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# Human Breath Detection using a Microphone

Master's thesis

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## **Abstract**

The detection of breath and analysis forms a major application in medical field. It helps in detecting the abnormalities in the breathing pattern. Detection of these abnormalities may lead to prevention of chronic respiratory diseases. Many techniques are developed in order to detect the breathing pattern.

This thesis dedicates to the technique for detecting and analyzing the breaths. We propose a simple experimental setup with an economical microphone and a laptop. We propose to record the breath of a human and perform analysis of the same in offline. We present an algorithm which detects the breaths and classify them according to their intensity levels. The algorithm proposed is used to analyze various breath sounds of humans with some breath disorders. We present our findings about the same in this thesis. Finally, we propose sleep stage classification as a potential application. We discuss briefly about sleep stage classification as well.

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# Chapter 1

## Introduction

Breathing forms one of the basic and essential factors for the survival of all the living beings. “Breathing is the mixture of predominantly nitrogen, oxygen, carbon-dioxide, water vapor & inert gases and trace amounts - parts per million by volume to parts per trillion of volatile organic compounds”, [1]. Inhalation and exhalation take place immediately one after the in a sequence. The breathing rate in the subject differs according to the activity he/she is into. For example, the breathing rate of the subject doing physical activity like walking, running or workout is different when he/she is asleep. Breathing rate slightly lowers when the subject is inactive or in sleep, [2].

Breathing also acts as a physiological indicator and is used as a critical measure of the subject’s psycho-physiological state, [3]. Breath detection basically involves capturing of breaths from the subjects using different devices and processing the data obtained from these devices. There are variety of techniques used for the breath detection. We mention some of the techniques here. There are different modalities used to capture the breath. Most popularly used modalities include contact and non-contact. The contact approach consists of wearable sensors such as thermistors, respiratory gauge transducers and acoustic sensors. The main advantage of using wearable sensors is that they deliver accurate breathing data. But this approach is not suitable for mobile applications or for people who have an aversion towards wearing sensors. The non-contact approach consists of infrared video cams, radar and doppler modalities. The main disadvantage is high-cost equipment and collecting and analyzing very large amounts of data at a high processing cost, [3]. Various breath detection techniques are available in the literature. In the following subsections, we mention briefly about few of them.

### 1.1 Using a high precision single point infrared sensor

A high precision single point infrared sensor is capable of reading temperatures within a range of  $30 - 150^{\circ}\text{C}$ . A USB camera is placed below the IR sensor for maintaining the correct aim of IR sensor at the subject’s sub-nasal region. The temperatures are continuously sampled using the IR sensor. The obtained data is then filtered using a low-pass filter. The breathing rate from the IR sensor



is extracted by suitable curve-fitting mechanism. This measurement technique is suitable for the rehabilitative robotics (RR) and socially assistive robotics (SAR) applications, [3].

## **1.2 Using pressure sensor, thermistor-temperature sensor and a microphone**

Temperature sensor helps in detecting the breath by comparing the temperatures of the inhaled and exhaled breaths. The inhaled air is cooler than the exhaled air. Pressure sensor helps in detecting cough or sneezing during breathing due to sudden changes in pressure. A high-quality microphone placed near the mouth of the person helps in detecting movements of talk, coughing or sneezing. The quality of detection is good and also the complete detection of breathing is done with simple sensors. This system is aimed mainly for patients suffering from spinal cord injuries, [4].

## **1.3 Using a miniature device consisting of an omnidirectional microphone and an aluminum conical bell**

The microphone is the one used in hearing aid applications. This sensor is mounted on the side of the neck and on the suprasternal notch of the subject with an adhesive tape. Breathing is recorded in a sitting position. The signals are recorded using the sensor connected to the sound card of the PC with a sampling rate of 11050 samples per second and at 16-bit resolution. Three signals are recorded first is slow breathing achieved by controlling the breath, second is normal breath is achieved by subject in a sitting position and third is fast breathing achieved by rigorous exercise on an exercise bike. This technique is mainly designed to implement in the electronic circuits that consume less than  $2\mu W$  power so that the size is reduced and can be mounted comfortably on the subject's skin, [5].

## **1.4 Using infrared imaging**

This technique requires cooled mid-wave infrared camera with a spectral range of  $3.0 - 5.0\mu m$  equipped with 50mm lens. This camera is used to capture the profile view of the subject from a distance of 6-8 feet. A piezo-strap transducer is wrapped around the diaphragm used for the measuring the thoracic circumference during the expiration and non-expiratory phase. The signal recorded by the transducer is sent to the PowerLab Data Acquisition System. This technique is used to predict the various life threatening disorders like sudden infant death syndrome and heart attacks, [6].

## 1.5 Using Remotely Enhanced Hand-Computer Interaction Devices (REHCID)

The hardware required for this mechanism consists of an Infrared (IR) illuminator and Infrared (IR) camera. The design of the system is based on a program in C sharp and VB.NET. REHCID is placed on both sides of the bed. The illuminator is projected above and reflective stickers of 28cm by 28cm are placed on the subject's thoracic cavity. The computer is used for carrying out the breath detection by calculating the displacement of the thoracic cavity movements via Bluetooth. REHCID is used for transmitting the Infrared (IR) received from the Bluetooth. If any abnormality in breathing is observed then the development is transmitted by means of a computer over a network to both distant family and hospital. This design is not implemented in practical applications, [7].

## 1.6 Using a non-invasive hydraulic bed sensor

A non-invasive hydraulic bed sensor is placed both on the top and underneath the mattress. An integrated pressure sensor has a range of 0 – 10kPa which is sufficient to handle the pressures transmitted from the weight of the body. This sensor is connected to the external circuitry for power interface to the analog-to-digital converter. This system is designed for in-home use for detection of illness and functional decline in elderly adults. This approach detects the rate of normal respiration as well as conditions of sleep apnea, [8].

The open challenges in breath detection are accurate detection of breaths per minute, real time processing of breath data, data analysis for large number of subjects, non-contact approach with optimized sensors and devices with low-cost equipment for efficient detection of breaths.

## 1.7 Objective of the thesis

In this thesis, we aim to design a simple and economical system to detect the breathing pattern of a subject using a microphone. This technique is economical because the devices used are optimal. We require a standard microphone with minimal complexity and a laptop with standard configuration is used. The cost of the microphone used is 10 Euros. Further in the sense of required setup, the approach used in this thesis is quite simple. At this point of time it is difficult to comment on the complexity of algorithm, since in the current setup a standard laptop is used for computing. The complexity can be evaluated when the constraints on computing power are also considered. In this thesis, we do not explicitly consider any constraints on computing. Nevertheless, this is certainly one of the aspects that are needed to be considered in the future. This approach is suitable for monitoring the breathing patterns for subjects with no mobility such as for patients in bed, with an aversion of wearing on-body sensors. Detecting and analyzing the data obtained from the microphone for a large number of subjects is a challenge.

In this project, we develop an algorithm for the detection and analysis of human breath. The main advantage of using such a set-up helps in increasing the comfort level of the subject and also helps in optimization of the devices.

Moreover, it is also user-friendly and economical. The practical application of this technique is mainly in the medical field where the breathing patterns help in finding the irregularities and abnormalities in the subject. The classification of different sleep stages based on the breathing rate of the subject is also one of the applications of this technique. The novelty in this approach lies in using economical setup for breath detection. The work presented in this thesis can be considered as the initial work for further possibilities like remote monitoring of breath, detection of sleep stages etc.

## 1.8 Organization of the thesis

In the following chapters the presented work focuses on the detection and classification of breaths using microphone based on a specific analysis algorithm. More precisely, we discuss the technique of detecting and analyzing different types of breaths with the help of a simple microphone. We also present the results of the experiment carried out for the evaluation of the project. The organization of the thesis is presented below:

In Chapter 2, we present the research done in the field of breath detection and analysis. We also discuss about the different techniques used and how they are practically applicable.

The sleep stage classification involves classifying the different stages of sleep by determining the breathing rate of a person. In Chapter 3, we discuss about how the breathing rate in a subject helps in finding out the different sleep stages like the Rapid Eye Movement (REM) and Non Rapid Eye Movement (NREM), different methodologies used currently and we also proposed a methodology to detect sleep stages using non-wearable body sensors.

In Chapter 4, we focus on the evaluation of our project. In order to detect the breaths and analyze them, we need to perform some experiments to get the breath samples. We present the experimental set-up, the hardware and software requirements and also few assumptions made to obtain the desired results. After obtaining the breath samples, we need to process and analyze those samples. For this purpose we propose an analysis algorithm. We also focus on concepts like envelope extraction and methodology for classifying the breaths and we also provide the pseudo code of our algorithm. The results obtained from the envelope extraction and the classification of the breaths needs to be verified and validated. We also discuss the implementation phase where we introduce the concept of down sampling, the purpose of down sampling, different effectiveness measures like Recall, Precision and F-measure for the breath samples and count of number of breaths taken per minute. We present the discussions after performing the experiment and also some challenges that need to be resolved.

Finally, in Chapter 5, we focus on the future directions of research in this field wherein we suggest some measures for improvisation. In the rest of the document, we refer the humans as the subjects.

## Chapter 2

# Related Work

The related work discusses the different breath detection and analysis techniques. It mainly focuses on two different approaches. The first approach is using wearable contact sensors, i.e., the sensors being mounted on the body of the subject. The second approach is using non-contact sensors where the subject is monitored without mounting the sensors on his/her body. There are certain advantages of using the non-contact approach over the contact approach. The wearable contact sensors cause inconvenience and discomfort for the subject. Moreover some subjects may develop skin allergies if used for longer duration due to adhesives used for mounting the sensors. Moreover, non-contact approach requires minimal or no wiring and the subject can be monitored potentially at his/her home and not in lab.

To overcome these drawbacks caused by wearable sensors, research to devise different techniques which require no contact with the body of the subjects is being carried out. Some of these techniques deal with the healthy subjects with no breathing disorders, and the others with breathing disorders caused due to injuries or post-surgery. The analysis of breath plays a very important role in detection of various sleep-related disorders such as sleep apnea, sudden infant death syndrome, pulmonary disorders, lung disorders and other chronic or acute breathing problems. We discuss some techniques which involve both contact and non-contact approaches used in the breath detection and analysis.

The first approach is detecting the breath using high precision, single-point infrared sensor, [3]. The sensor is placed on the sub-nasal region. The nose detection, extracting the nose region of interest is done using OpenCV Library. It also helps in computing the (x,y) co-ordinates. The initial breathing rate is computed by sampling the infrared (IR) sensor for 15 seconds and also the temperature dataset is stored. Samples are collected for 6 times per second. It uses the sliding window approach wherein subtle changes in the breathing rate can be detected. The individual breathing rates for the infrared (IR) sensor is obtained by fitting a sinusoidal curve to the infrared data. The fitting parameters include period  $T$ , mean  $B$ , amplitude  $A$  and offset  $C$

$$\left(\frac{2\Pi}{Tx} + C\right) + B \quad (2.1)$$

The gnuplot is a freely available graphing utility which provides the command for the curve fitting. The quality of the fit is determined by the sum of squared

differences known as the residuals. These residuals are calculated between the input data points and the function values evaluated at the same places. To assess the real-time data sets, an average of the residuals is determined and also the error threshold is defined. The results obtained from the curve-fitting are further improved using a Fast Fourier Transform (FFT). The future direction for this technique would be to implement on subjects with light activity and also to improve the sensitivity analysis of the imprecise nose detection.

The other approach is detection of breaths using three different sensors. A pressure sensor is used to detect the activities like cough and sneeze by observing the sudden changes of the pressure and the flow. It is used as an indirect flow meter based on the Bernoulli's equation defined below:

$$p + \frac{\rho v^2}{2} + \rho gh, \quad (2.2)$$

where  $p$  is pressure,  $\rho$  is fluid density,  $g$  is gravitational acceleration,  $v$  is velocity of fluid, and  $h$  is distance. The temperature or thermistor sensor is used to detect the breathing based on the principle that the inhaled air is cooler than the exhaled air. A high quality microphone placed near the mouth of the subject is used for the detection of the speech. The breaths are recorded by the subjects who have the ability of spontaneous breathing. The results obtained shows that the signals obtained from the thermistor and the pressure signal are in phase with each other. This occurs because of the temperature and the pressure that increases during expiration and decreases during inspiration. Based on all the parameters it is very easy to differentiate between each phase of breathing. The quality of detection of breaths is good, occurrence of errors is rare and implementation of new solutions increases the reliability and applicability of the system. However, there is still a scope of implementation which may include integration, minimization and preparation of mask on which all the sensors can be mounted without obstruction of the mouth, and also testing on real subjects.

There is one more approach which helps in breath detection with a miniaturized, wearable, battery-operated system consisting of an omni-directional microphone and an aluminum conical bell, [7]. The microphone which acts as an acoustic sensor is placed on the subject's neck and on the suprasternal notch with an adhesive tape. The recording of the signals is done with a subject in a sitting position with the help of the microphone and the bell. The sensor is connected to the sound card of the PC. The signal is recorded with a sampling rate of 11050 samples per second and at 16-bit resolution. This acoustic signal is split into 1024 frames and Fast Fourier Transform (FFT) is performed on it. The Root Mean Square (RMS) power density in the frequency band of 400 – 600Hz is summed up to provide an envelope of the signal. The spectrum of the signal can be determined using the FFT of the envelope of the signal and also with the help of the Hamming window. A total of three signals are recorded by each subject. Slow breathing corresponds to a subject controlling the breath. Normal breathing is measured with a subject in sitting position or at rest. Fast breathing is achieved by doing rigorous exercise on an exercise bike. The frequency response obtained for the fast breathing has two dominant peaks at 0.52Hz and 1.04Hz, whereas for the normal breathing it is 0.29Hz and 0.58Hz. These frequencies correspond to the fundamental frequency and the first harmonic of the acoustic signal. The frequency response obtained for the slow breath has a single spike rate at 0.13Hz, which is the fundamental frequency.

These fundamental frequencies correspond to the breathing rates of 31, 17, 8 per minute for fast, normal and slow breaths respectively. The values obtained are equal to the respiration frequencies. The noise sources considered are the speech, myo-acoustic noise, pulse, environmental speech and environmental vibrations. The algorithm is performed effectively with the average percentage of the time correct being 91.3%. There is still a scope of increasing the average percentage of the time by further optimization of the algorithm. This system is mainly suitable in electronic circuits which consume power of less than  $2\mu\text{W}$ .

The next approach is detection of breaths using Infrared (IR) imaging, [6]. The equipment required for performing this technique includes an Infrared (IR) camera with a spectral rate of  $3.0 - 5.0\mu\text{m}$  with 50mm lens. A piezo-strap transducer helps in determining the thoracic circumference during the expiration and the non-expiratory phase. Firstly the Region Of Interest, ROI, is defined wherever there is a possible presence of the airflow. It is characterized by its shape, size and position. In this case, a rectangular region is chosen as the ROI. The visualization of breath is done using image processing techniques to visually perceive the breath in infrared video frames. The operations performed on the video clips include, Otsu's adaptive thresholding, Differential Infrared Thermography (DIT) and Image opening. Otsu's thresholding is used to segment the skin region from the background. The DIT generates a breath mask of all the pixels whose temperature has increased beyond a preset threshold. An image opening operation is applied on the output binary mask of DIT to improve breath visualization. This technique also addresses the performance of the non-contact methodology against ground-truth measurements. We observe that there is an imperfect synchronization of the beginning of the two recordings. There is also mismatch in frequencies as the IR camera records 31 frames per second whereas the monitor belt samples at 100 times per second. The monitor belt records the ground truth data at the diaphragm level whereas the infrared imaging method classifies air flow at the nasal mandible level. This method based on the infrared imaging and the statistical computation measures passively breathing rate at a distance. It achieves an accuracy of 96.43%. It is helpful in monitoring chronic or acute breathing problems. However it also has few disadvantages like the Region Of Interest (ROI) fails to remain in the field of respiratory airflow when the subject rotates his/her head towards or away from the IR camera and if the source of the airflow either the nose or the mouth changes.

The other approach of detection of breaths is by using multiple remotely enhanced hand-computer interaction devices (REHCID), [7]. This technique uses an Infrared illuminator projected into the subject's chest and an IR camera to detect the location of the IR LED. This location information of the IR camera is transported via Bluetooth. This design is based on C#. It uses Wiimote library as an interface between a computer and the REHCID. The software used is VB.NET and C#. The IR camera helps in tracking the point of light. It provides the data in the form of two co-ordinates (x,y). Each co-ordinate describes the position of the IR marker used for tracking. The information from the REHCID is received via Bluetooth. The IR camera uses the matrix to indicate the location of the co-ordinates. After receiving the information from Bluetooth, the starting points are detected by the infrared light.

Another approach on breath detection is based on the Non-invasive bed sensor, [8]. It is placed underneath the mattress. It has a pressure range of  $0 - 10\text{kPa}$  which is sufficient for handling the weight of the body. This sensor is

connected to the external circuitry for power and interface to analog-to-digital converter (ADC). The signal obtained from the transducer is sampled using the 12-bit ADC at a sampling frequency of 10kHz, then low-pass filtered and down-sampled to 100Hz for further processing. A windowed peak-to-peak deviation is generated by finding the difference between the most negative and most positive within a sliding window of 25 samples. The respiration rate can be extracted by low-pass the filter with 1Hz cut-off frequency, identify 1-minute segments with motion artifacts, subtract the DC bias from each segment and count the zero-crossings dividing by two to yield breaths per minute. It is observed that the increased accuracy of the system with transducer below the mattress compared on the top seems to be due to the buffering effect of the mattress itself. This sensor is not effective for all the body types or ages. It should be tested over a range of pulse and respiration rates. This system is still not robust enough but it still can differentiate between the low pulse and shallow breathing.

