Deep Learning for Blood Pressure Estimation: an Approach using Local Measure of Arterial Dual Diameter Waveforms

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***Abstract*— In this work, we present a novel approach for ubiquitous blood pressure (BP) measurement that involves a deep learning technique based on the extraction of the inherent features that are indicative of arterial pressure–diameter and pulse transit relationships. The proposed artificial neural network (ANN) architecture is the first to use the combined features of local arterial dimensions and blood pulse propagation characteristics for continuous, cuffless BP estimation. A dual-channel A-mode ultrasound system and a probe with a pair of single-element ultrasound transducers were developed for simultaneous measurement of luminal diameter waveforms from small arterial segments. In our present system, the probe design was optimized to capture local vessel dynamics from the common carotid artery. The reference continuous BP corresponding to individual cardiac cycles was acquired from the same arterial segment using a tonometer synchronized with the diameter measurement system. The data required to train and validate the developed ANN-based BP estimation model was recorded by conducting an in-vivo study on 20 young subjects. Thirty-seven unique features derived from the dual diameter waveform were extracted for beat-by-beat measurement of BP parameters from the carotid site, and hence to construct the carotid pressure waveform. Experimental results showed that the proposed approach exhibited an acceptable accuracy, with a root-mean-square-error of 4 mmHg and 6 mmHg for DBP and SBP respectively. In conclusion, the proposed approach provides a potentially novel cuffless BP technique for continuous measurement of arterial pressure waveform.**

Keywords—Arterial diameter; blood pressure; carotid artery; deep learning; feature selection; multilayer perceptron; ultrasound.

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I. INTRODUCTION

Ubiquitous blood pressure (BP) monitoring technology that eliminates the use of occlusive cuff and offers ultra-convenient, unobtrusive, and continuous measurements is on the horizon due to: (1) profound need [1]; (2) clinical significance [2]; (3) non-invasiveness and measurement feasibility [1]; and (4) potential application in wearables and personal healthcare monitors [3]. Because of the global interest in this arena, there has been a surge in developing cuffless techniques for BP measurement in the last two decades. Among them, most commonly employed techniques for cuffless BP estimation are based on applanation tonometry [4], pulse transit time estimates [1], volume clamping [5], and pulse condor analysis [6]. Despite their wide acceptance in research, there are several outstanding issues (including the poor accuracy, need for frequent calibration, and operator dependence) in realizing these techniques for clinical applications [1], [2]. In recent years, with growing interest in data mining investigation, additional efforts have been made to address innate challenges and limitations of the existing cuffless BP measurement techniques. Nevertheless, there are still fundamental concerns ahead before its wide application [1], [2].

Many methods rooted in the principle of data mining have been proposed to predict BP parameters as well as to construct arterial pressure waveforms from various physiological signals. Machine learning is the most commonly employed technique. Algorithms such as support vector machines, multivariate linear regression, and artificial neural networks have already found their way in cuffless BP domain [2]. Currently, the most popular

approach is the development of BP estimation models using features of a physiologic waveform obtained from a single arterial site. Photoplethysmogram (PPG) from extremity sites (example: fingertip) is widely preferred due to its ultra-convenience and amenity to continuous and convenient measurement. This approach relies on the features derived from the amplitude indices of the PPG [7]. Some efforts employ electrocardiogram (ECG) along with the peripheral PPG [8], offering additional pulse arrival time features. It should be stressed that the PPG, an optically obtained plethysmogram, detect blood volume changes in the microvascular bed of tissue [9]. Consequently, all the features extracted in aforesaid approaches may not be directly associated with arterial pressure level; giving rise to a threat of overfitting in the learning algorithms. Additionally, the inherent sources of error in cuffless BP while using the time-span features derived from ECG-PPG cycle pair may be remembered [1]. A promising data mining modality that extracts features from the physiological signals which are direct functions of the arterial pressure yet to be deployed at present.

