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 during chest compression pauses from 26 patients with regular ECG during 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 mmHg and 100 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 chest compression pauses in CPR therapy.

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 Hz.

A total of 122 segments with concurrent recordings of ECG and ABP were extracted from 26 patients during chest compression pauses, periods without chest compressions artifacts. The top pannel of Figure 1 shows 5 s of

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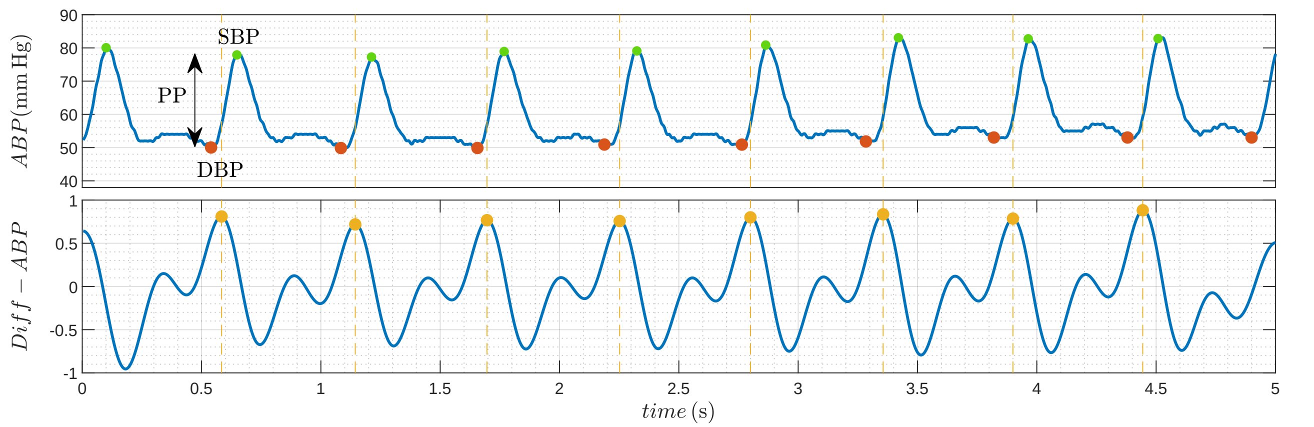

Figure 1. The top panel represents a 5 s segment of the ABP waveform. SBP and DBP, are indicated by green and red dots, respectively. The bottom panel shows the first difference of the ABP signal where yellow dots and dash lines show the peak value and instant of the first difference, respectively.

the ABP waveform, where the main variables, SBP, DBP and PP are annotated. The total duration of the dataset was $262\,\mathrm{min}$, with a mean duration of $2.15 \pm 5\,\mathrm{min}$ per segment. The systolic and diastolic peaks 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 peaks. 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 $1 - 4\,\mathrm{Hz}$ frequency band.

3.2. Pulse peak detection

The systolic peak, corresponding to the maximum pressure value of the heartbeat, and the diastolic peak, corresponding to the inflection just before heartbeat compression phase, were computed for each heartbeat. Heartbeats were detected using 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:

$$Th_i = \mathrm{median}(P_{i-1} : P_{i-5})/2 \qquad (1)$$

where the median amplitude of the previous 5 peaks were considered. A minimum distance of $300\,\mathrm{ms}$ was set between consecutive peaks.

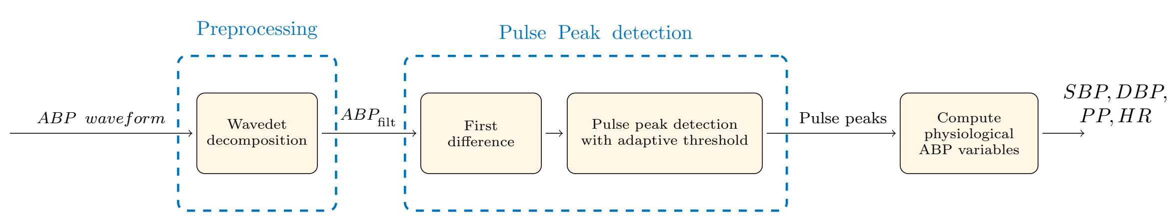

Figure 2. Overall scheme of the automated method applied to the ABP waveform to compute the pulse peaks and the ABP features.

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 peaks 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 systolic and diastolic peaks 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 peaks. 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 heartbeat 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 peaks were considered as ground truth to evaluate the methods. A detected peak was considered a positive heartbeat detection if it fell within 300 ms of the ground truth. Methods were evaluated in terms of sensitivity (Se): percentage of correctly detected peaks; positive predictive value (PPV): percentage of detected peaks that are actual peaks; 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 heartbeat 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.

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

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 peak. The second and third examples show cases where the wabp algorithm missed several peaks, which were correctly detected by the proposed algorithm.

