Cuffless Blood Prediction with Fingertip Pulse Wave

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Abstract. Cuffless method for blood pressure measurement is an important methods for continuous health status monitoring. A pulse wave is a periodic time-series signal that reflects a non-linear, non-stationary change in the pulse signal over time. Traditional ways of pulse wave based blood pressure assessment rely on feature extraction from pulse signals, which are usually signal quality dependent and lack of consistence among studies. In this paper, a method of blood pressure measurement of using continuous pulse waveform and long-term and short-term memory network is proposed, which avoids the process of manually extracting waveform features. Experiments were performed with both pulse wave signals and the arterial blood pressure signals form the MIMIC database. Empirical mode decomposition was applied for signal preprocessing, and the time series of the pulse wave was analyzed to establish a Long Short-Term Memory neural network for blood pressure assessment. An average prediction accuracy of 83.2% was achieved.

1. Introduction
In recent years, the prevalence rate of hypertension among Chinese residents is on the rise. According to the Fifth National Hypertension Control Survey released by the National Cardiovascular Disease Center in 2018, the prevalence rate of hypertension in China has reached 23.2%, but the control rate is only 15.3%. Hypertension causes many complications, one of which is cardiovascular disease. There is a close causal relationship between the level of blood pressure (BP) and the incidence of cardiovascular disease [1]. Blood pressure is an important indicator for the prevention and treatment of cardiovascular diseases [2,3]. It is one of the routine testing items in hospitals.

Blood pressure measurement methods are mainly divided into direct (invasive) and indirect (non-invasive) measurements. Traditional non-invasive measurement methods include auscultatory, oscillometric, tonometry and volume clamp method, which all need a cuff to apply force on measurement position[4]. Such processes may make patients feel uncomfortable, and is not suitable for continuous blood pressure monitoring[5] considering long-term force applyment may lead to venous congestion and arterial rupture.

One of the methods of non-invasive continuous blood pressure measurement is based on pulse wave signals. The rhythmic contraction and relaxation of the human heart will produce pulse waves that travel along the arterial system from the root of the aorta, which contains a wealth of information related to blood pressure. At present, there are three main methods of blood pressure measurement based on pulse wave: Pulse Transit Time (PTT), Pulse Wave Velocity (PWV) and Pulse Wave Parameter (PWP)[6]. PTT is derived from the time delay between the R-wave of ECG and the arrival
of pulse wave on finger, which is measured from PPG. Based on PTT, another parameter called pulse wave velocity (PWV) could be calculated in both processes [7], the patients need to wear extra ECG sensors, which is not comfortable for patient during daily activities, and the simultaneous collection for both pulse wave signals and ECG signals is not easy to guarantee. Kachuee et al. [8] presented an efficient algorithm, based on PTT, for the continuous and cuff-less estimation of the Systolic Blood Pressure (SBP), Diastolic Blood Pressure (DBP), and Mean Arterial Pressure (MAP) values. Pfugradt et al. [9] applied non-invasive blood pressure measurements based on PWV to wearable devices. Sarafidis et al. [10] used linear regression to evaluate MAP–PWV association for 242 patients.

The third type of pulse wave based blood pressure assessments is based on the waveform characteristics of pulse waves only. A large number of clinical experimental results have confirmed that the waveform characteristics of pulse waves are closely related to cardiovascular diseases [11]. Some pulse waveform characteristic parameters, such as amplitude, frequency and distance between peaks, which contain a lot of physiological and pathological information about human cardiovascular system. The method based on PWP usually needs to extract a large number of waveform characteristic parameters manually. Xie Hanshuang et al. [12] extracted 14 features from the pulse wave waveform and established a multivariate linear model for blood pressure estimation. Liu et al. [13] extracted 21 time-domain parameters from the amplitude of the pulse wave signal and 14 features from the second derivative of the signal. The support vector regression (SVR) technique was used to establish the relationship between pulse wave features and blood pressure.

Such feature extraction procedure relies on expert domain knowledge and manual performance could be very complex Meanwhile, automatic feature extraction algorithm may increase the calculation speed but also induce errors and a large deviation of some results.

Recently, deep learning methods has brought a new direction for non-invasive blood pressure monitoring, in which feature extraction and classification are performed together [14]. Among types of deep learning methods, Long Short-Term Memory (LSTM) network, a variant structure of Recurrent Neural Network (RNN), is proved more appropriate than other neural networks for chronological events with long intervals and delays. It has outstanding performances in many fields and has been used in image classification, speech recognition, natural language processing, biomedical signal analysis and other areas [15]. Yang Shuo et al [16] successfully detected arrhythmias without extracting ECG features by using LSTM networks, and the overall accuracy of the model was 98.34%.

