Breathing Detection in a Portable Apnea Detection Unit

by

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A Thesis Proposal by

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Abstract:

Apnea, the suspension of breathing, is a condition that affects millions of people; many of whom are completely unaware of the condition. Apnea can contribute to a variety of life threatening medical conditions. Clarkson Honors student Douglas Dawson has designed a system for portable apnea detection and user notification through the use of a microprocessor controlled blood oxygen sensor. I propose an extension of this work by integrating a patient worn microphone that will serve as a secondary means of detecting apnea events. The resulting device will be a discreetly wearable monitor that records both oxygen saturation of the blood and respiratory rate in order to alert the of an apnea event and help them to recover. The combination of respiratory rate and blood oxygen saturation data will also provide doctors with a detailed image of what their patient is experiencing providing a valuable tool for diagnosis and monitoring. Use of the device with appropriate biofeedback software could also provide the behavioral feedback necessary to retrain the user’s breathing response, which is part voluntary, resulting in fewer and less severe apnea events, thus improving patient health.

Introduction:

Apnea is the suspension of breathing for an abnormally long and potentially harmful duration. An apnea event is typically defined either as a 4% drop in blood oxygen saturation or as a suspension of breathing for 10 seconds or more [12]. Typically a person experiences involuntary apnea events in his sleep and is completely unaware they are occurring; this is called sleep apnea. However, this can also occur while a person is awake. Apneas can be caused by physical obstruction or damage to airways, neurological dysfunction, or both [12]. While fairly common, apnea is under diagnosed [11][15]. This is a serious condition that can have dire consequences including: high blood pressure, heart failure, heart rhythm disturbances, atherosclerotic heart disease, memory problems, weight gain, impotency, and headaches [11][12]. Untreated sleep apnea generally provides for a poorer quality of sleep, leaving the sufferer tired throughout daily activities; because of this, it has been shown that those with sleep apnea have a higher risk of traffic accidents [16][11]. Unfortunately, there are no portable devices on the market for monitoring a patient and alerting them that they have stopped breathing. What is needed is a portable yet discreet device that can be easily be worn throughout the day and monitor a patients breathing and blood oxygen saturation. This could serve two purposes, both diagnosis and treatment. The device could be given to patients to wear for a couple days; after which the doctor could review all of the recorded data and quickly determine if a patient needs further testing and treatment. The device could also be used as a way to alert a patient during an apnea event and “remind” him to breath. Receiving this type of biofeedback over a period of time could potentially retrain the patient’s brain and allow them to breathe better on their own, which could be tracked with the data from the device. Douglas Dawson, a Clarkson University Honors student class of 2010, has nearly completed the implementation of a device with this aim which
only has the capability to measure blood pulse oximetry, i.e., blood oxygen level and pulse rate. I propose furthering the development of this device to include a microphone sensor that will allow it to record a patient’s breathing rate. Using both the blood oxygen saturation and breathing data will allow the device to more accurately detect apnea events as well as provide doctors with a more complete representation of what is happening to the patient.

**Background:**

Sleep apnea is typically diagnosed using polysomnography (or a sleep lab study?); a test which monitors a variety of physical and physiological parameters while the subject sleeps. A polysomnograph usually monitors: electroencephalogram (EEG), electro-oculogram (EOG), electromyogram (EMG), oral and nasal airflow, chest and abdominal movement, blood oximetry, as well as recording video and audio. As a result of this test, a patient is given a apnea-hypopnea index (AHI) which represents the average number of times per hour that an individual stopped breathing or had a weak breath; it is a measure of the severity of a patient’s sleep apnea, with higher values indicating more significant apnea [12]. This form of monitoring requires a lot of expensive equipment and properly trained sleep lab staff to interpret the data and is not at all portable. Sleep apnea has three basic classifications: obstructive, central, and mixed. Obstructive sleep apnea (OSA) is caused by physical blockage (or collapse) of the airway. OSA is generally seen in people with a smaller than normal airway and is more common in those who are obese [12]. The treatments for OSA include surgical alterations to the airway, dental appliances, medications, and CPAP devices. Continuous positive airway pressure (CPAP) devices are masks worn during sleep that increase the air pressure in a person’s throat so that his airway will not collapse [2]. Central sleep apnea (CSA) occurs when the brain does not send the signal that a breath needs to be taken. It is typically more difficult to diagnose the underlying cause of CSA (which could be a neurological disease or trauma) and there are fewer treatments available [12]. There are devices for home apnea diagnosis ranging from comprehensive devices that monitor most everything a polysomnograph does to smaller apnea screening devices that only measure nasal air flow [3][10]. There are no portable devices currently on the market that are suitable for monitoring apnea events during the day which can also alert the wearer of apnea events in real time. The closest such device being researched is capable of monitoring blood oxygen saturation at night to detect sleep apnea [6]. This system is not ideal because it only measures oxygen saturation, is not easily worn during the day, and requires the user to have a cell phone that can run the signal processing software.

