A Novel Method for Arterial Blood Pressure Pulse Detection Based on a New Coupling Strategy and Discrete Wavelet Transform

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Abstract

In this study, a new method for detection of arterial blood pressure pulses (ABP) is presented. The algorithm employs discrete wavelet transform (DWT) decomposition to extract ABP waveform features. In the proposed method, two strategies are used. In the first strategy, the algorithm uses only the DWT coefficients of ABP. The second strategy which is introduced for the first time in this paper, the coupled DWT coefficients of ABP and electrocardiogram (ECG) are used. When DWT coefficients of ECG and ABP are coupled the detection of ABP pulses is easier and more accurate in noisy parts of the signals. Furthermore, this coupling strategy is useful for the detection of ECG R-peaks since the ABP pulses make the ECG R-peaks detectable when ECG is noisy. To meet this end, adaptive thresholding and different DWT functions were employed and fitted because of different morphologies of ABP and ECG signals. The ABP-ECG delay time is measured in different recordings and set for 254 milliseconds. For evaluation, 170 recordings of the multimodal training set of PhysioNet/Computing in Cardiology Challenge 2014 which contained both ECG and ABP waveforms were used. The first and second strategy obtained average accuracy of 87.56% and 88.53%, respectively.

1. Introduction

Indirect measurement of arterial blood pressure and information derived from the peripheral arterial pulse leads to improved assessment of cardiovascular function. The pulse wave analysis is a non-invasive approach based on the analysis of the Arterial Pressure Waveform (APW) components that implies accurate information about the cardiovascular status [1]. Recently many researchers are interested for pulse wave analysis-based devices due to the reduction risk factor management for cardiovascular diseases [2, 3].

APW is rich in physiological information and related pathological conditions such as heart rate, arterial wall integrity and arterial stiffness, and mean and diastolic pressure. Thereby APW attains an important aspect in cardiology. This waveform is induced by the interaction of the heart pumping the blood and the arterial vessels, and has rich physiological information embedded in its morphology. In other fields such as neurosurgery, waveform morphology of intracranial pressure through the analysis of peak locations [4] and the temporal dependency between successive pulses [5] have studied.

The morphology of the APW is determined by ejected heart blood volume, mechanical properties like elasticity and the integrity of blood vessels. Artery elasticity and heart function are the main factors, which shape the APW, but also age, gender and other physiological conditions affect the wave morphology [6]. APW vary somewhat in shape and frequency from one heartbeat to the next and variations are not necessarily cyclic, appearing as spurious high frequency components. Their separation from high frequency noise is challenging with Fourier analysis. Although in literature robust detection algorithm for cardiac output and pulse-wave analysis is proposed [7], but those fluctuation can be makes variation in arterial blood pressure frequency, amplitude or even shape of the waveform.

ECG signal can be very noisy because of electrical noise and electromagnetic interference, while noise on pressure signal is mechanical in its nature Therefore, information obtained from the APW can be used to estimate ECG and cardiac health, and parallel analysis with ECG has resulted in decreased false alarm for critical arrhythmias detection [8]. Combination of APW with ECG signal gives more accurate results for feature extraction than ECG signal itself.

With multimodal approach, both cardiovascular features and heart beat detection can be analyzed. The noninvasive methodology of estimating these features is gaining interest for the purpose of medical diagnosis, and novel computational methods in bio-signal processing. Hence, many researchers have focused their research on the analysis of the pulse waveform. Implied algorithms have in common preprocessing and logic section for peaks detection, and are based on rank filter and decision logic [9], peak and trough detection approach [10], weighted slope sum function [11], discrete wavelet transforms [12, 13], and combinatorial analysis of ABP waveform [14, 15]. In this study, we aim to propose an approach for detecting of ABP pulses by employing DWT and adaptive thresholding. In this approach, ABP signal is first decomposed by employing a proper mother wavelet function. Then, the decomposed signal was reconstructed at a specific level. From the available datasets which contain ABP and ECG signals, obtained DWT coefficients of ECG increase accuracy in detection of ABP pulses by coupling DWT coefficients of ECG and ABP.

2. Material and method

2.1 Data

The proposed method was evaluated using multimodal training set of PhysioNet/Computing in Cardiology Challenge 2014 [16]. This training dataset contained 200 signals at most 10 minutes in length (or occasionally shorter). The datasets contained ECG and a wide range of other pulsatile and non-pulsatile signals recorded simultaneously from human adults, including patients with a wide range of problems, and as well healthy volunteers. Each recording contains four to eight signals, where the first one was always an ECG signal. The remaining signals could be any of a variety of simultaneously recorded physiologic signals including blood pressure (BP), arterial line (ART), pulmonary arterial pressure (PAP), and respiration (Resp) which might be useful as well for robust beat detection. Recordings from the training set were sampled at 250 Hz and 360 Hz. Furthermore, for this dataset, a set of reference annotations was available which represented the locations of the QRS complexes in ECG signal.

