2022 44th Annual International Conference of
the IEEE Engineering in Medicine & Biology Society (EMBC)
Scottish Event Campus, Glasgow, UK, July 11-15, 2022

2022 44th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC) | 978-1-7281-2782-8/22/$31.00 ©2022 IEEE | DOI: 10.1109/EMBC48229.2022.9871653

Blood Pressure Estimation using a Single Channel Bio-Impedance Ring Sensor

Deen Osman, *Student Member, IEEE,* Matija Jankovic, Kaan Sel, *Student Member, IEEE,*
Roderic I. Pettigrew, *Member, IEEE,* and Roozbeh Jafari, *Senior Member, IEEE*

***Abstract*— The demand for non-obtrusive, accurate, and continuous blood pressure (BP) monitoring systems is becoming more prevalent with the realization of its significance in preventable cardiovascular disease (CVD) globally. Current cuff-based standards are bulky, uncomfortable, and are limited to discrete recording periods. Wearable sensor technologies such as those using optical photoplethysmography (PPG) have been used to develop blood pressure estimation models through a variety of methods. However, this technology falls short as optical based systems have bias favoring lighter skin tones and lower body fat compositions. Bioimpedance (Bio-Z) is a capable modality of sensing arterial blood flow without implicit inadvertent bias towards individuals. In this paper we propose a ring-based bioimpedance system to capture arterial blood flow from the digital artery of the finger. The ring design provides a more compact wearable device utilizing only a single Bio-Z channel, making it a familiar fit to individuals. Post-processing the acquired Bio-Z signals, we extracted 9 frequency domain features from windowed beat cycles to train subject specific regression models. Results indicate the average mean absolute errors for systolic/diastolic BP to be 4.38/3.63mmHg, consistent with AAMI standards.**

I. INTRODUCTION

Cardiovascular disease (CVD) has become the leading cause of death in many countries, accounting for approximately one-third of all deaths globally. As stated by the American Heart Association, the direct and total cost of CVD in the U.S. is projected to exceed $750 billion and $1.1 trillion in 2035 [1]. Complex hemodynamic parameters, such as blood pressure (BP), are indicators for determining proper cardiovascular system function among other health-related metrics. High BP is a major risk factor that is directly related to CVD [2]. While significant BP changes occur throughout the day, sleep BP monitoring is important in diagnosing hypertension and other CVD related illnesses as external stimuli is mitigated during sleep [3]. Consequently, there is a vital need to monitor BP continuously during these periods.

The current "gold standard" for clinical BP measurements relies on a brachial cuff device called a sphygmomanometer, or also simply known as a blood pressure gauge. This device is not viable for continuous BP measurements given its large size and constraint to discrete recording periods that must be performed either by a medical professional or the individual themselves [4]. In addition, clinical settings can often lead to measurement biases such as white coat syndrome, a rise in blood pressure due to medical anxiety [5]. The need for continuous BP measurements is ever present to provide more comprehensive medical diagnostics, which can include the moving average and variability of BP through time [6].

Previous work using electrocardiogram (ECG) and photoplethysmography (PPG) sensors for continuous estimation of blood pressure utilizes pulse arrival time (PAT), defined as the time interval from the ejection period of the heart to the arrival of blood to the fingertip. Consequently, PAT intervals are affected by the pre-ejection period (PEP), the delay in time from the depolarization and blood ejection from the left ventricle of the heart. Another time interval measurement called pulse transit time (PTT), takes the time interval of blood arrival at two locations of the body where one is more proximal (closer) to the center of the body and the other more distal (away) from the body. A disadvantage of using PTT is that the accuracy of BP estimations is substantially affected by placement of both sensors, for example upper arm to fingertip estimated BP using PTT will vary significantly compared to other locations [7]. Single channel measurements have been used to estimate systolic and diastolic BP using machine learning (ML). The processed signals are utilized to extract beat-to-beat time domain features [8], [9]. However, time domain features prove a considerable drawback as feature extraction from a beat-to-beat basis can be easily corrupted by motion artifacts and variations. Corrupted and noisy features will impact the ML adversely during both training and testing. To combat this issue, frequency domain features extracted from the Fast Fourier Transform (FFT) of physiological waveforms are utilized on a beat windowed basis. Frequency domain features captured over a series of heart beats are less sensitive to motion noise, and the out of band motion noise can be filtered out more effectively. Windowed cycles provide a more stable prediction model, mitigating beat-to-beat variations and reducing external noise. Additionally, the change in spectral

This work was supported in part by the National Institutes of Health, under grant 1R01EB028106. Any opinions, findings, conclusions, or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the funding organization.

