middle layer of the elastomer encases the circuitry on top of the board to prevent excess external vibrations. The final layer of silicone gel acts similar to a reusable adhesive that is cured onto a band-aid-like fabric and placed over the top of the microphone island section of the board. All the layers are shown in Figure 1b,c to aid the understanding of the entire device. This final silicone gel adhesive allows clothes to move freely over the top of the device with no interference from the device itself, and allows for an extreme ambulatory nature. The CCB patch attaches itself to the skin so well that in daily movement, unwanted sound waves, often denoted as interference or noise, are minimized. This is because the small and discreet device flexes and bends with the body. All these details about the mechanics of the device allow it to be accurate, efficient, subtle, and simple. This makes medical applications obvious—its ambulatory nature and ability to record continuously and remotely, despite being in such a small package, is its claim to fame.

2.2. Signal Processing and Feature Extraction

The integrated design, with the individuality of a heart sound, functions as the biometric key, with the CCB patch taking in the heart sounds and transmitting that information to a mobile device connected via Bluetooth. Leveraging the optimized two-stage signal processing, which involves a band-pass filter and a zero-phase filter, the heart sounds collected by several different people can have a distinct pattern. Since the heart sound ranges from 20 Hz to 200 Hz, the first-stage bandpass filter was designed to cut off the raw signal using a low-pass and a high-pass filter, and feed the signal into the zero-phase filter stage. A zero-phase filter is a linear phase filter with a phase slope, $\alpha = 0$. Every filter has its own impulse response, and its real impulse response is even. Even means that the signal is symmetric around 0 in terms of the time segments of a signal.

There are some causal filters, meaning the impulse response is 0 before the time is 0, but for zero-phase, it cannot be causal. Yet, in this application of processing sound signals, since the waveform audio file format (WAV) outputted from the CCB patch is in stereo, multiple signals from multiple channels contribute to the output; hence, causality is not a requirement. Finally, the frequency response for the zero-phase filter is $H(e^{j\omega t})$, which is a real and even function of radian frequency ω, and needs to be larger than 0 in the filter passband to be a zero-phase filter [8]. This is especially important in the biometric system for heart sounds because a lot of noise contributes to the signal, and unwanted peaks in noise could disrupt the CRR of the biometric information. For the signal to be cleaner and discreet, and for more accurate biometric information in a continuous monitoring environment, motion artifacts and noise should be eliminated through the pass and attenuation of the wanted frequency along with phase filtering. As shown in Figure 2a, the Kaiser window was used in the zero-phase filter for a better sidelobe amplitude at the same approximation error with lowpass FIR to minimize the round of noise error with the best stability and simplicity as possible.

After the two-stage filtering using bandpass and zero-phase filters, the filtered signals would then be preprocessed with labels indicating each participant's S1 and S2 heart sound peaks and fed into a machine learning program using a convolutional neural network where a profile of an individual's heart sound would be created. After several samples, the machine will have made a profile against which to compare future incoming signals to. If the incoming signal matches that of a profile in the database, the system would respond appropriately and, conversely, would also appropriately respond to a mismatch.

