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Blood Pressure Estimation Algorithm by a Cuff-Based Monitoring Unit

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Abstract. Blood pressure is a measurement used to interpret a person's cardiovascular health. There are invasive and non-invasive methods of obtaining it, including oscillometric methods. The challenge in developing algorithms for estimating blood pressure is accuracy. This metric can vary depending on the device used for measurement and the lack of standard procedures. This work aims to develop an oscillometric algorithm based on a custom cuff-based device. The proposed algorithm consists of a filtering step, then the calculation of the signal envelope, and finally a series of linear operations have been proposed to estimate the systolic and diastolic blood pressure. The presented algorithm achieved a standard deviation and mean absolute error for systolic and diastolic blood pressure of 4.42$\pm$6.93 and 3.63$\pm$5.82 mmHg, respectively, compared to Omrom's HEM-7600T.

Keywords. Blood pressure, systolic blood pressure, diastolic blood pressure, oscillometric method.

1 Introduction

One of the leading indicators of a person's cardiovascular health is blood pressure (BP). It is the pressure that blood exerts on the walls of the arteries [17]. This measurement varies with each heartbeat from a minimum, called diastolic blood pressure (DBP), to a maximum, called systolic blood pressure (SBP), and is expressed as DBP over SBP in millimeters of mercury (mmHg) [10].

Even though there are invasive and non-invasive methods to measure BP, non-invasive techniques, such as oscillometric, ultrasonic [22], and cuffless-based techniques [2, 11, 13, 28], are the most widely used to be less aggressive to the patient.

The traditional method, which has been used for decades, involves the use of a brachial pressure cuff and arterial auscultation to identify Korotkoff's sounds [29]. However, compared to automated devices, this method is more complex, takes longer, and needs to be able to identify Korotkoff's sounds [29].

Although automated devices are widely accepted for use in patients outside of hospitals and clinics, mercury sphygmomanometers and stethoscopes remain the gold standard for BP measurement [29].

The development of automated devices presents challenges such as developing portable systems, reducing noise levels, and improving accuracy [28].

Automated devices often use oscillometric techniques to measure cuff pressure changes during compression and decompression for BP estimation.

These pressure changes feed empirical algorithms that process small pressure fluctuations to estimate SBP and DBP from waveform features [30].

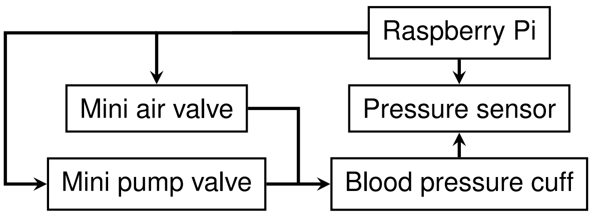

Fig. 1. BP module used for data acquisition

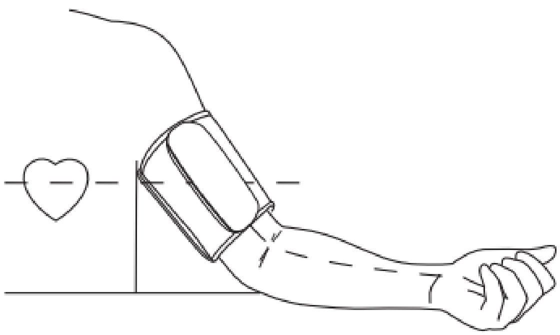

Fig. 2. Placement of the brachial cuff on the left arm. Image source [26]

Typically, these algorithms operate on a specific hardware platform [12, 13, 17], which is a drawback in obtaining comparable measurements due to the need for standardized procedures [29]. Their main disadvantage is that they estimate the BP of a sample of n subjects during the development or validation of the device [21].

Among the more popular BP estimation algorithms are the Maximum Amplitude Algorithm (MAA) [4, 12, 24] and the Maximum Slope (MS) [12, 32], which use the oscillometric signal envelope to detect peaks in the signal pulses.

MAA defines SBP and DBP as the cuff pressure values where the amplitude is related to the ratios of the normalized oscillometric signal [4, 12]. In MS, SBP and DBP are the pressures within the cuff, with the derivatives being the maximum and minimum of the signal [4, 12].

In recent years, with the technological development, it has been possible to develop and improve sensors for BP estimation, such as optical sensors (PPG sensors) [5], and thus popularize the use of deep learning for BP estimation [8, 14, 18, 25, 31].