2.2. Discrete Wavelet Transform

ABP waveform comprises clinically important information on a wide variety of time scales. Therefore the wavelet approach is suitable as it acts as a mathematical microscope for detecting different scales of signal by adjusting the focus. Discrete wavelet analysis corresponds to windowing method in a new coordinate system in which frequency and space are simultaneously localized that makes it helpful for pattern extraction. In addition, the spectral components of a feature may be located anywhere along the frequency axis even at the boundary of two near frequency bands. In this approach, compact representation of energy distribution of the signal in time and frequency is obtained and compressed in wavelet coefficients. In other words, optimal time–frequency resolution in different frequency range can be obtained by exhibiting different window sizes, based on statistical of signal (energy) or cross correlation analysis of signal (energy) [17,18].

A dyadic wavelet transform is implemented by high pass and low pass filter that are obtained by coefficient wavelet named as mother wavelet. Scaling function φ_(j,k) (t) and the mother wavelet function Ψ_(j,k) (t) in discrete domain are:

$$\varphi_{j,k}(t)=2^{\frac{j}{2}}\varphi(2^j n-k) \qquad (1)$$

$$\Psi_{j,k}(t)=2^{j/2}\Psi(2^j n-k) \qquad (2)$$

Wavelet transform is applied as:

$$\mathrm{X(n)}=\sum_n w_\phi\,(j_0,k)\phi_{j_{0,k}}(n)\sum_{j-j_0}^{\infty}\sum_k w_\phi\,(j_0,k)\Psi_{j,k}(n)(3)$$

$w_\phi(j_0,k)$ is approximation coefficient and $w\_\psi(j_0,k)$ is detailed coefficient. Detail signal and average signal are obtained as the output of high and low pass filters respectively. Wavelet approach is therefore used for artifacts removal from the ABP waveforms. The choice of a wavelet coefficient with suitable morphological characteristics in respect to the physiological signal, accordingly to the physiological condition, is crucial for the optimal use of this method.

2.3. Method

In this section different steps of the algorithm are explained. From the available datasets which contain ABP and ECG signals, the first step was to check whether the current recording contains a valid ECG. Based on the periodicity of the ECG waveform, if ECG existed beside the ABP signal, a new time series in which ABP and ECG are coupled is generated. The schematic flowchart of the proposed method is shown in Figure 1. Detection of the ABP pulses is described in the following steps.

Step 1: The ABP and ECG signals were first normalized, and then signals were decomposed by DWT. For decomposition of the ABP signal, the function 'haar' in level 5 was used, while the ECG signal was decomposed by with function 'db6 in level 5. As an example, the normalized ECG and ABP are shown in Figure 1 from which the delay between ECG R-peaks and ABP Pulses is visible.

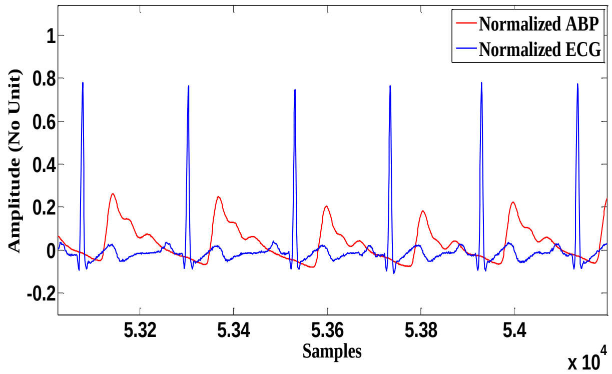

Figure 1. Typical ABP and ECG signal morphologies.

Step 2: In this step the decomposed signals were reconstructed. For reconstruction, wavelet coefficients of ABP in the second level of details part were reconstructed and named ABP-D2. The ABP signal and the related ABP-D2 corresponding to the recording 101 from the Challenge training set is presented in Figure 2. For ECG, wavelet coefficients in the third level of details were reconstructed and named ECG-D3. For further processing, only the reconstructed coefficients were considered instead of the original ECG and ABP waveforms. It should be mentioned that different functions for DWT were tested, in order to obtain decomposition functions with higher performance for ECG and ABP decomposition.

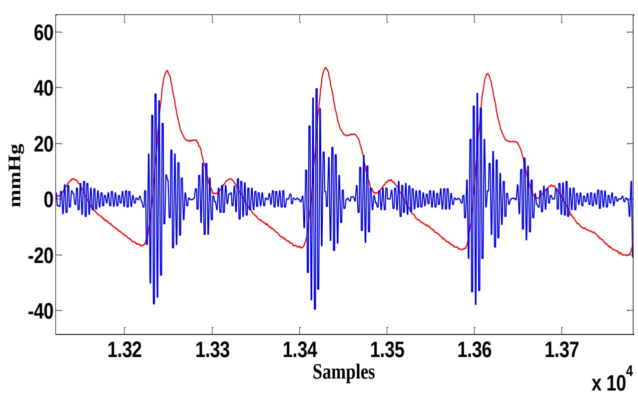

Figure 2. The ABP signal and related DWT coefficients.

