

1-Dimensional Convolutional Neural Network Based Blood Pressure Estimation with Photo plethysmography Signals and Semi-Classical Signal Analysis

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ABSTRACT: In this paper, we propose a 1-Dimensional Convolutional Neural Network (1D-CNN) based Blood Pressure (BP) estimation using Photo plethysmography (PPG) signals and their features obtained through Semi-classical Signal Analysis (SCSA). The procedure of the proposed BP estimation technique is as follows. First, PPG signals are divided into each beat. Then, 9 features are obtained through SCSA for the divided beats. In addition, 5 biometric data are used. The Biometrics data include Heart Rate (HR), age, sex, height, and weight. The total 14 features are used for training and validating the 1D-CNN BP estimation model. After testing three types of 1D-CNNs, the model with the most optimal performance is selected. The selected model structure consists of three convolutional layers and one fully connected layer. The performance is measured by Mean Error (ME) $\pm$ Standard Deviation (STD) following the Association for the Advancement of Medical Instrumentation (AAMI) standard. According to the results of the test, Systolic Blood Pressure (SBP) is -2.99 ± 14.48 mmHg and Diastolic Blood Pressure (DBP) is 1.16 ± 9.30 mmHg. Using the proposed technique, blood pressure can be easily predicted using PPG obtained with a non-invasive and cuff-less wearable sensor.

Keywords: SCSA, BP, Photo plethysmography, CNN, Non-invasive, Cuff-less.

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For early diagnosis, constant BP monitoring is important to catch a temporarily abnormal BP or changes of BP values. Most popular method to measure BP is using cuff-type sphygmomanometer [8]. However, since those devices are big and heavy, constant BP monitoring often makes the patients uncomfortable. On the other hand, photo plethysmography (PPG) measures changes in blood flow using LEDs, and various types of wearable devices have been released [9]. The PPG signal is generally used to measure heart rate or oxygen saturation (SpO₂).

In this paper, we develop a new technique to measure BP using the PPG signal. Specifically, we propose a 1-Dimensional Convolutional Neural Network (1D-CNN) based BP estimation technique through PPG features obtained through Semi-classical Signal Analysis (SCSA).

The proposed technique performs BP estimation by inputting 9 SCSA coefficients obtained through SCSA and 5 biometric features of the patient. The performance is measured by Mean Error (ME) $\pm$ Standard Deviation (STD) following the Association for the Advancement of Medical Instrumentation (AAMI) standard. According to the results of the test, SBP is -2.99 ± 14.48 mmHg and DBP is 1.16 ± 9.30 mmHg. Using the proposed technique, blood pressure can be easily predicted using PPG obtained with a non-invasive and cuff-less wearable sensor.

1. INTRODUCTION

Blood Pressure (BP) is one of the most important vital signals [1]. The unit of BP is mmHg, which is the unit of pressure. The types of BP include systolic blood pressure (SBP) and diastolic blood pressure (DBP) [2]. SBP is the blood pressure when the heart contracts and sends blood out to arterial blood vessels, and the blood pressure at this time is the highest [3]. DBP is the BP when the heart diastolic and receives blood, at which time the BP is the lowest.

Hypertension is a phenomenon that the pressure of blood flow through the arteries increases [4]. Hypertension leads to cerebral hemorrhage, heart failure, and kidney disease [5]. Hypotension is a phenomenon that blood flow pressure through the arteries decreases as opposed to hypertension [6]. Chronic hypotension may lead to shock and fainting [7]. Because of serious risk due to hypertension and hypotension, early detection is required.

2. SYSTEM MODEL

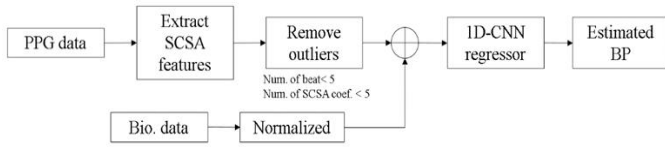


Figure 1: BP estimation system model

Figure 1 shows the block diagram of the proposed BP estimation technique. First, features are extracted from PPG through SCSA. Then, outliers are removed from the PPG signal. The criteria for identifying outliers are those with less than 5 beats per 10 seconds and less than 5 SCSA coefficients per beat. Additionally, biometric data are also used for input features along with SCSA features. Biometric data are used as a 1D-CNN input after normalization. The output of 1D-CNN is the predicted BP (SBP and DBP).

