Mimic Big Data and Low Power Infrastructure-based Small Blood Pressure Measurement for Internet of Things

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Abstract

Although estimation of average arterial blood pressure is possible using oscillometric methods based on the internet of things (IOT), there are no established methods in the literature for obtaining confidence interval (CI) for systolic blood pressure (SBP) and diastolic blood pressure (DBP) estimates obtained from such measurements. This paper adopts bootstrap methodologies to build the CI with a small sample set of measurements. The proposed methodologies use multiple pseudo maximum amplitude (MPMA) and pseudo envelope (PE) using big measurement based on bootstrap principles with recursive approach to solve the bias of the pseudo maximum amplitude (PMA) in IOT. The SBP and DBP are derived using the new relationships between mean cuff pressure and PE and then the CIs for such estimates are obtained. Application of the proposed methodology on an experimental dataset of 85 patients with 5 sets of measurements for each patient yielded a tighter Cl than the conventional student t-method.

Keywords: Blood pressure oscillometric method confidence interval bootstrap, IOT, CPSNR, Image quality enhancement

1 Introduction

Diastolic pressure is the minimum pressure in the arteries. This point occurs at the end of the cardiac cycle when the heart relaxes in between beats [1]. A variety of different methods for invasive and non-invasive measurement of BP exist [2], but the question of which is the preferred method to use is still up for debate. Even the trusted method of listening to Korotkoff sounds that doctors routinely use has come into question for not being supported by physics [3]. The maximum amplitude algorithm (MAA) is mostly used to estimate average arterial BP based on oscillometric method [4-10]. The MAA approximates the mean BP as cuff pressure at which the maximum oscillation occurs and then linearly relates the systolic and diastolic BPs to the mean pressure using experimentally obtained ratio [5]. These ratios provide to decide the time points at which the cuff pressure coincides with the systolic and diastolic pressures, respectively [5-6].

In our case, though the oscillometric methods are simpler and quicker compared to invasive measurement techniques, these methods are not easy for the patients or the physicians as over 100 measurements with respects to only one subject is required in order to estimate the confidence interval (CI) of systolic and diastolic. However, very few attempts have been made at the CI of the systolic and diastolic blood pressure. The study of the CI for systolic blood pressure (SBP) and diastolic blood pressure (DBP) have not been presented until recent years [13-15].

This work can be regarded as the extension of our previous study [8-12]. In this work, we propose that multiple pseudo maximum amplitude (MPMA) as a big parameter is used to obtain the CI of SBP and DBP using the non-parametric bootstrap method in IOT. The proposed method consist of two main components which are the processing to obtain the MPMA using the non-parametric bootstrap method with recursive approach and the other is used to estimate the pseudo envelope (PE). The SBP and DBP are detected from the new relationship among the MPMA, pseudo envelope (PE), and the mean cuff pressure (MCP). Consequently, the CI of the proposed method is influenced by the decrease in the variance which is due to the increase in the pseudo big measurements using the non-parametric bootstrap method with respect to each subject. Furthermore, we can see that the MPMA is more robust for small measurement than the pseudo maximum amplitude (PMA) [8] about biased problem about each subject. Note that, in this paper, another important part of an improvement over previous work [8] is the recursive estimation which is used to estimate the ratios of the SBP and DBP instead of the previous method [8] to determine the ratio of the experimental about the SBP and DBP. These methods can also largely decrease the final CI for the SBP and DBP.

The structure of this paper is organized as follows:

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DOI: 10.3966/160792642019012001029

in Section II, the bootstrap method is introduced; in Section III, discusses the PMA non-parametric bootstrap method; In Section IV, show the MPMA and PE. In Section V, show the results; finally, some discussion and conclusion remarks are given in Section VI.

2 Non-Parametric Bootstrap Methods and CI Estimation

In this section, we introduce the principle of the nonparametric bootstrap, offer a review of basic resampling approaches, and describe the use of bootstrap technique in order to evaluate the distribution of a parameter estimate [16]. The fundamental concept is to create many independent bootstrap samples by resampling the original data consisting of say n BP measurements, $\mathbf{X}=\{x_1,...,x_n\}$ at random from an unknown probability distribution F. Let μ is an unknown characteristic of F. The underlying assumption is that the x_i s are *independent*, and *identically distributed* (*i.i.d*) random variables, each having distribution F.

