Detecting Apnea Events Based on Pulse Oximetry’s Red Photoplethysmography Waveform

Anh Pham, University of Utah

Abstract—Hypoventilation remains a cause of unexpected hospital death due to limitations in detecting the problem and the associated high false positive alerts, alarm fatigue, and delayed diagnosis. Pulse oximetry, while affordable, is a delayed and indirect indicator of hypoventilation, especially for patients receiving supplemental oxygen. Capnometry is a direct measure of ventilation, but is too expensive and cumbersome for use in general ward patients, for whom the risk of mortality remains high during postoperative pain control via opioids. We hypothesize that we can identify changes in the pattern of the red photoplethysmography waveform and distinguish among periods of apnea, one minute preceding apnea, and normal breathing. Methods: Using data recorded from volunteers during administration of sedatives and opioids, we explored the feasibility of using machine learning to classify three types of events observed in the red photoplethysmography waveform including one minute preceding apnea, apnea and normal breathing. Nine feature parameters calculated from the red photoplethysmography waveform and a line fitted to the bottom of the photoplethysmography were used as inputs for a neural network pattern recognition algorithm which classified the three types of waveform—normal breathing, apnea and one minute before apnea. Results: We observed a high rate of success for classifying three types of events including one minute preceding apnea, apnea and normal breathing in the red photoplethysmography waveform. The neural network correctly classified 100% of the evaluation database as a measure of the three types of waveform accuracy.

Index Terms—Pulse Oximetry, Sleep Apnea, Pattern Recognition, Machine Learning, Neural Network, red photoplethysmography Waveform.

I. INTRODUCTION

HYPOVENTILATION is the underlying cause in two of every three types of unexpected hospital deaths—progressive metabolic acidosis, opioid-induced carbon dioxide narcosis, and drug-induced arousal failure with sleep apnea, results in reduction in respiratory rate and/or tidal volume or a repetitive sequence of cyclic apneas and self arousals (obstructive sleep apnea) [1]. Hypoventilation often happens during the postoperative period, when opioids are commonly used for treating pain [2]. In the first 24 hours after the initiation of opioids, postoperative patients have the highest risk of opioid-induced respiratory depression [3]. Throughout this 24-hour period, intermittent nursing observation and monitors such as pulse oximeter are normally used to identify and reverse adverse respiratory events.

Pulse oximeter alarms are frequently ignored by clinicians due to a high false-positive alarm rate often caused by movement artifacts and displacement [4]-[5]. Pulse oximetry mainly monitors oxygenation instead of ventilation, and it could take several minutes for blood oxygen saturation concentration (SpO$_2$) to start decreasing after the patient enters hypoventilation. The SpO$_2$ signal therefore is a delayed indicator for apnea or hypopnea, especially when supplemental oxygen is given. By the time the pulse oximeter alarms, an apneic patient is already in danger of hypoxia, brain injury and death [6]. Alternative technologies for directly monitoring respiration such as capnography (CO$_2$ monitor) or acoustic respiratory rate monitoring are either costly or difficult to implement [7]. Thus, there is an urgent need for a low cost, reliable hypoventilation monitoring technique to give additional and timely physiologic information about a patient’s sufficiency of ventilation in addition to oxygenation.

We propose using the red plethysmography signal of the pulse oximeter to detect both apnea and a one-minute period preceding apnea. During apnea, there are some expected changes in the plethysmography waveform pattern due to the small changes in peripheral blood circulation resulting from the changes in inspiration effort during apnea compared to normal breathing [8]. We explore using a neural network to distinguish among one minute breathing samples. We hypothesize that we can identify changes in the pattern of the red photoplethysmography waveform and distinguish among periods of apnea, one minute preceding apnea, and normal breathing. The primary outcome measure is a set of confusion matrices for the neural network outputs.

