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Abstract

Aim

The rates of chest compressions (CCs) and ventilations are both important metrics to monitor the quality of cardiopulmonary resuscitation (CPR). Capnography permits monitoring ventilation, but the CCs provided during CPR corrupt the capnogram and compromise the accuracy of automatic ventilation detectors. The aim of this study was to evaluate the feasibility of an automatic algorithm based on the capnogram to detect ventilations and provide feedback on ventilation rate during CPR, specifically addressing intervals where CCs are delivered.

Methods

The dataset used to develop and test the algorithm contained in-hospital and out-of-hospital cardiac arrest episodes. The method relies on adaptive thresholding to detect ventilations in the first derivative of the capnogram. The performance of the detector was reported in terms of sensitivity (SE) and Positive Predictive Value (PPV). The overall performance was reported in terms of the rate error and errors in the hyperventilation alarms. Results were given separately for the intervals with CCs.

Results

A total of 83 episodes were considered, resulting in 4880 min and 46,740 ventilations (8741 during CCs). The method showed an overall SE/PPV above 99% and 97% respectively, even in intervals with CCs. The error for the ventilation rate was below 1.8 $min^{-1}$ in any group, and >99% of the ventilation alarms were correctly detected.

Conclusion

A method to provide accurate feedback on ventilation rate using only the capnogram is proposed. Its accuracy was proven even in intervals where canpography signal was severely corrupted by CCs. This algorithm could be integrated into monitor/defibrillators to provide reliable feedback on ventilation rate during CPR.

Keywords: Capnography, Ventilation monitoring, Cardiopulmonary resuscitation, Hyperventilation

# Feasibility of the capnogram to monitor ventilation rate during cardiopulmonary resuscitation

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*Results*: A total of 83 episodes were considered, resulting in 4880 min and 46740 ventilations (8741 during CCs). The method showed an overall SE/PPV above 99% and 97% respectively, even in intervals with CCs. The error for the ventilation rate was below $1.8\,\text{min}^{-1}$ in any group, and $> 99\%$ of the ventilation alarms were correctly detected.

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## Keywords

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# 1. INTRODUCTION

Quality of cardiopulmonary resuscitation (CPR) is a key factor in the outcome of cardiac arrest patients. Advanced life support (ALS) treatment of out-of-hospital cardiac arrest (OHCA) includes good-quality chest compressions (CCs) and a reliable airway management. The 2015 resuscitation guidelines recommend continuous chest compressions after intubation, ventilation rates of $10\,\text{min}^{-1}$ and avoidance of hyperventilation.[1] Hyperventilation increases intrathoracic pressure, reshapes the oxygen dissociation curve (increasing oxygen affinity) and behaves as a cerebral vasoconstrictor.[2,3] It has also has been proven to lower coronary perfusion pressure and to contribute to hemodynamic deterioration in animal experiments.[4–8] All these factors decrease the probability of survival.[9,10] Nevertheless rescuers providing pre-hospital CPR often exceed the recommended ventilation rates. Several studies report rates ranging from moderate ($14\ \text{min}^{-1}$) to severe ($> 20\,\text{min}^{-1}$) hyperventilation during long duration OHCA.[5–7,9–12]

CPR feedback systems, either standalone or incorporated into defibrillators, have been shown to improve adherence to guideline recommendations.[13,14] Feedback on CCs based on acceleration, force or thoracic impedance (TI) has been extensively studied;[11,15–17] but little attention has been given to feedback on ventilation rate during CPR. The TI channel, recorded through the defibrillation pads, has been explored to monitor ventilation rate.[11,18,19] However, an analysis of long resuscitation episodes showed that artefacts limit the reliability of TI for instantaneous feedback on ventilation rate.[17] Currently, no commercial system is available for feedback on ventilation rate using the TI.

The recently released resuscitation guidelines have placed an increased emphasis on the use of the capnogram during CPR to monitor, among other things, ventilation rate and to avoid hyperventilation.[1] During CPR compression artefacts often corrupt the capnogram compromising the accuracy of automatic algorithms for ventilation rate feedback.[20–22] Few such algorithms have been published,[23,24] and their performance during CPR has not been systematically evaluated and/or documented.

This study proposes an automatic algorithm for ventilation detection during CPR based on the typical waveform characteristics of the capnogram and on the use of adaptive thresholds to identify ventilations. The aim of the study is to analyse the feasibility of using the capnogram to provide an accurate automated feedback on ventilation rate and hyperventilation alarms during CPR.