Much of the current apnea research is being done on classification of sleep apnea as well as new treatment methods. For example some researchers are trying different sleeping positions to lessen the severity of sleep apnea [4] and some are researching new ways to classify its severity once diagnosed [14]. The proposed portable device that monitors blood oximetry and respiratory rate could act as an inexpensive and convenient way for doctors to diagnose patients. This device
could provide potential treatment for those experiencing apneas during the day by alerting them when they stop breathing. The device could also act as a means for collecting data on apneas sufferers experience during their daytime activity; due to the equipment typically required for this monitoring, there is a distinct shortage of such data.

I propose to extend the work Douglas Dawson has already done by integrating a microphone breathing sensor and accompanying apnea detection algorithm. The addition of breathing data will make the device more accurate and provide more information to doctors using it. There is a wide variety throat microphones on the market due to their common use for cell phone communication, such as the Iasus NT3 [12]. Much of the research that has been done on breathing sounds is geared toward diagnosing breathing conditions or lung health [13]. Computer processing of lung sounds is often considered a superior method to using a stethoscope [7]. Much of the research and signal processing methods used in these studies is applicable to detecting apnea events [13]. Although it may be less difficult to detect apnea events than analyze breathing sounds for specific conditions, the challenge in this endeavor will be accurate detection with minimal processor resource requirements.

**Research Methodology:**

The current device that Douglas Dawson had developed has a pulse oximetry sensor on it; I propose the addition of a microphone to include monitor of patient breathing. Initial research will be done using an Iasus NT3 throat microphone. This is a microphone specially designed to reduce environmental noise and be worn comfortably; essential qualities for use in this wearable breathing monitor. This microphone has a frequency response of 20Hz to 20kHz, which is more than capable of capturing the breathing sounds from a human’s throat [5]. This microphone is also idea because it is a piezoelectric device, also known as a “contact microphone” which records sound via vibrations on the surface of some object rather than vibrations that have traveled through the air. The one downside to the NT3 is its cost; therefore, after a breathing detection algorithm has been developed we will attempt to replicate successful detection using a simple, inexpensive piezoelectric diaphragm. It may also be useful to try using an electret microphone with coupling chamber, as in used in some research that involves recording lung sounds [7].

The first stage in this research is to develop an adequate signal processing algorithm to accurately detect when breathing has stopped. A sample of a typical breathing signal is shown below (Figure 1), recorded using the Iasus NT3 throat microphone. The higher amplitude spikes are mostly heart beats and the three dense areas of waveform around 0.5 seconds, 1.75 seconds, and 3 seconds are breathing out, in, and out respectively.
Our goal is to be able to separate the breathing sound from all other noise in the signal and automatically detect breathing events. The time representation of the signal (Figure 1) is not particularly useful in this; so we will be looking to the frequency and energy distributions to gain further information from the signal. Since, we need to know when in time breathing events occur, we will need to view the signal’s frequency or energy behavior as time progresses; to do this we use time-frequency representations of the signal. Some of these potentially useful techniques are demonstrated as they apply to the analysis of lung sound to detect such events as wheezing and snoring [13]. Following are brief explanations of a commonly used time-frequency representations which may be useful to the detection of breathing signals.

**Short-Time Fourier Transform**

The Fourier transform (FT) is performed on small sections (or windows) of the signal at many places in time; each FT representing the frequency behavior of the signal at that particular point in time. Mathematically the short-time Fourier transform can be represented by the following:

Thus the STFT can be considered as the measurement of similarities between the signal and a time shifted, frequency modulated window function [8]. There is a distinct tradeoff between time and frequency resolution; therefore, we must choose a proper window shape (typically a Hamming or Gaussian function) in order to get accurate measurement results. A short window (with respect to time) means good time resolution and a long window results in good frequency resolution [8]. This will provide a simple representation of the breathing signal’s frequency behavior over time. When applied to the signal in Figure 1 we get the representation show in Figure 2. It is much easier to discern the breathing events in this image. We can see three distinct breathing which produce large amount of energy at lower frequencies; these are the red blotches in Figure 2.
Gabor Expansion

The Gabor Expansion is similar to STFT but the 2D time-frequency plane is broken into a grid, the dimensions of which can be specified in the computation of the Gabor coefficients (values in each position of the grid). The Gabor coefficients are determined by the following expression:

Thus, the resolution can easily be adjusted by changing the values of \( n \) and \( m \) [8]. This representation may be very useful to the implementation of the proposed device because it has a lower computational complexity than the other techniques examined [8]. When we apply this expansion to the signal in Figure 1 we get the representation show in Figure 3. This clearly highlights when the subject breathes out, around 0.75 and 3 seconds; seen as red blocks. These occur below a normalized frequency of 0.025.