II. METHOD

A. Study design

With IRB approval, twenty-six volunteers were recruited to participate in the study of the effects of sedative propofol and opioid remifentanil. Throughout the day, varying levels of both drugs were delivered to these patients through target controlled infusions. This project focuses on the group of
volunteers who received increasing doses of remifentanil and a fixed dose of propofol since remifentanil mainly causes central apnea. Data from a group of low cost and commonly used clinical monitors including chest band, pulse oximeter, nasal pressure sensor, capnometer, finger accelerometer, and thermistor, were digitized and recorded to a laptop computer from volunteer subjects at 100 Hz. The red photoplethysmography signal of the pulse oximeter was analyzed during the apneic periods to identify the typical patterns and differences in waveform between the periods of one minute before apnea, during apnea, and normal breathing. Periods of observed apnea were recorded real-time by agreement of two anesthesiologists.

B. Data extraction

MATLAB (Matlab R2010b, MathWorks, Natick, MA, USA) scripts were written to read the red component signal of the SpO2 photoplethysmography sensor (SET, Masimo Corporation, Irvine, CA), the nasal airway pressure sensor (1 INCH-D-4V, All Sensors, Morgan Hill, CA), a respiratory inductance plethysmography (RIP) chest bands (Q-RIP, Braebon Medical Corporation, Kanata, ON, Canada), finger accelerometer sensor (ADXL345, Analog Devices, Norwood, MA), nasal/oral thermistor (Disposable Adult Airflow Sensor, Braebon Medical Corporation, Kanata, ON, Canada) and oxygen saturation signals (SET, Masimo Corporation, Irvine, CA). These signals were then analyzed to determine all of the apnea periods that happened during the study to look for common patterns in SpO2 waveform. We identified periods of apnea with 1) at least a thirty-second period of baseline signal in nasal pressure and thermistor waveforms to be sure there was no sign of breathing out through nose and mouth and 2) a flat baseline in the chest band signal to confirm absence of intercostal muscle and diaphragm movement during apnea. The control (normal) breathing periods were collected when consistent breathing was detected in all signals (chest band, nasal pressure and thermistor signals) (Fig. 1). When the apneic and normal breathing periods were identified, three waveform samples were selected and saved in a separate file for further analysis: 1) one minute before the apnea event started, 2) one minute after the apnea event started and 3) one minute for normal breathing. Analysis was performed using a custom MATLAB script. A total of 100 samples- 34 apnea samples, 34 one-minute windows before apnea samples and 32 normal breathing samples were collected. The 34 samples of apnea and before apnea were collected from a total of 19 volunteers and the 32 samples of normal breathing were collected from 17 volunteers. The sample size was determined by convenience since the events were identified in a data set which had been collected for a different study. We used all available data samples.

C. Data Analysis

MATLAB code was written to normalize the red component of the SpO2 waveform and fit a line on the bottom of the normalized SpO2 waveform for all extracted data using the “envelope” built-in function in the program. Fig. 2 indicates a line fitted on the bottom baseline of the SpO2 waveform in red color. This bottom fitted line was saved in a separate folder for further analysis. Next, also using MATLAB, we calculated nine features that we believe describe the characteristics of the SpO2 waveform pattern visually observed from the SpO2 waveform raw signal and the ‘envelope’ fitted bottom baseline. The nine feature parameters were calculated including the slope of the SpO2 waveform baseline, mean, variance and standard deviation of SpO2 value within 1 minute collected; for the ‘envelope’ line of SpO2 waveform, the number of peaks, average peak height, average peak-to-peak distance, variance and standard deviation were also determined in MATLAB.

All nine features from 100 samples collected were saved in a 9 by 100 matrix as an input matrix for the pattern recognition MATLAB application tool. An output 3 by 100 matrix is created to include only zero and one value to indicate which type of waveform the input sample belongs to. The value one on the first row indicates normal breathing, on the second row for one minute before apnea period and on the third row indicates an apnea period. These input and output
matrices were implemented into the neural network pattern recognition tool in MATLAB for training. The total samples is divided randomly into 3 datasets with 70% number of samples for training, 15% samples for validation and 15% samples for testing under 10 hidden neurons and 2 layers.

