

Tracheal Sound Analysis for Automatic Detection of Respiratory Depression in Adult Patients during Cataract Surgery under Sedation

Abstract

Background: Tracheal sound analysis is a simple way to study the abnormalities of upper airway like airway obstruction. Hence, it may be an effective method for detection of alveolar hypoventilation and respiratory depression. This study was designed to investigate the importance of tracheal sound analysis to detect respiratory depression during cataract surgery under sedation. **Methods:** After Institutional Ethical Committee approval and informed patients' consent, we studied thirty adults American Society of Anesthesiologists I and II patients scheduled for cataract surgery under sedation anesthesia. Recording of tracheal sounds started 1 min before administration of sedative drugs using a microphone. Recorded sounds were examined by the anesthesiologist to detect periods of respiratory depression longer than 10 s. Then, tracheal sound signals converted to spectrogram images, and image processing was done to detect respiratory depression. Finally, depression periods detected from tracheal sound analysis were compared to the depression periods detected by the anesthesiologist. **Results:** We extracted five features from spectrogram images of tracheal sounds for the detection of respiratory depression. Then, decision tree and support vector machine (SVM) with Radial Basis Function (RBF) kernel were used to classify the data using these features, where the designed decision tree outperforms the SVM with a sensitivity of 89% and specificity of 97%. **Conclusions:** The results of this study show that morphological processing of spectrogram images of tracheal sound signals from a microphone placed over suprasternal notch may reliably provide an early warning of respiratory depression and the onset of airway obstruction in patients under sedation.

Keywords: Breathing sound analysis, respiratory depression, spectrogram image, support vector machine network

Introduction

Increasingly, many surgical and nonsurgical operations such as dental and endoscopic procedures, cosmetics, and cataract surgery are performed under sedation analgesia using a combination of sedative and narcotic drugs. The anesthesiologist must carefully titrate hypnotics and opiates to the patient needs, with close monitoring of their effects on respiratory functions. Under-sedation and over-sedation carry potential risks of surgical complications and respiratory depression, respectively. During ophthalmic microscopic surgeries, patient's movement may lead to serious operative complications.^[1] Hence, many anesthesiologists prefer to use stronger sedative techniques,^[2] which increases adverse cardiorespiratory complications.^[2] Since the airway is not sufficiently protected during sedation analgesia, these patients have an increased risk of severe

respiratory depression and obstruction,^[3] which necessitates close and continuous monitoring of airway patency and adequacy throughout the period of sedation. Commonly used monitoring techniques such as pulse oximetry usually have a considerable delay in detecting respiratory complications.^[4,5] Sidestream capnography is of limited value for the detection of respiratory depression, due to usage difficulty, sampling error, lumen obstruction by airway secretion, and frequent detachment from the patient's airway opening.^[6,7] Therefore, direct monitoring of airway patency using auscultation techniques is of paramount importance during sedation analgesia.^[8] Continuous tracheal sounds' monitoring using traditional or electronic stethoscope can reliably and rapidly detect airway complications^[9] before these events lead to serious complications. The overall efficacy of tracheal stethoscope as an airway monitor depends on continuous

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listening to the respiratory sounds by the anesthesia team. Continuous operator listening may not be practical, and intermittent auscultations may incidentally overlook major airway problems. Therefore, using real-time automatic and continuous techniques for tracheal sound monitoring and analysis is of particular importance for airway monitoring under sedation analgesia.

Tracheal sounds originate from different sources contributing to the final sound recorded by a receiver over the suprasternal notch.^[10,11] Some previous studies have used entropy of the audio signal as a measure of the complexity of tracheal sounds and reported that its changes could be a warning for impending obstructive pattern in airway.^[12] Time domain analysis of tracheal sound does not provide a clear insight into the frequency content of components but may be useful for detecting respiratory events. On the other hand, frequency domain provides the frequency content of signal without information about which frequencies are dominant in which moment, which is necessary to recognize different events. Therefore, using joint time-frequency analysis approach, we would be able to simultaneously employ both time and frequency information. The superiority of time-frequency analysis against the time domain and frequency domain techniques has been shown in previous studies on respiratory sound analysis in the current years.^[13-15] It allows to analyze which frequencies of a signal under study are present at a certain time. For example, short-time frequency transform (STFT) can be employed because of its power in resembling the original appearance of signals.^[16] If $x(n)$ and $w(n)$ represent the signal and region of interest (ROI) window, respectively, using spectrogram image of spectral density, i.e., $|STFT(w, m)|^2 = \left| \sum_{n=-\infty}^{+\infty} x(n)w(n-m)e^{-j\omega t} \right|^2$ seems to be a logical method of applying tracheal sound analysis for real-time detection of airway problems.