The next approach is automatic breath and snore detection from tracheal and ambient sounds recording of the subjects suffering from obstructive sleep apnea, [13]. Two microphones known as tracheal and ambient are used to record the breaths by placing them in two different positions. The tracheal microphone is placed over the trachea and the ambient microphone is placed over the forehead of the subject. The patients Polysomnography (PSG) data is also recorded simultaneously. An automatic classification method is used based on the sound's energy in dB zero crossing rate and formants of the sound signals. Linear Predictive Coding (LPC) is used to find the formant frequencies. The three features are transformed into a new 1-D space by using the Fisher Linear Discriminant (FLD). In order to classify the breath sounds a Bayesian threshold is applied to the new 1D space. The overall accuracy is more than 90% in classifying the breath sounds irrespective of the position of the neck of the subject.

The other approach is to represent and classify the breath sounds recorded in an Intensive Care Unit (ICU), [14]. The breath sounds from the bronchial region of the chest is recorded. These sounds are represented using the averaged power spectral density. These sounds are classified as the individual breaths and each breath is classified as the inspiratory and expiratory segments. They are also classified as the normal and abnormal. The recording of the breaths are done using the microphones which are placed in the on the anterior of the chest. The two sensors are placed on the lungs one on each lung. The classification of the breath sounds are based on the multilayer feedforward neural networks. It is one of the most widely used neural networks. It consists of three layers, input layer, hidden layer and output layer. The input layer contains sensory units, hidden layer and output layer contains the computational nodes. The algorithm used for the classification is the Back propagation algorithm. It trains the multilayer feedforward neural networks where the information is propagated back through the network to adjust the connection weights. This is mainly based on the least-mean-square (LMS) algorithm. The performance of the classification is measured using true positive, true negative, false positive and false negative rates. However, this method is not suitable for long term monitoring of breath sounds as it requires a quiet environment. The quality of the breath sounds can be more improved by reducing the background noise.

The other approach mainly focuses on the analysis of breath sounds for the diagnosis of pulmonary diseases, [15]. In this approach, we classify the breath sounds in two stages based on linear prediction coefficients and energy envelope

Approach	Hardware
Non-contact	Infrared (IR) sensor, USB camera
Non-contact	Pressure sensor, Temperature sensor & Microphone
Contact	Omnidirectional microphone, aluminum conical bell
Non-contact	Mid-wave Infrared(IR) camera, piezo-strap transducer
Non-contact	Infrared (IR) illuminator, Infrared (IR) camera
Non-contact	Non-invasive hydraulic bed sensor ie.pressure sensor
Contact	Tracheal & ambient microphone
Non-contact	Microphones

Table 2.1: Hardware used in different approaches

features. These methods are used in solving the pattern recognition problems. In the first stage, each breath sound is represented by its mean features vector and by its covariance matrix. These breath sounds are obtained from a training set classified by a physician. A specific distance measure is used for comparing the unknown breath sounds to the sound types represented in the system. If the distance between the two sounds is minimal then the unknown signal is hypothesized to belong to the type of the known signal. The second stage is the envelope feature extraction where the power spectral density estimation by means of linear prediction is used. The goal of this project is to implement on a microprocessor. Hence the time domain analysis and frequency domain analysis techniques are not being used, as they are unsuitable for small microprocessor-based system. The drawback of this method is the amount of accuracy in classification due to lack of sufficient data. The practical application would be in developing a low-cost clinical instrument.

Another approach also mainly focuses on the detection and classification of breaths for the diagnosis of lung diseases by frequency based classification, [16]. In this method, breathing phases are categorized into four types: inspiratory phase, inspiratory pause, expiratory phase and expiratory pause. For this classification, a technique known as Mel-Frequency Cepstral Coefficients (MFCC) is used. This MFCC features depict the differences between the inhale and the exhale in the frequency domain. Here the pauses that occur after each inhale and exhale are also taken into consideration. For this, the intervals of local sharp maximums are split into half. As the human ear is sensitive to low frequencies and ambiguous to high frequencies, Mel frequency simulates the hearing characteristics. It converts spectrum to non-linear spectrum based on the Mel frequency co-ordinates and then converts it into the spectrum domain. As of now, there is no practical application of this method. But the plan is to integrate this classification technique within a smart phone to reflect the breathing classification in real-time. We summarize the above mentioned techniques in Table 2.1.

From the above mentioned techniques we observe that both contact and non-contact techniques are helpful in practical applications involving breath detection and analysis. The contact approach involves mounting the sensors on the body of the subject. It involves expensive hardware and adhesives. It should be performed only in labs and hospitals where such hardware needs to be installed. It incurs high maintenance costs. Apart from this, the subject



feels discomfort in wearing these sensors for a longer duration. Moreover, as the sensors are wearable, the area where they are mounted on the body should be clean and dry. There is high risk of skin allergies in the subjects as the adhesives used for mounting the sensors are not suitable for all.

On the other hand when we observe the non-contact techniques, we find that though it involves expensive equipment like Infrared sensors, transducers etc. The subject can be monitored from any location such as home instead of labs. There is no wiring involved. The installation and maintenance costs involved are comparatively low. As they are not in contact with the body of the subject, chances of developing skin allergies is zero. The subject is free from wearing any sensors on the body and can easily carry out his/her daily activities with ease. The above observations led us to the aspect of designing a more economical and user-friendly system with simple non-contact body sensors such as microphones. In the following chapters we discuss in detail about the analysis algorithm and the implementation details.

## Chapter 3

# Classification of Sleep stages

Sleep is a naturally recurring state characterized by reduced or absent consciousness, relatively suspended sensory activity and inactivity of nearly all voluntary muscles, [10]. It is basically classified into two types: Rapid Eye Movement (REM) sleep and Non-Rapid Eye Movement (NREM) sleep. These sleep stages are discussed in detail as follows:

**Rapid Eye Movement (REM) sleep:** The REM sleep is a mixture of the encephalic (brain) states excitement and muscular immobility. There also occurs a rapid and random movement of the eye. The brain is very active during this stage resulting in intense dreaming. The subjects with no sleep disorders suffer from rapid heartbeat and respiration and also become erratic during the REM sleep. It usually occurs 90 – 120 minutes from the onset of sleep. The REM stage occurs for a longer duration in infants almost 50% of their sleep, whereas in adults, it decreases to 20%. The breathing rate of the subject during REM sleep is usually between 24 to 36 breaths per minute.

**Non Rapid Eye Movement (NREM) sleep:** The NREM sleep is basically characterized with little or no eye movement. The subject is not prone to dreaming and muscular activity is not paralyzed. The NREM sleep is categorized further as follows:

**Stage 1 :** The duration of this stage is 1 – 7 minutes at the onset of the sleep. There is low arousal threshold and the subject can easily discontinue from sleep by soft noises or physical contact etc. The movement of the eyes is also slow.

**Stage 2:** The duration of this stage is 10 – 25 minutes after stage-1. The heart rate slows down and temperature decreases. Dreaming occurs very rarely and there is no eye movement. The body prepares to enter into deep sleep. The blood pressure, secretions and metabolism decreases. A sleeper can be easily awakened by little sounds.

**Stage 3:** This stage is basically the start of the deep sleep. The duration of the sleep occurs 30 – 40 minutes from the first onset of sleep. The sleeper is far more difficult to awaken as compared to stage-1 and stage-2. A louder noise is essential for waking up the subject.

**Stage 4:** This stage is a stage where the subject is in his/her deepest sleep. The bodily functions continue to decline to the deepest possible state of physical rest. Dreaming is more common in this stage than in the other stages of work. The sleeper awakened from the deep sleep becomes confused, groggy or disoriented.

### 3.1 Different methodologies for classification of sleep stages

The standard method used for the classification of sleep stages is the Rechtschaffen and the Kales methodology. This method uses polysomnography (PSG). Polysomnography helps in monitoring the body functions including the brain activity (EEG), eye movement (EOG), skeletal muscle activation (EMG) and heart rhythm (ECG) during the sleep, [11]. Electroencephalography (EEG) is one of the important tools for studying and diagnosing sleep disorders. But the major drawback of using polysomnography is it is very expensive. There is one more approach for determining the sleep stage based on non-invasive and unstrained pneumatic biomeasurement method. In this approach, a mathematical model is designed based on which a sleep stage classifier is developed.

### 3.2 Classification of sleep stages based on the breath rate

According to the research study it is found that the sleep stage classification can be done based on the body temperature of the subject and also on the breathing rate. The breathing rate and the body temperature differ from subject to subject and also from one sleep stage to the other. It is observed that there is remarkable change in breath rates when the subject is awake and when he/she is in REM stage. However, the breathing rate of the subject in the NREM stages remains almost the same. Table 3.1 displays the breathing rate of a subject in different sleep stages:

Sleep stage	Breaths per minute
Awake	12 – 18 breaths per minute
NREM sleep Stage-1	3-4 breaths per minute
NREM sleep Stage-2	3-4 breaths per minute
NREM sleep Stage-3	3-4 breaths per minute
NREM sleep Stage-4	3-4 breaths per minute
REM sleep	24 – 36 breaths per minute [12]

Table 3.1: Sleep stages and associated breaths per minute

The body temperature of the subject is measured using a wearable temperature sensor. We observe that the values differ in each sleep stage. Table 3.2 displays the body temperature of the subject in different sleep stages.

Sleep stage	Temperature in °C
Awake	37 – 37.5
NREM sleep Stage-1	35 – 36
NREM sleep Stage-2	35 – 36
NREM sleep Stage-3	35 – 36
NREM sleep Stage-4	35 – 36
REM sleep	36 – 38

Table 3.2: Sleep stages and associated temperatures

### 3.2.1 Methodology to detect sleep stages using non-wearable sensors

We propose methodology to detect sleep stages using non-wearable sensors. As explained in the previous section, sleep stages can be detected using breath rate. We therefore propose a classifier to determine the sleep stages based on the breathing rate of the subject in Figure 3.1.

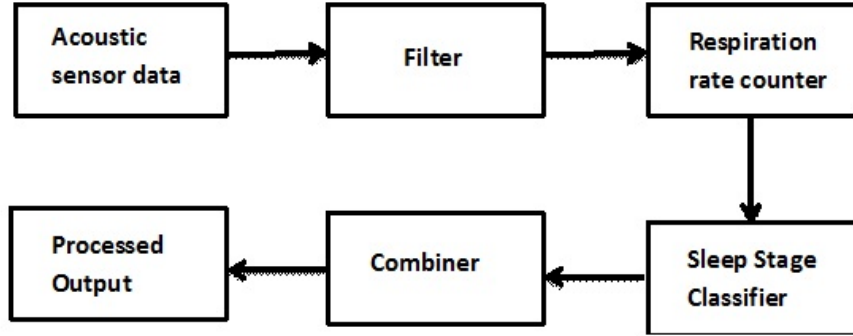


Figure 3.1: Sleep stage classifier

Now, we explain each of the components briefly:

**Acoustic sensor data:** In order to record the breaths of the subject, we use a standard microphone. The data collected from the recorded signal is used for further processing.

**Filters:** The data obtained from the original signal is the raw signal contaminated by a lot of external noise. In order to remove the noise and to smoothen the signal we use a low pass filter probably third order Butterworth filter. Due to filtering, unwanted noise in the raw signal is removed and good quality signal is obtained.

**Respiration/Breathing rate counter:** The breathing counter helps in detecting the number of breaths taken in one minute. This count is very important for the classification as it is based on number of breaths per minute.

Sleep Stage	Breaths per minute (bpm)	Boolean result
Awake	12 – 18 bpm	1,0,0,0,0,0
NREM sleep Stage-1	3 – 4 bpm	0,1,0,0,0,0
NREM sleep Stage-2	3 – 4 bpm	0,0,1,0,0,0
NREM sleep Stage-3	3 – 4 bpm	0,0,0,1,0,0
NREM sleep Stage- 4	3 – 4 bpm	0,0,0,0,1,0
REM sleep	24 – 36 bpm	0,0,0,0,0,1

Table 3.3: Sleep stage classification

**Sleep stage classifier:** The main function of the classifier is to classify each breath based on the breathing rate of the subject. It also classifies the different sleep stages such as awake, REM and NREM sleep. We normally set some predefined values which help us in classification. We use Boolean values like 0 = false and 1 = true. As the breaths per minute are different in different stages, this criterion would be useful for the classification. Table 3.3 displays the Boolean values in each stage based on which we classify the sleep stages:

**Combiner:** The main goal of the combiner is to combine the results obtained from the classifier. According to the algorithm developed in the project, breaths per minute can be detected and based on that classify whether the subject is awake, in Stage 1, 2, 3, 4 and also if he/she is in REM stage.

In the above proposed methodology, the breath sounds are captured using a microphone and breaths per minute are calculated based on the algorithm developed in this project. The above proposed methodology is not implemented as part of this project. There are certain challenges in determining the breaths per minute in each of the NREM sleep stages. Accurately capturing the breath signal is the biggest challenge involved. When a person makes any movements during the sleep, there is a noise involved with it. This noise poses a problem in identifying breaths. Also the amplitude of breaths during sleep varies from subject to subject. To capture low intensity breaths and placement of the microphone, especially distance from the subject as well as the location needs to be determined accurately. This aspect plays a major role in recording breaths. There is also a possibility of noisy indoor environment due to fan, air conditioning etc., that are located in the room. The sound of this equipment might also interfere with recording process. The proposed breath detection algorithm is not robust enough to reduce the effect of noise.

### 3.2.2 Issues with wearable temperature sensors

We observe that the acoustic sensor like the microphone can be placed near the nose of the subject for capturing the breaths. They can be used as non-body contact sensors. However, with temperature sensors, we need to attach the sensor on any part of the body of the subject. For example, we can attach it on the hand, legs, stomach etc. This is important because, it is difficult to determine the body temperature without any contact. The major drawback of using the wearable temperature sensor is that the subject must attach the

sensor to his body till the end of the experiment. Wearing the sensor for a long duration might be uncomfortable for the subject.

## Chapter 4

# Evaluation

The main objective of the project is to detect the human breath by a non-contact body sensor like microphone and analyze the breathing pattern obtained using various techniques. In the following subsections, we discuss about the experimental set-up, assumptions, analysis algorithm and implementation details. In the rest of the document, by breath we mean a single instance of inhale or exhale.

### 4.1 Experimental setup

In order to detect the breath of a subject, we conduct an experiment in an indoor environment using a microphone placed at a distance of 10-12 cm from the nose of a subject. We need to consider certain factors such as physical environment, hardware and software to be used and also certain assumptions to be made at the start of the experiment. The schematic representation of the set-up is represented in Figure 4.1.

#### 4.1.1 Physical Environment

The experiment requires low-noise intensity environment to capture breaths with very less noise intensity. We assume that the subject is present in an environment which is free from external noises to the extent possible.

#### 4.1.2 Hardware requirements

In this experiment, we use a standard microphone with stand to capture the breaths. Now-a-days, as the mobile is the common device, we use mobile application for microphone for the recording of the breaths. We also have a laptop for the processing of the data obtained from the microphone. The configuration details of the laptop include Intel core i3 processor, 4GB RAM and 64-bit operating system. However, this configuration is not mandatory to perform the experiment. A laptop which can successfully run Matlab is suitable for the experiment.

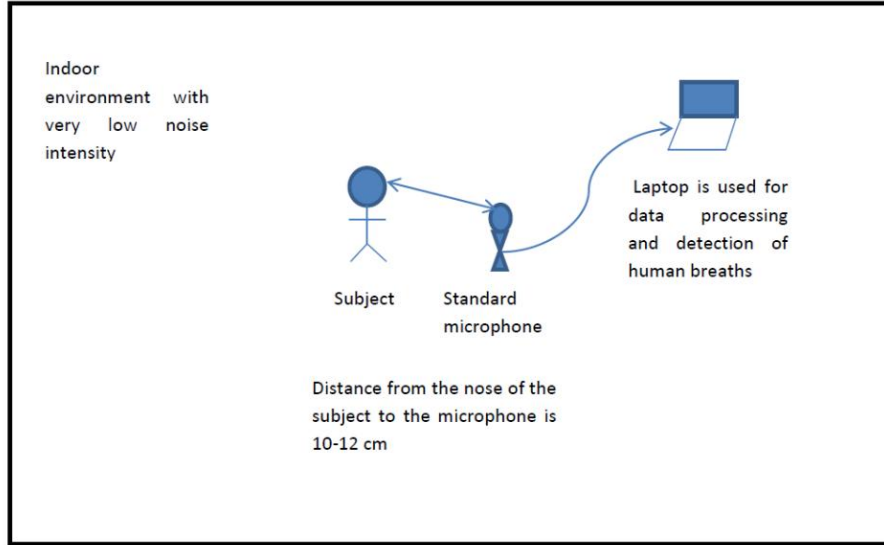


Figure 4.1: Experimental setup

#### 4.1.3 Software requirements

In this experiment, the data that is available to analyze the breaths depends on the sampling rate of recording. This data is stored in a wave file. We use Matlab to analyze the breaths recorded. Since the signal processing toolbox is extensively developed in Matlab, we consider it as a possible option for analyzing the breath samples. Also to verify high noise intensity sounds we use Audacity software which an open-source used for the recording and editing sound.

