Evaluation of the Accuracy and Noise Response of an Open-source Pulse Onset Detection Algorithm on Pulsatile Waveform Databases

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Abstract

Zong's open-source algorithm 'wabp.c' (2003) has been widely used for onset detection of arterial blood pressure (ABP) waveforms. This code was subsequently modified by Li and Clifford (2012) to avoid possible double detections in a beat cycle. However, its performance was not systematically validated, especially on a noisy pulse database. This study aimed to evaluate its detection accuracy on both clean and noisy ABP pulse signals. Synchronously recorded ECG and ABP signals in two databases from the PhysioNet/Computing in Cardiology Challenge 2014 were used. Reference QRS positions were used as the benchmarks for pulse onset detection. Three signal quality assessment (SQA) methods, i.e., Sun's jSQI (2006), a modified jSQI (jSQI2) and Gaussian Template Matching (GTM), were performed and the onset detection results were compared with and without each SQA. For the clean set-p database, the algorithm achieved an accuracy of 99.56% without SQA and slightly enhanced its accuracy to 99.97%, 99.84% and 99.79% when using the jSQI, jSQI2 and GTM methods respectively. For the noisy set-p2 database, the algorithm achieved an accuracy of only 76.42% without SQA but significantly increased to 96.73%, 90.60% and 90.79% respectively. The jSQI2 and GTM methods exhibited a higher accuracy for assessing the ABP signal quality compared to the jSQI method. In summary, the open-source pulse onset detection algorithm was found to achieve high detection accuracy in a low noise pulsatile database while relative low detection accuracy was observed when using a relatively noisy database. Combining the algorithm with an appropriate SQA procedure significantly improved beat detection accuracy.

1. Introduction

Pulsatile signals such as arterial blood pressure (ABP) and photoplethysmograph (PPG) contain rich information about the cardiovascular system and can be used to monitor the cardiac activity and verify electrocardiogram (ECG)-based alarms for patients in an intensive care unit (ICU) [1]. Automatic pulse onset detection is a fundamental stage for the beat-level analysis of pulsatile signals. With the onset of each pulse first identified, many other features, as well as the useful clinical parameters, can be calculated and derived, such as slope, pulse peak, pulse amplitude, pulse transit time (PTT), pulse wave velocity (PWV), etc [2]. These features and parameters can be further used for arrhythmia detection, blood pressure and cardiac output estimation, respiration rate estimation and vascular assessment [3].

Accurate and robust detection of pulse onset can be achieved on clean pulsatile signals [4, 5]. However, in an active clinical environment where noise and artifacts are inevitable, pulse onsets can be easily blurred by noise and motion artifacts due to their intrinsically small amplitude. Thus, accurate and robust pulse onset detection is challenging in a noisy environment.

The open-source algorithm 'wabp.c' proposed by Zong *et al.* [6] from www.physionet.org has been widely used for clinical applications. This algorithm was subsequently modified by Li and Clifford [7] with a time and amplitude threshold adjustment by changing the slope width of pulse rising edge from 130 to 170 ms and extending the eye-closing period after each detection from 250 to 340 ms, to avoid possible double detections in a beat cycle. Since there is no formal validation of this modified algorithm, this study attempts to do so in the context of noisy data.

2. Methods

2.1. Data

A total of 173 synchronously recorded ECG and ABP pulsatile signals from the PhysioNet/Computing in Cardiology Challenge 2014 were used [8]. These recordings were from two databases (100 from set-p and 73 from set-p2). Recordings in set-p had relatively high signal quality (SQ) and thus were used as the clean database, whereas the SQ in recordings from set-p2 was relatively poor and set-p2 was therefore used as noisy database. Signals had a duration of 10 minutes and had a varied sample rate between 120 and 1,000 Hz. Manually annotated QRS locations in

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ECG signals were provided as the reference benchmarks for pulse onset detection.

2.2. Signal quality assessment

Some ABP pulsatile signals, especially from the set-p2 database are very noisy, resulting in the pulse onsets are almost impossible to be identified by visual inspection. It is therefore reasonable to perform a signal quality assessment (SQA) prior to analysis.

