Camera-based On-line Short Cessation of Breathing Detection

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Abstract

Apnea detection is extremely important in neonatal settings because hypoxia can lead to permanent impairment. Short cessations of breathing are very common in infants and could be used for example for the prediction of longer apneas. The aim of this study is to investigate the accuracy of our on-line cessation of breathing detector. Signals obtained through camera-based respiration monitoring were analyzed in five infants with 91 annotated cessations of breathing. The method proposed is based on the comparison of short-term and long-term standard deviations allowing the detection of sudden amplitude reduction in the signal with a low latency. A new strategy able to detect short cessations of breathing on-line was successfully validated yielding an average accuracy of 93%.

1. Introduction

Vital signs are of critical value to check the health of premature infants. Their monitoring is therefore standard practice in Neonatal Intensive Care Units (NICUs). Since Apnea Of Prematurity (AOP) is common in this population, continuous respiration monitoring is crucial [11]. Apneas are prolonged pauses in the respiration and are common in infants with a gestational age below 34 weeks [12], the hypoxia typically associated with apnea could cause long-term or permanent impairment [14]. Respiration monitoring based on Chest Impedance (CI) currently used in NICUs presents limitations when detecting apneas, in particular, cardiac artifacts are a common cause of missed apnea detection [24], moreover, motion artifacts and other thoracic movements can also be misinterpreted as respiration [7]. Apneas are strictly defined as a Cessation Of Breathing (COB) longer than 20 seconds or a COB of 10 seconds accompanied by bradycardia and/or desaturation [28]. However, discussions on the definition of clinically relevant apneas move the focus also on shorter COB [13]. Short apneic episodes are common in infants and are defined as a respiratory pause of at least 3 seconds [8]. Moreover, this type of events can provide insights on the infant's respiratory system [33] and lead possibly to apnea prediction [6].

Since adhesive electrodes and sensors can cause stress or even skin damage to the infants' sensitive skin [1], research in this field has been focusing on alternative non-contact respiration monitoring techniques. Between these, radars [21, 15], RGB or Near InfraRed (NIR) cameras [35, 23, 22], vision system based on depth sensing [5, 29] , thermal cameras [27, 2], and pressure sensitive mattress [19, 4] are the most researched for respiration monitoring in a NICU environment. Cameras represent one of the best solutions for NICUs applications. In the first place, because they are completely unobtrusive passive sensors and they allow to monitor multiple vital signs simultaneously. Moreover, cameras also provide contextual information that would be useful to nursing staff for infants' observation, and it would promote family-centred NICUs through live video feed to parents [31].

In this paper, we propose an approach for the on-line detection of short apneic events through camera-based respiration monitoring. Many methods for respiration detection algorithms using cameras have been proposed targeting

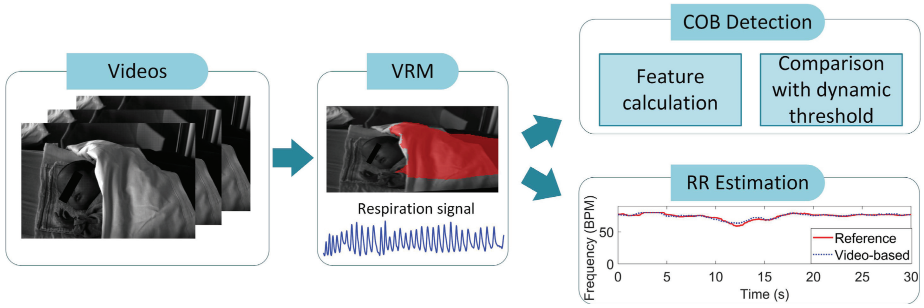


Figure 1. Main processing steps leading to the detection of Cessation Of Breathing (COB).