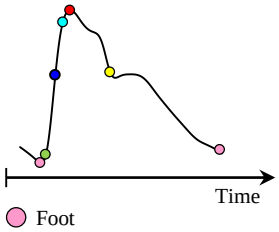
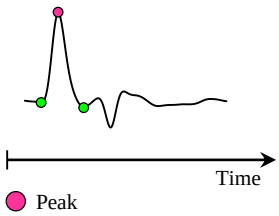
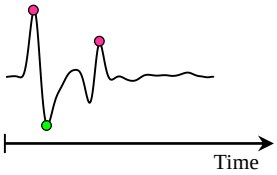
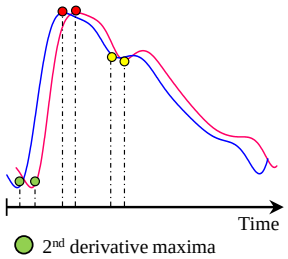
The present study is the first to demonstrate measurement of BP parameters from individual target arteries in a cuffless and continuous manner, using deep learning technique. This novel approach is motivated by the well-established relationships of the BP level in an arterial segment versus its vessel diameter variations and local pulse wave velocity [10]. In our present system, the BP of a target artery was estimated with the help of an artificial neural network (ANN) architecture using features extracted from a pair of arterial diameter waveform (described in Section II). Localized measurement of dual diameter waveforms was achieved using a custom image-free ultrasound system (presented in Section II). The reference BP parameters corresponding to the features of individual cardiac cycles were acquired from the same arterial segment using a clinical-grade tonometer synchronized with the diameter measurement system. The in-vivo study conducted for data collection, training and evaluation of the developed model are discussed in Section III. The experimental study results, the performance of the proposed techniques, and future research scopes are highlighted in Section IV, followed by conclusions.

II. Methodology

A. Problem Formulation and Feature Extraction

Arterial diameter is nonlinearly related to the transmural pressure, and the degree of this nonlinearity is dependent on the vessel elastic properties. The morphology of the diameter waveform at any given arterial site is a direct indicative and is the result of the forward and backward traversing pressure wave trains. Though the various characteristic features of the diameter waveform are strongly associated with the transmural pressure, they are not fully sufficient to characterize or quantify the pressure in the artery. Whereas, these diameter features combined with the localized information relating to the arterial elastic properties (material or functional) would fully be required to quantify the same. The pulse propagation speed is a physiological parameter that is related to the elastic properties of the artery and is inherently dependent on the local transmural pressure. In this regard, the goal of this work is to develop a deep learning model that estimates BP parameters by taking as input:

TABLE I. Waveform Illustration and Extracted Features

Waveforms	Features
Diameter waveform  Foot 2nd derivative maxima 1st derivative maxima Shoulder point Peak systolic Dicrotic notch	a. Systolic and diastolic phase times b. Systolic and diastolic areas c. Peak systolic and diastolic amplitudes d. Ascending and descending slopes e. Ascending and descending areas f. Inflection point to systolic g. Dicrotic notch time h. Dicrotic notch to systolic peak slope i. End diastolic diameter j. Peak distension k. Distensibilty l. Time period of the cycle
1st derivative waveform  Peak 1st and 2nd Valley	a. Rise and decay times b. Rise and decay amplitudes c. Ascending and descending slopes d. Ascending and descending areas
2nd derivative waveform  1st and 2nd dominant peak Valley	a. Rise and decay times b. Rise and decay amplitudes c. Ascending and descending slopes d. Ascending and descending areas
Dual diameter waveforms  2nd derivative maxima Peak systolic Dicrotic notch	a. Local transit time at 2nd derivative maxima b. Local transit time systolic peak derivative maxima c. Local transit time dicrotic notch

(1) the features of the local arterial diameter waveform; (2) and the features relating to the pulse propagation speed derived from dual diameter waveforms that are measured from proximally spaced locations. The features extracted from the diameter waveform also include those that are related to the arterial reflections which would adequately suffice to quantify the pressure accurately. Table I summarizes the list of physiological and characteristic features extracted from the diameter waveforms along with their first and second-time derivatives.

