Article

BPNet : Continuous Arterial Blood Pressure Estimation with Single PPG Signal and its Higher Derivatives

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**Abstract:** Monitoring accurate continuous Blood Pressure (BP) can be an adequate precaution for cardiovascular disease (CVD). Currently, most BP measurement relies on uncomfortable cuff-based devices. Patients need to be sedentary, and it shows only Systolic and Diastolic BP. It gets trickier for those lying on a med bed. For many Intensive Care Unit (ICU) patients, many vital signs including photoplethysmography (PPG) and BP need to be monitored constantly. To do so, an invasive Arterial Blood Pressure (ABP) line is required and must be replaced every couple of days which can cause unnecessary infection in patients.

To overcome all these inconveniences and inefficiencies, PPG-based technologies are actively studied for BP measurements. In this study, we propose BPNet, which estimates continuous ABP from a single PPG signal using 1D convolution. To enhance the robustness of the model, its first and second derivativeinformation is also used. Experimental results with a public medical database (UCI, which contains 360 hours long PPG and ABP signal) achieved 93.5% correlation (r), 8.94 MAE for SBP, and 4.36 MAE for DBP respectively. Additionally, this study verified that considering derivatives of signal enhances signal-to-signal estimation.

**Keywords:** Arterial Blood Pressure; Photoplethysmography; Deep learning; 1D Convolution; Signal processing.

1. Introduction

BP refers to the pressure of blood against the walls of arteries. The BP is highest when the left ventricle of the heart contracts to send blood to the arterial blood vessels, and this BP is called SBP. Also, when the left ventricle is stretched to receive blood into the heart, the BP is the lowest, and the BP at this time is called DBP [1].

![Chart, line chart

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**Figure 1.** Example of a single cycle of ABP. The highest number in a cycle of ABP indicates SBP, and the opposite indicates DBP.

The American Heart Association (AHA) divides BP health into five categories based on these two numbers. The classification includes Normal, Elevated, Hypertension Stage 1, Hypertension Stage 2, and Hypertensive Crisis. Table 1 shows the criteria for blood pressure classification [2].

**Table 1.** 5 categories of Blood pressure from AHA. They are classified based on systolic and diastolic blood pressure measured with cuff-based BP measurement.

|  |  |  |  |
| --- | --- | --- | --- |
| **Blood pressure category** | **Systolic (mmHg)** | **And/Or** | **Diastolic (mmHg)** |
| Normal | 120< | And | 80< |
| Elevated | 120-129 | And | 80< |
| High Blood Pressure Stage 1 | 130-139 | Or | 80-89 |
| High Blood Pressure Stage2 | 140 | Or | 90 |
| Hypertensive Crisis | 180 | And/Or | 120 |

Hypertension is caused by neurogenic factors by the sympathetic nerve and humoral factors by the renin-angiotensin system (RAS) that controls blood pressure and extracellular fluid volume [3]. However, heredity, smoking, and aging are factors that promote the development of hypertension. More than 90% of high blood pressure (HBP) is essential, and the cause is mostly unknown. The remaining 5-10% are secondary hypertension with a clear cause. Essential hypertension, which accounts for most of the HBP, is not caused by a single reason. Several factors build HBP. Among them, genetic factors (family history) are the most common, and other factors include aging, obesity, salty eating habits, lack of exercise, and stress [4].

Since hypertension rarely has apparent symptoms indicating something is wrong, it is often discovered unexpectedly during a physical examination or medical treatment for diagnosing other diseases. Occasionally, patients who visit a hospital with symptoms complain of discomfort caused by increased BP, such as headache, dizziness, heart palpitations, and fatigue [5]. In addition, they often have symptoms such as nosebleeds, hematuria, blurred vision, cerebrovascular disorders, and angina, and then go to the hospital and find out that HBP is causing them. Early detection of HBP requires periodic blood pressure monitoring and close observation of the blood pressure waveforms created by the heart. However, most current BP measuring devices are cuff-based, which is uncomfortable, and a problem in that it makes it challenging to measure BP frequently. In addition, even when measuring using a smartwatch, there is cumbersome that it needs to be calibrated with BP measured with a cuff-based device periodically.