an infant population. Jorge *et al*. [18] proposed a camera-based approach for respiration monitoring based on a skin detection algorithm, which is not ideal for NICUs applications since infants' abdominal areas are commonly covered with blankets or snuggles. Though remote PPG-based approaches, *e.g*. [32], also rely on skin visibility, they can work on facial skin that is more likely uncovered. However, motion robustness necessitates multi-wavelength cameras. RGB-cameras are a seemingly logical choice, but visible illumination may disturb sleep and is therefore not allowed. Proposals using wavelengths in the infrared range suffer from high cost of multi-wavelength cameras, or parallax when using 3 cameras in parallel. Therefore, remote PPG-based solutions are not straightforward in such a complex environment. However, when monitoring respiration based on motion, skin visibility and color information are not indispensable for the signal detection. For example, Allinovi *et al*. [3] proposed a method based on maximum likelihood modeling and motion magnification able to automatically select the Region Of Interest (ROI). The method proposed was tested on a limited dataset of adults and infants videos, with a window size of 20 seconds for estimation of the respiration signal and the respiration rate. The latency (caused by the processing window) is particularly important when aiming at apnea detection and therefore, the method proposed by Janssen *et al*. [16] was preferred as a starting point for our work. The method, called Video Respiration Monitoring (VRM), was extensively tested on adults videos, but limited experiments were performed on infants. Still, we consider this method very appealing for NICU-applications, particularly because of its attractive automatic ROI detection independent on skin visibility and the low latency of the method.

The output of the VRM algorithm is used as starting point for the detection of short apneic events in the respiration signal. Other works have been focusing on apnea detection strategies starting from video extracted respiratory signals, Jorge *et al*. [17] proposed an approach based on camera where COB longer than 20 seconds were classified based on the Respiration Rates (RRs). If the RRs of the videos were lower than 20 breaths per minute for a period longer than 20 s and no other motion was present in the video segments then it was classified as an apnea. However, aiming at the detection of short apneas time-domain approaches are preferable being more sensitive to particularly short variations. Also Cattani *et al*. [9] tested camera-based respiration signal for the detection of apneas. The apnea detection strategy was to compare the time domain signal with an empirical constant threshold equal to 0.14. Constant thresholds have the drawback of not being able to adapt dynamically to changes in the signals, such as reductions in amplitude. Lee *et al*. [24], instead, proposed an approach based on modeling the distribution of normal breathing patterns and apnea ones reaching an average detection performance over 90% by analysing chest impedance signals. The approach is, however, suitable only for retrospective analysis as specified by the authors, since the empirical parameters were optimized after filtering and baseline removal of the entire signal. This method has been widely used in apnea related publications, *e.g*. [26, 25, 10, 34], and has also been employed for the detection of short apneic events [6], therefore we decided to use it for comparison purposes.

The main contribution of this work is the development of an on-line short cessation of breathing detection strategy based on the comparison of the short-term standard deviation with the long-term standard deviation. The respiration rate is obtained as a byproduct of our processing. This is the first method able to detect short cessations of breathing with a low latency. The rest of the paper is organized as follows: Section 2 explains the method used and the dataset, Section 3 presents the results. Sections 4 and 5 contain respectively the discussion and the conclusion.

2. Materials and methods

2.1. Method

Figure 1 summarizes the principal steps of the processing algorithm. The NICU-videos are input to our processing. The VRM-algorithm of Janssen *et al*. (Section 2.1.1) is used to extract the respiratory signal. On this respiratory signal, we run our COB-detector described in Section 2.1.2. Additionally, we compute and output the respiratory rate. In our benchmarking, we shall compare our COB-detector with the results from Lee *et al*. [24], and the RR with the CI-reference. The proposed algorithm was implemented in MATLAB (MATLAB 2018b, The MathWorks Inc., Natick, MA, USA).

2.1.1 Video respiration monitoring algorithm

The VRM algorithm proposed by Janssen *et al*. in [16] is a respiration-motion detection algorithm based on Optical Flow (OF). The algorithm automatically detects the ROI for respiration detection and returns the respiration signal. When motion not related to the respiration is detected, the respiration waveform is put to zero and a template indicating that motion unrelated to respiration is present can be obtained. The same parameters introduced in the paper for the neonatal case were used in this work.
The CI signal and the respiration signal obtained from the videos are both filtered using a band-pass Butterworth filter of the 4^{th} order between 30 and 80 Breaths Per Minutes (BPM) since this is the normal range of respiration rate in NICU infants including also tachypnea cases [30]. The signals have different sampling frequencies corresponding to 15 frames per second or 20 frames per second depending on the acquisition and are processed with a sliding window approach with a window size of 3 seconds and a slide of 1 frame.