## 2. MATERIALS AND METHODS

### *2.1. Data materials*

Two datasets of episodes with signals from monitor/defibrillators were used in this study, an out-of-hospital dataset (OHD) and an in-hospital dataset (IHD). The OHD was recorded during cardiac arrest, with manual CPR (CCs and ventilations) provided in all episodes. The signals available to monitor ventilations were the TI and the capnogram. The IHD corresponded to patients who suffered cardiac arrest, some recorded during manual CPR (CCs and ventilations) and some recorded after cardiac arrest during postresucitation care (mechanical ventilation). They were monitored with the capnogram and the expired air flow.

The OHD was a subset of a large OHCA registry containing 623 episodes maintained by the Tualatin Valley Fire & Rescue (Tigard, Oregon, USA), an ALS first response agency. The episodes were collected using the HeartStart MRx monitor/defibrillator (Philips, Andover, MA) between 2006 and 2009. Ventilations in these episodes were provided manually with an endotracheal tube or laryngeal tube airway. Episodes with at least 20 minutes of concurrent and readable recordings of the compression depth (CD), the TI and the capnogram were included in this study, resulting in a dataset of 62 episodes. The CD signal from the Q-CPR assist pad by Philips was used to identify the intervals with CCs. The capnogram was acquired using Microstream (sidestream acquisition) with a sampling rate of 40/125 Hz and a resolution of 0.004 mmHg per bit. The instants of ventilations were marked in the TI ventilation channel,[11,17] first automatically and then manually reviewed by three experienced biomedical engineers. Reviewers used the capnogram to make a decision in unclear intervals. Fig. 1 shows examples of two episodes of the OHD, where ventilations are visible in both the TI ventilation channel (in black) and the capnogram, for an artefact free interval (panel a), and when CCs were provided (panel b).

The IHD was a subset of the APACHI study conducted by Philips Healthcare at the Medical University of Vienna between November 2012 and January 2014. The APACHI study recorded physiological signals (arterial blood pressure, electrocardiogram, photoplethysmogram, capnogram and airway flow and pressure) from multiple monitors during hemodynamic crisis in the emergency department of the Vienna General Hospital, under the direction of Drs. Sterz and Hubner. From a total of 50 patients enrolled in the trial, the 21 that suffered cardiac arrest and had concurrent recordings of capnogram and ventilatory flow were included. Six of the episodes were recorded during CPR and 15 after resuscitation. The mainstream capnogram was acquired by the NICO 7300 monitor using the Capnostat $CO_2$ sensor by Philips (-125/125 L/min, 4 mV/L/min, 100 Hz). The respiratory signals were acquired by the same monitor; the airflow and the air volume signals were used as gold standard (GS) to annotate the ventilations. Fig. 1 shows examples of two episodes of the IHD, where ventilations are visible in the air volume and the capnogram, for an artefact free interval (panel c) and when CCs were provided (panel d).

### *2.2. Ventilation detector*

An automated algorithm that detects ventilations in the capnogram was developed based on the four basic phases of a normal capnogram shown in Fig. 2: the inspiration baseline (phase I), the expiration upstroke (phase II), the expiratory plateau (phase III) and the expiration downstroke (phase IV).

The capnogram was first low-pass filtered to remove spectral components above 10 Hz, and then a value of 5 mmHg was adopted as baseline. The inspiration ($t_{insp}$) and expiration ($t_{exp}$) times of potential ventilations were automatically detected from positive and negative peaks in the first difference of the signal. For every potential ventilation the five features shown in Fig. 2 were computed:

- Duration of the inspiration baseline, $D_{insp}$, in seconds.
- Mean $CO_2$ value of the inspiration baseline, $A_{insp}$, in mmHg.
- Mean $CO_2$ value of the expiratory plateau, $A_{exp}$, in mmHg.
- Area of the first second of the expiratory plateau, $S_{exp}$, in $\mathrm{mmHg} \cdot \mathrm{s}^{-1}$.
- Relative $CO_2$ increase, $A_r = \frac{A_{exp} - A_{insp}}{A_{exp}}$.

The ventilation detector consists of a feature based decision algorithm which detects ventilations by comparing $D_{insp}$ and the minimum distance between ventilations with a fixed threshold value (0.3 s and 1.5 s respectively) and features $A_{exp}$, $S_{exp}$ and $A_r$ with adaptive thresholds based on the last $p$ ventilations as follows:

$$Th_k = \frac{w}{p} \cdot \sum_{n=k-p}^{k} x_n \tag{1}$$

where $Th_k$ is the adaptive threshold for $k$-th potential ventilation, $w$ is a weighting factor between 0 and 1, and $x_n$ represents the value of the feature for ventilation $n$.

A more detailed technical description of the algorithm is supplied in the Appendix A, where signal processing techniques and ventilation detection criteria for the decision algorithm are supplied. Two illustrative examples are also included to provide intermediate results that clarify the implementation of the algorithm.

