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Automatic Onsets and Systolic Peaks Detection and Segmentation of Arterial Blood Pressure Waveforms using Fully Convolutional Neural Networks

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***Abstract*—Arterial blood pressure (ABP) waveform is a common physiological signal that contains a wealth of cardiovascular information. According to the cardiac cycle, the ABP waveform is divided into rapid ejection, systolic and diastolic phases. Therefore, the characteristic points of the arterial blood pressure waveform, i.e. their onsets, systolic peaks, represent the timing of the minimum and maximum pressures. It is important to detect these characteristic points accurately. Recently, many researchers have introduced some feature points detection methods, but the accuracy is not particularly high. In this paper, a deep learning method is proposed to achieve periodic segmentation and feature points detection of ABP signals using a one-dimensional U-Net network. The network can split the ABP signal into two parts and accurately detect the feature points. The method is validated on an ABP dataset of 126 people, 500 people each. Performances are good at different tolerance thresholds, with an average time difference of less than 1.5 ms. Finally, the method performs with 99.79% and 99.79% sensitivity, 99.99% and 99.94% positive predictivity, and 0.23% and 0.27% error rates for both onsets and systolic peaks at a tolerance threshold of 30 ms. To our knowledge, this is the first paper to use deep learning methods for the onsets and systolic peaks detections of ABP signals.**

I. Introduction

Blood pressure (BP) is the pressure in the blood vessels caused by blood flow. Arterial blood pressure is a vital sign that reflects the health of the body's cardiovascular system. The arterial blood pressure (ABP) waveform includes a large amount of information such as heart rate, systolic pressure, mean arterial pressure, diastolic pressure, arterial stiffness [1] and many cardiovascular parameters [2]. The blood pressure at onsets and systolic peaks represents diastolic blood pressure (DBP) and systolic blood pressure (SBP) during the cardiac cycle, respectively. When SBP and DBP values exceed a certain level, it is called hypertension. Millions of people worldwide currently suffer from hypertension.

A typical ABP waveform and feature points are shown in Fig.1. According to the staging of the ejection phase, the onset is considered as the starting point of the systolic phase, and the systolic peak point is considered as the peak point of the blood pressure waveform and the end point of the rapid ejection phase. Moreover, the time interval between onset and peak systole is the time of the rapid ejection phase [3], and detection of these feature points can be used for ABP waveform cycle segmentation and heart rate information extraction.

The onsets and systolic peaks detections of ABP signals are used to obtain relevant diagnostic markers, such as pulse transit time (PTT) and pulse wave velocity (PWV), etc. The Heart rate variability (HRV) [4] and augmentation index (AI) can also be easily obtained by localizing the onsets and systolic peaks.

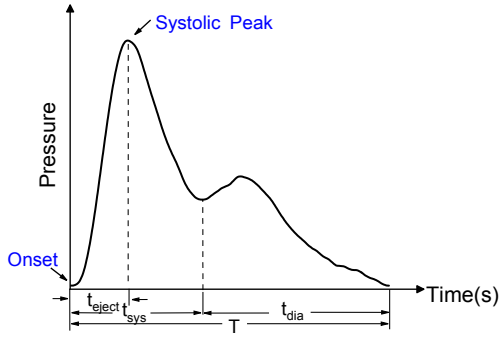

Figure1. A typical ABP waveform and its feature points.

Several methods have been proposed for these feature point detections. However, many of them focus either on the onsets or on the systolic peaks. There are relatively few systems and algorithms dedicated to these two feature points, and the detection accuracies of many of the methods are not very high. W. Zong et al. proposed a windowed and weighted slope sum function (SSF) to detect ABP onset points and achieved 96.41% accuracy on 39,848 beats by manual annotation [5]. B. N. Li et al. proposed an automated delineator for detecting arterial blood pressure waveforms by finding inflection points and zero-crossing pairs and using combined amplitude and interval criteria methods [6]. M. Schmidt et al. proposed a systolic peak detector for blood pressure waveforms using 4th order cumulant [7]. O. Singh et al. proposed a delineator based on empirical wavelet transform for the detection of onset and systolic peaks in ABP signals [8]. B. T. Ricardo Ferro et al. used the Hilbert transform method for the automatic detection of onset and systolic peaks [9]. L. Yang et al. investigated the performance of algorithm waveform descriptor (WD), global minimum within a sliding window (GM) on the detection of onsets [10]. Pander, T. et al. used derivative Gaussian filters and moving average filters to

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obtain smoothed signals, and then applied amplitude thresholding and fuzzy median clustering methods to improve the accuracy [11].

