Nonlinear Cuff-less Blood Pressure Estimation of Healthy Subjects Using Pulse Transit Time and Arrival Time

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Abstract—This paper presents a novel blood pressure (BP) estimation method based on pulse transit time (PTT) and pulse arrival time (PAT) to estimate the systolic BP (SBP) and the diastolic BP (DBP). A data acquisition hardware is designed for high-resolution sampling of phonocardiogram (PCG), photoplethysmogram, and electrocardiogram (ECG). PCG and ECG perform as the proximal timing reference to obtain PTT and PAT indices, respectively. In order to derive a BP estimator model, a calibration procedure, including a supervised physical exercise, is conducted for each individual, which causes changes in their BP, and then, a number of reference BPs are measured alongside the acquisition of the signals per subject. It is suggested to use a force-sensing resistor that is placed under the cuff of the BP reference device to mark the exact moments of reference BP measurements, which are corresponding to the inflation of the cuff. Additionally, a novel BP estimator nonlinear model, based on the theory of elastic tubes, is introduced to estimate the BP using PTT/PAT values precisely. The proposed method is evaluated on 32 subjects. Using the PTT index, the correlation coefficients for SBP and DBP estimation are 0.95 and 0.84, respectively. Using the PAT index, the correlation coefficients for SBP and DBP estimation are 0.89 and 0.84, respectively. The results show that the proposed method, exploiting the introduced nonlinear model with the use of PAT index or PTT index, provides a reliable estimation of SBP and DBP.

Index Terms—Cuff-less blood pressure, mobile health (mHealth), pulse arrival time (PAT), pulse transit time (PTT), vital signals.

I. INTRODUCTION

Hypertension, or long-term high blood pressure (BP), is a primary factor increasing the risk of ischemic heart disease, heart failure, aortic aneurysms and so forth [1], [2]. Hypertension is prevalent among about 26% and 23% percent of men and women, respectively. Also, it is more frequent in countries with low GDP values [3]. These facts necessitate the usage of effective methods for continuous BP monitoring.

BP is defined as the pressure that the blood applies to the vessel walls during the blood circulation. BP is a periodic vital signal with the same period of its changing over time. Therefore, it would be highly desirable to monitor BP continuously and in a non-invasive and cuff-less manner that is convenient.

A wide variety of research has been conducted in devising methods for the continuous and cuff-less measurement of BP. Among these, using cardiovascular parameters such as pulse wave velocity (PWV) are the most studied ones. PWV is defined as the velocity of the pressure wave that is propagating through arteries. PWV is usually estimated by measuring the PTT. PTT is the time that takes for the pressure wave to travel from a proximal point to a distal point in the arterial tree, within the same cardiac cycle. The fundamental principle is that arterial elasticity increases with BP and it also influences the PWV. As a result, BP can be estimated by the measurement of PTT or PWV. The exact relation between BP and PTT is, however, individual-specific and depends on the physical properties of the vessels and blood of each person. Therefore, to approximate this relation, a calibration procedure in which a number of reference BP measurements are done, is required for each individual [6].

Usually, in the literature, electrocardiogram (ECG) is used as a proximal timing reference and the photoplethysmogram (PPG) is used as a distal timing reference for PTT measurement [7], [8], [9], [10], [11]. However, using ECG and PPG signals leads to the measurement of another cardiovascular parameter that is pulse arrival time (PAT). PAT includes not only the desired PTT but also a pre-ejection period (PEP). The PAT has shown a high correlation with BP (especially...
SBP) [12]. Some papers have used other vital signals, instead of ECG, such as phonocardiogram (PCG) in [13] and [14], or ballistocardiogram (BCG) in [6], as the proximal timing reference to obtain PTT index instead of PAT index.

A major portion of research works have used estimator models that assume a simple linear relation between PTT/PAT and BP [8], [13]. However the relationship between PTT/PAT and BP is actually nonlinear and parameters defining this nonlinear relation are individual-specific and depend on physical properties of vessels and blood (see Section II-A for more details). The authors in [15] have assumed this nonlinearity between PAT and BP. However, parameters of this nonlinear relation are determined globally, using a train set of subjects, and the same parameters are employed to estimate BP for a test set of subjects with different physical properties.