### *2.3. Instantaneous ventilation rate and hyperventilation alarm*

The instants of ventilations detected in the capnogram were used to compute the ventilation rate and to report hyperventilation alarms when an established rate was exceeded. Both measures could be used to give real-time feedback to the rescuer. The instantaneous ventilation rate was computed every 15 s as the inverse of the median interval between ventilations in the previous minute. Hyperventilation was defined for rates exceeding $15\,\mathrm{min}^{-1}$, following the criteria established by Kramer Johansen et al.[13]

### *2.4. Evaluation and statistical analysis*

The episodes of the OHD were randomly allocated to training and test sets. The ventilation detector was developed with the training set of the OHD, and evaluated with OHD test set and the complete IHD. Results are given separately for intervals with and without CCs. All the results were reported as median (interquartile range, IQR), as data did not pass the Anderson-Darling normality test.

The performance of the ventilation detector was evaluated in terms of Sensitivity (SE), the proportion of correctly detected ventilations, and Positive Predictive Value (PPV), the proportion of detected ventilations corresponding to real ventilations.

The Concordance Correlation Coefficient (CCC) was reported in order to quantify the agreement between the ventilation rate calculated from the GS and from the algorithm. The percentage of ventilation rate errors $> 2\,\mathrm{min}^{-1}$ per episode were reported. Bland-Altman plots were used to show the level of agreement (95% LOA) between the algorithm and the GS.

The performance of the hyperventilation detector was evaluated in terms of correctly detected hyperventilation alarms and the number of false hyperventilation alarms.

## 3. RESULTS

Table 1 summarizes the main characteristics of the datasets. For the 62 episodes of the OHD the duration was 38 (34-46) min, the median ventilation rate per episode was 9.9 (8.7-13.1) $\text{min}^{-1}$ and the hyperventilation fraction per episode was 10 (2-35)%. For the 21 episodes of the IHD the duration was 91 (50-141) min, the median ventilation rate per episode was 14.3 (12.6-18.2) $\text{min}^{-1}$ with 14 (0-88)% of hyperventilation fraction.

The OHD episodes were allocated randomly to training (37) and test sets (25). Fig. 3 shows the boxplot of the performance of the ventilation detector for both the OHD and IHD datasets. The SE was above 99% and the PPV above 97% overall. The boxplots show a slight deterioration for the intervals during CCs. The median SE and PPV decreased at most one point during CCs, and the lower quartile between 1 and 7 points.

Fig. 4 shows four examples where the dashed lines represent ventilations annotated in the GS and the red triangles represent the ventilations detected by the algorithm. Panels a and b show two examples of OHD where ventilations were missed due to too short inspiration intervals (panel a) and because of the 'shark fin' waveform of the capnogram (panel b). Panels c and d show intervals of the OHD and IHD, where the ventilations were correctly identified despite severe CC artefacts.

The concordance between the instantaneous ventilation rate obtained from the GS and from the algorithm was high (CCC $> 0.98$) for the two datasets, even during CCs. The proportion of errors larger than $> 2\,\text{min}^{-1}$ were 0 (0-4.2)% per episode for the OHD and 0 (0-1.2)% for the IHD. Fig. 5 shows the Bland-Altman plots and the 95% LOA between the GS and the algorithm, which was in all cases smaller than $1.8\,\text{min}^{-1}$.

For the OHD, the algorithm correctly detected 841 of 860 alarms, and 26 of the 867 given alarms were false. For the IHD, the hyperventilation detector correctly reported 3563 of the 3566 hyperventilation alarms, and 12 of the 3575 given were false.

## 4. DISCUSSION

This study proposes an automatic algorithm to detect ventilations using the capnogram, and thoroughly tests its accuracy for ventilation rate feedback during CPR, specifically addressing intervals in which CCs were delivered. The algorithm identifies the instants of ventilations based on adaptive thresholds to accommodate to the time-varying levels of $CO_2$, and avoids the rapidly changing artefacts added by the CCs. This algorithm would permit an accurate ventilation rate monitoring and a better control of hyperventilation both in- and out-of-hospital, where rates recommended by resuscitation guidelines are frequently exceeded.[5–7,9–12]

### *4.1. The dataset and the gold standard*

The dataset used in this study includes both in-hospital and OHCA episodes, with a total of 46740 ventilations (8741 during CCs). In the OHD impedance was used as gold standard, and annotations were reviewed with the capnogram, but only in unclear intervals (see panel a of Fig. 4). This procedure, which was a standard practice in previous studies because no better gold standard is available for the OHCA data,[23] might limit the validity of the results. In order to overcome this limitation an independent GS, not available in the OHCA setting, was introduced in the IHD, the airway flow signal which provides reliable information for ventilation monitoring.[1,23] In our IHD the airway flow and volume signals from the NICO respiratory monitor by Philips were used as GS. The number of episodes in our IHD is small, however this dataset contains the most reliable GS used to date to validate capnogram based ventilation detectors during cardiac arrest. The results obtained with this dataset confirmed the accuracy observed for the ventilation detection algorithm with the OHCA dataset.