D. Osman is with the Department of Biomedical Engineering, Texas A&M University, College Station, TX 77843 USA (e-mail: deenos25@tamu.edu).

M. Jankovic and K. Sel are with the Department of Electrical and Computer Engineering, Texas A&M University, College Station, TX 77843 USA (e-mail: jankma15@tamu.edu, ksel@tamu.edu).

R. I. Pettigrew is with Texas A&M University and Houston Methodist Hospital, Engineering Medicine (EnMed), Houston, TX 77030 USA (e-mail: pettigrew@tamu.edu).

R. Jafari is with the Departments of Biomedical, Computer Science and Engineering, and Electrical and Computer Engineering, Texas A&M University, College Station, TX 77843 USA (e-mail: rjafari@tamu.edu).

Authorized licensed use limited to: Texas A M University. Downloaded on October 04,2022 at 14:59:40 UTC from IEEE Xplore. Restrictions apply.

amplitudes of multiple frequencies up to 10.8Hz have been shown to have high correlation with change in BP [10], [11]. The reduction of samples with increased noise and promising correlations between frequency domain features aids in creating an optimal fully wearable system for continuous monitoring of BP. Nevertheless, the standardized measuring systems such as the ECG and PPG sensors are susceptible to ambient noise (ex. External light sources), require increased power consumption, are biased towards individuals with lower body fat and lighter skin tones, and are not feasible for everyday wearable applications (ex. Multiple electrode chest leads) [12].

High resolution bioimpedance (Bio-Z) sensors inject high-frequency low-amplitude alternating current into an individual's tissue to measure voltage potential changes due to body composition, blood flow at the artery, and other physiological parameters such as arterial compliance [13]. Specifically, employment of Bio-Z sensors has advantages, over other modalities, due to deep tissue penetration, reduced power consumption, and the ability to use close proximity electrodes [14]. When electrodes are directly placed over arterial sites, the captured Bio-Z signals are representative of elastic arterial wall expansion due to arriving pulse waves and accompanying harmonic reflections [15]. Explicitly, the arrival of the blood pulse wave is indicated by the largest trough of the signal followed by reflections as shown in Fig. 1 [16]. Previous Bio-Z systems captured arterial blood flow from the radial and ulnar arteries of the wrist. This setup utilized multiple sensing channels and PTT to build BP prediction models but lacked to provide wearable compatibility and familiarity. The wristband used had at least six columns of electrodes and was tightly fitted on participants to calculate PTT [15]. The anatomical structure of the radial and ulnar arteries proves to be challenging as placing a column of straight-lined electrodes does not match precisely with the curvature of the artery each time [17]. In this paper, we propose a compact single channel Bio-Z ring capable of using fewer electrodes placed in parallel with the digital artery as seen in Fig. 2. The same benchtop Bio-Z hardware system previously used on the wristband is utilized for data collection from the ring. Acquired signals from the Bio-Z ring are processed into frequency domain features from consecutive windowed beat cycles. Participant specific ML models are

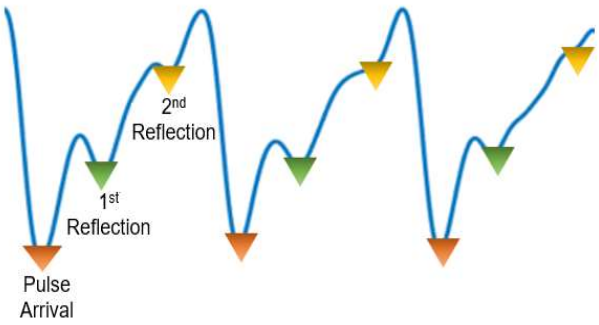

Fig. 1. Pulse arrival trough on Bio-Z waveform indicated by orange marker followed by the 1st pulse wave reflection in green, and then 2nd pulse wave reflection in yellow.

