Deep Learning-Based Estimation of Blood Pressure and Anxiety Using PPG and ECG

Xiaohong Yu
Dept. of Computer Science and Engineering
Sungkyunkwan University
Suwon, Republic of Korea
Email: dawnyu@skku.edu

Jaehoon (Paul) Jeong
Dept. of Computer Science and Engineering
Sungkyunkwan University
Suwon, Republic of Korea
Email: pauljeong@skku.edu

MiHye Park
Dept. of Medicine
Sungkyunkwan University
Suwon, Republic of Korea
Email: dukiduck@skku.edu

***Abstract*—In the preoperative period, patients often experience heightened anxiety and stress, which can manifest hypertension or tachycardia, potentially leading to adverse clinical outcomes. Therefore, it is crucial to detect patients in an anxious state to implement effective hypertension management and improve long-term outcomes. In this study, we extract blood pressure and heart rate variability features from both photoplethysmography (PPG) and electrocardiogram (ECG) signals using wavelet transform. Subsequently, we employ deep learning-based models for the classification of hypertension.**

***Index Terms*—Blood Pressure (BP), Photoplethysmography (PPG), Electrocardiogram (ECG), Deep Learning, Anxiety, Hypertension.**

I. Introduction

In the preoperative phase, patients often experience heightened anxiety and stress, potentially leading to manifestations like hypertension or achycardia, which can result in adverse clinical outcomes [1]. Notably, elevated blood pressure before anesthesia induction may lead to significant fluctuations during and after surgery, posing a risk of cardiovascular or cerebrovascular events. Adequate management is crucial. Stress-induced hypertension may respond well to sedation or anxiolysis, while uncontrolled blood pressure due to underlying vascular or cardiac issues may necessitate surgery delay. Therefore, identifying the root cause of hypertension in surgical patients before administering anesthesia is essential.

To assess anxiety or stress status, relying solely on patient self-report may be subjective. Alternatively, various noninvasive devices, such as photoplethysmography (PPG) and electrocardiogram (ECG), can provide valuable measures to medical doctors. Analyzing the waves in PPG and ECG allows for the measurement of blood pressure and heart rate variability. While inflatable blood pressure cuffs are commonly used, they can cause discomfort and skin damage. For critically ill patients or those in prolonged surgeries, invasive arterial blood pressure measurement carries risks like infection and vascular damage.

Measuring blood pressure or tension through PPG or ECG is believed to offer a less invasive approach for assessing blood pressure and anxiety levels. Furthermore, this method can be adapted beyond surgical settings, providing a means to detect stress-related hypertension in daily life, such as in cases of white coat syndrome. Additionally, monitoring blood pressure and anxiety levels with PPG and ECG can be beneficial for individuals with mental health disorders.

In this paper, we propose a framework to estimate blood pressure and anxiety through PPG and ECG. The architecture of our study is shown in Fig. 1.

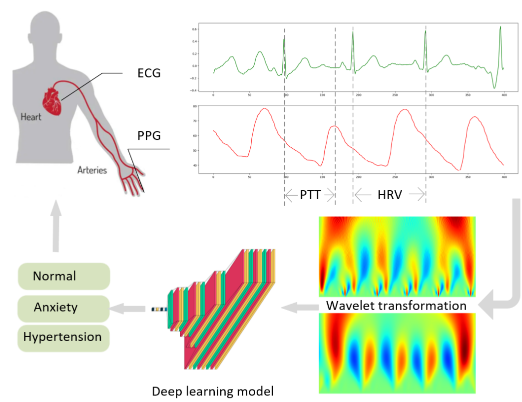

Fig. 1. The architecture of the hypertension estimation

The rest of this paper is organized as follows. Section II summarizes and analyzes the current research work about anxiety and blood pressure classification and prediction. Section III describes the design of the anxiety and hypertension definitions, and a framework to detect those symptoms with datasets. Section IV describes the experiment situation, including the data preprocessing segmentation and model selection. Finally, in Section V, we conclude this paper along with future work.

II. Related Work

The blood pressure prediction and classification are widely researched. Treebupachatsakul et al. use the Fourier transformation to convert the signal into an image to extract useful information for blood pressure prediction [2]. Malliani et al. [3] and Rosenberg et al. [4] seek the relationship between anxiety and the frequency domain of heart rate. Stress can be measured via physiological measurements. Those measurements can be extracted from common wearable devices [5].

III. Design

Blood pressure is mainly measured by two indexes called systolic blood pressure (SBP) and diastolic blood pressure (DBP). In medicine, SBP greater than 140 mmHg or DBP greater than 110 mmHg are regarded as high blood pressure, also called hypertension. The measurements in the frequency domain of HRV include high frequencies (HF), between 0.14 and 0.4 Hz, and low frequencies (LF), between 0.05 and 0.15 Hz. The ratio of LF to HF (LF/HF) represents the relative activity between the sympathetic nervous system and the parasympathetic nervous system under controlled conditions [6]. The ratio of (LF/HF) is subsequently adopted as a marker of stress in a number of studies [3], [4]. We can combine the blood pressure information and heart rate ratio to detect people with anxiety and hypertension.