The global SE/PPV of the detector were 0.7/2.8 points better for the IHD than for the OHD (Fig. 3), which may reflect various factors. On the one hand, the capnography technique was different in our two datasets, mainstream for the IHD and sidestream for the OHD.[25] In mainstream capnography the sensor is located directly in the way of the expired flow. In sidestream capnography a sample of the patient's expired gases is trasported to the sensor site using a 1-2 meter long tube. This produces a delay in the capnogram with respect to the TI (4 seconds in our data) and the diffusion of the gases during transport lowers the slopes (dampening) of the capnogram.[26] This last effect might jeopardize the discrimination of ventilations in the OHD, as the algorithm is based on the detection of abrupt changes in the capnogram, and might partially explain the lower accuracy obtained for the OHD dataset. On the other hand, the OHD reflects more challenging scenarios in which ventilations were manual and CPR was delivered in most of the cases, while 15 of the 21 in-hospital cases were mechanically ventilated and/or had no CCs. However, when cases during CPR were considered the results were similar for the OHD and IHD (see Fig. 3 during CPR). This primarily is because during CPR both datasets reflected the effects of greater variability in ventilation patterns, CC artefacts and the intervention of multiple rescuers. The results for the IHD data with a reliable and independent GS confirm the observations on the larger OHD, and the accuracy of the algorithm with both mainstream and sidestream capnography.

### *4.2. The capnogram based ventilation detector*

To date few capnogram based ventilation detectors applicable to OHCA data have been described. However, the universalization of the capnogram during ALS and the importance of adequate ventilation for the survival of the patient call for new and improved capnogram based ventilation feedback algorithms. Our method relies on an adaptive thresholding to classify possible ventilations detected in the first derivative (slope) of the capnogram. A preliminary version of the method was previously described.[27] Edelson et al. proposed an adaptive CPR artefact suppressing filter before detecting ventilations in the first derivative of the filtered signal and then used fixed detection thresholds.[23] Adaptive filtering requires additional CPR-assist pad signals, such as depth, acceleration and/or force signal. These signals need to be synchronized to the capnogram which is often recorded by a different device. Edelson et al. reported SE/PPV of 82/91% respectively for the ventilation detector, slightly below our results, and $> 80\%$ of the rate errors below $\pm 2\,\text{min}^{-1}$, compared to the $> 90\%$ of our algorithm. As it can be observed in Fig. 4 the error of our algorithm hardly increased for the intervals with CCs in the OHD, with LOAs close to 1.8 $\text{min}^{-1}$; the difference is higher in the IHD where the LOA is 1.5 $\text{min}^{-1}$ in the intervals with CCs, and 0.5 $\text{min}^{-1}$ for the complete dataset. This difference is attributable to the CC artefacts as well as to the mechanical ventilations of the IHD .

Panels c and d of Fig. 4 show two cases where the algorithm was effective in the presence of large CC artefacts. Panels a and b, are two exceptional cases that show the limitations of the algorithm. Panel a corresponds to a ventilation technique leading to baselines too short to be detected as true ventilations. Panel b shows a capnogram of a patient with airway obstruction, due to bronchospasm, asthma or chronic obstructive pulmonary disease. In both cases the detector missed most of the ventilations of the interval.

The artefacts in the capnogram due to CCs were visually identified in previous studies[20,24] and are frequent in OHCA episodes, 73.3% of the cases in the study by Idris et al.[22] and 78.8% in our study (37.6% of the ventilations). The severity of the artefact has not been characterized yet and might vary with the position/depth of the CCs, the physiology of the patient, and probably with the technology used to acquire. It is known that the sidestream capnography shows artifacts and distortions that may appears as false disease waveforms,[26] and it might also show different susceptibility to CC artifacts compared to mainstream capnography. A thorough research is needed for a better understanding of the level, characteristics and differences of the CC artefact in both capnography sampling techniques.

### *4.3. Application scenarios*

Monitoring ventilation rate to avoid hyperventilation is a challenge in OHCA scenarios where many feedback systems are available for CCs but not for ventilatory assistance. During BLS, the impedance measured through defibrillation pads has been proposed to monitor ventilations. Although impedance can be used for debriefing, it showed limited performance for monitoring instantaneous ventilation rate. Alonso et al. reported significant errors due to non ventilatory components of the impedance waveform,[17] an observation consistent with the manual annotations required in several studies on CPR quality.[11,28] For ALS, where advance airway management is integrated, the latest guidelines encourage the use of the capnogram to monitor CPR quality. Our results show that ventilation rate algorithms should be further evaluated with capnograms acquired during CCs before they are incorporated into feedback systems.

