Cuffless Hypertension Risk Assessment and the Significance of Calibration

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Abstract

Early detection of high blood pressure (BP) is of paramount relevance because hypertension is the main risk factor for many cardiovascular diseases. This work evaluates the need of per-subject calibration for discrimination between normotensive (NTS) and hypertensive (HTS) subjects. 668 electrocardiographic (ECG), photoplethysmographic (PPG) and BP recordings from 51 subjects were analyzed. After signal preprocessing and feature selection, 17 discriminatory features were obtained to train machine learning based classifiers. Previous per-subject calibration relevance was evaluated by sequential validation, using both close and distant in time calibration measurements varying from less than 1h to more than 24h with respect to test measurements. The k-nearest neighbors classifier provided an accuracy for new subjects before calibration of 56.79%. The inclusion of just one calibration measurement into the model improved classification accuracy by 30%, reaching gradually more than 97%. Classification accuracy decreased with distance to calibration, but remained well above 83% even days after the last calibration. Thus, discrimination of NTS and HTS subjects can be significantly improved combining PPG and ECG recordings with previous per-subject calibration and, therefore, could be used for the detection of hypertension implementing these techniques in wearable devices.

1. Introduction

High blood pressure or hypertension (HT) is the main risk factor for many cardiovascular diseases (CVDs) as coronary disease, cardiac arrhythmia or stroke [1]. Furthermore, most patients with HT are undiagnosed, as until very advanced stages, HT rarely cause symptoms. For these reasons, regular blood pressure monitoring is crucial for the prevention and early detection of asymptomatic HT and the continuous monitoring of diagnosed subjects [2].

For non-invasive blood pressure (BP) estimation, conventional cuff-based devices offer adequate accuracy. However, they are not wearable and only offer one-off measures. Therefore, they are not compatible with continuous measurement, are uncomfortable, and their measurement procedure is tedious, requiring patient attention [3].

Consequently, work in this field is focused on the development of cuff-less systems that can provide BP information in near real time [4]. The development of these systems is facilitated by new wristbands and smartwatches that monitor physiological signals that change according to BP level, as the electrocardiogram (ECG) and photoplethysmogram (PPG) [5]. The most promising signal is PPG, an optical measurement technique employed to detect changes in blood volume that is low cost, simple and noninvasive [6].

BP classification models can automatically know in a continuous and non-invasive way the subject's blood pressure condition, detecting hypertensive subjects with high BP. Thus, Liang et al. [7] combined PPG morphological features and propagation features as pulse arrival times (PAT) with four distinctive classifiers for the hypertension risk classification.

However, the relationship between PPG-based propagation parameters and BP depends on many physiological factors, such as arterial walls condition, age and gender, posture and CVDs risk factors. Thus, calibration is needed when new subjects are evaluated by an automated classification methods. Moreover, calibration before measurement is essential to adapt the algorithms to the variations on PPG waveforms between subjects. [8].

The aim of the present study is to develop a classification system for hypertension risk assessment and to evaluate the need and relevance of per-subject calibration. For this purpose, PPG and ECG simultaneous recordings were analyzed and propagation features combined with other PPG morphological features have been extracted and used to train advanced machine learning classification models.

2. Materials and Methods

2.1. Materials

The recordings were obtained from the MIMIC database, which contains simultaneous ECG, PPG and invasive BP recordings from ICU patients [9]. Noisy or morphologically distorted signals were dismissed due to the presence of artifacts.

In this study, a binary classification between normotensive (NTS) and hypertensive (HTS) subjects was developed. Clinically, a third hypertension category for prehypertensive subjects between 120 and 130 mmHg is included. However, since there are few subjects with BP values maintained between 120 and 140 mmHg, these subjects were dismissed. Furthermore, subjects with oscillating values between two HT labels or with huge alterations of their BP values were dismissed. Finally, 668 recordings from 51 subjects with acceptable signal quality conditions were selected. The signals were recorded simultaneously with a duration of 120 seconds, a common sampling frequency of 125 Hz and a resolution of 8-10 bits [10].

2.2. Signal Preprocessing

The PPG signals were processed by a fourth order Chebyshev II bandpass filter with cutoff frequencies between 0.5 Hz and 10 Hz to remove minor noises and artifacts [11]. Furthermore, PPG mean value was removed to prevent drifts and improve signals comparison. In addition, the velocity plethysmogram (VPG) and the acceleration plethysmogram (APG) were obtained by applying the first and the second order derivatives to the PPG signal.

