GAZİANTEP UNIVERSITY GRADUATE
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DIAGNOSIS USING PULMONARY SOUNDS AND DESIGN OF AN ELECTRONIC AUSCULTATION DEVICE

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Diagnosis Using Pulmonary Sounds And Design Of An Electronic Auscultation Device

M.Sc. Thesis
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Supervisor
Assoc.Prof.Dr. H.Rıdvan ÖZ

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This is to certify that we have read this thesis and that in our opinion it is fully adequate, in scope and quality, as a thesis for the degree of Master of Science.

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ABSTRACT

DIAGNOSIS USING PULMONARY SOUNDS AND DESIGN OF AN ELECTRONIC AUSCULTATION DEVICE

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The aim of this thesis is to find out relations between sounds and pulmonary diseases. Every pulmonary disease has distinguishing sound. Physicians diagnose pulmonary disease by using a stethoscope. This is a qualitative approach, but this should be measurable and recordable for a quantitative diagnosis. Mathematical transformations are applied to signals to obtain further information from that signal that is not readily available in the raw signal. In this study, a literature survey is performed on analyzing lung sounds and diagnosis as in computer based approach. There are many articles about electronic recording and analysis of sounds. They are not completely distinguishable due to the mixing of heart, muscle and other sounds. Some of them can be filtered easily. It is possible to distinguish Chronic Obstructive Pulmonary Disease (COPD) and other diseases using sounds. Unfortunately, there is no clear distinction among diseases. Nevertheless, digital signal processing and its filtering methods can be used to analyze pulmonary sounds. Many parameters (age, sex, smoking, pulmonary drugs, weight, muscle and heart sounds etc.) can affect the groupings in the signal analyzing systems and their meanings. These can be eliminated by means of separation technique and filtering methods. New techniques may make to pre-diagnosis and pulmonary disease relations possible. Thus, sound recordings of the all patients can be easily stored by using computer as sound library. In the study the patients are diagnosed and the sounds are recorded at University Hospital in Gaziantep. FFT and STFT techniques are used to analyze the sound recordings. Pneumonia and wheezing characteristics are observed after the analysis. It is aimed to have a database about the patients; the sound recordings are stored in a computer and will be used for revisiting and comparisons. Title includes design of an auscultation device. Unfortunately, thoughts are improved related to design of device and signal processing methods were indicated from computer based systems. Software is improved to be used for diagnosis by the clinicians.