III. RESULTS

There were 34 periods of apnea, 34 periods of one minute before apnea from 19 volunteers, and 32 periods of normal breathing from 17 volunteers detected and extracted from the study record of all participants. After the analysis of the photoplethysmography red waveforms of apnea, before apnea and normal breathing, a typical pattern could be recognized for each event. Fig. 3 indicates the pattern for normal breathing, usually collected at the beginning of each study, before the affection of drugs. Fig. 4 indicates the pattern for one minute of apnea and the pattern for one-minute right before the apnea event happened.

![Fig. 3](image1.png)

Fig. 3. Pattern of a co-ntrrolled SpO2 signal during normal breathing (amplitude in uncalibrated voltage units versus time) collected at the beginning of a study.

![Fig. 4](image2.png)

Fig. 4. SpO2 waveforms plotted with time (amplitude in uncalibrated voltage units versus time) indicating the typical patterns for apnea period (top) and one-minute window right before apnea started (bottom). These patterns are visually different from the controlled normal breathing waveform shown in Fig. 2.

After analyzing the waveform patterns of normal breathing, before and during apnea, the features for pattern recognition were identified based on the visual characteristic differences in each waveform type. During normal breathing, the baseline appears horizontal with minimal respiratory bumps on the bottom ‘envelope’ baseline of the waveform. Meanwhile, during the time when an apnea event occurred, there was an increase in variance of the plethysmographic SpO2 waveform compared to normal breathing and before apnea. In addition, the slope of the SpO2 waveform baseline tended to be negative and the respiratory bumps on the bottom ‘envelope’ baseline disappeared, leaving the waveform with a smooth bottom baseline. Meanwhile, the period of one minute before apnea displayed two main patterns: hypoventilation or consecutive short apnea periods, depending on different samples. Short apnea periods between 5 to 15 seconds are more likely to happen than hypoventilation, which yields cycles of rise and fall in the bottom fitted baseline of SpO2 waveform as depicted in Fig. 4 (bottom picture). Based on the visual differences analyzed from the three types of waveform, 9 input features from 100 samples of the normalized SpO2 photoplethysmography and the bottom baseline were used for the pattern recognition tool.

From the confusion matrix, the result for training 70 samples, validating 15 samples and testing 15 samples shows 100% correct with no error. The correctly classified samples are indicated in the green cells, from the training matrix, 22 samples from class 1 (normal breathing) was correctly classified as class 1, 27 samples from class 2 (one-minute before apnea) was correctly classified as class 2, and 21 samples from class 3 (apnea) was correctly classified as class 3. Similarly, we also observed 100% accuracy on the validation and testing dataset.
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IV. DISCUSSION

In this study, we used the red photoplethysmography waveform component of the pulse oximeter collected from volunteers to analyze the waveform pattern for every one-minute window of normal breathing, one-minute before apnea and one-minute after apnea had begun.

We have achieved our goal to discriminate pre-apneic event, apneic event and normal breathing, using a neural network pattern recognition tool in MATLAB. For the validation and test result, total 10 samples from class 1 (normal breathing) was correctly classified as class 1, 7 samples from class 2 (one-minute before apnea) was correctly classified as class 2, and 13 samples from class 3 (sleep apnea) was correctly classified as class 3. The training set size and quality primarily decide the quality of a learned system as supported by evidence from various application areas [10].

