ECG and PPG-Based Hypertension Screening Under Non-Hypertensive Blood Pressure Recordings

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Abstract

Blood pressure (BP) fluctuates throughout the day, mainly due to circadian oscillations as well as a response to physical and mental stimuli. This study aims at investigating whether machine learning (ML) classifiers can detect hypertension pathology regardless of absolute BP values. The goal is to identify HTS patients from non-HTS recordings and NTS subjects from non-NTS recordings using photoplethysmography (PPG) and electrocardiography (ECG). 803 simultaneous PPG, ECG and invasive BP recordings from 51 subjects were analyzed. 668 were coherent BP segments, with high BP for HTS patients and normal BP for NTS subjects, and 135 were incoherent segments, with normal BP for HTS patients and high BP for NTS subjects. PPG and BP relationship was evaluated with discriminant features and classification models were employed to classify incoherent segments. Using the discriminant features of coherent segments for training and the set of incoherent segments for validation, K-nearest neighbors provided the best outcomes, with F1-score of 88.30%. Combining PPG and ECG recordings with ML-based methodologies would be of high interest for hypertension screening, so that HTS and NTS subjects could be properly discerned even in the case of incoherent or altered BP values. This method could be used as a support for clinical decision-making when diagnosing hypertension.

1. Introduction

Blood pressure (BP) is one of the main vital signs as hypertension is an early indicator of cardiovascular disease (CVDs). Systolic and diastolic BP are not static, changing from one pulse to another and as a result of circadian rhythm throughout the day. BP variability is larger in hypertensive (HTS) patients than in normotensive (NTS) subjects, being proportional to the increase in mean BP [1]. Exercise, stress, drugs and nutrition are external factors that may change BP [2]. White-coat hypertension and masked hypertension are two popular concepts associated to BP variability. They are characterized by elevate office BP for normotensive subjects caused by anxiety or responding to unusual clinical settings and normal office BP in hypertensive subjects [1].

Nowadays, BP is mainly measured by obstructive inflatable cuffs that provide accurate BP readings. However, cuff-based devices offer one-shot measurements, not allowing continuous evaluation of BP state throughout the day. Moreover, they are not wearable, are uncomfortable and their procedure is cumbersome and require patient attention and knowledge [3]. In the event of a variation in BP when the measurement is being carried out, the risk of hypertension would be misdiagnosed, what would avoid an early diagnosis of HTS subjects or wrongly labeling as HTS healthy subjects. This motivates the need for monitoring devices to screen hypertension in a continuous and unobstructive way.

The proposed method consists of machine learning (ML) classification models trained to predict if the analyzed subjects were NTS or HTS in the case of altered BP values. Thus, this method detects the hypertensive condition and not a punctual BP value that could be affected by short or long term BP variations. The employed physiological signals were electrocardiogram (ECG) and photoplethysmogram (PPG) recordings, as they can be obtained in a simple, noninvasive and low cost way by wearable devices and their waveform is related to changes in total and pulsatile tissue blood volume [4].

To achieve the aforesaid purpose of detecting the hypertension pathology regardless of absolute BP values, PPG morphological features combined with propagation features from the ECG were derived and analyzed from simultaneous PPG and ECG recordings and employed as inputs for the classification models.

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2. Materials and Methods

2.1. Data processing

ECG, PPG and invasive BP recordings were obtained from the MIMIC database, which contains simultaneous recordings from ICU patients [5]. In order to remove minor noises and artifacts, PPG signals were processed by a fourth order Chebyshev II bandpass filter with cutoff frequencies between 0.5 Hz and 10 Hz [6]. Furthermore, for signal comparison improvement, PPG mean value was removed. In addition, the velocity plethysmogram (VPG) and the acceleration plethysmogram (APG) were obtained by applying the first and the second order derivatives to the processed PPG signal.

Each ECG was high-pass filtered with cutoff frequency of 0.5 Hz to remove the baseline, and then low-pass filtered with cutoff frequency of 50 Hz to reduce high-frequency muscle noise and power line interference [7]. Finally, foreach ECG recording, an R-peak detector based on the phasor transform was applied to the processed ECG signal to obtain the position of each beat [8]. The BP value was obtained from the maximum systolic BP, the maximum peak from each BP pulse without requiring pre-processing. Artifacts causing very noisy recordings or morphologically distorted signals were dismissed.