As one does not know the underlying distribution, F, for the BP measurement samples, the bootstrap technique supposes that resamples are chosen from a distribution $\hat{F}$, that becomes F in some sense. Let $\mathbf{X}$ denotes the sample space of BP measurements for a subject. Let A be a set of BP measurements in the sample space $\mathbf{X}$. Then $\hat{F}$ would be the probability measure that allocates to the set A in $\mathbf{X}$ a measure equivalent the proportion of the sample values that lie in A and as $n \to \infty$, $\hat{F} \to F$. The procedures of the non-parametric bootstrap are given follows [17]:

(1) Carry out the experiment (or the measurement process) to acquire the random sample and obtain the estimated mean $\hat{\mu}$ from the sample $\mathbf{X}=\{x_1,...,x_n\}$.

(2) Construct the empirical distribution $\hat{F}$, which puts equal mass $1/n$ at each observation $\{x_1,...,x_n\}$, where x_i is the observation measurements, $\forall i=1$ to n.

(3) Generate a sample $\mathbf{X}^*=\left\{x_1^*,...,x_n^*\right\}$ based on the empirical distribution $\hat{F}$, which is called the bootstrap resample.

(4) Approximate the distribution of the estimated average $\hat{\mu}$ by the distribution of the pseudo estimated average $\hat{\mu}^*$ calculated from the bootstrap resample vector $\mathbf{X}^*=\left\{x_1^*,...,x_n^*\right\}$.

We assume that there are n random variables using some unknown distribution $F_{\mu,\sigma}$ in step 1). We decide an estimator and a $100\cdot(1-\alpha)$ interval for the average μ. Generally, we can use the sample mean as an estimated mean for μ,

$$\mathrm{E}(\mu,\sigma^2 \mid \mathbf{X})=\hat{\mu}=\frac{1}{n}\sum_{i=1}^{n}x_i. \quad \textbf{(1)}$$

The CI for μ can be calculated by determining the distribution of $\hat{\mu}$ such that

$$P\left(\hat{\mu}_L \le \mu \le \hat{\mu}_U\right)=1-\alpha. \quad \textbf{(2)}$$

The distribution of $\hat{\mu}$ relies on the distribution of the $x_i^{'}$s, which is unknown. In the case when $n \to \infty$, the distribution of $\hat{\mu}$ could be approximated by the Gaussian distribution as per the central limit theorem, however, such an approximation is not reasonable in applications where n is small [16]. As mentioned before, the bootstrap supposes that the random sample in step 1) itself constitutes the underlying distribution. Next, through resampling from $\mathbf{X}$ many times and calculating $\hat{\mu}$ for each of these resamples, we can acquire a bootstrap distribution for $\hat{\mu}$ that approximates the distribution of $\hat{\mu}$, and from which the CI for μ may be acquired. Thus, the estimated mean based on the bootstrap technique is given by

$$\hat{\mu}^*=\frac{1}{n}\sum_{i=1}^{n}x_i^*. \quad \textbf{(3)}$$

As represented in [16, 18] if $E\left[x^2\right]<\infty$, then for $\forall x \in R$,

$$\left\|P_*\left[\sqrt{n}\left(\hat{\mu}^*-\hat{\mu}\right)\le x\right]-P\left[\sqrt{n}\left(\hat{\mu}-\mu\right)\le x\right]\right\|_\infty \to 0. \quad \textbf{(4)}$$

where $P_*[\cdot]$ denotes the bootstrap probability conditioned on the observed BP measurements [16]. The result above confirms that the distribution of $\sqrt{n}\left(\hat{\mu}^*-\hat{\mu}\right)$ and $\sqrt{n}\left(\hat{\mu}-\mu\right)$ in the sense that the sup-norm of the difference is almost clearly zero. We can find the convergence and consistency results for many statistics other than the mean [16]. As the measurement is supposed to be *i.i.d*, the bootstrap resamples will contain the same statistical information as the original measurement.