We identified that the red light waveform has apparent changes in baseline and pattern during the three types of waveforms we collected. During normal breathing, the pulse oximeter red light waveform had a stable baseline and variation. The respiratory pattern was partially hidden in this waveform; therefore, the baseline shows a minimal wavy pattern of respiratory rate. The respiratory rate occurs regularly and keeps the oxygenation in blood stable; hence, the baseline of heart rate stayed horizontal. During the one minute period before apnea occurs, multiple cyclical rise and fall cycles were commonly identified in the photoplethysmography waveform baseline. These cycles were the result of multiple short apneas between 5-30 seconds, one after another, in between one or more breaths. When a breath is taken between apnea periods, it increases the blood amount in vessels and the concentration of oxygen in blood decreases the absorbance of light transmitted through the finger, the intensity of light detected from the pulse oximeter light sensor hence also decreases. During an apnea period, blood becomes more deoxygenated and absorbs more red light intensity, and thus causes a fall in pulse oximetry waveform. In consequence, consecutive short apneic periods between breaths directly alters the photoplethysmography waveform and is transferred into the rise and fall cycles in the photoplethysmographic waveform. This change in the photoplethysmography waveform represents the changes in respiratory rate as also mentioned in Wendelken, Suzanne M. et al. reporting that respiratory induced variations in the photoplethysmogram take place in the waveform envelope [9]. Thus the respiratory rate is detectable using the waveform envelope, pulse height and shape.

A reliance on the respiratory rate is implied in the photoplethysmography waveform envelope. We analyzed the lower envelope of the SpO₂ waveform for apneic events because respiratory rate could be used to detect a breathing problem significantly faster than using oxygen saturation alone [11]. The absence of respiratory rate in the red waveform was observed in the lower envelope fitted curve due to a lack of contraction of diaphragm and thoracic muscles and disappearance of respiratory bumps in the envelope curve. Hence, we calculated the number of peaks, average peak height, average peak-to-peak distance, variance and standard deviation as an input for the neural network to differentiate apneic event with normal breathing and pre-apneic.

Post-operative patients under the effect of opioid drugs commonly have a higher rate of apnea. Therefore, an innovation in an apnea detection technique is crucial for reducing the risk of unexpected death caused by apnea, while also making post-operative monitoring affordable and
available to all at-risk patients. Identification of pre-apnea and apnea using a component of the pulse oximeter signal will facilitate the development of a novel method for monitoring post-operative patient’s adverse events, and will possibly improve apnea diagnosis in the future. Minimizing the delay time in diagnosing apnea is one of the main goals of this research study in response to the time-constrained manner of detecting apnea.

An advantage of using a neural network for pattern recognition is that it learns and generalizes complex relationships between inputs and outputs and makes a prediction of unseen data based on the generalized model.

In relation to vasoconstriction associated to apnea, the decreases in amplitude fluctuations of the photoplethysmography signal events have been proposed as OSAS discriminator [12]. This decrease in amplitude fluctuation in photoplethysmography waveform was again observed in our dataset for apnea samples. In addition, the baseline of the photoplethysmography waveform also declines due to the increasing of deoxygenated blood also observed through the apneic period. Therefore, the slope of the heart rate baseline, variance and amplitude was considered as one important feature for pattern recognition of apneic event. The total of 9 features from the photoplethysmography waveform and envelope curve have been used as an input to accomplishing the purpose of discriminating normal, pre-apnea and apnea pattern and yields 100% in accuracy.

Even though our result showed 100% in accuracy of pattern recognition for classifying normal breathing, apnea, and one-minute window before apnea, the small sample size could have been a factor that affected the result and biased toward multiple samples from the same volunteer data. To further investigate the reliability of the result, the training has been repeated on a neural network with the removal of samples from the same volunteer (maintaining only one sample for each volunteer). This sample withholding method reduced the sample size down to 55, however it still yielded 0% error in classifying the waveform patterns. If this experiment was performed with a larger number of volunteers, we believe the neural network could mitigate the limitation in bias training process and provide a more reliable result. Regardless of the limitation, the current results of this study are promising findings, which set up fundamental method to identify apnea at least one minute in advance. This neural network could also be used to create a machine learning pattern recognition cost effective device in the future.

The differences in pattern of photoplethysmography waveform between pre-apnea, apnea and normal breathing is a potential solution to develop an apnea detecting device, which can eliminate the limitation of the current devices such as delay in time, high false positive alarm, and cost ineffective in order to reduce the rate of unexpected death in the hospital. The success in detecting hypventilation might have a significant impact to develop a method used to detect apnea in the future.

Future work will include a more formal exploration of the ideal machine learning approach as well as rigorous testing in a sufficiently sized patient data set.

REFERENCES