Although they have good results, they still need extensive data [7], to obtain accurate estimates and to generalize with different training and validation data. However, because of the validity of the cuff for measuring BP and because it has been used routinely in healthcare, the use of the brachial cuff to estimate blood pressure will be considered in this paper.

It should be noted that for the development of the proposed algorithm, a monitoring unit is used with the aim of testing a functional algorithm that could later be used in IoT and Smart Cities applications. The main contribution of this paper is an algorithm for BP cuff-based, and highlights the following:

1. Algorithm input data do not require an amplification and filtering electronic stage.
2. The algorithm includes a digital filtering stage that pre-processes data from the sensor and simplifies implementation in another device with a sensor with similar output voltage, resolution, and sensitivity characteristics.
3. It integrates a series of linear operations on the output of the Hilbert transform, improving the estimation with the selected hardware.
4. This algorithm, which uses traditional computational techniques, does not require the amount of data required by deep learning algorithms.

This paper is organized as follows. Section 2 shows a recopilation of the related work for BP estimation. Section 3 describes the proposed methodology, including data acquisition and methods.

Section 4 presents the experimental results, while Section 5 gives a discussion of the results obtained and describe some alternatives for future work. Finally, Section 6 presents the conclusions.

2 Related Work

This paper presents a BP estimation algorithm implemented in a portable vital signs monitor. The goal is to provide medical professionals for tracking the BP of patients.

For this purpose, this section describes the proposed methods and technologies in the state of the art of BP estimation.

Most automated monitors use oscillometric methods to estimate blood pressure using cuffs or optical sensors. Often, these methods define their procedure for estimating pressure values by pulse oscillations within the cuff [6].

In the case of cuff-based methods, almost all algorithms follow this procedure [3, 6, 15, 16, 24]: the oscillometric waveform (OMW) is extracted from the deflation curve, then the signal envelope is calculated, and finally the pressure values are estimated using height or slope criteria [16]. From the latter, the MAA and MS algorithms and their variants are implemented [15, 24].

A variant of MAA is the method proposed in [16], unlike the traditional method where the authors calculated the signal envelope by identifying the maximum slope in the pulse in the OMW using the oscillometric pulse index (OPI) and finally calculating the pressure values similarly to MAA, achieving a mean absolute error (MAE) of 4.69 ± 3.70 for SBP and 4.31 ± 3.48 for DBP.

The authors obtained a similar mean absolute pressure as the Omron device used as a reference, and they also suggest that methods based on OPI are more robust than the traditional MAA calculation.

On the other hand, the proposal in [15] explored machine learning algorithms using multiple linear regression (MLR) and support vector regression (SVR) for BP estimation, achieving error values of -0.3 ± 8.6 and -0.6 ± 5.4 from MLR and SVR, respectively.

In addition, there are other proposals that use neural networks [3, 24] for BP estimation or prediction that show results similar to traditional methods.

For example, using five layers, [24] shows accurate results with an MAE of 3 and 5 mmHg for SBP and DBP, respectively.

While [3] presents a proposal using recurrent neural layers that achieves similar results. Although the results show accurate behavior, there are drawbacks, such as the need for sufficient data for training and validation.

Algorithm 1 Proposed algorithm

1: Apply the high-pass filter to the input signal to obtain $\vec{x}$.
2: Apply the Hilbert transform to $\vec{x}$ to get the analytic signal x_a.
3: Compute the absolute values of x_a.
4: Get the maximum vector of $|x_a|$ and compute $vm_{\max}$.
5: Get the minimum vector of $vm_{\min}$ from the instant frequency.
6: Compute the average of $vm_{\max}$ to get SPB.
7: Compute the average of $vm_{\min}$ and subtract κ to obtain DBP.

Table 1. Dataset characteristics

Samples	**Subject**	**Age**	**Data distribution SBP/DBP**
65	44	20-60	109/68

On the other hand, there are cuffless estimation methods, which use photoplethysmography (PPG) signals from optical sensors placed on a patient's finger [2, 5, 30, 28]. At least two variants exist to estimate pressure using this kind of technology.

The first uses electrocardiography to complement data and obtain an accurate estimation; the second, more complicated method uses PPG signals to estimate pressures. Proposals in this area often use the MIMIC dataset to train and test their algorithms.

