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Artificial Intelligence Model for an Electrocardiography-based Blood Pressure Estimation System

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In this study, we propose a novel artificial intelligence model for blood pressure estimation that establishes a method to estimate both systolic and diastolic blood pressures based on an electrocardiogram. Experimental results show that the root mean square errors for systolic and diastolic blood pressures are 3.82 and 2.17, respectively. Therefore, the proposed approach complies with the Association for the Advancement of Medical Instrumentation standard. The proposed structure is feasible and can be implemented by being integrated with electrode sensors and a signal processing platform. In the future, this technology can replace home care systems or wearable devices to provide warnings of health issues.

1. Introduction

Blood pressure (BP) is an important physiological parameter, the monitoring of which is significant for preventing BP-related diseases such as cardiovascular diseases and hypertension. BP is defined as the force when the blood pushes against the arterial wall when the heart pumps blood, expressed in millimeters of mercury (mmHg).[(1)] The maximum pressure during one heartbeat is systolic BP (SBP), and the minimum pressure between two heartbeats is diastolic BP (DBP). BP is closely related to cardiac activity, which can be monitored using electrocardiogram (ECG) signals. Therefore, developing an ECG-based BP estimation system would be very useful for healthcare.

The ECG plays a key role in diagnosing human heart function. The ECG signal is composed of a P wave, a QRS wave, and a T wave. These waves represent specific electrical phenomena in which an induced field passes through the surface of the heart. The P wave corresponds to atrial fibrillation depolarization, the QRS wave is produced by ventricular depolarization, and the T wave is generated by ventricular repolarization. The recording of an ECG wave requires a standard 12-lead system and the placement of electrodes at designated locations on the human chest and limbs. All wires carry different ECG signals. The shape of the different waves and the

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polarity of the ECG depend on changes in the leads and their positions.(2) A detailed description of an ECG can also be used for many medical diagnoses, such as those involving heart rate, tachycardia, bradycardia, myocardial infarction, arrhythmia, ECG compression, ectopic beat classification, and heart rate variability.

The latest technology has brought wearable biosensors (such as ECG and breathing rate body sensors) into everyday life. Wearable biosensors provide the possibility of real-time monitoring of human vital signs for prevention, timely notification, and real-time diagnosis.(3) Some systems developed for non-invasive BP monitoring include photoplethysmography (PPG) optical sensors based on electron waves, a BP estimation device based on the volume compensation principle, a blood modulation magnetic signal mechanism, and a portable cuff BP sensing system.(4–11) However, these devices are all in the form of stand-alone devices and are only used for BP measurement and do not include other vital signs. In addition, when some of them are used in real life, especially by specific user groups, the ideal laboratory effect cannot be achieved. In recent years, with the advancement and maturity of artificial intelligence (AI) technology, AI has been widely used in medical treatment, transportation, information security, speech and image recognition, and in other fields. The term artificial intelligence was defined at the Dartmouth Conference (1956) as follows: "Learning or any other characteristic intelligence can in principle be described so precisely that it enables a machine to simulate every aspect of it."

In terms of medical treatments, the Ministry of Health and Welfare in Taiwan counted the top ten causes of death in 2018, with heart disease ranking second, cerebrovascular disease ranking fourth, and hypertension ranking eighth. Cardiovascular diseases accounted for three of the top ten causes of death. Therefore, preventing these diseases is particularly important. The heart is a major organ that maintains the vital functions of the human body. Under normal operation, it can transport blood to the whole body to keep the body healthy. Conversely, if it does not work properly, the body will be sick, so it is necessary to effectively understand the function of the heart.

Many studies have proven that the heart and BP are closely related. In daily life, everyone can measure BP with a sphygmomanometer as a preliminary basis for judgment regarding cardiovascular disease, which can be further evaluated using an ECG in a hospital. The determination of whether the heart function is abnormal requires the interpretation of professional doctors, and each doctor may have a different opinion. Wrong judgments not only delay the identification of disease but also affect the timeliness of treatment. Patients with cardiovascular disease, such as hypertension or myocardial infarction, often fail to be identified as soon as they develop the disease owing to a lack of a good early warning mechanism. Therefore, this research has the goal of using machine learning to reduce errors. A home-based ECG BP monitoring with an early warning system allows people to perform heart function tests at home and pay attention to their physical condition at any time. If a problem occurs, they can seek medical treatment early to avoid accidents. In this study, the ECG signal is used as the basis to construct an early warning system using AI. The system trains on collected ECG and BP signals to predict a person's BP, examine heart function, and find the best model to apply to a device that a person can wear during their daily life to monitor and hopefully prevent cardiovascular disease.

2. Materials and Methods

In this study, we designed a one-dimensional convolutional neural network (CNN) architecture model for BP estimation by AI using ECG signals; the structure of the CNN included a convolution layer and a fully connected layer. The proposed structure can be implemented by integrating it with electrode sensors and a signal processing platform. The proposed AI structure is shown in Fig. 1.

