Automated detection of pulse using continuous invasive arterial blood pressure in patients during cardiopulmonary resuscitation

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Abstract

Continuous invasive arterial blood pressure (ABP) and its characteristic waveform features are widely used to monitor cardiovascular health. The invasive ABP signal has been proven useful to guide therapy during cardiopulmonary resuscitation (CPR) of patients in cardiac arrest. Automated algorithms to compute ABP parameters were not designed to work during CPR, so their performance in this scenario is unknown. The aim of this study was to develop automated algorithms to detect pulse and measure physiological ABP variables during CPR. A dataset of 122 segments of invasive ABP were extracted from 26 patients with regular ECG and a total duration of 262 min*. The ABP was denoised using a stationary wavelet decomposition and pulse peaks were detected in the first difference of the ABP by applying adaptive thresholding. The following parameters were computed: systolic blood pressure (SBP), diastolic blood pressure (DBP), pulse pressure (PP) and heart rate (HR). The algorithm presented a median (IQR) Se/PPV/F1 of* $97.6(17.5)/99.3(10.0)/97.2(10.1)\%$ *for diastolic peak detection, 4-points above the F1 obtained with Physionet's wabp algorithm. The absolute and relative errors were* $0.62(1.40)mmHg$ *and* $1.22(1.62)\%$*,* $0.74(1.43)mmHg$ *and* $1.81(2.76)\%$*,* $1.13(1.67)mmHg$ *and* $4.68(4.86)\%$*,* $0.50(1.42)min^{-1}$ *and* $0.58(1.31)\%$ *for SBP, DBP, PP and HR, respectively.*

1. Introduction

Arterial blood pressure (ABP) monitoring is widely used in modern medicine to prevent, detect and evaluate cardiovascular diseases [1–3]. The ABP signal waveform contains valuable information about the cardiovascular system, including heart rate, blood pressure values and pulse waveform [4, 5].

The invasive ABP signal is also used to monitor cardiovascular health during post cardiac arrest care and in intensive care units, and it is recommended to monitor hemodynamically unstable patients [3, 6, 7]. To improve survival rates, the American Heart Association and the Australian Resuscitation guidelines recommended that during post resuscitation care systolic blood pressure (SBP) to be mantained above $90\,\mathrm{mmHg}$ and $100\,\mathrm{mmHg}$, respectively [8–10]. Furthermore, invasive ABP has been proven to be useful to guide therapy during cardiopulmonary resuscitation (CPR) [11–14].

Several automatic algorithms have been proposed to denoise and characterize the ABP signal [4, 5, 15], which is usually corrupted by artifacts such as clotting, movement artifacts and high frequency noise [1, 16]. Filters are applied to remove noise and artefact before calculating physiological ABP variables, such as systolic blood pressure (SBP), diastolic blood pressure (DBP), pulse pressure (PP), heart rate (HR) and the dicrotic notch [4, 5, 15].

Known automated algorithms were designed for hemodynamically stable patients, but they have not been tested during CPR. The aim of this study was to develop automated algorithms to detect pulse and measure physiological ABP variables in patients during CPR once spontaneous circulation was restored..

2. Materials

The dataset used in this study was recorded by the physician manned rapid response car of the Oslo Emergency Medical System in patients during out-of-hospital cardiac arrest. All episodes were recorded using LifePak 15 defibrillators, and include the ECG and the invasive ABP (radial cannulation) signals, both with a sampling frequency of $250\,\mathrm{Hz}$.

A total of 122 segments with concurrent recordings of ECG and ABP were extracted from 26 patients during periods without chest compressions. The top pannel of Figure 1 shows $5\,\mathrm{s}$ of the ABP waveform, where the main variables, SBP, DBP and PP are annotated. The total du-

