HSPI The Open Access Publisher

JCCM ISSN 2575-0143 JOURNAL OF CARDIOLOGY AND CARDIOVASCULAR MEDICINE

Short Communication

Noninvasive Cuffless Blood Pressure Monitoring. How Mechanism-Driven and Data-Driven Models Can Help in Clinical Practice

Mohamed Zaid[1]*, Mihail Popescu[2], Laurel Despins[3], James Keller[4], Marjorie Skubic[4] and Giovanna Guidoboni[5]

[1]Graduate School of Biomedical Science and Engineering, University of Maine, Orono, ME, USA
[2]Health Management and Informatics, School of Medicine, University of Missouri, Columbia, MO, USA
[3]Sinclair School of Nursing, University of Missouri, Columbia, MO, USA
[4]Electrical Engineering and Computer Science, College of Engineering, University of Missouri, Columbia, MO, USA
[5]Electrical and Computer Engineering, Maine College of Engineering and Computing, University of Maine, Orono, ME, USA

Abstract

Continuous noninvasive cuffless blood pressure (BP) monitoring is essential for early detection and treatment of hypertension. In this paper, we provide an overview of the recent advancements in cuffless BP sensors. These include contact wearable sensors such as electrocardiography (ECG), photoplethysmography (PPG), contact non-wearable sensors such as ballistocardiography (BCG), and contactless sensors such as video plethysmography (VPG). These sensors employ different measuring mechanisms such as pulse arrival time (PAT), pulse transit time (PTT), and pulse wave analysis (PWA) to estimate BP. However, challenges exist in the effective use and interpretation of signal features to obtain clinically reliable BP measurements. The correlations between signal features and BP are obtained by mechanism-driven models which use physiological principles to identify mathematical correlations, and data-driven models which use machine learning algorithms to analyze observational data to identify multidimensional correlations. On the one hand, applying mechanism-driven models to non-linear scenarios and incomplete or noisy data is challenging On the other hand, data-driven models require a large amount of data in order to prevent physically inconsistent predictions, resulting in poor generalization. From this perspective, this paper proposes to combine the strengths of mechanism-driven and data-driven approaches to obtain a more comprehensive approach, the physiology-informed machine-learning approach, with the goal of enhancing the accuracy, interpretability, and scalability of continuous cuffless BP monitoring. This holds promise for personalized clinical applications and the advancement of hypertension management.

More Information

***Address for correspondence:** Mohamed Zaid, Graduate School of Biomedical Science and Engineering, University of Maine, Orono, ME, USA, Email: mzcbb@missouri.edu

Submitted: April 24, 2023
Approved: July 11, 2023
Published: July 12, 2023

How to cite this article: Zaid M, Popescu M, Despins L, Keller J, Skubic M, et al. Noninvasive Cuffless Blood Pressure Monitoring. How Mechanism-Driven and Data-Driven Models Can Help in Clinical Practice. J Cardiol Cardiovasc Med. 2023; 8: 081-085.

DOI: 10.29328/journal.jccm.1001157

Copyright license: © 2023 Zaid M, et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Keywords: Hypertension; Continuous noninvasive blood pressure monitoring; Cuffless blood pressure; Mechanism-driven model; Data-driven model; Physics-informed machine learning

Check for updates

OPEN ACCESS

Introduction

Blood Pressure (BP), one of the most important metrics in health monitoring, represents the response of the cardiovascular system to provide adequate blood perfusion to tissues [1,2]. High BP, known as hypertension, is the leading cause of death worldwide and a critical factor that increases cardiovascular complications as well as brain, kidney, and ocular damage [2-4]. Globally, approximately 1.28 billion adults between 30 and 79 years of age have hypertension with an estimated 46% of this population unaware that they have this condition [5]. In the United States, nearly one out of two adults, roughly 108 million, have hypertension, and only one in four adults have it under control. Each year, high BP is responsible for about 500,000 deaths and costs the nation up to almost 200 million dollars [6]. Therefore, it is essential to provide an early diagnosis to intervene with therapies to reduce high BP and avoid the risk of further complications before microvascular and macrovascular damage has occurred [7]. In the current clinical practice, BP is measured by either invasive intra-arterial catheterization or a