33 subjects with predominant BP values below 120 mmHg were labeled as NTS and 18 subjects with predominant BP values over 140 mmHg were labeled as HTS. From them, 668 segments were extracted with coherent BP segments, having high BP for HTS patients and normal BP for NTS subjects. In addition, 135 incoherent segments, with normal BP for HTS patients and high BP for NTS subjects were obtained, representing recordings with BP alterations. All PPG, ECG and invasive BP were recorded simultaneously with a duration of 120 seconds, a common sampling frequency of 125 Hz and a resolution of 8-10 bits [9]. Then, this recordings were divided into 12 segments with a duration of 10 seconds to increase training and validation datasets.

As represented in Figure 1, for each recording, the systolic peaks from PPG, VPG and APG signals (S, W, a), the initial pulse point from PPG signal (O), and two local maxima and minima of the APG signal (b, c, d, e) were extracted [10]. For fiducial points definition, thresholds and slope criteria were established after obtaining all local minima and maxima from pulses.

2.2. Features extraction

Discriminatory features were defined to evaluate the relationship between BP and PPG signal. Pulse wave propagation theory features were pulse arrival times (PAT) or time interval between R-peak and the O-notch

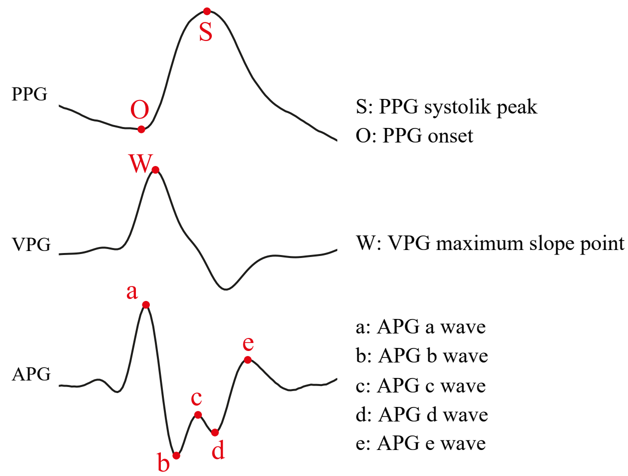

Figure 1. Fiducial points definition from photoplethysmogram (PPG), velocity plethysmogram (VPG) and acceleration plethysmogram (APG) signals.

(PAT_{foot}), W peak of VPG signal ($PAT_{derivate}$) and S-peak (PAT_{peak}), and pulse transit time (PTT) or time interval between BP signal peak and S-peak. Moreover, morphological theory based features as S and W amplitudes, time peak to peak (TPP), time pulse interval (TPI), rising time, width, pulse areas, ratio between areas, time interval between two consecutive a-peaks in APG signal, ratios between APG waves and a-wave and complex APG ratios were defined and illustrated in Figure 2 [10, 11].

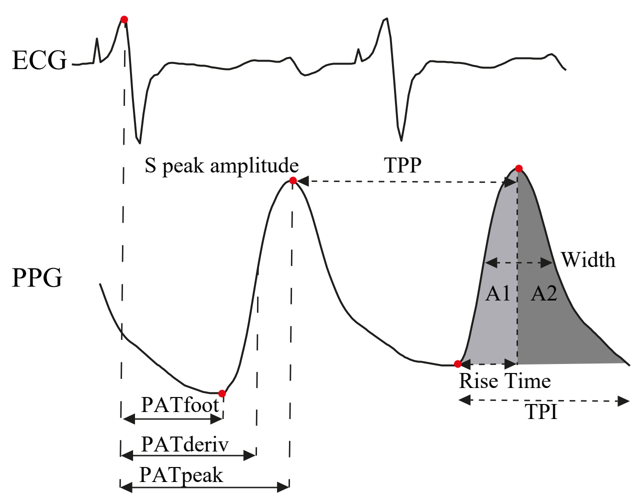

Figure 2. Representation of PAT defined features and PPG morphological parameters.

