Automatic Detection and Classification of Acoustic Breathing Cycles

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***Abstract*— This paper focuses on respiratory phase detection and classification without the help of the airflow measurements. Instead of using the airflow measurements to identify breathing phases, the proposed work depends on advanced digital signal processing techniques to process the acoustic signal of respiration that was collected using a microphone placed in front of the subject's nose. The recorded signal is processed using the voiced-unvoiced algorithm to differentiate between the voiced period and the unvoiced (silence) period. The desired features are extracted from each voiced phase. Finally, support vector machine is used to distinguish between the inspiration and the expiration phases according to the extracted features. The signals were recorded from a number of subjects who do not have a history of pulmonary diseases. The proposed method has achieved an accuracy of 95% when tested on the subjects.**

Keyword— Acoustical signal of respiration, Airflow, Microphone, Breathing Phases.

I. INTRODUCTION

A. Background

IN the recent years, significant efforts have been made by researchers to solve many issues in the diagnosis of certain health complications. The respiratory system has, especially, grabbed a lot of attention because of the variety of diseases that affect the body and are relevant to this system, such as various breathing disorders, wheezing-episode, wheezes in asthma, lung cancer, and many more. Researchers have been studying the acoustical sounds for the purpose of diagnosis of many diseases including the respiratory system diseases. They have also investigated the relationship between the respiratory phases (exhale/inhale) and the airflow which is considered to be an important factor in identifying some diseases or swallowing problems. Many researchers have been trying to find efficient techniques to detect and classify the breathing phases and estimate the airflow automatically to make the test faster and easier for the physician.

B. Related Work

Various methods have been used to detect the respiration. Some methods use the Electroencephalogram (EEG) signals, while other methods use the airflow measurements. Respiratory phases are currently detected by using the airflow measurements [1]. There are many techniques for measuring the airflow. One technique is nasal cannula. Another technique is resistance band. These two techniques have less accuracy [2, 3] and need high level maintenance [4].

Because of the limitations of the previous techniques, researchers have suggested other techniques that depend on the acoustical signal for this purpose [5-8]. Current techniques use two signals to specify the phase and to estimate the flow. They usually consist of accelerators or microphones placed on the chest. Each type of microphone has a specific task. Some collect the lung sounds in order to detect the respiratory phases (inhale/exhale), while the tracheal ones are used to collect the tracheal respiratory signals for estimating the air flow [6]. Detecting the breathing phases from tracheal sounds instead of the lung sounds was a part of [9]. Also, in [10] the authors proposed a method of breathing phase detection based on the acoustical signal in tracheal sounds using two sensors. However, these techniques are more suitable for long time monitoring and require contact sensors that are placed on the body of the subject. Another approach is the use of non-contact sensors to capture and analyze the acoustical signal [11, 12]. In regard to the detection of breathing phases, there are some proposed techniques that used the non-contact approach. The works presented in [13-16], proposed some techniques for this purpose. However, the authors focused on obtaining a result with the desired accuracy, while paying less attention to the complexity of the technique.

C. Contribution and Paper Organization

The work presented in this paper tends to increase the ability of diagnosis of certain health issues, especially those related to airflow as well as those that require the identification of breathing phases as a part of the requirements to implement the entire work. This is done by proposing an automated method to detect and classify the respiratory phases into expirations and inspirations. Support vector machine is used for classification based on the features that were extracted from the acoustic breathing signals collected from the subject's nose using a typical microphone. The acoustical signal is processed using the voiced-unvoiced algorithm to find the voiced periods that carry the interested features. Feature extraction was done by feasible math calculations on the acoustical signal in time domain.

The rest of the paper organized as follows: In section II we provided the whole description of the proposed method. This section is divided into subsections. Each subsection explains a specific part of the work. The first subsection explains how the signals have been collected. The second subsection describes the idea behind processing the signal. In the third subsection, an explanation regarding the features and how they are extracted is

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given. The fourth subsection describes the classification method. In section III, we then discussed the results of the proposed work tested on a number of subjects. Finally, concluding remarks appear in section IV.