noninvasive cuff-based method [8]. The first method requires the introduction of a catheter inside the artery; this provides reliable continuous BP monitoring. However, due to its high invasiveness, this method can be applied only in critical care settings such as intensive care units [8]. The second method is based on an inflatable cuff wrapped around the arm that occludes the brachial artery; the pressure wave oscillations in the vessels generated by the gradual reduction of the cuff pressure are recorded. Health care providers can also listen to Korotkoff sounds once the cuff pressure is released [4,9]. This auscultation method has not changed too much since Scipione Riva-Rocci introduced it in 1896. Although this method provides non-invasive reliable measurements, it cannot describe the nature of BP dynamics over time and the cuff itself is often the cause of discomfort and sometimes pain, especially in hypertensive patients [10]. Therefore, despite the high importance of continuous monitoring of BP to provide early diagnosis and treatment of hypertension, there is still the need for a method that can provide continuous noninvasive cuffless BP monitoring.

Current advances in the BP monitoring field

In the last few decades, research interest is increasing in developing continuous BP measurements by means of cuffless devices [4,8]. Contact sensors require being in direct contact to provide measurements; they can be wearable and non-wearable [2,3]. Examples of wearable sensors include electrocardiography (ECG) and photoplethysmography (PPG). ECG captures the electrical activity at each heartbeat by electrodes attached to the chest and limbs. PPG measures the waveforms of pulsatile arterial blood volume by using light to illuminate a side of a tissue volume, then receive the reflected light on the same side or transmitted light on the other side [9,11]. Ballistocardiography (BCG) is an example of a non-wearable sensor. BCG records the repetitive motion of the center of mass of the human body as blood moves from the heart to the circulatory system, capturing the mechanical and hemodynamic properties of the cardiovascular system as a whole. BCG can be recorded by different sensing modalities such as weighing scales, accelerometers, and hydraulic bed sensors [12-15]. Contactless sensors, such as the hydraulic bed sensor, can provide measurements without being worn or being in direct contact with the subject [15]. Video Plethysmography (VPG) and Doppler radar are other types of contactless sensors. VPG captures the light absorbed and then reflected by the skin surface, the intensity of the light changes as the hemoglobin absorbs light. The video cameras capture the characteristics peak in the green light frequency, which decreases when there is an increase in bloodstream hemoglobin due to the pumping of the heart. VPG can be recorded on the forehead, palms, and cheeks [16]. Radar generates electromagnetic waves and an antenna records reflected waves by using the Doppler effect. The movement captured on the surface of the sternum is the vasomotion caused by the pulse wave that moves through the aortic artery [17,18].

BP sensors also differ in measuring mechanisms. Pulse Arrival Time (PAT) and pulse transit time (PTT) are two widespread techniques [3,9]. PAT is defined as the time interval between the heart's electrical activity acquired by ECG and a peripheral pulse detected lower down the arterial tree, acquired for example by a PPG sensor. PTT is defined as the time delay between two waveforms acquired in different parts of the body and typically relies on two mechanical measurements of pulse wave activity, such as BCG-PPG time delay [3,12,13]. Despite these differences, both approaches aim to precisely compute pulse wave velocity (PWV), which defines the velocity at which pressure waves propagate and it has proved to be closely associated with BP measurements [8,9]. Another measuring mechanism is based on pulse wave analysis (PWA), a technique that analyzes the morphology of the pressure pulse wave, with the aim of extracting crucial features and information that can indirectly assess the BP [3] PWA has been used in the applanation tonometry method, which involves lightly pressing a pressure sensor against the artery so that the artery is flattened between the sensor and the supporting structures [2,3]. This method is well suited for single snapshot measurements of BP, but its measurements are affected by sensor positioning. The method also requires a trained operator and it remains impractical for continuous and unsupervised measurements of BP [10]. PWA is also applied by using optical measurements via PPG to measure the variation of the local blood volume changes in the tissues. This method does not need an operator and is easy to place. However, the analysis of the PPG pulse wave is more challenging because it involves an indirect observation of the central hemodynamic variables and because the underlying mechanisms generating the PPG signal are only partially known [9,19]. Many studies recently started to employ machine learning algorithms with the goal of extracting meaningful features from these signals and modeling the relationship between the learned features and BP. The aim is to minimize the error between the predicted value and BP reference. However, this method requires a large amount of data to train the machine learning model [4,9]. So, why is a reliable continuous cuffless BP monitoring method not available yet?

