Finger Photoplethysmography to Monitor Chest Compression Rate During Out-of-Hospital Cardiac Arrest

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Abstract

Cardiac arrest survival rate is strongly associated with high quality cardiopulmonary resuscitation (CPR), which includes chest compression (CC) rates above 100 min^{-1}. Currently, defibrillator monitors use external hardware such as CPR assist pads to monitor CC rate and give feedback to the rescuer. The photoplethysmogram (PPG) provides information about the level of oxygen saturation in blood and can be easily recorded by a pulse oximeter in the fingertip. The aim of this study was to analyze the feasibility of using the finger PPG to monitor the presence and rate of CCs in out-of-hospital cardiac arrest (OHCA). The dataset used in the study consisted of 112 segments from 46 OHCA patients, with a total duration of 256 min and 27667 CCs. The method is based on the power spectral density analysis of 10 s segments of the PPG. CC presence was determined through thresholding, and CC rate was computed applying a maximum slope criterion. The dataset was divided patient-wise intro training (60%) and testing (40%) sets. For the test set the algorithm presented a sensitivity and a positive predictive value of 85.2% and 98.1% respectively for CC detection, a CC rate error of 2.8 (6.8)min^{-1} and 3.4% of the values with an error above 10%.

1. Introduction

Cardiac arrest is the sudden and unexpected loss of heart function, which if not treated may lead the patient to sudden cardiac death (SCD). SCD is the main cause of death in the industrialized world with an incidence of 38 cases per 100000 person-year in Europe [1]. Early defibrillation and cardiopulmonary resuscitation (CPR), consisting of chest compressions (CCs) and ventilations, permit restoring spontaneous circulation. The latest European Resuscitation Council (ERC) guidelines recommend CCs with a rate of 100-120 min^{-1} and a minimum depth of 5 cm [2].

Some comertial defibrillators are equipped with additional devices that include accelerometers and force sensors to monitor rate and depth of CCs, which are then used to provide real time feedback to rescuers providing CPR [3–6].

The photopletismogram (PPG) signal acquired by fingertip sensors estimates the arterial oxygen saturation of the patient [7, 8] and is widely used to monitor hemodinamically stable patients. For instance, pulse or respiration rates are frequently monitored using the PPG in stress tests [9].

Due to its simplicity and low cost, the PPG signal has been used in different applications. Recently new applications of PPG signal have been proposed in out-of-hospital cardiac arrest (OHCA) [10, 11]. This study analyzes the feasibility of the PPG to accurately provide information on the presence and rate of CCs during OHCA.

2. Materials

The dataset used in this study is a subset of a large database acquired from OHCA patients. The episodes were recorded by the DFW Center for Resuscitation Research (UTSW, Dallas) and the Clackamas County Fire District # 1 (Clackamas, Oregon).

The electronic files recorded by Zoll E-Series defibrillators were collected from 46 patients. A total of 112 segments were extracted with concurrent PPG and the CC-wave signal acquired by the CPR-padz feedack device. The CC-depth signal was also available with the instants and depths of every CC detected by the CPR-padz. The segments included at least 60 s of CCs with gaps of maximum 10 s.

Figure 1 shows an example of a raw PPG segment (top panel) and the CC-depth signal (bottom panel) that provides information about the depth and the instants of CCs.

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3. Methods

3.1. Preprocessing and filtering

The PPG signal was preprocessed firstly with an interpolation filter (cubic spline) to fill the gaps presented in the raw signal. Then it was band-pass filtered between 1-3.2 Hz using an order 3 Butterworth filter to removed the baseline drift and low and high frequency noise. Figure 1 also shows the preprocessed PPG and the band-pass filtered signal.

3.2. CC presence detection

The preprocessed PPG signal was windowed using 10 s Kaiser (β=3) window with 50% of overlap. Then, the power spectral density (PED) was calculated as the square of the module of the 4096-point Fast Fourier Transform. First the main frequency of the compressions, f_{cc}, was identified as the frequency correspondig to the PED peak for which the lobe around the peak presented the highest value. If the power around f_{cc} was higher than a given percentage, P_{th}, the segment was labelled as a CC segment.

Figure 2 shows a 10 s window of the PPG and the PED in terms of CC rate(min^{-1}).