In the past few years, deep learning methods have been widely used in the fields of visual recognition and image recognition. Typical deep learning methods include deep neural networks (DNNs), convolutional neural networks (CNNs), and recurrent neural networks (RNNs), as well as long short-term memory (LSTMs). U-Net is a fully convolutional network developed in [12] for biomedical image segmentation. The goal of U-Net is to produce semantic segmentation where the output is the same size as the original input image, but each pixel in the image is colored as one of X colors, where X represents the number of classes to be segmented. U-Net is more suitable for image segmentation and physiological signal segmentation than other convolutional neural networks, such as AlexNet, VGGNet, etc. Nowadays, U-Net has been successfully used in ECG signals for R-wave localization [13] or P-wave localization [14], so U-Net is also considered to be suitable for application in ABP signals.

In this paper, since the ABP waveform is a one-dimensional (1D) signal, we convert the original U-Net into a one-dimensional network. The network can divide the ABP signal into two parts and accurately detect the feature points. The method is validated on a 126-person ABP dataset and achieves very high accuracy.

II. Materials and Methods

A. Data

The data source comes from a total of 126 individuals, and is extracted from the arterial data (ABP) of the VitalDB database [15], which is an open-access public dataset of vital signs and biosignals collected by the Seoul National University Hospital Department of Anesthesia using the Vital Recorder program. The Vital Recorder program is a free research tool for recording time-synchronized physiological data from multiple intraoperative devices and patient monitors. The collected ABP waveforms are measured from the radial artery by a device called SNUADC with a sampling rate of 100 Hz.

B. Data Preprocessing

The entire preprocessing process is described as follows. Each individual's ABP waveform is 500s with an initial sampling rate of 100 Hz, and then the data is resampled to 200 Hz. Since the original ABP signals contain several types of noise, including power line interferences and other high frequency noises, a wavelet filter based on the "sym5" basis function is used to remove high frequency noises. After manual annotation of the systolic peaks and onset points, each ABP segment was divided into 5.12 seconds of 1024 sample points. Finally, the amplitude of each segment was normalized to between 0 and 1, since the amplitude does not affect the location of the feature points. The data set was distributed using approximately 80% of the data (101 individuals) as the training set and approximately 20% of the data (25 individuals) as the test set.

Since the purpose of this paper is to detect onsets and systolic peaks, the ABP waveform is divided into two types according to the characteristics: rapid ejection phase and residual phase. Therefore, the labeled signal has two parts: 0 (rapid ejection cycle), 1 (rapid ejection cycle to the end of a pulse cycle), and the starting point of each phase is the characteristic point. The entire annotation is done manually by an experienced engineer with the help of softwares. A typical annotation of an ABP waveform is shown in Fig.2.

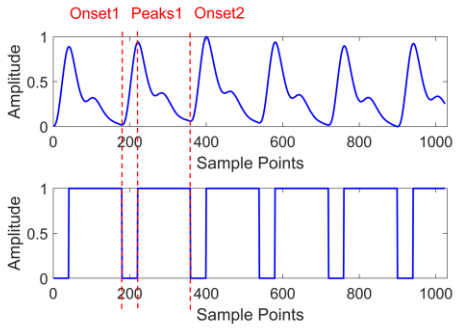

Figure 2. An ABP waveform and its annotations.

C. Networks Architecture

In this paper, the U-Net model is transformed into a one-dimensional network for signal processing of ABP waveform time series data. The network is shown in Fig.3. The encoder path on the left side contains a series of convolutional networks consisting of two repeated 3 × 1 convolutions, each followed by a rectified linear unit (ReLU) layer. After the two convolutional layers, each downsampling uses a 2 × 1 maximum pooling layer with a step size of 1. In each downsampling step, the network doubles the number of feature maps and halves their size. There are five downsampling stages in total.

The decoder path on the right is used for precise localization using transposed convolution and includes upsampling of the feature maps, followed by a 1×1 convolution layer at each step, which halves the number of feature maps. Then, high-resolution features are copied directly from the systolic path and combined with the upsampled features for subsequent convolution. In the final layer, 1×1 convolution with a sigmoid layer is used to classify the ABP waveforms into 2 classes and predict the locations of the ABP feature points. In summary, the input to the model is 1024 × 1 one-dimensional data, and the final layer outputs the probabilities for each sample point using a sigmoid layer through a U-Net fully convolutional network. The output is smoothed using a binary method with a threshold of 0.5.