2.1 PPG data

In this paper, 3,308 PPG signals are used for 1D-CNN training, and 1,828 PPG signals are used for test. The consecutively measured PPG signals are divided into 10 second intervals. Through this, a total of 242,496 learning PPG data and 62,188 test PPG data are generated from 2,308 training signals and 1,828 test signals. Figure 2 shows the PPG signals divided into 10 seconds.

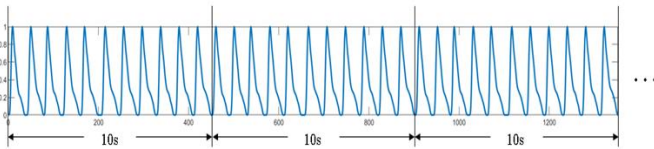


Figure 2: Division of PPG signal by 10 seconds

Each beat of the PPG signal can be divided into two parts. The first part of the signal is the result of the contraction of the heart order systole while the second part is related to cardiac expansion or diastole. The two parts can be seen as two peaks respectively. However, in many PPG signals, those two peaks are too close and it looks like a single pulse. When it looks like a single pulse, it is difficult to distinguish between a portion related to contraction of the heart and a portion related to relaxation.

To solve this problem, the features of the PPG signal are extracted through SCSA that decomposes one signal into several signals. A SCSA method has been proposed for pulse shaped signal analysis in [10]. Application of SCSA to BP waveform has been shown in previous studies [11]. In this paper, PPG signals are divided by beat, 9 SCSA coefficients are extracted for each beat, and the median value of the SCSA coefficient is used as the feature SCSA of the PPG. The formula for SCSA is (1)

$$y_h(n) = 4h \sum_{n=1}^{N_h} k_{nh} \psi_{nh}^2(n) \quad (1)$$

In the formula, N_h is the value of how many signals to decompose, and k_{nh} is the weight of the decomposed signal. $y_h(n)$ is the 1 beat PPG signal and $\psi_{nh}^2(n)$ is the basis functions. Decomposed signals are arranged in descending order of magnitude, and when all the decomposed signals are added, the original signal is restored. In this paper, one PPG beat is divided into nine signals, i.e., $N_h=9$. SCSA features used as 1D-CNN input data are k_1 to k_9 .

In order to solve the problem caused by the outlier, the outlier removal processing is performed. In this paper, the criteria for outliers are defined as two. The first case is when there are less than 5 beats generated from a 10 second PPG signal. Another case is when the SCSA coefficient of the PPG signal for 10 seconds is less than 5.

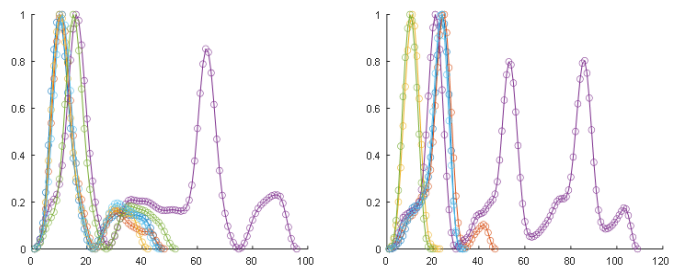


Figure 3: Examples of outliers

Figure 3 shows examples of the removed outlier PPG. There was a problem in dividing PPG by beat. In this case, a problem arises in the operation of extracting the SCSA coefficient from the beat. In order not to cause this problem, an outlier removal operation is performed.