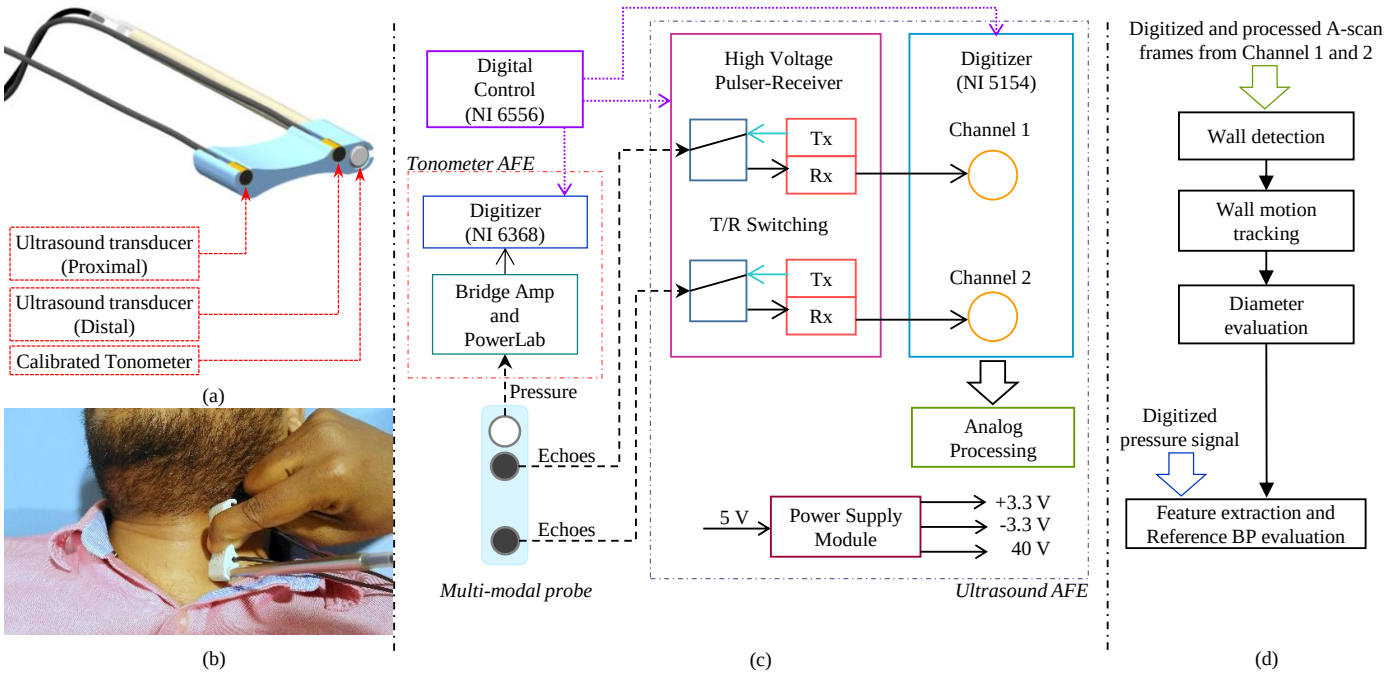


Fig. 1. (a) Design schematic of the dual-element ultrasound probe integrated with tonometer, (b) Multi-modal probe placement at the carotid artery, (c) Hardware schematic of the proposed dual-channel system, (d) Signal processing stages incorporated in the software for measurement and feature extraction.

