engineering proceedings

Proceeding Paper

Soft, Wearable, Digital Stethoscope for Continuous Cardiac Biometric Security †

Sung Hoon Lee [1,4], Yun-Soung Kim [2,4] and Woon-Hong Yeo [2,3,4,*]

[1] College of Electrical and Computer Engineering, Georgia Institute of Technology, Atlanta, GA 30332, USA; slee870@gatech.edu
[2] George W. Woodruff School of Mechanical Engineering, Institute for Electronics and Nanotechnology, Georgia Institute of Technology, Atlanta, GA 30332, USA
[3] Wallace H. Coulter Department of Biomedical Engineering and Parker H. Petit Institute for Bioengineering and Biosciences, Georgia Institute of Technology, Atlanta, GA 30332, USA
[4] Center for Human-Centric Interfaces and Engineering, Neural Engineering Center, Institute for Materials, and Institute for Robotics and Intelligent Machines, Georgia Institute of Technology, Atlanta, GA 30332, USA
* Correspondence: whyeo@gatech.edu; Tel.: +1-404-385-5710; Fax: +1-404-894-1658
† Presented at 8th International Electronic Conference on Sensors and Applications, 1–15 November 2021; Available online: https://ecsa-8.sciforum.net.

Abstract: The Continuous Cardiac Biometric (CCB) Patch is a non-invasive, discreet, and accurate device designed to gather biometric data from an individual's heart sounds. Despite having an obvious and effective medical application for continuous cardiopulmonary monitoring, further research has been conducted to shed light on another application of the device-the possibility of using the heart sound biometric of an individual as a type of biometric security system. Using the discreet and functional properties of the device, as well as CNN-based machine learning, creating an identification key that is specific to an individual is markedly easier and more effective than other biometric systems currently in use because of its consistency and ability to be used continuously.

Keywords: continuous monitoring; cardiac biometric; soft; flexible; wearable patch

Citation: Lee, S.H.; Kim, Y.-S.; Yeo, W.-H. Soft, Wearable, Digital Stethoscope for Continuous Cardiac Biometric Security. *Proceedings Paper* **2021**, *3*, x. https://doi.org/10.3390/xxxxx

Academic Editor(s):

Published: 01 November 2021

1. Introduction

The cardiovascular system supervises a huge part 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 by medical professionals for monitoring these body systems, called auscultation [2], using the collecting chest wall vibrations as what is called phonocardiography (PCG).

The idea of heart sound as a biometric was first introduced by Beritelli and Spadaccini where they use chirp-z transform (CZT) to extract features and Euclidean distance (ED) for classification of the biometric for heart sounds [3]. The overall security level depends on using various feature extraction techniques and classification networks, ending up with the speed of the recognition, correct recognition rate (CRR) which is the accuracy of the classification, and finally kappa coefficient which measures inter-rater reliability for qualitative items such as 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 with the following categories: susceptibility, replicability, danger in use, invasiveness of continuous scanning. Table 1 shows the approximate error rate, replicability, permanence, the sensor types of various biometrics use, and the cost for each sensor [6]. As shown in the table, heart biometric has the lowest cost with the highest permanence and most importantly, the only biometric which enables continuous verification for the users, offering a reliable biometric for human identification based on vulnerability, acceptability, usability, and uniqueness [7].

This paper focuses on the continuous biometric characteristics of 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 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. Bio-compatible silicone encapsulation on the entire board with the battery makes the CCB patch for a continuous biometric security system.

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

Biometric	Continuous Verification	Approx. Error Rate	Replicability	Permanence *	Sensor Type	Cost
This Work (Heart)	Yes	1.7%	No	4	MEMS microphone	Low (<$5)
Fingerprint	No	5.0 %	Yes	3	Optical, ultrasound, and multispectral image	Medium (>$50)
Signature Recognition	No	2.0%	Yes	1	Digitizing tablets using electromagnetic transduction	Medium (>$100)
Hand Geometry	No	0.2%	Yes	3	CCD (charge-coupled device) camera	High (>$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 (electromagnetic motion sensor)	Medium (>$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 (>$1000)
Iris	No	0.0008%	Yes	4	Basic camera using infrared light	Medium (>$100)
Palm Veins	No	0.88%	Yes	3	Infrared light	Medium (>$200)

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

2. Materials and Methods

2.1. Proposed Continuous Cardiac Biometric System

The application of any device begins with the device itself-its mechanics, specifications, fabrication, and range of abilities will enable a deeper understanding of why the biometric security system application of the CCB patch functions better than digital stethoscopes in the market. Figure 1a shows the flexible board itself, which is rectangular, with a MEMS microphone hole on the back to gather sound from. 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, gets converted to a digital signal to feed the BLE microcontroller to send data wirelessly via Bluetooth to mobile devices.