ABP is an essential indicator of cardiovascular health, driven by the repetition of contraction and relaxation of the heart's left ventricle; thus, a waveform of ABP represents heart functionality [6]. As the diameter and elasticity of the arterial walls change with age and physical condition, there is a difference between normal BP and the waveforms of hypertensive patients [7]. Further, recent research shows that in middle age, every 20-mmHg increment of SBP (or 10-mmHg increment of DBP) doubles the risk of stroke [8]. Therefore, tracking the exact waveform and amplitude of BP through periodic precise ABP measurements can be helpful in cardiovascular disease (CVD) management [9]. Currently, cuff-based BP measurement devices are widely used in hospitals, which are uncomfortable to use and give limited information. Not only can they show only SBP and DBP measured through a limited period, but they also don’t display any waveform of the BP to determine the health of the left ventricle [10].

In this paper, we propose a new non-invasive method that can accurately estimate ABP signal from a single PPG and its derivatives using 1D convolution. This model does not just classify whether a patient has hypertension nor predicts a single BP. As it predicts continuous ABP signal induced from PPG, it is possible to diagnose the patient’s heart condition. Since it shows the ABP waveform, it is possible to analyze the current patient’s heart condition, such as the stiffness of the left ventricle, before the SBP and DBP measured by the conventional cuff-based method show dangerous values. The main contributions of this work are as follows:

* This study is conducted with a large dataset that contains 12,000 people’s arterial blood pressure (ABP) and photoplethysmography (PPG) simultaneously measured and synchronized at a sampling rate of 125 Hz. A general model based on a normally distributed large dataset covers a dynamic BP range.
* Compared to the other studies that predict BP with a single PPG, the suggested model uses a PPG signal and its first and second derivative simultaneously to generate the predicted ABP signal, improving the robustness to noise.
* Diverse signal-to-signal estimation tasks can be done with this proposed network to meet the various requirements. The specification of the BPNet will be shown in the following section.

2. A study on cuff-less BP measurement using PPG signal

In 1981, for the first time, a correlation between pulse arrival time (PAT) and BP was found in an animal study in dogs. As a result of the experiment found a correlation between the PAT and DBP, and it was shown that the pulse wave velocity was calculated using the pulse delivery time. It increased almost linearly with the blood pressure. According to this study's correlation between pulse wave velocity and blood pressure, cuff-less bp measurement studies were conducted using the PTT-based BP measurement method and the single ppg-based BP measurement method [11].

2.1 PTT based BP measurement method

In 2001, a method for predicting SBP, DBP, and mean BP using the time difference between electrocardiogram (ECG) and PPG was proposed. Calibration was carried out for each measurement target, and SBP-Mean Error (ME) 7.5mmHg and DBP-ME 4.1mmHg were obtained, and it was shown that cardiovascular status could be monitored non-invasively [12]. In 2017, a method using AdaBoost, one of the regression analysis methods, was proposed. SBP-Mean Absolute Error (MAE) 11.17mmHg and DBP-MAE 5.35mmHg were achieved, and the proposed method was evaluated using AAMI (Association for the Advancement of Medical Instrumentation) and BHS (British Hypertension Society) standards with 1000 subjects. As a result of BHS evaluation, grade A was achieved for DBP estimation and grade B for MAP estimation [13]. In 2018, a Recurrent Neural Network (RNN)-based blood pressure estimation method using deep learning was first proposed. This study achieved SBP-Root Mean Square Error (RMSE) of 3.9mmHg and DBP-RMSE of 2.66mHg [14]. In [15], unlike the existing method using ECG and PPG information as input, BCG data was additionally used, and SBP-MAE 3.29 mmHg and DBP-MAE 2.60 mmHg were achieved by adding an attention mechanism.