B. Model Architecture

The deep learning model implemented here for the proposed technique is a feed-forward neural network (FFNN). This model was implemented using PyTorch framework on Python 3.6. The network consists of an input layer with 73 neurons, an output layer with 2 neurons and four hidden layers (sizes: 70, 70, 40, and 10 respectively). Each layer was associated with 1D batch normalization in order to accelerate the network training. Each neuron in the successive layer is connected to all the neurons in the previous layer forming a fully interconnected architecture. Let $w_{ij}^{(k)}$ represent the weight associated with the connection from i^{th} neuron in layer k and j^{th} neuron in layer $k+1$. Then the output of a neuron $n_{(k+1)j}$ (j^{th} neuron in the $(k+1)^{th}$ layer) can be derived as expressed below.

$$n_{(k+1)j} = \sigma\left(\sum_i w_{ij}^{(k)} n_{ki}\right) \quad (1)$$

Here, m is the number of neurons in the k^{th} layer and σ denotes the activation function which are responsible for the introduction of non-linearity in the model. Tanh, sigmoid, ReLU are some of the commonly used activation functions for FFNN. Of these activation functions, ReLU that yields minimal computation complexity was chosen for the developed architecture. For a given input vector X (i.e., a set of 73 features extracted from the dual diameter waveforms), the network traverses through the layers to compute a corresponding output $\hat{Y}$; i.e. $[\hat{y}_0, \hat{y}_1]$ (BP parameters). This is a process commonly known as the forward pass. The respective loss for the particular forward pass was calculated using a loss function. The loss function chosen for the model was Huber loss. The partial derivatives of the loss with respect to each weight was calculated and, this gradient was used to update the respective weight using an extended stochastic gradient descent algorithm, Adam optimizer. This process of itertively updating the weights to minimise the loss function is called as back propagation. Training and evalutaion of the developed model are discussed in the following section.

C. Acquisition Hardware and Signal Processing

Our extensively validated image-free ultrasound technology, ARTSENS® [11], was employed for measuring the instantaneous arterial diameter from two proximally spaced locations (distance = 35 mm) using a custom dual-channel probe with a pair of single-element ultrasound transducers. The probe consists of a broadband, focused single element ultrasound transducer (center-frequency = 5 MHz, spatial half angle < 1.3°, diameter = 5 mm) to perform continuous measurement of changes in arterial diameter. A calibrated clinical-grade tonometer (SPT-301 – Millar Instruments) was placed along with the distal ultrasound sensor to record reference BP parameters from the same arterial segment. These transducers were integrated into a 3D printed enclosure that acted as a probe holder. The distance between the pressure transducer and the single element ultrasound transducer is kept minimal so that the signals are approximately recorded from a single arterial site. The schematic of the compact multi-modal probe assembly is presented in Fig. 1(a) and the probe placement at the carotid artery is depicted in Fig. 1(b).

The signal acquisition hardware consists of a dedicated dual channel analog front end (AFE) to interface the proximal and distal ultrasound transducers. As illustrated in Fig. 1(c), the AFE comprises of necessary pulser-receiver circuitry and control units for operating the ultrasound transducer in pulse-echo mode and obtaining A-scans of the targeted region at high frame rates. A high frame rate of 1 kHz was achieved for the developed ultrasound system to capture high fidelity diameter waveforms with adequate temporal resolution necessary for accurate evaluation of the required physiologic and characteristic

features. The digital logic required to control the pulser-receiver was implemented using a high-speed digital input-output card (NI PXIe 6556 – National Instruments). To digitize the received ultrasound A-scan frames a high-speed digitizer (NI PXI 5154 – National Instruments) with a sampling rate of 50 MHz was used. The AFE also consists of a dual stage amplifier for preprocessing of the frames before digitization.

The reference pressure signal from tonometer was acquired using ADInstuments' PowerLab and BrigdAmp. For digitization of the preprocessed pressure signals a data acquisition card (NI PXIe 6368 – National Instruments) was employed and the sampling rate was configured to 1 kHz, ensuring a matched frequency response for both the modules. A trigger pulse generated by NI PXIe 6556 controlled the acquisition thereby ensuring synchronized acquisition of dual diameter and pressure waveform in a beat-by-beat manner.

