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Deep learning ensemble with asymptotic techniques for oscillometric blood pressure estimation

Soojeong Lee, Joon-Hyuk Chang*

School of Electronic Engineering, Hanyang University, 222 Wangsimni-ro, Seongdong, Seoul 133-791, Republic of Korea

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ABSTRACT

Background and Objective: This paper proposes a deep learning based ensemble regression estimator with asymptotic techniques, and offers a method that can decrease uncertainty for oscillometric blood pressure (BP) measurements using the bootstrap and Monte-Carlo approach. While the former is used to estimate SBP and DBP, the latter attempts to determine confidence intervals (CIs) for SBP and DBP based on oscillometric BP measurements.

Method: This work originally employs deep belief networks (DBN)-deep neural networks (DNN) to effectively estimate BPs based on oscillometric measurements. However, there are some inherent problems with these methods. First, it is not easy to determine the best DBN-DNN estimator, and worthy information might be omitted when selecting one DBN-DNN estimator and discarding the others. Additionally, our input feature vectors, obtained from only five measurements per subject, represent a very small sample size; this is a critical weakness when using the DBN-DNN technique and can cause overfitting or underfitting, depending on the structure of the algorithm. To address these problems, an ensemble with an asymptotic approach (based on combining the bootstrap with the DBN-DNN technique) is utilized to generate the pseudo features needed to estimate the SBP and DBP. In the first stage, the bootstrap-aggregation technique is used to create ensemble parameters. Afterward, the AdaBoost approach is employed for the second-stage SBP and DBP estimation. We then use the bootstrap and Monte-Carlo techniques in order to determine the CIs based on the target BP estimated using the DBN-DNN ensemble regression estimator with the asymptotic technique in the third stage.

Results: The proposed method can mitigate the estimation uncertainty such as large the standard deviation of error (SDE) on comparing the proposed DBN-DNN ensemble regression estimator with the DBN-DNN single regression estimator, we identify that the SDEs of the SBP and DBP are reduced by 0.58 and 0.57 mmHg, respectively. These indicate that the proposed method actually enhances the performance by 9.18% and 10.88% compared with the DBN-DNN single estimator.

Conclusion: The proposed methodology improves the accuracy of BP estimation and reduces the uncertainty for BP estimation.

1. Introduction

Blood pressure (BP) is one of the most important vital signals and is key to make a decision for the cardiovascular activity of patients. It is known that an estimated 18 million people died from cardiovascular diseases in 2012, representing 31% of all global deaths [1]. Oscillometric automated BP monitors are currently available at the home, office, and hospital. The maximum amplitude algorithm (MAA) is generally used to estimate average arterial blood pressure, systolic blood pressure (SBP), and diastolic blood pressure (DBP) based on an oscillometric method [2]. Specifically, the MAA estimates the mean BP via cuff pressure, where the maximum oscillation linearly relates the SBP and DBP to the mean BP using heuristically fixed ratios [2,3]. These characterized fixed ratios allow us to determine the time points at which the cuff pressure corresponds to the SBP and DBP, respectively [4,5]. However, using an MAA based on fixed ratios makes it hard to obtain reliable BP estimations because individual subjects exhibit their own unique physiological characteristics [5]. A recent study [6] has shown that physiological properties yield significant effects on these ratios; hence, in [7], a model-based method was proposed to identify the error mechanisms of the fixed ratios used to estimate the SBP and DBP based on oscillometric measurements. To address the problem of the fixed ratios in the estimation of BP, a feed-forward neural network (FFNN) was considered [8]. However,

* Corresponding author:
E-mail address: jchang@hanyang.ac.kr (J.-H. Chang).

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this approach has drawbacks such as the complexity of the input data, the time consumed, and the computational burden. To mitigate the computational load, a feature-based FFNN was developed to estimate the BPs based on the oscillometric measurements [9]. This method did not satisfy the recommendations of the American National Standards Institute and the Association for the Advancement of Medical Instrumentation (ANSI/AAMI) Sphygmomanometer Committee (SP10) [10]. Thus, an intelligent approach is required to estimate the SBP and DBP, which motivates this work.

Since the BP is changing over time because of physiological oscillations in response to factors such as food, emotion, exercise, and disease, it can shift up to 20 mmHg within a few heartbeats [11–13]. These physiological oscillations in BP measurements are not perceived by most clinicians. Thus, oscillometric BP monitors commonly offer a single point estimate with no confidence intervals (CIs) and fail to consider fluctuations in BP or distinguish them from variations due to physiological properties [14]. When CI estimates are available in these BP device, broad CI estimates can be used to recommend repeat analysis of BP measurement. Without a CI estimate, it is not easy to make any meaningful determination based on BP estimates. On the basis of some aggregated statistics, repeated, broad CIs can alarm the patient and/or caretakers [15]. Although it is very important to determine CIs during BP estimation, ironically, there has not been significant research to find the CIs to oscillometric BP measurements [15]. Indeed, many BP measurements are required to determine CIs using Student's t-distribution [16]. However, it is not feasible to obtain a large number of measurements for each subject using oscillometric BP monitors because repeatable situations for reproducible measurements can not be guaranteed [2]. In this case, it is necessary to calculate CIs based on fewer measurements. Thus, the bootstrap technique to obtain CI estimates from BP measurements using small sample sizes was introduced in [2]. However, this method exceeds the allowable error specified by the ANSI/AAMI protocol because the proposed technique uses characteristic ratios [17] based on the MAA technique.