2.2 Single-PPG based BP measurement method

In 2013, a single-PPG-based blood pressure measurement method was first studied based on the relationship between PPG signal, blood pressure, and pulse duration. [??] More than 15,000 heartbeats were analyzed, and 21 parameters were used as inputs for the input of the ANN. The measurements were superior to the linear regression technique and met the American Standard of the Association for the Advancement of Medical Instrumentation. Although it showed excellent results, the experiment was conducted with small data [16]. An experiment was conducted to classify types of hypertension using PPG signals based on wavelet transform and pre-trained GoogleNet. 121 data were collected from the Multiparameter Intelligent Monitoring in Intensive Care (MIMIC) database, and ABP and PPG signals were included. According to the 7th report of the National Joint Committee, blood pressure was classified into normotension (NT), prehypertension (PHT), and hypertension (HT), with an accuracy of 80.52%, 92.55%, and 82.95% for each [17]. In a later study, the Multitaper Method (MTM) was used for feature extraction, and SBP-MAE 4.02±2.8 mmHg and DBP-MAE 2.27±1.82 mmHg were obtained using ANN [18].

3. Proposed Method

Diagram

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**Figure 2.** The total architecture of our multi-task learning neural network.

The total architecture of the proposed method is shown in Figure 2. This study was mainly conducted in three parts. It is divided into a signal preprocessor that refines a signal containing noise into an input signal, a multi-task neural network (NN) that creates the shape and amplitude of an ABP signal from a PPG signal, and a feature-mixer that reconstructs one signal with the output of NN. We will take a closer look at each component in the sections below. The UCI dataset contains arterial blood pressure(ABP) and photoplethysmography(PPG), which is available at <http://archive.ics.uci.edu/ml/datasets/Cuff-Less+Blood+Pressure+Estimation>. And the whole process of BPNet is fully available at <https://github.com/paperchae/VBPNet>.

3.1 Dataset Preprocessing

A screenshot of a computer

Description automatically generated with medium confidence

**Figure 3.** Preprocess method for raw PPG and ABP signals. It contains a signal quality verification method for time and frequency domains. Derivative features were extracted from PPG signals and DBP, and SBP labels were generated from ABP signals.

Figure 3 is a schematic of how the PPG and ABP signals containing a lot of noise were pre-processed. Blue, red, and green lines indicate processing for the PPG signal, for the ABP signal, and for both, respectively.

3.1.1 Signal quality verification

Since the data used is from the intensive care unit (ICU), including a patient moving to a ward or an emergency, it is necessary to remove the data that is not measured correctly. First, the measured data varies in time, ranging from several tens of seconds to several hours, and were divided into 6 seconds, in the same length, for the model input. The raw dataset sampled at 125 Hz was down-sampled to 60 Hz to broaden the application range and reduce the model's load. Remove data that includes unmeasured parts. After that, PPG and ABP peak detection was performed to ensure that both measurement equipments extracted the data without noise. In addition, the single cycle of signals was extracted through FFT, and the correlation was obtained for every cycle. Data including abnormal correlation within 6 seconds were also deleted. After signal quality verification, refined PPG and ABP signals were used to create inputs for the model.

3.1.2 Derivative feature extraction

In BP Measurement, SBP and DBP can indicate one’s cardiovascular health. Though, as mentioned above, inspecting the shape of a signal that the left ventricle creates implies many bio signs. Thus, it is essential to learn the morphological characteristics of a signal, such as systolic upslope, dicrotic notch, and diastolic decay, included in the PPG signal. To achieve the goal, we propose a method using first and second derivatives conjugated with the original signal. The first differential signal implies the velocity of the original signal, and the second differential signal is an acceleration of the signal, which are Velocity Plethysmography (VPG) and Acceleration Plethysmography (APG) respectively. Calculating the derivatives can be simplified by obtaining the difference between the time-shifted signal and the original signal[19]. To address the shortening problem after differential, the last two components of the original signal’s gradient is used to fill the blank. (1) shows the method of getting VPG. (2) APG is done the same way as (1).

(1)

(2)

Figure 4 shows the first and second derivatives of PPG signal.

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**Figure 4.** Original signal and its derivatives; VPG and APG.

3.1.3 ABP signal Preprocessing

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**Figure 5.** Distribution of preprocessed ABP signal from UCI dataset. Both train and test dataset is normally distributed, covering a wide range of ABP.

Preprocessed ABP distributions of the train and test datasets are shown in Figure 5. After Signal quality verification, DBP and SBP labels are extracted from sliced signals. It was done by detecting systolic peaks and diastolic min values. Although the input signal is cut to the same length, each person has a different heart rate, so the labels were calculated by getting a mean value of detected peaks for each.