3 Pseudo Maximum Amplitude (PMA)

Our main goal is to provide the unbiased CI of the SBP and DBP with respect to subject using small measurement. As a first phase, we acquire the maximum amplitudes and the time of occurrence of the maxima from all the five measurements per subject, respectively. These preliminary values of the maximum amplitude are utilized to determine the final pseudo maximum amplitudes (PMA) using the non-parametric bootstrap technique [19-20]. Let $\mathbf{X}=\{x_1,...,x_5\}$ denote the set of 5 time position of the maximum amplitudes and $\mathbf{Y}=\{y_1,...,y_5\}$ denote the set of corresponding 5 maximum amplitude values. Based on the non-parametric bootstrap on these two sets, we create a number B of resamples, $\mathbf{X}_j^*,\mathbf{Y}_j^*,\forall j=1\ to\ B$ where $\mathbf{X}_j^*=\left\{x_{1,j}^*,...,x_{5,j}^*\right\}$ and $\mathbf{Y}_j^*=\left\{y_{1,j}^*,...,y_{5,j}^*\right\}$, respectively. We then compute the mean of all measurements in $\mathbf{X}_j^*\ and\,\mathbf{Y}_j^*$ in order to acquire $\hat{\mu}_{\mathbf{X}(j)}^*$ and $\hat{\mu}_{\mathbf{Y}(j)}^*$ given by (5) and (6).

$$\hat{\mu}_{\mathbf{X}(j)}^*=\frac{1}{n}\sum_{i=1}^{n}x_{i,j}^* \quad \textbf{(5)}$$

$$\hat{\mu}_{\mathbf{Y}(j)}^*=\frac{1}{n}\sum_{i=1}^{n}y_{i,j}^* \quad \textbf{(6)}$$

The number of measurement $n\to\infty$, the distribution is close to Gaussian distribution. The means of these two distributions are given follow:

$$\mathrm{E}(\mu,\sigma^2\,|\,\mathbf{X}^*)=\hat{\mu}_{\mathbf{X}}^*=\frac{1}{B}\sum_{j=1}^{B}\hat{\mu}_{\mathbf{X}(j)}^* \quad \textbf{(7)}$$

$$\mathrm{E}(\mu,\sigma^2\,|\,\mathbf{Y}^*)=\hat{\mu}_{\mathbf{Y}}^*=\frac{1}{B}\sum_{j=1}^{B}\hat{\mu}_{\mathbf{Y}(j)}^* \quad \textbf{(8)}$$

We then sort the bootstrap estimates, $\hat{\mu}_{\mathbf{X}(j)}^*$ and $\hat{\mu}_{\mathbf{Y}(j)}^*$ in ascending order. The sorted PMA is given by $\hat{\mu}_{\mathbf{Y}(1)}^*\le\hat{\mu}_{\mathbf{Y}(2)}^*\cdots\le\hat{\mu}_{\mathbf{Y}(B)}^*$ and the time locations of PMA be given by $\hat{\mu}_{\mathbf{X}(1)}^*\le\hat{\mu}_{\mathbf{X}(2)}^*\cdots\le\hat{\mu}_{\mathbf{X}(B)}^*$. Therefore, the CI for position of maximum amplitude and the maximum amplitude are respectively given by

$$\left(\hat{\mu}_{\mathbf{X}(Q_1)}^*,\hat{\mu}_{\mathbf{X}(Q_2)}^*\right) \quad \textbf{(9)}$$

$$\left(\hat{\mu}_{\mathbf{Y}(Q_1)}^*,\hat{\mu}_{\mathbf{Y}(Q_2)}^*\right) \quad \textbf{(10)}$$

where Q_1 denotes the integer part of $(B\alpha/2)$, $Q_2(=B-Q_1+1)$, and $Q_3(=B/2)$. Thus, we obtain $Q_1=25,Q_2=976,\ and\ Q_3=500(\alpha=0.05\ and\ B=1000)$. We note that

$$\hat{\mu}_{\mathbf{X}(Q3)}^*\cong\mu_{\mathbf{X}}^* \quad \textbf{(11)}$$

$$\hat{\mu}_{\mathbf{Y}(Q3)}^*\cong\mu_{\mathbf{Y}}^* \quad \textbf{(12)}$$

where the median point $Q_3(=B/2)$ is almost identical to the mean as in (11) and (12). We therefore obtain the 3 positions of the PMA that will be used by the algorithm to estimate the confidence intervals (CIs) of the SBP and DBP, the SBP and DBP, respectively.

4 Multiple Pseudo Maximum Amplitude (MPMA) and Pseudo Envelope (PE)

The bootstrap methodology allows us to calculate standard errors for statistics for which we do not have formulas and to check normality for statistics that theory does not easily handle [15]. However, we also know that in general statisticians prefer large measurement because small measurement gives more variable results. We can see that the CIs of the bootstrap methodology will sometimes be too long or too short, or too long in one direction and too short in the other [15]. The bootstrap methodology also has the drawback of small measurements to estimate an inference. We will also describe the non-parametric bootstrap procedures that are usually more accurate than standard methods, but even they may not be accurate for very small measurements.