#### 4.1.4 Assumptions

We assume certain conditions before conducting the experiment, to obtain the desired results. Some of the major assumptions include recording the breaths in a low-noise intensity environment. The breaths are recorded using a microphone at a maximum distance of 10-12 cm from the nose of the subject. If the distance from the nose to the microphone increases, then the quality of sound captured decreases. The final results obtained after processing eliminate certain breaths which have very low noise intensity. It is very hard to capture such breaths using a standard microphone. We can capture such breaths by using advanced microphones like condenser microphones that have the capacity to capture very minute sounds. This forms one of the major drawbacks of using a standard microphone. Also, during the time of recording, certain external sounds may give rise to some high amplitude glitches in the signal which may affect the final output. We assume that such glitches are eliminated in the recorded breath sample. We also assume that the recording of the breath signal is of type mono.



## 4.2 Implementation

We discuss the algorithm used for the breath analysis in this project. We also discuss the data we extract by analyzing the breath signal. Before we proceed further, we introduce several concepts which are helpful to understand the analysis algorithm.

- **Peak of a signal:** The highest point on a wave is called a peak. It is depicted in Figure 4.2.

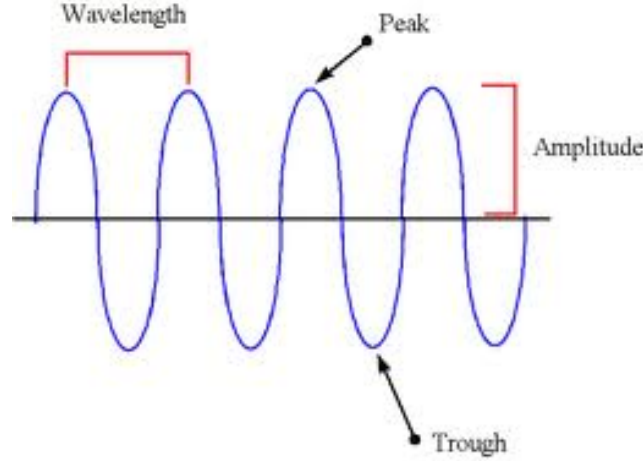


Figure 4.2: Peak of Signal

- **Hilbert Transform:** The Hilbert transform is useful in calculating instantaneous attributes of a time series especially amplitude and frequency. A detailed discussion of Hilbert Transform is beyond the scope of this thesis (refer to [9]).
- **Envelope of a signal:** An envelope of a signal is the apparent signal seen by tracking successive peak values and pretending that they are connected. In Figure 4.3, the envelope is denoted in red. Analytically, an envelope,  $e(t)$ , of a signal,  $x(t)$ , is defined as the magnitude of the analytic signal as shown in the following equation:

$$e(t) = \sqrt{x(t)^2 + \hat{x}(t)^2} \quad (4.1)$$

where  $\hat{x}(t)$  denotes the Hilbert transform of  $x(t)$ .

- **Downsampling:** Down sampling is the process of the reducing the sampling rate of a signal. This is done to reduce the data rate or the size of the data. This process is useful as we handle fewer samples for analysis. Though there is a risk of data loss, in our project, this risk poses no major threat for the analysis.
- **Precision:** The precision is ratio of the number of relevant records retrieved to the total number of irrelevant and relevant records retrieved.

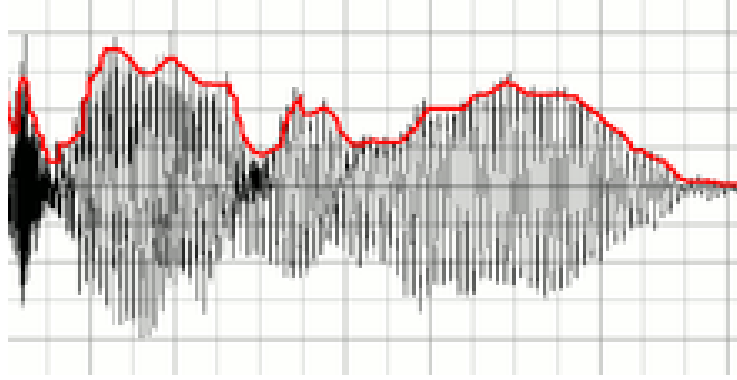


Figure 4.3: Envelope of a signal

It is usually expressed as a percentage. Mathematically, precision is expressed as follows:

$$\text{Precision} = \frac{\text{No. of relevant records retrieved}}{\text{Total no. of irrelevant and relevant records retrieved}} \quad (4.2)$$

- **Recall :** The recall is the ratio of the number of relevant records retrieved to the total number of relevant records. It is also expressed as a percentage. Mathematically, recall is expressed as follows:

$$\text{Recall} = \frac{\text{No. of relevant records retrieved}}{\text{Total no. of relevant records}} \quad (4.3)$$

- **F-measure:** F-measure is the measure of effectiveness of information retrieval with respect to the user. It is the harmonic mean of the precision and the recall. Mathematically, F-measure is expressed as follows:

$$\text{F - measure} = 2 * \left( \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \right) \quad (4.4)$$

Broadly, the breath detection and analysis technique used in this thesis can be described in the following three steps:

1. Reduce the data related to breath samples into a convenient form.
  - Extract envelope of the breath samples.
2. Analyze the reduced data to extract relevant information. The relevant information in this project are
  - Classification of breath on basis of amplitude
  - Extract the information regarding breaths per minute, i.e., bpm.

As a first step, we reduce the data available for analysis into a convenient form. We then proceed to analyze the data in the next two steps. In the below sub-sections we discuss each of these in detail.

### 4.2.1 Extraction of envelope

A recorded breath sample contains enormous data. At times, extracting the required information using this huge data is not an easy task. Therefore it is indeed necessary to bring this data into a convenient form before we do any further processing. Also, this huge data poses practical constraints at times like memory, processing time etc. In Figure 4.4, we observe that the breathing

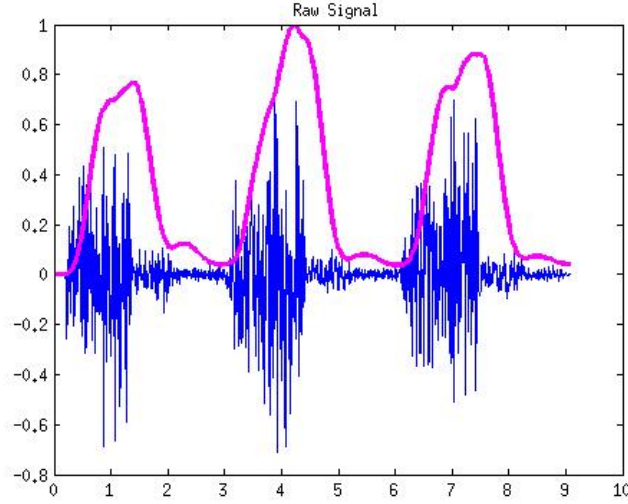


Figure 4.4: Envelope of a normal breath signal

pattern of a subject can be closely associated to a sinusoidal waveform. Further, the peak of the envelope extracted is either related to the instance of the inhale or exhale of the breath. This idea indeed plays an important role in detecting the breath. In this project, we reduce the data available for processing using the algorithm called *envelope extraction*.

Now, we briefly explain the envelope extraction technique. A standard envelope extraction algorithm involves three steps. In the first step, the signal is squared, further it is passed through a low pass filter and in the final step we take square root of the signal attained from the previous step.

In this project, we choose a low-pass Butterworth filter of order 3 where the cut-off frequency of the filter is approximately equal to half the sampling frequency of the breath signal. We arrived at this value after experimentation.

### 4.2.2 Classification of the breath

In this project, we classify the breath with respect to the maximum amplitude of the recorded breath signal. In general, the amplitude of the recorded breath signal depends on the following factors:

1. The distance from the recording source, i.e., microphone/smart phone.
2. The type of microphone i.e., omnidirectional/unidirectional etc.

Peak amplitude of inhale/exhale	Breath type
0-0.3	Mild Breath
0.3-0.7	Soft Breath
above 0.7	Hard Breath

Table 4.1: Classification of breaths based on the peak amplitude

3. The angle of the recording source to the nose of the subject.
4. The maximum signal strength that can be captured using the recording source. In case the signal strength exceeds the signal capture strength it will lead to saturation in the recorded signal.
5. The attenuation settings done during the recording.
6. The type of the analog filters used for noise reduction in the recording source.
7. The shielding of the cable that runs from the microphone to the PC.

Among the above mentioned factors, few of them may be irrelevant depending on the recording source. Since we classify a breath signal using the amplitude, evidently, to classify the signal in an absolute sense, we need to construct a function which takes into consideration all the above factors. The other way is to: normalize the breath signal according to the maximum recorded signal amplitude and proceed to classify the breath. This classification is indeed relative, but it is easy to annihilate the effects of the above mentioned factors in this procedure. We use a simple heuristic approach to classify the breath signal. It is evident that after the normalization the amplitude range is  $[0, 1]$ . We consider the peak amplitude of the inhale or exhale of breath and define ranges as mentioned in Table 4.1.

#### 4.2.3 Pseudo code

The implementation of the code is done in Matlab. We present the pseudo code of the algorithm used in the project. Before we proceed further, we need to set a precondition that the breathing of the subject is recorded using a microphone placed at a distance of 10-12 cm from the nose of the subject. This recorded breath signal is saved as a .wav file format.

- Calculate the sampling frequency ( $F_s$ ) of the recorded signal.
- Down-sample the recorded signal, i.e., reduce the sampling rate of a signal.
- Remove noise from the recorded signal using filter (we use third-order Butterworth filter).
- Detect the envelope of the recorded signal.
- Normalize the recorded signal.
- Determine the largest peak in the normalized recorded signal.

Time in (secs)	No. of bits	No. of channels	Sampling frequency in Hz	Size of .wav file in MB
60	8	1	8000	0.458
60	8	1	44100	2.523
60	16	1	8000	0.916
60	16	1	44100	5.047

Table 4.2: Calculation of the size of the wave file

- Classify the recorded signal using the following criterion:
  - If ( normalized peak amplitude  $\leq 0.3$ ) then declare mild breath
  - else if (normalized peak amplitude  $> 0.3$ ) && (normalized peak amplitude  $\leq 0.7$ ) then declare soft breath.
  - else declare hard breath.
- Determine the number of breaths per minute.

#### 4.2.4 Experiment

In this section, we discuss in detail about the actual implementation of the project. The digitized data is stored in the form of a wave file. It is one of the standards for storing an audio bit stream in PC's. We read the digitized data from the wave file using a Matlab program. We further proceed to the analysis of the data extracted. Before we proceed further, we introduce an important concept known as down sampling that plays a major role in implementation.

#### 4.2.5 Down sampling

As mentioned above, the wave file is read using a Matlab program. The size of the file and the digitized data depends on the duration of recording, sampling frequency and number of bits. It is discussed in Table 4.2. From the above table, it is evident that if the sampling frequency is high, the digitized data would be too huge, depending upon the duration of recording. In this case, the system runs out of memory while processing the data. Also, such a huge data poses the problem of redundancy. In order to overcome this constraint, we use a technique called down sampling.

#### 4.2.6 Measures for validating information retrieval

The envelope extraction helps us in providing information such as the number of correct breaths retrieved, the number of incorrect breaths retrieved and also the number of breaths not retrieved. In order to get this information, we use certain information retrieval measures such as precision, recall and F-measure.

### 4.3 Analysis of Results

To validate the classification technique suggested above, we use different types of breath samples like bronchial, broncho vesicular, crackles, vesicular, diminished vesicular, harsh vesicular etc. in addition to the normal breath.

1. The breaths recorded are stored in a .wav file. The first step is to read the .wav file. This is carried out using an inbuilt Matlab function.
2. The second step is the down-sampling process. In our project, the down sampling factor for the frequencies more than 10 KHz is set to 100, and for frequencies less than 10 KHz and more than 1000 Hz the down sampling factor is 10, else down sampling factor is set to 1. The sampling frequency,  $F_s$ , is also reduced according to the down sampling as

$$F_s = F_s / (\text{down sampling factor}). \quad (4.5)$$

Down sampling of the read breath signal is also performed using an inbuilt Matlab function.

3. The third step is the extraction of the envelope of the wave. We do this according to the procedure mentioned in previous section.
4. The fourth step is to find the peaks in the envelope which basically indicate the instances of inhales and exhales.
5. The fifth step is to classify the breath signal and plot them accordingly.
6. The sixth step is to count breaths per minute and plot accordingly as a bar graph.

We now discuss the precision, recall and F-measure for various types of breath samples used for validating our classification procedure.

**Bronchial:** This breath sounds as a harsh or blowing quality. The duration of the expiratory sound and the pitch is as long as or longer than the inspiratory sound. In the considered breath sample, we actually have 4 inhales and exhales. The Matlab program detects 4 inhales and exhales and 0 inhales and exhales were not detected and 0 inhales and exhales were falsely detected. Using the formulae discussed in the above subsection, the precision is 100%, the recall is 100% and the F-measure is 1. The envelope extraction and classification are shown in Figure 4.5.

**Broncho vesicular:** This breath consists of full inspiratory phase with a shortened softer expiratory phase. The inspiratory and expiratory sounds are of equal length. These are the breath sounds of the intermediate and pitch. In this breath sample, we actually have 4 inhales and exhales. The Matlab program detects 4 inhales and exhales and 0 inhales and exhales were not detected and 0 inhales and exhales were falsely detected. Using the formulae discussed in the above subsection, the precision is 100%, the recall is 100% and the F-measure is 1. The envelope extraction and classification are shown in Figure 4.6.

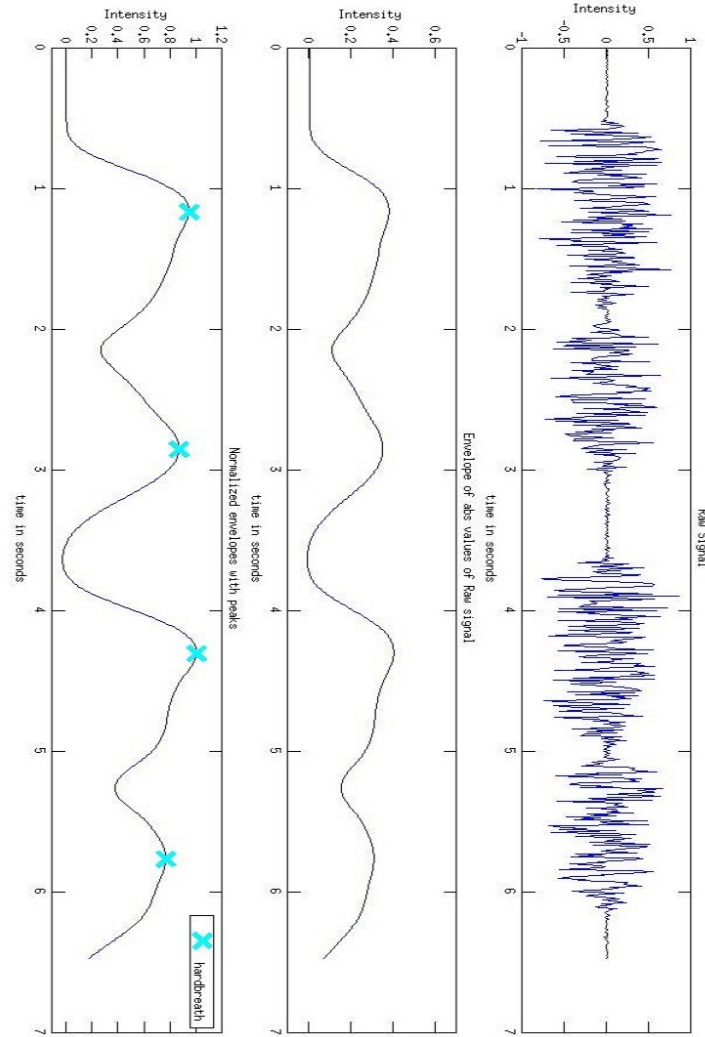


Figure 4.5: Envelope extraction and classification for the Bronchial breath

**Crackles:** These breath sounds are discontinuous, non-musical, brief sounds heard more commonly on inspiration. They can be classified as fine (high-pitched, soft or coarse). The loudness, pitch, duration, number, time in respiratory cycle, location, pattern from breath to breath, change after a cough or shift in position. In this breath sample, we actually have 6 inhales and exhales. The Matlab program detects 3 inhales and 3 exhale and 0 inhales and exhales were not detected and 0 inhales and exhales were falsely detected. Using the formulae discussed in the above subsection, the precision is 100%, the recall is 100% and the F-measure is 1. The envelope extraction and classification are shown in Figure 4.7.