2. METHODOLOGY

The overall flow diagram of the proposed research methodology is presented in Fig.1, which is summarized in the following steps:

1. Obtaining training data from public data sets, including data of pulse wave and blood pressure;
2. Selecting the original data and save it as a data segment for 10 seconds;
3. Preprocessing data segment, including remove noise and baseline drift of pulse wave signals and extracting reference DBPs and SBPs from arterial blood pressure waveform segment;
4. Using the 5-Fold cross-validation of the LSTM deep learning model for training and testing to compare the overall estimation accuracy.
2.1. Data sources
In this paper, training data with both fingertip pulse wave signals and blood pressure signals was obtained from MIMIC [17] database. MIMIC database is a collection of clinical physiological signals and resources, which aims to provide support for the development and evaluation of intensive care automatic decision-making system. The fingertip pulse wave signal in MIMIC database is collected by photoelectric volume sensor, and the Arterial blood pressure (ABP) is measured by arterial catheterization, which is the international gold standard for blood pressure measurement. For daily blood pressure monitoring, we set a time period of 10 seconds for data extraction. Fig. 2 shows a typical 10 seconds segment from MIMIC.

2.2. Data selection
Raw data from MIMIC database including errors which needs to be removed before further processing. Two types of defective segments were defined and removed: Firstly, segments with missing data: neither pulse wave signal nor arterial blood pressure signals was not recorded at the segment or were invalidly recorded as NAN; Secondly, segments with noisy data: signals were with disordered and aperiodic fluctuations in the segment.

2.3. Data preprocessing

2.3.1. EMD-based pulse wave signal preprocessing
Empirical Mode Decomposition (EMD) [18] is a signal adaptive analysis method proposed by Dr. Huang E, in 1998. According to the local time variation of signal, EMD can decompose signal into several intrinsic mode functions (IMF), which can reduce the interference or coupling of signal feature information and promote deep-seated information mining. Compared with time domain and frequency domain analysis methods, it is more suitable for the analysis of non-stationary and nonlinear signals, and has been widely used in machinery, Image processing, biomedical signal processing and other fields[19]. As noticed, there are high frequency noise and low frequency baseline drift interference in fingertip pulse wave signal, which need to be further processed. The high frequency noise mainly...
includes noises from power supply and electromyography noise. Low frequency baseline drift is caused by physical activity and breathing, as shown in Fig. 3(d).

EMD method was used to decompose the fingertip pulse wave signal (Fig. 3 (a)). From top to bottom, there are IMF component and residual waveforms in the first to fourth layers. Fourier transform is performed on all IMF components and residual terms, and the result is shown in Fig. 3 (b). It can be seen that the IMF1 layer mainly contains the high-frequency information of the pulse wave signal, but the amplitude of the signal is not high, all below 0.01mV. The energy of the pulse wave signal is mainly concentrated in the IMF2 and IMF3 layers, while the IMF4 and Residual layers are mainly low frequency information. Therefore, the signal is reconstructed with the first to third IMF components. Fig. 3 (c) gives a comparison between the synthesis signal and the original signal.

2.3.2. Reference blood pressure extraction and normalization
For each 10 seconds segment, the corresponding value of systolic blood pressure (SBP) was calculated as the average value of all the peaks in the ABP signals, and diastolic blood pressure (DBP) was calculated as the average value of all the valleys in the ABP signals. (Fig. 4 (a)).

Standardization of reference BP values. In order to accelerate the convergence speed of the model training and improve the accuracy of the model, the reference SBP and DBP values will be standardized. In this paper, We choose the Min-max standardized method to deal with the data and make a linear transformation of the original data, so that the converted data fall in the [0, 1] range, as shown in equation (1):

\[ X^* = \frac{x - \text{min}}{\text{max} - \text{min}} \]

In Eqs. 1, \( x \) is reference BP values, \( \text{max} \) represents the maximum of all samples, \( \text{min} \) represents the minimum of all samples, \( X^* \) is standardized BP values.