Different researchers have widely utilized this technique in audio and speech analysis. Converting audio signals to time-frequency spectrogram images and subsequent processing using ultra-rapid image processing algorithms is a way of full signal sound analysis to extract essential sound components, known as features explained in methods, associated with respiratory depression. Image analysis of the spectrogram of the audio signal is performed to extract the best features. Using image processing methods on such time-frequency images makes it possible to differentiate normal respiration from unusual ones. This approach has been utilized in the past for extracting heart sounds.^[16] In this study, tracheal sounds were electronically recorded and subsequently listened by expert anesthesiologists. The aim of this research was to determine the feasibility of tracheal sound analysis to detect respiratory depression in adult patients under sedation for cataract surgery.

Materials and Methods

After Institutional Ethical Committee approval and informed patients' consent, we studied thirty adults, 22 American Society of Anesthesiologists (ASA) I and 8 ASA II patients, aged 50–80 years, scheduled for cataract surgery under mild-to-moderate degrees of sedation. Patients with a history of respiratory diseases were excluded from the study. Furthermore, patients with thyroid diseases, anatomical abnormalities in the airway, severely obese patients (body mass index ≥ 35), and those with a history of severe obstructive sleep apnea were excluded from this study. After positioning on the operating table, all the patients received supplemental oxygen through a mask. Monitoring consisted of electrocardiography, noninvasive blood pressure, capnography, and pulse oximetry. Recording of tracheal sound started 1 min before administration of sedative drugs using C417 omnidirectional condenser lavalier microphone (AKG Acoustics, Vienna, Austria), secured over suprasternal notch with double-sided adhesives. The tracheal sound recording continued throughout the procedure at a sampling rate of 44,100 Hz. Recorded sounds transferred into a personal computer for final analysis.

Although we used capnography monitoring in this study, on many occasions, it produced false alarms of respiratory depression which were ruled out by tracheal auscultation. These false events were mainly due to extreme dilution of expiration by a high flow of oxygen and also obstruction of capnography catheter by direct contact with skin or secretions. Therefore, in this study, we compare auscultation results with sound analysis. Intravenous sedation consisted of 2–5 mg of midazolam and 1–3 ml of fentanyl intravenously, administered within 5 min and titrated to the patients need to achieve an initial sedation within 5 min, as evidenced by a sedated but easily arousable patient. Further doses of 1 mg of midazolam or 0.5 ml of fentanyl were administered if the patient exhibited motions or expressed pain.

After collecting data, recorded sounds were examined by the anesthesiologist to detect periods of respiratory depression, as defined by the occurrence of apnea, breath-holding, or airway obstruction longer than 10 s. Apnea and breath-holding defined as complete absence of tracheal sounds. Airway obstruction was defined as an obstructive pattern (stridor-like breath sound) when listening to recorded sound.

Signal processing

We used Matlab 8.1.0 for signal and image processing. Signals were segmented into 100-ms windows (4410 samples) with 50% overlap for converting into consecutive spectrogram images. The window size and overlap were selected based on the results of studies on tracheal sound.^[12,17] Spectrogram images were obtained using STFT and applying hamming window to each segment.^[4] Since the minimum period valuable for the

detection of respiratory depression is 10 s, the spectrogram images are obtained in each 10 s. Then, images were labeled as positive or negative. The absence of respiratory sound (including inspiration and expiration) through auscultation by the anesthesiologist in each 10 s was proposed as a clinical manifestation of respiratory depression and their corresponding spectrogram images were labeled as positive ones. In contrast, the spectrogram images corresponding to normal respiration (detected by anesthesiologist in each 10 s) were labeled as negative [Figure 1].

In the first step of the analysis, spectrograms from seven randomly chosen patients were used to investigate the proposed features in previous studies. The related features to spectrogram images were local texture properties such as smoothness, roughness, and orientation, and statistical texture properties such as skewness, standard deviation, kurtosis, variance, entropy, mean, and also gray level co-occurrence matrices properties such as contrast, correlation, energy, and homogeneity.^[18,19]

Image processing

First, original spectrogram images were converted to a black and white mode (binary image) to eliminate low-frequency

