CP-Net: A Deep Learning Framework for Simultaneous Measurement of Heart Rate, Blood Pressure and Respiration Rate from PPG

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Abstract

Cardiopulmonary diseases are the primary reason behind worldwide mortality. Sudden and abnormal changes in heart rate (HR), respiration rate (RR), and blood pressure (BP) are some of the primary indicators of these diseases. Hence, monitoring these parameters regularly in an unobtrusive manner is crucial so they can also be used in the home environment. However, no prior study has been found that extracted all these parameters simultaneously from PPG. In this paper, we have proposed a first-of-its-kind deep learning framework, 'CP-Net', for estimating RR, HR, and BP (both systolic and diastolic) simultaneously from PPG without extracting any feature manually. The proposed model is designed by incorporating the framework of both gated and long-short-term recurrent convolutional networks and yields normalized mean absolute error of 0.0714 breath rate per minute, 0.0619 beats per minute, 0.162 mmHg, and 0.0321 mmHg for RR, HR, SBP, and DBP respectively.

1. Introduction

Nowadays, cardio-pulmonary diseases become a major health concern as they cause millions of morbidity and mortality worldwide. The increasing prevalence of these diseases can be effectively controlled if diagnosed and treated early [1]. Continuous monitoring of vital parameters such as respiration rate (RR), heart rate (HR), and blood pressure (BP) are very important for detecting the onset and progression of these diseases and to check the overall health status of the patient [2]. Although, HR and BP are widely known risk indicators for cardiovascular diseases, abnormal RR is a significant and independent indicator of cardiac arrest, chronic pulmonary diseases and even for patients with high risk [3]. In spite of enormous clinical importance, RR is recorded significantly less compared to other vital signs mostly due to time constraint and lack of respiration monitoring devices [4]. Conventionally respiration rate is monitored using capnography, inductance plethysmography, impedance pneumography, and oro-nasal pressure transducers [5]. However, these methods are often obtrusive, costly, require cumbersome set-up with multiple attachments to body, and cause intrusion in natural breathing. Whereas, traditional methods for heart rate (electrocardiography) and blood pressure (sphygmomanometry and oscillometry) estimation involve a number of electrodes and inflatable cuff to be attached to the body that cause obtrusion, hence, unsuitable for continuous monitoring [6]. Therefore, it is very important to develop a technique for unobtrusive, accurate and reliable estimation of RR, HR, and BP.
Advancements in smart health technology and the development of various wearable biosensors that are more user-friendly are gaining popularity for their vast applications in personalized health care and monitoring [7]. Recent studies show a vast possibility of photoplethysmography (PPG) in unobtrusive and continuous measurement of vital signs [8]. PPG measures the blood volume changes from the light beam emission through the finger, wrist, earlobe, or toe during the cardiac cycle [9], [10]. The ease of use, cost-effectiveness, and portability make PPG quickly incorporated into mobile phones and wearable devices, thus making it suitable for ambulatory and continuous monitoring. Although most wearable smart devices utilize PPG signals to derive only heart rate and blood pressure, respiration rate can also be derived from PPG instead of its' difficulty in estimation from PPG [11]. Respiration waveform can be derived from PPG based on three different modulations. Amplitude modulation shows the variation in stroke volume and intrathoracic pressure (IP) during respiration cycles. Baseline wander is reflected by IP variation and vasoconstriction of arteries at the time of inspiration. In contrast, frequency modulation represents respiratory sinus arrhythmia in which HR elevates during inhalation and decreases at the time of exhalation. RR can be extracted from these PPG-derived respiratory signals. PPG often gets distorted by motion artifacts (MA), which affects the accurate and robust estimation of vital parameters and makes them inefficient for clinical applications [12]. Several approaches for measuring HR and BP from PPG have been proposed in previous literature [13], [14].

However, these methods mostly depend on customized rules, analytical approaches, different modulated parameters, and several features optimized for specific models, and depicted for general or specific population [9]. In [15], the researchers used convolutional neural network (CNN) layers for estimating arterial blood pressure from

PPG. Whereas, [16] utilized CNN for estimating heart rate during various physical activities. Panwar et al. [13] developed a customized long term recurrent convolutional network (LRCN) to extract HR, BP simultaneously from PPG. However, previous approaches extracted either RR or HR or BP or a combination of two vital parameters simultaneously.

Hence, a compact and automatic approach would be highly beneficial if all these three vital parameters can be extracted simultaneously from PPG. In this work, we propose a novel deep-learning framework CP-Net for measuring RR, HR, and BP simultaneously from PPG signal without extracting any feature manually. We hypothesize that our model provide generalized and light-weight network for estimating four parameters i.e., RR, HR, systolic BP (SBP), and diastolic BP (DBP) using single input (PPG). We tested the effectiveness of our methodology on publicly available MIMIC-III database. The main contributions of this proposed work are stated as follows:

- We proposed a novel method for calculating four parameters (RR, HR, SBP, DBP) simultaneously using only PPG signal.
- The developed deep learning based methodology eliminates the necessity to extract features manually from the signal for vital parameter estimation.
- The proposed approach achieved comparable results to other techniques that employ a single PPG for measuring vital signs.