Our main aim is to provide the unbiased CI of the SBP and DBP in terms of subject using small measurement in IOT. Thus, we propose the novel method to address the problem of basis due to small measurement. The first step is to ignore the mean as a measure of center in favor of a statistic that is more measurement to outliers. Specifically, the 50% trimmed distribution ignores the smallest 25% and the largest 25% of the MPMA [15]. It is the distribution of the middle 50% of the MPMA. The MPMA with recursive estimation procedure can be outlined in the following.

(1) (Measurement)

Five sets of oscillometric BP measurements were obtained from each volunteer $(425=5\times 85)$ measurement.

(2) (PMA)

In this step, we obtain the maximum amplitudes and the time of occurrence of the maxima from all the five measurements per subject. Let $\mathbf{X}=\{x_1,...,x_5\}$ represent the set of 5 time position of the maximum amplitudes and $\mathbf{Y}=\{y_1,...,y_5\}$ represent the set of corresponding 5 maximum amplitude values. Using the non-parametric bootstrap on these two sets, we generate B number of resamples $\mathbf{X}_j^*,\mathbf{Y}_j^*,\forall j=1\ to\ B$, respectively.

(3) (PE)

In order to obtain the pseudo envelopes for estimating the CI, we construct a measurement matrix $\mathbf{E}$ as in (23) consisting of envelopes for five measurements of each subject:

(4) (Connecting MPMA, PE, and MCP)

We obtained the values of the MPMA and the PE using the non-parametric bootstrap method. We connect the MPMA and the PE estimates using the second-order polynomial [21]. In the final step, we need to obtain the MCP. This step is required to eliminate the fluctuations present in the CP curve, such that the MCP represents only the deflation of the cuff.

(5) (CI of SBP and DBP)

To find the SBP and DBP, systolic and diastolic ratios must be defined. The systolic ratio and diastolic ratio used in our method are 0.70 and 0.45, respectively, which were decided experimentally [4].

(6) (Decision I)

If the recursive count of the bootstrap m is greater than or equal to two, go to Step 7. Otherwise, go to Step. 9. For m = 1 to M which is 5.

(7) (MPMA using recursive estimation)

First, if m is greater than or equal to two, we obtain a multiple pseudo measurement $\mathbf{X}_j^m = \left\{ \hat{\mu}_{\mathbf{X}(Q_4)}^{m-1}, ..., \hat{\mu}_{\mathbf{X}(Q_5)}^{m-1} \right\}$ and $\mathbf{Y}_j^m = \left\{ \hat{\mu}_{\mathbf{Y}(Q_4)}^{m-1}, ..., \hat{\mu}_{\mathbf{Y}(Q_5)}^{m-1} \right\}$ as a multiple bootstrap resample. Herein, we create a number of B = 1000 of resample $\mathbf{X}_j^m$ *and* $\mathbf{Y}_j^m$ for j = 1 to B and for m = 1 to M, where M is 5, and m represents bootstrap count. Namely, if m is two which denotes **.

(8) (Decision II)

If the recursive count m is greater than or equal to three or (min_s and min_d) is greater than or equal to 0.01, let $m = m-1$ updated ratios go to Step 7. Otherwise, go to Step. 4. Here 0.01 is given constant.

(9) (Evaluation and terminate the process) Output the results of the SBP, DBP, and CI.

Note that, we can see the proposed method as more explained in follow subsection. If m is equal to three, we can obtain a triple PMA $\mathbf{X}_j^{***} = \left\{ \hat{\mu}_{\mathbf{X}(Q_4)}^{***}, ..., \hat{\mu}_{\mathbf{X}(Q_5)}^{***} \right\}$ and $\mathbf{Y}_j^{***} = \left\{ \hat{\mu}_{\mathbf{Y}(Q_4)}^{***}, ..., \hat{\mu}_{\mathbf{Y}(Q_5)}^{***} \right\}$ as the bootstrap resample from the MPMA. Herein, we also create a number of B=1000 of resample $\mathbf{X}_j^{***}$ *and* $\mathbf{Y}_j^{***}$ for j=1 to B, respectively. Next, we calculate the mean of the all measurements in $\mathbf{X}_j^{***}$ *and* $\mathbf{Y}_j^{***}$ where obtain the mean of all 1000 pseudo maximum amplitudes are given by

$$\hat{\mu}_{\mathbf{X}(j)}^{***} = \frac{1}{C} \sum_{k=1}^{C} \hat{\mu}_{\mathbf{X}(k,j)}^{***} \tag{13}$$