**Vesicular:** The vesicular breath sounds soft and low-pitched. The inspiratory sounds are longer than the expiratory sounds. Sounds are harsher and

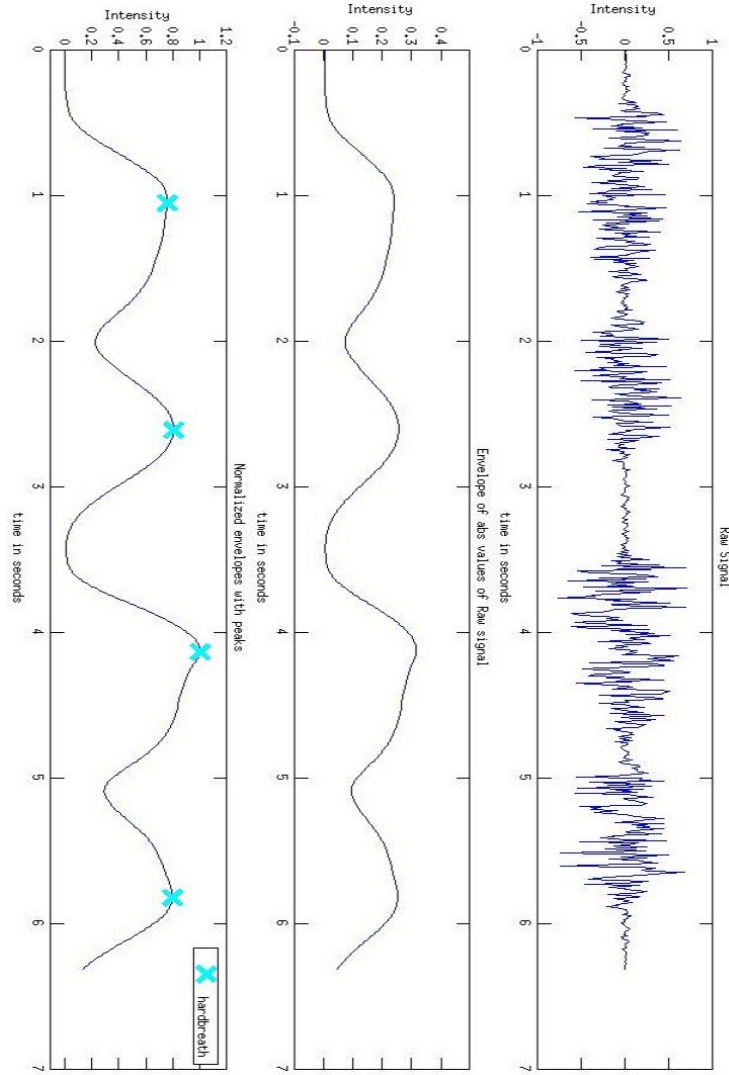


Figure 4.6: Envelope extraction and classification in Broncho-vesicular breath

slightly longer if there is rapid deep ventilation. In this breath sample, we actually have 2 inhales and 2 exhailes. The Matlab program detects 2 inhailes and 2 exhailes and 0 inhailes and exhailes were not detected and 0 inhailes and exhailes were falsely detected. Using the formulae discussed in the above subsection, the precision is 100%, the recall is 100% and the F-measure is 1. The envelope extraction and classification are shown in Figure 4.8.

**Diminished vesicular breath:** These sounds are less robust than vesicular sounds. These sounds occur in patients who move a lowered volume of air, such as frail, in elderly patients or shallow breathing patients. In this breath sample, we actually have 2 inhailes and 2 exhailes. The Matlab pro-



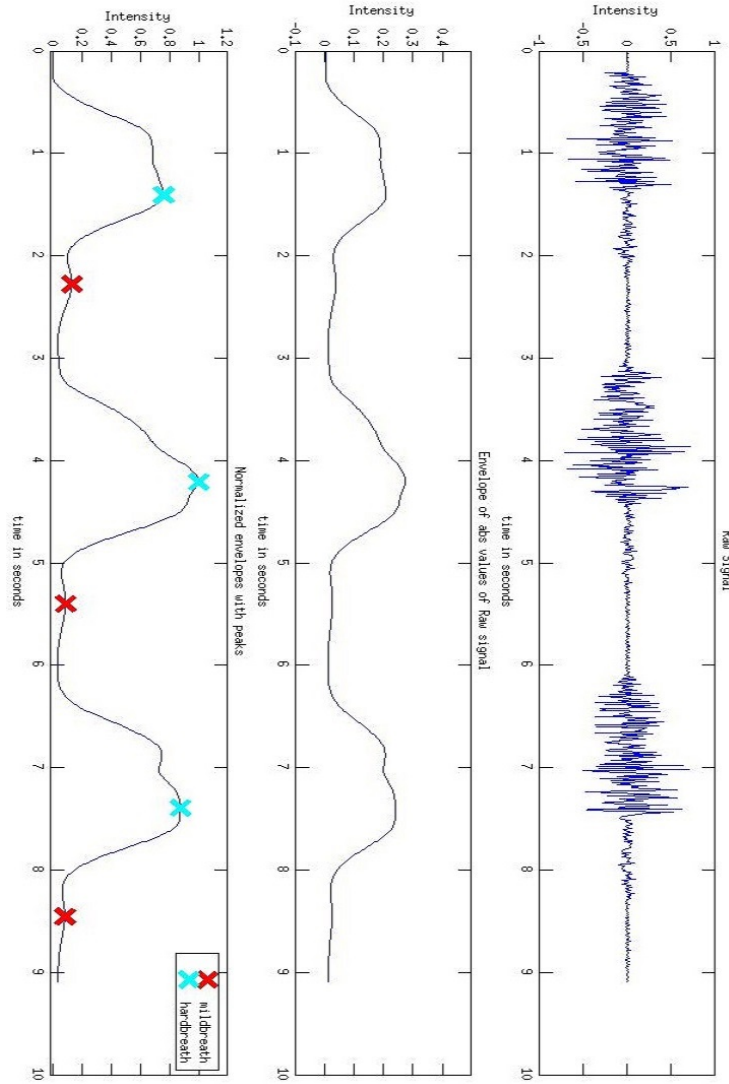


Figure 4.7: Envelope extraction and classification in Crackles breath

gram detects 2 inhales and 2 exhales and 0 inhales and exhales were not detected and 0 inhales and exhales were falsely detected. Using the formulae discussed in the above subsection, the precision is 100%, the recall is 100% and the F-measure is 1. The envelope extraction and classification are shown in Figure 4.9.

**Harsh vesicular breath:** These sounds may result from the vigorous exercises. With exercises, the ventilations are rapid and deep. In this breath sample, we actually have 2 inhales and 2 exhales. The Matlab program detects 2 inhales and 2 exhales and 0 inhales and exhales were not detected and 0 inhales and exhales were falsely detected. Using the formulae dis-

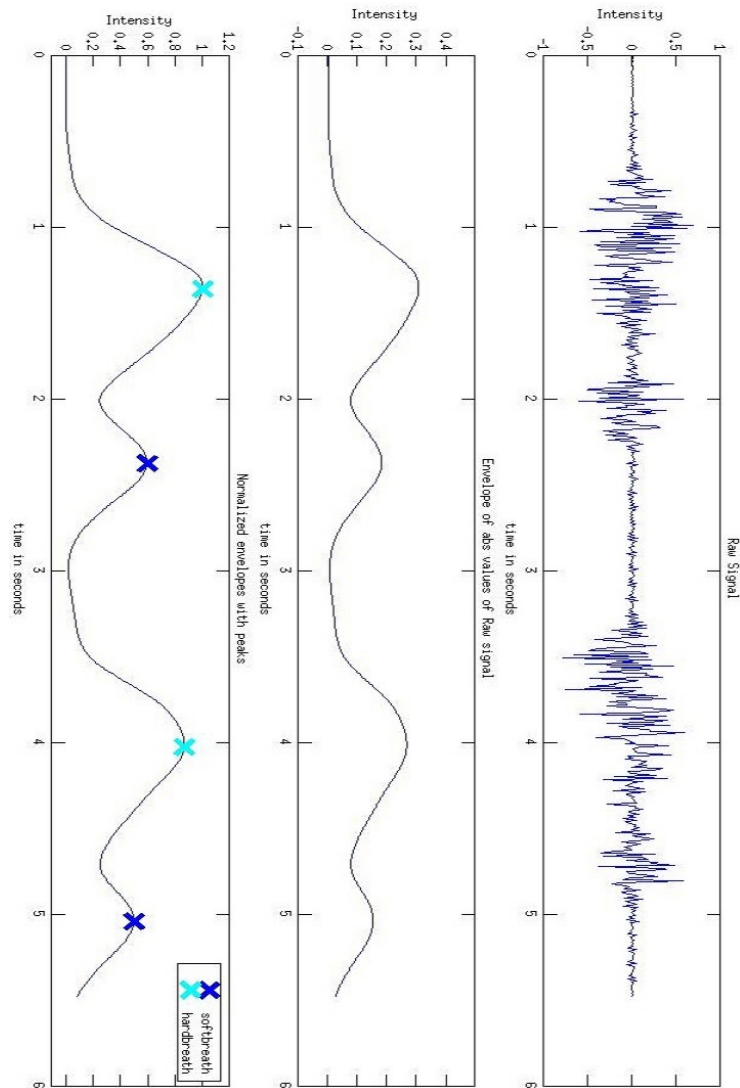


Figure 4.8: Envelope extraction and classification of the Vesicular breath

cussed in the above subsection, the precision is 100%, the recall is 100% and the F-measure is 1. The envelope extraction and classification are shown in Figure 4.10.

**Wheezes breath:** The sounds are continuous, high pitched, hissing sounds heard normally expiration also sometimes on inspiration. It is produced when air flows through airways narrowed by secretions, foreign bodies or obstructive lesions. The wheezes occur if there is a change after deep breath and cough. In this breath sample, we actually have 3 inhales and 3 exhales. The Matlab program detects 2 inhales and 3 exhales and 1 inhale or exhale was not detected and 0 inhales and exhales were

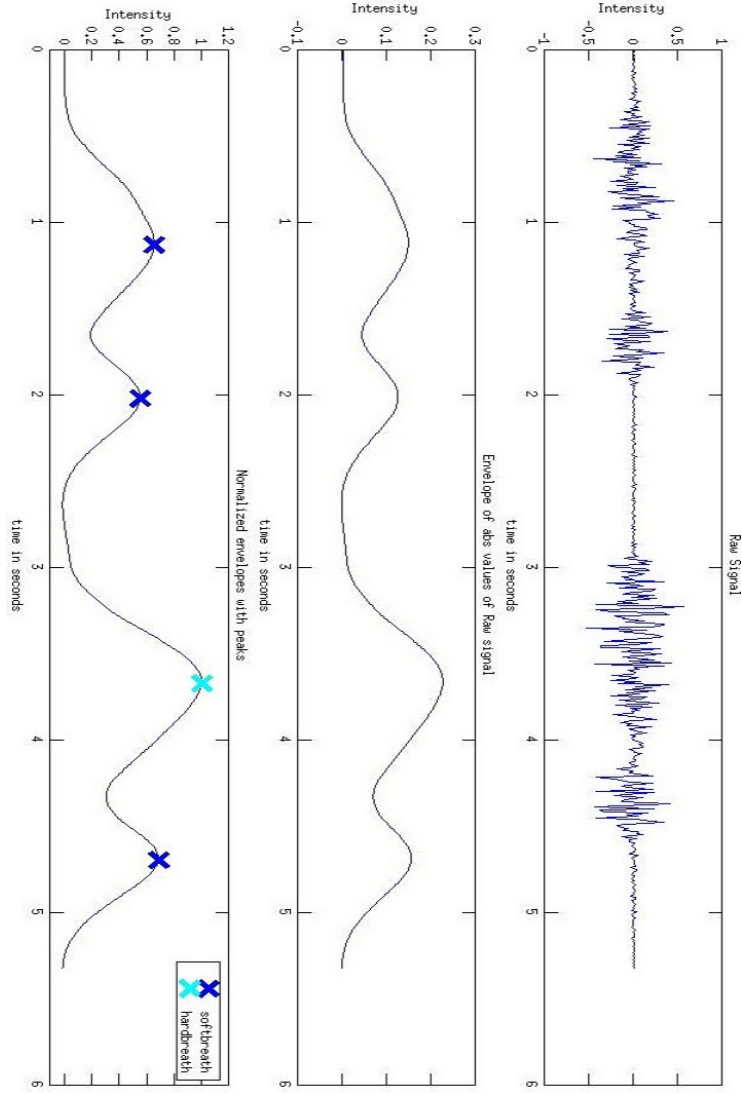


Figure 4.9: Envelope extraction and classification in the Diminished vesicular breath

falsely detected. Using the formulae discussed in the above subsection, the precision is 100%, the recall is 83.33% and the F-measure is 0.908. The envelope extraction and classification are shown in Figure 4.11.

**Normal breath recording for 5 minutes** The normal breath is recorded using a microphone for 5 minutes. For this recording, we used breaths per minute (bpm) for the analysis. The values obtained from the Matlab program and from the actual recording are described in Table 4.3. Using the formulae discussed in the above subsection, the precision is 98.56%, the recall is 100% and the F-measure is 0.992. Here the actual values represent

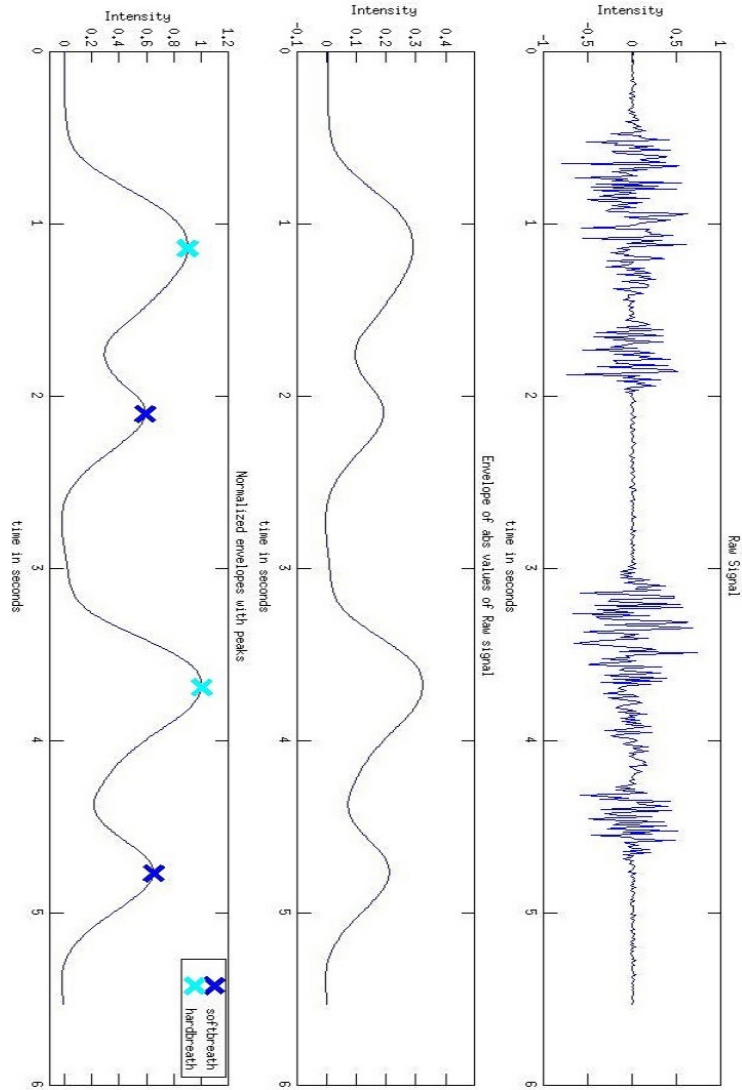


Figure 4.10: Envelope extraction and classification in the Harsh vesicular breath

the number of breaths counted manually for every minute by hearing to the recorded signal. The results obtained are placed in the appendix.

**Normal breath recording for 1 hour** The normal breath is recorded using a microphone for 1 hour. For this recording, we use breaths per minute (bpm) for the analysis. The total number of breaths obtained in the actual recording is 4208. The total number of breaths obtained using Matlab program is 3924. The breaths lost were due to low-intensity of the recorded breath. The results obtained are placed in the appendix.

**Normal breath recording in a disturbed environment** The normal breath is recorded using a microphone for 5 minutes in a disturbing environ-

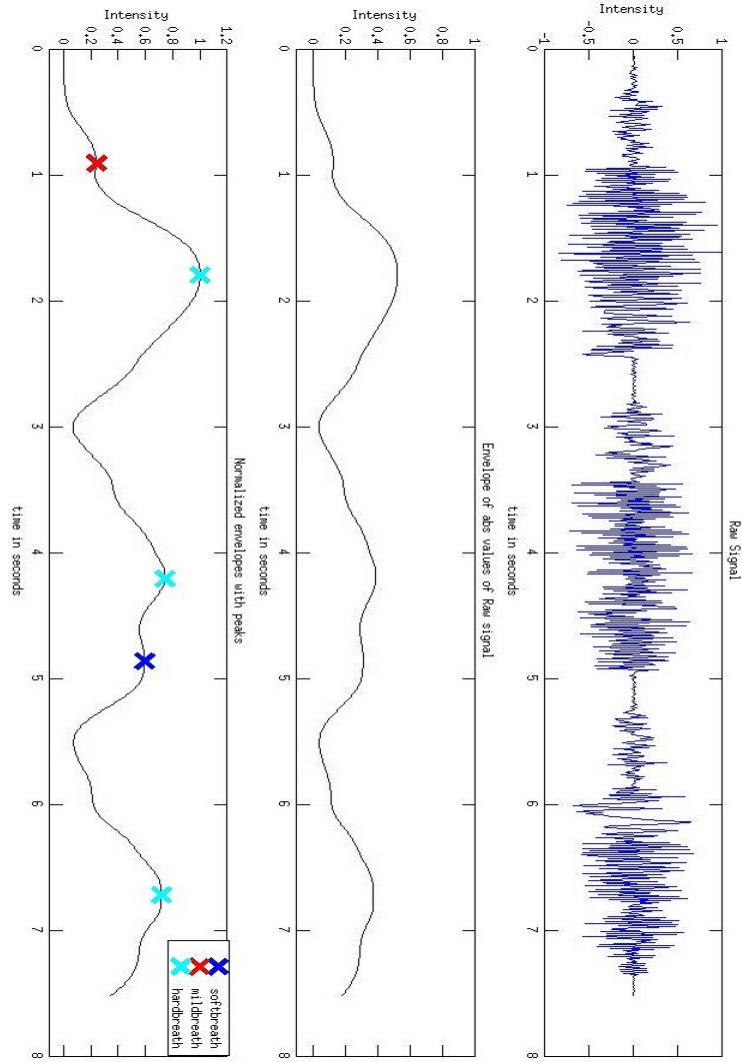


Figure 4.11: Envelope extraction and classification in the Wheezes breath

ment. For this recording, we use breaths per minute (bpm) for the analysis. The total number of breaths obtained in the actual recording is 467. The total number of breaths obtained using Matlab program is 235. The details are listed in Table 4.4 The breaths lost due to the external noise of the recorded breath. The results obtained are placed in the appendix.