2. Method

The proposed methodology is designed for simultaneous measurement of RR, HR, SBP, and DBP from PPG. The overview of the proposed method is represented via the block diagram shown in Fig. 1.

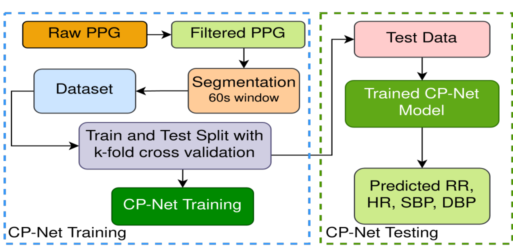

Figure 1. Block diagram of the proposed methodology

2.1. Dataset

We have tested our framework on Medical Information Mart for Intensive Care (MIMIC-III) widely accepted and used database, available at Physionet repository [14]. The database comprises of simultaneously recorded multiple physiological signals collected from intensive care unit patients. Simultaneously recorded respiration, PPG, electrocardiogram (ECG), and arterial blood pressure signals of 38 subjects with sampling frequency of 125 Hz are used for this work.

2.2. Pre-processing of signals

The raw signals are filtered using Bandpass Butterworth filter to remove noises for further pre-processing. Then, data is segmented by taking a window of 60 seconds with 75% overlapping to capture significant information as observed earlier [9]. The RR and HR are measured using a peak detection algorithm, and the SBP and DBP are calculated from ABP, as mentioned in [20].

2.3. Deep learning framework

Proposed deep learning framework employs both long-short term memory (LSTM) and gated recurrent unit (GRU) along with convolutional neural network (CNN) making it a hybrid model. The framework is designed specifically for multi-score output that makes it capable to assess RR, HR, SBP, and DBP simultaneously from single PPG input. The topology of the proposed framework is shown in Fig. 2.

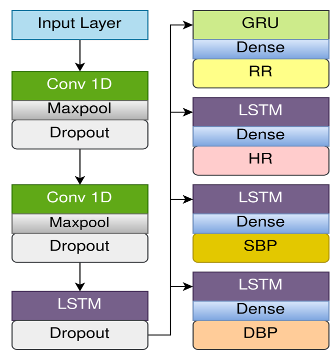

Figure 2. Topology of the proposed architecture

The model includes two 1D CNN layers which are used for extracting features, each interleaved with Scaled Exponential Linear Unit (SELU) activation, one maxpooling and one dropout layer. Each CNN layer consists of twenty filters of size 9×1, calculating dot product between their weights with a small 9×1 region. This results twenty activation maps providing the response of individual filter at each spatial position. Maxpooling is used alongside the spatial positions by 4×1 using the max procedure, thus, decreasing the size of spatial dimension while maintaining the same depth dimension. For this, the generated features become location-independent results in reduction of number of weights/parameters and decrease over-fitting. The features acquired from the second dropout layer are sent to the LSTM layer and then passed through GRU layer for RR estimation and separate LSTM layers for HR, SBP, and DBP estimation. Both GRU and LSTM layers for parameter prediction are interleaved with one dropout and one dense layer. The GRU and LSTM layers used hyperbolic tangent (tanh) activation.

2.4. Training and performance evaluation

For training the model, 5-fold cross validation technique is used and the model is validated based on the test results. Adam optimizer is used for optimization and loss is calculated via mean squared error (MSE) to assess the performance of CP-Net. The performance of the model is evaluated by calculating metrics like normalized mean absolute error (NMAE) and normalized root mean square error (NRMSE) using following equations.

$$NMAE = \Big(\sum_{m=1}^{z} \frac{|P_{pred}^m - P_{act}^m|}{z}\Big) / \Big(\frac{1}{z}\sum_{m=1}^{z} |P_{pred}^m|\Big) \quad (1)$$

$$NRMSE = \sqrt{\frac{\sum_{m=1}^{z} \left(P_{pred}^m - P_{act}^m\right)^2}{z}} / \Big(\frac{1}{z}\sum_{m=1}^{z} |P_{pred}^m|\Big) \quad (2)$$

where, z is the total number of PPG segments, and Pact and Ppred denote the actual and predicted parameters respectively for the m-th segment.

3. Experimental Results

The proposed model was implemented in Python with Tensor-flow based on a deep learning framework that was trained with a maximum of 30 epochs. The learning rate was 0.001 and the dropout rate was set to 0.1 for the whole network.

3.1. Evaluation of performance

The model is trained using PPG along with actual respiration rate, heart rate, systolic and diastolic BPs calculated from original respiration, ECG, and ABP signals respectively. Table 1 exhibits the qualitative comparison between the proposed methodology with related earlier studies.