3.2 Network Design

A neural net trained using only one input has a problem that is highly dependent on the precision of the input signal. To solve this problem, we propose a model that trains to estimate the shape of the ABP signal by learning the same number of signals as one but the differentiation. The first differential signal indicates the slope characteristic of the original signal, and the second differential signal includes the acceleration characteristic of the original signal. This helps estimate the next signal based on the previous shape even when the measurement was not adequately measured due to noise, such as when the patient moves.

We propose BPNet, a model that generates ABP Signals from PPG signals using 1D convolution. First, the encoder-decoder type feature extractor learns from the input PPG and its derivatives to extract various morphological features. These features are fed into the Linear Module, which produces a primitive shape of the predicted signal, and the Amplitude Module, which estimates SBP and DBP.

3.2.1 Feature Extractor

Feature extractor consists of Trend Module for detecting large scale trend of ABP signal and Detail module that learns small ripple of the signal with a smaller kernel size of 1D convolution. The outputs of the Trend module are fed into the Detail module to help the Detail module to learn not only small morphological features but also consider the trend of the target data. Despite BPNet being built to learn from the sequential, the reason recurrent neural network (RNN) series is not used in this work is that the minimum data length in the time domain is required to make a continuous signal by inferring the characteristics of a physiological signal. As a result of several experiments with various signal lengths, six-second-long input data showed the best result. The size of the down-sampled data is 360, and as a result of an experiment using an RNN series LSTM, 1D Conv showed much better performance.

3.2.1.1 Trend Module

Graphical user interface, text, application

Description automatically generated

**Figure 6.** The architecture of the Trend module. PPG, VPG, and APG signal is fed to the Trend module to compress bold information of an input signal.

Figure 6 is the architecture of the Trend module. The Trend module is designed to infer large morphological characteristics of signals. An encoder and decoder structure that compresses an input signal and creates a feature with that information is adopted. This is implemented through 1D Convolution with a kernel size of 5, and the compressed feature of the signal is delivered to the Detail module as an input.

3.2.1.2 Detail Module

Graphical user interface, text, application, chat or text message

Description automatically generated

**Figure 7.** Detail module design inherits Trend module only with a smaller kernel size.

Figure 7 is the architecture of the Detail module. The Detail module serves the purpose of making the suggested model learn detailed morphological characteristics like small ripples and gradients in PPG signal and has a similar structure to the Trend module. The kernel size of 3 was used to learn the delicate characteristics of the signal, which is smaller than the one used in the Trend module. The output of the Trend module is fed into the encoding and decoding process to be incorporated into the Detail module learning process.

3.2.2 Linear Module

The extracted PPG features are first fed into the linear module. It plays a role in reconstructing the encoded information to make the same length as the original signal, which creates only the morphological characteristics of the ABP signal. The shape of the generated signal is trained with Pearson correlation loss.

3.2.3 Amplitude Module

The characteristics of the PPG are also fed into the Amplitude module. It has a structure opposite the Linear module that stretches out features to make the original signal length; it condenses the feature and estimates DBP and SBP by several dense layers.

3.3 Feature Combiner

Diagram

Description automatically generated

**Figure 8.** flow chart of the Feature Combiner.

Figure 8 is the flow chart of the Feature Combiner. The multi-output obtained from the Linear module and the Amplitude module plays a role in regenerating the target signal through the feature combiner. ABP information can be obtained by extending the value using SBP and DBP in the predicted signal shape

3.4 Loss Function

We proposed a modified MAE loss that can be used with Negative Pearson Correlation Loss to learn waveform, SBP, and DBP with the same weight.

* Negative Pearson Correlation Loss(PCC): It tends to learn the trend and peak of the target waveform. The range of values is between 0 and 1.

(3)

* Modified MAE Loss(modMAE): MAE is used to indicate absolute accuracy, and changes according to the absolute value of the target value. The traditional MAE function in the BP measurement task showed an error over 3 for 360-length input to our model. It is significantly larger than the 0 to 1 scale, which is the range of Negative Pearson Correlation Loss, and thus it makes it hard for the model to fit in training process. modMAE is a loss function inheriting MAE; it can be used when more than two loss functions are needed in a very different scale.