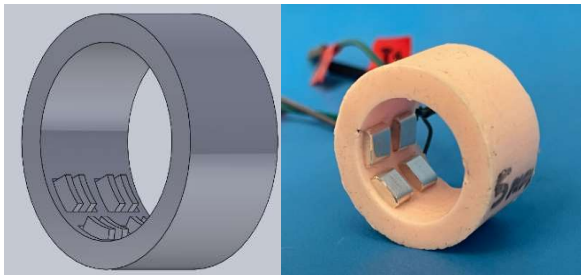

Fig. 2. Ring design in SOLIDWORKS (Left); Fabricated silicon ring with silver electrodes (Right).

used to enhance continuous, cuff-less, and noninvasive BP estimation. This novel Bio-Z system is proposed to be more power efficient, less susceptible to ambient noise, and provide familiarity as a ring wearable. The novelty lies in the ring Bio-Z form factor, the placement of Bio-Z sensors directly on the digital artery as well as the transmissive view of the blood volume changes in the artery by the Bio-Z sensor. The specific placement of the electrodes and the fitting nature of the sensor are among the innovative claims. The notion of single channel sensing and the use of frequency domain features in ML uniquely contribute to estimation of BP with required accuracy.

The proposed advancements reported in this paper are as follows:

- Design and fabricate a Bio-Z ring system that is compact, has adequate electrode contact, capable of capturing arterial blood flow, and provides a familiar fit as a wearable device for the finger.
- Collect Bio-Z signals from the digital artery of the ring finger from five participants, with corresponding systolic and diastolic BPs at rest and at a physically elevated state.
- Create subject specific regression models to estimate BP with high accuracy using frequency domain features obtained from windowed Bio-Z samples.

The next portions of the paper are organized as follows, with the experimental procedures and setup described in Section II, estimated BP analysis in Section III, and the conclusion in Section IV.

II. Methods

A. Bio-Z Hardware

We acquired simultaneous Bio-Z and PPG readings with our custom developed multichannel benchtop Bio-Z hardware, namely Bio-Z XL board that integrates high-performance and low-noise IC as shown in Fig. 3 [18]. An ARM Cortex M4 microcontroller (TM4C1294, Texas Instruments, US) provides the digital operation, running a 16-bit digital-to-analog converter (DAC, DAC8811, Texas Instruments, US) to provide programmable amplitude and frequency sinusoidal voltage signal, and receiving continuously sampled signals from an analog-to-digital converter (ADC, ADS1278, Texas Instruments, US) at a

Authorized licensed use limited to: Texas A M University. Downloaded on October 04,2022 at 14:59:40 UTC from IEEE Xplore. Restrictions apply.

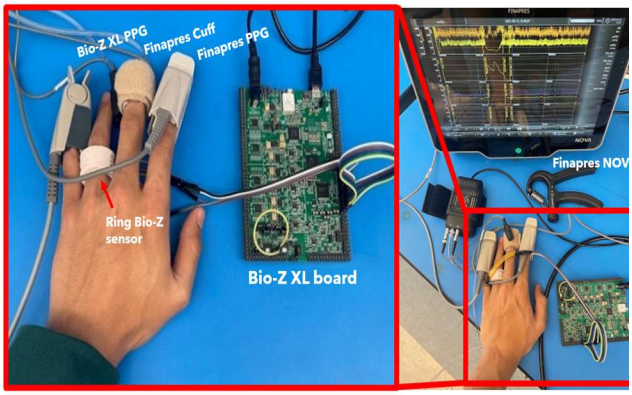

Fig. 3. Experimental setup with Bio-Z XL Board, Finapres® NOVA, and reference PPG sensors.

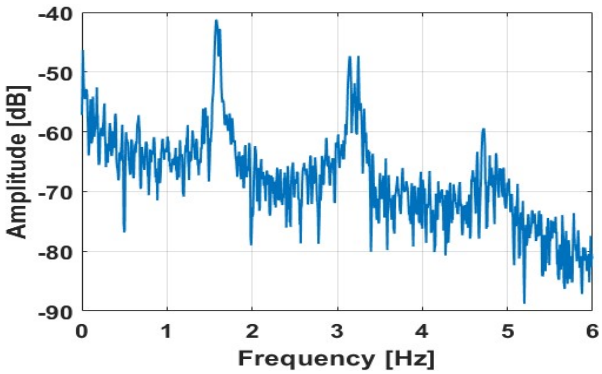

Fig 4. Frequency domain representation of a Bio-Z signal captured from the digital artery.