Then, a feature selection stage was carried out to select only those features with relevant information for the classification task. Relieff algorithm was applied to rank the normalized features. Those variables that did not provide new information were discarded studying the correlation matrix. Finally, the last three ranked features as well as three features with high correlation with other features were removed, obtaining a matrix of 17 normalized features used as input for the classification models.

2.3. Experimental details

As stated before, the aim of this work is to investigate if PPG recordings are correctly classified when an alteration in BP from the analyzed subject occurs. Discriminant features after feature selection from coherent segments were used to train the classification models and discriminant features from incoherent segments were used for validation.

Searching the best ML-based classification model for the hypertension screening task, up to 37 different classification strategies were tested, including support vector machines (SVM), decision trees, discriminant analysis, logistic regression, Naive Bayes, K-Nearest Neighbors (KNN) and ensemble classifiers [12]. Finally, Fine KNN, Cubic SVM and Bagging Ensemble were selected because they provided the highest classification accuracy percentages.

Accuracy (*Acc*), sensitivity (*Se*), specificity (*Sp*) and *F1-Score* statistical tests were employed to assess the classification performance. *Acc* represented the correctly classified PPG segments percentage. *Se* was defined as the ability to detect as positive incoherent segments from HTS subjects, whereas *Sp* was defined as the ability to detect as negative incoherent segments from NTS subjects. Finally, *F1-Score* was considered to be the harmonic mean of *Se* and *Acc*.

3. Results

Table 1 presents the statistical results of this study. It can be seen that the classification model that provided the best outcomes was Fine KNN, with *F1-Score* of 88.30%. Cubic SVM and Bagging Ensemble classifiers worsened the results in the four statistical tests studied. High *Sp* values in the three classification models reflected correctly identified NTS individuals when BP reached prehipertensive or HTS values.

Table 1. Performance of the three classification models analyzed to screen hypertension under Non-Hypertensive BP recordings and normotension under hypertensive BP recordings. Accuracy (*Acc*), sensitivity (*Se*), specificity (*Sp*) and *F1-Score*.

	Acc	*Se*	*Sp*	*F1-Score*
KNN	83.70%	79.81%	96.77%	88.30%
SVM	75.56%	72.12%	87.10%	81.97%
Ensemble	79.26%	75.00%	93.55%	84.78%

4. Discussion

Cuff-less devices providing continuous BP monitoring are of great interest for the early detection of hypertension, one of the main risk factors for many CVDs. Their objective is to obtain and process physiological signals to train artificial intelligence models and obtain BP information as systolic BP values or the hypertension risk level. The most used signal for this task is PPG, as is simple, low cost, noninvasive and directly related to changes in blood volume.

However, most BP monitoring devices provide punctual information and artificial intelligence methods provide an BP value estimation [13]. Thus, in case of BP variation caused by physical or mental stimuli, the diagnosis of the BP condition would not be adequate. For this reason, the present study investigated if an adequate subject diagnosis is provided in case of altered BP. To this end, a combination of propagation features requiring ECG signal and PPG, VPG and APG morphological features were extracted to train ML-based models for the classification task.

Any previous study about hypertension risk assessment has studied the hypertension detection under non-hypertensive BP recordings. Radha et al. [14] estimated the nocturnal BP dip through PPG sensors and a deep neural network. Long- and short-term memory (LSTM) networks, dense networks, random forests, and linear regression models were employed to track the trends in BP. Finnegan et al. [15] investigated the presence of circadian rhythm in PAT and its applications in nocturnal BP dip or rise classification, as it is a strong indicator for CVDs.

The present study proposed incorporating coherent segments from each subject for training and incoherent segments corresponding to BP variations for validation. Fine KNN provided the best classification results, with *F1-Score* of 88.30%. *Sp* result was almost perfect, 96.77%, whereas *Se* was almost 17% lower. This indicated that BP variations affected less to PPG characteristics of NTS subjects than PPG characteristics of HTS subjects.

This approach demonstrated that the proposed classification models provided an adequate hypertension risk assessment in the subjects analyzed regardless of absolute BP values. This fact is of high interest as high accuracy was obtained despite physical or mental stimuli that caused BP variability.