(4)

4. Experiments and Results

This section will show that the model is improved by adding the differential signal and will compare the estimation performance for each specific blood pressure range based on the PPG + VPG + APG model, which shows the best performance.. After the signal preprocessing, all data are combined and shuffled. The training and test datasets are divided into an 80/20 ratio to make as general a model as possible with limited data.

4.1 Model comparison

Through this work, we tried to prove that the differentiation of signals helps improve model performance when creating artificial intelligence models that estimate signals. To prove this, we used the dataset with the addition of VPG and both VPG and APG signals, respectively.Diagram

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**Figure 9.** Loss table according to learning step.

Figure 9 shows the results of experimenting with three datasets with only one variable. To train BPNet PCC and modMAE for SBP and DBP are used. Learning performance was improved when VPG and APG signals were used simultaneously than when PPG signals were independently used as inputs of BPNet.

4.2 Scatter plot

Chart, scatter chart

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**Figure 10.** Scatter plot for DBP, SBP (Blue: DBP, Red: SBP)

Figure 10 is a scatter plot of measuring BP with test data. It can be confirmed that the BPNet (PPG + VPG + APG) model shows the highest linearity among the three models.

4.3 Prediction Result

Shape

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**Figure 11.** ABP estimation with BPNet. The blue signals are targets, and the orange signals are predicted ones. It shows that BPNet covers a wide range of blood pressure. In the top-right, the predicted signal is robust with detection noise.

4.4 Model Evaluation

**Table 2.** Model comparison for BPNet. Adding VPG information improved DBP MAE, SBP MAE, and r by 0.12 mmHg, 0.36 mmHg, and 0.11%, respectively. Adding VPG and APG information improved DBP MAE, SBP MAE, and r by 0.03 mmHg, 0.16 mmHg, and 0.13%, respectively.

|  |  |  |  |
| --- | --- | --- | --- |
|  | **DBP MAE**  **(**mmHg**)** | **SBP MAE**  **(**mmHg**)** | **r**  **(%)** |
| BPNet(PPG) | 4.52 | 9.46 | 93.26 |
| BPNet(PPG+VPG) | 4.4 | 9.1 | 93.37 |
| **BPNet(PPG+VPG+APG)**  **(proposed model)** | **4.37** | **8.94** | **93.5** |

5. Conclusions

The results obtained through this study are as follows.

* It is the first attempt for estimating Continuous ABP signals from PPG, VPG, and APG signals.
* The experiment is conducted on a large dataset covering the full spectrum of BP (50 to 200).
* We achieved 93.5% correlation (r), 8.94 MAE for SBP, and 4.36 MAE for DBP, respectively. Our model can estimate much more accurate waveforms that can derive various blood pressure-related biomarkers and can be utilized for various applications.

This paper proposes a new factor to evaluate predicted BP as a study considering the shape of the waveform in a single ppg-based BP estimation model for the first time. If it is possible to measure the shape of ABP as well as numbers by estimating continuous ABP, there is an advantage in that it is possible to predict an individual's heart health in advance compared to the currently used cuff-based BP measuring device.

Our model estimates continuous ABP signals with high correlation using only single-PPG information. However, there are many factors to consider, such as age and personal health condition, that determine BP. Due to the nature of medical data, detailed patient information is very limited due to privacy concerns. In the presented study, vital signs other than PPG were not used for learning. Still, if other vital signals are added to help the model narrow down, very low or high BP estimation accuracy can be improved.

As seen from the distribution, there are relatively little data on people with very low or high blood pressure. In addition, the data used in this experiment was extracted from the ICU; there is a high probability that the data on healthy patients is relatively small. It is expected that performance will be improved if fine-tuning is performed by adding insufficient data to the currently trained model.

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**Institutional Review Board Statement:**

Not appliable.

**Informed Consent Statement:**

Not appliable.

**Data Availability Statement:**

The UCI-dataset is available at <http://archive.ics.uci.edu/ml/datasets/Cuff-Less+Blood+Pressure+Estimation>. (accessed date 30 September 2022).

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**Conflicts of Interest:**

The authors declare no conflict of interest.

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