2.1.2 Cessation of breathing detection

In case of a central apnea breathing cessation, a strong decrease in amplitude of the respiratory signal could be expected. Hence, our proposed COB-detector aims at signaling relative decreases in standard deviation of the respiratory signal. Such a decrease can be recognized, by the short-term standard deviation σ_s becoming significantly smaller than the long-term standard deviation σ_l. Parameters in such an approach are the window-lengths for computation of the two standard deviations, and the threshold to define if a drop is "significant". Therefore, two window lengths are defined: a short window l_s in which a feature, corresponding to the short-term standard deviation, is estimated, and a long window l_l in which the long-term standard deviation is calculated. The calculation of σ_l is performed as median of the previously evaluated σ_s. The median operation was preferred to the average for its robustness to outliers that can be present as sudden high signal amplitude due to undetected non-respiratory motion. The duration of l_s and l_l was chosen considering the length of the targeted COBs, which varies from 3 to 10 seconds. Moreover, the short window should contain at least a single period of respiration to be able to detect also the RR. Since the minimum RR expected is 30 BPM, l_s can be minimum 2 seconds. We arbitrarily decided to use a l_s equal to 3 seconds. Furthermore, a too long l_l will cause the threshold to not adapt dynamically to changes in the amplitude of the signal. While, a too short l_l will result in adapting also during apneic events. Therefore, as a compromise l_l was chosen to be equal to 11 seconds.
More formally, let $resp(nT_s)$ be the time domain signal after filtering obtained either from videos or from the reference, n depends on the current window and it is defined as $n = 0 + (j-1), 1 + (j-1), ..., N + (j-1)$. Where, j indicates the current window, the number of samples per window is $N = l_s/T_s$ and T_s the sampling time. Then the short-term standard deviation is evaluated according to:

$$\sigma_s(j) = \sqrt{\frac{\sum_{n=0+(j-1)}^{N+(j-1)} (resp(nT_s) - \mu(j))^2}{N}}, \quad (1)$$

where, $\mu(j)$ is the average of $resp(nT_s)$. Thus, a value corresponding to the standard deviation of the time-domain signal will be obtained for each 3 seconds window. The long-term standard deviation will be evaluated on a window length l_l equal to 11 seconds, however to reduce the delay in the detection, σ_l is estimated with a fewer number of σ_s until $j > H$ with $H = \frac{l_l}{T_s}$:

$$\sigma_l(j) = \begin{cases} \underset{1 \le k \le j-1}{\text{median}} (\sigma_s(k)) & j \le H \\ \underset{j-H \le k \le j-1}{\text{median}} (\sigma_s(k)) & otherwise. \end{cases} \quad (2)$$

In each window $\sigma_s(j)$ and $\sigma_l(j)$ are compared. If the ratio between the two standard deviations results in being lower than 33%, the j-th window is considered to contain a COB and a binary template, CD, is created as follows:

$$CD(j) = \begin{cases} 1 & \sigma_s(j) \le \sigma_l(j)/3 \\ 0 & otherwise. \end{cases} \quad (3)$$

$CD(j)$ indicates if the window j contains a COB. Figure 2 shows two examples, a signal containing COBs and one without.
Lee's method is applied on each video retrospectively on both CI and VRM signals. The method returns a probability of apnea, that is then converted to the weighted apnea duration as the area under the probability curve. The limit on the duration of the apneas detected, previously defined by Lee *et al*. as 5 seconds, is adjusted to this case making the smaller apnea detectable equal to 3 seconds, and obtaining therefore a second binary template for reference.
In the VRM respiration signal, since also motion information is available, cessations are not considered when motion unrelated to respiration is present and the standard deviation value $\sigma_s(j)$ for a j-th window containing motion is not considered in the calculation of the $\sigma_l(j)$.