$$\hat{\mu}_{\mathbf{Y}(j)}^{***} = \frac{1}{C} \sum_{k=1}^{C} \hat{\mu}_{\mathbf{Y}(k,j)}^{***} \tag{14}$$

where C=C/2 is the number (from Q_4 to Q_5) as the 50% trimmed distribution using the MPMA. The means of these two distributions are given as:

$$\hat{\mu}_{\mathbf{X}}^{***} = \frac{1}{B} \sum_{j=1}^{B} \hat{\mu}_{\mathbf{X}(j)}^{***} \tag{15}$$

$$\hat{\mu}_{\mathbf{Y}}^{***} = \frac{1}{B} \sum_{j=1}^{B} \hat{\mu}_{\mathbf{Y}(j)}^{***} \tag{16}$$

In the next step, we also sort the triple bootstrap estimate in increasing order to obtain $\hat{\mu}_{\mathbf{Y}(1)}^{***} \le \hat{\mu}_{\mathbf{Y}(2)}^{***} \cdots \le \hat{\mu}_{\mathbf{Y}(B)}^{***}$ and the time locations of MPMA be given by $\hat{\mu}_{\mathbf{X}(1)}^{***} \le \hat{\mu}_{\mathbf{X}(2)}^{***} \cdots \le \hat{\mu}_{\mathbf{X}(B)}^{***}$. The desired $100 \cdot (1-\alpha)$ % non-parametric CI for position of maximum amplitude and the maximum amplitude are respectively given by, $\left(\hat{\mu}_{\mathbf{X}(Q_1)}^{***}, \hat{\mu}_{\mathbf{X}(Q_2)}^{***} \right)$ and $\left(\hat{\mu}_{\mathbf{Y}(Q_1)}^{***}, \hat{\mu}_{\mathbf{Y}(Q_2)}^{***} \right)$, where Q_1 denotes the integer part of $(B\alpha/2)$, $Q_2 (= B - Q_1 + 1)$, and $Q_3 (= B/2)$. For $\alpha = 0.05$ and B=1000, is we can obtain Q_1, Q_2 and Q_3.

$$\hat{\mu}_{\mathbf{X}(Q3)}^{***} \cong \mu_{\mathbf{X}}^{***} \tag{17}$$

$$\hat{\mu}_{\mathbf{Y}(Q3)}^{***} \cong \mu_{\mathbf{Y}}^{***} \tag{18}$$

The median point $Q_3 (= B/2)$ is almost identical to the mean as (21) and (22). Thus, we also obtain the 3 positions of the MPMA that will be used by the algorithm to estimate the CIs of the SBP and DBP, the SBP and DBP, respectively. To find the MPMAs of the fourfold and fivefold, the same procedure as described in the previous method is then followed.

4.1 Review of PE Using NB Method [8]

To obtain the pseudo envelopes for estimating the CI, we construct a measurement matrix **E** as in (19) consisting of envelopes for five measurements of each subject:

$$\mathbf{E} = \begin{bmatrix} e_{11} & . & . & . & e_{1N} \\ . & . & . & . & . \\ . & . & . & . & . \\ . & . & . & . & . \\ e_{L1} & . & . & . & e_{LN} \end{bmatrix}, \tag{19}$$

where L is length of pseudo envelope and N(= 5) is the number of envelopes. Actually, all measurements are forced to be of length L, by either truncating the length to L, if the measurement is longer or by extrapolating to length L, if the measurement is shorter.

From the measurement matrix **E**, using non-parametric bootstrap method, we obtain B_1 resample matrices $\mathbf{E}_1^*, ..., \mathbf{E}_{B_1}^*$. In our method, B_1 = 100. Using the sorting technique as described in the previous section, we reorder the above matrices. It may be noted that each of the sorted matrix has 5 columns, each corresponding to a measurement of length L. We then obtain one envelope per subject using equations (20) to (22) as the last step of the part of **PE** process, where the desired $100 \cdot (1-\alpha)$ % non-parametric percentile bootstrap CI are given by

$$\mathbf{PE}_{Q_1} = \frac{1}{N} \sum_{i=1}^{N} \mathbf{E}_{Q_1,i}^* \tag{20}$$

$$\mathbf{PE}_{Q2} = \frac{1}{N} \sum_{i=1}^{N} \mathbf{E}_{Q_2,i}^* \tag{21}$$

$$\mathbf{PE}_{Q_3} = \frac{1}{N}\sum_{i=1}^{N}\mathbf{E}^{*}_{Q_3,i} \tag{22}$$

4.2 SBP and DBP Ratio Using Recursive Approach

We first review the conventional approach for ratio estimation of SBP and DBP in which the parameters $\hat{\alpha}$ *and* $\hat{\beta}$ of interest are assumed to be a deterministic but unknown constant. To find the systolic and diastolic pressures one must first define the systolic and diastolic ratios based on the MAA [7].