Key Words: Respiratory sound analysis, Respiratory disease, FFT, STFT

ÖZET

SOLUNUM YOLLARI SESLERİNİ KULLANARAK TEŞHİS VE ELEKTRONİK OSKÜLTASYON CİHAZI TASARIMI

AKA, Levent

Yüksek Lisans Tezi, Makine Mühendisliği Bölümü

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Sesler ve akciğer yollarına bağlı hastalıkları arasındaki ilişkileri bulmak bu tezin amacıdır. Her akciğer yollarına bağlı hastalığın ayırt edici bir sesi vardır. Doktorlar akciğer hastalıklarını stetoskopla teşhis etmektedirler. Bu niteliksel bir yaklaşımdır. Ama niceliksel bir teşhis için ölçülebilir ve kaydedilebilir olmalıdır. İşlenmemiş sinyalde hazır olarak bulunmayan sinyalden daha fazla bilgi edinmek için, sinyallere matematiksel dönüşümler uygulanır. Bu araştırmada, bilgisayar tabanlı yaklaşımda olduğu gibi, akciğer sesleri ve teşhisi hakkında bir literatür araştırması yapılmıştır. Elektronik kayıt ve ses analizi hakkında birçok makale vardır. Bu sesler, kalp, kas ve diğer seslerin karışmasından dolayı tam olarak ayırt edilemezler. Bazıları kolaylıkla filtre edilebilir. KOAH ve diğer hastalıklarının ayırt edici teşhisinin bu alandaki başarılı çalışmalardan sonra mümkün olacağına inanıyoruz. Ne yazık ki hastalıklar arasında belli ayrımlar yoktur. Yine de, sayısal sinyal işleme ve filtre metotları akciğer seslerini analiz etmede kullanılabilir. Ama birçok etmen (yaş, cinsiyet, sigara kullanımı, akciğer ilaçları, vücut ağırlığı, kas ve kalp sesleri vs.) sinyal analizi sistemlerindeki gruplandırmaları etkileyebilir. Yine de, bunlar ayırma teknikleri ve filtre yöntemleri aracılığıyla ortadan kaldırabilir. Yeni teknikler önceden teşhis ve akciğer hastalıkları ilişkilerini mümkün kılabilir. Böylece, bütün hastaların ses kayıtları ses kütüphanesi şeklinde kullanılacak olan bilgisayar yardımıyla saklanabilir. Bu çalışmada, Gaziantep Üniversitesi Hastanesine gelen hastalardan ses kayıtları alınmıştır. FFT ve STFT teknikleri ile analizler gerçekleştirilmiştir. Pnömoni ve hırıltı seslerinin karakteristikleri elde edilmiştir. Hastalık sesleri için bir veri tabanı oluşturulmaktadır. Bu bilgiler hastaların hastaneyi tekrar ziyaretlerinde karşılaştırma amacıyla kullanılacaktır. Tez başlığında cihaz tasarımı geçmektedir. Ancak cihaz tasarımı hakkında düşünceler geliştirilmiş, bilgisayar üzerinden işaret işlemenin nasıl yapılacağı gösterilmiştir. Doktorlar tarafından teşhiste kullanılmak üzere yazılım geliştirilmiştir.

Anahtar kelimeler: Solunum sistemleri ses analizi, Solunum hastalıkları, FFT, STFT

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LIST OF SYMBOLS/ABBREVIATIONS

A/D	Analog-to-digital
AGC	Automated gain control
ANN	Artificial Neural Network
COPD	Chronic Obstructive Pulmonary Disease
CORSA	Computer based Respiratory Sound Analysis
CPNN	Constructive probabilistic neural network
DC	Direct current
DFT	Discrete Fourier transform
ECG	Electrocardiogram
ECM	Electret condenser type michrophone
EEG	Electroencephalogram
FFT	Fast Fourier Transform
FIR	Finite impulse filter
FT	Fourier Transform
IIR	Infinite impulse filter
k-NN	k-Nearest Neighbor
kΩ	Kilo ohm
LS	Lung sounds
MLP	Multi Layer Perceptron
OSAS	Obstructive Sleep Apnea Syndrome
RBFN	Radial basis function network
RLS-ANC	Adaptive Noise Cancellation with Recursive Least Square
SPL	Sound pressure level relative to 20 micropascals
TDAF	Transform domain adaptive filter
THD	Total harmonic distortion
WHT	Walsh-Hadamard transform
WP	Wavelet packet
HOS	Higher Order Statistics
GMM	Gaussian Mixture Models

CHAPTER 1

INTRODUCTION

In this section an introduction will be given about respiratory system and sounds.

1.1 Respiratory system

It consists of following elements.

LARNYX
TRACHEA
TWO BRONCHEALS
RIGHT LUNG (3 PARTS)
LEFT LUNG (2 PARTS)
BRONCHIOLES
ALVEOLI

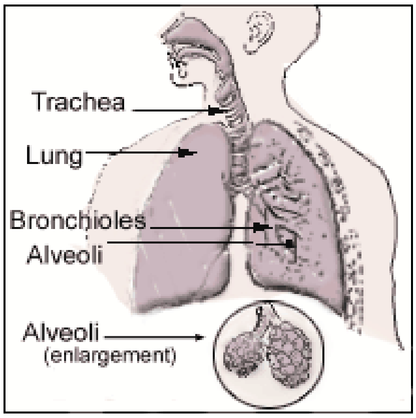


Figure 1.1 Human Respiratory system parts

Auscultation is the way of sound listening technique at the human body. There are three sound categories from auscultation hearing sounds as given below.

- Normal Sounds
- Supplementary Sounds
- Talking Sounds

1.2 Normal Sounds

These types of sounds are physiological. These can be determined as normal working sounds of the organs. Normal sounds can be separated into two sub-groups as bronchioles and vesicular sounds. Bronchioles sounds can vary incrementally or detrimentally. Vesicular sounds are normally breath sounds.