A. Dataset

In this study, anxiety and tension were measured through a preoperative survey conducted with patients. The dataset was collected from 100 patients in the operating room at Samsung Medical Center. As the data is from the operating room, the ECG, PLETH (PPG), and non-invasive Blood Pressure (NIBP) values were examined for their normalcy, specifically in relation to hypertension.

IV. Experiment

The data collected has missing data points in the signal. The interpolation method is used to deal with the missing data problem. Fig. 2 shows the signal interpolation using quadratic interpolation.

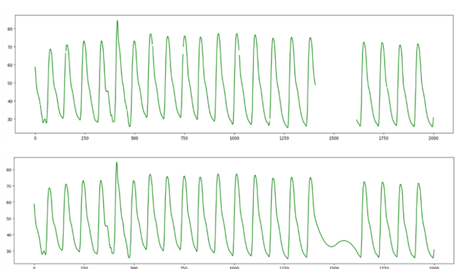

Fig. 2. The architecture of the hypertension estimation

The signal was segmented into multiple signal samples, with every sample having 20-second data points, including the ECG and PPG signals and also the discrete blood pressure value. The data samples are shown in Fig. 3. Then the data samples were transformed using wavelet transformation to convert the signal to image data.

The model we are using in this paper is a pre-trained convolutional neural network called Alexnet [7]. It includes five convolutional layers combined with three linear layers. We change the output layer according to our classification task.

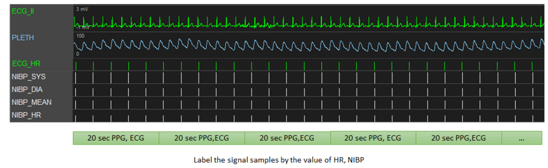

Fig. 3. The segmentation of signal

V. Conclusion

This paper proposes a framework for the conversion of the PPG and ECG signals to an image using the wavelet transformation to extract the features of the patient. The wavelet transformation can not only extract the frequency of the signal but also the location of the frequency. With the features in the image, the image was classified using a convolutional neural network into three categories: people with normal situations, people with pre-existing hypertension, and people with hypertension caused by anxiety. As future work, we will implement the proposed framework and compare its performance with the state-of-the-art schemes.

Acknowledgments

This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIT) (No. 2023R1A2C2002990). This work was supported in part by the Korea MSIT under the Institute for Information & Communications Technology Planning & Evaluation (IITP) (No. 2022-0-01199) and by AI Convergence Research Fund, Sungkyunkwan University, 2023. Note that Jaehoon (Paul) Jeong is the corresponding author.

References

[1] W. T. Kassahun, M. Mehdorn, T. C. Wagner, J. Babel, H. Danker, and I. Gockel, "The effect of preoperative patient-reported anxiety on morbidity and mortality outcomes in patients undergoing major general surgery," *Scientific Reports*, vol. 12, no. 1, p. 6312, Apr 2022. [Online]. Available: https://doi.org/10.1038/s41598-022-10302-z

[2] T. Treebupachatsakul, A. Boosamalee, S. Shinnakerdchoke, S. Pechprasarn, and N. Thongpance, "Cuff-Less blood pressure prediction from ECG and PPG signals using fourier transformation and amplitude randomization preprocessing for context aggregation network training," *Biosensors (Basel)*, vol. 12, no. 3, Mar. 2022.

[3] A. Malliani, M. Pagani, F. Lombardi, and S. Cerutti, "Cardiovascular neural regulation explored in the frequency domain," *Circulation*, vol. 84, no. 2, pp. 482–492, Aug. 1991.

[4] W. von Rosenberg, T. Chanwimalueang, T. Adjei, U. Jaffer, V. Goverdovsky, and D. P. Mandic, "Resolving ambiguities in the lf/hf ratio: Lf-hf scatter plots for the categorization of mental and physical stress from hrv," *Frontiers in Physiology*, vol. 8, 2017. [Online]. Available: https://www.frontiersin.org/articles/10.3389/fphys.2017.00360

[5] K. M. Dalmeida and G. L. Masala, "Hrv features as viable physiological markers for stress detection using wearable devices," *Sensors*, vol. 21, no. 8, 2021. [Online]. Available: https://www.mdpi.com/1424-8220/21/8/2873

[6] C.-H. Shih, P.-C. Chou, J.-H. Chen, T.-L. Chou, J.-H. Lai, C.-Y. Lu, and T.-W. Huang, "Cancer-related fatigue classification based on heart rate variability signals from wearables," *Front Med (Lausanne)*, vol. 10, p. 1103979, Apr. 2023.

[7] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "Imagenet classification with deep convolutional neural networks," in *Advances in Neural Information Processing Systems*, F. Pereira, C. Burges, L. Bottou, and K. Weinberger, Eds., vol. 25. Curran Associates, Inc., 2012. [Online]. Available: https://proceedings.neurips.cc/paper_files/paper/2012/file/c399862d3b9d6b76c8436e924a68c45b-Paper.pdf