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Oscillometric blood pressure estimation by combining nonparametric bootstrap with Gaussian mixture model

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ABSTRACT

Background: Blood pressure (BP) is one of the most important vital indicators and plays a key role in determining the cardiovascular activity of patients.

Methods: This paper proposes a hybrid approach consisting of nonparametric bootstrap (NPB) and machine learning techniques to obtain the characteristic ratios (CR) used in the blood pressure estimation algorithm to improve the accuracy of systolic blood pressure (SBP) and diastolic blood pressure (DBP) estimates and obtain confidence intervals (CI). The NPB technique is used to circumvent the requirement for large sample set for obtaining the CI. A mixture of Gaussian densities is assumed for the CRs and Gaussian mixture model (GMM) is chosen to estimate the SBP and DBP ratios. The *K*-means clustering technique is used to obtain the mixture order of the Gaussian densities.

Results: The proposed approach achieves grade "A" under British Society of Hypertension testing protocol and is superior to the conventional approach based on maximum amplitude algorithm (MAA) that uses fixed CR ratios. The proposed approach also yields a lower mean error (ME) and the standard deviation of the error (SDE) in the estimates when compared to the conventional MAA method. In addition, CIs obtained through the proposed hybrid approach are also narrower with a lower SDE.

Conclusions: The proposed approach combining the NPB technique with the GMM provides a methodology to derive individualized characteristic ratio. The results exhibit that the proposed approach enhances the accuracy of SBP and DBP estimation and provides narrower confidence intervals for the estimates.

1. Introduction

Blood pressure (BP) is one of the most commonly measured physiological parameters in medicine. However, a recent editorial in journal Hypertension of the American Heart Association asserts that, "few measurements in medicine are done as poorly and inconsistently as blood pressure measurement…Though there is a clear recognition of biological variability, we continue to make decision largely on measurements taken at random times under poorly controlled conditions" [1]. This assertion emphasizes the need for accounting for variabilities in the measures of BP. BP is constantly changing due to intrinsic physiological variabilities in response of several factors such as stress, exercise, and disease and thus it makes the measurement of BP an arduous task [2]. Variations up to 20 mmHg within a few heartbeats and even larger variations over the course of the day can be expected [2]. These

Abbreviations: AAMI, Advancement of Medical Instrumentation; AE, Area of the OMW's envelope; AG, Age; AR, Asymmetry ratio; ANSI, American National Standard Institute; BIC, Bayesian information criterion; BHS, British hypertension society; BP, Blood pressure; CI, Confidence interval; CR, Characteristic ratios; CP, Cuff pressure; DBP, Diastolic blood pressure; DBPR, Diastolic blood pressure's ratio; EL, Envelope's length; EM, Expectation-maximization; GMM, Gaussian mixture model; GMR, Gaussian mixture regression; HR, The OMW's heart rate; MA, Maximum amplitude; MAP, Mean arterial pressure; MAPL, A length position of the maximum amplitude; MAXROC, OMW's maximum positive rate of change; MINROC, Maximum negative rate of change; MCP, Mean cuff pressure; ME, Mean error; NPB, Nonparametric bootstrap; OMW, Oscillometric waveform; PE, Pseudo envelope; PMA, Pseudo maximum amplitude; PMAE, Pseudo maximum amplitude and pseudo envelope; SBP, Systolic blood pressure; SBPR, Systolic blood pressure's ratio; SDE, Standard deviation of the error; SV, Silhouette value.

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variabilities and their impact on BP measurements are not recognized and accounted for by most clinicians. Also, the BP estimates obtained in the process are often inaccurate [3] as they may be beyond the allowable limits set by the American National Standard Institute (ANSI) at which ANSI recommends a maximum allowable device mean error of 5 mmHg with a standard deviation 8 mmHg compared to an auscultatory reference reading done by at least two trained observers [4]. Interestingly, the Korotkoff auscultatory method continues to be the golden standard in which trained physicians listen to sounds that correspond to SBP and DBP. The auscultatory method has no means to account for the variabilities as it typically involves a single measurement or at most two measurements.

Oscillometric methods for BP estimation have, of late, gained popularity as the measurement process is automated and is available for home use [2]. Oscillometric blood pressure measurement devices generally provide just a single point estimate with no confidence intervals (CIs) [5] and do not provide any means to distinguish between the statistical variance in the estimates (errors due to the estimates) from the variations in the estimates due to intrinsic variabilities due to physiology [3]. It could therefore be helpful to specify the CI for blood pressure measurements. For this, we specify the CI of these values like 120 ± 5 for SBP and 70 ± 3 for DBP, which implies that 95% (or other predefined percentage) of measurements collected in identical conditions will fall in ranges of SBP=[115,125] and DBP=[67,73]. Indeed, the CI is affected by the precision of the hardware components of the blood pressure device, the algorithm employed in the blood pressure device, and the quality of the measurement, i.e., pressure in the cuff when deflating [6]. As there is no non-invasive golden standard other than the auscultatory method, there is currently no method to determine the fluctuations in the BP estimates. If CI estimates were available in these devices, then wider CI estimates could trigger another measurement and recommend discarding the current measurement. Without having CI estimates, it is difficult to meaningfully interpret the BP estimates. In a home monitoring setting, based on an aggregate statistics, repeated wide CI can trigger an alarm and alert a health care provider [7].