Sun *et al.* [5] described an open-source method ('jSQI') that tends to capture high energy noise and would invalidate a beat if neighboring beats have low SQ. It is therefore overly sensitive for identifying poor quality beats. Johnson *et al.* [9] subsequently modified the jSQI code to address these issues (termed jSQI2 here).

In this study, in addition to jSQI and jSQI2, we propose a new method for assessing the ABP signal quality based on Gaussian Template Matching (GTM). For GTM method, we firstly generated four hand-crafted typical pulse templates as shown in Figure 1. Each template, $f(n)$, consisted of three positive Gaussian functions ($f_1^*(n)$, $f_2^*(n)$ and $f_3^*(n)$) defined as [10, 11]:

$$f(n) = \sum_{k=1}^{3} f_k^*(n)$$

$$f_k^*(n) = H_k \times exp(-\frac{2\times(n-C_k)^2}{W_k^2})$$

where H_k denotes the Gaussian peak amplitude, C_k denotes the Gaussian peak position, W_k denotes the Gaussian half-width and n is the sample index (running from 1 to 1000). The amplitude of template $f(n)$ is normalized to be 1. The parameter settings for each Gaussian function for each of the four archetypical pulse templates are given in Table 1.

The GTM SQ was then determined by calculating the maximum correlation (MaxCor) between each detected pulse and the four templates. Single beat pulse was regarded having poor SQ if MaxCor meets one of the following two conditions:

Condition 1: MaxCor$<$55%

Condition 2: MaxCor$<$80% and (meets A1 or A2)

where A1: pulse amplitude$<$20 mmHg and A2: maximum of the pulse derivative signal$>$10 mmHg.

2.3. Pulse onset detection algorithm

The open-source pulse onset detection algorithm consisted of three components: a low-pass filter, a windowed and weighted slope sum function, and a decision rule module [6]. First, a second order recursive filter with a 3 dB cut-off frequency of 16 Hz was used to suppress high frequency noise [12]. Then a slope sum function (SSF) was calculated by summing the difference signal of the filtered ABP pulse within a fixed time window. This SSF signal was used to enhance the upslope of ABP pulse, as well as

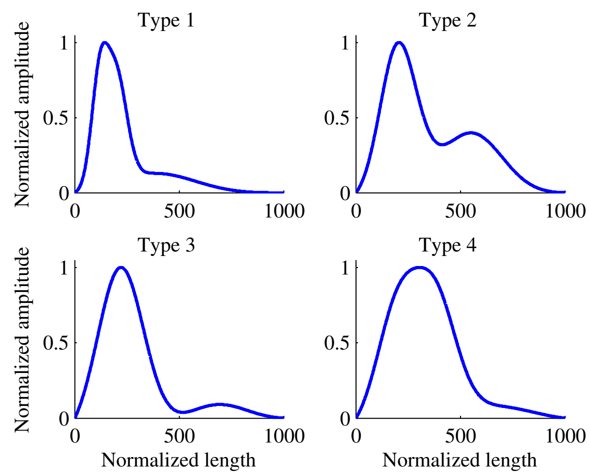

Figure 1. Archetypical ABP pulse templates for the GTM SQ method.

Parameter	Pulse template			
	Type 1	Type 2	Type 3	Type 4
H_1	0.7	0.7	0.8	0.6
H_2	0.7	0.05	0.01	0.6
H_3	0.15	0.3	0.1	0.1
C_1	120	200	220	200
C_2	200	320	500	380
C_3	380	550	680	650
W_1	80	170	220	200
W_2	100	150	400	200
W_3	400	300	300	400

Table 1. Parameter settings for the Gaussian functions for each type of pulse template.

to suppress the remainder of the ABP waveform. The fixed time window was set as 130 ms in Zong *et al.*'s work [6] and was subsequently modified to 170 ms by Li and Clifford [7]. The onsets of the SSF pulse coincide with the onsets of the ABP pulse and the SSF signal is simple to process. Thus, the pulse onsets were detected from the SSF pulse by a decision rule module. First, an adaptive thresholding method was applied to the SSF signal to detect the appropriate amplitude and then a local search strategy for identifying the likely pulse onsets was employed. Finally, to avoid double detection on the same pulse beat, a 250 ms eye-closing period was applied, during which the new detected pulse onset was rejected. This eye-closing period was changed to 340 ms by Li and Clifford [7].