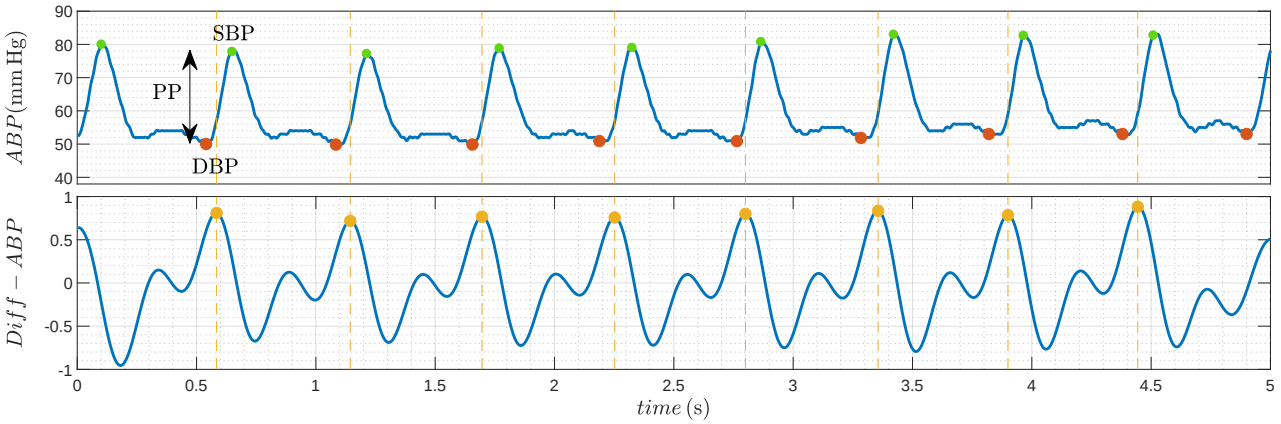

Figure 1. The top panel represents a 5 s segment of the ABP waveform. SBP and DBP, are indicated by green and red dots, respectively. The bottom panel shows the first difference of the ABP signal where yellow dots and dash lines show the peak value and instant of the first difference, respectively, ,associated to the time-stamp of the CBP.

ration of the dataset was 262 min, with a mean duration of 2.15 $\pm$ 5 min per segment. The SBP and DBP of each heartbeat were manually annotated to be used as gold standard.

3. Methods

Figure 2 shows the overall scheme followed in this study to detect peaks in the ABP signal and measure the ABP variables. First, the ABP signal was preprocessed to remove undesired components. Then, an adaptive peak detector was applied to the first difference of the ABP waveform to determine systolic and diastolic instants. Finally, the physiological variables were computed from the original ABP signal.

3.1. Signal preprocessing

The ABP signal was preprocessed using the stationary wavelet transform (SWT) to remove baseline wandering and high frequency noise. An 8-level SWT decomposition was used with a Daubechies-4 mother wavelet and soft thresholding. Detail coefficients d_6 and d_7 were used to reconstruct the denoised ABP signal, $\mathrm{ABP}_{\mathrm{filt}}$, corresponding to the $1 - 4$ Hz frequency band.

3.2. Pulse peak detection

The pulse peaks were detected in the first difference of the ABP signal. Peaks with first difference above a threshold for i-th pulse were considered, and the threshold was adapted according to the following equation:

$$Th_i = \text{median}(P_{i-1} : P_{i-5}) \quad (1)$$

where the median amplitude of the previous 5 peaks were considered. A minimum distance of 300 ms was set between consecutive peaks.

The local maxima of the first difference in each heartbeat correspond to the maximum upslope of the ABP pulse, as shown in Figure 1. The systolic and diastolic

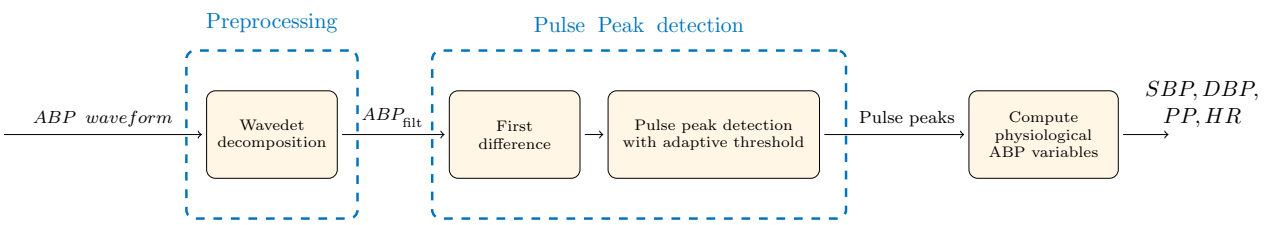

Figure 2. Overall scheme of the automated method applied to the ABP waveform to compute the pulse peaks and the ABP features.

time-stamp were computed by identifying the posterior and previous inflexion points to the instance of the maximum upslope in ABP signal, respectively. At the top panel of Figure 1 the instant of the maximum upslope is shown as a yellow dash line, and the SBP and DBP by red and green dots, respectively.

3.3. Computation of the physiological ABP variables

Variables used to monitor cardiovascular health were computed from the raw ABP signal using the systolic and diastolic time-stamp. SBP and DBP were used to compute the PP, their difference. The HR was computed as the inverse of the median distance between consecutive diastolic peaks.

3.4. Statistical evaluation

The ABP time-point detector proposed in this study was compared to the wabp algorithm from Physionet, a well known method proposed by Zong et al. [4].

Manually annotated diastolic time-stamp were considered as ground truth to evaluate the methods. A detected time-point was considered a positive heartbeat detection if it fell within $300\,\mathrm{ms}$ of the ground truth. Methods were evaluated in terms of sensitivity (Se): percentage of correctly detected heartbeats; positive predictive value (PPV): percentage of detected heartbeats that are actual heartbeats; and F-score (F1): the harmonic mean of Se and PPV. The performance metrics were computed per patient and the final results were presented as the median (interquartile range, IQR) of all patients.

