

Cuff-Less Blood Pressure Classification from ECG and PPG Signals using Deep Learning

RAKKRIT DUANGSOITHONG^{†1} KULIKA PAHUKARN^{†1}
DUJDOW BURANAPANICHKIT^{†1}

Abstract: Blood Pressure (BP) monitoring provides crucial information for individual healthcare conditions. Generally, BP measurement uses cuff-based instruments, however, it might be inconvenient for pain-sensitive patients or the elderly and it can also get gummy, especially in public places. This paper presents the cuff-less blood pressure classification to improve ease of use and reduce potential physical effects on pain-sensitive patients. The electrocardiogram signal (ECG), the photoplethysmography signal (PPG), and the combination of ECG and PPG were used to create models for blood pressure classification. The traditional Neural Network trains and classifies blood pressure values, which divide blood pressure into four classes. This study discovered that the results when using the combination of PPG and ECG signals provided the highest accuracy. In the future work, deep learning will be analyzed and compared with the results of neural networks.

Keywords: Blood pressure monitoring, neural networks, electrocardiogram, photoplethysmography

1. Introduction

According to the report of the World Health Organization (WHO), The prevalence of high blood pressure was 24.0 and 20.5 percent among men and women respectively. High blood pressure or abnormally high blood pressure is a major cause of death worldwide. Measuring blood pressure appears important to help doctors make a diagnosis and able to evaluate a patient's treatment effectively. Blood pressure is measured by the action of circulating blood on the artery walls based on the principle of heart muscle contraction. Blood pressure measurement can be evaluated in two ways. One is direct blood pressure measurement which is called invasive blood pressure and the other is indirect blood pressure measurement which is called non-invasive blood pressure. Indirect blood pressure measurement is the measurement of arterial pressure. It can be done by wrapping an arm sleeve with a cuff or inserting the arm all the way to the upper arm into an automatic machine. Using a cloth wraps around the arm and inflates the cloth until it creates pressure on the arm. It can be seen that the cuff is used to measure blood pressure. This method is inconvenient and you can pick up germs from repeated use of the cuff, especially in public places. Moreover, this is because the use of cuffs to bind the arms causes physical effects on some patients, especially in sensitive patients.

Currently, blood pressure measurement is done without a cuff or cuff-less for the goal of monitoring blood pressure. It is an interesting method that uses pulse wave velocity (PWV). A related parameter, PWV, is defined as the speed at which the arterial pulse flows in the artery from the proximal point to the endpoint, and blood pressure is estimated using pulse transit time (PTT). It is the time that takes for the pulse wave to travel between two different points. In 2019, the testing [1] analyzed a large bio-signal with a database to study the estimation of blood pressure based on pulse duration (PAT) or PTT records

physiological data including raw arterial blood pressure (ABP), ECG, and PPG waveforms after averaging all signals. The PAT and PTT correlation coefficient analysis for systolic and diastolic blood pressure estimation is performed. The study [2] aims to extract waveform data that bring specific features and create a systolic and diastolic pressure estimation model using a convolutional neural network (CNN) with backward propagation of errors. This work records ECG and PPG signals and processes them with the backpropagation method. The multiple population genetic algorithms (MPGA) are used to increase efficiency and compensate for potential shortcomings in neural networks (NN). Research [3] presents a PAT parameter-based algorithm for continuous blood pressure estimation. It uses an online waveform database from MIMIC as the source of ECG, PPG, and ABP signals.

This paper proposes the project of cuff-less blood pressure estimation with an algorithm used to process signals for classified blood pressure values without a cuff. It is how to measure blood pressure non-invasively into the body using an online waveform database from physionet monitoring in intensive care (MIMIC). Then the processed data has been classified with the neural network to group the same type of blood pressure categories.

2. Proposed method and experimental setup

In this project, the waveform database used in the study includes ECG, PPG, and ABP signals with frequencies of a sample of 125 Hz waveform. A database was obtained from eight elderly patients admitted to the ICU, consisting of three males and five females, aged between 44-78 years from physionet database. We brought the received signal files into the preprocessing state in order to select the channel of the signal that is the input signal of this system, which is the electrocardiogram (ECG) signal [4] and photoplethysmography (PPG) signal [5], as well as the arterial blood pressure (ABP) signal have been used. We specify the

^{†1} Electrical and Biomedical Engineering Department, Faculty of Engineering, Prince of Songkla University.

range of blood pressure values called class in each patient and then extract the signal to select the windows range of the signal to be trained. The system takes the signal that has been selected in the range or windows and save it in the form of a csv database file.

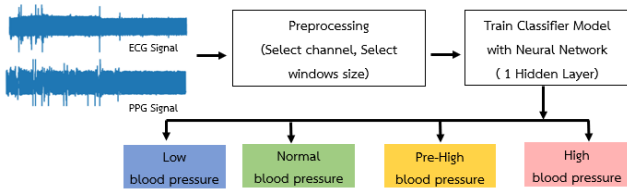


Figure 1. Proposed framework

The input sample signal file for the experimental setup has been divided into train and test groups. The input signal value in each sample enters to train in the classifier model by feeding the input signal to an artificial neural network with one hidden layer as shown in Figure 1. Finally, the system tests to measure the accuracy by classified range or level of blood pressure values divided into four classes based on the stages of hypertension standard: (1) Low blood pressure: < 90/60 mmHg (2) Normal blood pressure: 90/60 to 120/80 mmHg (3) Pre-high blood pressure: 120/80 to 140/90 mmHg (4) High blood pressure: >140/90 mmHg. In this process, the input data has four formats as seen in Figure 2 of two input signals: electrocardiogram signal (ECG), and photoplethysmography signal (PPG). Format one is the ECG signal, format two inputs the PPG signal, format three enters the ECG signal together with the PPG signal (ECG+PPG) and the last model inputs the PPG signal together with the ECG signal (PPG+ECG).

