Cuff-less blood pressure measurement using fingertip photoplethysmogram signals and physiological characteristics

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Cuff-less blood pressure measurement using fingertip photoplethysmogram signals and physiological characteristics

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ABSTRACT

Blood pressure (BP) measurement data is an important indication of health and quality of life in clinical medicine and daily life. However, conventional measurement does not provide continuous monitoring data and sometimes is considered as inconvenient. With the ever increased urge for cuff-less continuous BP measurement, novel methods based on pulse transit time (PTT) obtained from the photoplethysmogram (PPG) and electrocardiogram (ECG) signals have gained its popularity. However, the collection of ECG signals involves the application of electrodes and inconvenience due to lengthy continuous measurement. In contrast, the collection of PPG signals is comparatively simpler and easier, therefore, novel methods that extract features from PPG signal are receiving more attentions. However, previous studies only focus on the features extracted from the PPG signal and did not include the physiological characteristics, which can serve as important predictors for BP. To improve the accuracy in the estimation of BP based on the PPG signal, this study not only extracts features from the PPG signal, but also includes the physiological characteristics of total 191 sets of subjects, such as height, weight, and age. After pre-processing the raw PPG signal, different machine learning methods are used to estimate the diastolic blood pressure (DBP) and the systolic blood pressure (SBP). The mean absolute error of DBP and SBP are 4.13 mmHg and 9.18 mmHg respectively. The results complied with the British Hypertension Society (BHS) standards and the implementation of physiological characteristics improved the accuracy of BP estimation.

Keywords: Fingertip Photoplethysmogram (PPG), Blood pressure (BP), Physiological characteristics

1. INTRODUCTION

Continuous BP measurement can help to provide timely diagnosis and hence immediate treatment of hypertension. BP is a periodic signal with maximum and minimum values corresponding to SBP and DBP, respectively. By standard measurement, while subjects are at resting state, if their SBP and DBP are respectively above 140 mmHg or 90 mmHg, the subjects are diagnosed as hypertensive. According to the World Health Organization, about one in five people experiences hypertension. However, majority of these hypertensive people are unaware of their health issues, suffering from internal organs damage without knowing. This is the reason that hypertension is called a 'silent killer' [1]. BP measurement could be affected by many factors, such as physical exercise, mental status, stress, food intake and noise. In addition, BP changes over time, which suggests the importance of the continuous BP measurement and monitoring.

Cardiovascular disease is a major cause of disability and premature death through the world where hypertension is a long-term medical condition that causes symptoms [2]. BP is a good indicator to help physicians adjust the status of cardiovascular system and provide appropriate treatment. The ‘gold standard’ for BP measurement is invasive arterial line which is a clinical standard used to detect BP beat-to-beat with high accuracy [3]. Though this method offers reliable measurement, there are inherent disadvantages associated with difficulties of routine use and invasive measurement. Hence, non-invasive continuous BP monitoring methods have potential to bridge the gap between traditional sphygmomanometry and modern health care.

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The current widespread BP measurement methods are divided into invasive and non-invasive measurements. Invasive BP measurement includes catheterization and non-invasive measurements include auscultation, oscillometry, volume clamping, and tonometry. In terms of non-invasive BP measurement methods, a cuff is used in auscultation, oscillometry and volumetric clamping methods. Therefore, many of the traditional methods that currently exist are invasive, manual and/or require cuffs. In general, it is not convenient, and continuous BP measurement cannot be achieved with traditional noninvasive measurement methods.

In recent years, various continuous cuff-less measurements have emerged. Using PTT to measure BP is one of them. PTT that can be calculated from two physical signals, ECG and PPG signals, uses photometric technique to test BP. It has been studied widely and gained much improvement [4]. However, due to the limitations inherent in collecting ECG signals, a few studies started to estimate BP using only PPG signals [5]. In addition, more researchers are considering using the shape and features of PPG signals to estimation BP [6]. The advantages in estimating BP in a non-invasive and cuff-less way using PPG signal are becoming more recognized.

This paper reports a novel method to estimate BP continuously and non-invasively based on the PPG signal only. Various features are extracted from the PPG signals and physiological characteristics are employed for the first time to the authors' knowledge. Along with the physiological characteristics as predictors, these features are used to estimate BP via different machine learning techniques. This is the first reported study that combines the physiological characteristics with the features of PPG to estimate BP, which has improved the accuracy of the BP measurement of non-invasive and cuff-less methods. This study has therefore presented a unique contribution to the literature of the research.