On the basis of the above findings, this research considers two main issues. The first is a way to estimate the SBP and DBP correctly, and the second is to a way determine uncertainty (CIs for the SBP and DBP based on the oscillometric BP measurements). To address the first issue, we employ machine learning techniques such as a deep belief networks (DBN)-deep neural networks (DNN) [18] which has been attracted attention in machine learning and information processing fields as a promising technique. Based on this advantage, we recently introduced the DBN-DNN regression estimator [19]. However, it is still not easy to determine the best DBN-DNN estimator, and worthy information can be discarded when selecting one DBN-DNN estimator and discarding the others. Additionally, our input feature vectors obtained from only five measurements per subject represented a very small sample size, which is a critical weakness when using the DBN-DNN technique. This critical limitation can cause overfitting or underfitting depending on the structure of the algorithm [9]. Indeed, the DBN was used to address the overfitting problem on the training data set at the pre-training stage. However, this stage can cause an unstable estimation, such as a large standard deviation of error (SDE) with mean error (ME), since there are many random, initialized parameters like weights and biases in the training data set. In order to solve these problems, the ensemble with an asymptotic approach based on combining the bootstrap with the DBN-DNN technique is utilized to enhance the SBP and DBP estimation.

As we mentioned earlier, the bootstrap and Monte-Carlo techniques [20,21] are utilized to determine the CIs based on the target BPs estimated using the DBN-DNN ensemble regression estimator with the asymptotic technique. To the best of our knowledge, this is one of the first studies using the ensemble with asymptotic regression based on the DBN-DNN technique to estimate BP (SBP and DBP) with CIs of a small training sample. The main concept behind our proposed methodology is that BPs are directly estimated using the DBN-DNN ensemble regression estimator with the asymptotic technique, which concurrently provides a solution that can decrease uncertainty for oscillometric BP measurements using the bootstrap and Monte Carlo techniques according to the following additional augmentations and contributions:

- A novel approach is proposed to acquire accurate BP estimates from a limited sample of oscillometric blood pressure measurements using the ensemble with an asymptotic technique based on the DBN-DNN regression estimator.
- Our approach can mitigate overfitting and unstable estimation (such as a large ME with SDE on the pseudo training feature set) through the DBN-DNN-based ensemble with asymptotic regression estimator.
- Our approach provides CIs for oscillometric BP measurements using the ensemble with an asymptotic approach based on the DBN-DNN techniques, in order to address the problem of small sample sizes for each subject.

This paper is organized in the following manner. The next section describes the experimental data set and the measurement methodology used in this paper. Section 3 briefly describes the preprocessing and conventional techniques. We propose the BP estimation with CIs based on the ensemble with asymptotic technique based on the DBN-DNN regression estimator in Section 4. Section 5 explains the results and finally provides discussion in Section 6.

2. Study population and data set

This study was conformed by a local research ethics committee, and every participant signed informed consent prior to measurement, according to the BP measurement protocol of the institutional research ethics board. The BP measurements were measured from 85 healthy subjects with no history of cardiovascular disease, aged 12–80 years, of which 37 were females and 48 were males. Five sets of BP measurements from each subject (duration range of a single measurement: 31–95 s, duration median: 55 s) were acquired utilizing a wrist-worn blood pressure device according to the recommendations of the ANSI/AAMI SP 10 standard [10,15]. Specifically, the readings of two independent nurses were averaged to offer one SBP and one DBP reading [2]. Our BP measurements were comprised of an oscillometric BP recording led by two trained nurses following one minute of rest. This process was repeated four more times to build a recording of five BP measurements. Each participant comfortably sat upright in a chair in which the device cuff was strapped to the left wrist of the subject and raised to heart level during data collection. The auscultatory cuff, that was the reference device, was placed on the upper left arm, also at heart level [22]. The upper cuff was inflated around the arm in order to occlude the brachial artery. When the cuff signal deflated, blood flow generated Korotkoff sounds, that could be readily heard through a stethoscope placed next to the upper cuff. The first Korotkoff sound (K1), that was measured in mmHg by a manometer of the upper cuff, was utilized to estimate SBP, whereas the fifth sound (K5) was used to estimate DBP [23].

Concurrent brachial and wrist measurements were not possible due to the difficulty of occlusion of brachial arteries by upper arm sphygmomanometers. Thus, almost 1.5 min after each signal was obtained by the monitor, two trained nurses concurrently recorded systolic blood pressure (SBP_1 and SBP_2) and diastolic blood pressure (DBP_1 and DBP_2) using a classic upper arm sphygmomanometer. Therefore, the mean values of concurrent readings was utilized as the reference BPs (SBP and DBP). Readings with subscript 1 were