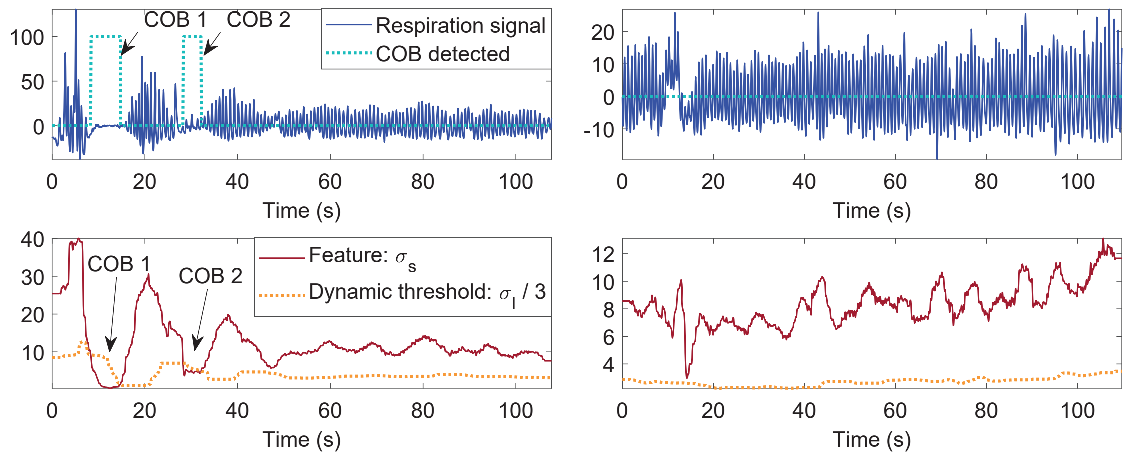


Figure 2. Examples of respiration signals, the two upper plots show a VRM respiration signal containing two cessations of breathing and a VRM respiration signal without cessations. The binary template, CD, labelled as "COB detected" has been multiplied for 100 for visualization purposes. The two plots in the bottom show the σ_s used as feature for cessation of breathing detection and the threshold based on the σ_l.

2.1.3 Respiration rate estimation

In each 3 seconds window the respiration rate is estimated as the frequency corresponding to the peak in the spectrum for both VRM signal and CI. The spectrum is evaluated using FFT, zeropadding is performed reaching a number of samples equal to $120 \cdot 3 \cdot f_s$ with f_s equal to the sampling frequency. Moreover, to compensate for small variations, the RRs obtained are filtered using a moving mean filter followed by a moving median filter each with a window size of half a second.

2.1.4 Evaluation

To compare respiration rates obtained with CI and VRM respiration signals the percentage of time in which the difference between the two is within ± 6 BPM is used as metric. This percentage has been evaluated in each video and then averaged. Moreover, for fair comparison, the RRs estimated in windows containing COBs according to the annotations and those estimated in windows where motion of the infant unrelated to the respiration was detected from VRM algorithm have not been considered in the calculation of this metric.

To evaluate the difference between the COB detection algorithm proposed in this work and the one proposed by Lee *et al.* [24], sensitivity and specificity are calculated for each method using the manual annotation of the videos as reference. As defined in [9] sensitivity will be:

$$SE = \frac{TTP}{TTP + TFN}, \tag{4}$$

with Time True Positive (TTP) and Time False Negative (TFN) being respectively the total duration of the time intervals with COBs detected correctly and with COBs incorrectly missed by the algorithm. And specificity will be:

$$SP = \frac{TTN}{TTN + TFP}, \tag{5}$$

with Time True Negative (TTN) being the duration of the time intervals with no COBs in which there are no wrong detection while, Time False Positive (TFP) is the total length of the time segments with no COBs in which COBs are erroneously detected. Therefore, sensitivity represents the ability of the algorithm to correctly detect COBs when present whereas specificity is the ability to correctly exclude the presence of COBs particularly important to avoid false alarms. The accuracy can be therefore defined as:

$$ACC = \frac{TTN + TTP}{TTN + TTP + TFP + TFN}. \tag{6}$$

2.2. Study design

Videos were collected in the NICU of the Maxima Medical Center (MMC) in Veldhoven, The Netherlands. Two different setups were used for the data collection. Both studies received approval from MMC and one study also received approval from the Internal Committee for Biomedical Ethics in Philips Research (ICBE2013-41-3797). Informed parental consent was obtained for all the infants involved in the studies.