An application-specific signal acquisition, processing, and the feature extraction were performed using software built on National Instruments' LabVIEW platform. Fig. 1(d) exhibits the architecture of the measurement software. For the continuous measurement of diameter using the A-scan acquired frames, the automatic algorithms of our ARTSENS® technology [11] were employed. These intelligent algorithms auto-detect a pair of echoes corresponding to the arterial walls from the A-scan frames of each channel and continuously track their locations to calculate the proximal and distal inner-lumen diameter. The pressure signals were processed via low pass filter with cutoff frequency 15 Hz, in-order to remove any high-frequency noise. An automatic cycle-cutting algorithm cuts and extract all the defined features along with the reference BP parameters (SBP and DBP) from each cardiac cycles.

III. Experiments

A. Data Collection

The physiological data required to train and validate the proposed ANN-based BP estimation model was recorded by conducting an in-vivo study on 20 young subjects with a mean age of 27 ± 6.5 years. The study protocol was reviewed and approved by the review committee of Healthcare Technology Innovation Centre (HTIC), IIT Madras and the procedures were performed in accordance with the guidelines of the review committee. This study was carried out in compliance with the Helsinki Declaration of 1975, as revised in 2000. All the participants gave their informed consent before the trials, after explaining the study protocol.

All the measurements during the course of study were performed in a temperature (~ 23°C) controlled room, by a single operator on the left common carotid artery while the subject was in the supine posture. The measurement location was identified by palpating in the left side of the neck. The developed multimodal probe was placed at the identified location and aligned to obtain high fidelity pressure waveform and good quality ultrasound signals with strong and sharp arterial wall echoes. Visual feedback of the signals provided by the developed graphical user interface helped the operator adjust the orientation and hold-down pressure of the probe in order to ensure the signals fidelity. The pressure and diameter signals were recorded for more than 100 cardiac cycles.

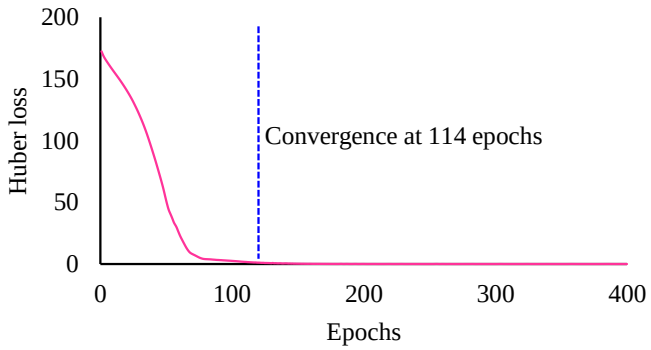


Fig. 2. Loss plot of developed BP estimation model on training dataset.

B. Training Method

The entire dataset (comprise of features of individual beat) was split randomly into train and test dataset, in a ratio of 7:3. For the training, the network was initialized with weights sampled from a 'xamarin' distribution with a bias 0.01. The Huber loss is defined as in (2), with y and $\hat{y}$ are of arbitrary size.

$$L_\delta(y,\hat{y}) = \begin{cases} \frac{1}{2}(y-\hat{y})^2, \ for\ |y-\hat{y}| \le \delta \\ \delta|y-\hat{y}| - \frac{1}{2}\delta^2, \ otherwise \end{cases} \quad (2)$$

This loss was calculated between the target values and output of the network for a batch size of 200 input vectors with $\delta = 1$, which is then back-propagated. The weights were optimized using Adam optimizer with a learning rate of 0.01, exponential decay rate for 1st moment as 0.9, and 2nd moment as 0.999. The network was trained for 400 epochs. Fig. 2. Illustrates the minimization of the loss function during the training phase. It was observed that the convergence of this minimization occurred for 114 epochs. The model was implemented in PyTorch framework and was trained on an intel core i7 8700K CPU machine.