The study of CI for SBP and DBP estimates is still in its infancy. A recent study on CI for SBP and DBP utilized Student's t-distribution [8]. Generally, an asymptotic normal distribution is used for obtaining CIs under large sample size assumption. However, such assumptions are generally invalid for blood pressure measurements, as identical and repeatable conditions can never be guaranteed due to physiological factors [3,5,7]. Realizing this, in [5], a bootstrap approach was proposed to obtain the CI from a smaller sample size. Although the bootstrap approach proposed in [5,10] provided the CI along with the estimates and had a lower standard deviation of the error (SDE), this method was not significantly different from the standard algorithm used in the literature, namely, the maximum amplitude algorithm (MAA) [5,9,11,12], in terms of the mean error (ME) and SDE when the reference auscultatory method is used as a golden standard. The MAA uses fixed ratios (also called characteristic ratios, CR) that are obtained experimentally and which are widely used to decide the time points at which the cuff pressure (CP) corresponds to the systolic and diastolic pressures [11]. These CRs, that is to say the systolic and diastolic ratios, are determined using quasi-empirical manners [9,11]. However, the assumption that these ratios are fixed is itself not valid [3,13] and a recent study [14] has proposed that physiological factors have significant effects on these ratios; hence, in [15], a model-based approach was devised to identify the error mechanisms of this fixed ratio oscillometric blood pressure estimation method. This approach identified the factors that cause large errors, particularly with changes in arterial stiffness at zero transmural pressure and pulse pressure. In order to circumvent the explicit use of fixed ratios in the estimation of BP, artificial neural network approaches with the raw signal as input were proposed [16–18]. To reduce the computational burden, a feature-based neural network estimation was also attempted [19]. None of these supervised learning methods could satisfy the recommendations of the ANSI/AAMI SP 10 standards [4]. In order to meet the ANSI/AAMI SP 10 standards, there is a need to develop a method that provides better estimation. Furthermore, to avoid the use of fixed ratios, a technique that derives non-fixed characteristic ratios from the measurements needs to be developed. Also, such a technique should be able to provide the CI along with the BP estimates. This paper essentially provides a solution that addresses all the above needs.

This paper provides a methodology that can decrease uncertainty for oscillometric blood pressure measurements and provide accurate blood pressure estimates without using fixed characteristic ratios (CRs). This paper adopts a hybrid approach [20,21] by combining machine learning algorithms for obtaining the CRs for each subject and the bootstrap technique, which offers the blood pressure estimates with the CIs. To the best of authors' knowledge, this is the first time such a hybrid approach has been proposed for estimation of blood pressure along with CI from oscillometric measurements. The proposed methodology is a combination of the earlier proposed learning methodology for obtaining the ratios that was used with the well-known MAA technique in [13] and the bootstrap methodology introduced in [5] for obtaining CI.

To summarize, the proposed work [5] is first presented for providing the CIs, and then Gaussian mixture model and the Gaussian mixture regression [13] to determine accurate blood pressure estimates are further combined into the proposed work [5]. Interested readers are referred to [5], which deals with how to organize the pseudo maximum amplitude (PMA) and pseudo envelope (PE) for determining the CI.

The paper has the following additional enhancements and contributions when compared with [5] and [13]:

- We propose a novel technique to obtain accurate BP estimates and improved CIs from a small sample of oscillometric blood pressure measurements by combining bootstrap and machine learning techniques.
- An efficient method is presented to select the number of clusters in K-means algorithm utilizing silhouette value.
- It provides additional comparisons of BP estimation over different K in the K-means algorithm.
- We perform performance validation using two training and test scenarios.
- Evidences for superiority of the proposed method are offered by utilizing the grading criteria used by the British Society of Hypertension (BSH) [2] and the American National Standards Institute (ANSI)/American Association of Medical Instruments (AAMI) [4].

This paper is arranged in the following manner. The following section also describes the experimental data set and the measurement methodology used in this paper. Section 3 briefly describes the proposed hybrid methodology while the subsections describe the machine learning approach and the bootstrap approach that are part of this methodology. Section 4 provides the results obtained using the proposed hybrid methodology while Section 5 discusses the results and provides conclusions.

2. Data set

This work was approved by the local research ethics committee, and all subjects provided informed consent prior to the BP