### *4.4. Limitations*

The use of the algorithm is limited by the characteristics of the capnograms. As capnogram is dependent on the perfusion and metabolism of the patient, for very low levels ($< 5\,\text{mmHg}$ in our algorithm), ventilations would not be detected. The IHD used to test the algorithm is limited by the number of episodes, 6 out of 21, which include CCs. Although few cases were available, the inclusion of this dataset enabled the validation of the algorithm with a robust and independent GS.

## 5. Conclusions

Our study proves that an accurate feedback on ventilation rate using only the capnogram is feasible, even in intervals where the capnogram signal is severely corrupted by CCs. Technology based on this type of algorithms could be integrated in monitor/defibrillators to provide reliable feedback on ventilation rate and alarms on hyperventilation during CPR.

## Ethical Approval

The CPR process files used in the OHD were collected as part of an effort to develop an airway check algorithm using the capnogram. Since these raw data files have no identifying information, the Institutional Review Board at the Oregon Health & Science University determined that the proposed activity is not human subject research because the proposed activity does not meet the definition of human subject per 45 CFR 46.102(f).

The files used in the IHD were collected as part of the investigation approved by the ethics committee of the Medical University in Vienna. Subjects resuscitated successfully signed written informed consent. For all others the Institutional Review Board waived the need for informed consent. [https://ekmeduniwien.at/core/catalog/2012 (EK-Nr: 1574/2012)]

## Conflict of interest

Mohamud Daya is an unpaid consultant for Philips Healthcare.

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# Figure Legends

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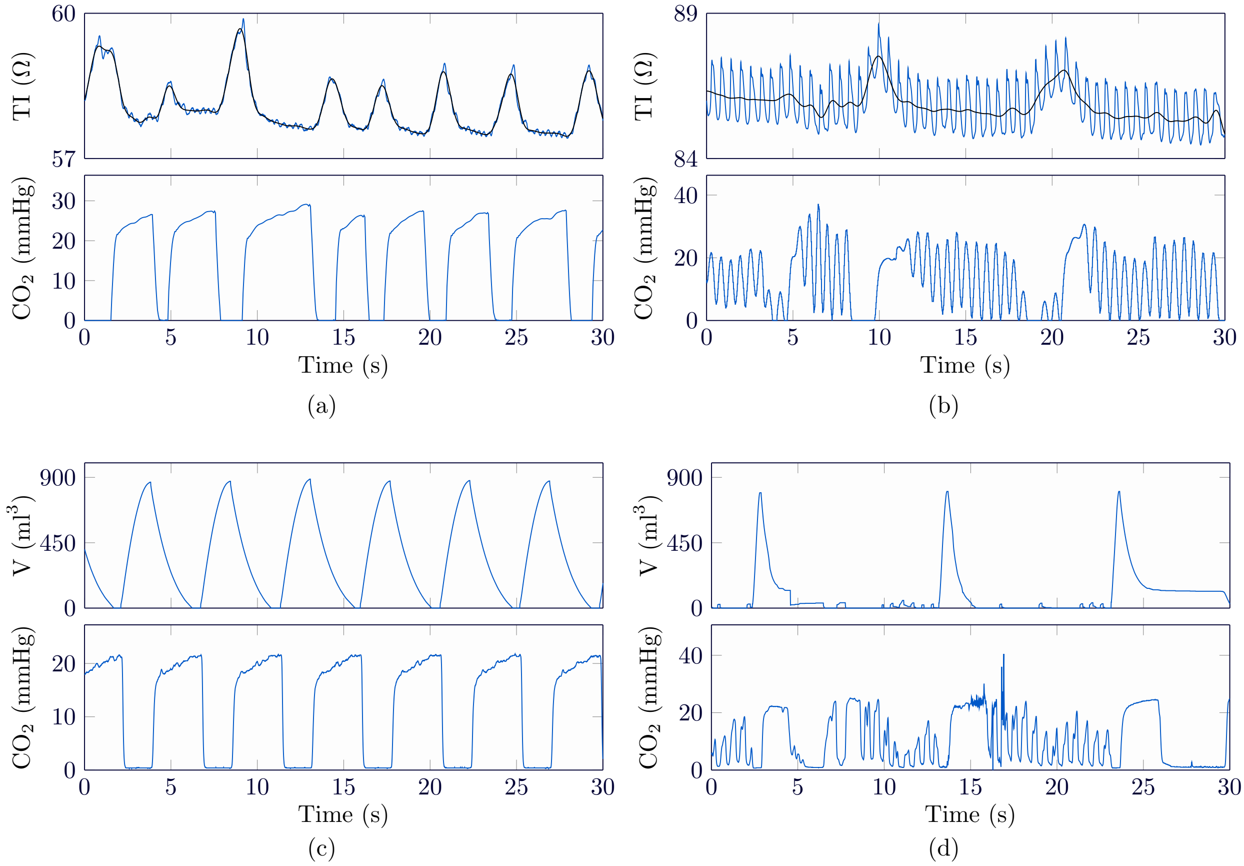
| Figure 1 | Intervals from the out-of-hospital and in-hospital datasets, OHD and IHD, showing the capnogram and the Gold Standard (GS) to annotate ventilations. Panels a and b show OHD examples without and with chest compressions, with the impedance ventilation channel (GS) in black on top and the capnogram below. Panels c and d show IHD examples without and with CCs, with the air volume (GS) on top and the capnogram below. |
| Figure 2 | The four phases of the normal capnogram and the features of the ventilation detector associated to potential ventilation number $k$. The time stamps $t_{insp,k}$ and $t_{exp,k}$ correspond to the inspiration and expiration times respectively. |
| Figure 3 | Box plots showing the performance of the ventilation detector for the out-of-hospital dataset, OHD, in panel a, and for the in-hospital dataset, IHD, in panel b. Results are also given for the intervals with chest compressions (CCs). |
| Figure 4 | Performance of the ventilation detection algorithm with four episodes. The examples of panels a, b and c correspond to episodes from the out-of-hospital dataset, and example of panel d to an episode from the in-hospital dataset. For every example the gold standard (GS) is shown (impedance ventilation signal or air flow volume signal). The GS annotations are shown with black dashed lines, and the detected ventilations with red triangles. |
| Figure 5 | Bland-Altman plots for the out-of-hospital and in-hospital datasets, OHD and IHD respectively, for all cases and for the intervals with chest compressions. The horizontal lines show the 95% level of agreement. |