Step 3: In this step, first the reconstructed signals of ABP (ABP-D2) and ECG (ECG-D3) were normalized. Then, the ABP-D2 was shifted backward for a delay time between ABP andECG peaks. Afterwards, the normalized ABP-D2 was sum with four times of normalized ECG-D3. Then, the energy of this new generated signal named ECG-ABP was obtained by powering by two. The reason of using coefficient of 4 before summing the two signals is that with such correction, the amplitude of the real heartbeats after summation were bigger than 1. Consequently, after generating the energy signal the real amplitude peaks would be bigger which make their detection easier. On the other side noisy parts would be smaller when powered by two as they are smaller than 1 (see Figures 3 and 4).

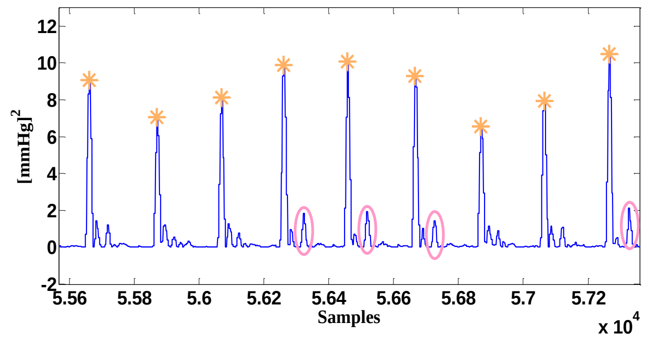

Figure 3. Energy of DWT coefficients of ABP signal

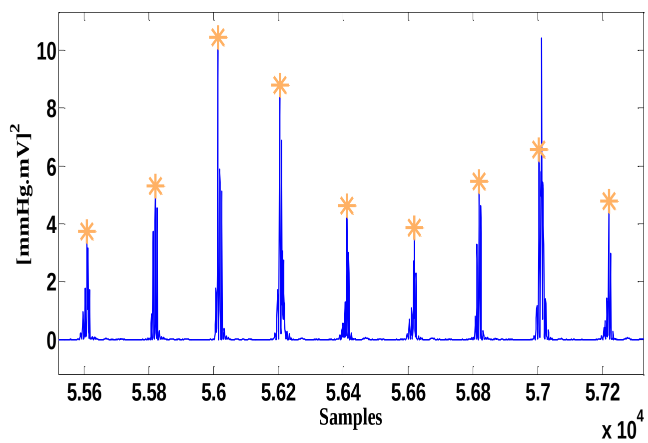

Figure 4. Energy of coupled DWT coefficients of ABP and ECG signal

Step 4: In this step, the peaks were detected through employing an adaptive threshold which was defined as $\frac{4}{L}\sum_{i=0}^{L} |ECG - ABP|$, where L is the length of ECG-ABP signal.

Step 5: In the final step, the consequent detections which were closer than 0.5 times a median value of all detected beat to beat intervals were corrected based on the corresponding value of their DWT coefficients. The maximum value between consequent detections whose intervals were bigger than 1.7 times the median value was considered as a missed pulse and added to other detections. In order to obtain the ECG-ABP delay time, the ABP-D2 was generated by the same strategy. Then, the ABP pulses were detected such as in Step 4 using the energy of the ABP-D2 signal, and shifted backwards, in order to synchronize the detected pulses with the ECG. Comparing the detected ABP pulses with reference ECG-based heartbeats in 100 10-minutes recordings of training set of PhysioNet/CinC 2014 Challenge the delay time of 254 ms was obtained. In [13] the ECG-ABP delay time was considered to be 200 ms.

3. Results

The proposed method was applied on the training set of PhysioNet/CinC 2014 Challenge. Only 170 recording of 200 training records contained blood pressure waveforms along ECG. In 112 recordings which contained ABP signal only ABP was processed and in 58 recordings one of ART or PAP signals was used. The exhausted results are shown in Table 1.

Table 1. The obtained results

Method	Se (%)	PDV (%)	Acc (%)
ABP wavelet coefficients	89.43	92.79	87.56
ECG-ABP wavelet coefficients	91.78	91.74	88.53

4. Discussion and conclusion

In this study implementation of wavelet based approach for feature extraction of arterial blood pressure is proposed. ABP signal under test at different scale is decomposed and algorithm is proven to be robust against variation of signal amplitudes and noise interferences. Performance of the algorithm for pressure beat detection is tested on the training set of PhysioNet/CinC 2014 Challenge. Pulse wave analysis and exact feature extraction of ABP signal can be employed for obtaining of pressure pulse index, arterial stiffness and cardiac output monitoring. In addition, with exact extraction of information in ABP waveform and combination of this algorithm with ECG signal, reduction of false alarm in noisy condition of ECG and disease identification can be obtained. According to Table 1, with coupling of DWT coefficients of ECG and ABP the result of pulse detection was improved. This shows how existence of ECG can improve the results instead of using ABP signal alone. The big advantage of this coupling is that on the other side ABP pulses can make ECG R-peaks detectable in noisy regions of ECG which can improve the R-peak detection significantly, reducing the false positive and negative detections and reporting more accurate heart rate.

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