In this paper, a novel nonlinear model, based on modeling vessels as elastic tubes, is introduced for BP estimation based on PTT/PAT values. A calibration procedure for each subject, which uses a novel way to mark the moments of reference BP measurements, is utilized to determine the subject-specific parameters of the proposed model per individual. The PCG and ECG signals are employed as the proximal timing references for obtaining PTT index and PAT index, respectively. PPG is used as the distal timing reference for obtaining both PAT and PTT indices.

The rest of the paper is structured as follows: Section II explains the physical background behind the relation between PTT and BP in each individual. Section III describes the sampling hardware setup and the data acquisition procedure employed for each subject. Section IV presents the processing pipeline exploited to measure PTT/PAT values from acquired signals. Section V provides results and compares them with existing related works. Section VI presents some discussions on the results and some limitations of the paper. Finally, Section VII concludes the paper.

II. BACKGROUND

A. The Relationship between BP and PTT

The key principle behind using PWV for BP estimation is that the blood flow in the arteries can be modeled as the propagation of pressure waves inside elastic tubes. Specifically, by assuming vessels like elastic tubes, Elastic modulus ($E$) of the vessel walls can be written as:

$$E = E_0 e^{\alpha(P-P_0)},$$

where $P$ is the fluid pressure (here BP), and $E_0$, $P_0$ and $\alpha$ are individual-specific parameters [15]. The compliance ($C$) is defined as the rate at which the tube cross section changes in terms of $P$. Considering the conservation of mass and momentum equations, it can be seen that $C$ is a function of $P$:

$$C(P) = \frac{A_m}{\pi P_1 [1 + (\frac{P-P_0}{P_1})^2]},$$

where $P_0$, $P_1$, and $A_m$ are individual-specific parameters [16]. Writing the wave propagation equations inside the vessels, which are assumed as elastic tubes, leads to the following equation [17]:

$$P(x, t) = f(x \pm t/\sqrt{\text{LC}(P)}),$$

where $L = \rho/A$; in which, $\rho$ and $A$ are the blood density and vessel cross section, respectively. Therefore, PTT for a tube of length $l$ can be derived as:

$$PTT = \frac{l}{\text{PWV}} = l \sqrt{\text{LC}(P)}.$$

Furthermore, by substituting $L$ and $C(P)$, PTT can also be formulated as:

$$PTT = l \left( \frac{\rho A_m}{\pi A} \right),$$

The PTT-BP relationship for each individual is described in [5] with the aid of individual-specific parameters. $l$ is related to the distance between the distal and proximal points at the time of PTT measurement. By solving (5) for $P$ (BP here), $BP$ can be derived as a function of $PTT$:

$$BP = P_0 + \sqrt{P_1^2 + \frac{\rho A_m}{\pi A}} \times \frac{1}{PTT^2},$$

which can be rewritten in a more simplified form as:

$$BP = a_0 + \sqrt{a_1 + a_2 \frac{1}{PTT^2}},$$

where $a_0$, $a_1$, and $a_2$ are derived for each subject. In other words, instead of directly determining the individual-specific parameters of (6), the BP-PTT relationship can be obtained by determining $a_0$, $a_1$, and $a_2$ parameters in (7).

PAT can also be used instead of PTT for the purpose of cuffless BP estimation. PAT is defined as PTT plus the PEP time interval, where PEP is the time it takes for the myocardium to raise enough pressure to open the aortic valve and start forcing the blood out of the ventricle. Yet, it has been shown that PAT has a high correlation with BP.

In this paper, we have proposed using the non-linear BP-PTT relation of (7) to present a more accurate estimation of individual’s BP. To derive the constant parameters of (7) for each individual, a calibration procedure is required in which the subject’s BP is varied by means of some interventions [15], [16], [19], [20]. After the interventions, a number of reference BP measurements are acquired (see Section III). Using acquired signals, PTT/PAT values, corresponding to the reference BP measurements are obtained as it is indicated in Section IV-B. The obtained pairs of PTT/PAT values and reference BP measurements enables us to derive the parameters of (7) as it is presented in Section IV-C.