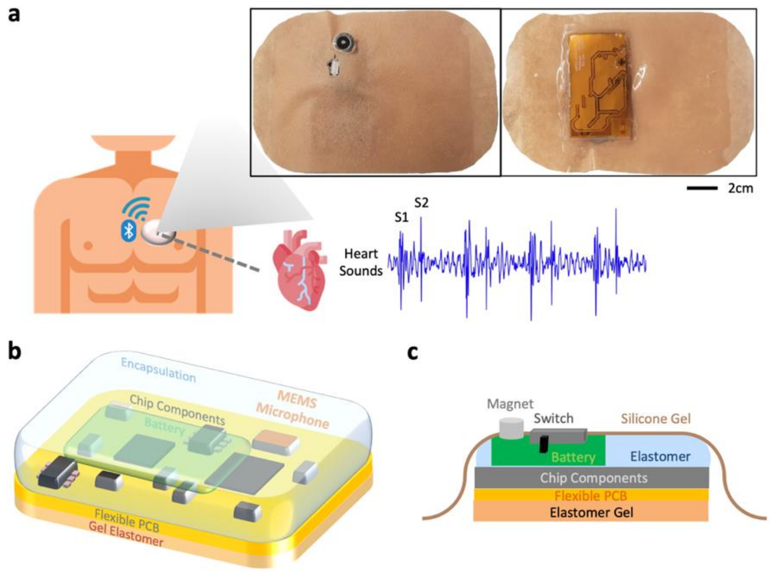

Figure 1. System Overview. (**a**) Summary of the soft, wearable, digital stethoscope on the chest collecting heart sounds, (**b**) 3D view of the device with layers and components, (**c**) 2D side view representation of the device.

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 layer acts more like 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 device flexes and bends with the body and is small and discreet enough. All these details about the mechanics of the device allow it to be accurate, efficient, subtle, and simple. This makes medical applications obvious-the ambulatory nature and ability to record in such a small package continuously and remotely is its claim to fame.

2.2. Signal Processing and Feature Extraction

The integrated design with the individuality of a heart sound sets up the biometric key, which the CCB patch would take in the heart sounds and transmit that information to a mobile device connected via Bluetooth. Leveraging on optimized two-stage signal processing involving a band-pass filter and a zero-phase filter, 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 low-pass and a high-pass filter and fed onto 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 about 0 in terms of time segments of a signal. There are some causal filters meaning the impulse response is 0 before time is 0, but for zero-phase, it cannot be causal. Yet, in this application of processing sound signals, since Waveform Audio File Format (WAV) outputted from the CCB patch is 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. For the signal to be cleaner and discreet for more accuracy in biometric in a continuous monitoring environment, motion artifacts and noise should be eliminated through pass and attenuation of the wanted frequency along with phase filtering. As shown in Figure 2a, Kaiser window was used in the zero-phase filter for better sidelobe amplitude at same approximation error with lowpass FIR to minimize round of noise error in 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 peaks of heart sound and fed into a machine learning program using 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 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.

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 waveforms were 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 next.

Leveraging on preprocessing code to label each S1 and S2 peaks of each participant, the labeled CSV files were fed into the CNN based machine learning for classification, to train the model that each participant's heart sound waves have distinct patterns and shapes for each S1 and S2 pair segment in time series. Since the average beats per minute of the participants were around 60 beats per minute, 60 samples were fed 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, series of layers in the machine learning model were used.