sampling rate of 93.75 kSPS. The analog-front end (AFE) of the Bio-Z XL board uses the negative feedback loop of a precision op-Amp (OPA211, Texas Instruments) to convert the DAC-generated voltage signal into electrical current that is injected into the skin via two electrodes. The second electrode pair provides voltage sensing that is amplified with an instrumentation amplifier (IA, AD8421, Analog Devices, US), which is then connected to ADC inputs through an anti-aliasing filter (THS4511, Texas Instruments). The sampled Bio-Z signal is sent to a PC for digital signal processing through USB communication. We programmed the board to inject a 0.5mA signal at 15.6kHz to mitigate the low-frequency interference and to allow higher amplitude current injection at higher frequencies due to lowered electrode-skin impedance [19], which also complies with the electrical device safety standards [20].

B. Biometric Data Collection

The experimental setup used to collect physiological data is composed of the Bio-Z XL board with a wire connected silicon mold ring incorporating two 5mmx5mm silver electrode pairs for current injection and voltage sensing, and the Finapres® NOVA system for capturing reference BP continuously. We recruited five presumably healthy participants under IRB approved by Texas A&M University (IRB2017-0086D). Each of the participants were made a custom fit ring according to their finger size. The five participants partook in four 6-minute trials while seated, with their left arm extended flat on the workbench. Each participant started the trial engaging in 2 minutes of hand-gripper exercises using their right hand to raise BP, followed by 1 minute of the cold-pressor test (CPT) and 3 minutes of rest to allow for complete recovery. The CPT involves the participant immersing their right hand in ice-water and is used clinically to trigger responses in the cardiovascular system that includes increased BP. The combination of hand-gripper exercises and the cold-pressor test was chosen in this study due to their combined ability to attain high BP readings while reducing sharp BP variations during the transition from one maneuver to the next.

Two of the four trials conducted by each participant followed the procedure described above, and two followed the same procedure described after detaching and reattaching the ring sensor, which aims to show the repeatability of the ring sensor system for long-term monitoring. The Bio-Z and BP signals acquired are then digitally processed and aligned using calculated inter-beat-intervals (IBIs) from the two reference PPG sensors. Sections of collected data heavily affected by motion artifacts are manually omitted.

1) Frequency Domain Features

With synchronized Bio-Z and BP data, frequency domain feature extraction is performed on windowed Bio-Z samples. The advantages of using frequency domain features relative to time domain features includes reduced beat to beat variations and external noise. In addition, the change in spectral amplitudes of frequencies from 0Hz to 10.8Hz have high correlation with change in BP [10], [11]. Each of the windowed Bio-Z and BP samples incorporates a total of 12 beat cycles, equivalent to about 10 seconds of data, with 50% overlap. The BP windows are averaged for both systolic and diastolic BP. The FFT of windowed cycles is taken to obtain a total of 9 features unique to the frequency domain. The amplitude and band powers (area under FFT curve) ±0.5Hz of the fundamental frequency and next two harmonics are used. Additionally, the band powers from 0-2, 2-4, and 4-6Hz are extracted to give insight into lower, middle, and higher frequency information of our Bio-Z signal. Fig. 4 displays the FFT of a Bio-Z signal obtained from the ring, ranged from 0 to 6Hz. The 9 frequency domain features are then normalized for each participant's data collection, a standardized machine learning processing step in preparation for building models to estimate systolic and diastolic BP.

2) Machine Learning Model

The AdaBoost regression model is used as our ML tool to predict BP with high accuracy given its performance in prior BP estimation work using Bio-Z, compared to other models [15]. Each of the models are trained subject specific due to the individuality of cardiac rhythms and vascular tone for each of the five participants. In addition, separate models are used for systolic and diastolic BP prediction, highlighting

Authorized licensed use limited to: Texas A M University. Downloaded on October 04,2022 at 14:59:40 UTC from IEEE Xplore. Restrictions apply.

the distinctiveness between the two phases. Given the smaller dataset with windowed samples a 10-fold K-fold is performed on the unshuffled feature and BP data with 90% of the iterated dataset used for training and 10% for testing. To prevent under and overfitting within our model, specified with low RMSE results, the optimal number of decision trees from 9 to 12 and tree depth from 3 to 18 is utilized for each training iteration. The average error in mmHg for the folds is reported for each participant as well as percentile threshold errors for performance analysis.