The model is built on the Keras 2.3.1 platform with Tensorflow 1.15.0 as the runtime backend and programmed in Jupyter notebook using Python 3.7.6. Finally, the model runs on an AMD Ryzen5 2400G computer with 32G DDR4 memory, OS win10, and graphics card GTX-1660 with 6G memory for acceleration. The model was trained using the Adam optimizer at a learning rate of 0.0001 for 80 epochs with a batch size of 128.

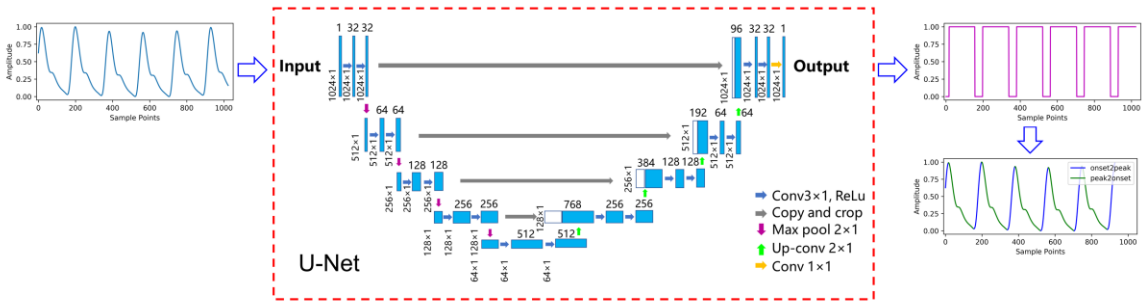

Figure 3. The proposed networks.

III. RESULT

A. Evaluation Metrics & Test Performance

The performances of ABP feature points detection algorithms were evaluated by several metrics [6]: sensitivity (Se), positive predictivity (P^+), and error rate (Err), which are given by equations (1-3).

Sensitivity:

$$Se = \frac{TP}{TP + FN} \tag{1}$$

Positive predictivity:

$$P^+ = \frac{TP}{TP + FP} \tag{2}$$

Error rate:

$$Err = \frac{FP + FN}{TP + FP} \tag{3}$$

Where TP represents the number of true positives, FN represents the number of false negatives, and FP represents the number of false positives. Thus, Se represents the percentage of true beats detected to the overall beats of the ABP waveforms, while P^+ calculates the percentage of true beats detected to all beat annotations. As in many other systems [10], a tolerance threshold of 30 ms (±6 sample points) is used to judge the annotation results.

Table I shows the results of the algorithm on the test set consisting of 2440 segments with more than 15,000 cycles of ABP signals. Different thresholds were chosen to demonstrate the performance of the algorithm, including 5 ms (±1 sample point), 10 ms (±2 sample points), 20 ms (±4 sample points), and 30 ms (±6 sample points). The detailed performances are shown in Table I. It can be seen that the algorithm performs very well even at the 5 ms and 10 ms thresholds. And the performance of the algorithm improves very slowly as the threshold value increases. Finally, Se and P^+ are both better than 99.7% in the 20 ms and 30 ms tolerance ranges, and the error rate is less than 0.3%, respectively.

In addition, the time difference between manually labeled and detected feature points can be defined as the parameter Δt, which can further evaluate the accuracy of the model. The average Δt for the onsets and systolic peaks in Table II is 1.3 ms (0.26 sample points) and 1.24 ms (0.25 sample points), both of which are much smaller than one sample point.

TABLE I. TEST PERFORMANCE ON DIFFERENT THRESHOLDS

Time	Onsets			Systolic peaks		
	Se(%)	P^+(%)	Err(%)	Se(%)	P^+(%)	Err(%)
5 ms	99.76	99.95	0.29	99.67	99.82	0.52
10 ms	99.79	99.99	0.23	99.74	99.90	0.36
20 ms	99.79	99.99	0.23	99.78	99.94	0.28
30 ms	99.79	99.99	0.23	99.79	99.94	0.27

TABLE II. TIME DIFFERENCE WITH MANUAL ANNOTATIONS

Parameter	Onsets	Systolic peaks
Δt	1.3 ms	1.24 ms

B. Annotations for different types of ABP waveforms

Fig.4 shows the labeling results of different ABP waveforms using the algorithm. It can be seen that the proposed model correctly completes the segmentation for different ABP waveforms from 6 individuals with different rhythms and waveform morphologies. The phases from the onset points to the peak points are marked as blue and called onset2peak, and the phases from the peak points to the next onset points are marked as green and called peak2onset.