The maximum systolic blood pressure (SBP) was extracted directly from BP recordings without preprocessing. It was employed to label subjects whose selected segments had SBP < 120 mmHg as NTS, and subjects whose selected segments had SBP > 140 mmHg as HTS.

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 [12]. Finally, an R-peak detector was applied to obtain beats positions.

After signal preprocessing, the systolic peaks of the three signals (S, W, a), the onset point of the PPG signal (O), and two local maxima and minimum of the APG signal (b, c, d, e) were extracted [13]. This fiducial points were obtained based on searching local minima and maxima, calculated establishing threshold and slope criteria.

2.3. Features extraction

Discriminatory features based on pulse wave propagation theory as PAT and pulse transit time (PTT), and signals morphological theory as PPG and VPG systolic peak 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 and ratios between APG waves were defined [13, 14].

Afterwards, feature selection stage was applied 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 (TPP, TPI and pulse area) as well as three complex APG ratios were removed, obtaining a matrix of 17 normalized features.

2.4. Need for calibration of new subjects

Calibration was defined as the inclusion of, at least, one previous measurement of the subject under study in the training dataset. Aimed at studying the importance of calibration in the classification of new subjects as NTS or HTS, three approaches were taken:

1. Classification performance of new subjects without prior subject-based calibration.
2. After signals segmentation into 12 sub-segments of 10 seconds, a sequential validation study was developed to analyze the classification improvement as the model was gradually calibrated by introducing previous sub-segments in the training dataset very close in time.
3. Sequential validation to study the classification improvement as the model was calibrated by introducing previous measurements of the same patient in the training dataset far away in time. Groups of segments that were less than 1h, between 1h and 6h, between 6h and 24h and more than one day apart were selected.

3. Results

K-Nearest Neighbors (KNN) model was chosen for the classification task as provided the best results from up to 37 different classification strategies. Firstly, classification accuracy discriminating between NTS and HTS individuals with no previous calibration was 56.79%.

Next, aiming at improving this result by means of calibration, Figure 1 shows classification accuracy for sequential validation of consecutive sub-segments. The accuracy improved progressively until it was established above 97% when more than 6 prior and close in time sub-segments from the same subject were present in the training dataset.

Finally, Figure 2 shows classification outcomes of sequential validation with different distances between measurements. With calibration and measurement separated less than one hour, the model obtained an accuracy beyond 94% from the sixth measurement onwards. As expected,

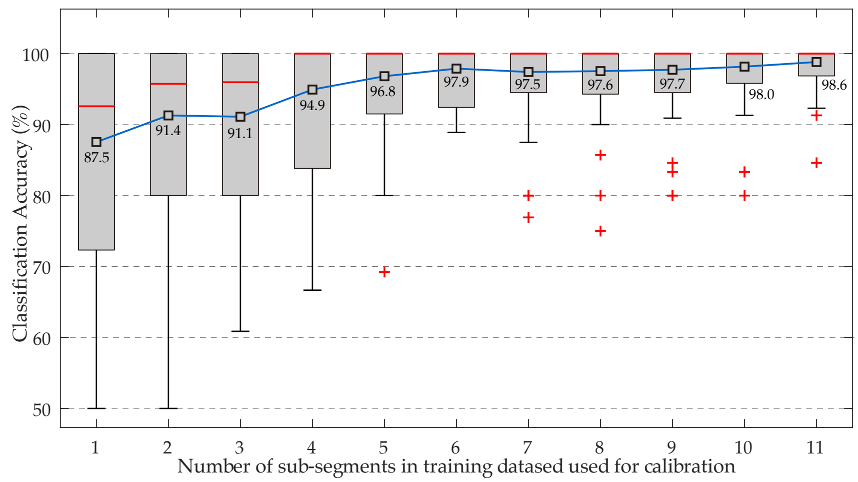

Figure 1. Results obtained for sequential validation of consecutive sub-segments. Red lines indicate the median and the bottom and top edges indicate the 15th and 85th percentiles. The whiskers extend to the most extreme data points not considered outliers, and the red symbol (+) stands for outliers. Black squares inside each box indicate mean accuracies.

these outcomes decreased as the distance between calibrations and test measurement increased, thus requiring up to five calibration measurements with distances between 6h and 24h to obtain accuracies above 80%.