III. Experimental Results

The five participants for this experiment comprised of healthy normotensive individuals with an age ranged from 20 to 24, with three of the five being males and the other two females. The systolic BP ranges for all participants were from 91 to 171mmHg and diastolic range from 51 to 95mmHg. Tables I & II summarize the predicted systolic and diastolic errors in mean absolute error (MAE), standard deviation of the absolute error (STD), and root mean squared error (RMSE) for all participants and the average amongst them. Table III provides the percentage values that meet defined error thresholds in mmHg for all predicted data. These reported results from five participants helps to provide initial insight to the promising potential of utilizing ring-based single channel bioimpedance systems for BP estimation.

TABLE I

Predicted Systolic BP Error (mmHg)			
Participant	**MAE**	**STD**	**RMSE**
S1	5.72	3.99	7.11
S2	2.66	1.53	3.08
S3	3.88	2.80	4.82
S4	5.41	3.79	6.61
S5	4.22	2.34	4.90
Avg.	**4.38**	**2.89**	**5.30**

TABLE II

Predicted Diastolic BP Error (mmHg)			
Participant	**MAE**	**STD**	**RMSE**
S1	4.25	2.64	5.06
S2	2.29	1.64	2.83
S3	2.42	1.59	2.91
S4	5.89	3.80	7.03
S5	3.31	2.43	4.13
Avg.	**3.63**	**2.42**	**4.39**

TABLE III

Threshold Error Percentage for Estimated Blood Pressures				
BP Phase	**≤5mmHg**	**≤10mmHg**	**≤15mmHg**	**≥15mmHg**
Systolic	68%	90%	97%	3%
Diastolic	77%	93%	98%	2%

The statistical results amongst all five participants shows promising potential with mean absolute errors, standard deviations, and root mean square errors all under 5mmHg, except for the predicted systolic RMSE. Additionally, with 90-93% of predicted values having less than or equal to 10mmHg of error, the system is on track to receive A/passing grades from blood pressure associations such as the British Hypertension Society (BHS) and Association for the Advancement of Medical Instrumentation (AAMI) [21]. Fig. 5-6 graphically display the histogram and density plots of the real BP (blue) and predicted BP (red), in which the ML models lacked in predicting values with increased presence within the dataset. Fig. 7, plots the real and predicted systolic and diastolic BP values through a windowed beat cycle.

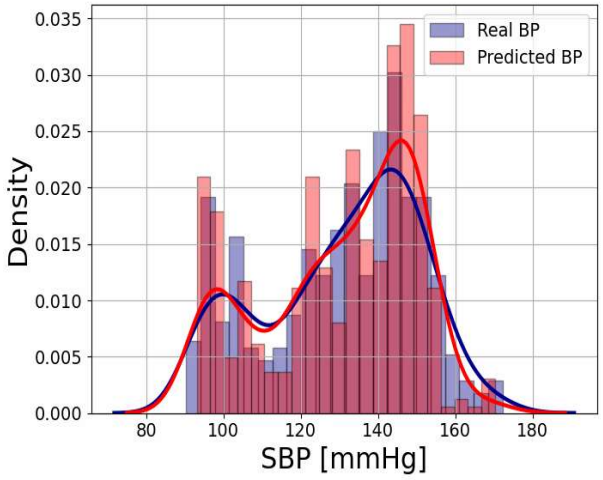

Fig. 5. Systolic blood pressure histogram and density plot. Data represented encompasses all five participants. Mean SBP of 131mmHg and range from 91 to 171mmHg.

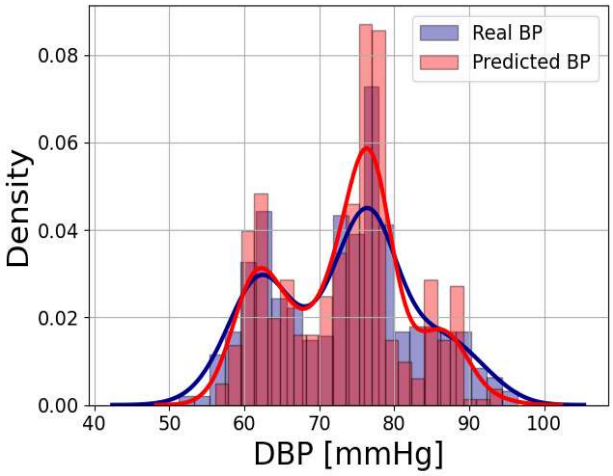

Fig. 6. Diastolic blood pressure histogram and density plot. Data represented encompasses all five participants. Mean DBP of 73mmHg and range from 51 to 95mmHg.