The absolute error of the physiological ABP variables were computed patient wise so all patients contributed equally.

4. Results

Table 1 shows the Se, PPV and F1 of the proposed pulsebeat detector, and results are compared those of the wabp algorithm. It can be observed that the new algorithm outperformed the wabp algorithm in 27-points of Se, 1-point of PPV and 5-points of F1.

Table 1. Performance of the method introduced in this study compared to the wabp algorithm for heartbeat detection (using the diastolic time-point). The table shows the median (IQR) values for Se, PPV and F1.

	Se (%)	PPV (%)	F1 (%)
This study	97.6 (17.5)	99.3 (10.0)	97.2 (10.1)
Zong et al. [4]	70.2 (85.0)	98.3 (100.0)	92.9 (61.1)

In Table 2 the absolute and percentage errors are reported for the SBP, DBP, PP and HR derived from the diastolic and systolic time-point detections. It can be observed that absolute errors were below or close to $1\,\%$ for the pressure values, and bellow $5\,\%$ in percentage errors.

Table 2. Performance of the method to compute physiological ABP variables. The table shows the median (IQR) absolute and percentage errors for SBP, DBP, PP and HR.

	Absolute error	Percentage error
SBP	$0.62\,(1.40)\,\mathrm{mmHg}$	$1.22\,(1.62)\,\%$
DBP	$0.74\,(1.43)\,\mathrm{mmHg}$	$1.81\,(2.76)\,\%$
PP	$1.13\,(1.67)\,\mathrm{mmHg}$	$4.68\,(4.86)\,\%$
HR	$0.50\,(1.42)\,\mathrm{min}^{-1}$	$0.58\,(1.31)\,\%$

Figure 3 shows three examples of ABP segments of the dataset. In the first example the proposed diastolic peak detector and the wabp algorithm correctly identified every diastolic time-point. The second and third examples show cases where the wabp algorithm missed several heartbeats, which were correctly detected by the proposed algorithm.

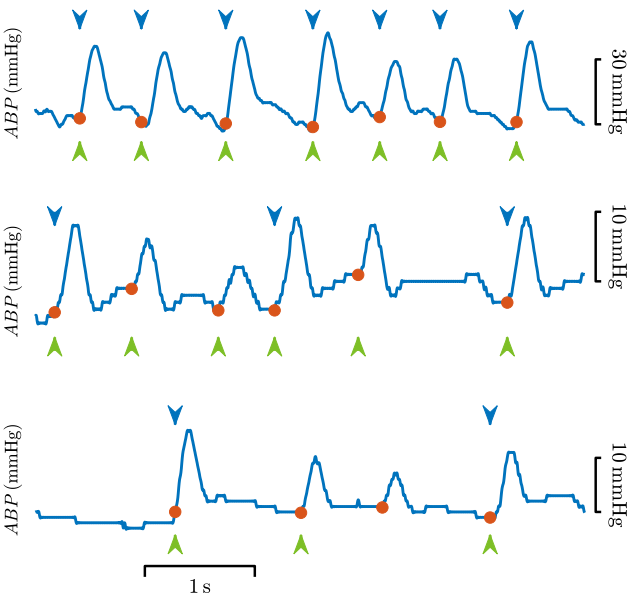

Figure 3. Three examples of the performance of the diastolic time-point detection algorithm. The gold standard annotations are shown as red dots, and the annotations of the algorithms in green (this study) and blue (wabp algorithm).

5. Discussion and conclusions

The invasive ABP signal is widely used to monitor cardiovascular health in patients with different diseases. However, current methods to automatically monitor the ABP signal were designed to be used with hemodynamically stable patients. This is, to the best of our knowledge, the first automatic method that detects diastolic and systolic time-stamp during CPR, which could be used thereafter to accurately compute the characteristic ABP variables.

Current ABP algorithms are inaccurate durig CPR due to the irregular waveform and the noise/artifact components of the ABP signal. The wabp algorithm showed low sensitivity compared to the algorithm proposed in this study ($70\,\%$ vs $97\,\%$). During CPR the pulse pressure showed high amplitude variability in short intervals, intrapatient SD of $3.3\,\mathrm{mmHg}$ and interpatient SD of $20.6\,\mathrm{mmHg}$ in this dataset, and the proposed algorithm based on adaptive thresholding outperformed the classical method. Filtering the signal using the SWT was also more efficient than using constant coefficient filters, and improved the accuracy of the heartbeat detector. Consequently the overall F1 score was more than four points above, and the physiological variables were computed with errors below or close to $1\,\%$.

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