VPE-Net: Simultaneous Measurement of Heart Rate, Respiration Rate, and Blood Pressure 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, unobtrusively monitoring these parameters is crucial for their use 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, 'VPE-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]. Along with HR and BP, abnormal RR is also a significant indicator of cardiovascular and pulmonary diseases, even for patients with high risk [3]. In spite of its enormous clinical importance, RR is recorded significantly less compared to other vital signs, mostly due to time constraints and lack of respiration monitoring devices [4]. Conventionally, RR is monitored using capnography, inductance plethysmography, impedance pneumography, and oro-nasal pressure transducers [5]. However, these methods are often obtrusive, costly, require cumbersome setups with multiple attachments to the body, and cause intrusion into natural breathing. Whereas traditional methods for HR (electrocardiography) and BP (sphygmomanometry and oscillometry) estimation involve a number of electrodes and inflatable cuff to be attached to the body that causes obtrusion, hence, unsuitable for continuous monitoring. Therefore, developing a technique for unobtrusive, accurate, and reliable estimation of RR, HR, and BP is very important.

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. Recent studies show a vast possibility of photoplethysmography (PPG) in unobtrusive and continuous measurement of vital signs [6]. PPG measures the blood volume changes during the cardiac cycle [6]. 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. Several approaches for measuring HR and BP from PPG have been proposed in previous literature [7]. Although, most wearable smart devices utilize PPG signals to derive only HR and BP, RR can also be derived from PPG instead of its' difficulty in estimation from PPG [8]. 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.

However, these methods mostly depend on customized rules, analytical approaches, different modulated param-

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eters, and several features optimized for specific models and depicted for general or specific populations [6]. In [9], the researchers used convolutional neural network (CNN) layers for estimating arterial blood pressure (ABP) from PPG. Whereas [10] utilized CNN for estimating heart rate during various physical activities. Panwar et al. [7] developed a customized long-term recurrent convolutional network (LRCN) to extract HR and BP simultaneously from PPG. However, previous approaches extracted either RR or HR, 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 could be extracted simultaneously from PPG. In this work, we propose a novel deep-learning framework, VPE-Net, for measuring RR, HR, and BP simultaneously from PPG signals without extracting any feature manually. We hypothesize that our model provides a generalized and lightweight 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 the 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 the 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 to simultaneously measure RR, HR, SBP, and DBP from PPG. The overview of the proposed method is represented via the block diagram shown in Fig. 1.

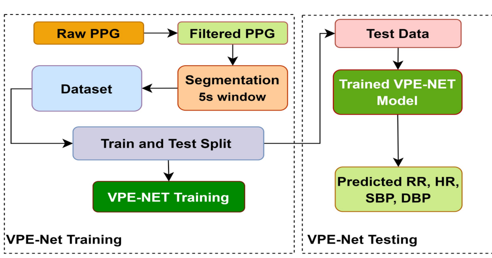

Figure 1. Block diagram of the proposed methodology

2.1. Dataset

We have tested our framework on MIMIC-III, a widely accepted and used database, available at Physionet repository. The database comprises simultaneously recorded physiological signals collected from intensive care unit patients. Simultaneously recorded respiration, PPG, electrocardiogram (ECG), and ABP signals of 38 subjects with a sampling frequency of 125 Hz are used for this work.

2.2. Pre-processing of signals

The raw signals are filtered using the 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 [11]. The RR and HR are measured using a peak detection algorithm, and the SBP and DBP are calculated from ABP.

2.3. Deep learning framework

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

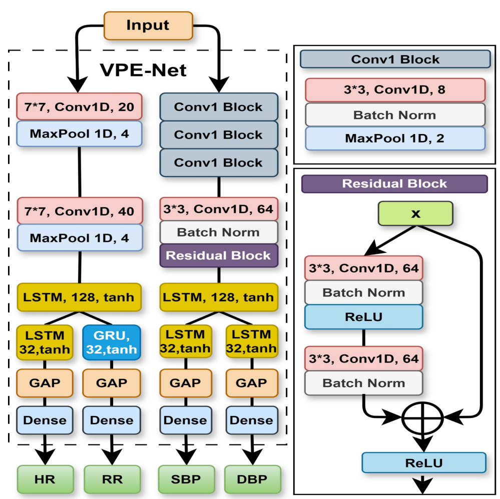

Figure 2. Topology of the proposed architecture

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 in twenty activation maps providing the response of individual filters at each spatial position. Max pooling is used alongside the spatial positions by 4×1 using the max procedure, thus decreasing the size of the spatial dimension while maintaining the same depth dimension. For this, the generated features become location-independent, resulting in a reduction of the number of weights/parameters and a decrease in over-fitting. The features acquired from the second dropout layer are sent to the LSTM layer and then passed through the GRU layer for RR estimation and separate LSTM layers for HR, SBP, and DBP estimation. 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