3.3. CC rate calculation

For segments labelled as CC segments, the rate of the compressions was considered to be f_{cc}, the main frequency on the PED. Figure 2 shows a 10 s window of the filtered PPG, the CC-wave and the PED in terms of CC rate (min^{-1}). The dashed green line in the PED represents f_{cc}, while the dashed red line depicts f_g, the CC rate computed from the instants, t_i, marked on the CC-wave. f_g was computed as the inverse of the median time intervals between compressions (t_{i+1}- t_i) and it was used as gold standard to evaluate the accuracy of the algorithm based on the PPG.

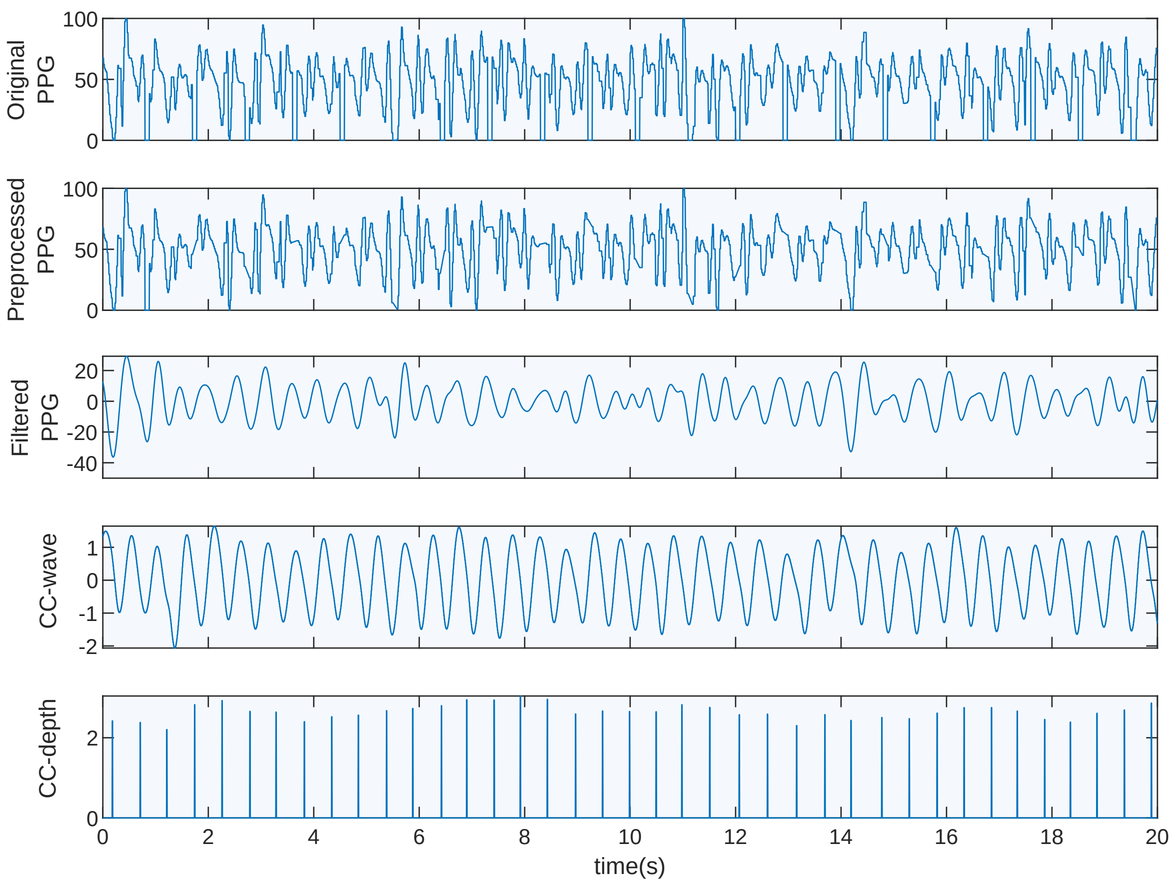

Figure 1. An example of a segment of the dataset of the study. From top to bottom: the segment of the original, preprocessed and filtered PPG; the signal provided by the CPR-padz, the CC-wave and the CC-depth, used as gold standard.