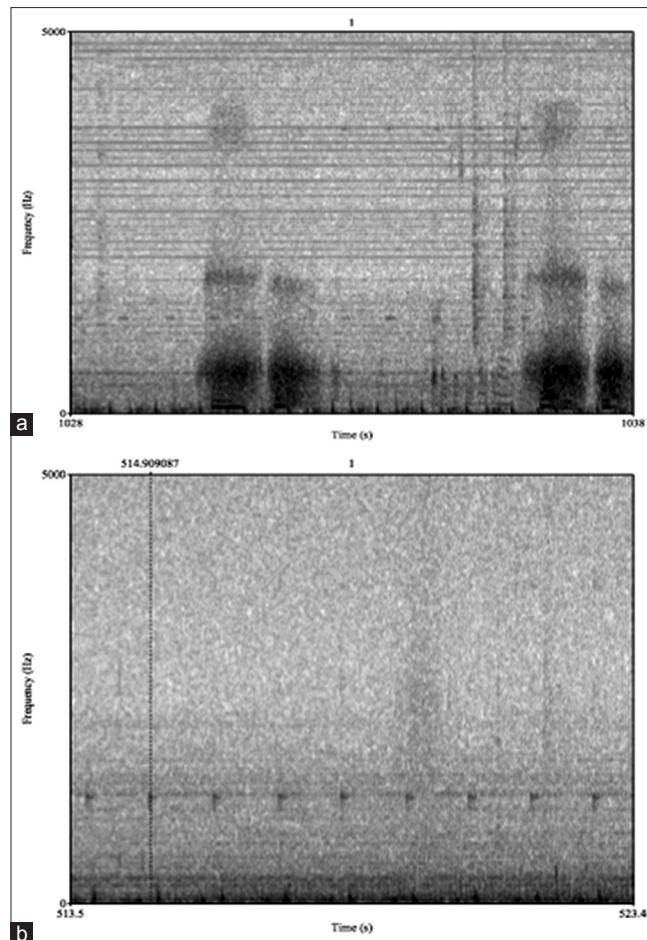


Figure 1: The gray-scale spectrogram images (high values are displayed in black). (a) 10 s normal respiration (labeled-). (b) 10 s apnea (labeled +)

signal and keep the higher frequency ones in the range of respiratory signals [Figure 2a]. We applied the opening and closing morphological operations in this analysis for preprocessing.^[18] Opening tends to remove some of the foreground pixels that help to have separate white areas. In contrast, closing tends to fill the holes of foreground and make the united regions larger. We used opening operation on the original binary images to achieve better results by omitting the irrelevant white dots. The produced black and white images would be appropriate for extraction of some useful features for recognizing respiratory depression periods.

Results

From 128 patients scheduled for cataract surgery, 98 participants were excluded from the study: 56 patients underwent general anesthesia, 32 patients had a history of respiratory disorders, obstructive sleep apnea, or higher levels of ASA, and 10 patients were severely obese. Therefore, the study was performed on the remaining thirty patients including 22 ASA I and 8 ASA II patients.

Due to the operating room noises and movement of the patient, samples from ten participants were not appropriate for analysis. Therefore, signal processing was performed on 2000 samples from the remaining twenty participants.

Figure 3 shows the events of respiratory depressions in the test group.

Features obtained from the first step were strongly associated (individually or in combination) with respiratory depression and were tested on image samples from the remaining 13 patients to determine their sensitivity for detecting respiratory depression. We set a diagram with these features that consecutively recognized the depression periods from normal ones [Figure 4]. These features are standard deviation,^[20] energy, kurtosis,^[21] the white area related to normal respiration, and white space height which are defined as follows:

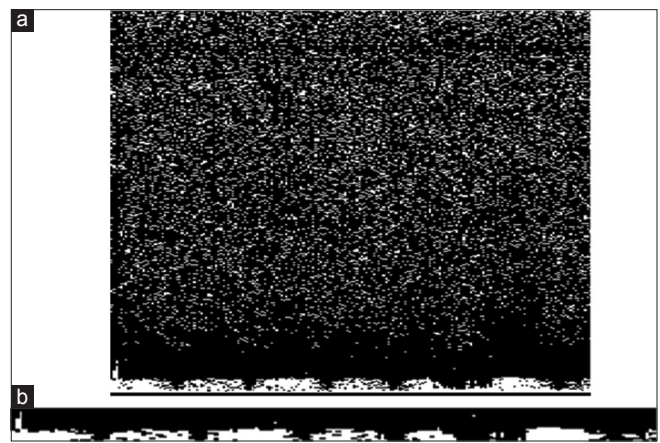


Figure 2: (a) A sample binary image produced from a spectrogram of a normal respiration ($t = 0.75$). (b) Extracted binary image after applying morphological operators and removing noninformative areas (outside frequency range of 150–800 Hz which is related to respiratory sound)