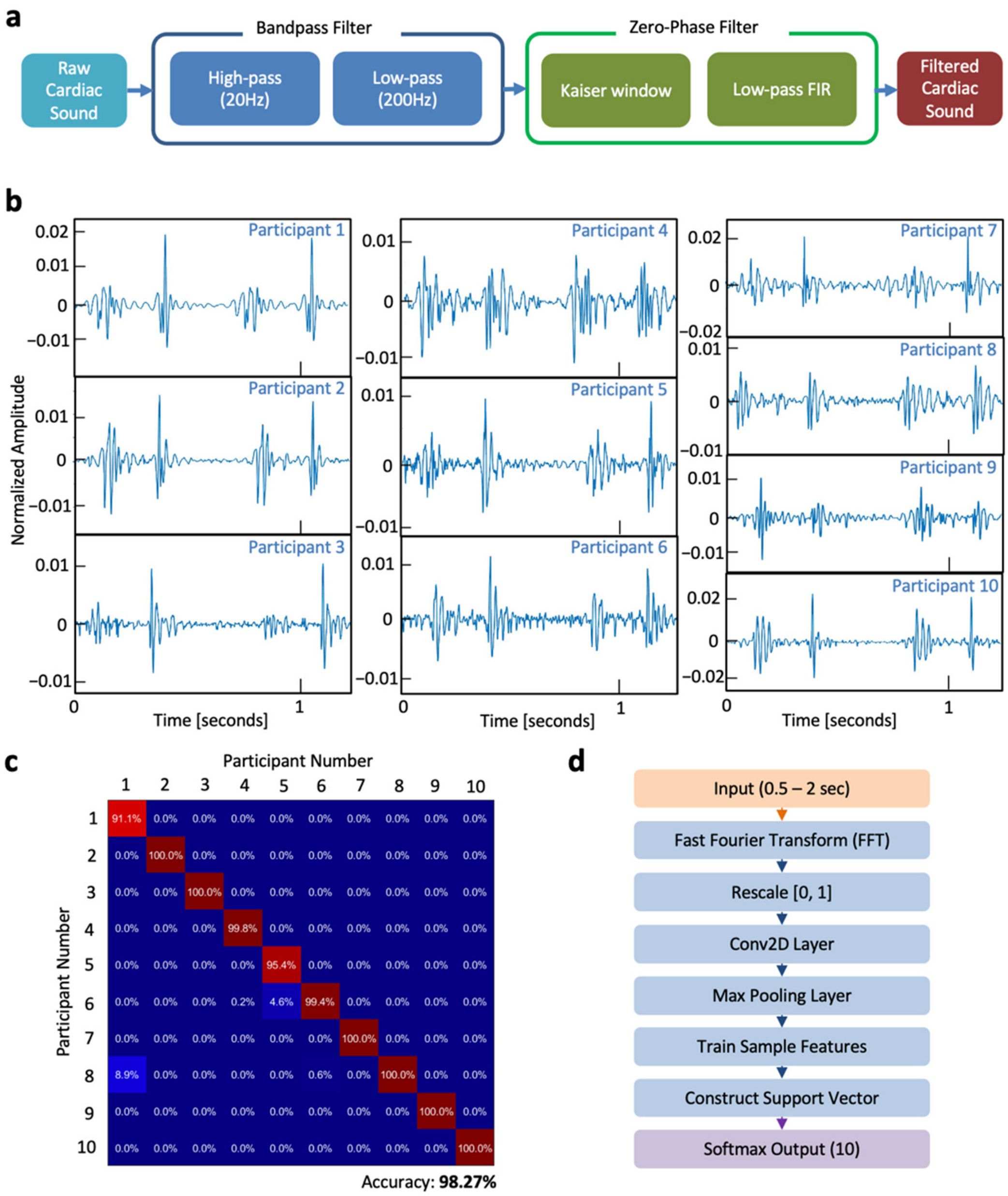

Figure 2. Feature extraction and the machine learning basis of the system. (**a**) Flow chart of the feature extraction process using two-stage filtering, (**b**) filtered sound plots for each participant, (**c**) confusion matrix of heart sound classification, and (**d**) flow chart of the machine learning model.

3. Results and Discussion

For each participant, the CCB patch was placed on Erb's point in auscultation, which is approximately the center of the heart [9]. After collecting a minute of heart sounds for each patient via Bluetooth using a mobile device, the autosaved recordings in comma-separated value (CSV) files were fed into the two-stage filtering MATLAB code. Figure 2b shows each participant's heart sound data after filtering. Each amplitude and waveform was different, along with the time differences between each S1 and S2 peak due to the various heart rates of participants. These extracted features would then be labeled.

Leveraging the preprocessing code to label each S1 and S2 peak of each participant, the labeled CSV files were fed into the convolutional neural network (CNN)-based machine learning for classification to train the model to recognize each participant's heart sound waves, given that they have distinct patterns and shapes for each S1 and S2 pair segment in the time series. Since the average beats per minute of the participants were around

60 beats per minute, 60 samples were fed through the algorithm for each participant's class. Figure 2c shows the confusion matrix of each participant's distinct waveform trained in the model to show that the machine indeed identifies each participant's heart sounds. As shown in Figure 2d, several series of layers in the machine learning model were used.