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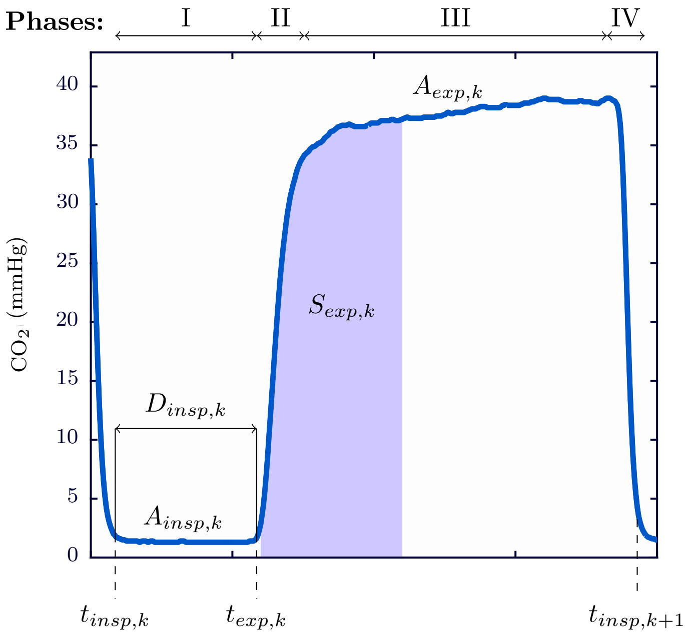


Figure 2: The four phases of the normal capnogram and the features of the ventilation detector associated to potential ventilation number $k$. The time stamps $t_{insp,k}$ and $t_{exp,k}$ correspond to the inspiration and expiration times respectively.