$$SP_m \cong \hat{\alpha}_m \cdot MA_m \tag{23}$$

$$DP_m \cong \hat{\beta}_m \cdot MA_m \tag{24}$$

where $\hat{\alpha}_1 = 0.70$ *and* $\hat{\beta}_1 = 0.45$, respectively, MA_m is the position of maximum amplitude, *m* is the recursive count for $m = 1,...,M$, here $M = 5$. The SP_m and DP_m represent the index of position.

First, we obtain the results of the SP_1 and DP_1 using the MAA as in (23) and (24). Then, we can also obtain the updated ratio as in (25) and (26) using the results of the MPMA and the previous MA_m.

$$\hat{\alpha}_{m+1} \cong \frac{SP_{m+1}}{MA_m} \tag{25}$$

$$\hat{\beta}_{m+1} \cong \frac{DP_{m+1}}{MA_m} \tag{26}$$

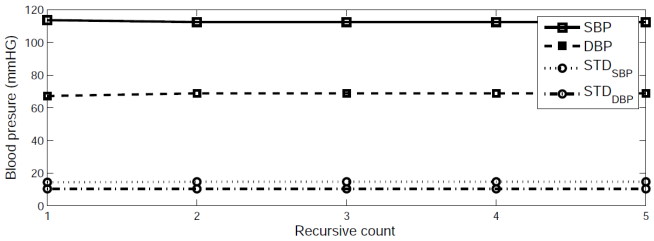
where SP_{m+1} and DP_{m+1} are the index of the updated position using the MPMA and PE in step 2), step 3), step 4), and step 5).

$$\min_{s,m} \cong \mathrm{E}\left[(\hat{\alpha}_m - \hat{\alpha}_{m-1})^2\right] \tag{27}$$

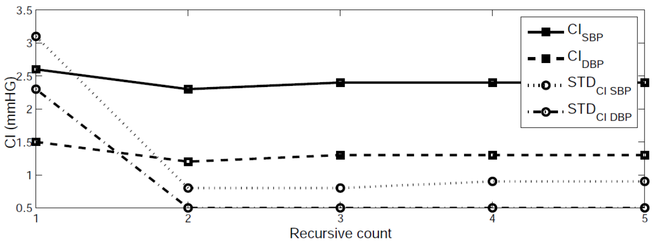
$$\min_{d,m} \cong \mathrm{E}\left[(\hat{\beta}_m - \hat{\beta}_{m-1})^2\right] \tag{28}$$

In (27) and (28), we have minimum estimators about the SBP and DBP, respectively. In particular, minimal estimators are sought that minimized the mean-square error between the initial ratios and the updated ratios. These are used to determine the repeat number of MPMA with the recursive count m as step 8). Finally, if the recursive bootstrap count m is equal to 5, we obtain the final results of position index about the SBP and DBP, respectively.

Here, in order to determine properly systolic and diastolic ratios as mentioned at the end of Section 1, we use recursive estimation with the MPMA using the non-parametric bootstrap approach. The main reason we use the recursive approach using bootstrap method to estimate the ratios of the SBP and DBP. The results of the SBP and DBP have the almost constant values though increasing the recursive count from 2 to 5 as shown Figure 1. This may be thought as a very important characteristic since the CIs of the SBP and DBP converge the constant ranges. Therefore, we use it to estimate the updated ratios of the SBP and DBP.



(a) Blood pressure SBP and DBP (mmHG) as increase recursive count; one is PMAE; two is DMAE; three is MPMA (triple); four is MPMA (fourfold); five is MPMA (fivefold)



(b) CIs of SBP and DBP as increase recursive count

Figure 1.

5 Experimental Results

The experimental data set was obtained from 85 healthy recruited subjects aged from 12 to 80, out of which thirty seven were females and forty eight were males participated in the study. No recruited subjects had any history of cardiovascular disease. Five sets of oscillometric BP measurements were obtained (duration range of a single measurement: 31-95 sec., deration median: 55 sec.) from each volunteer $(425 = 5 \times 85)$ total measurements using a wrist worn BP device of (UFIT TEN-10, Biosign Technologies Inc.,Toronto, Ontario, Canada) at a sample rate of 100 Hz.