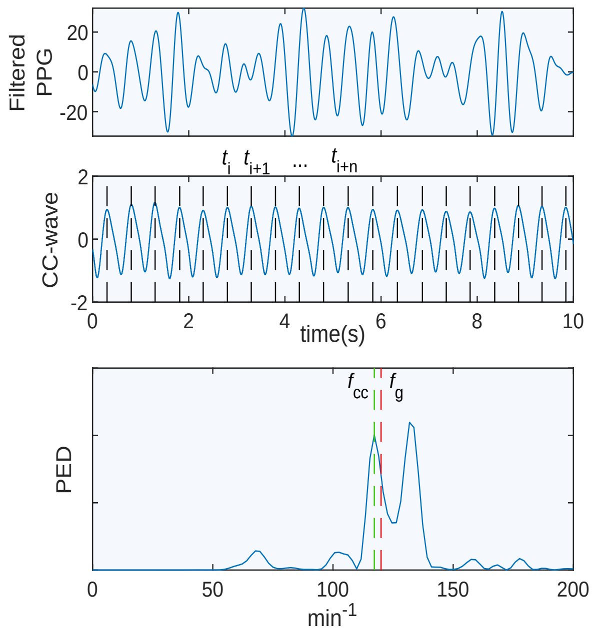

Figure 2. A 10 s window of the filtered PPG, the CC-wave signal and the PED used to compute the presence and rate of CCs. The instants of CCs, t_{i}, are depicted as vertical lines on the CC-wave signal. The peak of the PED was identified as the CC rate, f_{cc}, and compared the rate obtained from the gold standard, f_{g}.

3.4. Statistical evaluation of the algorithm performance

CC presence was evaluated in terms of sensitivity (Se), proportion of windows with CCs correctly identified, and positive predictive value (PPV), proportion of windows identified with CCs that truly had CCs. A segment was labelled as CC segment if the more than 10 compressions were present in the 10 s interval.

The accuracy of the algorithm computing the CC rate was evaluated by comparing f_{cc} and f_{g}. The mean (standard deviation, SD) of the absolute error and the percentage of errors above 10% (Pe_{10}) were calculated. The Bland-Altman plot for the error for the complete dataset and the error per patient were computed.

Data were randomly split patient-wise into training/test sets (60/40%), to optimize the P_{th} and validate the method, respectively. This procedure was repeated 50 times to obtain statistically meaningful results.

4. Results

The dataset containing 112 segments with a total duration of 256 min and 27667 CCs were analyzed. The mean (SD) duration of the segments was 137 (115) s with 247 (213) CCs per segment. A total of 2907 windows

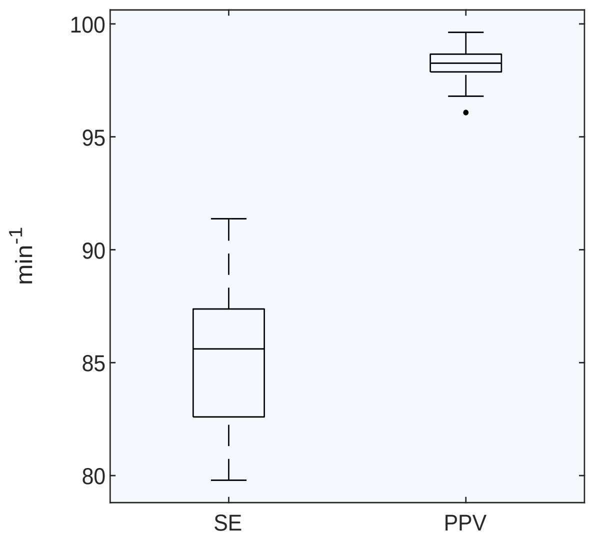

Figure 3. Sensitivity and positive predictive value per replica for the test set. The box shows the median and interquartile range (IQR), and the whiskers the last values within ±1.5 IQR

(84.4% with CCs) were processed.

The average performance of the algorithm in terms of mean (SD) in the training dataset was Se= 87.6 (2.1)%, PPV= 98.1 (0.4)%, absolute CC rate error of 2.4 (0.3) min^{-1} and Pe_{10}= 2.4 (0.8)%. For the test set the average performance was Se= 85.2 (3.1)%, PPV= 98.1 (0.7)%, absolute CC rate of 2.8 (0.5) min^{-1} and Pe_{10}= 3.4 (1.4)%.

Figure 3 shows the performance of CC rate calculation. The box plots represents the sensitivity and positive predictive value for the 50 repetitions for the test set.

Figure 4 shows the Bland-Altman plot for the error f_{cc}-f_{g} for one replica with P_{th}= 26. The black line shows the mean error, 1.39 min^{-1}, and the dashed black lines show the 95% level of agreement.