The videos were annotated by a single author, the COBs were annotated only when clearly visible in the video. In total, 5 infants were included, Table 1 shows the PostMenstrual Age (PMA) expressed as the gestational age plus the postnatal age, the total duration of the videos per infant, and the number of short apneic event annotated. The

ID	PMA (weeks)	Number of videos	Total Duration (min)	COB annotated
1	36+6.71	10	16.5	11
2	30+4.85	20	34.3	4
3	30+2.42	10	49.8	31
4	30+2.42	10	46.2	24
5	29+1.14	9	43.6	21
Overall		59	190.4	91

Table 1. Video details and parameters of the infants in the dataset.

		SE (%)	SP (%)	ACC (%)
VRM	Ours	76.32	**94.39**	**93.16**
	Lee's method	**86.68**	91.50	90.64
CI	Ours	**83.15**	96.97	96.00
	Lee's method	77.02	**97.99**	**96.60**

Table 2. Average sensitivity, specificity, and accuracy results obtained with the method proposed in this work, indicated as ours, and Lee *et al*. method.

dataset includes both videos containing COBs and videos not containing any cessation events for control purposes. The videos have different duration going from 1 minute to 5 minutes reaching a total cumulative duration of 190.4 minutes. In total 91 short apneic events were annotated, the average duration and standard deviation of the COBs population are 5.4 ± 1.9 seconds.

2.3. Experimental setup

The dataset compromises of videos collected with two different setups. In both cases the CI from the patient monitor (Philips MX800) was also acquired for reference purposes. In the first study a camera (UI-2220SE, IDS) was positioned using a tripod to have view of the infants chest/abdomen area, some videos were collected from the top and others from the side. The videos were collected under visible light conditions with a frame rate of 20 frames per second and with a resolution of 768×576 pixels. Since color information is not relevant for respiration-motion detection we used the raw gray-scale images. The videos were selected based on the quality of the reference signal and on the light conditions since the dataset also included measurements taken in particularly dark settings. Two infants (ID 1 and 2 in Table 1) were selected with a total video duration of 50.8 minutes.

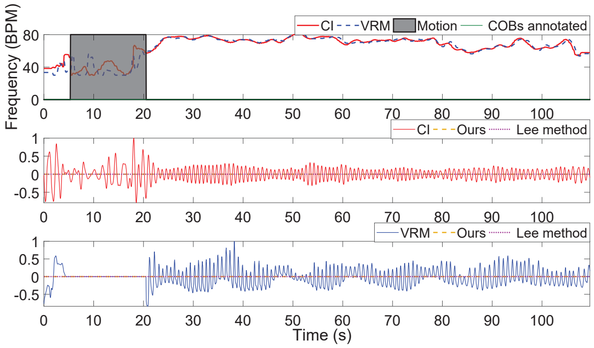
The second setup included a monochrome visible light camera with the NIR filter removed (UI-22330SE, IDS) positioned on the incubator using suction cup mounting and visualizing an overview of the infant. NIR custom made illumination was used since the normal workflow of the NICU was not disrupted and the incubator was covered, as common practice, limiting the ambient light. The illumination unit comprised of LED arrays at three different wavelengths (660, 760, and 810 nm). The illumination level of all LEDs resulted in being around 0.2 mW/cm2 at the skin level of a patient, definitely below the imposed limits (ANSI/AAMI/IEC 60601-2-21:2009). The videos were collected with a frame rate of 15 frames per second, a resolution of 608×864 pixels, and subjected to compression. In this case, the videos were selected only based on the quality of the reference signal. Using this setup, three infants are recorded as part of this dataset with a total video duration of 139.6 minutes.