Table 1. QUALITATIVE COMPARISON OF THE PROPOSED METHODOLOGY WITH OTHER RELATED STUDIES

Related study	Parameters extracted			
	RR	HR	SBP	DBP
Our work	✓	✓	✓	✓
Chowdhury et al. [17]	✓	–	–	–
Ismail et al. [18]	–	✓	–	–
Yen et al. [19]	–	–	✓	✓
Lei et al. [20]	✓	✓	–	–
Panwar et al. [9]	–	✓	✓	✓

The qualitative comparison show that two studies estimated only one among the four parameters (RR, HR, SBP, DBP). Whereas, Yen et al. calculated SBP and DBP and Lei et al. estimated RR and HR simultaneously. Panwar et al., on the other hand, able to extract three parameters (HR, SBP, DBP) at once. However, none of these studies have extracted all four parameters simultaneously from PPG signal like the proposed method which proves its uniqueness in measuring multiple vital parameters from one input. The predicted outputs for RR, HR, SBP, and DBP are compared with their original values and NMAE and loss are calculated for each of them as shown in Table 2. The measurement unit of errors for RR, HR, and BP (SBP, DBP) are brpm, bpm, and mmHg respectively.

Table 2. PERFORMANCE ANALYSIS OF THE PROPOSED WORK

Parameter	NMAE	NRMSE	Parameter	NMAE	NRMSE
RR	0.0714	0.1054	SBP	0.1620	0.2050
HR	0.0619	0.0710	DBP	0.0321	0.0390

The overall loss 0.0597 along with calculated errors for all four parameters indicate that the difference between actual and predicted values are very less which reflects the effectiveness of the proposed method for measuring all four vital parameters. The normalized value of actual and predicted parameters are represented through box-whisker plot as shown in Fig. 3. The median values attained

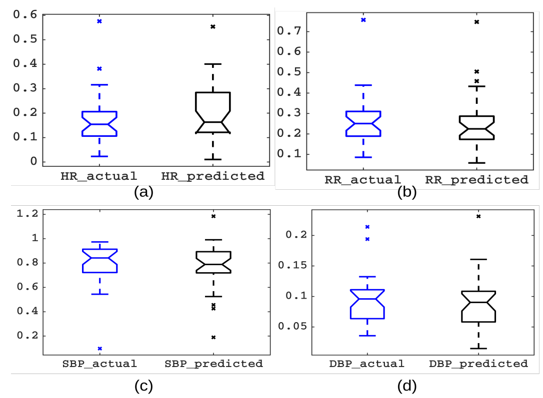

Figure 3. Actual and predicted normalized values of each parameter

for the actual parameters are: 0.2509 for RR, 0.1543 for HR, 0.8414 for SBP, and 0.0959 for DBP. Whereas, predicted parameters show median values of 0.2249 for RR, 0.163 for HR, 0.7887 for SBP, and 0.09027 for DBP. The close proximity of the predicted parameters with the actual ones represents the effectiveness of the proposed model in extracting parameters from PPG.

3.2. Performance comparison with other works

The detailed quantitative analysis of these previous works with the proposed study is shown in Table 2.

Results from Table 3 demonstrates that our proposed CP-Net framework produces very low NMAE values for calculating all four parameters which makes the output comparable to other related works mentioned in the Table 3. Although, the database is less compared to most of the studies, inclusion of a larger database will increase the efficacy of the proposed method for extracting parameters from PPG. Therefore, we can expect that the proposed model can be used for simultaneous measurement of RR, HR, SBP, and DBP from single PPG input.

Table 3. QUANTITATIVE COMPARISON OF THE PROPOSED METHOD WITH OTHER RELTED STUDIES

Work	Database	Subject	Method used	Performance (MAE±SD)			
				RR (brpm)	HR (bpm)	SBP (mmHg)	DBP (mmHg)
Chowdhury et al. [17]	VORTAL(i), BIDMC (ii)	39 (i), 53(ii)	ConvMixer	1.27(i), 0.77(ii)	–	–	–
Ismail et al. [18]	IEEE signal processing cup	22	Conv-recurrent regressor	–	2.41±2.9	–	–
Yen et al. [19]	Own	100	CNN	–	–	0.17 ±0.46	0.27±0.52
Lei et al. [20]	MIMIC	90	Comp-ensemble EMD	97.78%	99.95%	–	–
Panwar et al. [9]	MIMIC-II	1557	LRCN	–	2.32±0.095	3.97±0.064	2.30±0.196
Our work	MIMIC-III	31	CNN-GRU-LSTM	**0.0714 NMAE**	**0.0619 NMAE**	**0.162 NMAE**	**0.0321 NMAE**

4. Conclusion

This study proposes CP-Net, a deep learning network, for unobtrusive and simultaneous measurement of RR, HR, SBP, and DBP using only the PPG signal. The maximum obtained NMAE (0.162) and NRMSE (0.205) for extracting these parameters exhibits the effectiveness of the proposed methodology. Moreover, the ability to calculate multiple outputs and data-driven feature derivation makes the methodology cost-effective and less time-consuming. Moreover, using PPG-only input for estimating vital parameters simultaneously proposes an unobtrusive, low-cost, convenient, and user-friendly health monitoring mode.

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