- White area: As shown in Figures 1 and 2, there are some periodic regions related to inspiration and expiration in a 10 s normal respiration.^[6,22] After converting to a binary image, these periodical regions converted to white areas. Adversely, in a 10 s period related to apnea, there was no white region or maybe a small region for other reasons such as noises. Furthermore, in respiratory depression, there were white regions smaller than normal respiration but without rhythm. The next step was to find a threshold for the size of these white regions distinguishing between normal respiration and depression. Due to the differences between respirations of different people, no single threshold could be useful for all images. Hence, there was a need for other features for completing the detection protocol
- White area height: In the spectrogram image, as shown in Figures 1 and 2, the vertical axis is related to signal frequency. Hence, the height of white area could be a useful feature. The frequency of 150–800 Hz is related to respiratory sound.^[22,23] Hence, the white area height between 150 and 800 Hz in spectrogram image would be related to normal respiration and should not be considered as depression [Figure 2b].

Image classification

Two different approaches were used to classify data based on the extracted features from tracheal sounds, decision tree^[24] and support vector machine (SVM).^[17] SVM is one of the well-known methods for image classification. SVM builds the optimal separating hyperplanes based on a kernel function (K).^[25] This classifier also has been used in respiratory signal processing.^[17,26] A decision tree is a relatively straightforward classifier that lacks the expressive power of semantic networks and its learning methodologies are less complex than those in systems that can express the results of their learning in a more powerful language.^[24] In

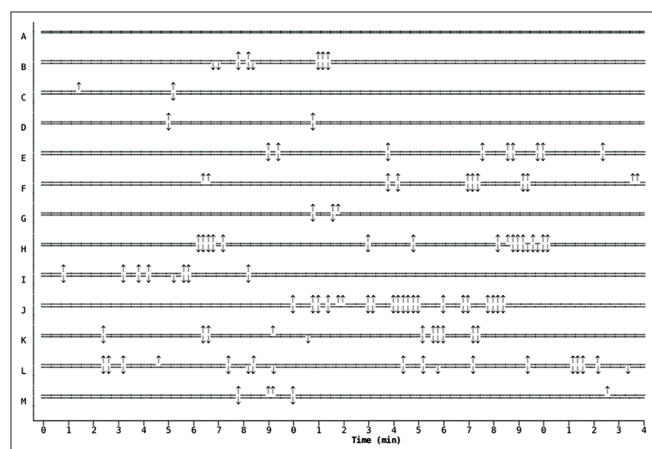


Figure 3: Respiratory status data for 13 patients. For each subject, lower arrows show auscultatory finding synchronized with results of the respiratory sound analysis in upper tracing. Symbols: Upward arrow ↑: An event of respiratory depression for a duration of least 10 s detected by respiratory sound analysis. Downward arrow ↓: An event of respiratory depression for least 10 s detected by auscultation

this study, we tried to find the best discriminative features using train and test for decision tree. In the next step, we fed the extracted features from decision tree to SVM as a more advanced classifier.

- Decision tree based on selected measures: We randomly chose seven patients for checking the features to find a suitable level for each of them. These levels should be sufficient for most of the images in different patients. None of them alone could be adequate, and all features together were necessary to make a useful decision. Hence, a decision tree was plotted that could be able to separate abnormal 10s respiration from normal ones, step by step [Figure 4]. Then, the rest 13 patients were checked with this flowchart [Table 1]
- SVM classifier: The number of samples with label 0 (normal respiration) was much more than samples with label 1 (respiratory depression). Therefore, we decided to replicate the samples with label 1 to compensate the effect of unbalanced classes.^[27] The test data set consists of 1212 samples; 69 of which were from apnea class and the rest from the normal class. We repeated the samples of the apnea class 17 times $(\sim[1212-69]/69)$ so that the number of sample from two classes becomes close together. SVM classifier with RBF kernel trained on the depression data set. We used k-fold

Table 1: Accuracy, specificity, and sensitivity for detecting respiratory depression

	Accuracy (%)	Sensitivity (%)	Specificity (%)
SVM	83.69	83.80	82.08
Decision tree	91	89	97