B. PTT/PAT Measurement Method

Corresponding PTT/PAT to each pair of proximal and distal time instances is measured by the calculation of distal time minus proximal time. In this paper, PCG S1-peak is considered as the proximal timing reference to measure PTT, as it approximately represents the moment that blood pressure wave leaves the heart. S1 and S2 are two dominant types of
The utilized hardware setup in this work includes a data acquisition board developed in our team, a portable computer, and a commercial BP monitor. The board acquires the vital signals (i.e., PCG, PPG, and ECG) in addition to the signal from a force-sensing resistor (FSR). The signals are recorded synchronously from four separate ADC channels using 1KHz sampling frequency. Fig. 2 presents the block diagram of the designed data acquisition board. The board and the portable computer are connected via Universal Serial Bus (USB) protocol and the board sends data frames of 1-second length to the computer. Accordingly, there is a maximum 1-second latency between the channels and the computer, which considerably facilitates appropriate placement of the sensors. In order to ensure that data samples from different channels are acquired and transferred to the computer synchronously, ADC inputs from all channels were read in the burst mode and placed in the data frame in an interleaved fashion. Via the proposed synchronization method, the offset among the four signals at the start of the recording can be assumed to be constant for each specific individual and hardware pair and therefore, the effect of these constant offset values is compensated and cancelled by the calibration procedure. Also, a software is designed for the computer, which saves the time series data of ADC channels sent from the board as well as storing each subjects physiological information (i.e., height, weight, arm length, age, etc.) and reference BP measurements.

In this setup, reflection PPG with the wavelength of 530 nm (green) is acquired from the finger of the left hand. Reflectance PPG is preferred over its transmissive counterpart due to its convenience of sensor placement for end users. The AD8232 (fully integrated single-lead ECG front-end) chip was used to acquire high-resolution ECG from the left and right hands (leg drive was not connected). An electret condenser microphone, which is connected to a diaphragm by means of a hollow tube, was used to acquire PCG signal. A chest-belt was used to fix the diaphragm on the subject’s chest. An automatic digital BP monitor device (Model M3, OMRON, Japan) was used to measure reference BP values. According to the manufacturer’s datasheet, the accuracy of this device is about 3 mmHg, which is compliant with the conventional health standards such as AAMI and BHS. For instance, the mean absolute error of about 5 mmHg is considered to be the acceptable error rate according to the AAMI guidelines [21]. In addition, before starting the data collection process, we also measured the BP of 7 subjects randomly using both Omron M3 device and a conventional mercury sphygmomanometer. The measured BPs for each person were approximately the same (each person was at the rest condition during BP measurement using both monitors, so approximate same values for BPs for each person were expected). Specifically, the mean absolute error of SBP and DBP measurements using these two devices were 3.4 mmHg and 5.0 mmHg, respectively.

Since the PPG sensor was placed on the subject’s left hand, BP measurements were taken from the right hand to reduce the effects of BP measurement on the PPG signal (see Fig. 3). The FSR was placed under the BP monitor cuff to measure the instantaneous cuff pressure. Using FSR is an effective and novel approach to measure the instantaneous cuff pressure synchronized with other vital signals. Further, it can be used to find the exact time instances of each BP measurement during the calibration process. Details of processing the FSR signal and using them will be discussed in Section IV-B.

B. Data Acquisition Procedure

In total, we had 32 healthy subjects in the age range of 21-50 years (including 24 male and 8 female subjects). Subjects were informed and agreed about the data collection procedure in advance. Also, the data collection procedure was approved by Health Center authorities at Sharif University of Technology. Among common interventions proposed in the literature for perturbing BP [22], [23], [24], [25], [26]. [12], here, physical exercise is employed since it has been shown to cause a sensible increase in both SBP and DBP up to 40 mmHg [27]. For data collection for the calibration procedure,
Fig. 2: Block diagram of the data acquisition board.