An 80:20 train-test split was used to train the model, and the model was 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 VPE-Net. The model's performance is evaluated by calculating metrics like normalized mean absolute error, $NMAE = \left(\sum_{m=1}^{z} \frac{|P_{pred}^{m} - P_{act}^{m}|}{z}\right) / \left(\frac{1}{z}\sum_{m=1}^{z} |P_{pred}^{m}|\right)$ and normalized root mean square error, $NRMSE = \sqrt{\frac{\sum_{m=1}^{z}\left(P_{pred}^{m} - P_{act}^{m}\right)^2}{z}} / \left(\frac{1}{z}\sum_{m=1}^{z} |P_{pred}^{m}|\right)$, where z is the total number of PPG segments, and *P*act and *P*pred 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 trained with a maximum of 200 epochs. The learning rate was 0.0008, and the dropout rate was set at 0.1 for the whole network.

3.1. Evaluation of performance

The model is trained using PPG and actual respiration rate, heart rate, and systolic and diastolic BPs. Table 1 exhibits the qualitative comparison between the proposed methodology and related earlier studies.

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

Related study	Parameters extracted			
	RR	HR	SBP	DBP
Our work	✓	✓	✓	✓
Chowdhury et al. [12]	✓	–	–	–
Ismail et al. [13]	–	✓	–	–
Yen et al. [14]	–	–	✓	✓
Lei et al. [15]	✓	✓	–	–
Panwar et al. [11]	–	✓	✓	✓

The qualitative comparison shows that two studies estimated only one among the four parameters (RR, HR, SBP, DBP). Yen et al. calculated SBP and DBP, and Lei et al. simultaneously estimated RR and HR. Panwar et al., on the other hand, were able to extract three parameters (HR, SBP, DBP) at once. However, none of these studies have extracted all four parameters simultaneously from a 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 units of errors for RR, HR, and BP (SBP, DBP) are bpm, bpm, and mmHg, respectively.

Table 2. PERFORMANCE ANALYSIS OF THE PROPOSED WORK

Parameter	NMAE	NRMSE	Parameter	NMAE	NRMSE
RR	0.072	0.109	SBP	0.008	0.027
HR	0.016	0.026	DBP	0.013	0.040

The loss of 16.8, along with calculated errors for all four parameters, indicates that the difference between actual and predicted values is very small, reflecting the proposed method's effectiveness for measuring all four vital parameters. The normalized value of actual and predicted parameters are represented through a box-whisker plot, as shown in Fig. 3. The median values attained for the actual parameters are 17.2 for RR, 89.8 for HR, 118.0 for SBP, and 57.0 for DBP. Whereas predicted parameters show median values of 17.65 for RR, 89.44 for HR, 117.9 for SBP, and 57.2 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.

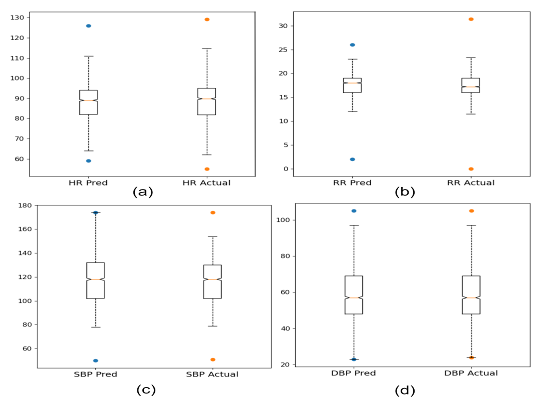

Figure 3. Actual and predicted values of each parameter

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 demonstrate that our proposed VPE-Net framework produces very low NMAE values for