The results obtained for each of the above mentioned breaths are summarized in Table 4.5.

Actual values in the recoding in breaths per minute (bpm)	Values obtained from the Matlab program in breaths per minute (bpm)
60	60
64	68
72	71
75	76
73	73
Total = 344	Total = 349

Table 4.3: Comparison of actual values with the values obtained using Matlab

Actual values in the recoding in breaths per minute (bpm)	Values obtained from the Matlab program in breaths per minute (bpm)
83	42
89	45
94	47
99	50
102	50
Total = 467	Total = 234

Table 4.4: Comparison of actual values with the values obtained in Matlab for disturbed audio recorded for 5 minutes

## 4.4 Discussions

In this section, we discuss about the experimental results obtained from the algorithm used in this project. The results are derived from the samples of data stored in a file. In short, this method works for the breath samples recorded offline. There is no real-time processing of the data. The noise and high amplitude glitches still pose a challenge to the technique we adopted. The background noise is unavoidable in certain circumstances. So, it is difficult to eliminate the background noise completely. To address this issue, we feel that a more rigorous signal processing methods are necessary. The peak values represent the instances of inhales and exhales. But in some cases, our peak detection algorithm is not robust enough. This also is one of problems that result from background noise and sudden glitches. For a good quality of recording, the technique works satisfactorily. This is evidenced in the experiments conducted as part of validation as shown in Table 4.3. The method did not perform to a satisfactory extent for long duration recording, i.e., one hour in this case. It is observed that this resulted in lack of quality recording. According to our observation we found that if the amplitude of the breath is very low, it is difficult to detect such breaths. Therefore some of the breaths were not detected. Since classification depends on the maximum value occurring in the recording, presence of high amplitude glitches would lead to erroneous results.

Type of breath	Precision in (%)	Recall in (%)	F-measure
Bronchial	100	100	1
Broncho vesicular	100	100	1
Crackles	100	100	1
Vesicular	100	100	1
Diminished vesicular	100	100	1
Harsh vesicular	100	100	1
Wheezes	100	83.33	0.908
Normal breath for 5mins	98.5	99.7	0.99
Normal breath for 1 hour	94.5	88.2	0.91
Normal breath for 5 minutes in a disturbed environment	100	33.38	0.5

Table 4.5: Calculation of the precision, recall and F-measure for the different breaths

#### 4.4.1 Challenges in real time processing

There are few challenges which we encounter by implementing real-time processing of data. Generally, the real-time processing of a continuous time signal is performed by dividing the signal into several parts. Each part is usually referred to as a window.

The first challenge in real-time processing is to decide the length of the window. It depends on the time required to implement the breath detection algorithm and the length of buffers (hardware buffers) from where the program reads the value from an analog signal. The length of the buffer usually depends on the hardware configuration of the laptop. If the duration of the recording stored in the buffers is less than the time taken to process the data of the selected window length, there is a potential risk of losing some breaths in the recording.

The next challenge is stitching of the envelope of various windows. This can be explained with the help of an example. Let us assume that the duration of the breath recording is 10 seconds and the length of the window is assigned 5 seconds. Then the envelope calculated for each of the two windows combined should be the envelope of the complete breath signal.

However, to achieve this is really challenging. In order to achieve this, we require efficient signal processing techniques. The classification algorithm that we proposed basically relies on the maximum amplitude of the signal that occurred in the entire recording. It is therefore not possible to attain this value during online/ real-time processing, since this varies from window to window and therefore the classification that we proposed will again be dependent on the window. Using such classification, the data/ information obtained will not be of much use. The other challenge is that if the data is displayed in real-time, then it contributes to processing time. We therefore propose addressing the above mentioned issues as one of the future research directions.

## Chapter 5

# Conclusions/Future work

The detection and analysis of breath is helpful in detecting different abnormalities in breathing patterns. The different techniques for breath detection and analysis are primarily categorized into contact and non-contact techniques. As explained in the thesis, one of the main drawbacks in using contact techniques is that the subject has to wear the sensors which can be uncomfortable for the subject. It also involves high maintenance and installation costs. In this thesis, we discussed some of the breath analysis and detection techniques developed in recent times.

We proposed a technique based on non-contact approach for determining the breaths which involves less equipment and also incur low installation and maintenance costs. The proposed hardware consists of a standard microphone (usually connected to PC/laptop) and a laptop with a certain standard configuration. The breath of a subject is recorded using the microphone and is further processed using breath detection and analysis algorithm which we developed.

Using the developed algorithm, we classified the breath of the subject into soft, mild and hard breaths, and also determined the number of breaths per minute. We evaluated our algorithm by testing various kinds of breathing sounds like the bronchial, brocho-vesicular, vesicular, diminished vesicular, harsh vesicular, crackles apart from normal breath. To study the robustness of the algorithm, we tested normal breath sounds with more external noise.

For each of the above mentioned breath sounds, the algorithm has been validated using different measures like the precision, recall and F-measure. From these validation techniques we observed that the precision achieved is 94.68%, recall is 88.94% and F-measure is 0.917 for normal breaths. In most cases, precision is 100%, recall is 100% and F-measure is 1.

We also discussed about the different sleep stages of a subject. The classification of sleep stages mentioned in the thesis is based on the respiration rate as well as the body temperature of the subject. As an immediate application of the algorithm, we suggest to use our experimental setup to classify sleep stages.

The efficiency of the proposed experimental setup and the breath detection and analysis algorithm is limited by noise intensity levels in the surrounding environment. Currently, the duration of the recording of breaths is limited to one hour. If the duration is extended, the time taken for detecting and analyzing the breaths would also be increased, apart from memory issues in computing. These are some issues still remaining out of scope of the presented work and



can be considered for future direction.

## 5.1 Future research directions

We recommend the following future research directions:

**Robustness to background noise and high amplitude glitches:** The current algorithm is sensitive to the background noise. The efficiency is reduced in the presence of high amplitude glitches. These limitations can be overcome using advanced filtering techniques. The option of designing hardware filters and/or using a better noise cancellation microphone can be considered. Using external hardware may result in a less economical solution. We refer to the following literature in this direction: [26], [27], [28], [29], [30].

**Real-time breath detection and classification:** The current algorithm is only used for offline breath detection. The immediate extension of the current work is to make the algorithm real-time. This can be achieved by using windowing techniques available in digital signal processing. We refer to the following works: [17], [18], [19].

**Work in conjunction with other analog/digital sensors:** We already have discussed about sleep stage classification. In the sleep stage classification, temperature sensor is also used. Therefore, it is necessary to extend the current algorithm such that the breath detection and analysis is carried out along with processing of other sensor data. Some of the works in this directions are [20], [21], [22], [23], [24], [25].

**Porting the algorithm on to a microcontroller:** The current setup and algorithm needs a standard microphone and a laptop. This seriously limits the applicability. Porting the algorithm on to a microcontroller along with real-time processing opens up several application areas.

## Appendix A

# Matlab code of the project

```
1 %Matlab code for the project%
2 clc
3 clear all
4 close all
5 %Read wave file .
6 [wave,Fs,nbts]=wavread('/home/divya/Desktop/Breath sounds/audiohr1.
7 wav');
8 %Downsampling Factor. Depends on Sampling Frequency. For sampling
9 %frequency > 10kHz Downsampling factor =100, for sampling frequency
10 %<10kHz
11 %and > 1000Hz, Downsampling factor=10.
12 dnsample=1;
13 if Fs>10000
14 dnsample=100;
15 else ((Fs>1000) & (Fs<10000))
16 dnsample=10;
17 end
18 %wave1 contains downsampled data.
19 wave1=downsample(wave,dnsample);
20 wave=wave1;
21 %Frequency is also reduced according to Downsampling.
22 Fs=Fs/dnsample;
23 %Calculates time of recording.
24 t=length(wave)/Fs;
25 x = wave;
26 %Time axis reconstruction
27 time1 = (0:length(wave)-1) / (Fs);
28 %Multiply the two together to get something interesting
29 y = x;
30 %Filter wave data using third order butterworth low pass filter .
31 [a,b]=butter(3,1/(Fs/2.15),'low');
32 yabs=abs(y);
33 %calculate envelope of the recorded voice signal
34 env = filter(a,b,yabs);
35 %Calculate peaks in the envelope which basically indicate the
36 instances of
37 %Inhale and exhale of breath.
38 [b1,a1]=findpeaks(env,'MINPEAKDISTANCE',60);
39 %[a,b]=peakfinder(env);
40 %calculate the largest peak and then normalize the entire envelope
41 %accordingly.
42 c=0;
```

```

41 c=b1(1);
   for i=1:size(b1,1)
43     if c<b1(i)
         c=b1(i);
45     end
   end
47
   %Using the largest peak value to normalize the entire signal with
   respect
49 %to the largest peak value.
   env1=env/c;
51
   %Find inhales and exchales according to the normalized envelope
53 [b,a]=findpeaks(env1,'MINPEAKDISTANCE',60);
   %[a,b]=peakfinder(env1);
55 %Set ranges for classifying breath.
   mildbreathrange=0.3;
57 softbreathrange=0.7;
   %hardbreathrange= 0.6;
59 mbc=0; %mildbreath counter
   sbc=0;%softbreath counter
61 hbc=0;%hardbreath counter
   softbreath=[];
63 mildbreath=[];
   hardbreath=[];
65 %Classification of breath according to amplitude of exhale/inhale
   for i=1:(size(b,1))
67     if b(i)<=mildbreathrange
         mbc=mbc+1;
69     mildbreath(mbc,1)=b(i);%save mildbreath amplitude
         mildbreath(mbc,2)=a(i);%save mildbreath time instance
71     end
         if b(i)<=softbreathrange && b(i)>mildbreathrange
73         sbc=sbc+1;
         softbreath(sbc,1)=b(i);%save softbreath amplitude
75         softbreath(sbc,2)=a(i);%save softbreath time instance
         end
77         if b(i)>softbreathrange
             hbc=hbc+1;
79         hardbreath(hbc,1)=b(i);%save hardbreath amplitude
             hardbreath(hbc,2)=a(i);%save hardbreath time instance
81         end
         end
83     leg_ctr=0;
         %Plotting the signal and the classified breath.
85     %set(axes_handle,'YLim',[0,3])
         xlim=ceil(length(time1)/Fs);
87     subplot(3,1,1);

89     plot(time1,wave);
         axis([0,xlim,-2,2]);
91     %hold on;
         title('Raw Signal');
93     xlabel('time in seconds');
         ylabel('Normalized Intensity');
95     subplot(3,1,2);
         plot(time1,env1);
97     axis([0,xlim,-2,2]);
         hold on;
99     if (sbc>0)
         leg_ctr=leg_ctr+1;

```

```

101 leg(leg_ctr)=plot(softbreath(:,2)/Fs,env1(softbreath(:,2)),'bx','
    MarkerSize',8,'linewidth',2);
leg_str(leg_ctr,:)= 'softbreath';
103 %legend(sb,'softbreath','Location','SouthEastOutside')
hold on;
105 end
if (mbc>0)
107 leg_ctr=leg_ctr+1;
leg(leg_ctr)=plot(mildbreath(:,2)/Fs,env1(mildbreath(:,2)),'rx','
    MarkerSize',8,'linewidth',2);
109 leg_str(leg_ctr,:)= 'mildbreath';
%legend(mb,'mildbreath','Location','SouthEastOutside')
111 hold on;
end
113 if (hbc>0)
leg_ctr=leg_ctr+1;
115 leg(leg_ctr)=plot(hardbreath(:,2)/Fs,env1(hardbreath(:,2)),'cx','
    MarkerSize',8,'linewidth',2);
leg_str(leg_ctr,:)= 'hardbreath';
117 %legend(hb,'hardbreath','Location','SouthEastOutside')
end
119 legend(leg,leg_str,'Location','NorthEast')
title('Normalized envelopes with peaks');
121 xlabel('time in seconds');
ylabel('Normalized Intensity');
123 subplot(3,1,3);
plot(time1,env);
125 axis([0,xlim,-2,2]);
%hold on;
127 %plot(a/Fs,env(a),'rx','MarkerSize',16,'linewidth',4);

129 title('Envelope of abs values of Raw signal');
xlabel('time in seconds');
131 ylabel('Normalized Intensity');
totalbreaths=length(b)
133 ctr=0;
bpm=[];
135 for i=1:round((length(time1)/Fs)/60)
    j=1;
137 while (((a(j)/Fs)/60)<i)
        ctr=ctr+1;
139        j=j+1;
        if (j>length(a))
141            break;
        end
143    end
    bpm(i)=ctr;
145    ctr=0;
end
147 i=length(bpm);
while i>1
149 bpm(i)=bpm(i)-bpm(i-1);
i=i-1;
151 end
if (length(bpm)>0)
153 figure();
lab=num2str(bpm);
155 bar(bpm);
title('Bar graph indicating breaths per minute');
157 x=[1:length(bpm)]';
%set(gca,'XTickLabel',lab);
159 for i1=1:numel(bpm)

```

```

161         text(x(i1),bpm(i1),num2str(bpm(i1)),...
               'HorizontalAlignment','center',...
               'VerticalAlignment','bottom')
163     end
164 end
165 figure();
166 x=[1:3]';
167 y=[length(hardbreath),length(softbreath),length(mildbreath)];
168 h=bar(y);
169 title('Bar graph of classified breaths');
170 axis('auto');
171 for i1=1:numel(y)
172     text(x(i1),y(i1),num2str(y(i1)),...
          'HorizontalAlignment','center',...
          'VerticalAlignment','bottom')
173 end
174 lab={'Hard';'Soft';'Mild'};
175 set(gca,'XTickLabel',lab);

```

Listing A.1: Matlab code of the project

## Appendix B

### Psuedo code

```
1 %%%#Read data and sampling frequency (Fs) from wav file
  [wave,samplingfrequency]=wavread(wavefile)
3 %%%Set the downsampling factor
  if sampling frequency > 10 KHz
5 Set downsampling factor = 10
  else
7 Set downsampling factor = 100
  endif
9 %%%Reduce the sampling frequency with respect to the downsampling
  factor
  Fs = Fs/downsamplingfactor
11 %%%Begin the filtering process by using third order Butterworth
  low pass filter
  [a,b]=butter(3,1/(Fs/2.15),'low');
13 %%%Extract the envelope of the recorded audio signal
  env = filter(a,b,yabs);
15 %%%Determine the amplitude peaks which are the instances of the
  inhales and the exhales
  %%%b1 is an array that contains all the peaks in the envelope and
  a1 contains the instances where these peaks occurred.
17 [b1,a1]=findpeaks(env,'MINPEAKDISTANCE',60);
  %%%Determine the largest peak and normalize the entire signal
  accordingly
19 %%%Find the maximum value in b1.
  C=max(b1);
21 %%%Divide the entire envelope signal by C to normalize C with
  respect to the maximum peak.
  env1=env/C;
23 %%%Detect number of inhales and exhales with the help of the
  normalized signal
  [b2,a2]=findpeaks(env1,'MINPEAKDISTANCE',60);
25 %%%Set the range limit value for each breath type
  mildbreath = 0.3
27 softbreath = 0.7
  hardbreath > 0.7
29 %%% Classify each breath as soft, mild and hard according to the
  amplitude values of inhales %%% and exhales
  for i=1 to length(b1)
31   if b1(i)<mildbreath
      Declare b1(i) as mildbreath
33   else if b1(i) >mildbreath and b1(i)<softbreath
      Declare b1(i) as softbreath
35   else if b1(i)>softbreath
```

```

        Declare b1(i) as hardbreath
37     end if
end %%%end of for
39 %%%The signal and the classified breath are plotted
    %%%Determine the breaths per minute and plot it in the form of a
        bar graph
41 %%% Initialize breath counter
    ctr=0;
43     for i=1 to length of recording in minutes.
        while (instance of breath detected < ith minute)
45             %%%increment the breath counter
                ctr=ctr+1;
47             end %%%end of while
        %%%assign the breaths counted till ith minute to bpm(i)
49         bpm(i)=ctr;
        %%% reset the breath counter
51         ctr=0;
    end %%%end of ith minute
53 %%%calculate breaths per minute
    for i= length of bpm to 2
55     breaths per ith minute = (breaths till ith minute) -
        (breaths till (i-1)th minute)
57 end %%%end of for loop