2.1 ECG signal acquisition

In this study, we used ECG and ambulatory BP (ABP) signals from the CHARIS database as experimental data.(12) ECG signals were acquired from the outputs of clinical monitors routinely employed in a surgical intensive care unit via isolated and filtered (25 Hz cutoff frequency) outputs from a General Electric TRAM-rac 4A. The sampling rate was 50 Hz with a resolution of 1.41 mV over a ±5 V analog input range, which is equivalent to a pressure resolution of 0.14 mmHg and a dynamic range of ±500 mmHg. ABP was registered with a fluid-filled catheter in the radial artery (Arterial Line, Edwards Lifesciences Inc.).

2.2 ECG preprocessing

The input data of the AI structure takes a cycle of the ECG as the input layer and the peaks and troughs of ABP as the signals of SBPs and DBPs. The one-dimensional CNN architecture is used to create the ECG BP model. To obtain a periodic ECG signal, the R wave position is detected. So and Chan's algorithm(13) is used to find the position of the QRS wave group in the ECG sequence, and such information is combined with a fuzzy threshold algorithm that adjusts the slope threshold in real time to improve the accuracy of locating the R wave.(14)

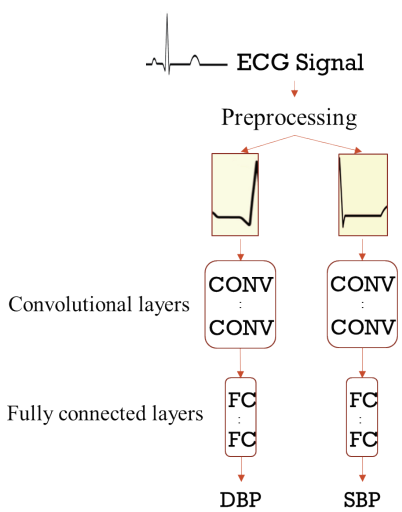

Fig. 1. (Color online) AI structure of an ECG-based BP estimation system.

2.3 One-dimensional CNN-based architecture model

A one-dimensional CNN-based architecture model for BP estimation is developed using ECG signals. The CNN-based architecture model includes the input, convolution, and fully connected layers, described as follows.

The data is preprocessed so that each data record contains 0.7 s ECG signals; the data is recorded at a sampling rate of 50 Hz. The input data is passed into the neural network as a flat vector. In the AI structure in this study, we create SBP and DBP models to estimate the BP. In the cardiac cycle (Fig. 2), ventricular systole refers to the time between the R and T waves, which corresponds to the SBP; therefore, we take this segment as the input layer data for the SBP model. The DBP corresponds to the atrial diastole and refers to the time between R and P waves; therefore, we take this segment as the input layer data for the DBP model.

For the CNN layer, the first layer defines n_1 filters with kernel size k. The filters allow the neural network to automatically learn the features from the input data. The convolution is modeled as a deterministic mapping function $M_\theta = \{W, b\}$, which can effectively map the input vector $x(t)$ to a hidden representation, $y(t)$, which is written as

$$y(t) = M_\theta\left(x(t)\right) = Wx(t) + b, \tag{1}$$

where W and b are the weight matrix and the bias vector, respectively. The output of the first neural network layer is an $(l - k + 1) \times n_1$ neuron matrix. Each column of the output matrix holds the weights of one single filter. With the defined kernel size and considering the length of the input matrix, each filter contains $l - k + 1$ weight. A parametric rectified linear unit (Relu), $f(y)$, is adopted as the activation function and is defined as

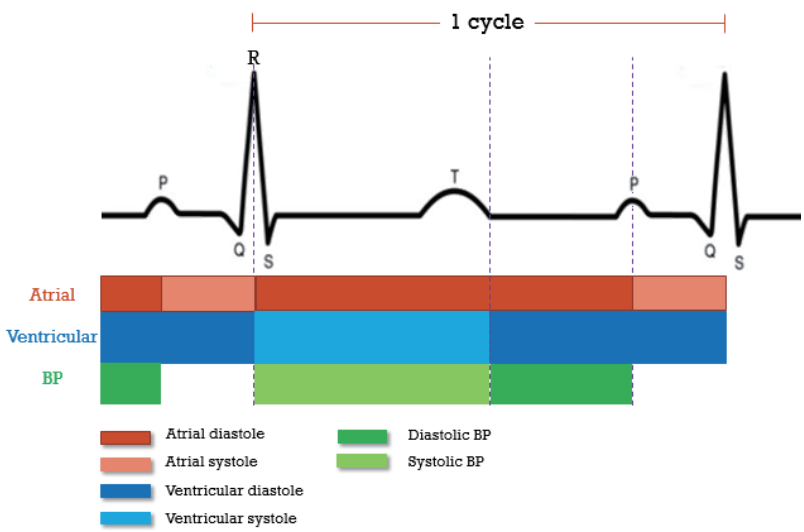

Fig. 2. (Color online) Relationship between ECG and BP.

$$f(y)=\begin{cases}0, & \text{if } y\le 0\\ y. & \text{if } y>0\end{cases} \tag{2}$$

The result from the first CNN layer is fed into the second CNN layer. We again define n_2 different filters to be trained on this level. Following the same logic as that for the first layer, the output matrix is of size $l - 2k + 2 \times n_2$. Another sequence of CNN layers follows to learn higher-level features.

