A Method to Measure Ventilation Rate during Cardiopulmonary Resuscitation using the Capnogram

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Abstract

The survival rate in cardiac arrest is associated to the quality of the chest compressions (CCs) and ventilations provided during cardiopulmonary resuscitation (CPR). Hyperventilation remains common whenever ventilation is manual during resuscitation from cardiac arrest. The capnogram is used to monitor respiration and ventilation rates. During CPR chest compressions induce artefacts in the capnogram signal that challenge the detection of ventilations. The evaluation of ventilation detectors during CCs has not been well characterized. In this study an algorithm for ventilation rate monitoring and hyperventilation detection was developed. The processing method consists of detecting transitions in the first difference of the signal, and applying feature based classification to identify every ventilation. The instantaneous rate and hyperventilation minutes were then computed. A set of 20 out-of-hospital episodes, totalling 50864 s (86.6% during CCs) and 6305 ventilations was used to define and evaluate the algorithm. The algorithm had a sensitivity/positive predictive value of 96.9%/96.2% respectively for the ventilation detection (96.7%/95.8% during ongoing CCs), 98.7%/98.7% for the hyperventilation detection, and a mean error of 0.4 (0.8) min^{-1} for the instantaneous ventilation rate.

1. Introduction

The quality of cardiopulmonary resuscitation (CPR) is an important predictor of favourable outcome during cardiac arrest. In order to be effective chest compressions (CCs) and ventilations during CPR should follow current international resuscitation guideline recommendations. For ventilations, a rate of 10-12 ventilations per minute is recommended.

Hyperventilation during CPR decreases cerebral and coronary perfusion pressure contributing to poorer survival rates. Nevertheless, hyperventilation is common in both in- and out-of-hospital cardiac arrest [1, 2].

The 2010 resuscitation guidelines recommend continuous monitoring of the exhaled carbon dioxide (CO_2) during CPR [3]. The capnogram provides a picture of the patients cardiopulmonary respiratory system in form of the CO_2 waveform. In patients with perfusing rhythms the capnogram shows fluctuations with every ventilation, as the CO_2 expired is essentially zero during inspiration, and the concentration rapidly increases during exhalation. The capnogram can be used to detect ventilations and provide feedback to the rescuer on the ventilation rate.

Chest compressions provided to the patient during CPR induce artefacts in the capnogram, and make the automatic computation of the ventilation rate difficult. Few algorithms have been described to detect ventilations using the capnogram signal [2, 4, 5], and their performance during CCs has not been documented. In this study a method is proposed to compute the ventilation rate, and is tested with real out-of-hospital cardiac arrest (OHCA) episodes.

2. Materials

The dataset used in this study was a subset of an OHCA database containing 623 episodes maintained by Tualatin Valley & Fire Rescue (Tigard, Oregon, USA). Every episode was collected using the Philips HeartStartx MRx monitor/defibrillator between 2006 and 2009. Only 199 episodes had the capnogram, the transthoracic impedance (TI) and the compression depth (CD) signals. The capnogram was acquired using sidestream acquisition with a sampling frequency of 40 Hz or 125 Hz, and a resolution of 0.004 mmHg per bit. The CD signal was computed from the force and acceleration of a CPR assist pad, and was used to identify the CC intervals. The TI signal, recorded through defibrillation pads, was used to visually detect the ventilations.

To establish the gold standard, every ventilation was manually annotated by three signal processing engineers visually inspecting the TI and the capnogram. A majority criterion was applied in absence of consensus.