```

Listing B.1: Psuedo code

## Appendix C

### More results

Actual values in the recoding in breaths per minute (bpm)	Values obtained from the Matlab program in breaths per minute (bpm)
54	57
60	60
58	58
62	61
57	61
61	60
62	63
67	65
68	71
67	72
60	73
69	70
70	70
54	66
46	64
51	62
52	64
63	65
66	69
48	65
60	60
63	64
54	66
54	59
67	64
55	70
76	69
60	74
52	70
64	69
78	70



77	73
75	68
80	69
77	67
76	64
91	67
57	64
49	69
61	68
60	75
60	72
72	69
68	58
74	66
84	72
83	73
82	74
77	67
79	58
92	60
85	57
93	58
90	49
93	54
98	56
100	61
97	61
102	78
98	62
Total = 4208	Total = 3920

Table C.1: Comparison of actual values with the values obtained in Matlab for disturbed audio recorded for 1 hour

Figure C.1: Envelope extraction and classification for a normal breath recorded for 5 minutes -1

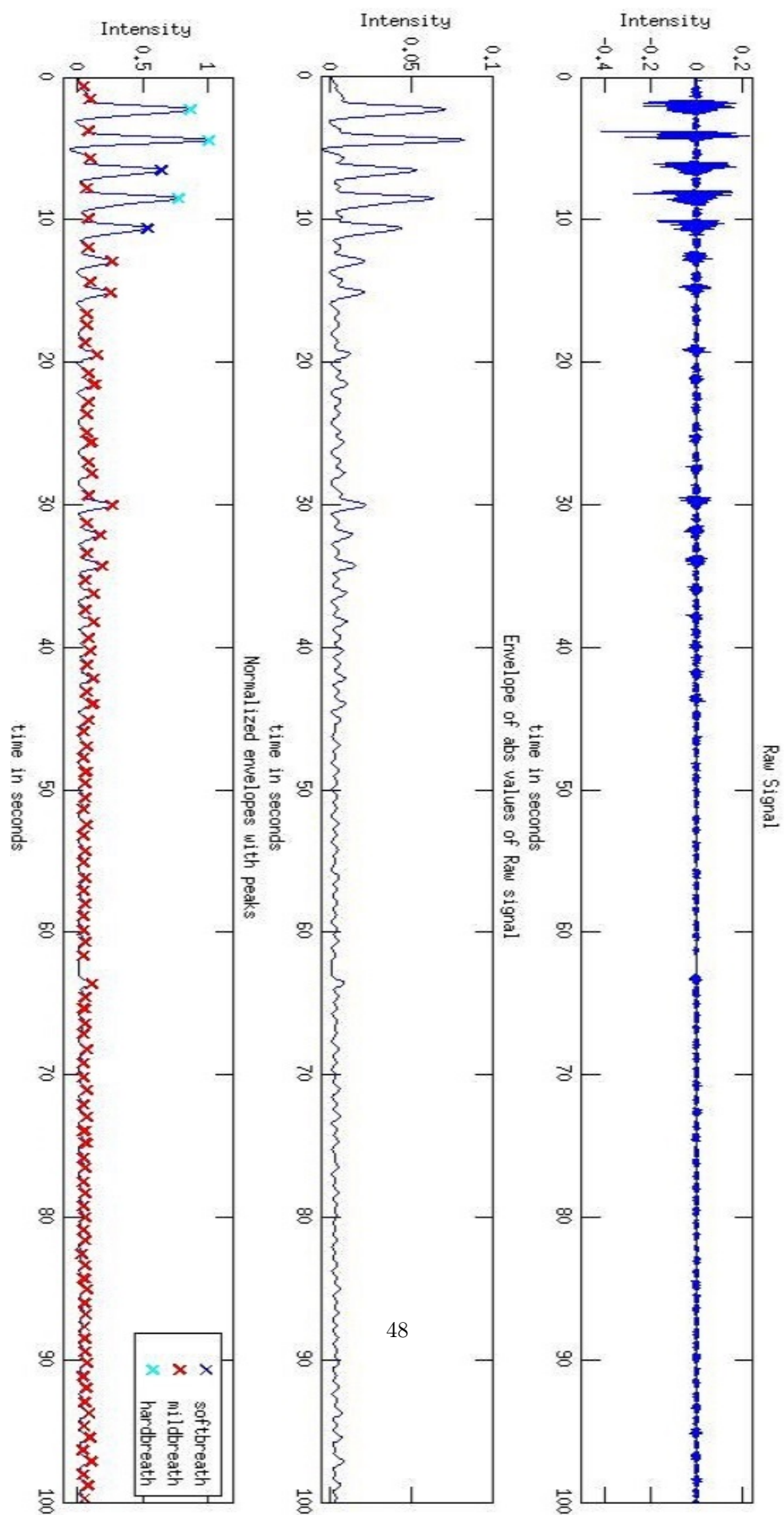


Figure C.2: Envelope extraction and classification for a normal breath recorded for 5 minutes -2

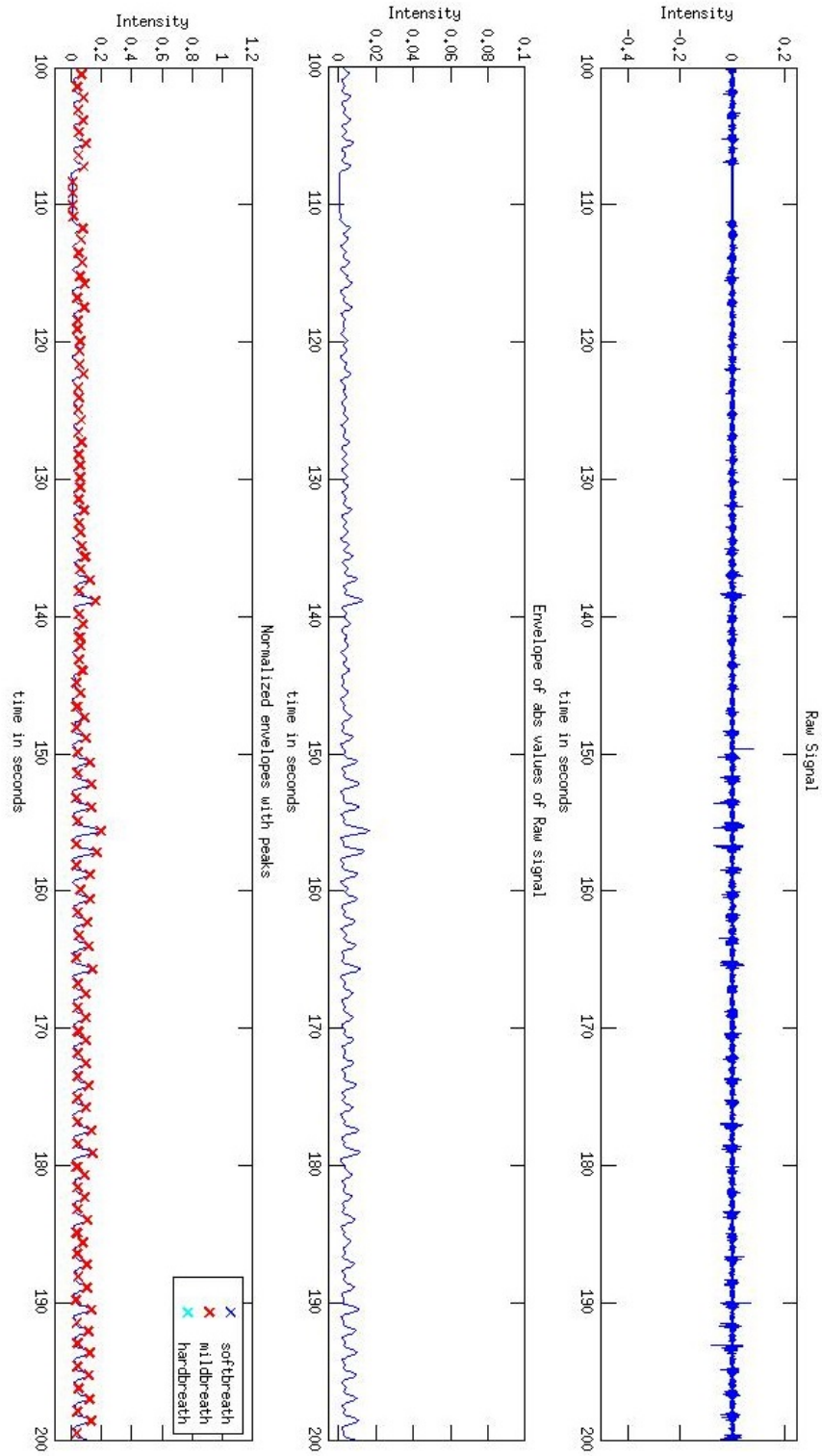


Figure C.3: Envelope extraction and classification for a normal breath recorded for 5 minutes-3

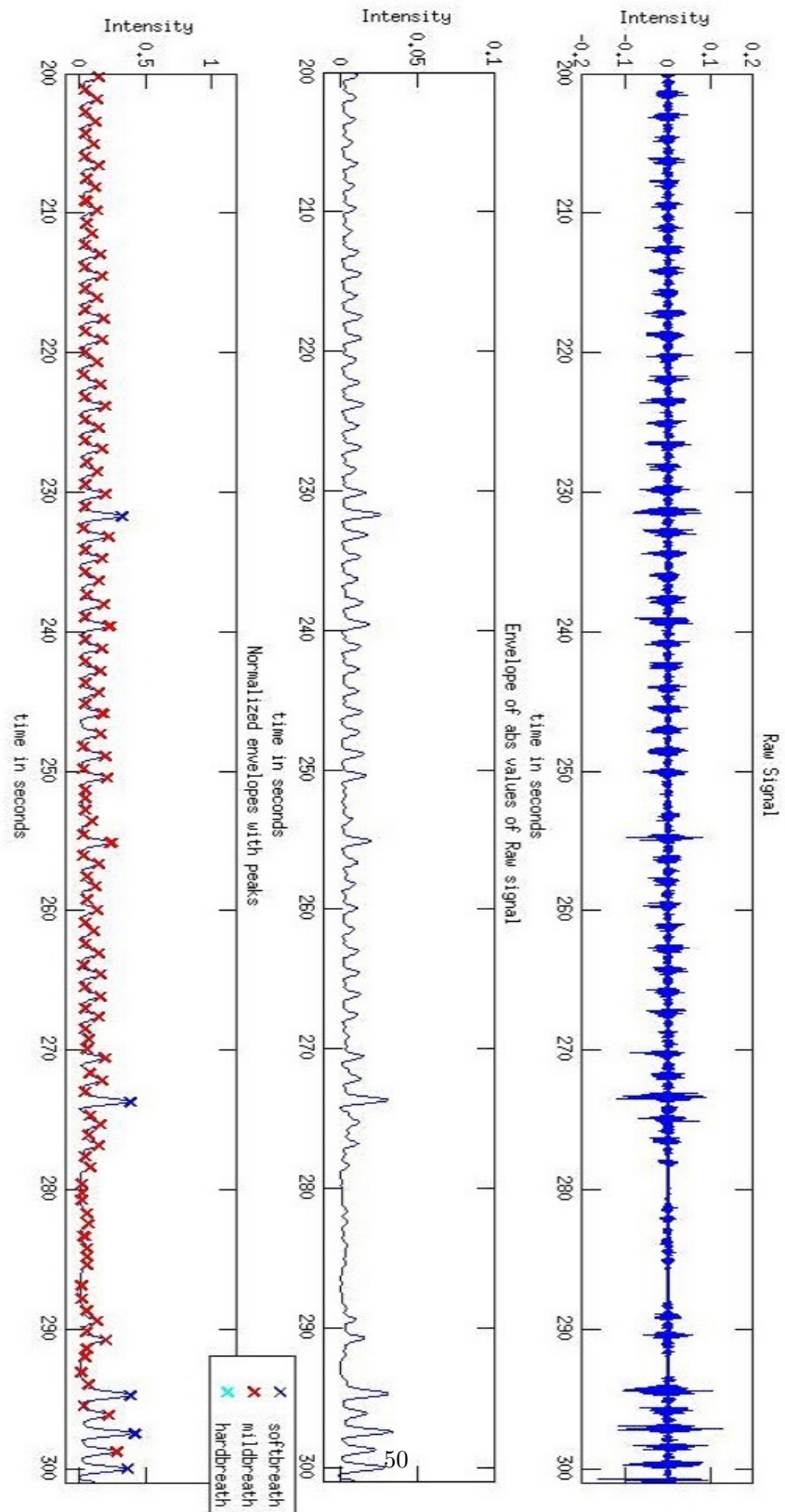


Figure C.4: Classification of breaths for a normal breath recorded for 5 minutes

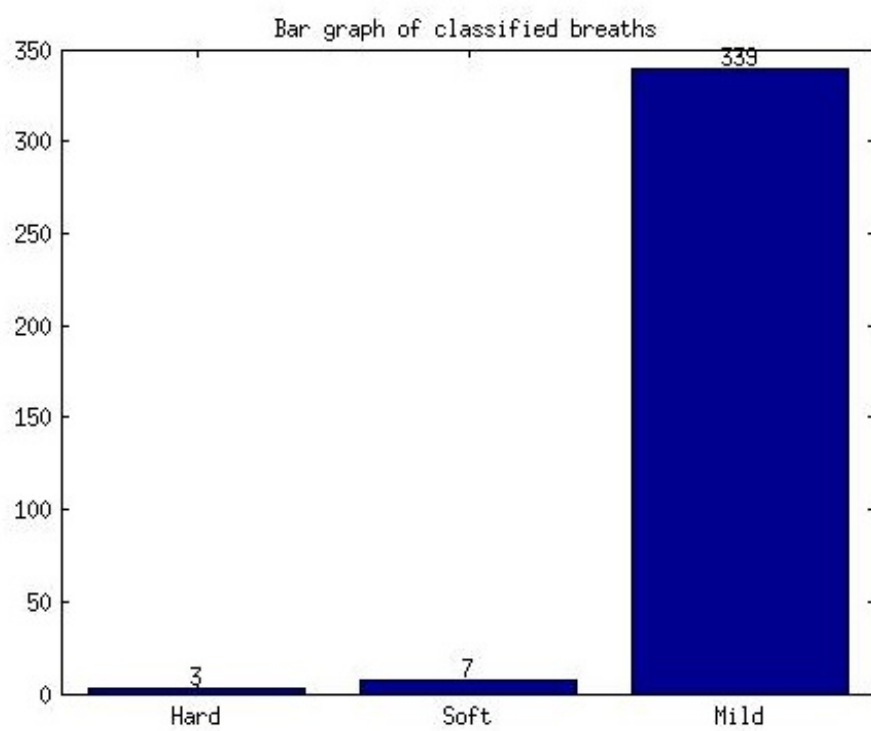


Figure C.5: Envelope extraction and classification of normal breath for 1 hour  
-1

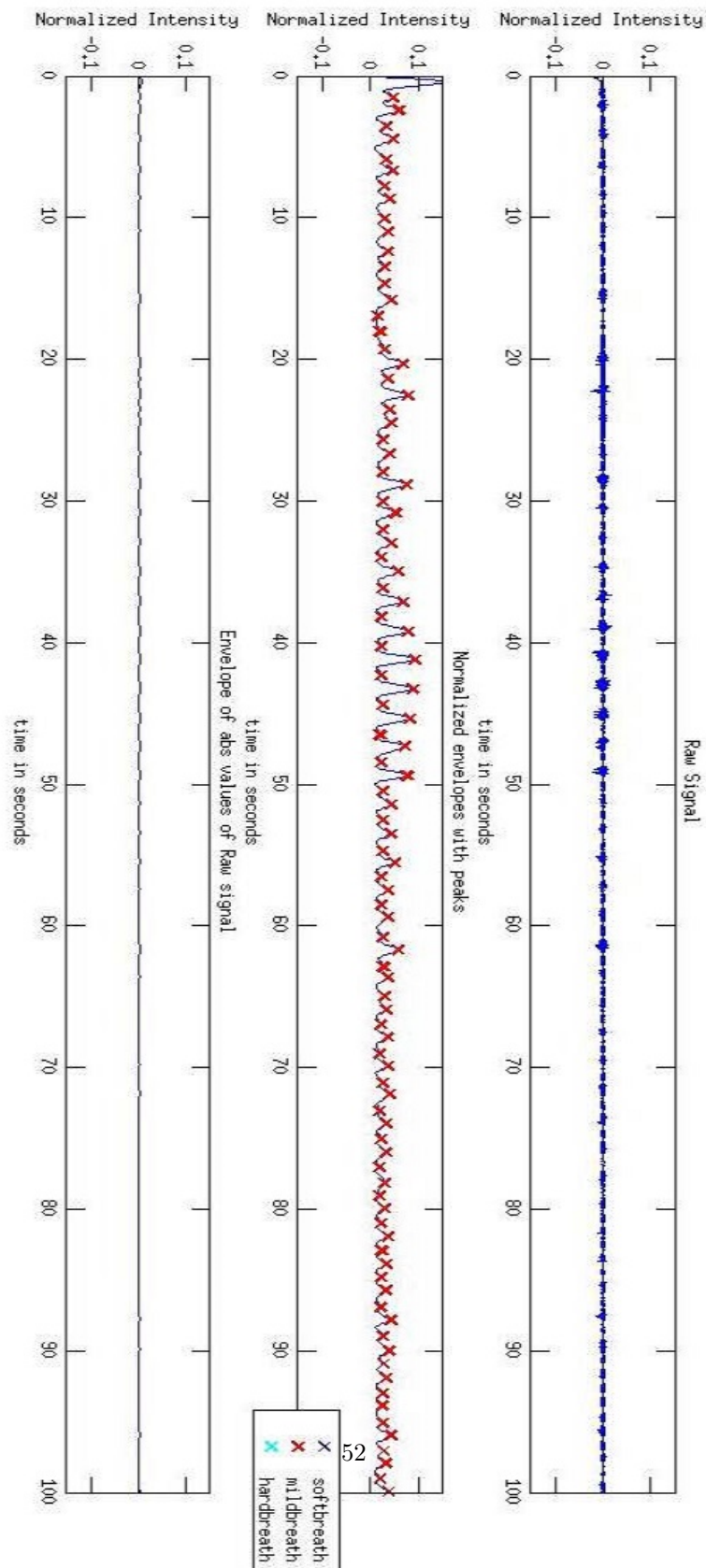


Figure C.6: Envelope extraction and classification of normal breath for 1 hour  
-2