Prior work that used PAT to estimate BP resulted in mean absolute errors of 5.92/5.35mmHg with standard deviations of 5.38/6.14mmHg for systolic/diastolic BP, below par to our results [22]. Additionally, comparing to an optical modality from a standard fingertip PPG sensor, our systolic estimations outperformed with their error percentages being 61%, 86%, and 95% for the same respective thresholds of ≤5, ≤10, ≤15mmHg of deviation from reference BP [8]. A limiting factor that occurred during experimentation included the lack in diversity amongst participants and the constrained time allotted for data collection.

Authorized licensed use limited to: Texas A M University. Downloaded on October 04,2022 at 14:59:40 UTC from IEEE Xplore. Restrictions apply.

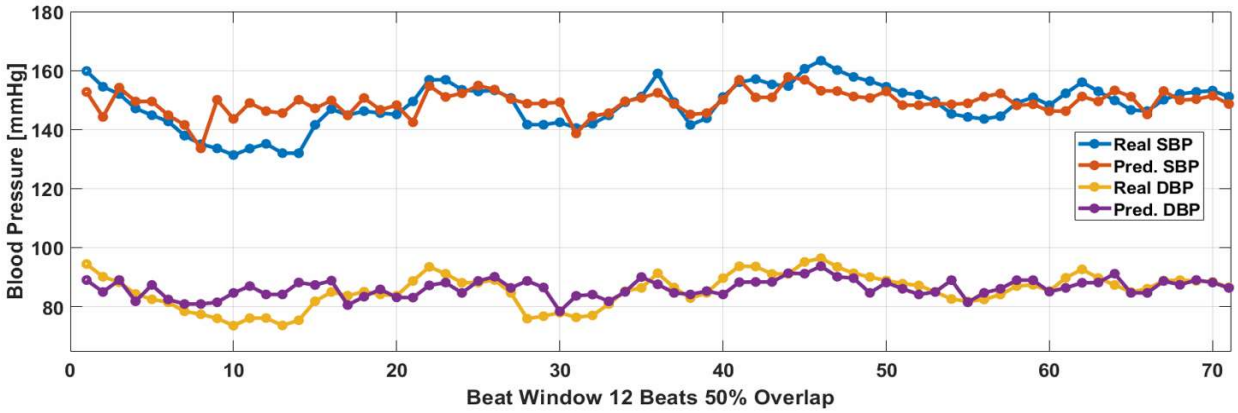

Fig. 7. Time series plot of real & predicted systolic and diastolic blood pressure values for a single participant (S1)

IV. Conclusion

This paper proposes a novel ring-based bioimpedance system that operates solely on a single voltage sensing channel. The use of bioimpedance measurements from the digital arteries of the fingers provides a comfortable fit for wearable applications, unbiased signal quality with respect to skin tones, and reduced power consumption compared to standardized medical monitoring equipment. The results of this five-participant experiment yield encouraging statistical errors to help motivate future work using bioimpedance and ring wearables. Factors that were observed to affect performance and need to be addressed in future research includes the tightness of the ring and the geometry of the electrodes. We plan to incorporate more participants to increase diversity within our sampled population. Further solutions to reduce noise caused by motion artifacts during data collection can be researched to create more accurate and generalizable BP prediction models for a greater population of individuals.

References

[1] S. S. Virani *et al.*, "Heart disease and stroke statistics—2020 update: A report from the American Heart Association," *Circulation*. 2020.

[2] E. J. Benjamin *et al.*, "Heart disease and stroke statistics - 2018 update: A report from the American Heart Association," *Circulation*, vol. 137, no. 12, 2018.

[3] E. Dolan *et al.*, "Superiority of ambulatory over clinic blood pressure measurement in predicting mortality: The Dublin outcome study," *Hypertension*, vol. 46, no. 1, 2005.

[4] G. Ogedegbe and T. Pickering, "Principles and Techniques of Blood Pressure Measurement," *Cardiology Clinics*, vol. 28, no. 4. 2010.