2.4. Algorithm evaluation

Let $x_1, x_2, \cdots, x_N$ denote the reference QRS positions. For each position x_i, the numbers of detected pulse onsets within two time regions: $[x_i, x_i + \delta]$ and $(x_i + \delta, x_{i+1})$

were recorded. The detected pulse onsets were expected to appear in the former region. Parameter δ is a tolerance for determining the true positive (TP), false positive (FP) and false negative (FN) detections and was set as $0.6 \times (x_{i+1} - x_i)$ in this study. The numbers of TP, FP and FN detections were counted and the evaluation metrics of sensitivity (Se), positive predictivity (P_+) and accuracy (Acc) were calculated in the standard manner as:

$Se = TP/(TP + FN) \times 100\%$

$P_+ = TP/(TP + FP) \times 100\%$

$Acc = TP/(TP + FN + FP) \times 100\%$

3. Results

As shown in Table 2, for the clean set-p database, the open-source pulse onset detection algorithm without SQA accurately detected 72,132 (TP) pulse onsets among a total of 72,313 beats, falsely detected 141 (FP) extra pulse onsets and missed 181 (FN) actual pulse onsets, which produced an Acc measure of 99.56%. We also observed that SQA procedures filtered the potential incorrect onset detection pulse beats with poor SQ and thus improved the detection accuracy. The numbers of filtered pulse beats were 3,381 for jSQI but only 502 for jSQI2 and 203 for GTM respectively, demonstrating that jSQI is considerably more aggressive in beat removal. For this clean data, the pulse onset detection algorithm with SQA produced slightly higher Acc measures than without SQA, with improvements going from 99.56% to 99.97%, 99.84% and 99.79% respectively for the three SQA procedures.

The use of SQA generated more obvious effect on the noisy set-p2 database. Without SQA, the pulse onset detection algorithm truly detected 49,482 (TP) pulse onsets but falsely detected 7,532 (FP) extra pulse onsets and missed 7,740 (FN) actual pulse onsets, which produced a low Acc measure of 76.42%. By contrast, Acc measures were significantly improved to 96.73%, 90.60% and 90.79% when performing jSQI, jSQI2 and GTM SQA methods respectively. However, the number of filtered pulsatile beats by the SQA procedures was also large. They were as many as 21,303 (accounting for 37%) removed for jSQI, 14,658 (26%) removed for jSQI2 and 13,346 (23%) removed for the GTM method. The highest Acc result reported by the jSQI method is due to the significantly larger number of the removed pulse beats by this method creating a bias towards far easier detections.

Figure 2 shows a SQA and onset detection example for an ABP pulse signal from recording 2850 in set-p2. Three SQA methods, i.e., jSQI, jSQI2 and GTM, were used for assessing the ABP pulse signal quality. The wabp code modified by Li and Clifford [7] was used for detecting the pulse onsets. The upper panel shows the ECG signal (reference QRS positions are marked as red circles) and the lower three panels shows the corresponding SQA and onset detection results for ABP pulse (detected pulse onsets are marked as pink circles). The shaded areas show the expected area of detected onsets and the solid colours indicate poor SQ (black), a TP detection (green), and a FP and/or a FN detection (red). It is clear that jSQI method tends to report poor SQ beats even though the pulse beat has little noise component. jSQI2 and the new GTM methods give more accurate SQA results than jSQI. In addition, the fourth beat has incorrect FP onset detection and thus it is labelled as red indicator.