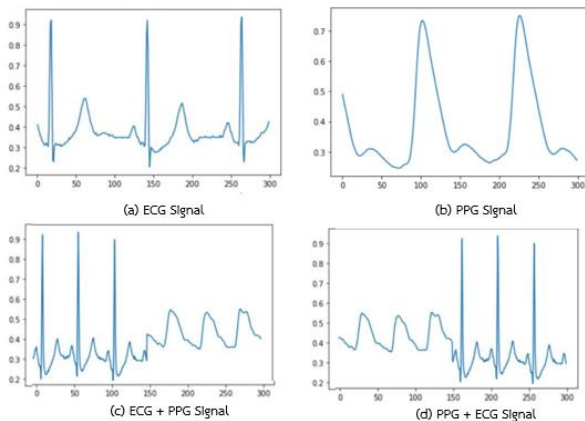


Figure 2 Input data signal for all formats

Each sample has a total of 160 samples from all patients consisting of ECG and PPG signals. Each sample of each signal is fed to the neural network with one hidden layer for learning by dividing the data set into a train set of 70% and a test set of 30% for the pilot study.

3. Results and discussion

This system studied blood pressure measurement with a cuff-less to create a model for classifying blood pressure values into four classes, which rely on two input signals and enter the input signal divided into four formats to the structure of the neural network with one hidden layer when entering the input signal in each format and running the program by a total of ten epochs and

repeated three times. As demonstrated in Figure 3 is an example training results for each pattern.

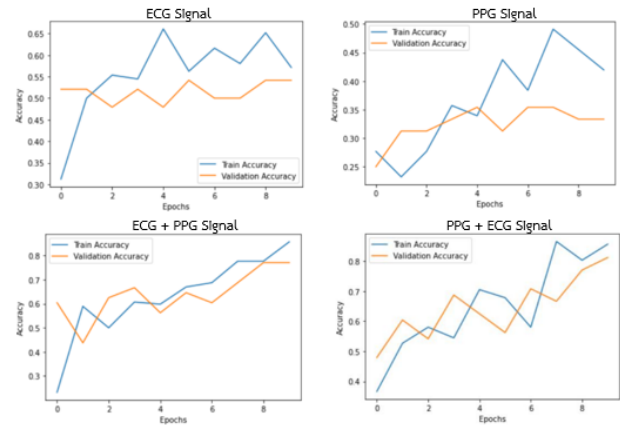


Figure 3. Results of NN with one hidden layer for all patterns

From the experimental results of all structures, it was found that inputting the ECG signal together with the PPG signal (ECG+PPG) will provide the highest accuracy of the model (validation accuracy) which has an average value of 79.86%, while the lowest accuracy is 34.72%.

Table 1. Results of the neural network for every case

Neural network (1 Hidden Layer)					
Input Signal	1 st time	2 nd time	3 rd time	Average	Standard deviation
ECG	52.00%	50.00%	54.00%	52.00%	0.0210
PPG	39.58%	31.25%	33.33%	34.72%	0.0433
ECG+PPG	81.25%	81.25%	77.08%	79.86%	0.0241
PPG+ECG	77.08%	70.83%	81.25%	76.39%	0.0524

4. Conclusion

This paper can create a prototype of a model for classifying blood pressure values by providing input signals to the structure of a neural network with one hidden layer. We analyze any one signal of electrocardiogram (ECG) and photoplethysmography (PPG) signals and the signals together of ECG+PPG and PPG+ECG, it was found that the combined ECG and PPG signals provide the highest accuracy for blood pressure classification. We will analyze and compare these results with deep learning algorithm in the future.

Reference

- [1] J. Lee, S. Yang, S. Lee, and H. C. Kim, "Analysis of Pulse Arrival Time as an Indicator of Blood Pressure in a Large Surgical Biosignal Database: Recommendations for Developing Ubiquitous Blood Pressure Monitoring Methods," *Journal of clinical medicine*, 8(11), 1773, pp.1-19, 2019.
- [2] H. Wu, Z. Ji, and Mengze, "Non-Invasive Continuous Blood-Pressure Monitoring Models Based on Photoplethysmography and Electrocardiography," *Sensors*, 19(24), 5543, pp.1-19, 2019.
- [3] M. Kachudee, M. Madhi, H. Mohammadzade, and M. Shabany, "Cuff-Less Blood Pressure Estimation Algorithms for Continuous Health-Care Monitoring," *IEEE Transactions on Biomedical Engineering*, vol. 64, no. 4 pp. 859 - 869, 2016.
- [4] P. Phruengkhattaranon, "ECG signal processing. Songkhla: Department of Electrical Engineering, Faculty of Engineering Prince of Songkla University," pp. 3-8, 2022.
- [5] W. Amsiri, "Photoplethysmography signal generator set in teaching and practicing for medical signal analysis," 1st printing, Bangkok, pp. 55-56, 2015.