II. Methodology

A. Collection of the signal

The acoustical signals of breathing were collected from 9 healthy subjects in a noise-free room at the University of Bridgeport. The subjects were between 27 and 33, nonsmokers, normal weight, with clean history of respiratory diseases, two of which were female. The signals were recorded using the SAMSON C01U USB microphone placed at a distance of 2-4 cm from the nose. The distance between the subject's nose and the microphone has an important effect on the captured signal. If the distance is increased, the quality of the captured signals will decrease. The subjects were asked to sit on a chair in front of a table that has the microphone connected to the laptop on it (Fig.1). After a description of the experiment has been given to the subject, he/she was asked to breathe close the microphone. The recording times were between 40 to 90 seconds. The recorded signals were stored as .wav files to be used in the signal processing software (MATLAB).

B. Signal Processing

After recording the breathing signals, all the signals were processed and analyzed by MATLAB R2012a software. The signals were sampled at 44.1 *KHz* sampling rate and segmented into a number of frames because it is easier to deal with small frames of information when it comes to processing the signals using certain techniques. After many rounds of experiments to choose the suitable length of the frames, frames of length 600 samples gave the best result. Then, the Voice Activity Detection (VAD) algorithm was applied to the framed signals for the purpose of segmenting the signal to differentiate between the voiced and unvoiced segments.

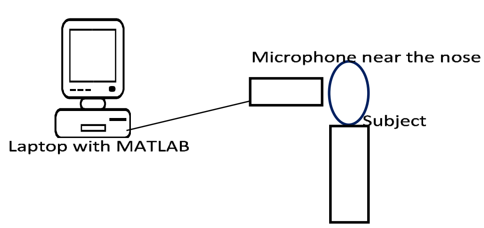

Fig. 1. Schematic diagram of the experiment.

The basic idea of this algorithm is to bound the voiced periods of the framed signal by considering that the voiced signal has a higher level than the unvoiced (silent) levels and the background noise changes slowly [17]. In this work, the VAD algorithm was applied to the acoustical breathing signal to distinguish between the silent periods and the breathing activity periods (the desired periods that are needed to detect the inspiration and the expiration). Fig. 2 shows the acoustical signal of the breathing. Fig. 3 shows the VAD algorithm applied on the breathing signal. During the implementation of this algorithm, the segmented breath signal was low pass filtered to remove the unwanted low frequency components, and it was converted to Fast Fourier Transform (FFT) to calculate the power of windows from different sizes [18].

C. Breathing Phase Detection

After differentiating between the voiced and unvoiced periods of the signal using the VAD algorithm, the breathing phase detection algorithm takes the voiced periods of the acoustical signal and decides whether it is inhale or exhale. The detection algorithm considers the voiced periods of the signal for further analysis and eliminates the unvoiced periods that are considered as silent or pauses.

The method is implemented by calculating the sum of peaks in the signal per phase. In this method, the calculation performed on the voiced activity periods identify the start and end points of each window according to the bounds of the VAD (the whole period of the breathing phase). The size of the window changes according to the breathing phase length, and therefore it is considered more reliable than other techniques that depend on the onsets of the phases. This approach eliminates the need to estimate windows with an approximate time. Each breathing phase has one window. In each window, the features were calculated to decide the best approach that could separate the voiced phases extracted.

Consequently, in the analysis of the breathing phases for each subject, several parameters were studied, especially the sum of the maximum amplitude values and the number of the frames in each window of the acoustical signal (voiced phase). For this, the peaks of the signal for each frame were found. This step gave the samples that have higher values to represent the value of the frame. Then, the summation of these values was considered (Eq. 1) in order to distinguish between the phases because of the clear differences between the exhales and inhales peak values.

$$Sum_k = \sum_{i=1}^{Nframe_k} (Peak_i) \qquad (1)$$

where k ranges from 1 to the number of voiced periods detected form VAD, $Nframe_k$ refers to the number of frames in breathing phase k, and $Peak_i$ refers to the peak (maximum amplitude) in frame i of breathing phase k.

One major advantage of this approach is that the complexity of the summation function is relatively easier than other signal processing techniques, making this technique highly attractive for hardware implementations. The number of desired peaks was calculated as it gives an estimation of the phase duration by giving the number of frames for each phase. After these calculations, the respiratory phases can be detected which also indicate the airflow direction.