5. Discussion and conclusions

Monitoring the quality of CPR is crucial to adhere the rate of CCs to the range recommended by resuscitation guidelines. Current defibrillators require additional hardware with accelerometers or force sensors to evaluate the CC rate. The PPG signal is a commonly used to estimate the arterial oxygen saturation of the patient, and it can be easily acquired by simple fingertip sensors. This study evaluates the feasibility of using the PPG to detect the presence and rate of CCs in OHCA.

The proposed method was tested with segments of PPG signals including CCs. The algorithm processed windows of 10 s and provided a Se/PPV of 85/98% and a mean CC

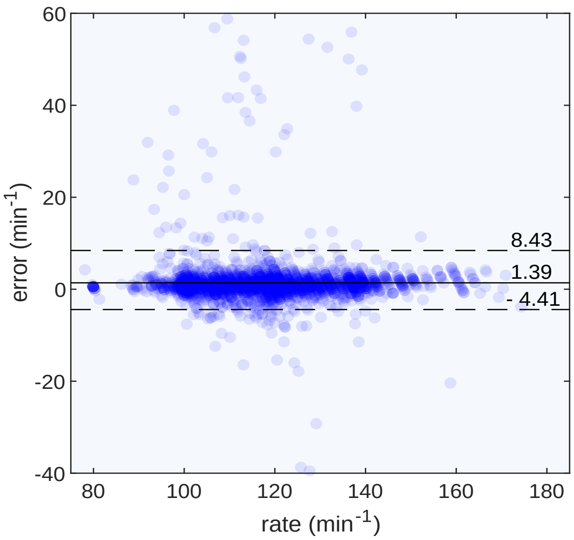

Figure 4. Blad-Altman plot of the CC rate error for one replica with P_{th}=26. The black line shows the mean error, and the dashed black lines depict the 95% level of agreement.

rate absolute error of of 2.8 min^{-1}.

This algorithm would permit giving feedback to the rescuer on the CC rate every 5 s. Nevertheless, further analysis are required with complete PPG signals of larger datasets.

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References

[1] Atwood C, Eisenberg MS, Herlitz J, Rea TD. Incidence of EMS-treated out-of-hospital cardiac arrest in Europe. Resuscitation 2005;67(1):75–80.

[2] Nolan JP, Soar J, Zideman DA, Biarent D, Bossaert LL, Deakin C, Koster RW, Wyllie J, Böttiger B. European resuscitation council guidelines for resuscitation 2010 section 1. Executive summary. Resuscitation 2010;81(10):1219–1276.

[3] Abella BS, Edelson DP, Kim S, Retzer E, Myklebust H, Barry AM, OHearn N, Hoek TLV, Becker LB. CPR quality improvement during in-hospital cardiac arrest using a real-time audiovisual feedback system. Resuscitation 2007; 73(1):54–61.

[4] Kramer-Johansen J, Myklebust H, Wik L, Fellows B, Svensson L, Sørebø H, Steen PA. Quality of out-of-hospital cardiopulmonary resuscitation with real time automated feedback: a prospective interventional study. Resuscitation 2006;71(3):283–292.

[5] Yeung J, Meeks R, Edelson D, Gao F, Soar J, Perkins GD. The use of CPR feedback/prompt devices during training and CPR performance: a systematic review. Resuscitation 2009;80(7):743–751.

[6] Gruber J, Stumpf D, Zapletal B, Neuhold S, Fischer H. Real-time feedback systems in CPR. Trends in Anaesthesia and Critical Care 2012;2(6):287–294.

[7] Tamura T, Maeda Y, Sekine M, Yoshida M. Wearable photoplethysmographic sensorspast and present. Electronics 2014;3(2):282–302.

[8] Elgendi M. On the analysis of fingertip photoplethysmogram signals. Current cardiology reviews 2012;8(1):14–25.

[9] Allen J. Photoplethysmography and its application in clinical physiological measurement. Physiological Measurement 2007;28(3):R1.

[10] Wijshoff RW, van der Sar T, Peeters WH, Bezemer R, Aelen P, Paulussen IW, Ordelman SC, Venema A, van Berkom PF, Aarts RM, et al. Detection of a spontaneous pulse in photoplethysmograms during automated cardiopulmonary resuscitation in a porcine model. Resuscitation 2013;84(11):1625–1632.

[11] Xu J, Li C, Zheng L, Han F, Li Y, Walline J, Fu Y, Yao D, Zhang X, Zhang H, et al. Pulse oximetry: A noninvasive, novel marker for the quality of chest compressions in porcine models of cardiac arrest. PLoS ONE 2015; 10(10):e0139707.

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