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

Work	Database	Subject	Method used	Performance (MAE$\pm$SD)			
				RR (brpm)	HR (bpm)	SBP (mmHg)	DBP (mmHg)
Chowdhury et al. [12]	VORTAL(i), BIDMC (ii)	39 (i), 53(ii)	ConvMixer	1.27(i), 0.77(ii)	–	–	–
Ismail et al. [13]	IEEE signal processing cup	22	Conv-recurrent regressor	–	2.41$\pm$2.9	–	–
Yen et al. [14]	Own	100	CNN	–	–	0.17 $\pm$0.46	0.27$\pm$0.52
Lei et al. [15]	MIMIC	90	Comp-ensemble EMD	97.78%	99.95%	–	–
Panwar et al. [11]	MIMIC-II	1557	LRCN	–	2.32$\pm$0.095	3.97$\pm$0.064	2.30$\pm$0.196
Our work	MIMIC-II	53	CNN-GRU-LSTM	**1.23**	**1.50**	**0.95**	**0.79**

calculating all four parameters, which makes the output comparable to other related works mentioned in Table 3. Although the database is smaller than most of the studies, inclusion of a larger one will increase the efficacy of the proposed method for extracting parameters from PPG. Therefore, we can expect that the proposed model can be used to simultaneously measure RR, HR, SBP, and DBP from a single PPG input.

4. Conclusion

This study proposes VPE-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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References

[1] W. G. H. Estimates, “The top 10 causes of death,” *WHO*, vol. 9, December 2020.

[2] G. Ribeiro and F. F. Martín, “A practical approach to health status monitoring based on heart rate and respiratory rate assessment,” *ISMMA*, no. 3, pp. 1–6, 2022.

[3] S. Cook, M. Togni, M. C. Schaub, P. Wenaweser, and O. M. Hess, “High heart rate: a cardiovascular risk factor?,” *European Heart Journal*, vol. 27, pp. 2387–2393, 0 2006.

[4] W. X. S. Baker and I. Atkinson, “Determining respiratory rate from photoplethysmogram and electrocardiogram signals using respiratory quality indices and neural networks,” *PLoS One*, vol. 16, pp. 5–12, Apr 2021.

[5] L. Zhao, F. Zhang, H. Zhang, and Y. e. Liang, “Robust respiratory rate monitoring using smartwatch photoplethysmography,” *IEEE Internet of Things Journal*, vol. 10, March 2018.

[6] Y. Sun and N. Thakor, “Photoplethysmography revisited: From contact to noncontact, from point to imaging,” *Transactions on Biomedical Engineering*, vol. 63, pp. 463–477, March 2016.

[7] D. Biswas, L. Everson, M. Liu, M. Panwar, B.-E. Verhoef, and S. e. Patki, “Cornet: Deep learning framework for ppg-based heart rate estimation and biometric identification in ambulant environment,” *IEEE TBCS*, vol. 13, pp. 282–291, April 2019.

[8] M. H. M. S. Shuzan, Md. Nazmul Islam, “A novel non-invasive estimation of respiration rate from motion corrupted photoplethysmograph signal using machine learning model,” *IEEE Access*, vol. 9, pp. 775–790, July 2021.

[9] H. Yang, M. Li, D. He, X. Che, and X. Qin, “Respiratory rate estimation from the photoplethysmogram combining multiple respiratory-induced variations based on sqi,” *ICMA*, pp. 382–387, August 2019.

[10] S. Sarkar, S. Bhattacherjee, P. Bhattacharyya, M. Mitra, and S. Pal, “Automatic identification of asthma from ecg derived respiration using complete ensemble empirical mode decomposition with adaptive noise and principal component analysis,” *BSPC*, vol. 77, pp. 1–9, August 2022.

[11] M. Panwar, A. Gautam, D. Biswas, and A. Acharyya, “Pp-net: A deep learning framework for ppg-based blood pressure and heart rate estimation,” *IEEE Sensors Journal*, vol. 20, pp. 10000–10011, Sept 2020.

[12] C. M. Hossain, M. N. I. Shuzan, and M. E. H. C. et.al., “Lightweight end-to-end deep learning solution for estimating the respiration rate from photoplethysmogram signal,” *Bioengineering*, vol. 9, October 2022.

[13] S. Ismail, I. Siddiqi, and U. Akram, “Heart rate estimation in ppg signals using convolutional-recurrent regressor,” *Computers in Biology and Medicine*, vol. 145, June 2022.

[14] C.-T. Yen, S.-N. Chang, and Y.-K. Huang, “A deep learning-based continuous blood pressure measurement by dual photoplethysmography signals,” *Computers, Materials Continua*, vol. 70, pp. 2937–2952, September 2022.

[15] R. Lei, B. W.-K. Ling, P. Feng, and J. Chen, “Estimation of heart rate and respiratory rate from ppg signal using complementary ensemble empirical mode decomposition with both independent component analysis and non-negative matrix factorization,” *Sensors*, vol. 20, pp. 1–8, June 2020.

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