During data recording, each subject easily sat upright in a chair in which the UFIT monitor cuff was strapped to the left wrist of the subject and raised to heart level. The auscultatory cuff, which was the reference device, was placed on the upper left arm, also at heart level. The upper cuff was inflated around the arm in order to occlude the brachial artery. For more details on extraction of oscillometric wave (OMW), the reader is referred to [1]. Corresponding to each pressure waveform, two reference readings were also recorded using the auscultatory method by two independent trained observers (nurses) and these readings are used for deriving the reference reading.

The average value of these two measurements was computed as the reference BP of each subject. We used the derivative of the cuff pressure waveform for the OMW signal, using software which we developed in Matlab R2008b (The MathWorks Inc., Natick, MA, USA) [22].

Table 1 lists the values of systolic and diastolic blood pressures determined by the nurse, estimated by our proposed algorithm and the MAA referred to in [1]. The difference between the systolic blood pressures measured with the auscultation and that with the PMAE was found to have similar standard error of estimates (SEE) to the nurse measurement and MAA of [7]. Note that, the MPMAE was lower SEE compared to the MAA as seen in Table 2. In addition, the linear regression between the estimates of our method and the nurse also gave a similar fit (as shown by R value) to that of MAA as in Table 2. The linear regression results for blood pressure measurement was obtained as in Table 2 using the statistical software (SPSS Inc., Chicago, IL) [23].

Table 1. Summary of blood pressure (BP) measurements by the nurse, proposed pseudo maximum amplitude and pseudo envelop (PMAE), double PMAE (DPMAE), multiple PMAE (MPMAE), and MAA, where see is standard error of estimate; n=85 is number of subjects with five measurements

BP(mmHg)	SBP(std)	DBP(std)
Nurse	109.0(13.3)	67.6(9.9)
PMAE	113.6(14.4)	67.2(10.4)
DPMAE	112.5(14.7)	68.8(10.2)
MPMAE	112.4(14.7)	68.8(10.3)
MAA	113.4(14.9)	67.1(10.3)

Table 2. Summary of blod pressure (BP) measurements by the nurse, proposed pseudo maximum amplitude and pseudo envelope (PMAE), double PMAE (DPMAE), multiple PMAE (MPMAE), and MAA, where SEE is standard error of estimate; **R** is correlation coefficient; n=85 is number of subjects; std is standard deviation

BP (mmHg, n=85)	SEE (Nurse vs .PMAE)	SEE (Nurse vs .DPMAE)	SEE (Nurse vs .MPMAE)	SEE (Nurse vs .MAA)	R (Nurse vs .PMAE)	R (Nurse vs .DPMAE)	R (Nurse vs .MPMAE)	R (Nurse vs .MAA)
SBP	8.48	8.22	8.22	8.49	0.79	0.79	0.79	0.78
DBP	7.23	7.10	7.10	7.25	0.70	0.70	0.70	0.69

The confidence interval (CI) results of the blood pressure measurements are provided in Table 3. It is seen that the CI results obtained using the proposed method is lower than methods for obtaining CI using the MAA algorithm with bootstrap (Boot), MAA with the student-t (ST), and MAA with the measurement uncertainty (MU) [24-26]. The decrease in the standard deviation in the CI results obtained through our method is substantial and demonstrates the advantage of the proposed method over the existing methods for obtaining CI from a small set of measurements.

Table 3. Compared average results in CI of SBP and DBP using the proposed method and the conventional methods; std is standard deviation; n=85 is number of subjects

BP(mmHg)	SBP (std) 95% CI	DBP (std) 95% CI	SBP Lower (std)	SBP Upper (std)	DBP Lower (std)	DBP Upper (std)
PMAE	2.6(3.1)	1.5(2.3)	112.4(13.9)	115.0(14.9)	66.7(10.5)	68.2(9.9)
DPMAE	2.4(0.9)	1.3(0.5)	111.4(14.5)	113.7(14.8)	68.8(10.2)	70.1(10.5)
MPMAE (triple)	2.3(0.8)	1.3(0.5)	111.4(14.5)	113.7(14.8)	68.8(10.2)	70.1(10.5)
MPMAE (fourfold)	2.4(0.9)	1.3(0.5)	111.4(14.5)	113.7(14.8)	68.8(10.2)	70.1(10.5)
MPMAE (fivefold)	2.4(0.9)	1.3(0.5)	111.4(14.5)	113.7(14.8)	68.8(10.2)	70.1(10.5)
MAA with Boot	8.4(5.1)	5.8(3.6)	109.5(14.4)	117.8(15.9)	64.3(10.2)	70.1(10.7)
MAA with ST	13.5(8.1)	9.3(5.7)	106.7(14.3)	120.2(16.5)	62.4(10.4)	71.7(11.0)
MAA with GUM [24]	14.1(7.8)	10.1(5.3)	106.4(14.3)	120.5(16.4)	62.0(10.4)	72.1(10.9)