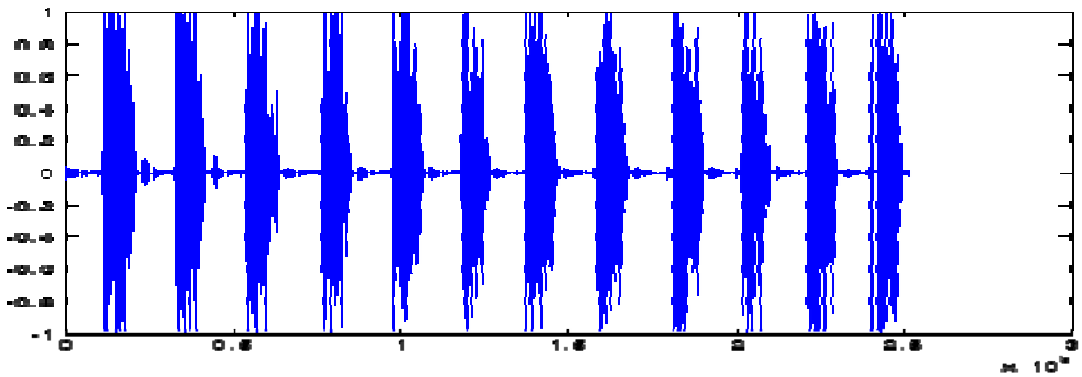

Fig. 2. Breathing signal captured using a microphone.

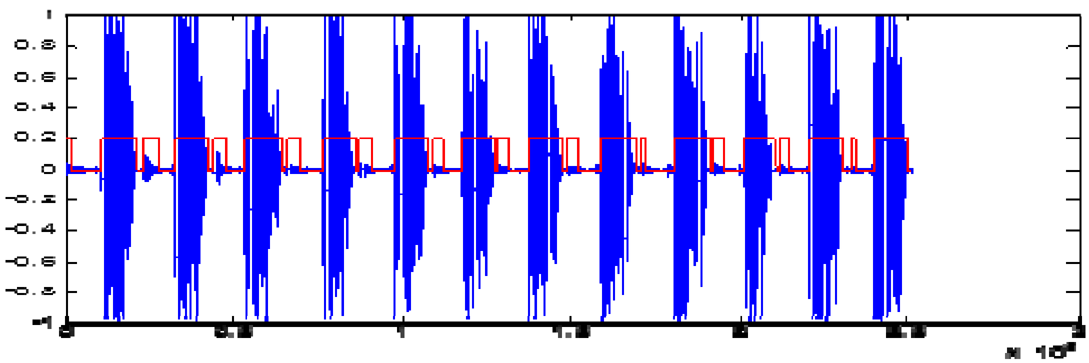

Fig.3. Breathing signal after applying the VAD.

D. Breathing Cycle Classification

The aim of this section is to clarify the process of the automated breathing phase classification. In addition to the automated detection of the breathing phases, it is recommended that the entire classification process and implementation be automated not only to achieve higher accuracy results but to also overcome the limitations and errors the time consuming manual classification process encounters. Many machine-based techniques have been used for classification purposes. One of these techniques is the Support vector Machine (SVM).

Briefly, the support vector machine is a supervised machine learning algorithm that has been used for some time of the last century for classification purposes in many fields. The basic concept of this classifier is based on two main steps. First, training the support vector machine classifier using a training set of data from two known classes (groups). Second, according to the training data, the classifier will specify a bound that will be used to separate the new data to give the final result in one of the two classes. This separation is done by the hyper-planes that will draw the bounds among the features that represent the values of some parameters. In the training step, the sample training data and the two classes' labels should be given to the classifier. After this step is done, the classifier model will contain the information about the trained classifier. Finally, any new data sample that is to be classified, and the information from the classifier model should be given to the classification function. The classification will be constructed according to these given information. The implementation of the classifier in this work was by giving the training data and the classes' labels to the SVM with linear kernel training function. The data were given to the support vector machine as an array of features that contain the sum values (Eq. 1) and the energy of each voiced period that were extracted from the detection algorithm, and the classes were labeled as (1,-1) for the exhale and the inhale phases. Then, the data that are required to be classified with the trained classifier information were given to the classification function of the classifier. The classification part is the last module of the proposed method. Fig. 4 shows a diagram of the entire proposed method.