2. BACKGROUND OF THE RESEARCH

BP is the pressure created from circulating blood on vessels walls. With heart beats, blood is forced from the ventricle to the aorta which helps blood travel from the heart to peripheral vessels. The pressure wave travels along the arterial tree and its flow depends on arterial properties, such as elasticity, stiffness and thickness of artery wall and the size of artery.

From the Moens-Korteweg equation

$$PWV = \sqrt{\frac{Eh}{2r\rho}} \tag{1}$$

where *PWV* is the velocity of the pulse wave, *E* is the Young's modulus of the elasticity of the arterial wall, ρ is the blood density, *h* is vessel wall thickness and *r* is the radius of vessel [7].

The Young's modulus of the arterial wall E is not a constant value, but follows the empirical exponential relationship with the fluid pressure P.

$$E = E_0 e^{\gamma P} \tag{2}$$

where E_0 and γ are subject-specific parameters which depend on the thoracic aorta and abdominal aorta, and $e = 2.718$ is the Euler's number [8].

From the above two formulae, the velocity of pulse wave propagation can be derived. A typical example was reported by estimating BP with PTT [9], which required at least two signals, ECG and PPG signals, and encounted cumbersome problems with the measurement and processing of signals. Therefore it is preferred to find a simple and feasible method for the measurement of BP continuously. One of the novel methods is to use one signal only, namely the PPG. This normally involves the extraction of useful PPG features and the implementation of a variety of machine learning methods to achieve the accurate and continuous estimation of BP in medical monitoring [10].

PPG is an optical plethysmography to detect blood volume changes in peripheral circulation [11]. This is a non-invasive monitoring method used on the surface of the skin. This technique provides useful information to medical doctors regarding patients' cardiovascular systems. Applications have been implemented widely in clinical physiological measurement and monitoring recently. It has been integrated into wearable devices, for example, wearable pulse rate monitors [12]. These low-cost, reliable, simple and small devices realize non-invasive pulse rate monitoring and these sensors can detect the variation of intensity of transmitted light or reflected light which contains information of blood flow and cardiovascular activities.

3. METHODOLOGY OF STUDY

The following block diagram shows the analytical method applied in this study for the establishment of the evaluation model. This is used to achieve the non-invasive, continuous and cuff-less BP measurement using PPG signal only.

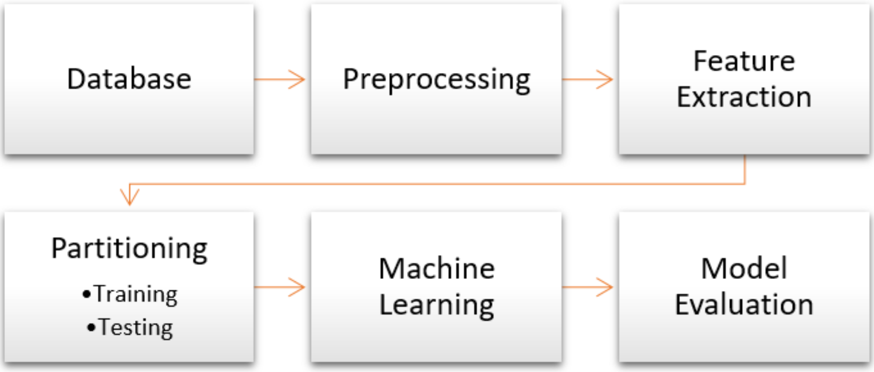

Figure 1. Block diagram of the proposed BP estimation with PPG signals only

The details and criteria in the implementation above approach are: 1) there should be enough high quality and detailed information in the database; 2) pre-processing is required to remove noise of the raw data and smooth the curves; 3) feature extraction is obtained from the PPG signal based on its first and second derivatives; 4) data partitioning is arranged according to the needs of model training and model evaluation; 5) machine learning is used to establish an appropriate model for the BP estimation; 6) the established model is tested by examining the test data of the database.

3.1 Database

To achieve a non-invasive, continuous and cuff-less measurement of BP using PPG signal only, the first step is to carry out sufficient measurements and collect PPG signals to establish a reliable database. In this study, a high-quality well-established PPG signal database provided by Yongbo et al. [13] is used for the data analysis and model establishment and validation. The database includes 657 data segments from 219 subjects, including records of people from a broad range of age groups, ranging from 20 years old to 89 year old, and their illness records. Data collection was conducted in accordance with standard experimental conditions and specifications. This database is very effective for the establishment of the relationship between PPG waveforms and BP in this study.