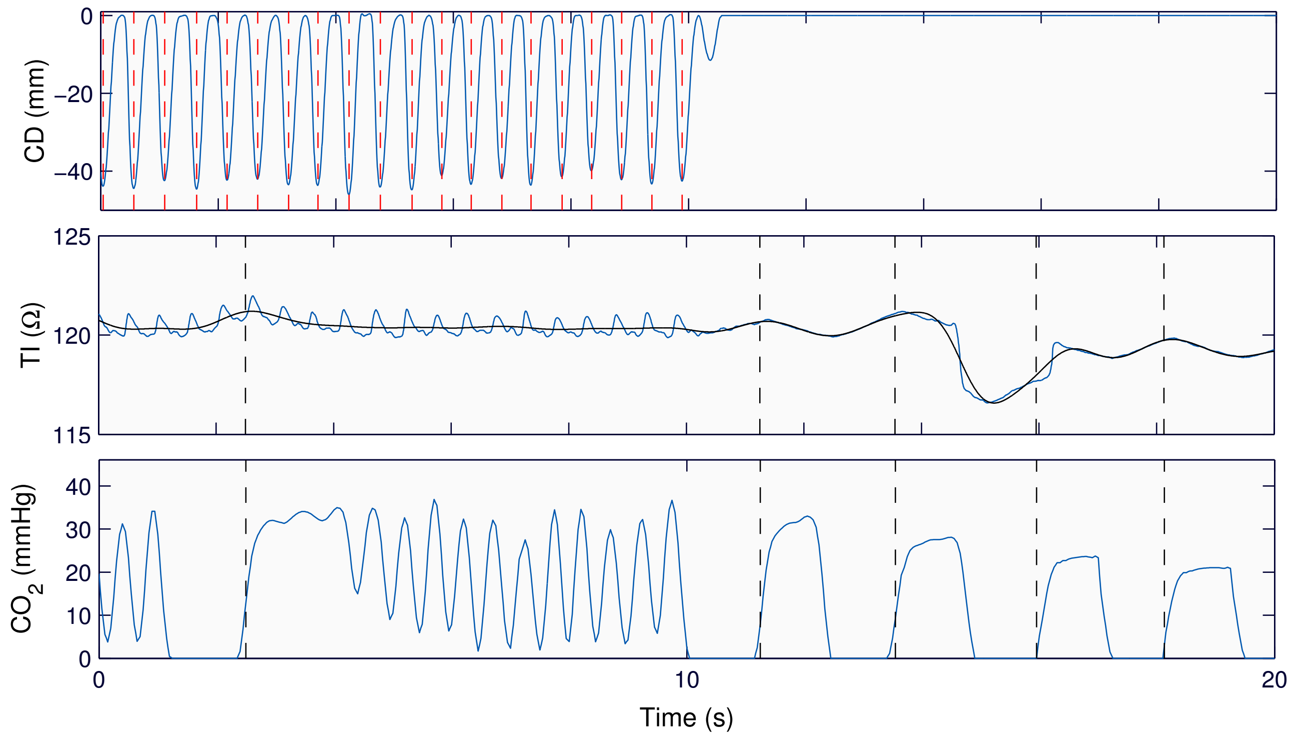

Figure 1. Signals of the database. From top to botton: the CD, the TI (the lowpass filtered TI is shown in black), and the capnogram. CCs are marked with red dashed lines in the CD, and ventilations are marked in black dashed lines in the TI and the capnogram.

A subset of 20 episodes met the following inclusion criteria: concurrent recording of the three signals for at least 2000 s, CCs during 75% of time, and more than 200 ventilations. The episodes amounted to 50864 s (86.6% of time with CCs) and contained 6305 ventilations. The mean (standard deviation) of the episodes was 2543 (400) s.

Figure 1 shows an interval of the signals in an episode of the dataset, including the CD, the TI (overlapped with the signal after filtering the CC artefacts) and the capnogram. CCs are marked in the CD, and ventilation instants are marked both in the TI and the capnogram.

3. Methods

The fluctuations in the capnogram due to ventilations repeat the basic waveform associated to the inflation (inspiration) and deflation (expiration) intervals. Figure 2 shows the intervals associated to the n-th ventilation. The interval between $t_i[n-1]$ and $t_e[n]$ corresponds to the inspiration baseline (first phase). The upstroke/downstroke intervals, second and fourth phase respectively, confine the expiratory plateau interval (third phase).

In this section, first the algorithm to detect the instants of ventilation in the capnogram is described. Then the quality metrics and the procedure to asses the accuracy of the method are defined.