For example, [9] achieves an MAE and STD of 7.16 ± 10.83 and 3.89 ± 5.9. There is also the work of [23], which uses signal features with a pulse train time method and achieves 7.16 ± 10.83 and 3.89 ± 5.9 MAE for SBP and DBP, respectively.

3 Methods

This paper outlines the development of a BP estimation algorithm with a proposed methodology divided into four stages: data acquisition, method development, testing, and validation.

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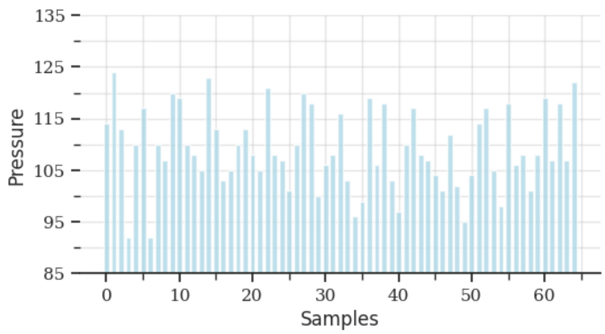
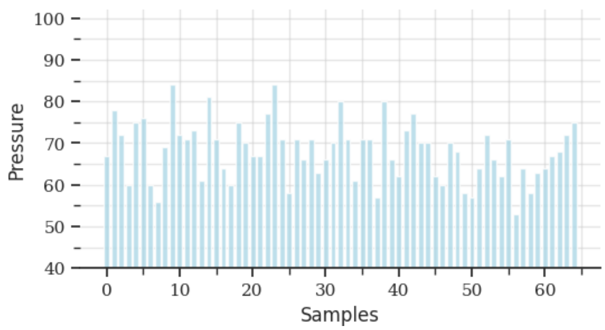


(a) SBP measurements



(b) DBP measurements

Fig. 3. Data used to validate the performance of the proposed algorithm

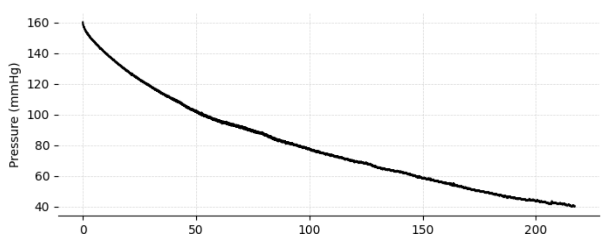


Fig. 4. Cuff deflation curve

Section 3.1 describes the device used for data acquisition, Section 3.2 describes the proposed algorithm, and Section 3.3 describes how testing and validation were done.

3.1 Data Acquisition

Data acquisition was conducted using a mobile monitoring unit based on a Raspberry Pi Zero W with a BP measurement module consisting of an MP3v505 pressure sensor, mini air valve, mini pump valve, and brachial cuff as shown in Figure 1.

The data acquisition method used consists of taking a reference measurement with Omron's HEM-7600T [19] and then taking pressure measurement samples with our mobile monitoring unit. The sampling procedure is described below:

1. The subject is seated.
2. The brachial cuff was placed on the left arm, as shown in Fig. 2.
3. The subject remained still during the inflation and deflation of the brachial cuff.
4. The Raspberry Pi Zero recorded the pressure values from 150 mmHg to 40 mmHg, i.e., until the brachial cuff was considered deflated.

It should be noted that the pressure values recorded from 150 mmHg to 40 mmHg are referred to as the raw signal, which is referred to in the next section. Finally, 65 samples were taken from 44 subjects using the procedure described in this section.

3.2 Proposed Algorithm

The proposed algorithm 1 for BP estimation consists of a filtering step, calculating the envelope of the signal, extracting the peaks, and applying a linear operation.

The filtering step consists of a 0.5 Hz Butterwoth-type high-pass filter to which the raw signal is input to eliminate possible noise caused by some external factor such as sudden movement of the patient, resulting in the filtered signal $\overrightarrow{x_f}$.

Considering that BP fluctuates during different phases of the cardiac cycle, which involves the regular contraction and relaxation of the atria and ventricles to circulate blood throughout the body, it is important to note that diastole refers to the relaxation phase and systole refers to the contraction phase.

Therefore, the peak pressure value recorded in the arteries during this cycle is known as the systolic pressure, whereas the minimum value is referred to as the diastolic pressure. Then the amplitude of the signal recovered by the sensor refers to the maximum pressure reached in the artery during a complete cardiac cycle, while the

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phase is useful to identify specific events such as the onset of systole or diastole, hence the benefit of applying the Hilbert transform [27] to the filtered signal $\overrightarrow{x_f}$:

$$x_a = F^{-1}(F(x_f)2U) = x_f + iy, \tag{1}$$

where F is the Fourier transform, U the unit step function, and y the Hilbert transform of x_f.