5. Conclusions

The combination of discriminant features extracted from PPG and ECG recordings with ML-based classification methodologies would be of high interest for the continuous monitoring of the subject's hypertensive condition. Thus, HTS and NTS subjects could be properly discerned even in the case of incoherent or altered BP values caused by long and short term BP variability. The incorporation of this new methodologies in cuff-less devices could be used as a support for clinical decision-making when diagnosing hypertension in a continuous and unobstructive way.

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References

[1] Chadachan VM, Ye MT, Tay JC, Subramaniam K, Setia S. Understanding short-term blood-pressure-variability phenotypes: from concept to clinical practice. International Journal of General Medicine jun 2018;Volume 11:241–254. ISSN 1178-7074.

[2] Fortino G, Giampa V. PPG-based methods for non invasive and continuous blood pressure measurement: an overview and development issues in body sensor networks. In 2010 IEEE International Workshop on Medical Measurements and Applications. IEEE. ISBN 978-1-4244-6288-9, apr 2010; 10–13.

[3] Frese EM, Fick A, Sadowsky SH. Blood Pressure Measurement Guidelines for Physical Therapists. Cardiopulmonary Physical Therapy Journal jun 2011;22(2):5–12. ISSN 1541-7891.

[4] Babchenko A, Davidson E, Ginosar Y, Kurz V, Faib I, Adler D, Nitzan M. Photoplethysmographic measurement of changes in total and pulsatile tissue blood volume, following sympathetic blockade. Physiological Measurement may 2001;22(2):389–396. ISSN 0967-3334.

[5] Johnson AE, Pollard TJ, Shen L, Lehman LWH, Feng M, Ghassemi M, Moody B, Szolovits P, Anthony Celi L, Mark RG. MIMIC-III, a Freely Accessible Critical Care Database. Scientific Data may 2016;3(1):1–9. ISSN 20524463.

[6] Liang Y, Elgendi M, Chen Z, Ward R. An optimal filter for short photoplethysmogram signals. Scientific Data dec 2018;5(1):180076. ISSN 2052-4463.

[7] Sörnmo L, Laguna P. Bioelectrical Signal Processing in Cardiac and Neurological Applications. Elsevier, 2005. ISBN 9780124375529.

[8] Martínez A, Alcaraz R, Rieta JJ. Application of the phasor transform for automatic delineation of single-lead ECG fiducial points. Physiological Measurement nov 2010; 31(11):1467–1485. ISSN 0967-3334.

[9] Goldberger AL, Amaral LAN, Glass L, Hausdorff JM, Ivanov PC, Mark RG, Mietus JE, Moody GB, Peng CK, Stanley HE. PhysioBank, PhysioToolkit, and PhysioNet. Circulation jun 2000;101(23). ISSN 0009-7322.

[10] Elgendi M. On the Analysis of Fingertip Photoplethysmogram Signals. Current Cardiology Reviews jun 2012; 8(1):14–25. ISSN 1573403X.

[11] Mousavi SS, Firouzmand M, Charmi M, Hemmati M, Moghadam M, Ghorbani Y. Blood pressure estimation from appropriate and inappropriate PPG signals using A whole-based method. Biomedical Signal Processing and Control jan 2019;47:196–206. ISSN 17468094.

[12] Shalev-Shwartz S, Ben-David S. Understanding Machine Learning, volume 9781107057. Cambridge: Cambridge University Press, jan 2014. ISBN 9781107298019.

[13] El-Hajj C, Kyriacou P. A review of machine learning techniques in photoplethysmography for the non-invasive cuff-less measurement of blood pressure. Biomedical Signal Processing and Control apr 2020;58:101870. ISSN 17468094.

[14] Radha M, de Groot K, Rajani N, Wong CCP, Kobold N, Vos V, Fonseca P, Mastellos N, Wark PA, Velthoven N, Haakma R, Aarts RM. Estimating blood pressure trends and the nocturnal dip from photoplethysmography. Physiological Measurement feb 2019;40(2):025006. ISSN 1361-6579.

[15] Finnegan E, Davidson S, Harford M, Jorge J, Villarroel M. The presence of a circadian rhythm in pulse arrival time and its application for classifying blood pressure night-time dip. In 2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), volume 2021. IEEE. ISBN 978-1-7281-1179-7. ISSN 2694-0604, nov 2021; 488–491.

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