Challenges of mechanism-driven and data-driven methods for waveform analysis

Despite the great progress in the field of cuffless BP monitoring and the many different sensing modalities adopted for the measurement, the effective use and interpretation of signal features remain quite challenging. The interpretation of signals is possible through BP estimation models that have the task to provide standardized and reproducible measurements of BP, ensuring consistency across devices and sensing modalities. The models have the goal to help healthcare providers to monitor and manage changes in BP due to changes in cardiovascular health and to evaluate the impact of interventions and the efficacy of treatments. Two main approaches have been proposed for signal feature identification and extraction.

One approach is mechanism-driven modeling, where physics-based mathematical models are used to interpret the signal based on fundamental principles of physiology [20]. The other approach is data-driven, where large amounts of multi-fidelity observational data are analyzed via machine learning and artificial intelligence techniques to identify multidimensional correlations between signal features and BP [4,21].

There are four major differences between the mechanism-driven and data-driven models, in terms of interpretability, scalability to clinical application, generalization, and data demand and fitting.

1) Interpretability: Mechanism-driven models have the ability to translate physiology principles into quantifiable metrics by using mathematical modeling. Thus, the model predictions are clearly interpretable in terms of fundamental physiology mechanisms. Conversely, data-driven models are based on data, not principles. The learning is driven by a well-defined objective function, but the process is often perceived as a black box, and it remains challenging to explain how results have been achieved [9].

2) Scalability to clinical applications: When data and boundary conditions are noisy and incomplete, mechanism-driven modeling becomes very challenging. In these situations, data-driven approaches can be helpful in identifying latent states that cannot be taken into account directly in mechanism-driven models [9].

3) Generalization: Data-driven models are achieved by using a specific dataset with the goal of solving a very specific problem, which makes it challenging to generalize to different conditions or across different sensors or populations. Data-driven models may fit observations quite well, but predictions may be physically inconsistent, which can result in poor generalization performance [22]. Mechanism-driven models are based on the principles of physiology, and can provide a generalized description of the problem that holds beyond a specific population subset [20].

4) Data demand and fitting: Mechanism-driven models map BP indicators to BP via a mathematical model based on some assumptions that do not require a huge amount of data. On the other hand, data-driven models require an enormous amount of data to train and make the network learn relevant features. Small datasets lead to the data fitting issue, which has an effect on the performance of machine learning algorithms. These algorithms provide good performance when the training error is kept to a minimum and the training and test distributions are similar. However, overfitting to the training data can happen and produce substandard results on a test set when the training dataset is not adequately representative of the overall population. In contrast, under fitting may occur if the training dataset is too small, which can lead to insufficient error reduction on the training dataset and bad performance on the test set [22].

In summary, mechanism-driven models have the advantage to translate physiology principles into quantifiable metrics by using mathematical modeling, though applications where data and boundary conditions are missing and noisy, become computationally challenging. On the other side, data-driven models can achieve automatic feature extraction from a dataset of waveforms used as training sets without the need to use any expert knowledge of the physiological mechanisms that generate the waveforms. A data-driven model may fit observations very well, but predictions may be physically inconsistent, resulting in poor generalization performance. Therefore, to leverage their strengths and overcome their shortcomings, there is the need to combine mechanism-driven models and data-driven models to achieve both interpretability and scalability.