Wavelet Transform
The wavelet transform uses the same windowing concept as the STFT but the window changes shape at different frequencies to produce better time resolution at higher frequency and better frequency resolution at lower frequencies. Mathematically it can be expressed as the following expression:

\[
\text{(t)} \quad \text{(a)} \quad \text{(b)}
\]

Where \( (t) \) is the windowing function to be dilated and translated, known as the mother wavelet. The parameter \( a \) indicates the scale index, determining the center frequency of \( (t) \), and \( b \) indicates the time shifting. This allows us to partially overcome the resolution limitations of the STFT and Gabor representation; because of this, it is capable of detecting frequency spikes that occur for a very short period of time [8]. When the wavelet transform is applied to the signal in Figure 1 we get what is shown in Figure 4. It is not so easy to pick out the breathing event; however, this representation makes the heart beat extremely prominent and may be useful in removing it from the signal.

![Figure 4: Scalogram of a Typical Breathing Signal](image)

**Wigner-Ville Distribution**

The Wigner-Ville distribution (WVD) does not window the signal as in the previously discussed representations; but rather, it represents the signal based on the energy distribution in terms of both time and frequency. The WVD can be represented mathematically by the following expression:

\[
\text{Wigner-Ville Distribution}
\]

The Wigner-Ville distribution does not have the same trade-off between time and frequency resolution; rather, it has cross-terms that interfere with the interpretation of the distribution. By using a smoothing 2D lowpass filter (Smoothed WVD) these cross terms can be reduced; however, smoothing will reduce the resolution. Alternatively, we can introduce a running window (in the DWVD called the Pseudo WVD) to lessen cross-term interference which also reduces
resolution. A narrow window will reduce the portion of the cross terms related to time differences and a wide window will reduce the portion of cross-terms related to frequency differences. [8] When applied to the breathing signal in Figure 1 we get what is shown in Figure 5. This representation is not particularly useful to this application; however, with further alteration of the smoothing function better results may be possible.

![Smoothed Pseudo WVD of a Typical Breathing Signal](image)

From looking at the preliminary analysis of raw breathing signals, the interference of sound produced by the heart is an issue that must be addressed. A simple is to apply a filter to the signal before attempting to detect breathing. When recording lung sounds for analysis a high pass filter with cut-off frequency of 60Hz and a slope greater than 18 dB/octave is commonly used [13]. However, in this application it may be necessary to apply band pass filter of some form since we are placing the microphone in a different body location and analyzing the signal for different traits [1].

Once a signal processing algorithm has been fully developed and successfully applied to a typical breathing signal, the algorithm must be tested with a variety of different breathing samples. Breathing samples will collected while the subject exhibits the following non-typical characteristics:

- elevated heart rate
- reduced heart rate
- elevated breathing rate
- reduced breathing rate
- breathing through mouth
- breathing through nose
- breathing with chest
- breathing with diaphragm
The algorithm will likely need to be adjusted based on the results of these tests to successfully detect breathing in all circumstances.

The second stage of this research is to integrate the new apnea detection algorithm and microphone into the existing device hardware. The device is currently built around the Rabbit RCM4100 microprocessor which offers a wide variety of features useful to this application; most notably an onboard multichannel analog to digital converter which will be used for reading both pulse oximetry and the microphone [9]. This processor is optimized for use with Dynamic C so the first step in this stage of the research is to code the microphone signal processing algorithm in Dynamic C. The existing apnea detection algorithm designed for the blood oximetry data will need to be merged with the new microphone algorithm to utilize both sets of data for apnea detection and subsequent alert. The next step in this stage of research is to build the microphone input circuit and interface it with the processor. Depending on the complexity of the new algorithm as well as the sampling rate required, we may need to replace existing processor with a more powerful one that will be capable of handling the increased computational demands.

The final stage of the research is to introduce new functionality into the existing software in order to utilize the breathing microphone data. The existing software allows data from sessions of device use to be dumped onto the computer, stored and accessed through an easy to use graphical user interface (GUI). The pulse rate blood oxygen levels can be displayed graphically and any given point can be viewed. Upon the completion of this research, breathing rate should be visible alongside the other two signals. Additionally, a medical professional will be consulted to determine if there are other useful features that should be added. For example, it would be useful to display statistics, such as the frequency of apnea events as well as highlight these events on the signal plots and provide some means of quickly skipping through them.

Currently I am part way through the first stage of research. I have begun investigating which time frequency representations are most useful in determining breathing events. Some preliminary results have been shown above.

**Timetable:**

Project has been broken into the following 4 stages; the dates given are when the task is expected to be completed by.

1. Develop signal processing methods
   - 3/13 - apply different signal processing methods sample breathing data, also determine if there are other useful breathing characteristics that can be monitor. (inhale/exhale, how hard, nose vs. mouth, chest vs. diaphragm)
   - 4/3 - identify simplest method for measuring respiratory rate, develop initial breathing detection algorithm.
4/10 - collect a variety of data (breathing rates, sensor position, ways of breathing)
5/1 - refine algorithm to work under all conditions
2. 5/15 - Test algorithm with other microphone’s to see if it will work with a less expensive device
3. Integrate new sensor into current device
6/19 - code the data acquisition and signal processing algorithm for processor
7/24 – modify current hardware if necessary
4. Develop UI for breathing data viewing and management.
7/31 - determine features required by medical professional
8/21 - modify existing GUI to include new respiratory monitoring features.

References:


