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

Andoni Elola¹, Jon Urteaga¹, Elisabete Aramendi¹, Unai Irusta¹, Erik Alonso¹, Mohamud Daya², Pamela Owens³, Ahamed Idris³

¹ University of the Basque Country, Bilbao, Spain
² Oregon Health & Science University, Portland, OR, USA
³ University of Texas SouthWestern Medical Center, TX, USA

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%.

Some commercial 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 photoplethysmogram (PPG) signal acquired by fingertip sensors estimates the arterial oxygen saturation of the patient [7, 8] and is widely used to monitor hemodynamically 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 feedback 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.
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 ($\beta$=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

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.
compressions ($t_{i+1} - t_i$) and it was used as gold standard to evaluate the accuracy of the algorithm based on the PPG.

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 (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 esti-
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 rate absolute error 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.

**Acknowledgements**

This work received financial support from the Spanish Ministerio de Economía y Competitividad, project TEC2015-64678-R, jointly with the Fondo Europeo de Desarrollo Regional (FEDER), from the University of the Basque Country via Ayuda a Grupos de Investigación GIU17/03, from the Basque Government through the grant PRE 2017 1 0112, and was also partially supported by NIH grant HL 077887 (AHI) and HL 077873.

**References**


Address for correspondence:
E. Aramendi
Engineering School of Bilbao
elisabete.aramendi@ehu.eus