3. Results

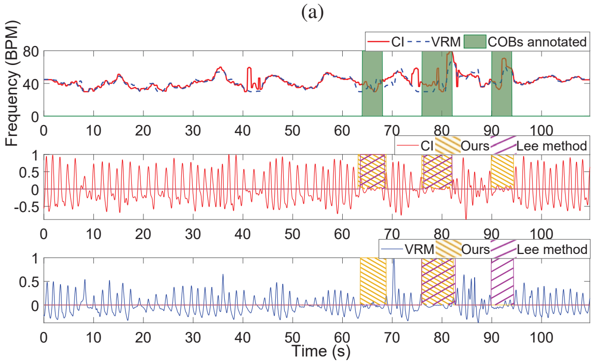
Table 2 contains the average results obtained for all the infants, sensitivity, specificity, and accuracy were estimated by comparing the detection of COBs performed with the method proposed in this work and Lee's method on both CI and VRM signals. The results were obtained using the parameters described in Section 2.1.2. In bold are indicated the best results comparing our method and Lee's. Figure 3 shows some examples of the obtained results. Figure 3a contains an example where motion but no COB was present, while Figure 3b shows the results obtained when three COBs were present. In the CI case, the COBs were all correctly detected by our methods, while the detection is incomplete in the video signal case for both the proposed method and the benchmark one.

4. Discussion

The method proposed in this work was proven to be able to detect short apneic events. Preliminary results were obtained with videos of five infants containing 91 COBs in total. The comparison between our method and the one previously proposed by Lee *et al*. shows that our method resulted in higher specificity and accuracy for the respiration signals obtained on the videos, while the opposite happens in the chest impedance case. Moreover, the results were always higher in the case of Chest Impedance signal compared to the VRM signal using our COB detector. This is most likely due to the noisiness of the signals, the VRM respiration signal relies on the correct detection of the ROI, that can be momentarily lost after strong movements causing low amplitude in the signal that can be misinterpreted as COBs. On average for both CI and VRM signals our method reached an accuracy of 94.6% against the 93.5% of Lee's method. Considering the high false alarm rate already present in the NICUs [20] it is of paramount importance to prefer specificity to sensitivity especially in the short apnea cases for which



(a)



(b)

Figure 3. Example of results obtained: (a) CI and VRM respiration signal and RR when motion unrelated to respiration is detected; (b) case with COB annotated. The amplitudes of the respiration time-domain signals were scaled to 1 for visualization.

clinical relevance is still under discussion. Moreover, our method is able to work in an on-line fashion while, Lee *et al*. claim that their method requires several minutes of clean signal to work accurately and that an adaptation is needed for on-line detection [24], this is mostly due to the filtering and removal of baseline from the signal before the estimation of the moving standard deviation, on which the parameters of the Fermi function were optimized. Our method is also based on standard deviation but proved to work with a sliding window of 3 seconds, making COB rapidly detectable by the system.
Moreover, the respiration rate obtained with the video signal and the CI as reference were compared. The RR extracted from the VRM signal is 75% of the time within 6 BPM from the Chest Impedance one. Higher errors were obtained for infants with ID 3,4, and 5, this can be due to the compression of the videos and/or to a higher number of events with small motions unrelated to respiration. It should be considered that most of the studies using frequency-based RR detection used windows ranging from 8 to 20 seconds [32, 3, 17] in our case the 3 second window in which the FFT was performed leads to fast estimations but can also cause higher errors due to the poor frequency resolution.

This work introduced a new method for the detection of short apneas that can work on-line. The results are still considered preliminary, first of all the cessations of breathing were not annotated by an expert, however the use of videos and not of CI for the annotations makes the result less subjective. Moreover, also longer apnea should be considered, there is no suggestion that such a method would not work for a different COB population, however, parameters such as l_l would need to be adjusted. The parameters used in this work were chosen arbitrarily or based on reasoning and the same parameters were chosen for CI and VRM signals, an optimization of these parameters could lead to improved results.
VRM delivered a respiration signal from videos with varying orientations and settings, *e.g*. containing motion or with infants covered. The algorithm is characterized by a set of empirically chosen parameters, we believe that adjusting the parameters could lead to improved respiration signal thanks to a more accurate detection of unwanted motion and a faster adaptation of the ROI following big movements.

5. Conclusion

The method described in this study proved in being able to detect short apneic events yielding an accuracy equal to 93.16% in the video signal case. The method can on-line detect cessations of breathing with a low latency and it is based on the comparison of short-term and long-term standard deviations. The detection of such short apneic events could lead to apnea prediction preventing hypoxic damages in infants.

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