Data collection was conducted at the People's Hospital of Guilin, China. The sampling frequency was 1 kHz using 12-bit analogue to digital converter (ADC). Totally 657 PPG signal data segments from 219 subjects were collected, while each segment had 2100 sampling points, corresponding to 2.1 seconds. A bandpass filter of 0.5-12Hz was used. Most importantly, the database also includes physiological information and illness information for each subject. Information records include ID, gender, age, height, weight, SBP, DBP, heart rate and illness records. Some inconsistent, abnormal, and noisy data was removed to form a high-quality data set for the establishment of the model. The prediction of BP requires high-quality PPG signals and physiological information is important [13].

3.2 Pre-processing

Since the PPG signals in the database are all in a segment of 2.1 seconds, signal pre-processing is mainly carried out for signal smoothing and filtering, which does not involve baseline calibration. The high quality of the signals in the database facilitates data pre-processing. In this study, the 1-D median filtering technique and finite impulse response (FIR) filter are selected as the filters, and cubic smoothing spline are used to facilitate the extraction of feature points [14]. Figure 2 shows the PPG signal shapes after the filters and spline interpolation.

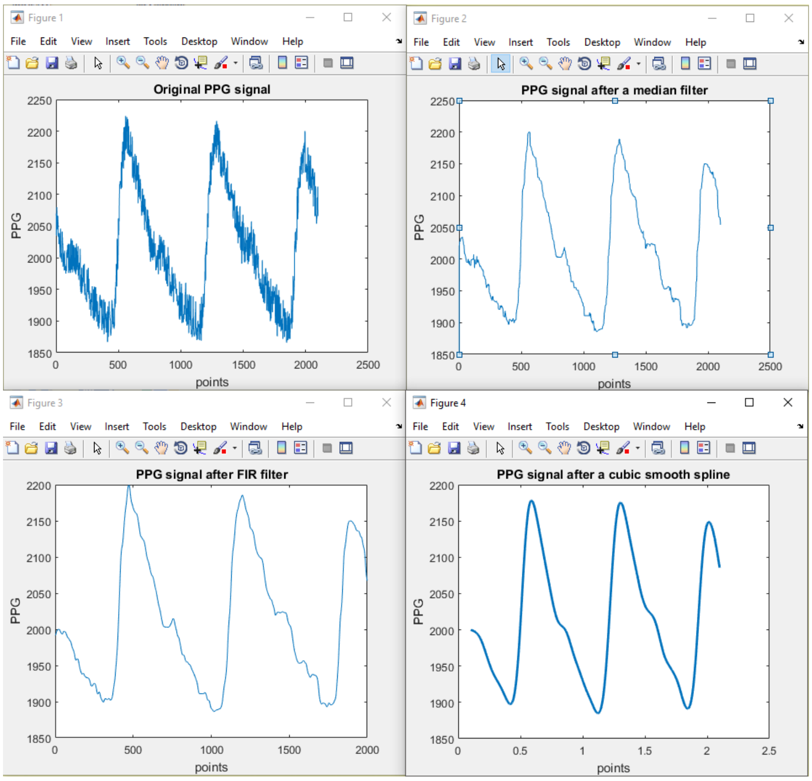

Figure 2. PPG original signals and different shapes after median filter, FIR filter and cubic smoothing spline

To be more specific, a median filter was used to improve the results of post processing, so as to make the signal curve smoother; a FIR filter was used to filter out the high frequency signal; a cubic spline was used to carry out interpolation, in order to ensure that PPG signal has continuous first and second derivatives which are needed for the extraction of various features.

After the pre-processing, some signals exhibit clearly abnormal patterns which indicate that there might be some significant errors in the data acquisition and therefore are discarded for the purpose of this study. This ends up with a total of 191 remaining subjects used to estimate BP in this paper.

3.3 Feature extraction

A total of 17 features are extracted and used in this experiment, of which 12 are extracted from the PPG signal and its first and second derivatives according to the literature [15]. The other 5 features are physiological characteristics of the subjects of the database. Figure 3 shows a PPG signal and some of its features [6]. These features are extracted from each subject’s PPG signals using MATLAB.

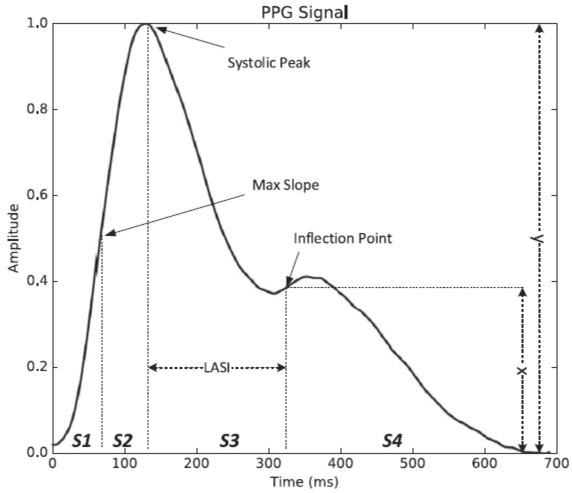

Figure 3. A PPG signal and its characteristic parameters including systolic peak, inflection point, S1, S2, S3 and S4 [6]