Table 1. Performance of the method introduced in this study compared to the wabp algorithm for heartbeat detection (using the diastolic peak). 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)

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) mmHg	1.22 (1.62) %
DBP	0.74 (1.43) mmHg	1.81 (2.76) %
PP	1.13 (1.67) mmHg	4.68 (4.86) %
HR	0.50 (1.42) min^{-1}	0.58 (1.31) %

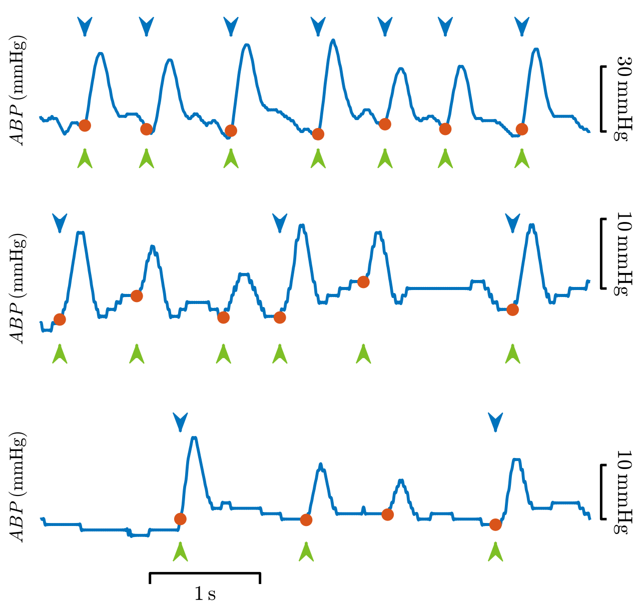

Figure 3. Three examples of the performance of the diastolic peak detection algorithm. The gold standard annotations are shown as red dots, and the annotations of the algorithms in green (this study) and blue (wabp algorithm).

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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References

[1] Marino PL. The ICU book. Lippincott Williams & Wilkins, 2007.

[2] Williams JS, Brown SM, Conlin PR. Blood-pressure measurement. N Engl J Med 2009;360(5):e6.

[3] Muntner P, Shimbo D, Carey RM, Charleston JB, Gaillard T, Misra S, Myers MG, Ogedegbe G, Schwartz JE, Townsend RR, et al. Measurement of blood pressure in humans: a scientific statement from the American Heart Association. Hypertension 2019;73(5):e35–e66.

[4] Zong W, Heldt T, Moody G, Mark R. An open-source algorithm to detect onset of arterial blood pressure pulses. In Computers in Cardiology, 2003. IEEE, 2003; 259–262.

[5] Li BN, Dong MC, Vai MI. On an automatic delineator for arterial blood pressure waveforms. Biomedical Signal Processing and Control 2010;5(1):76–81.

[6] Avolio AP, Butlin M, Walsh A. Arterial blood pressure measurement and pulse wave analysis—their role in enhancing cardiovascular assessment. Physiological Measurement 2009;31(1):R1.

[7] Li-wei HL, Saeed M, Talmor D, Mark R, Malhotra A. Methods of blood pressure measurement in the icu. Critical Care Medicine 2013;41(1):34.

[8] Bray JE, Bernard S, Cantwell K, Stephenson M, Smith K, Committee VS, et al. The association between systolic blood pressure on arrival at hospital and outcome in adults surviving from out-of-hospital cardiac arrests of presumed cardiac aetiology. Resuscitation 2014;85(4):509–515.

[9] Peberdy MA, Callaway CW, Neumar RW, Geocadin RG, Zimmerman JL, Donnino M, Gabrielli A, Silvers SM, Zaritsky AL, Merchant R, et al. Part 9: post–cardiac arrest care: 2010 american heart association guidelines for cardiopulmonary resuscitation and emergency cardiovascular care. Circulation 2010;122(18_suppl_3):S768–S786.

[10] Australian Resuscitation Council NZRC. Post-resuscitation therapy in adult advanced life support. arc and nzrc guideline 2010. Emergency Medicine Australia 2011;23(3):292–296.

[11] Martin GB, Carden DL, Nowak RM, Lewinter JR, Johnston W, Tomlanovich MC. Aortic and right atrial pressures during standard and simultaneous compression and ventilation cpr in human beings. Annals of Emergency Medicine 1986; 15(2):125–130.

[12] Niemann JT, Rosborough JP, Ung S, Criley JM. Coronary perfusion pressure during experimental cardiopulmonary resuscitation. Annals of Emergency Medicine 1982;11(3):127–131.

[13] Sutton RM, French B, Nishisaki A, Niles DE, Maltese MR, Boyle L, Stavland M, Eilevstjønn J, Arbogast KB, Berg RA, et al. American heart association cardiopulmonary resuscitation quality targets are associated with improved arterial blood pressure during pediatric cardiac arrest. Resuscitation 2013;84(2):168–172.

[14] Sutton RM, Friess SH, Naim MY, Lampe JW, Bratinov G, Weiland III TR, Garuccio M, Nadkarni VM, Becker LB, Berg RA. Patient-centric blood pressure–targeted cardiopulmonary resuscitation improves survival from cardiac arrest. American Journal of Respiratory and Critical Care Medicine 2014;190(11):1255–1262.

[15] Navakatikyan MA, Barrett CJ, Head GA, Ricketts JH, Malpas SC. A real-time algorithm for the quantification of blood pressure waveforms. IEEE Transactions on Biomedical Engineering 2002;49(7):662–670.

[16] Li Q, Mark RG, Clifford GD. Artificial arterial blood pressure artifact models and an evaluation of a robust blood pressure and heart rate estimator. Biomedical Engineering Online 2009;8(1):1–15.

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