This mathematical function 1 has multiple applications, one of which is to obtain the analytical signal that provides information about the amplitude and phase of the frequency components of the original signal.

The procedure for estimating SBP and DBP differs in the last step of the slice to the traditional MAA. The steps to obtain the SBP are described below and in Equation 2:

Obtain a vector of maximum values from $|x_a|$, apply a dot product to the previous vector, and square the above result, the value of the SBP corresponds to the average of vm_{max}:

$$vm_{\mathsf{max}} = \frac{\max(x_a)^2}{\mathrm{media}(\max(x_a))}. \tag{2}$$

For another hand, the steps to obtain the DBP are as follows: compute the instantaneous frequency, obtain a minimum values vector, obtain the vector media, and subtract κ, with $\kappa = 10 + \overrightarrow{x_f}$, where $f = \arg_{\mathsf{max}}(x_a)$.

3.3 Testing and Validation

The validation process consisted of three phases:

1. The recorded data was validated using a manometer in the monitoring unit to verify that the stored pressure values were correct.
2. Reference data were recorded using the commercial Omron device [19].
3. The algorithm was tested using the raw signals recorded in 3.1.

The estimated BP values were compared with the reference values to verify the algorithm's performance.

Table 2. Maximum, minimum and mean values of validation data in mmHg

	Max	Min	Mean
SBP	92	124	109
DBP	84	53	68.13

Table 3. Comparison of estimated pressure and the reference values expressed in mmHg. Note: * reference value measured with Omron device [19]

Parameter	Avg	Max	Min
SBP*	109	124	92
DBP*	68.13	84	53
Estimated SBP	110.58	119.89	100.52
Estimated DBP	71.88	82.37	62.47

4 Experimental Results

This section presents the data used to validate the performance of the proposed algorithm and the results obtained.

4.1 Data Characteristics

The device described in Section 3.1 generated the data used for this study.

Table 1 shows the general characteristics of the data generated; 65 pressure samples and their respective reference values were recorded from 44 healthy subjects (22 females, and 22 males).

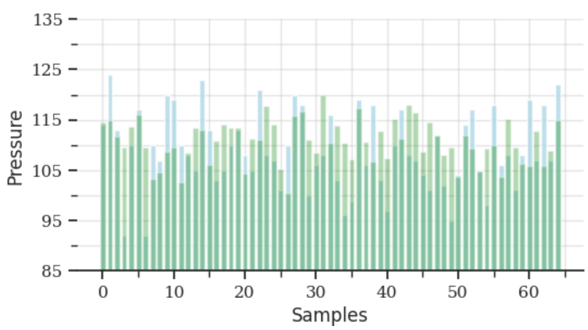
Fig. 3 shows the distribution of the reference values; the maximum, minimum and average reference values are shown in 2. Measurement acquisition involves controlling the inflation and deflation of the branchial cuff.

The valuable features are found during the deflation phase, Fig. 4 shows the set of values from a recorded sample from the maximum peak around 150 mmHg to above 50 mmHg.

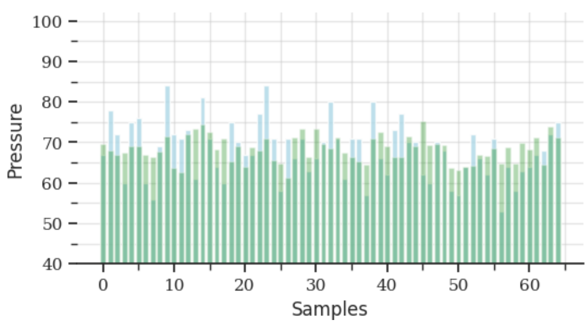
Table 3 shows relatively similar average pressure data for the measured and estimated values. However, the estimated values have a standard deviation of 5.78 and 5.86 for SBP and DBP, respectively.

Table 4. Error and variance between estimated and reference values

	Variance	Abs. error	Relative error
SBP	18.38	6.93	6.49
DBP	18.44	5.82	8.66



(a) Comparison of SBP measurement vs estimation



(b) Comparison of DBP measurement vs estimation.