C. Evaluation Method

To evaluate the accuracy performance of the developed FFNN BP estimation model, a comparison was carried out against the reference pressure measurements performed by the tonometer. Initially, a regression analysis was carried out, in which the correlation coefficient was computed and its significance was tested considering the significance level (alpha) as 0.05. Further, the Bland-Altman analysis was performed to investigate the mean bias between both measurements. A paired t-test was performed to test the significance of the obtained bias, setting the significance level as 0.05. The root-mean-square-error (RMSE) was also calculated for the BP parameters. Post investigation of the measurement accuracy, the beat-to-beat repeatability was also evaluated based on the coefficient of variation (CoV) in the BP values measured over 15 consecutive cycles. CoV for the individual subjects was calculated as the ratio standard deviation to mean of the measurements, expressed in percentage.

IV. Results and Discussion

A. Reliability of In-Vivo Data Collection

The developed multimodal probe and the associated system could acquire high fidelity waveforms of arterial pressure and

diameter from the carotid site for continuous cardiac cycles. A sample of these waveforms obtained from a particular subject (age = 26 years, BMI = 21.4 kg/m^2) is depicted in Fig. 3. The system yielded similar high-fidelity waveform for all the subjects, demonstrating the expected functionality. These waveforms were reliable for extracting the amplitude-specific features enlisted in Table I in a beat-by-beat manner. The developed ultrasound measurement system achieved a temporal resolution of 1 ms with a frame rate of 1 kHz. Note that the typical value of the local blood pulse transit time for a propagation length of 35 mm, is of the orders smaller than 15 ms. Therefore, our measurement system possesses adequate time- resolution for extracting the time-specific features from the individual diameter cycle pair. These beat-to-beat features were first used to train the FFNN and then to compute the BP parameters as discussed in the previous section.

B. Performance of the Proposed Technique

We evaluated carotid BP parameters, DBP and SBP, from each cardiac cycle from the extracted beat-by-beat features. With the proposed model, continuous measurement of static DBP and SBP values were repeatable with a group average CoV of 9.5% for all the recruited cohort. The observed minimum and maximum CoV values were 4.4% and 12.8% respectively. Results from the present study highlight the reliability of proposed approach to evaluate BP parameters from each cardiac cycle, rather than a snapshot of pressure level (average value of several consecutive cycles) as given by the conventional cuff-based BP monitoring devices.

Additionally, by knowing the DBP and SBP values along with arterial diameter parameters from each cardiac cycle, the arterial pressure waveform was constructed with the help of fundamental arterial pressure–diameter relationship [12]. More specifically, the arterial stiffness index β was evaluated for each cardiac cycle using their respective systolic, diastolic pressure and diameter values as given in (3). Here, $D_{(t)}$ is the recorded proximal (or distal) diameter wave, and D_D is the end-diastolic diameter corresponding to DBP level. Using the obtained β, the apparent morphology of arterial pressure waveform was derived from the diameter waveform by substituting into (4); where $P_{(t)}$ is the arterial pressure waveform. A sample of the carotid pressure waveform assessed from a particular subject is shown in Fig. 4. Although the inherent characteristic features of true pressure waveform could vary due to various physiological factors, the locus of pressure wave obtained from the proposed technique can be reliably used for fundamental morphological analyses. Note that, further works as in progress to construct the arterial pressure waveform using the measurable physiological features via advanced data mining techniques.

$$\beta = \frac{ln\left(\frac{SBP}{DBP}\right)}{\left(\frac{D_{(t)}-D_D}{D_D}\right)} \quad (3)$$