2.4. LSTM-based model

In this paper, we proposed a four-layer LSTM structure, including the input layer, two LSTM layers and the full connection layer. The structure of the proposed LSTM for pulse wave signal time series information extraction and Blood pressure prediction tasks is shown in Fig. 4. LSTM mainly describes the relationship between the current data and the previous input data. Its memory ability retains the state information of the previous time step of the network and combines the input information of the current time step to affect the activation value and development trend of the current time step, which have an advantage of processing and classifying for time-series data such as pulse wave signal.

We obtained a total of 750 high-quality 10-seconds data segments from the MIMIC dataset, each of which included 5000-dimensional pulse wave signals and corresponding standardized reference SBP and DBP values. The 10-second pulse wave data were input into the input layer in turn, and then
passed through two LSTM layers. Finally, the estimated systolic blood pressure and diastolic blood pressure were output from the full connection layer.

3. Experiment and Results

3.1. Experiment

In total, 750 good quality signal segments and reference BPs were used to train and test the above LSTM deep learning algorithms with 5-Fold cross-validation. In each iteration, the ratio of test set to training set is 1:4, that is, the training set contains 600 segments and the test set contains 150 segments. After 5 iterations, each segment has an estimated SBP and an estimated DBP.

In this paper, we choose mean absolute error (MAE), standard deviation (SD) and root mean square error (RMSE) to evaluate the estimated results, and we stipulate that the estimated result is correct when the difference between the reference BP and the estimated BP is within $\pm 5$ mmHg.

$$\text{MAE} = \frac{1}{N} \sum_{i=1}^{N} |y_i - \hat{y}_i|$$  \hspace{1cm} (2)

$$SD = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (E_i - \bar{E})^2}$$  \hspace{1cm} (3)

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2}$$  \hspace{1cm} (4)

$$AC = \frac{n(|y_i - \hat{y}_i| \leq 5)}{N} \times 100\%$$  \hspace{1cm} (5)

In Eqs.2–5, $y_i$ is reference BP values, $\hat{y}_i$ is estimated BP values, $N$ is the number of test set samples, $E_i$ is difference between reference BP and estimated BP, $\bar{E}$ is mean difference between reference BP and estimated BP, $n(|y_i - \hat{y}_i| \leq 5)$ is the number of correct estimated BP.

3.2. Results

| BP       | MAE(mmHg) | SD(mmHg) | RMSE(mmHg) |
|----------|-----------|----------|-------------|
| Our results |           |          |             |
| SBP      | 2.96±0.37 | 4.81±0.59| 5.65±0.69   |
| DBP      | 2.80±0.15 | 2.28±0.18| 3.62±0.20   |
| AAMI     |           |          |             |
| SBP&DBP  | $\leq 5$  | $\leq 8$ |             |

Tab. 1 demonstrates overall results of 5-Fold cross-validation. The AAMI of American medical devices requires BP measurement devices to have MAE and SD values lower than 5 mmHg and 8.
mmHg. According to Tab. 1, the proposed method achieved MAE and SD values much lower than the AAMI, the estimated SBPs and DBPs both meet the AAMI standard; And the average estimation accuracy of SBPs and DBPs are 83.96% and 82.80%, respectively. Fig. 5 shows the Bland-Altman plots for the estimated BPs from our method. (a) shows the differences between the reference SBPs and the estimated SBPs are mostly within ±2SD, but it can be observed that some of the differences are much larger than 2SD, and the estimated SBPs in this part is smaller than the reference SBPs; (b) shows the difference between the reference value and the estimated value of diastolic blood pressure is concentrated in ±2SD, which is uniformly distributed on both sides of the Abscissa. According to Tab. 1 and Fig. 5, the method proposed in this paper is feasible in the field of BP measurement.

Meanwhile, We compared results of EMD with results of the original pulse signal: the estimated results of signal processed by EMD are improved compared with the estimated results of original pulse wave signal, that DBP results is obviously improved: The MAE and RMSE of DBP are reduced by 1.2mmHg, and the accuracy is improved by 23.24%; The MAE and RMSE of SBP also reduced 2.6mmHg and 2mmHg, and the accuracy increased by 20.49%. The improvement of the estimated results after processing demonstrates that the proposed model for blood pressure estimation of pulse wave signals is positive and can effectively improve the accuracy of blood pressure estimation.

4. Results and Discussion

In this paper, we designed a four-layer LSTM neural network to measure blood pressure. Although the overall results meet the AAMI for medical equipment, there are some cases where the estimated values of SBP are less than the reference values.