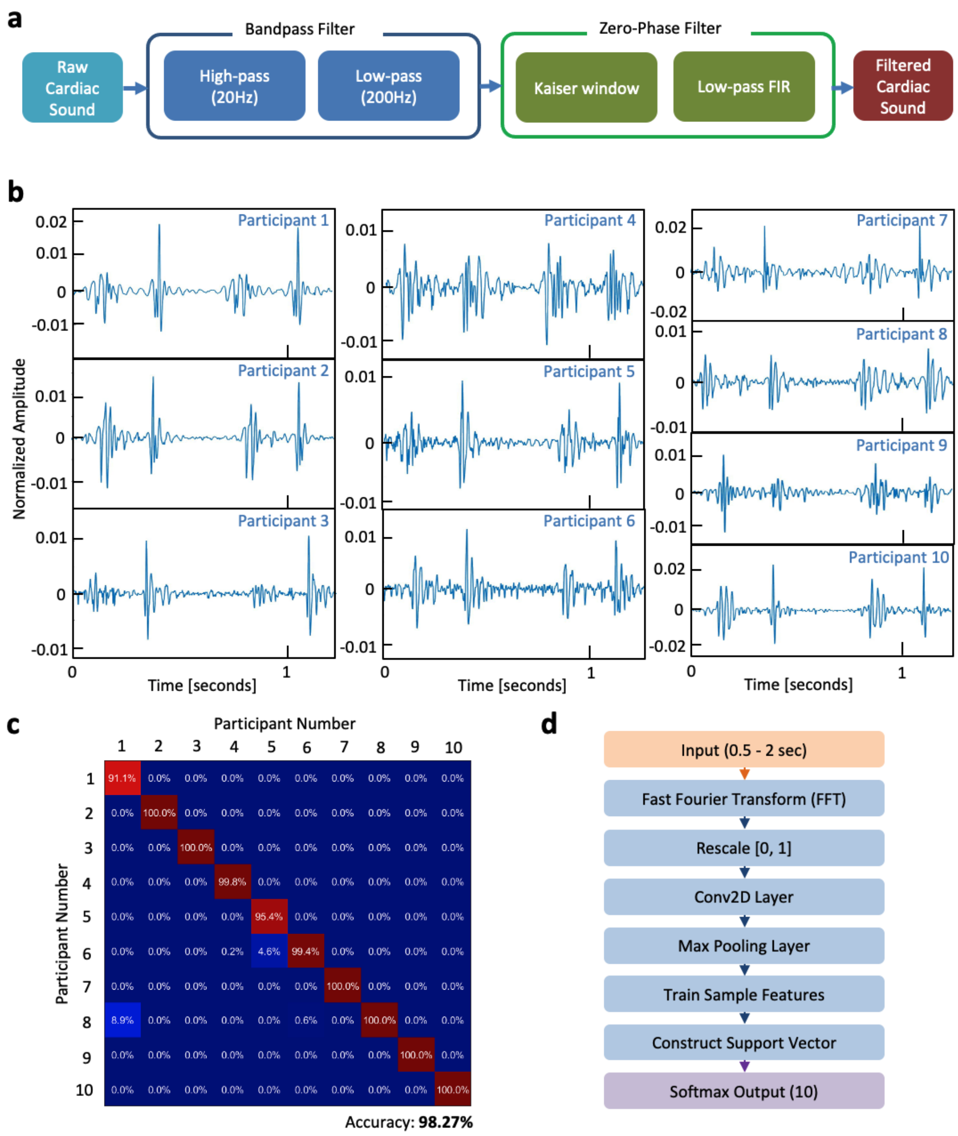

Figure 2. Feature Extraction and Machine Learning of the system. (**a**) Flow chart of the feature extraction process using two stage filtering, (**b**) Filtered sound plots for each participant, (**c**) Confusion matrix of heart sound classification, (**d**) Flow chart of the machine learning model.

As shown from the accuracy or CRR of the proposed biometric as 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 to reach towards the error rate of the retina/iris biometric. Yet, the proposed heart biometric 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 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 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 heart rate.

4. Conclusions and Outlook

In this work, a biometric system based on cardiac sounds is developed using a soft, wearable stethoscope offering a continuous security system for the users. 10 participants' individual heart sounds were collected using the device and after going through the two-stage filtering, unique waveforms were achieved for individuals for the CNN-based machine learning model. It is observed that 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 biometrics for the purpose of a biometric security system.

Author Contributions: All authors conceived, designed, and wrote the paper. All authors have read and agreed to the published version of the manuscript.

Institutional Review Board Statement:

Informed Consent Statement:

Data Availability Statement:

Conflicts of Interest: The authors declare no conflict of interest.

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, doi:10.1155/2020/5846191.
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**, 2101400, doi:10.1002/adhm.202101400.
3. Beritelli, F.; Serrano, S. Biometric Identification Based on Frequency Analysis of Cardiac Sounds. *IEEE Trans. Inf. Forensics Secur.* **2007**, *2*, 596–604, doi:10.1109/tifs.2007.902922.
4. Zhao, Z.; Shen, Q.; Ren, F. Heart Sound Biometric System Based on Marginal Spectrum Analysis. *Sensors* **2013**, *13*, 2530–2551, doi:10.3390/s130202530.
5. Ortega-Garcia, J.; Bigun, J.; Reynolds, D.; Gonzalez-Rodriguez, J. Authentication gets personal with biometrics. *IEEE Signal Process. Mag.* **2004**, *21*, 50–62, doi:10.1109/msp.2004.1276113.
6. Young, C.S. Chapter 14-Physical Security Controls. In *Information Security Science*; Young, C.S., Ed.; Syngress: 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, doi:10.1016/j.patcog.2007.07.018.
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, doi:10.1055/a-0596-4733.