3.1. Ventilation detection in the capnogram

The capnogram was preprocessed using an order 4 butterworth low-pass filter to remove high frequency noise

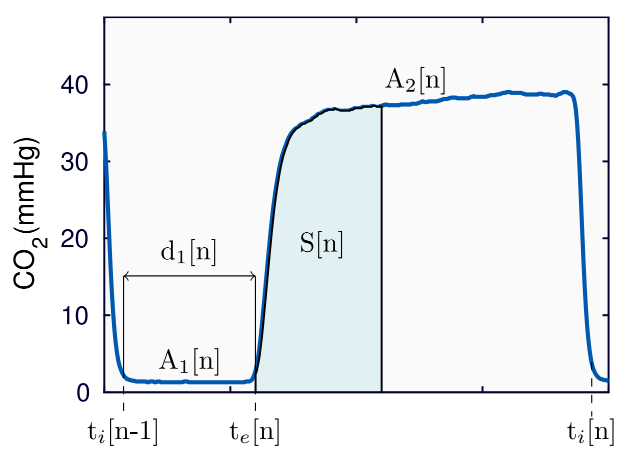

Figure 2. Basic waveform of the capnogram including the features associated to the n-th ventilation. The instants t_e and t_i correspond to the expiration and inspiration times.

($f_c = 10$ Hz). The initial expiration ($t_e[n]$) and inspiration ($t_i[n]$) times of potential ventilations were automatically detected from the positive and negative peaks in the first difference of the capnogram. For every potential ventilation the following features were computed (see Figure 2 for a visual display of the features):

- d_1, duration of the inspiration baseline
- A_1 and A_2, mean amplitudes of the baseline and the plateau intervals, respectively
- S, the area of the 1st second of the expiratory plateau
- $R = \dfrac{A_2 - A_1}{A_2}$, the relative amplitude difference

A feature based decision algorithm discriminated ventilations applying the following criteria:

- $d_1[n]$ must be greater than 0.3 s.
- The refractory interval between ventilations greater than 1.5 s (corresponding to a maximum ventilation rate of 40 min^{-1}).
- $R[n]$, $A_2[n]$ and $S[n]$ must be greater than an adaptive threshold based on the last k ventilations (two ventilations for $S[n]$, and 5 ventilations for $R[n]$ and $A_2[n]$), which was computed as:

$$x_{min}[n] = p \cdot \frac{1}{k} \cdot \sum_{i=n-k}^{n-1} x[i] \qquad (1)$$

where p is a factor between 0 and 1, and $x[n]$ one of the three features mentioned above.

3.2. Ventilation metrics

The instants of ventilations detected in the capnogram can be used to compute the ventilation rate and give feedback to the rescuer. Two CPR quality metrics were evaluated in this study. The instantaneous ventilation rate was defined as the mean rate during a minute and was computed every 15 s. The hyperventilation alarm was defined for instantaneous ventilation rates above 15 min^{-1}, following the criteria established in [6].

3.3. Evaluation

The performance of the ventilation detector was evaluated in terms of Sensitivity (SE) and Positive Predictive Value (PPV) for intervals with and without CCs. SE was defined as the proportion of correctly detected ventilations, and PPV as the proportion of detected ventilations corresponding to real ventilations.

The performance of the hyperventilation detector was also evaluated in terms of SE and PPV. SE was defined as the proportion of minutes manually annotated as hyperventilation that the algorithm identified correctly; PPV was