4. Discussion

The continuous measurement of BP is of great importance for early detection and prevention of HT. Cuff-less devices that obtain continuous physiological signals have been proposed as an alternative to traditional cuff-based one-off BP measurement methods. These signals can be processed to apply artificial intelligence techniques for BP estimation. PPG is the most used signal, as its morphological variations are related to heart's activity and BP values.

Most studies for BP risk classification use both PPG and ECG signals, as PAT is directly related with BP values. Liang et al. [7] reported a higher correlation with HT risk levels combining PAT with additional PPG features.

The present study proposed two calibration approaches, trying to improve the poor initial classification accuracy of 56.76% when a new subject entered the method without any previous calibration. The first approach investigated how HT risk assessment could be improved employing consecutive sub-segments both for calibration and classification. Thus, high similarity was supposed between calibration and test measurements. The second approach studied the benefit of calibration between distant measurements, varying from less than 1h to more than 24h. This way, it was studied if the PPG signal properties remained across time or changed along the day or week.

For close distances to calibration and below 1h, classification accuracy improved by 30% with just one calibration. Although this improvement decreased as the distance between calibration and measurement increased, calibration always improved classification results compared to classifying a new uncalibrated subject. Thus, after the fifth calibration, all the experiments provided high accuracy.

These approaches demonstrated that each subject's PPG features properties were variable over time, as worse results were obtained with measurements distant from calibration. Therefore, several re-calibrations at distant recording times and in different situations are recommended to assure high classification accuracy assessing the risk of HT with PPG and ECG recordings.

5. Conclusions

The application of per-subject calibration, both in close and distant measurements, has proved its relevance for the discrimination between NTS and HTS subjects. For this purpose, discriminant features extraction from PPG and ECG recordings, together with the use of machine learning classification models were employed. The implementation of these artificial intelligence techniques in wearable devices would improve the early diagnosis and prevention of cardiovascular diseases associated to hypertension.

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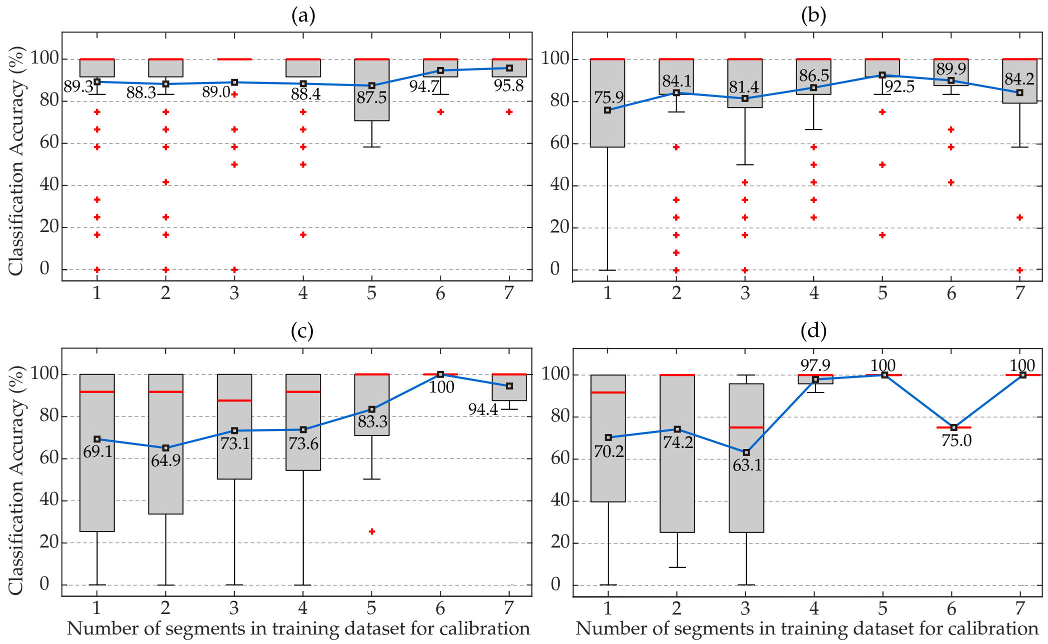

Figure 2. Results obtained for sequential validation of distant measurements. (a) Distance below one hour. (b) Distance between one and six hours. (c) Distance between six and 24h. (d) Distance above 24h. Red lines indicate the median and the bottom and top edges indicate the 15th and 85th percentiles. The whiskers extend to the most extreme data points not considered outliers, and the red symbol (+) stands for outliers. Black squares inside each box indicate mean accuracies.

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