As shown from the accuracy, or CRR, of the proposed biometric, which was 98.3%, the heart sounds biometric is a solution to nearly all these problems, even though it has an error rate of 1.7% and has room for improvement where it can reach towards the error rate of the retina/iris biometric systems. However, the proposed heart biometric system exceeded the approximate error rate of fingerprint, signature, and voice recognition [6]. There is a very low possibility of a change in heart sound for an individual over a sampled period. Heart sounds are nearly impossible to forge, unless someone had the ability to clone a heart that was the same as another individual's and place it inside of a chest cavity that would reverberate the exact same way. There is also no danger in the use of the device. The largest and most obvious advantage is the ability to continuously monitor the heart sound of an individual for continuous identification across multiple levels of security. The idea is to eliminate the need to re-scan at every access point where another biometric system would require yet another scan. The CCB patch is an efficient, adaptable, discreet, and accurate piece of technology designed for analyzing the biometric sounds of the body, specifically the heart.

4. Conclusions and Outlook

In this work, a biometric system based on cardiac sounds is developed using a wearable patch offering a continuous security system for the users. Heart sounds from 10 participants were collected using the device, and after going through the two-stage filtering, unique waveforms were achieved for individuals with the CNN-based machine learning model. As a result, the accuracy of the CNN classifier is 98.3%. Using this classification, the model could be implemented in the real-time application for the CCB system when worn by users. Because of its cross-disciplinary abilities and novel technologies, the CCB patch has a high likelihood of outperforming other biometric systems for the purpose of a biometric security system.

Supplementary Materials: The poster presentation is available online at https://www.mdpi.com/article/10.3390/ecsa-8-11336/s1.

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Institutional Review Board Statement: The study was conducted according to the guidelines of the approved IRB protocol (H21038) from Georgia Tech. All subjects gave their informed consent.

Data Availability Statement: Deidentified participant data will be available from the corresponding author on formal request.

Conflicts of Interest: Georgia Tech has a pending U.S. patent application related to the work described here.

References

1. Li, S.; Li, F.; Tang, S.; Xiong, W. A Review of Computer-Aided Heart Sound Detection Techniques. *BioMed Res. Int.* **2020**, *2020*, 1–10. [CrossRef] [PubMed]
2. Lee, S.H.; Kim, Y.-S.; Yeo, W.-H. Advances in Microsensors and Wearable Bioelectronics for Digital Stethoscopes in Health Monitoring and Disease Diagnosis. *Adv. Healthc. Mater.* **2021**, *10*, 2101400. [CrossRef] [PubMed]
3. Beritelli, F.; Serrano, S. Biometric Identification Based on Frequency Analysis of Cardiac Sounds. *IEEE Trans. Inf. Forensics Secur.* **2007**, *2*, 596–604. [CrossRef]

4. Zhao, Z.; Shen, Q.; Ren, F. Heart Sound Biometric System Based on Marginal Spectrum Analysis. *Sensors* **2013**, *13*, 2530–2551. [CrossRef] [PubMed]
5. Ortega-Garcia, J.; Bigun, J.; Reynolds, D.; Gonzalez-Rodriguez, J. Authentication gets personal with biometrics. *IEEE Signal Process. Mag.* **2004**, *21*, 50–62. [CrossRef]
6. Young, C.S. Chapter 14-Physical Security Controls. In *Information Security Science*; Young, C.S., Ed.; Syngress: Oxford, UK, 2016; pp. 317–338.
7. Phua, K.; Chen, J.; Dat, T.H.; Shue, L. Heart sound as a biometric. *Pattern Recognit.* **2008**, *41*, 906–919. [CrossRef]
8. Humayun, A.I.; Ghaffarzadegan, S.; Feng, Z.; Hasan, T. Learning Front-end Filter-bank Parameters using Convolutional Neural Networks for Abnormal Heart Sound Detection. In Proceedings of the 2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Honolulu, HI, USA, 18–21 July 2018.
9. Kolb, F.; Spanke, J.; Winkelmann, A. Auf den Spuren des Erb'schen Auskultationspunkts: Rätsel gelöst. *DMW-Dtsch. Med. Wochenschr.* **2018**, *143*, 1852–1857. [CrossRef] [PubMed]