Fig. 3: An illustration of the data collection procedure and the data sampling board.

is devised in order to enhance the quality of the signals. Afterwards, PTT/PAT values corresponding to each of the reference BP measurements are extracted. At last, using these values and the nonlinear model introduced in Section II, SBP and DBP are estimated.

In this work, we have implemented the whole preprocessing, feature extraction, calibration, and estimation process using Python programming language. Also, the scikit-learn library [28] was used for training the regression models.

A. Preprocessing on the Signals

For preprocessing on the signals, firstly, all four signals are smoothed using the median filter technique to reduce the impulsive noise effect. As the median filtering is a non-linear technique, the employed window width is limited to a few milliseconds (5 milliseconds). Next, all the signals are statically normalized. At the end, frequency filtering is performed on the signals. For frequency filtering, infinite impulse response (IIR) filters, which are more computational efficient than finite impulse response (FIR) filters, are used. IIR filters, however, have non-linear phase responses, which may lead to distortions in signals that adversely affect the accuracy of PTT/PAT measurements. To avoid this pitfall, IIR filters are applied using a non-causal forward-backward fashion (i.e. applying the filter in both directions), which produces a fixed zero phase response.

Particularly, for the FSR signal, because of the relatively long time intervals between reference BP measurements, a low-pass filter is exploited. For the rest of the signals, band-pass filtering is used. The filter specifications for each of the acquired signals in the data collection process are represented in Table I. Each filter’s frequency response and order are set such that the main content of the corresponding input signal is retained.

B. PTT/PAT Measurement and Post-Processing

At the beginning, the three main signals (i.e. PCG, PPG and ECG) are divided to time intervals, where each interval corresponds to one of the BP measurements by the automatic
### TABLE I: Filter Specifications

| Signal Name | Filter Type  | Low Cutoff | High Cutoff | Order |
|-------------|--------------|------------|-------------|-------|
| FSR Signal  | Bidirectional IIR, Low-Pass | -          | 0.3 Hz      | 3     |
| PPG         | Bidirectional IIR, Band-Pass   | 0.5        | 20          | 3     |
| ECG         | Bidirectional IIR, Band-Pass   | 1          | 40          | 3     |
| PCG         | Bidirectional IIR, Band-Pass   | 20         | 240         | 3     |

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BP monitor. There are three key moments in each reference BP measurement:

1. When the cuff begins to inflate ($t_1$),
2. When the cuff begins to deflate ($t_2$),
3. When cuff deflation finishes and SBP and DBP values are measured and read by the automatic BP monitor ($t_3$).

The FSR signal can distinguish these three moments since it represents instantaneous applied pressure by the cuff (see Fig. 4). The $t_3$ moments are used to divide the main signals to the mentioned time intervals (see Fig. 4). Next, PTT and PAT values corresponding to each of reference BP measurements are calculated from corresponding time intervals.

Each time interval itself is divided into equal-sized time windows. The size of each time window is chosen such that at least 2 complete cardiac cycles of all the three main signals exist in each of them (e.g. 2.5 seconds). Moreover, a scaling is done in each time window to bring all the values into the range between 0 and 1 (see Fig. 5).

For PTT/PAT measurement in each time window, the main signals should be delineated reliably. To determine the ECG R-peak and distinguish it from other peak types in ECG, the ECG itself and its first derivative are analyzed simultaneously. As the R-peak is more isolated than other peak types in ECG, the value of the first derivative of ECG is higher near the R-peak position (see Fig. 6). Accordingly, we applied a threshold of about 0.9 on the normalized ECG signal to find a few R-peak candidates and then we used the value of derivatives before and after each candidate to select the R-peak. For delineating PCG, however, the fact that S2-peak is closer than S1-peak to $PPG_p$ in each cardiac cycle can be employed to distinguish S1-peak from S2-peak (see Fig. 7). Therefore, after finding a few candidate points for S1 and S2 peaks, we used their relative positions to the PPG systolic peak to decide on S1 and S2 assignments. $PPG_f$, $PPG_d$, and $PPG_p$ are determined through their definitions. Afterwards, PTT/PAT values corresponding to each of these distal points are measured. It is worth mentioning that, in each time window, if the proximal or distal points cannot be delineated reliably, that specific window is excluded from our analysis.