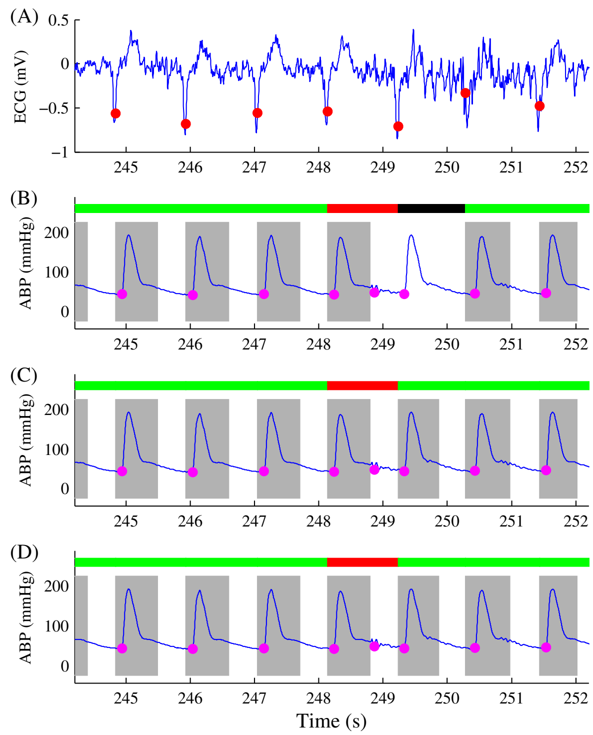

Figure 2. Example of SQA and onset detection results for ABP signal from recording 2850. The upper panel (A) shows the synchronous ECG signal and three lower panels show ABP signal using different SQA methods: (B) jSQI, (C) jSQI2 and (D) GTM. Reference QRS positions are marked as red circles (•) and the detected ABP pulse onsets marked are marked as pink circles (•). The shaded areas indicate the region of detected onsets. Three flag indicators at the top of pulse signal indicate the SQ results for each beat pulse: a poor SQ beat (black), a TP detection (green), and a FP and/or a FN detection (red). Note that jSQI incorrectly labels the beat as noisy.

4. Discussion and conclusion

In this study, we tested an open-source pulse onset detection algorithm on both clean and noisy ABP pulsatile signals. The results showed that the tested algorithm could

Variable	Clean data (set-p)				Noisy data (set-p2)			
	Without SQA	jSQI	jSQI2	GTM	Without SQA	jSQI	jSQI2	GTM
# recording	100	100	100	100	73	73	73	73
# total onsets	72,313	68,932	71,811	72,110	57,222	35,919	42,546	43,876
# TP onsets	72,132	68,932	71,810	72,079	49,482	35,546	42,114	43,437
# FN onsets	181	0	1	31	7,740	373	432	439
# FP onsets	141	23	115	123	7,532	828	3,925	3,970
Se (%)	99.75	100	100	99.96	86.47	98.96	98.98	99.00
P_+ (%)	99.80	99.97	99.84	99.83	86.79	97.72	91.47	91.63
Acc (%)	99.56	99.97	99.84	99.79	76.42	96.73	90.62	90.79

Table 2. Results of the tested open-source pulse onset detection algorithm for both clean and noisy databases.

achieve high detection accuracy on the clean data with Acc measure of 99.56%. However, the Acc measure dropped to 76.42% when evaluated on the noisy data, indicating the strong noise response on the tested algorithm.

We compared the accuracy of the tested algorithm between with and without SQA applied. By using SQA to remove noisy beats, Acc measures were slightly enhanced for the clean data, and greatly enhanced for noisy data. Thus, implementing a SQA procedure is necessary for the pulse onset detection algorithm, especially when processing low quality signals. We also compared the performances of three different SQA procedures and the results showed that the open-source jSQI method tends to identify many high SQ pulse beats as poor SQ beats. jSQI2 and a novel GTM methods were shown to be more accurate for assessing the ABP signal quality than jSQI.

The novelty of the GTM method described here for assessing the ABP pulse signal quality, like the other two methods, does not require a pre-learning process to obtain the pulse templates and can perform the analysis from the first beat. The GTM method has potential utility for use in the SQA of pulsatile signals in real-time environments. Moreover, the creation of a bespoke template on a per-patient basis, during a rapid learning period, and then later adapting over time, provides the potential for a more accurate system, tuned to a variety of waveforms, which do not exhibit natural upper and lower bounds (such as the photoplethysmogram).

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