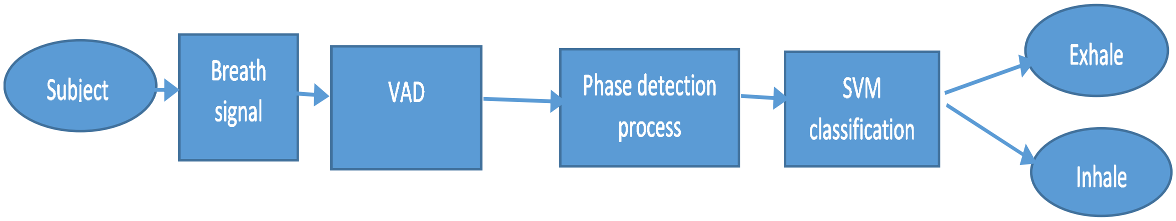

Fig. 4. Block diagram of the proposed method.

III. RESULTS

The results in Table I show the performance of the proposed classification technique for a few subjects when evaluated by the statistical measures of the performance of a binary classification test. Although there is no obvious difference between the respiratory phases in terms of time, the results have shown that there are some other parameters that can be extracted from the captured breath activity recorded using a microphone near the nose to differentiate between the respiratory phases and then classify them into exhale and inhale. This is because of the nature of breathing when it is analyzed as a voice source from the nose where the expiration voice has values higher than the inspirational voice. This approach was the start point of further analysis. It is important to point out that it may seem obvious that once an inhalation is detected, the next voiced phase would be exhalation. Although, in many circumstances this is the case, it may not be the case always, especially, for patients with breathing disorders, or even athletes. Some users may inhale twice or multiple times consequently, or exhale multiple times consequently without inhaling in between. The advantage of the proposed method is that since the classification relies on acoustical signal features, such cases would be identified correctly. Many features such as the summation of the peak values, the energy of the voiced activity, and the average value have been studied to achieve high accuracy once it can be the base for detection and classification approaches. All these calculations were performed on each voiced window. The features have resulted in high accuracy to distinguish between the exhales and the inhales. This design particularly considers the sum of the peak values along with the energy features in the classification method**.** Table I shows the result of using these parameters in the classification algorithm to decide the phase of the tested signal. In this table, the statistical parameters derived for each subject include the True Positive (TP) and the True Negative (TN) representing the number of the correctly classified exhales and inhales respectively, whereas the False Positive (FP) and the False Negative (FN) represent the number of missed exhales and inhales respectively. The number of Actual Breathing Activities (ABA), the number of Actual Exhales (AEX), and the number of Actual Inhales (AIN) were annotated manually to be compared with the classifier results. Finally, the values of the Accuracy (ACC) and the Error (ERR) were calculated using the TP, TN, FP, and FN values. The average accuracy was found to be 95.06%.

TABLE I: BREATHING CYCLE CLASSIFICATION RESULTS.

Data	ABA	AEX	AIN	TP	TN	FP	FN	ACC%	ERR%
1	19	10	9	9	9	0	1	94.73%	5.26%
2	16	8	8	8	8	0	0	100%	0%
3	18	9	9	8	9	0	1	94.44%	5.55%
4	15	7	8	7	7	1	0	93.33%	6.66%
5	19	9	10	9	9	1	0	94.73%	5.26%
6	17	8	9	7	8	1	1	88.23%	11.76%
7	24	12	12	12	12	0	0	100%	0%

Discussion: The result of the classifier in this work depends heavily on some factors.

- First, it heavily depends on the voiced activity detection algorithm.
- Second, it highly depends on the type/sensitivity of the microphone. A microphone with high sensitivity results in better signals because it detects the voice of very low values.
- Finally, the distance of the microphone also affects the result.
- In addition, this work relies on deep breathing as a rather economical microphone with not very high sensitivity is used in recording the signals.

IV. CONCLUSION

This work presented a method for breathing phase detection based on the analysis of the acoustical breathing signals that were collected using a typical microphone near the nose. Most of the other related works require the use of microphones to be in contact with the chest area to identify the respiratory phases, while this proposed work used a non-contacted microphone for detecting and classifying the breathing phase and giving an estimation about the airflow. The promising results of the proposed method make it an attractive technique for further diagnostic analysis that require indicating the phases of the breath cycle activities.

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