At last, the average of the extracted PTT/PAT values from time windows in each time interval is used to give one PAT value and one PTT value for that time interval.
TABLE II: The SBP and DBP Estimation Results Using The Proposed Nonlinear Estimator Model in (7)

| Exploited Index for Estimation | The Performance of SBP Estimation | The Performance of DBP Estimation |
|--------------------------------|----------------------------------|----------------------------------|
|                                | ME (mmHg) | MAE (mmHg) | STD (mmHg) | r      | ME (mmHg) | MAE (mmHg) | STD (mmHg) | r      |
| PAT  | -0.21     | 7.92      | 12.16      | 0.81     | 0.73    | 5.93      | 8.72       | 0.64    |
| PAT  | 0.80      | 4.98      | 7.16       | 0.94     | 1.59    | 4.82      | 5.47       | 0.84    |
| PAT  | 0.12      | 4.71      | 6.15       | 0.95     | 1.31    | 4.44      | 5.36       | 0.84    |
| PTT  | 0.69      | 8.33      | 12.85      | 0.80     | 1.37    | 5.92      | 8.08       | 0.67    |
| PTT  | 0.22      | 6.17      | 9.36       | 0.88     | 1.09    | 3.91      | 5.12       | 0.83    |
| PTT  | -0.28     | 6.22      | 9.44       | 0.89     | 1.03    | 3.97      | 5.15       | 0.84    |

For testing the proposed approach, per subject, each time, we leave one of the extracted pairs of reference BPs and associated PTT/PAT values aside, and train the nonlinear model of (7) with the remaining pairs of that subject. Then, that subject’s BP is estimated using the obtained estimator model and the PAT or PTT index of the left-out pair. Then, the estimated BP value is compared with the actual reference BP value of the left-out pair. There are 5 or 6 extracted (PAT/PTT, reference BP) pairs for each subject in the data collection process. Therefore, we have 5 or 6 BP estimations per subject. In total, there are 173 BP estimations for all 32 subjects in this paper.

A. Comparison between different distal timing references on the PPG signal

Table III presents the performance of the proposed model for different variations of PAT/PTT values, corresponding to using different characteristic points on the PPG signal as the distal timing reference. Criteria for performance evaluation are mean error (ME), mean absolute error (MAE), standard deviation (STD) of estimation, and target-estimation correlation coefficient (r). According to Table III, some comparisons can be made. For instance, the estimation of the model, when \( PPG_f \) is selected as the distal point for measuring PTT or PAT, is inferior to estimation using other characteristic points on PPG. Using both \( PPG_d \) and \( PPG_p \) for estimation, performs nearly the same for both of SBP and DBP targets. It is noteworthy to mention that the subject-specific parameters of (7) are determined for each individual separately using the suggested calibration procedure.

B. PAT Versus PTT

For having a comparison between PAT and PTT in terms of their accuracy in both SBP and DBP estimations, \( PPG_d \) is used as the distal timing reference. As it is evident, for SBP estimation, PAT performs better than PTT, while the accuracy of DBP estimation using PTT is higher in compared to using PAT.

Fig. 8 demonstrates the histograms of errors for SBP and DBP estimations. Here, as Table III suggests, \( PTT_p \) index or \( PAT_p \) index are used for estimations. According to Fig. 8, it can be seen that error values are distributed around zero. Based on these histograms, a major portion of the error values lie within the threshold of \( \pm 10 \) mmHg for both of SBP and DBP targets.
Fig. 8: Error histograms for SBP and DBP targets (a) using PTT index and (b) using PAT index.

Fig. 9: Bland-Altman plots for SBP and DBP estimations. According to Fig. 9, a wide range of target BPs are able to be estimated with low errors (ranges for SBP and DBP targets are from 106 mmHg to 197 mmHg and from 51 mmHg to 93 mmHg, respectively.). Also, the limits of agreement (mean ± 1.96 × STD) are indicated. Using the PTT index, these limits are -0.28 ± 1.96 × 9.44 mmHg for SBP and 1.03 ± 1.96 × 5.15 mmHg for DBP. Using the PAT index, these limits are 0.12 ± 1.96 × 6.15 mmHg for SBP and 1.31 ± 1.96 × 5.36 mmHg for DBP.