Incremental and bilateral sounds can be heard in children or fatless people. Reducing and bilateral sounds can be heard oppositely in fat people. Incremental and unilateral sounds can be heard in pneumonia and atelectasia disease. Reducing sounds at one side can be heard in accumulating liquids at the lung lamina, atelectasia and big neoplasm diseases.

1.3 Supplementary Sounds

Supplementary sounds are generally pathological and point out secret disease. On the contrary, these types of sounds can also be heard physiologically in new born children and especially cesarean born children. Supplementary sounds can be divided into two sub-groups like *intermittent* and *uninterrupted* sounds. Intermittent sounds can be classified as tin, middle, rough sounds. We can hear; tin and intermittent sounds at the pneumonia, heart failure, and interstitial diseases; middle and intermittent sounds at the bronchitis, chronic bronchitis and still pneumonia. Pneumonia implies tin and middle intermittent sounds. Uninterrupted sounds are similar to classify tin and rough without middle. Tin uninterrupted sound signifies wheezing. When big and small air ways narrows, these types of sounds can be heard. Typical sample is the asthma**.**

1.4 Talking Sounds

- **Pectorilocy:** The distinct articulation of the sounds of a patient's voice, heard on applying the ear to the chest in auscultation.
- **Bronchophony:** A modification of the voice sounds, by which they are intensified and heightened in pitch; observed in auscultation of the chest in certain cases of intro-thoracic disease.
- **Egophony:** The sound of a patient's voice so modified as to resemble the bleating of a goat, heard on applying the ear to the chest in certain diseases within its cavity, as in pleurisy with effusion.

1.5 Sound Properties of the Respiratory Diseases

Stridor: a high-pitched, noisy respiration, like the blowing of the wind; a sign of respiratory obstruction, especially in the trachea or larynx. A high-pitched, noisy respiration, like the blowing of the wind; a sign of respiratory obstruction.

Asthma: Asthma is a chronic, inflammatory lung disease characterized by recurrent breathing problems. People with asthma have acute episodes or when the air passages in their lungs get narrower, and breathing becomes more difficult Sometimes episodes of asthma are triggered by allergens, although infection, exercise, cold air and other factors are also important triggers. Labored breathing caused by narrowing of the smaller air passages in the lungs, associated with shortness of breath, wheezing, cyanosis, and coughing.

Chronic Obstructive Pulmonary Disease (COPD): a nonreversible lung disease that is a combination of emphysema and chronic bronchitis; usually patients have been heavy cigarette smokers.

Lung Diseases:

- **Atelectasis:** collapse of an expanded lung; also failure of pulmonary alveoli to expand at birth.
- **Emphysema:** Emphysema is a non-reversible pulmonary disease causing extreme shortness of breath and eventual death. In this disease, the bronchial tubes of the lungs become blocked with mucus plugs and infection, inhibiting passage of air into and out of the alveoli. The disease is characterized by destruction of these sacs, which lose their elasticity, swell and rupture thereby interfering with the exchange of oxygen and carbon dioxide in the breathing process. Emphysema is often caused by smoking. That type of disease sound can be heard like; breathing sounds get reduces from both sides and exhaling time get bigger than normal.
- **Pneumonia :** Inflammation of the lungs characterized by fever, chills, muscle stiffness, chest pain, cough, shortness of breath, rapid heart rate and difficulty breathing Polysaccharide vaccines- Vaccines that are composed of long chains of sugar molecules that resemble the surface of certain types of bacteria. Polysaccharide vaccines are available for pneumococcal disease, meningococcal disease and Haemophilus Influenza type. That type of disease sound can be heard like; tin and middle intermittent sounds.
- **Lung oedema :**

- **Tuberculosis:** A constitutional disease characterized by the production of tubercles in the internal organs, and especially in the lungs, where it constitutes the most common variety of pulmonary consumption. Infection transmitted by inhalation or ingestion of tubercle bacilli and manifested in fever and small lesions. That type of disease sound can be heard like; middle and rough intermittent sounds.