Finally, the role of the fully connected layer is to flatten the previous results and connect to the neural network, and the output of the fully connected layer generates the decision of the neural network.

3. Experimental Results

3.1 Experimental setup

In this study, we used TensorFlow and Keras to build a system model, which performs in two ways. Method I uses the ECG cycle as the input signal to train SBP and DBP models; the total number of nodes is 198. Method II uses the interval between SBP and DBPs shown in Fig. 2 for model training. The number of nodes in the SBP model is 88, and in the DBP model, 128. The kernel sizes of the convolution layer in both methods I and II are adjustable. The filter size is 8 for the convolutional and fully connected layers. The kernel sizes of the output layer are 1 and 2 for methods I and II, respectively.

This experiment was carried out using charis3.dat from the CHARIS database. After preprocessing, 5471 ECG cycles were obtained. The k-folder cross-validation was adopted to evaluate this approach. The kernel size was examined and then the root mean square error (*RMSE*) and mean absolute percentage error (*MAPE*) were calculated as references for system performance.

3.2 Experimental results of CNN with method I

The kernel size of the CNN for method I was examined. Table 1 shows that the error in the estimated values of SBP and DBP changed as the kernel size changed. We can find that method I achieved the best performance for SBP and DBP when the kernel size was 9. The RMSEs and MAPEs for SBP and DBP were 3.76 and 2.17, and 2.39 and 3.91, respectively. The Association for the Advancement of Medical Instrumentation (AAMI) released the standard for non-invasive sphygmomanometers[15] and recommends a mean error of less than 5 mmHg and a standard deviation in the error of not more than 8 mmHg. The mean error and the standard deviation in the error for method I were less than 5 and 8 mmHg, respectively. On the basis of these results, method I could be grafted into medical devices.

Table 1
Experimental results of method I with different kernel sizes.

Kernel size	SBP		DBP	
	RMSE	*MAPE*	*RMSE*	*MAPE*
3	3.82	2.42	2.25	4.30
4	3.83	2.43	2.19	3.95
5	3.84	2.44	2.19	3.94
6	3.88	2.46	2.19	3.93
7	3.82	2.42	2.18	3.95
8	3.81	2.42	2.18	3.96
9	3.76	2.39	2.17	3.91
10	3.82	2.43	2.18	3.92

Table 2
Experimental results of method II with different kernel sizes.

Kernel size	SBP		DBP	
	RMSE	*MAPE*	*RMSE*	*MAPE*
3	3.84	2.44	2.19	3.92
4	3.86	2.45	2.19	3.90
5	3.86	2.46	2.21	4.10
6	3.82	2.42	2.19	3.91
7	3.85	2.44	2.21	3.96
8	3.83	2.45	2.18	3.89
9	3.84	2.44	2.17	3.89
10	3.82	2.44	2.17	3.89

3.3 Experimental results of CNN with method II

The kernel size of CNN was examined for method II. As shown by Table 2, the error in the estimated values of SBP and DBP varies with the kernel size. The performance was best when the kernel sizes were 6 and 8 for SBP and DBP, respectively. In addition, the RMSEs and MAPEs for SBP and DBP were 3.82 and 2.17, and 2.42 and 3.89, respectively. Comparison of the values in Tables 1 and 2 shows that method II slightly outperforms method I. However, the number of parameters is higher for method I than for method II. Therefore, method II is also very suitable for practical applications.

4. Conclusion

On the basis of the ECG and the concept of physiological action of cardiac contraction, we proposed an AI model for BP estimation (method II) to establish both a systolic model and a diastolic model to estimate BP. In the cases of similar accuracy, the structure of SBP and DBP is smaller in method II than in method I, but the performance of method I is higher than that of method I. The architecture proposed in this study is feasible and more accurate than that required by the AAMI standard. Thus, this technology can replace home care systems or wearable devices to provide warnings about one's health. In the future, more tests will be performed to improve the accuracy of the DBP measurement and make the system more complete. Moreover, the proposed structure, which can integrate with electrode sensors and a signal processing platform, can be implemented as a wearable device to provide warnings about health to those who wear it.

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