The estimation versus target regression plots for BP estimations using PTT index or PAT index are shown in Fig. 10. Using PTT index for estimation, r values for SBP and DBP estimations, obtained from all the subjects, are 0.89 and 0.84, respectively, with the aid of PAT index, r value for SBP and DBP estimations are 0.95 and 0.84, respectively. Consequently, there is a close correlation between estimated and target BPs for both of SBP and DBP. The
using PTT index, and 4.34 mmHg versus 4.57 mmHg using PAT index. Therefore, no significant differences are observed between male and female subjects in terms of the accuracy of the proposed model.

C. Comparison with Other Works

A comprehensive comparison between the proposed method in this paper and some of other works in literature, which use PTT or PAT index for BP estimation, is presented in Table III For each one, number of subjects as well as estimation methodology are mentioned. According to this table, in comparison with other methods using PAT index for BP estimation, the results for the PAT-based estimations in the proposed method in this paper are more encouraging for both of SBP and DBP estimations (by comparing r values). The same conclusion can be made by comparing the PTT-based estimations in this work and other methods using PTT index to estimate BP. It is worth mentioning that DBP estimations in this study, using PTT or PAT, have promising results in comparison to other studies. This fact is valuable since in many studies in literature, compared to SBP, correlation coefficients associated with DBP are considerably less (see [12], [30], [31] for example).

Furthermore, since using different subjects and datasets can lead to different results, for a fair comparison, we exploited the BP estimator model in [7] and applied it to our own dataset. The BP estimator in [7] uses a general exponential function based on PWV, which is derived using PAT. The parameters of this general function are obtained by least squares fitting the function to a train group. In this paper, we used first 17 subjects for this purpose. Then, the derived function is used to estimate the BP of a test group. Here, we used the remained 15 subjects for this purpose. Also, [7] suggests to use a one-point calibration method to compensate the subject-specific errors of the general function. Here, as we have 5 or 6 pairs of PAT values and reference BP measurements per subject, we used the first pair for the calibration and the rest for the evaluation of the model. The results for both SBP and DBP estimations are shown in Table III (In [7], only results for SBP estimations are reported). According to the results, by comparing the r values, the estimation accuracy of the proposed model in the paper is still higher, even after using our own dataset for the proposed model in [7].

VI. DISCUSSIONS AND LIMITATIONS

It is worth to mention the goal of using physical exercise in this paper was to obtain a number of reference BP estimates with a significant variance to derive the parameters of the model in [7] more accurately because of reasonably different calibration points, provided by the physical exercise. However, the physical exercise cause PEP and PTT to vary in the same directions [29], and therefore, since PTT is directly correlated to BP, the PAT can track BP more accurately compared to when we use other interventions such as cold pressor. Consequently, any approach that employs the same proposed model as in this paper but with other

![Fig. 11: 95% confidence intervals for SBP and DBP targets (a) using PTT index and (b) using PAT index.](image-url)
TABLE III: Comparison with Other Works *