6 Discussion and Conclusion

The goal of this paper was to derive CI for SBP and DBP estimates when only small number of blood pressure measurements is available in IOT. However, we begin by investigating the degree of similarity between the readings obtained with the proposed methods and those obtained with the reference ausculatory method (Table 2). To investigate the similarity, the correlation coefficient (R) was used following the approach taken in two previous studies [2, 23]. In Table 2, the systolic blood pressure measurement is represented that there is a correlation coefficient (r=0.79, SEE=8.48mmHG, and n=85) between the auscultatory results and the PMAE results, and there is also a correlation coefficient (r=0.78, SEE=8.49mmHG, and n=85) between the auscultatory results and the MAA results. The results of PMAE are quite similar to that of the MAA. However, the DPMAE and MPMAE are lower SEE (8.22 mmHG) in the SBP, the DBP showed slightly lower SEE (7.10 mmHG) compared to the MAA. It is represented to reduce the SEE of the DPMAE and MPMAE using recursive trim distribution.

As shown in Table 3, the CIs of the DPMAE and MPMAEs are narrower than those of the PMAE. Table 3 also shows the compared CI results of SBP and DBP using the PMAE, DPMAE, MPMAE methods and conventional methods. We show that the CIs of both the PMAE, DPMAE, and MPMAE methods are much smaller than that of the conventional methods for SBP and DBP probably since we think that the CIs of the PMAE, DPMAE, and MPMAE are effected by the decrease in the standard deviation which is due to the increase in the pseudo measurements using the bootstrap methods with respect to one subject. In addition, we note that the PMAE methods have also much smaller the STD of the CI when compared the conventional methods in compared average results with respect to 85 subjects. More so, we also note that the STDs of the SBP and DBP of the PMAE methods are similar to those of SBP and DBP of the MAA with statistical methods. According to the bootstrap principle, the distribution of the SBP and DBP of the PMAE well represents the sampling distribution of the original measurement [15]. In particular, the the STD of the CIs of the DPMAE and MPMAE have much smaller the STD of the CIs of the PMAE in third low of Table 3. So, we have also confirmed the effect of the MPMAE method. Table 4 represents the recursive estimators which are used to estimate the ratios of SBP and DBP instead of the previous method [8] to determine the ratio of the experimental about SBP and DBP. However, it has a drawback to estimate the ratios of the SBP and DBP like computational complexity. Also, the MPMAE, with recursive estimator to determine the ratios of SBP and DBP, shows almost similar results compared with the PMAE and MAA in SEE and R. It is a problem in the future we need to overcome.

Table 4. The estimated systolic and diastolic ratios using recursive bootstrap method with respect to one subject (Ex. 65 years old male), where $\min_s$ and $\min_d$ are minimum estimators about the SBP and the DBP

methods	SBP ratios	DBP ratios	$\min_{s,m}$	$\min_{d,m}$
MAA	0.70	0.45		
PMAE	0.70	0.45		
DPMAE	0.6985	0.4509	0.00000211	0.000000843
MPMAE (triple)	0.7009	0.4495	0.00000538	0.00000207
MPMAE (fourfold)	0.6983	0.4514	0.00000658	0.00000354
MPMAE (fivefold)	0.7014	0.4491	0.00000988	0.00000528

In conclusion, we demonstrated that the CI obtained through the proposed method is narrower and has a lower standard deviation. This is attributed to the increase in the effective number of samples due to resampling using bootstrap- principles. Experimental results show that all of the MPMA with recursive approach using non-parameters bootstrap are much smaller than the conventional method's obtained CI. In particular, we have represented that the proposed methodologies use the MPMAE using bootstrap principles to overcome the bias of the PMAE.

Acknowledgments

This work was supported by the Incheon National University Research Grant in 2014.

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