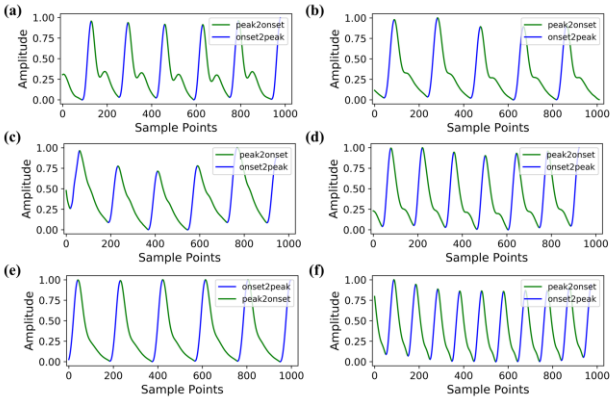

Figure 4. Annotations result for different types of ABP waveforms.

Fig.5 shows the annotation results of 25-second ABP waveforms using this algorithm. The algorithm first annotates the 5.12s data segment and then splices it into a 25s waveform. As can be seen in Fig. 5(a) and Fig. 5(b), the annotation is correct. It proves that the algorithm is able to annotate correctly in long ABP sequences.

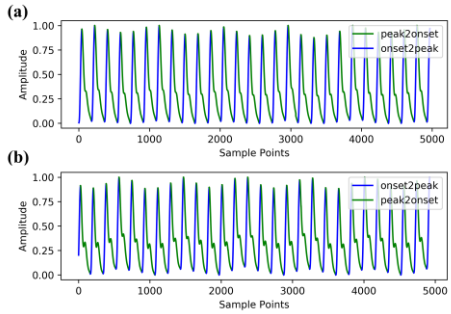

Figure 5. Annotations result for long ABP waveforms.

C. Performance comparison with other related works

The detailed test metrics of the different methods are shown in Table III, and all optimization parameters are shown in bold. Compared with other papers [10-11], [16-17], the method proposed in this paper shows a significant improvement in the metrics of onsets and systolic peaks. The results for both Se and P^+ were better than 99.7%. In the evaluation of onsets, the Se is about 0.17% lower than the value in Ref. [6], but its P^+ is much higher. The Err of this method is about 0.23%, which is significantly lower than the 1.43% to 11.27% of other papers. The situation is similar to systolic peaks. The Se is slightly lower than Ref. [6] with about 0.09%, but its P^+ is much higher, and the Err reduces to 0.27%, which is also significantly lower than the other references of 1.54% to 10.32%. This proves that the system has high accuracy.

TABLE III. COMPARE WITH OTHER WORKS

Papers	Onsets			Systolic peaks		
	Se(%)	P^+(%)	Err(%)	Se(%)	P^+(%)	Err(%)
Ref. [6]	**99.96**	98.73	1.43	**99.88**	98.69	1.54
Ref. [16]	96.89	94.55	8.47	/	/	/
Ref. [17]	99.83	94.31	5.8	99.83	95.24	4.9
Ref. [10]	97.23	91.36	11.27	/	/	/
Ref. [11]	/	/	/	95.87	94.33	10.32
Proposed	99.79	**99.99**	**0.23**	99.79	**99.94**	**0.27**

IV. CONCLUSION

As far as we know, this is the first paper to use a deep learning approach to annotate ABP waveforms. In this paper, a deep learning network U-Net is proposed to segment the arterial pressure pulse signal and label the feature points. It can adapt to the characteristics of different waveforms and find the feature points accurately. To detect onsets and systolic peaks, the model classifies ABP waveforms into 2 classes. The method is validated on an ABP dataset of 126 individuals. Using the method of this paper, the metrics are greatly improved. The sensitivity and positive predictivity rate of both onsets and systolic peaks are higher than 99.7%. More importantly, it has a much lower error rate of 0.23% and 0.27% for onsets and systolic peaks, respectively. It performs well on different types of test waveforms, proving that the method can be applied to different waveform morphologies.

However, the algorithm also has some drawbacks. The use of convolutional neural networks increases the hardware requirements of the computer, which usually requires GPU acceleration to guarantee the computational speed, and is therefore also more difficult to implement in real-time recognition areas, such as embedded applications. In addition, since the input length of the model is fixed, for processing long sequences, it needs to be segmented and then fed into the network, thus introducing an additional pre-processing process.

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