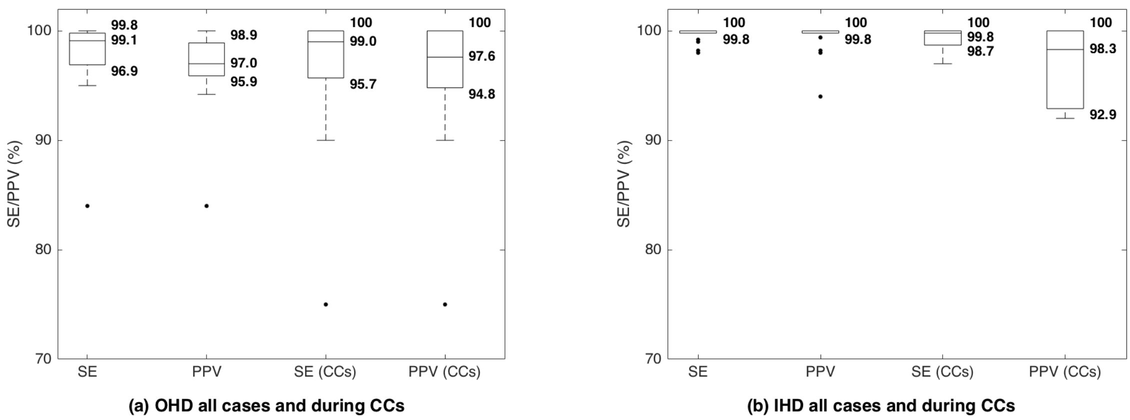


Figure 3: Box plots showing the performance of the ventilation detector for the out-of-hospital dataset, OHD, in panel a, and for the in-hospital dataset, IHD, in panel b. Results are also given for the intervals with chest compressions (CCs).

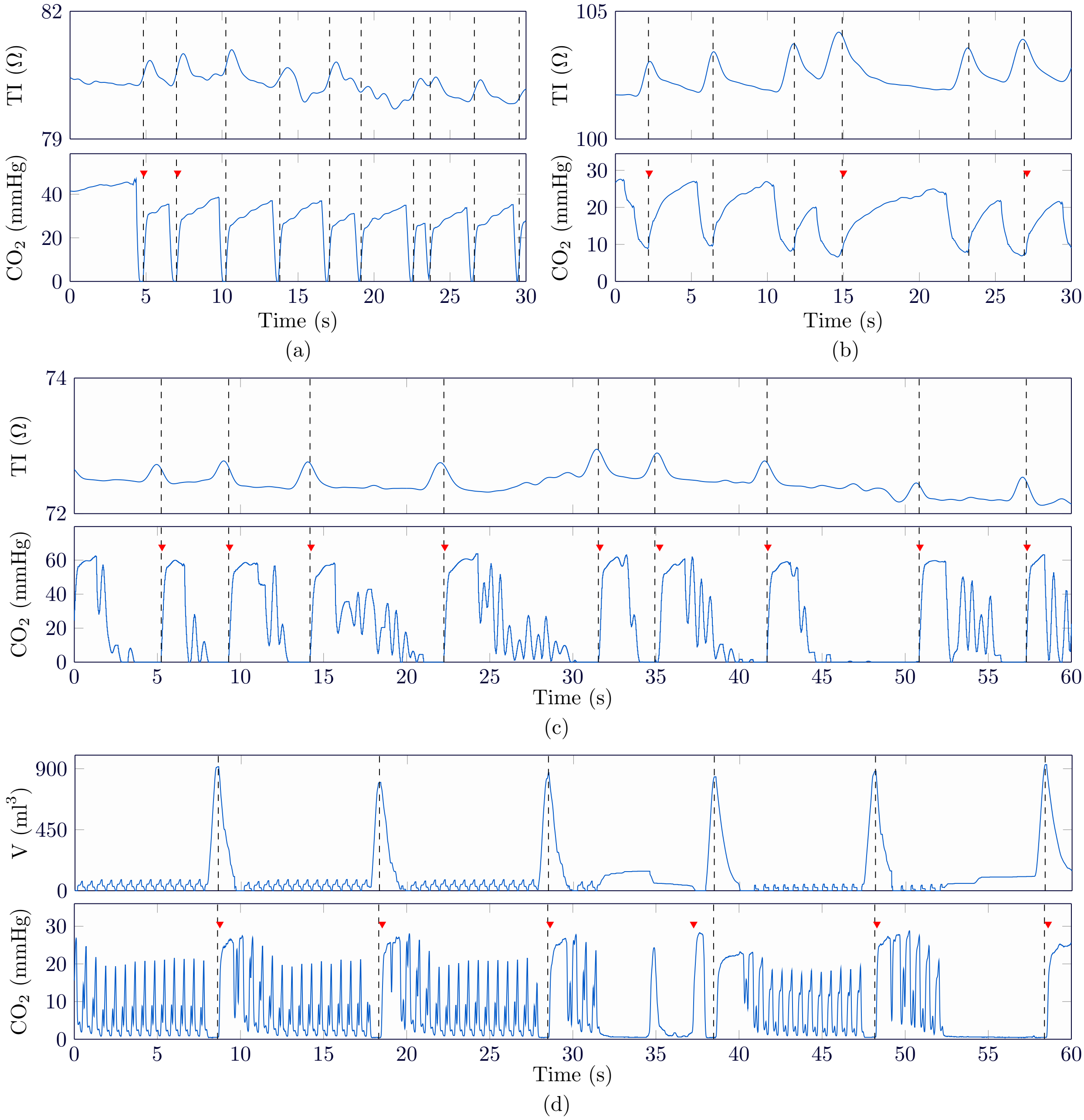


Figure 4: Performance of the ventilation detection algorithm with four episodes. The examples of panels a, b and c correspond to episodes from the out-of-hospital dataset, and example of panel d to an episode from the in-hospital dataset. For every example the gold standard (GS) is shown (impedance ventilation signal or air flow volume signal). The GS annotations are shown with black dashed lines, and the detected ventilations with red triangles.