| Work                  | Number of Subjects | Estimation Methodology | Calibration Interventions | SBP ME (mmHg) | MAE (mmHg) | STD (mmHg) | r | DBP ME (mmHg) | MAE (mmHg) | STD (mmHg) | r |
|-----------------------|--------------------|------------------------|---------------------------|---------------|------------|------------|---|---------------|------------|------------|---|
| This Work             | 32                 | PCG & PPG (PTT)        | Running Exercise          | -0.28         | 6.22       | 9.44       | 0.89| 1.03          | 3.97       | 5.15       | 0.84|
| This Work             | 32                 | ECG & PPG (PAT)        | Running Exercise          | 0.12          | 4.71       | 6.35       | 0.95| 1.31          | 4.44       | 5.36       | 0.84|
| [7]                   | 14                 | ECG & PPG (PAT)        | Treadmill Exercise        | 0.00          | 7.1        | 5.30       | 0.87| 0.00          | 5.1        | 2.90       | 0.30|
| [7]                   | 63                 | ECG & PPG (PAT)        | Cycle Ergometer Exercise  | -0.02†        | 8.1‡       | 10.10      | 0.83| DBP estimation not addressed in this paper |
| [6]                   | 15                 | BCG & PPG (PTT)        | Deep Breathing + Sustained Handgrip | -0.03†        | 9.2†       | 8.58†      | 0.70| -0.02†       | 7.1        | 5.81†      | 0.66|
| [16]                  | 57                 | ECG & PPG (PAT)        | No Intervention           | -0.04†        | 8.21       | 5.45       | 0.54| -0.03†       | 4.31       | 3.52       | 0.57|
| [29]                  | 22                 | BCG & PPG (PTT)        | Three Hemodynamic Interventions | -0.1†         | 11.8†      | 1.6        | 0.80| -0.2†        | 7.6†       | 0.5        | 0.80|
| modified [7]          | 32                 | ECG & PPG (PTT)        | Running Exercise          | 0.85          | 14.02      | 11.11      | 0.78| 1.31          | 4.99       | 4.77       | 0.82|

*The values represented with "-" are not either reported in corresponding other works or able to be estimated based on reported results.
† Approximated from the corresponding Bland-Altman plots.
‡ In [29], instead of MAE, root-mean-squared-error (RMSE) is reported.
§ Applying the BP estimator model in [7] to our own dataset to for a fair comparison. See the details in Section V-C.

Interventions for perturbing BP that change PEP and PTT in opposite directions, can affect the PAT-based results adversely.

Furthermore, in this paper, we measured PTT/PAT values through the brachial artery. The stiffness of the brachial artery, and therefore PTT/PAT values, may vary through the changes in vasomotor tone (controlled by the sympathetic nervous system), and not necessarily changes in BP [32]. Some studies have examined the effect of vasomotor tone on BP-PTT relationship [33], and central PPG instead of peripheral PPG was suggested to reduce this effect [19]. Some studies have done the measurement of PTT through larger, more elastic arteries including the aorta using a system in a way similar to a bathroom weighing scale [29]. Nonetheless, most studies have not attempted to take this factor into account in the PTT-BP estimation model to improve the accuracy.

One of the limitations of this work, which can be examined in future studies, is the fact that subjects used in this study were generally young and healthy subjects, while using a homogeneous dataset like this can affect the results. For instance, patients with cardiovascular diseases can have highly different heart rates over heartbeats, to the extent that the extraction of valid PTT and PAT values from vital signals could not be feasible. Therefore, one of the future directions could be investigating the proposed BP estimator model in this paper on more heterogeneous subjects having some specific cardiovascular diseases or wider age ranges.

VII. Conclusion

In this paper, we have addressed the problem of continuous and cuff-less BP estimation. PCG, ECG and PPG signals were acquired during the suggested data collection process, to obtain PTT and PAT indices, which are utilized for BP estimation. Each subject underwent a supervised physical exercise for perturbing BP in a sensible way for the calibration procedure. Exploiting the FSR signal was proposed for the sake of a precise synchronization between the reference BP measurements and the vital signals, which improved the calibration procedure significantly. The devised processing pipeline was employed for creating a BP estimator nonlinear model using PTT or PAT index for each individual. The parameters of this BP estimator model are individual-specific and determined for each subject separately through the suggested calibration procedure. Comparing different distal timing references for measuring PTT or PAT, it can be inferred that using $\text{PPG}_d$ or $\text{PPG}_p$ could provide better correlations with both SBP and DBP. Using the PAT index for estimation, which is more widely used in literature, leads to more precise SBP estimations, while the use of PTT performed better compared to using PAT for DBP estimations. In summary, this study showed that the proposed method and the nonlinear estimator model, using either PTT index (obtained from PCG & PPG signals) or PAT index (obtained from ECG & PPG signals), can be employed for accurate estimation of both of SBP and DBP targets.

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