SVM – Support vector machine

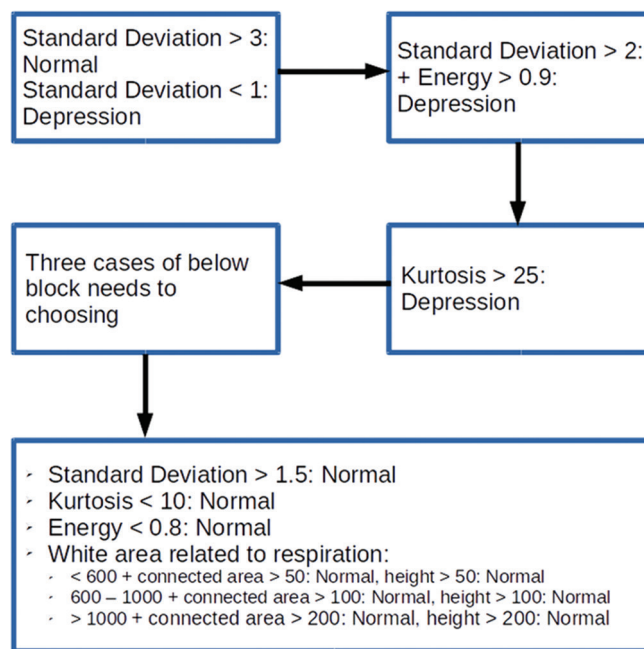


Figure 4: The proposed diagram based on five final features to distinguish depressed periods from normal ones

Table 2: The comparison of proposed method in this paper with related works

Other studies	Current study
Using entropy of respiratory signal ^[23]	Using features of spectrogram image
Using ECG, EEG, and capnogram ^[26,28]	Using respiratory signal recorded from trachea
Data gathered in experimental environment ^[23,28]	Data collected in hospital
Data related to healthy volunteers ^[23]	Data related to patients under surgery
Time-frequency method: Wavelet approach ^[29]	Time-frequency method: STFT approach
Aim was recognition of sleep apnea and wheeze ^[30,31]	Aim was apnea detection during sedation of patients under surgery

STFT – Short time-frequency transform; EEG – Electroencephalogram; ECG – Electrocardiography

cross validation algorithm with $k = 20$ to estimate the generalization performance. Accuracy, specificity, and sensitivity were calculated over 20 folds [Table 1].

Discussion

Analysis of tracheal sound spectrogram in the present study showed that features extracted from spectrogram image processing such as kurtosis, standard deviation, energy, and white area (in black and white images) are strongly associated with the occurrence of respiratory depression in patients undergoing intravenous sedation. It became apparent that using all of these features results in better performance for the detection of respiratory depression with a sensitivity of 89% and a specificity of 97% employing a decision tree and sensitivity of 84% and specificity of 82% employing SVM classifier.

In 2010, the analysis of spectrogram images to recognize and extract basic heart sounds and murmurs was introduced.^[16] However, to the best of our knowledge, it is the first time that spectrogram image processing is employed for analysis of respiratory depression.

The entropy of tracheal sound was used to detect the obstructive apnea, and central apnea in sedated healthy volunteers and a sensitivity of 95% and specificity of 92% was reported.^[23] Mazzanti *et al.* detected apnea in patients in a sleep laboratory with a sensitivity of 87% and a specificity of 85% using an electrocardiography-derived respiration monitoring method.^[28] Ramsay *et al.* evaluated a new acoustic monitor from Masimo Inc. (Irvine, California, USA) and a capnometer from Oridion Inc. (Needham, MA, USA) by collecting data from patients in the postanesthesia care unit. The acoustic monitor was able to detect the apnea with 81% sensitivity and 99% specificity and the capnometer detected the apnea with a low sensitivity of 62% sensitivity and specificity of 98% which leads to misdetection of apnea.^[32] Table 2 compares the current study with previous similar works. The method used in this study is a new approach for processing tracheal sound for depression recognition. However, in a comparison to other time-frequency methods on tracheal sound, Sello *et al.* provided a wavelet-based method to describe the frequency power distribution of the audio signal to detect the healthy state by the wavelet mean power spectra, but they did not measure the ability of their algorithm to detect depression.^[33]

Nakano *et al.* and Yadollahi and Moussavi demonstrated that tracheal sounds' analysis has a relatively high performance for the diagnosis of sleep apnea-hypopnea syndrome during normal sleep. However, they did not focus on the early detection of the onset of apnea, especially sedation-induced apnea.^[12,34]

Taplidou and Hadjileontiadis did a time-frequency analysis of breath sounds for wheeze detection, but they did not work on respiratory depression.^[30]

As a result, it seems that image processing could be useful besides other signal processing methods to have the best result to detect respiratory depression; however, more studies are needed for better results, especially in the presence of high-level of noise and distortions such as proposed signals in this study which were gathered from patients in a noisy environment, not from a controlled experiment.

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Conflict of interest

There are no conflicts of interest.

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