Physiology as a common denominator across technology and data: physiology-informed machine learning approach

Mechanism-driven models are based on well-defined physiology derived from clinical data without the need to access large amounts of data. For example, the mechanism-driven model of cardiovascular physiology proposed by Guidoboni, et al. [19] allows prediction of how changes in cardiac function will manifest in the Ballistocardiogram (BCG) signal, which represents the acceleration of blood distribution through the body at each heartbeat [22]. Specifically, a reduction in left ventricular contractility leads to a change in physiological markers defined as a reduction in BCG amplitude and an increase in the time delay between the R-peak in the electrocardiogram and the systolic peak in the BCG. The predicted changes in these markers have been validated on three swine during pre-and post-myocardial infarction conditions [14]. This finding advances the BCG technique as an effective method for non-invasive cardiovascular monitoring even in patients with critical conditions such as those hospitalized in the surgical intensive care unit [23]. Moreover, the ability of the BCG-based sensors to be non-wearable and embedded in the furniture we already use at home, such as beds and armchairs, does not require much compliance from subjects. This can provide great benefits to continuous BP monitoring with enormous healthcare implications, such as overnight or in-home BP monitoring [15,24]. However, in order for physiological variables estimated by a model to be clinically helpful, it is necessary to assess their correlation with relevant clinical outcomes. This is where data-driven approaches, for example, based on artificial intelligence and machine learning, can help connect theory with data. The two approaches were combined in [25], where a mechanism-driven cardiovascular model was used to estimate the BP of subjects based on their BCG waveforms, while an evolutionary computation algorithm was used to personalize the model parameters to each specific subject. This provided a means to estimate cardiovascular parameters, such as ventricular contractility and stiffness, whose direct measurement

requires highly invasive techniques (catheterization). In other words, mechanism-driven models have the ability to identify meaningful markers to relate to blood pressure and make them available across sensing modalities, while data-driven models can combine these markers with other multidimensional information to personalize and evaluate the condition of each individual patient. In that study, machine learning is embedded in the mathematical model to personalize the model to each subject. In addition, physics can be incorporated into machine learning algorithms to address the requirement of huge datasets. Large amounts of data are typically required for machine learning algorithms to successfully train the network. High-quality data, like BP measures, may not be enough for standard machine learning training in real-world situations. In these circumstances, physics-informed learning provides a significant benefit by demonstrating great generalization potential despite the dearth of available data. High-dimensional machine learning models can be effectively limited to a lower-dimensional manifold by including or upholding the laws of physics, which enables training on smaller datasets. The network architecture can incorporate physics and use penalty restrictions to direct the computational model's learning process. Therefore, combining mechanism-driven and data-driven models have more potential than using them separately.

Conclusions and perspectives

In this paper, we summarized the current advance in the research field of BP monitoring where those using just mechanism-driven models or just data-driven models have been proven to be not enough to provide reliable cuffless BP monitoring. Mechanism-driven modeling can provide empirical, physical, and mathematical insights into the mechanisms underlying BP genesis and fluctuations. Incorporating this approach into the design of sensors and the analysis of data can provide the opportunity to enhance the performance of learning algorithms and personalize BP monitoring for each person. Such personalized monitoring can promote early diagnosis and treatment of hypertension.

In conclusion, mechanism-driven modeling and data-driven modeling can help to overcome each other's challenges and to increase their own potential to provide continuous cuffless BP monitoring independent of the sensing modality used.