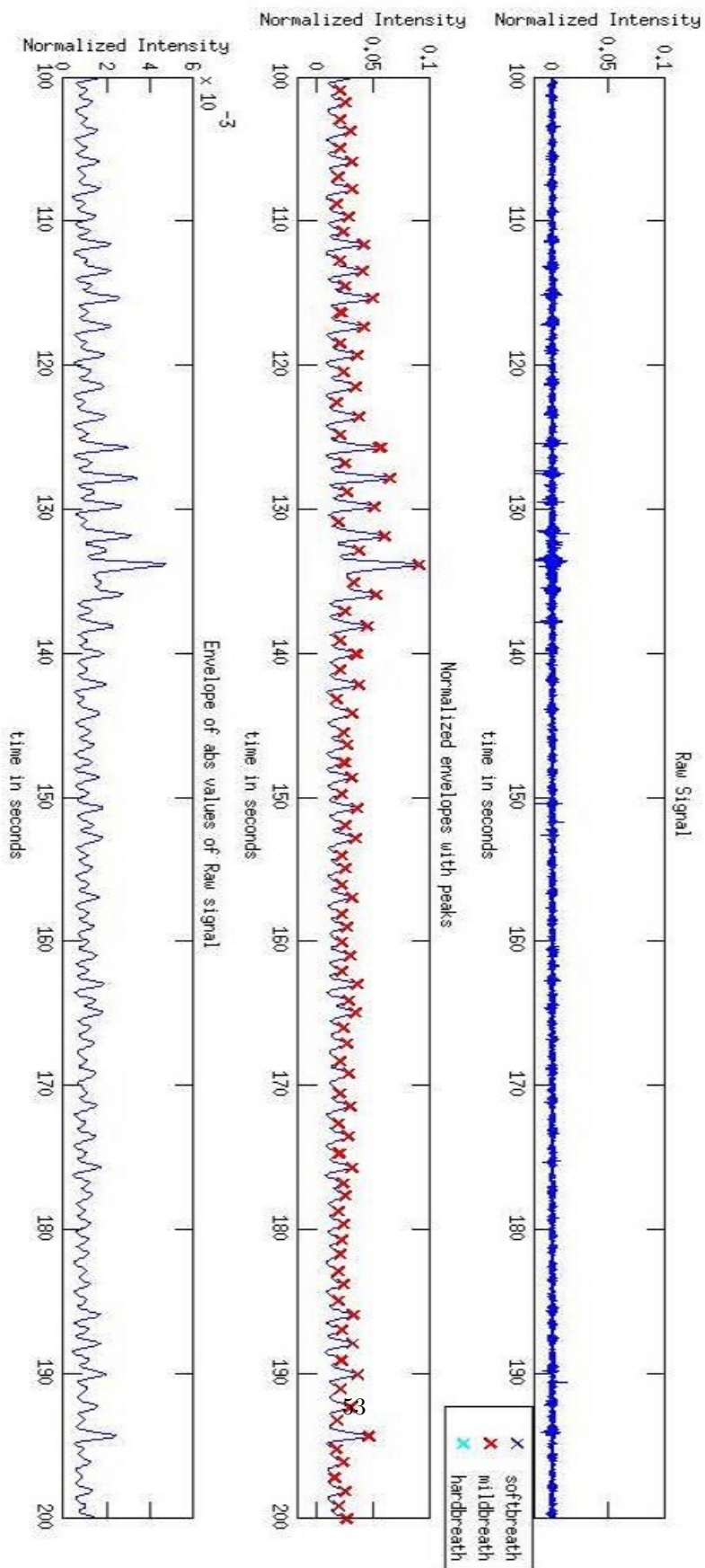




Figure C.7: Envelope extraction and classification of normal breath for 1 hour  
-3

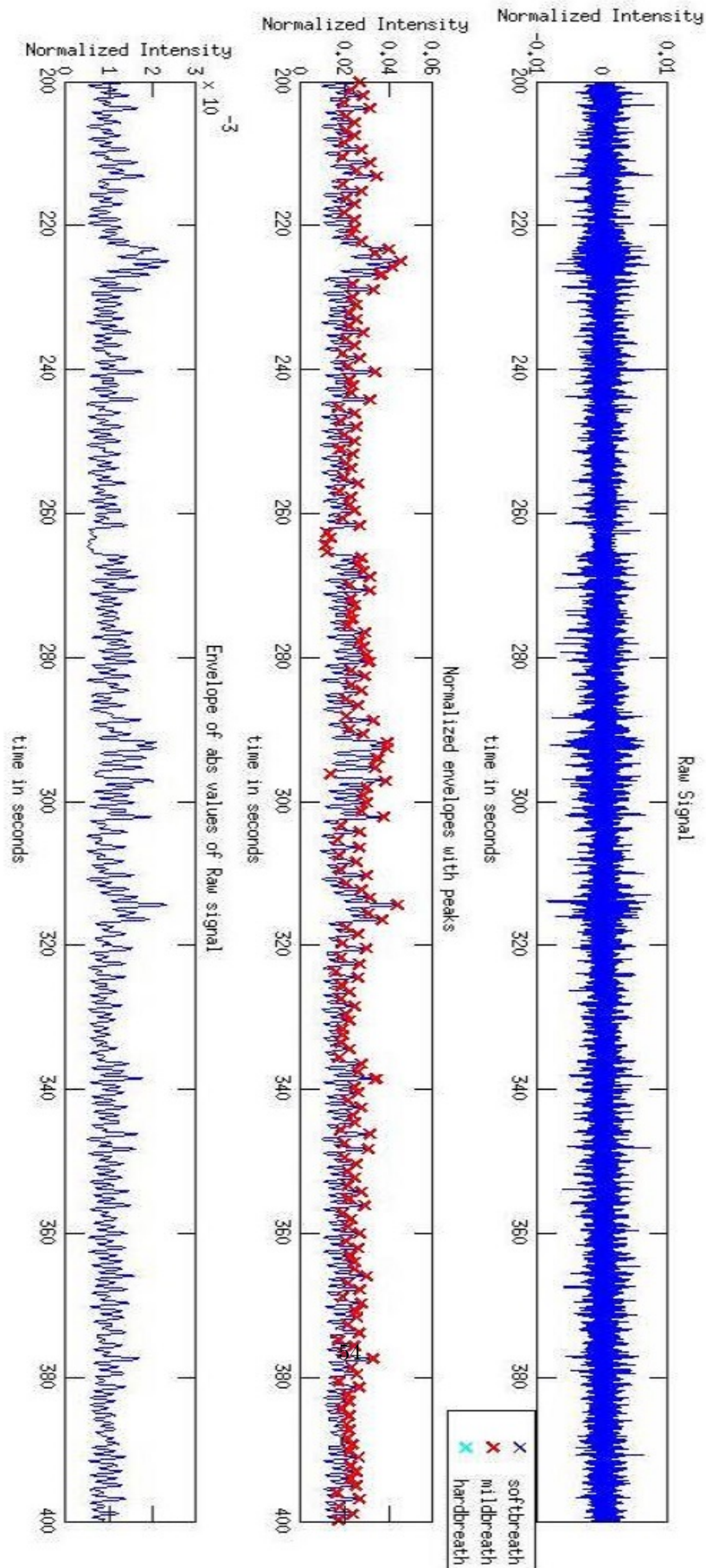




Figure C.8: Envelope extraction and classification of normal breath for 1 hour  
-4

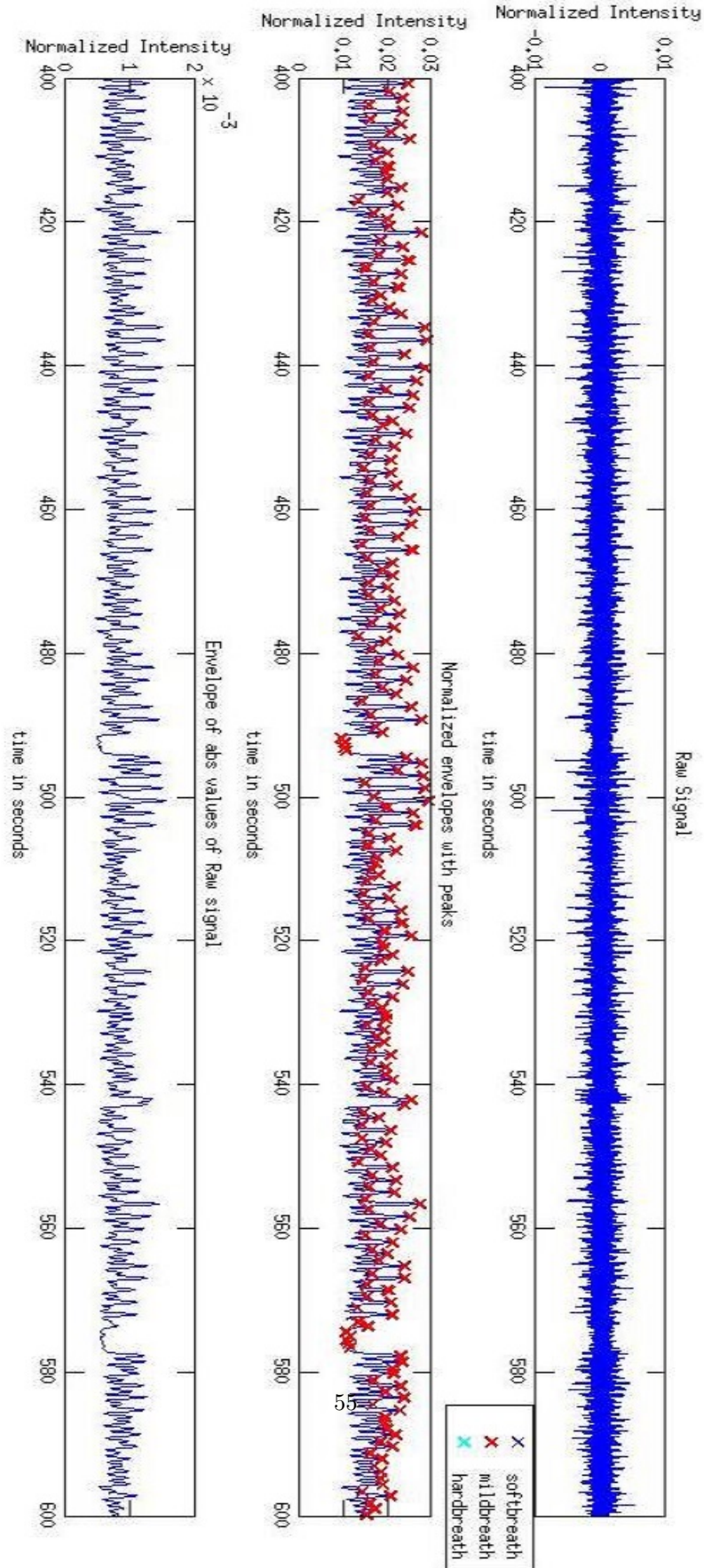


Figure C.9: Envelope extraction and classification of normal breath for 1 hour  
-5

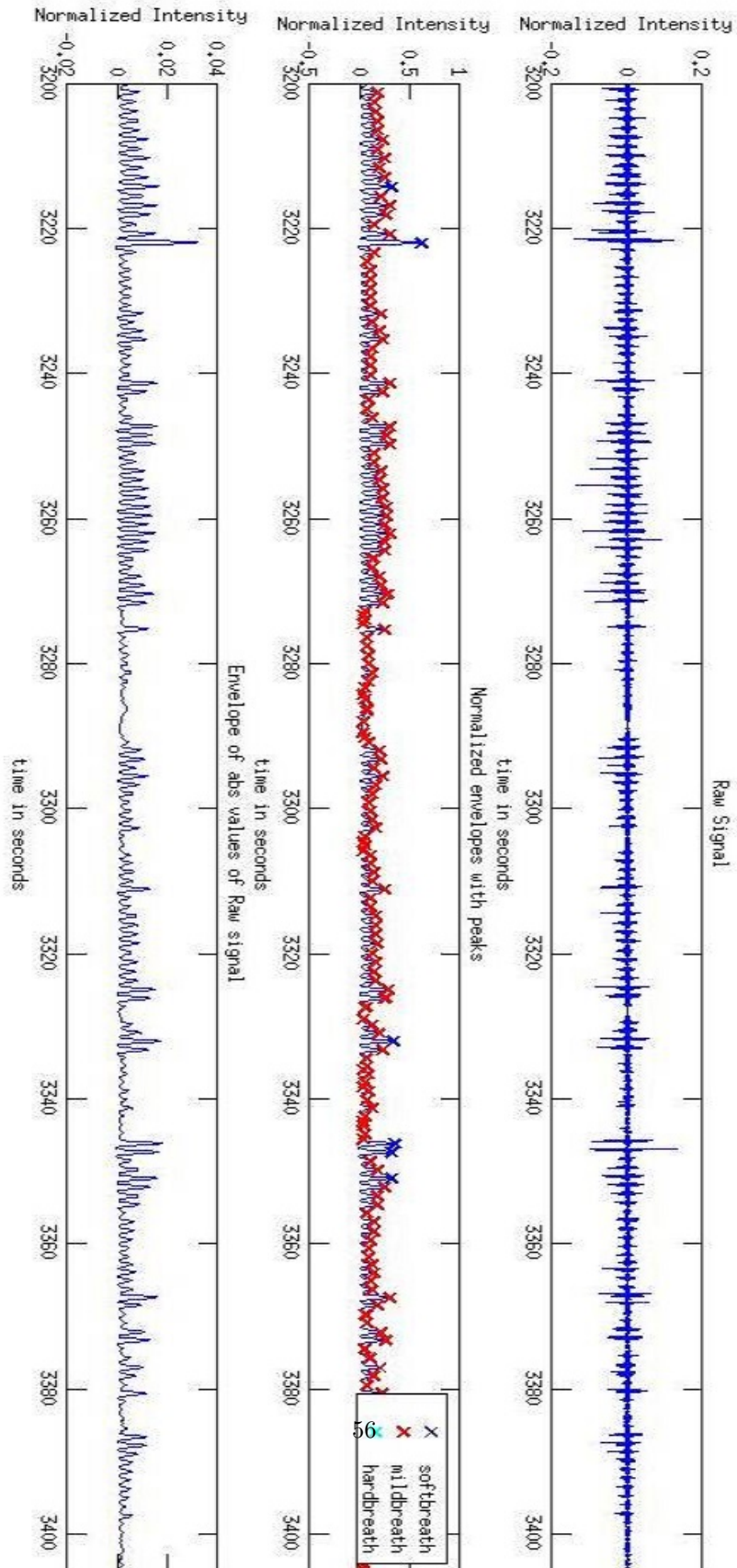


Figure C.10: Envelope extraction and classification of normal breath for 1 hour  
-6