2.2 Biometric data

Biometric data is also used as input features [12]. Biometric features used for training are Heart Rate (HR), height, weight, age, and gender. Max normalization is performed to make all biometric data a value of 0 to 1. The formula for the ME is (2).

$$x_{norm} = \frac{x}{x_{max}} \quad (2)$$

In the formula, x is biometric data value, and x_{max} is the maximum value of biometric data of the same category. By dividing biometric data by the maximum value among biometric data in the same category, all biometric data values are made from 0 to 1.

3. PROPOSED 1D-CNN MODELS

A technique for estimating BP using 1D-CNN is proposed. CNN is effective technique when the input signal is highly correlated between neighboring samples. As shown in Figure 2, neighboring samples of PPG are correlated. Unlike the other deep natural networks, CNN maintains temporal information of input data so that CNN is suitable for the locally correlated input data such as PPG signals. 3 CNN model are proposed and compared.

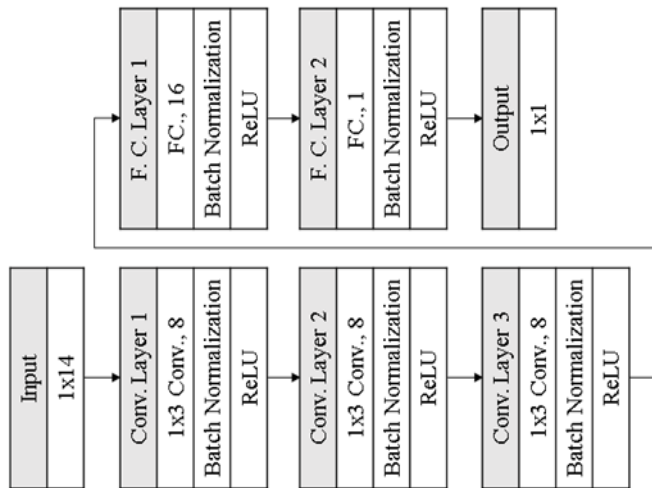


Figure 4: Proposed 1D-CNN Model 1

The structure of the proposed 1D-CNN Model 1 is shown in Figure 4. The proposed 1D-CNN consists of 3 convolutional layers and 2 fully connected layers. In 3 convolutional layers, the convolution filter length is all 3. The number of filters in all convolution layers is 8. The output of the first fully connected layer is 1x16, and the second fully connected layer output is 1x1, which is the estimated BP value.

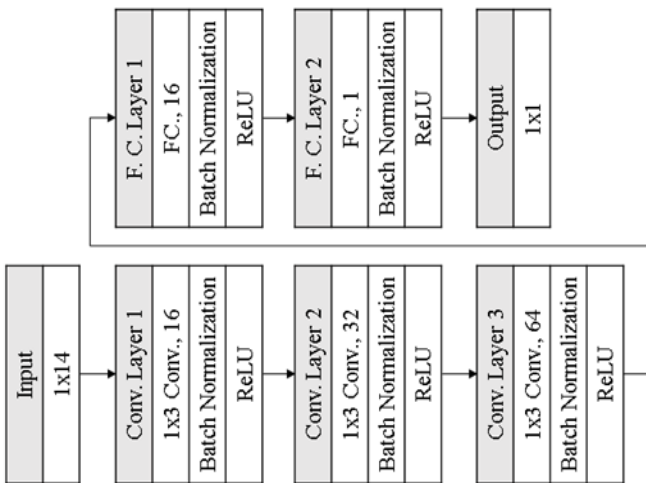


Figure 5: Proposed 1D-CNN Model 2

The structure of the proposed 1D-CNN Model 2 is shown in Figure 5. The proposed 1D-CNN consists of 3 convolutional layers and 2 fully connected layers. In 3 convolutional layers, the length of the convolution filter is all 3. The number of filters is 32 in the 1st layer, 64 in the 2nd, 128 in the 3rd layer. The deeper the layer, the larger the number of convolution filters. The output of the first fully connected layer is 1x16, and the second fully connected layer output is 1x1, which is the estimated BP value.

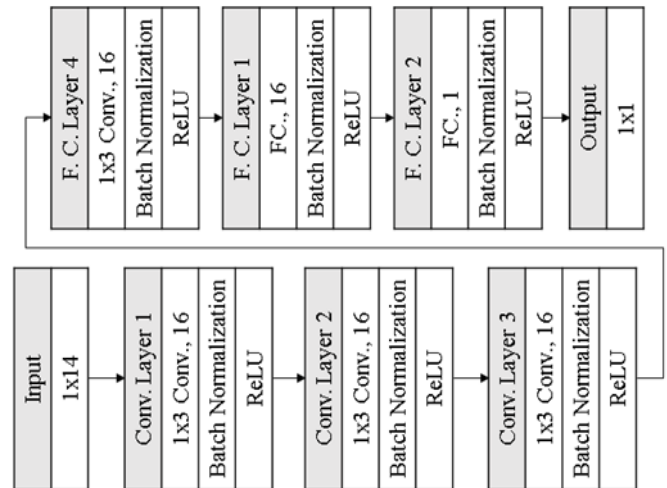


Figure 6: Proposed 1D-CNN Model 3

The structure of the proposed 1D-CNN Model 3 is shown in Figure 6. The proposed 1D-CNN consists of 4 convolutional layers and 2 fully connected layers. In 4 convolutional layers, the length of the convolution filter is all 3. The number of filters in all convolution layers is 16. The output of the first fully connected layer is 1x16, and the second fully connected layer output is 1x1, which is the estimated BP value.

4. SIMULATION RESULT

We compare the three models with different structures to find the optimal model. For each proposed 1D-CNN model, two identical models are used for estimation of SBP and DBP, respectively. The performance index of BP prediction checks the average error and standard deviation based on AAMI standard [13]. BP estimation AAMI standard are ME 5 and STD ± 8 . The formula for the ME is (3) and STD is (4).

$$ME = \frac{1}{n} \sum_{i=1}^n (x_i - x) \quad (3)$$

$$STD = \sqrt{\frac{\sum (x_i - x)^2}{n - 1}} \quad (4)$$

In the formula, x_i is the predicted BP, and x is the BP label (ground truth), n is the number of data. ME is the average of all errors, and STD is dispersion of a set of error.

Table 1. Performance comparison among proposed 1D-CNN models

1D-CNN Model	Performance (ME $\pm$ STD)		# of parameters
	SBP [mmHg]	DBP [mmHg]	
Model 1	-0.05 $\pm$ 14.64	0.79 $\pm$ 9.40	961
Model 2	2.99 $\pm$ 14.48	1.16 $\pm$ 9.30	1,665
Model 3	-0.48 $\pm$ 15.15	1.17 $\pm$ 9.80	1,265
AAMI standard	5.00 $\pm$ 8.00		

Table 1 shows the BP prediction performances and the number of model parameters for each models. As shown in the table, it can be seen that ME has reached the AAMI standard in all three models. Also, for the results of Model 2, it can be seen that SBP and DBP have the lowest STD among the three models. Through this, it can be seen that Model 2 shows the best BP estimation performance.

5. CONCLUSION

1D-CNN-based BP estimation technique using PPG signals obtained through SCSA was proposed. The proposed technique extracts features from PPG signals that can be obtained through non-invasive and cuff-less methods. PPG signals are divided into beat by beat and features are extracted through SCSA. 9 features for each beat are extracted. The patient's biometric data is also used as features. Biometric data are HR, height, weight, age, and gender. BP estimation is performed using 1D-CNN as input of the above features. The three models are compared to find the best 1D-CNN model. The best 1D-CNN model is composed of three convolutional layers and two fully connected layers. The performance of the best model is SBP 2.99 ± 14.48 and DBP 1.16 ± 9.30 . This result confirms that the proposed 1D-CNN BP estimator can be used as a simple BP monitor. If the proposed technique is applied to wearable PPG devices, it will be of great help in 24-hour, fast and accurate BP monitoring. However, in order to prove the generality of the proposed technique, further studies are needed to determine whether it shows reliable BP estimation for other PPG sensor signals. The authors will confirm this generality through additional research in the future.

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