[5] M. R. Pioli, A. M. V. Ritter, A. P. de Faria, and R. Modolo, "White coat syndrome and its variations: Differences and clinical impact," *Integrated Blood Pressure Control*, vol. 11. 2018.

[6] P. Palatini, "Ambulatory and home blood pressure measurement: Complementary rather than competitive methods," *Hypertension*, vol. 59, no. 1. 2012.

[7] M. Elgendi *et al.*, "The use of photoplethysmography for assessing hypertension," *npj Digital Medicine*, vol. 2, no. 1, 2019.

[8] S. G. Khalid, H. Liu, T. Zia, J. Zhang, F. Chen, and D. Zheng, "Cuffless Blood Pressure Estimation Using Single Channel Photoplethysmography: A Two-Step Method," *IEEE Access*, vol. 8, 2020.

[9] P. S. Addison, "Slope Transit Time (STT): A Pulse Transit Time Proxy requiring only a Single Signal Fiducial Point," *IEEE Transactions on Biomedical Engineering*, vol. 63, no. 11, 2016.

[10] X. Xing and M. Sun, "Optical blood pressure estimation with photoplethysmography and FFT-based neural networks," *Biomedical Optics Express*, vol. 7, no. 8, 2016.

[11] M. Simjanoska, M. Gjoreski, M. Gams, and A. M. Bogdanova, "Non-invasive blood pressure estimation from ECG using machine learning techniques," *Sensors (Switzerland)*, vol. 18, no. 4, 2018.

[12] M. Ghamari, "A review on wearable photoplethysmography sensors and their potential future applications in health care," *International Journal of Biosensors & Bioelectronics*, vol. 4, no. 4, 2018.

[13] X. Tang, M. Jankovic, and R. Jafari, "A Non-invasive Radial Arterial Compliance Measuring Method using Bio-Impedance.," *Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual International Conference*, vol. 2021, pp. 2330–2334, 2021.

[14] K. Sel, D. Osman, and R. Jafari, "Non-Invasive Cardiac and Respiratory Activity Assessment From Various Human Body Locations Using Bioimpedance," *IEEE Open Journal of Engineering in Medicine and Biology*, vol. 2, 2021.

[15] B. Ibrahim and R. Jafari, "Cuffless Blood Pressure Monitoring from an Array of Wrist Bio-Impedance Sensors Using Subject-Specific Regression Models: Proof of Concept.," *IEEE transactions on biomedical circuits and systems*, vol. 13, no. 6, pp. 1723–1735, 2019.

[16] B. Ibrahim, D. Mrugala, and R. Jafari, "Effects of Bio-Impedance Sensor Placement Relative to the Arterial Sites for Capturing Hemodynamic Parameters," 2019.

[17] B. Ibrahim and R. Jafari, "Continuous Blood Pressure Monitoring using Wrist-worn Bio-impedance Sensors with Wet Electrodes," 2018.

[18] K. Sel, A. Brown, H. Jang, H. M. Krumholz, N. Lu, and R. Jafari, "A Wrist-worn Respiration Monitoring Device using Bio-Impedance," in *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, 2020, vol. 2020-July.

[19] K. Sel, D. Kireev, A. Brown, B. Ibrahim, D. Akinwande, and R. Jafari, "Electrical Characterization of Graphene-based e-Tattoos for Bio-Impedance-based Physiological Sensing," 2019.

[20] IEC, "Medical electrical equipment - Part 1: General requirements for basic safety and essential performance," *AAMI Standards and Recommended Practices*, vol. 3, no. ES60601-1, 2005.

[21] G. S. Stergiou *et al.*, "A universal standard for the validation of blood pressure measuring devices: Association for the Advancement of Medical Instrumentation/European Society of Hypertension/International Organization for Standardization (AAMI/ESH/ISO) Collaboration Statement," *Hypertension*, vol. 71, no. 3, 2018.

[22] M. Kachuee, M. M. Kiani, H. Mohammadzade, and M. Shabany, "Cuffless Blood Pressure Estimation Algorithms for Continuous Health-Care Monitoring.," *IEEE transactions on bio-medical engineering*, vol. 64, no. 4, pp. 859–869, 2017.

Authorized licensed use limited to: Texas A M University. Downloaded on October 04,2022 at 14:59:40 UTC from IEEE Xplore. Restrictions apply.