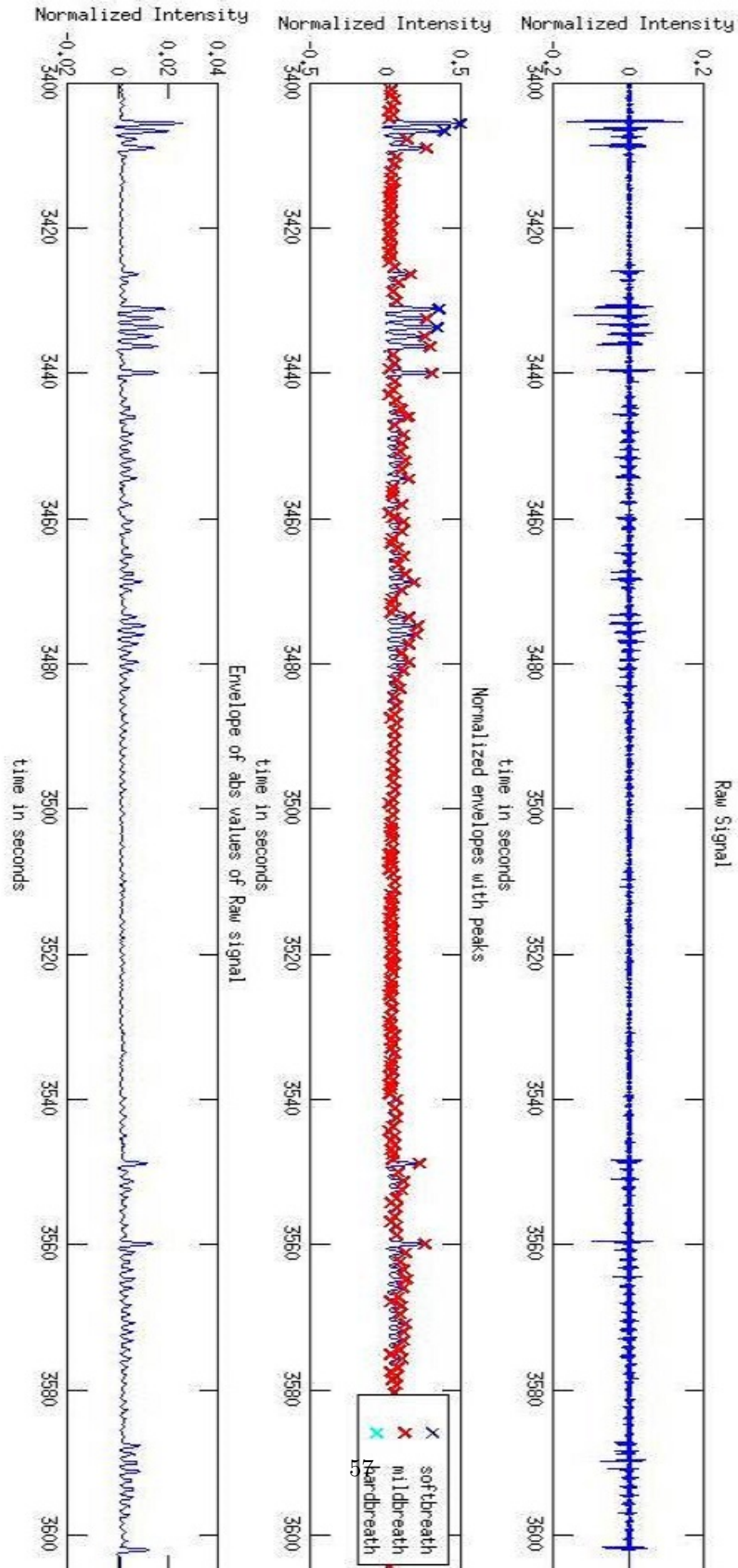


Figure C.11: Classification of breaths for a normal breath recorded for one hour

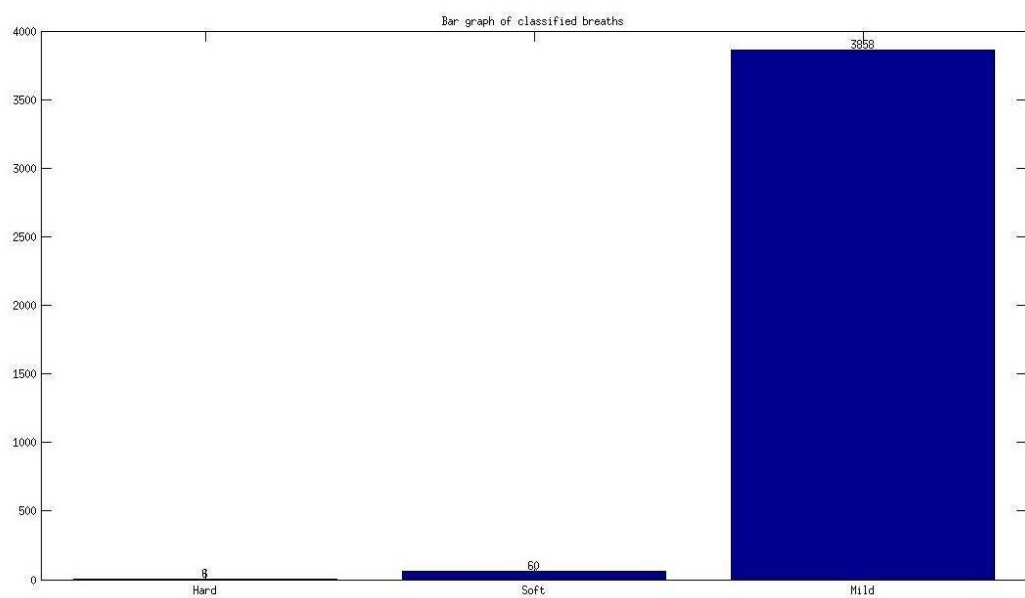




Figure C.12: Envelope extraction and classification of breaths in a disturbed environment recorded for 5 minutes-1

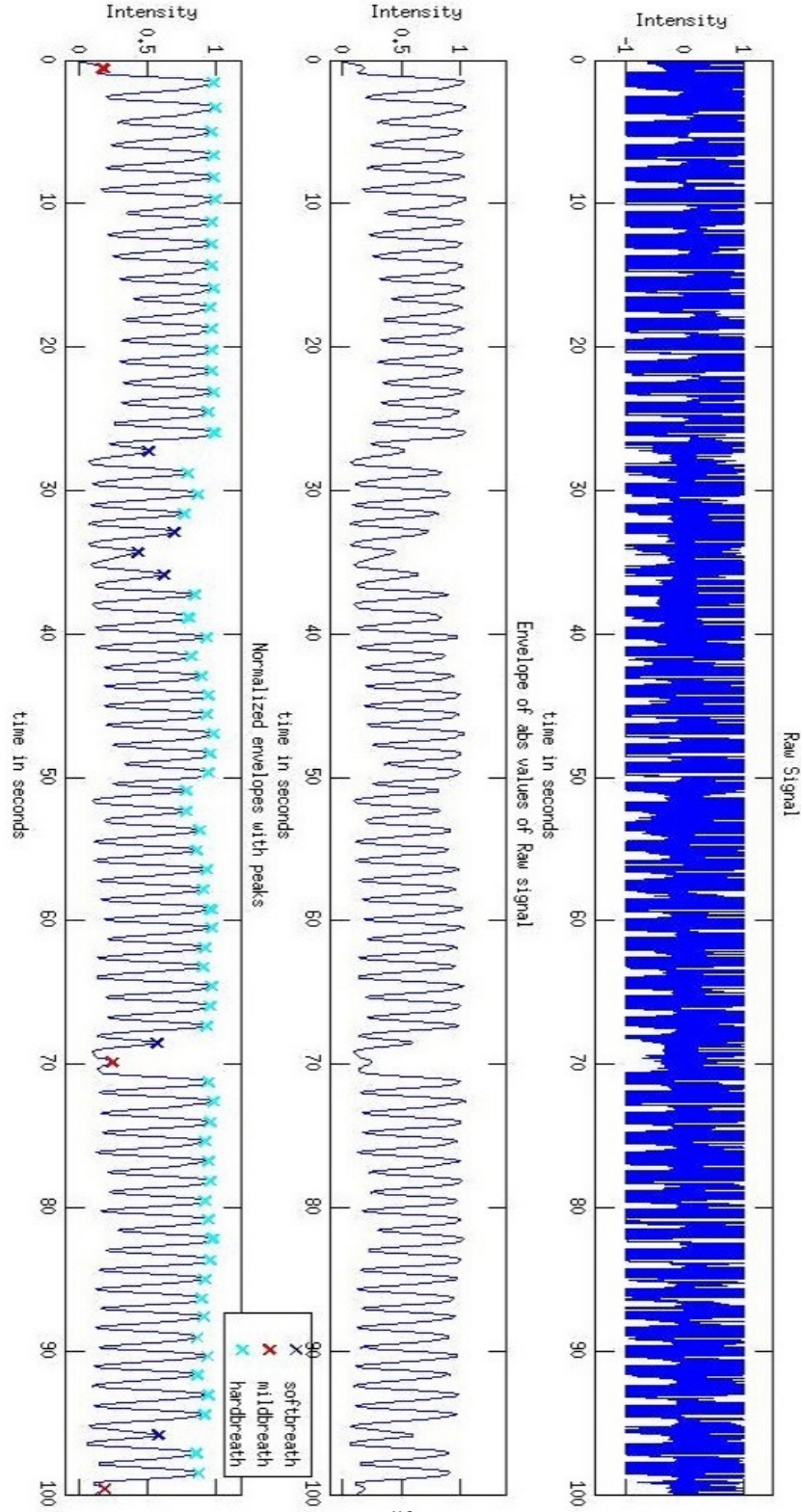


Figure C.13: Envelope extraction and classification of breaths in a disturbed environment recorded for 5 minutes-2

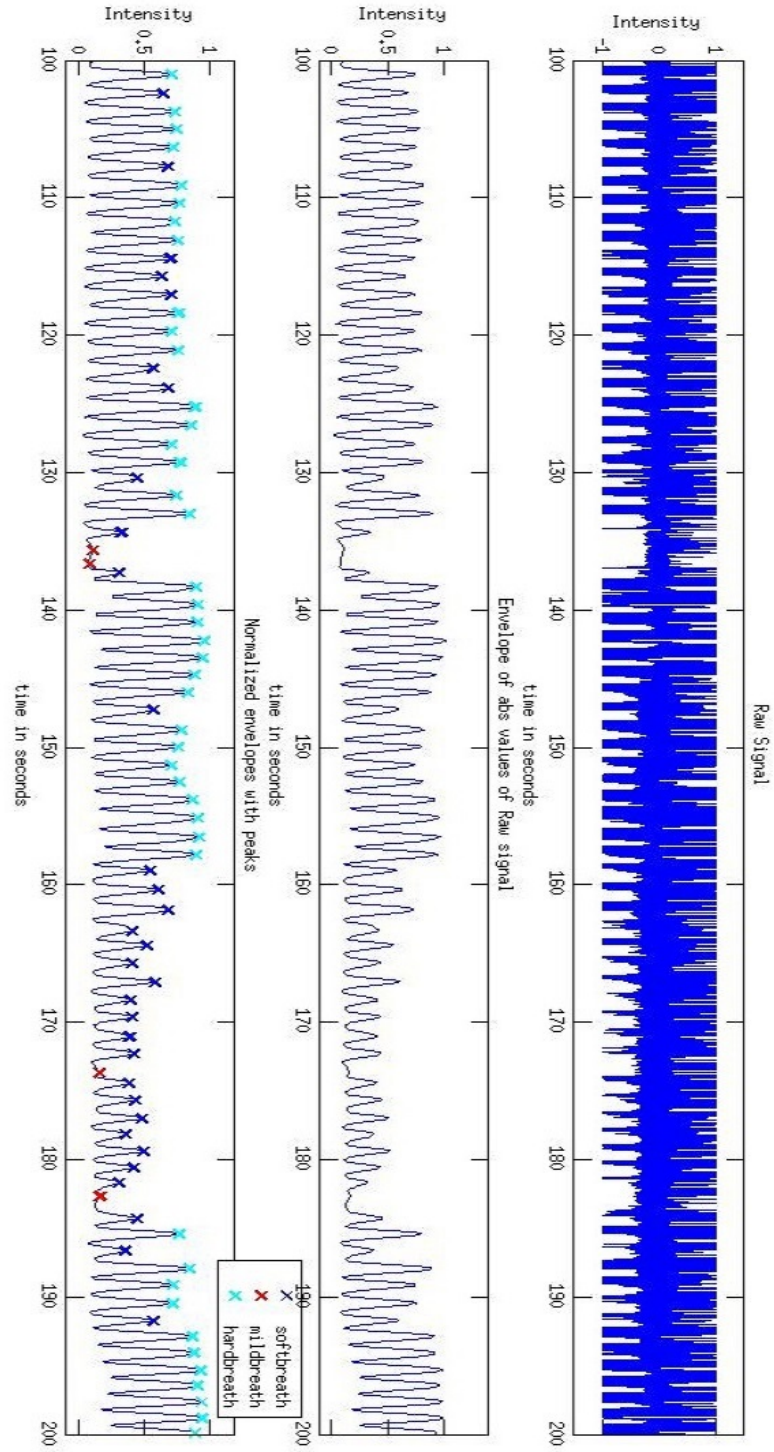


Figure C.14: Envelope extraction and classification of breaths in a disturbed environment recorded for 5 minutes-3

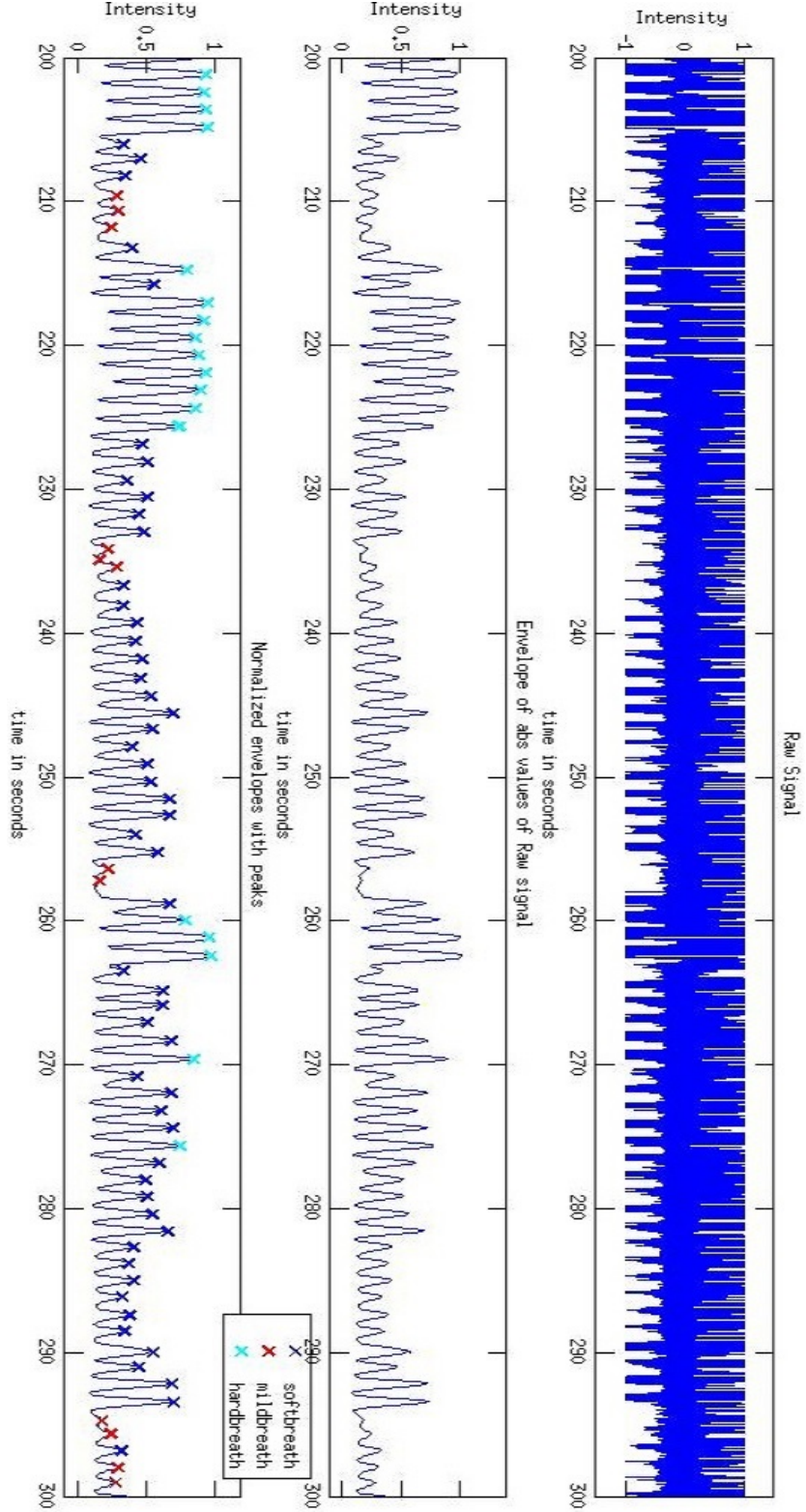
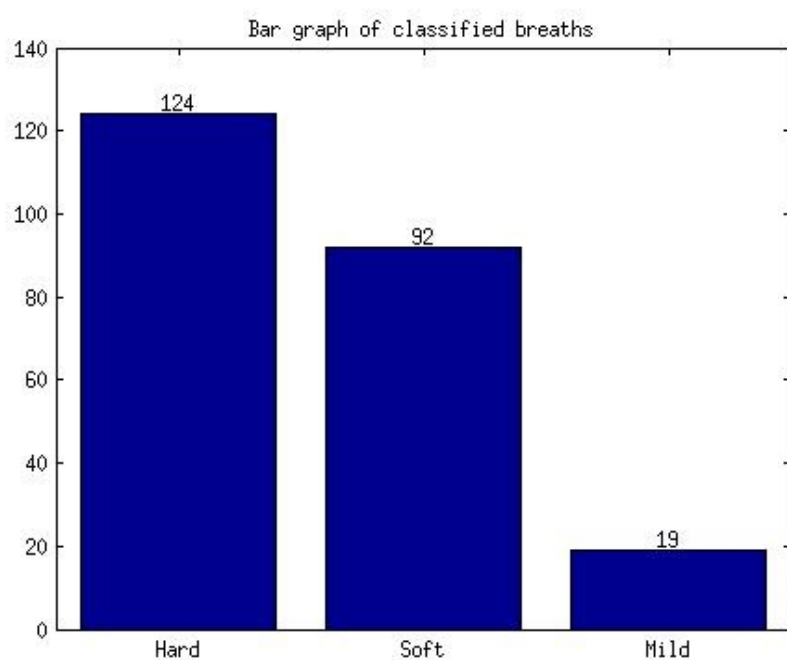


Figure C.15: Classification of the breaths in a disturbed environment recorded for 5 minutes





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