$$P_{(t)} = DBP\, e^{\beta\left(\frac{D_{(t)}-D_D}{D_D}\right)} \quad (4)$$

The measurement accuracy was further investigated by comparing the average value BP parameters estimated by the proposed technique with those measured using the reference device. Results obtained from statistical analyses are depicted in Fig. 5. The regression analysis demonstrated a statistically significant correlation between the reference and estimated values with r = 0.84, p<0.01 (Fig. 5(a)) for DBP and r = 0.81, p<0.01 (Fig. 5(c)) for SBP. Further, the Bland-Altman analyses (Fig. 5(b) and Fig. 5 (d)) demonstrated that the measurements exhibit an in-significant bias (DBP: 0.57 mmHg, p = 0.12; and SBP: 0.22 mmHg, p = 0.18) with RMSEs of 4 mmHg and 6 mmHg for DBP and SBP respectively. While the present study demonstrated the reliability and measurement accuracy of our newly proposed deep learning-based measurement system, its performance was validated only for short time periods under static BP conditions. It is worth noting that the accuracy of conventional cuffless BP techniques (example: based on transit time estimates alone or data mining approaches using a single physiological signal) deteriorate when applied to long-term estimates [1]. It is a well-known and widely reported limitation of cuffless BP monitors. The purpose of this research is to overcome this fundamental limitation by employing reliable features and physiological signals that hold a strict relationship with instantaneous arterial pressure level. Therefore, the performance of the current model should be further evaluated for long-term estimates (for instance 6 months from the initial model construction) to evaluate the BP tracking performance.

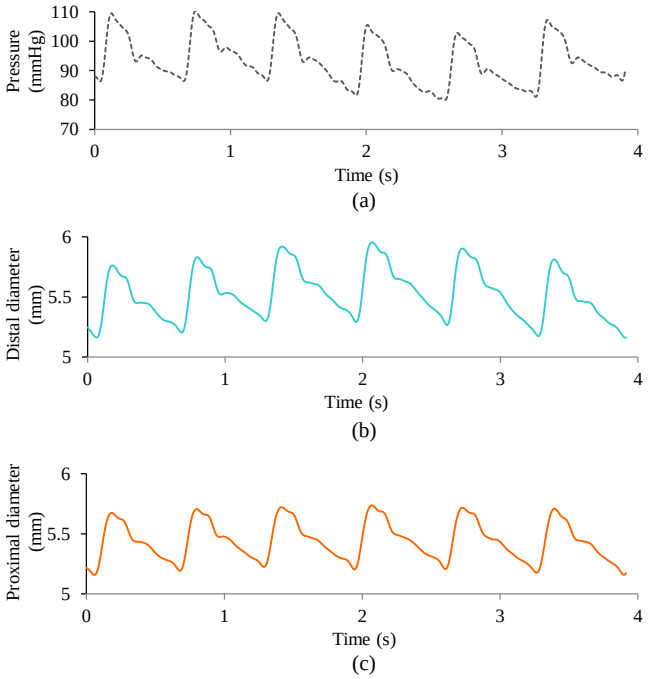


Fig. 3. (a) Pressure waveform measured using tonometer for a particular subject (age = 26 years, BMI = 21.4 kg/m^2) illustrated for continuous cardiac cycles. (b) and (c) are the corresponding proximal and distal diameter cycles respectively.

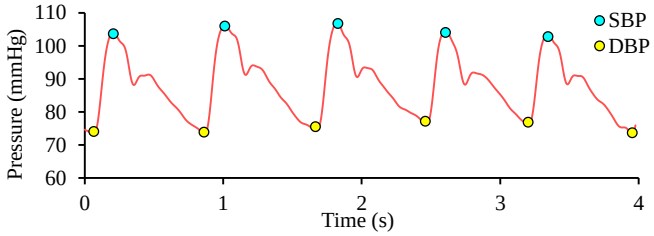


Fig. 4. Arterial pressure waveform at the carotid site measured using developed deep learning-based cuffless BP monitor.