Fig. 5. Comparison of reference measurements vs estimation

4.2 Blood Pressure Estimation

The tables and figures presented in this section result from the implementation of the algorithm presented in Section 3. The algorithm was implemented using Python 3.9 and the data was filtered using scipy.signal.

Averages, maxima and minima were obtained from the 65 samples described in the previous section and their respective estimates using the proposed algorithm.

Table 4 shows the average absolute and relative error between the reference and estimated values, where the estimation has a relative error of 8.66% for DBP and 6.49% for SBP, with the higher error trying to estimate de DBP, as it is shown in Fig. 5. Bar graphs shown in Figures 5a and 5b show each sample's reference vs. estimated SBP and DBP.

The reference pressure is shown in blue, while the estimated pressure is shown in green. Note that the bars where the light green color stands out correspond to an estimate above the reference pressure.

On the other hand, bars, where the color is light blue, indicate that the estimated value was below the reference. In 72% of the cases, the estimate of DBP was above the reference, which is reflected in the errors shown in Table 4.

To evaluate the performance of the algorithm, note the MAE and STD shown in Table 5. The MAE helps to understand the discrepancy between the values measured by the OMRON device and those predicted by the proposed algorithm.

While the STD indicates the variance between the MAE estimates, a high STD indicates a substantial distance between the measurement and the MAE. That is, the estimate has an error that is significantly further from the actual value of the reference. In this case, the algorithm obtained an MAE and STD of 6.93 ± 4.42 and 5.82 ± 3.93 for SBP and DBP, respectively.

5 Discussion and Future Work

In summary, this paper presents an algorithm for BP estimation that has been tested on data obtained from a vital signs monitoring unit with a brachial cuff and a pressure sensor.

For the validation of the pressure estimates a commercial device Omron HEM-7600T was used as a reference and the results of both devices were compared. The device used in this work has a pressure sensor MP3V5050, but it does not have an electronic module for amplification and filtering.

Therefore, the acquired data enter the algorithm without previous preprocessing, which is compensated by digital filtering. Considering this fact, another device implementing the algorithm proposed in this work could give comparable results if it uses a sensor with analog characteristics. Nevertheless, this will be the subject of future work.

Table 5. Comparison of results with cuff-based proposals. NR indicates that the data was not reported by the authors

Method	SBP		DBP	
	MAE	STD	MAE	STD
MS [16]	4.99	3.04	4.71	2.46
MAA [16]	4.69	3.70	4.31	3.48
MAA [24]	4.5	NR	8	NR
NN [24]	3	NR	5	NR
MAA [15]	4.5	NR	8	NR
Bagged Tree [1]	4.499	NR	13.069	NR
WKNN [1]	3.52	NR	11.077	NR
LSTM-RNN [3]	3.8	5.9	7.3	8.8
Ours	6.93	4.42	5.82	3.63

Since oscillometry is not a new concept, existing methods for BP estimation were reviewed. Among the more popular methods are the MAA and the MS, which process data and estimate SBP and DPB through maximum, minimum and average signal values, and machine learning algorithms such as neural networks were found.

However, this work led to an oscillometric estimation method with the MAA improved with some linear operations for BP estimation with the selected device. Regarding the results presented in Section 4.2, it is noticeable that the SBP estimation has a higher error than the DBP estimation. In accordance with the results reported [20], MAE and STD are within the validation criteria of BP devices.

However, it is essential to note that the works reported in Table 5 do not provide a conclusive verdict on the proposed algorithm's performance, as each uses different hardware platforms for data acquisition on which the algorithms have been validated or trained. In any case, they give an idea of the performance and accuracy of the proposal made in this paper.

6 Conclusion

This paper presents an algorithm for estimating blood pressure. The paper describes the methodology used for data acquisition, the proposed algorithm, and the experimental results.

According to the OMS specifications, the results show that the proposed algorithm is within the validation criteria of BP devices, and they suggest that the algorithm can be used as a support tool for healthcare workers to estimate blood pressure.

However, some points were observed during the experiments that need to be developed in future work. At the time of development, the samples were taken from people in good health, i.e. without cardiovascular problems such as hypertension.

However, given that hypertension is a disease that affects approximately 1280 million adults worldwide, it is expected that the algorithm can be validated later on a group of people with this problem, to perform validation tests of the algorithm on samples of different subjects and considering samples of subjects with cardiovascular problems such as hypertension, thus confirming its correct functioning.

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