These 12 features, extracted from PPG signal and its first and second derivatives, include systolic amplitude, pulse width, peak to peak interval, inflection point, augmentation index (AI), large arterial stiffness index (SI), S1, S2, S3, S4, crest time (CT) and ratio of b/a. Some of them are shown in Figure 3. Pulse width is the width at half maximum height of the systolic amplitude. Peak to peak interval is the time difference between two successive systolic peaks. Inflection point is used in this paper instead of diastolic point because it is easier to detect. AI is calculated as $\frac{y}{x}$ and x, y are shown in Figure 3. SI is calculated as $\frac{h}{\Delta T}$ where h is the height of subject and ΔT is the time difference between systolic peak and diastolic peak. S1, S2, S3 and S4 are the areas below the selected points of the PPG signal. They can be used directly as features. CT is the time from the beginning of the PPG waveform to the systolic peak. Ratio b/a is a feature related to the second derivative. The other five physiological features used as the inputs to artificial neural network (ANN) are: gender, age, height, weight and BMI.

The objective of this paper is to investigate whether physiological characteristics have an important impact on BP prediction, and if it can improve the accuracy of BP prediction.

3.4 Partitioning of database

The database of subjects is divided into two parts according to conventional approaches [16]: 90% of subjects are used to train the model and 10% are used for subsequent analysis and evaluation.

3.5 Machine learning

Various machine learning models have been tested in this study [6]. After the inclusion of physiological characteristics, the BP estimation accuracy has been generally improved for all the models used in this study. However, for the purpose of illustration, only the results of ANN is presented here. ANN is a mathematical model that simulates the behaviour characteristics of biological neural networks and performs distributed parallel information processing [17]. It relies on the complexity of the system to adjust the weight of the interconnection between internal nodes (neurons) to achieve the purpose of processing information. In this paper, the results of DBP and SBP measurements are presented with ANN.

3.6 Model evaluation

The mean absolute error (MAE) and standard deviation (STD) are calculated using the test data set to evaluate the performance of established neural network models. The results, with and without physiological characteristics, are presented. The British Hypertension Society (BHS) standard criteria are used to designate results according to accuracy. There are three grades given by the BHS standard according to the cumulative percentage of reading falling within 5 mmHg, 10 mmHg and 15 mmHg of the mercury standard [18].

4. RESULTS

Table 1 shows the estimated results of DBP and SBP in ANN. The MAE and STD are calculated for scenarios with and without physiological characteristics. It can be seen that the values of MAE and STD with physiological characteristic are smaller than those without. This indicates that the physiological characteristics can improve the estimation accuracy of BP.

Table 1. Estimation results of DBP and SBP with artificial neural network (ANN)

ANN	**Include Physiological Characteristics**		**Exclude Physiological Characteristics**	
	MAE (mmHg)	STD (mmHg)	MAE (mmHg)	STD (mmHg)
DBP	4.13	5.26	6.60	7.79
SBP	9.18	12.57	11.12	14.20

Table 2 presents the results from ANN with physiological characteristics, together with the BHS standard. The BHS standard grades BP measurement accuracy levels by cumulative error percentage under three different thresholds [18]. According to Table 2, the performance of using ANN to predict DBP in this study has achieved grade C of the BHS standard. However, the accuracy of SBP does not meet the BHS standard.

Table 2. The estimated results comparison with British Hypertension Society (BHS) standard

Comparison		**Cumulative Error Percentage**		
		≤ 5 mmHg	≤ 10 mmHg	≤ 15 mmHg
DBP		42.1%	94.7%	100%
SBP		31.6%	68.4%	84.2%
BHS standard [18]	Grade A	60%	85%	95%
	Grade B	50%	75%	90%
	Grade C	40%	65%	85%

5. CONCLUSION

The features of PPG signals and subjects' physiological characteristics have been used to estimate BP. The novelty of this research and the simplicity in terms of setting up the PPG signal measurement system have made important contributions to the non-invasive BP measurement field and opened a novel way of practice. The proposed method has established a cuff-less BP estimation model and demonstrated that the inclusion of physiological characteristics can improve the accuracy of BP prediction. The results comply with the BHS standards, which indicates that ANN is in consistent with grade C in the estimation of DBP.

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