References

1. Muntner P, Shimbo D, Carey RM, Charleston JB, Gaillard T, Misra S, Myers MG, Ogedegbe G, Schwartz JE, Townsend RR, Urbina EM, Viera AJ, White WB, Wright JT Jr. Measurement of Blood Pressure in Humans: A Scientific Statement from the American Heart Association. Hypertension. 2019 May;73(5):e35-e66. doi: 10.1161/HYP.0000000000000087. PMID: 30827125.
2. Mukkamala R, Stergiou GS, Avolio AP. Cuffless Blood Pressure Measurement. Annu Rev Biomed Eng. 2022 Jun 6;24: 203-230. doi: 10.1146/annurev-bioeng-110220-014644. Epub 2022 Apr 1. PMID: 35363536.
3. Bradley CK, Shimbo D, Colburn DA, Pugliese DN, Padwal R, Sia SK, Anstey DE. Cuffless Blood Pressure Devices. Am J Hypertens. 2022 May 10;35(5):380-387. doi: 10.1093/ajh/hpac017. PMID: 35136906; PMCID: PMC9088838.
4. Pandit JA, Lores E, Batlle D. Cuffless Blood Pressure Monitoring: Promises and Challenges. Clin J Am Soc Nephrol. 2020 Oct 7;15(10):1531-1538. doi: 10.2215/CJN.03680320. Epub 2020 Jul 17. PMID: 32680913; PMCID: PMC7536750.
5. Al-Makki A, DiPette D, Whelton PK, Murad MH, Mustafa RA, Acharya S, Beheiry HM, Champagne B, Connell K, Cooney MT, Ezeigwe N, Gaziano TA, Gidio A, Lopez-Jaramillo P, Khan UI, Kumarapeli V, Moran AE, Silwimba MM, Rayner B, Sukonthasan A, Yu J, Saraffzadegan N, Reddy KS, Khan T. Hypertension Pharmacological Treatment in Adults: A World Health Organization Guideline Executive Summary. Hypertension. 2022 Jan;79(1):293-301. doi: 10.1161/HYPERTENSIONAHA.121.18192. Epub 2021 Nov 15. PMID: 34775787; PMCID: PMC8654104.
6. C for Disease Control and Prevention. Health topics–high blood pressure. https://www.cdc.gov/policy/polaris/healthtopics/highbloodpressure/index.html, 2022.
7. Lackland DT. Early-Life Detection of Hypertension Risks: Implications for Clinical Practice and Research. Hypertension. 2017 Sep;70(3):486-487. doi: 10.1161/HYPERTENSIONAHA.117.09529. Epub 2017 Jul 3. PMID: 28674035.
8. Le T, Ellington F, Lee TY, Vo K, Khine M, Krishnan SK, Dutt N, Cao H. Continuous non-invasive blood pressure monitoring: a methodological review on measurement techniques. IEEE Access. 2020; 8:212478–212498.
9. Sola J, Delgado-Gonzalo R. The handbook of cuffless blood pressure monitoring. Cham: Springer, 2019.
10. Ding XR, Zhao N, Yang GZ, Pettigrew RI, Lo B, Miao F, Li Y, Liu J, Zhang YT. Continuous Blood Pressure Measurement from Invasive to Unobtrusive: Celebration of 200th Birth Anniversary of Carl Ludwig. IEEE J Biomed Health Inform. 2016 Nov;20(6):1455-1465. doi: 10.1109/JBHI.2016.2620995. PMID: 28113184.
11. Chandrasekhar A, Yavarimanesh M, Natarajan K, Hahn JO, Mukkamala R. PPG Sensor Contact Pressure Should Be Taken In to Account for Cuff-Less Blood Pressure Measurement. IEEE Trans Biomed Eng. 2020 Nov;67(11):3134-3140. doi: 10.1109/TBME.2020.2976989. Epub 2020 Feb 28. PMID: 32142414; PMCID: PMC8856571.
12. Mukkamala R, Hahn JO, Inan OT, Mestha LK, Kim CS, Töreyin H, Kyal S. Toward Ubiquitous Blood Pressure Monitoring via Pulse Transit Time: Theory and Practice. IEEE Trans Biomed Eng. 2015 Aug;62(8):1879-901. doi: 10.1109/TBME.2015.2441951. Epub 2015 Jun 5. PMID: 26057530; PMCID: PMC4515215.
13. Kim CS, Carek AM, Mukkamala R, Inan OT, Hahn JO. Ballistocardiogram as Proximal Timing Reference for Pulse Transit Time Measurement: Potential for Cuffless Blood Pressure Monitoring. IEEE Trans Biomed Eng. 2015 Nov;62(11):2657-64. doi: 10.1109/TBME.2015.2440291. Epub 2015 Jun 2. PMID: 26054058; PMCID: PMC4626385.
14. Zaid M, Sala L, Ivey JR, Tharp DL, Mueller CM, Thorne PK, Kelly SC, Silva KAS, Amin AR, Ruiz-Lozano P, Kapiloff MS, Despins L, Popescu M, Keller J, Skubic M, Ahmad S, Emter CA, Guidoboni G. Mechanism-Driven Modeling to Aid Non-invasive Monitoring of Cardiac Function via Ballistocardiography. Front Med Technol. 2022 Feb 16;4:788264. doi: 10.3389/fmedt.2022.788264. PMID: 35252962; PMCID: PMC8888976.
15. Su BY, Enayati M, Ho KC, Skubic M, Despins L, Keller J, Popescu M, Guidoboni G, Rantz M. Monitoring the Relative Blood Pressure Using a Hydraulic Bed Sensor System. IEEE Trans Biomed Eng. 2019 Mar;66(3):740-748. doi: 10.1109/TBME.2018.2855639. Epub 2018 Jul 13. PMID: 30010544.
16. Sugita N, Yoshizawa M, Abe M, Tanaka A, Homma N, Yambe T. Contactless technique for measuring blood-pressure variability from