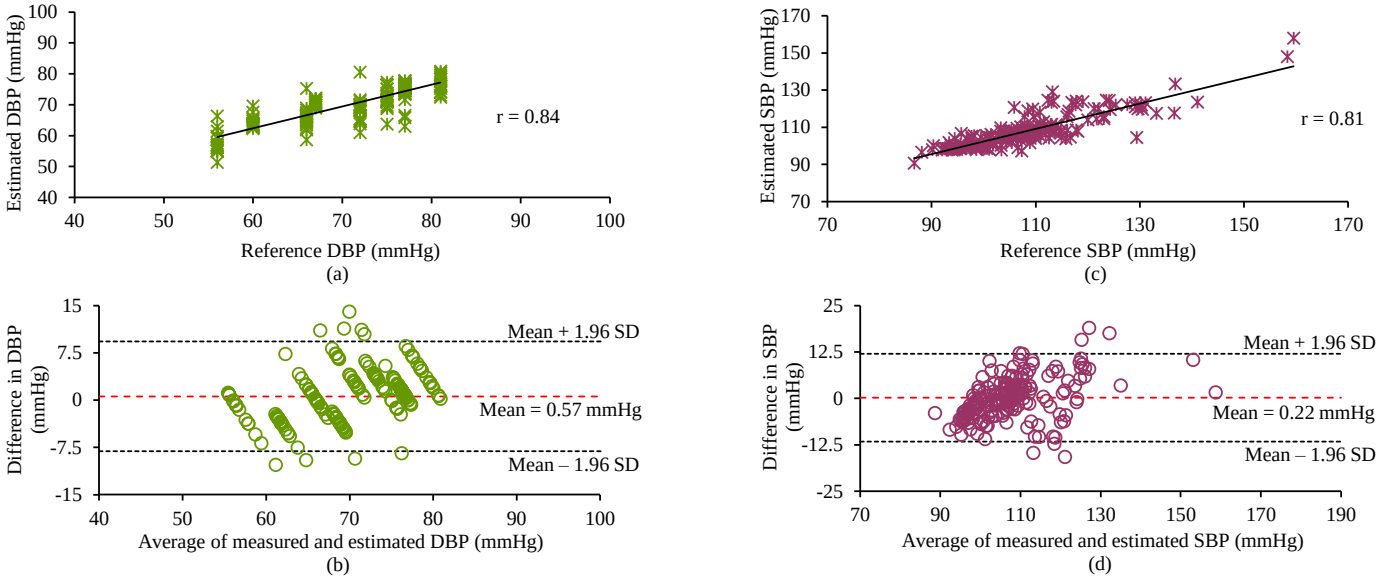


Fig. 5. Cuffless BP measurement accuracy: (a), (b) regression and Bland-Altman plots of DBP. (c), (d) regression and Bland-Altman plots of SBP.

Future efforts are also required to translate the proposed cuffless technique into a usable ergonomic device. Optimization of the probe design and sensory arrangement to perform BP measurements from various superficial arteries is in progress. Likewise, developments such as formulating efficient loss functions, identifying and implementing optimal configurations for the ANN model are also being carried out to improve the robustness of the current model. The configurations include the number of hidden layers, appropriate optimizer, and the activation function. In the present study, the dataset used for training and analysis was obtained from a subpopulation of healthy volunteers with a limited range of BP variation. Therefore, further data collection aims at large cohorts that span a wide range of physiological BP variations. Finally, this proposed technique needs to be extensively validated on a large heterogeneous population via multi-centric studies, to establish the accuracy and widespread applicability of the developed continuous cuffless BP monitor.

V. Conclusion

In this work, we have proposed a novel image-free ultrasound system supplemented by deep learning technique for cuffless and continuous monitoring of arterial BP parameters and the pressure waveform. The use of the local measure of arterial dual diameter waveforms enabled selection of multiple unique features, from individual cardiac cycles, that are directly related to beat-by-beat measure BP parameters. ANN architecture was employed to develop the deep learning model for continuous BP evaluation. The performance of the developed system was validated by conducting an in-vivo experiment to measure reliable BP from the carotid artery. Present study results have yielded acceptable beat-to-beat repeatability with CoV smaller than 9.5% and accuracy with an RMSE of 4 mmHg for DBP and 6 mmHg for SBP. The proposed approach provides a novel insight for cuffless BP estimation from any target artery in a non-invasive, unobtrusive, and continuous manner. While the potential application, measurement reliability, and accuracy of the proposed deep learning approach has been demonstrated, significant work is still needed to best realize this approach for routine clinical practice.

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