Fig. 6(a) is a violinplot of SBPs and DBPs, in which the distribution of SBP is between 90~140mmHg and the distribution of DBP is between 50 and 80 mmHg, but it can be seen from the violinplot that the distribution of DBP is more concentrated than that of SBP. Fig. 6(b) Red represents the bar chart corresponding to the reference SBP when the differences is greater than 10mmHg; blue represents the bar chart of all reference SBP. The width of the bar chart represents the interval and the height represents the quantity. It can be observed that the red part occurs only when the reference SBPs are greater than 110mmHg, and the ratio of red to blue increases with the increase of Abscissa (the reference SBPs are in 110~120mmHg, the proportion is 5.77%; the reference SBPs are in the 120~130mmHg, the proportion is 13.68%; the reference SBPs are greater than the 130mmHg range, the proportion is 55.17%). Further statistics showed that there were 212 segments with reference SBP within 120~130mmHg, accounting for 28.3% of the total number of SBP; 28 segments with reference SBP greater than 130mmHg, accounting for only 3.74%. This imbalanced SBP samples distribution has a great impact on the prediction results of the our proposed LSTM model. For this reason, we will conduct model training again after the SBP samples are balanced. We divide all the SBP samples into two parts referring to the normal SBP line (SBP=120mmHg), and randomly reserve 260 SBP samples from the samples below 120mmHg. In this way, we get 500 SBP samples again, and use 400 SBP samples as the training set and the remaining 100 SBP samples as the test set.
The Bland-Altman plot of the balanced SBP is shown in Fig. 7, in which the difference between the reference SBP and the estimated SBP is within ±2SD, and there are not only a few values greater than 2SD, but also a few values less than -2SD. Tab. 2 shows the estimated BPs of after balancing samples, in which the SD (2.17 mmHg) and RMSE (3.92 mmHg) are reduced. The above results show that after balancing the distribution of SBP samples, the situation that the some differences are more than 10 mmHg and the estimated SBP is less than the reference SBP are improved. Moreover, the estimated SBP after balance still meets the AAMI standard for American medical devices.

![Bland–Altman plot after balance](image)

**Figure 7 (a). Bland–Altman plot after balance.**

**Tab. 2 Prediction results of blood pressure before and after balance.**

| BP | MAE (mmHg) | SD (mmHg) | RMSE (mmHg) | AC/% |
|----|------------|-----------|-------------|------|
| Before | 2.97 | 4.87 | 5.70 | 83.60 |
| After | 3.27 | 2.17 | 3.92 | 79.00 |

**Tab. 3 Comparison with other works.**

| Literature | Parameters | Dataset | BP | MAE (mmHg) | SD (mmHg) |
|------------|------------|---------|----|------------|-----------|
| Xie[17]    | 14         | MIMIC   | SBP | 3.98       | 3.02      |
|            |            |         | DBP | 2.97       | 2.31      |
| Liu[18]    | 35         | Other   | SBP | 1.29       | 4.62      |
|            |            |         | DBP | 0.82       | 3.31      |

Comparison with other works, as Tab. 3 our method shown in this paper achieves the same effect as Xie[17]; Liu[18] extracted 35 parameters from the pulse wave signal and achieved the smallest MAE of SBP and DBP; our method mainly uses the LSTM model to automatically associate the pulse wave time series information, which avoids the feature extraction and has more advantages in SD. It is worth noting that Xie[17] only extracts 14 parameters from the pulse wave signal and achieves the same effect as this paper, them put the BP value of the previous moment as a parameter into the training sample and estimate the next moment BP value, which is meaningless in the actual blood pressure measurement. Xie and Liu results also show that the estimated DBP is better than SBP, which can also prove that the distribution of sample data will affect the results.

5. Conclusions and Future Work

In this paper, we designed a four-layer LSTM network to measure blood pressure, original pulse wave is processed by EMD, and the LSTM model automatically associate the pulse wave time series information, which avoids the tedious work of artificial feature engineering. The result of blood pressure estimation meets AAMI standard for American medical devices, which demonstrates that the method proposed in this paper is feasible in the field of blood pressure measurement and provides a new method for the cuffless blood pressure measurement. In future research, we plan to collect blood pressure and pulse wave signals from healthy people and hypertensive people to construct our own data sets, explore the differences in pulse wave signals among different blood pressure groups and
build a blood pressure estimation model that is more suitable for the physical characteristics of Chinese people, so as to provide convenience for undisturbed long-term health monitoring. In the aspect of neural network model, we will also try to reproduce and improve other time series models to predict blood pressure and compare the effects of different time series models.

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