one region in video plethysmography. Journal of Medical and Biological Engineering. 2019; 39:76–85.

17. Zhao H, Gu X, Hong H, Li Y, Zhu X, Li C. Non-contact beat-to-beat blood pressure measurement using continuous wave doppler radar. In the 2018 IEEE/MTT-S International Microwave Symposium-IMS. IEEE. 2018;1413–1415.

18. Vysotskaya N, Will C, Servadei L, Maul N, Mandl C, Nau M, Harnisch J, Maier A. Continuous Non-Invasive Blood Pressure Measurement Using 60 GHz-Radar-A Feasibility Study. Sensors (Basel). 2023 Apr 19;23(8):4111. doi: 10.3390/s23084111. PMID: 37112454; PMCID: PMC10145629.

19. Guidoboni G, Sala L, Enayati M, Sacco R, Szopos M, Keller JM, Popescu M, Despins L, Huxley VH, Skubic M. Cardiovascular Function and Ballistocardiogram: A Relationship Interpreted via Mathematical Modeling. IEEE Trans Biomed Eng. 2019 Oct;66(10):2906-2917. doi: 10.1109/TBME.2019.2897952. Epub 2019 Feb 6. Erratum in: IEEE Trans Biomed Eng. 2020 Oct;67(10):3001. PMID: 30735985; PMCID: PMC6752973.

20. El-Hajj C, Kyriacou PA. A review of machine learning techniques in photoplethysmography for the non-invasive cuff-less measurement of blood pressure. Biomedical Signal Processing and Control. 2020; 58: 101870.

21. Karniadakis GE, Kevrekidis IG, Lu L, Perdikaris P, Wang S, Yang L. Physics-informed machine learning. Nature Reviews Physics. 2021; 3(6):422–440.

22. Starr I, Noordergraaf A. Ballistocardiography in cardiovascular research: Physical aspects of the circulation in health and disease. Lippincott, 1967.

23. Zaid M, Ahmad S, Suliman A, Camazine M, Weber I, Sheppard J, Popescu M, Keller J, Despins L, Skubic M, Guidoboni G. Noninvasive cardiovascular monitoring based on electrocardiography and ballistocardiography: a feasibility study on patients in the surgical intensive care unit. Annu Int Conf IEEE Eng Med Biol Soc. 2021 Nov;2021:951-954. doi: 10.1109/EMBC46164.2021.9629531. PMID: 34891446.

24. Lee KJ, Roh J, Cho D, Hyeong J, Kim S. A Chair-Based Unconstrained/ Nonintrusive Cuffless Blood Pressure Monitoring System Using a Two-Channel Ballistocardiogram. Sensors (Basel). 2019 Jan 31;19(3):595. doi: 10.3390/s19030595. PMID: 30708934; PMCID: PMC6387459.

25. Marazzi NM, Guidoboni G, Zaid M, Sala L, Ahmad S, Despins L, Popescu M, Skubic M, Keller J. Combining Physiology-Based Modeling and Evolutionary Algorithms for Personalized, Noninvasive Cardiovascular Assessment Based on Electrocardiography and Ballistocardiography. Front Physiol. 2022 Jan 12;12:739035. doi: 10.3389/fphys.2021.739035. PMID: 35095545; PMCID: PMC8790319.