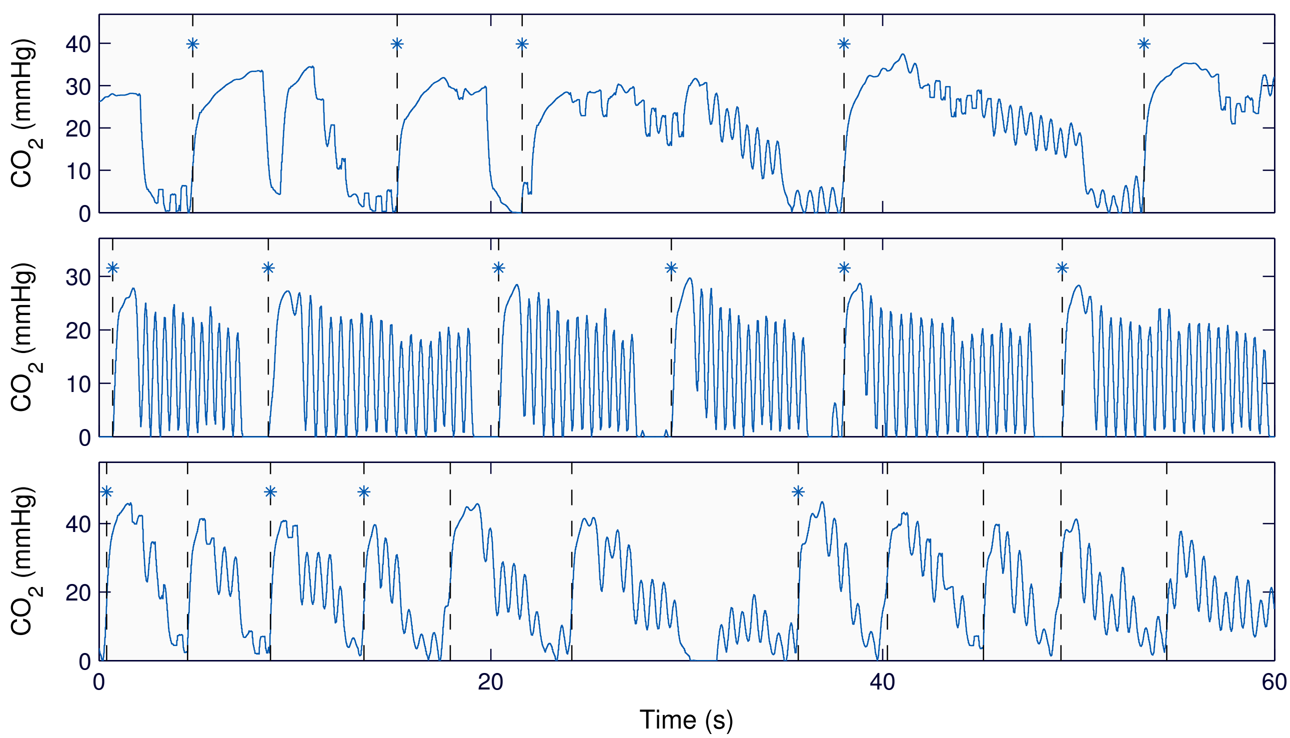

Figure 3. Performance of the algorithm with three episodes of the dataset. The manual annotations of the ventilation instants are shown with dotted lines, and the ventilations detected by the algorithm with asterisks.

defined as the proportion of detected hyperventilation minutes corresponding to manually annotated hyperventilation minutes.

The mean (standard deviation) error for the absolute instantaneous ventilation rate was reported in min^{-1}.

4. Results

For the 20 episodes from the database the instantaneous rate per episode was 12.55 (2.26) min^{-1} and the hyperventilation fraction 26.5 (19.61)%.

The ventilation detector provided SE and PPV of 96.9% and 96.2% respectively for the whole dataset, and 96.7% and 95.8% during ongoing CCs. Figure 3 shows three examples where dashed lines represent manually annotated ventilations, and the asterisks represent the ventilations detected by the algorithm. In the three cases the artefact induced by the CCs is visible in the capnogram. In the first two cases the algorithm reported 100% of SE and PPV. The third example showed very short inspiration baseline intervals, and the CC artefact strongly corrupted all the phases of the capnogram. This was the worst case of the dataset, with a SE and PPV of 84% and 84% respectively.

For hyperventilation detection, the SE/PPV were 98.7%/98.7% respectively, and the mean absolute error of the ventilation rate was 0.4 (0.8) min^{-1} for the entire dataset.

5. Discussion and conclusions

This study proves the feasibility of using the capnogram signal for an accurate detection of the ventilation rate during CPR. An algorithm was developed based on the processed capnogram, and was tested with real OHCA episodes. The algorithm showed a SE and PPV of 96.9% and 96.2% respectively. For validation, the instants of ventilation visually identified in both, the TI and the capnogram, were used. Although that is a well accepted gold standard during CPR [2, 4, 5], testing the algorithm with the reference of airway signals, as flow or volume signals, would improve the reliability of the results. Nevertheless, those reference signals are very rare in a CPR scenario.

The proposed algorithm can be used to give feedback on the instantaneous ventilation rate (mean error 0.4 min^{-1}) and to give a hyperventilation alarm reliably. It could be integrated into advanced monitor/defibrillators and also into the last generation automated external defibrillators that include the capnography signal.

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