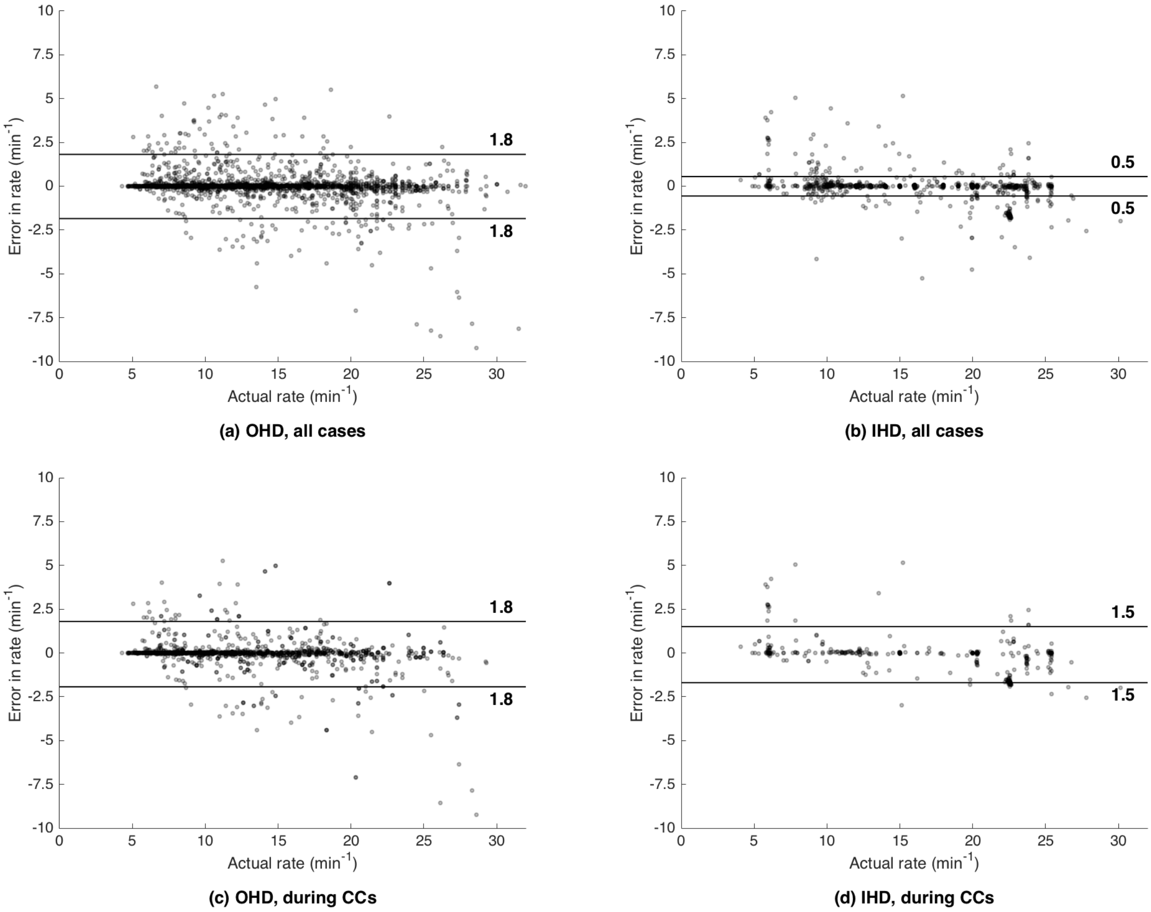


Figure 5: Bland-Altman plots for the out-of-hospital and in-hospital datasets, OHD and IHD respectively, for all cases and for the intervals with chest compressions. The horizontal lines show the 95% level of agreement.

# Table Legends

Table 1 Characteristics of the out-of-hospital dataset (OHD) and the in-hospital dataset (IHD)

| **Parameter** | **OHD** | **IHD** |
|---|---|---|
| Number of episodes | 62 | 21 |
| Total duration (min) | 2545 | 2335 |
| Total number of ventilations (% with CPR) | 16899 (37.6) | 29841 (8) |
| Instantaneous ventilation rate ($\text{min}^{-1}$) | 10 (8.7-13.1) | 14.3 (12.6-18.2) |
| Minutes with hyperventilation per episode (%) | 10 (2-35) | 14 (0-88) |

Table 1: Characteristics of the out-of-hospital dataset (OHD) and the in-hospital dataset (IHD)