Pleura Diseases:

It is a thin layer of tissue covering the lungs and the wall of the chest cavity to protect and cushion the lungs. A small amount of fluid that acts as a lubricant allows the lungs to move smoothly in the chest cavity during breathing

- Ampiem
- Pleurisy
- Hemothorax
- Pnuemothorax

That type of disease sound can be heard like; sound amplitude reduces or no sound can be heard. At the liquid top surface of the small area, bronchial sound can be heard.

Pneumothorax

Abnormal collection of air outside the lining of the lung, between the lung and the chest wall, is often a consequence of pressure injuries.

1.6 Clinical Methods

Clinical methods to diagnose respiratory diseases:

- Patient history and physical consultation
- Lung graphics: postero anterior and lateral graphics
- Chest ultrasonography (The use of sound waves to produce pictures of internal organs. High-frequency sound waves are directed into tissues and produce echoes, which are in turn changed into pictures. Because different

types of tissue reflect sound waves differently, ultrasonography often makes it possible to find abnormal growths.)

- Breath function tests

    1- Simple spirometer: Pneumatograph, an instrument for measuring the vital capacity of the lungs, or the volume of air which can be expelled from the chest after the deepest possible inspiration.

    2- Bronchodilator reversible test: A drug that relaxes and dilates the bronchial passageways and improves the passages of air into the lungs.

    3- Bronchi provocation test

    4- Carbon monoxide diffusion test

Auscultation of the lung is an important and simple diagnostic method [1-3]. At this area, there is no computerized system to analyze and understand the respiratory sound systems. Statistical approach can not be good solutions as seen from surveys [2]. Therefore, we believe that respiratory analysis can be varied region-to-region, people to people. Because of this, sound library and personal library have to be prepared to get good solutions. Auscultation gives direct information about the structure and function of the lung that cannot be obtained with any other simple and noninvasive method [4-9]. Conventionally, physicians use an instrument called stethoscope for listening the lung sounds. The stethoscope was the first diagnostic instrument to gain widespread use among physicians. With the help of this tool, physicians gained access to information from within the patient's body [10].

This device, invented in 1821 by the French Physician, Laennec, is still the most common diagnostic tool used by doctors. However, the method is considered of low diagnostic value due to its subjectivity in assessing lung sounds. Evaluation of respiratory sounds depends strongly on the experience of the physician and shows large intersubject variability. Another drawback of the method is the inability to produce a permanent record of the auscultation data thus to make an intersubject and intrasubject comparison. Moreover, a stethoscope attenuates frequency components above approximately 120Hz (in spite of the fact that respiratory sounds are known to contain frequencies up to 2000 Hz**)** and the human ear is not very sensitive to the lower-frequency band that remains [11].

The normal lung sound is defined as the sound associated with breathing, heard on the chest of a healthy person. This sound is noise-like, and the maximum of the power spectrum lies in the frequency range below 100 Hz. The energy of the spectrum decreases sharply between 100 Hz and 200 Hz, but it can be detected up to 1.2 kHz. The amplitude of the respiratory sounds varies with the square of the air flow, but is also individually dependent and dependent on the recording position on the chest [10]. Respiratory sounds which are roughly classified into breath sounds and adventitious sounds are heard on the chest wall and mouth. Breath sounds which are regarded as normal respiratory noises are synchronous with the flow of air changing from laminar to turbulent through the airways and have a frequency of 200-600 Hz in healthy lungs. Wheezing is considered to be a result of airway obstruction and flow limitation and it appears as continuous, musical sounds of more than 100 ms and crackles which are discontinuous, nonmusical, explosive sounds of less than 70 ms duration constitute the adventitious sounds. They are often attributed to the bubbling of secretions in the airways or to the explosive change in gas pressure. Crackles are classified by physicians according to pitch (high or low), number (scanty and profuse) and timing (inspiratory and expiratory; early and late) [13]. These characteristics aid physicians in the final diagnosis. For example, crackles of interstitial fibrosis are high pitched or fine and occur in mid to late inspiration. On the other hand, early inspiratory crackles are associated with severe expiratory obstruction. Low-pitched crackles, known as coarse crackles, are produced in patients with chronic airflow obstruction and bronchiectasis.

1.7 Microphones

A microphone, sometimes referred to as a mike or mic (pronounced "mike"), is an acoustic to electric transducer that converts sound into an electrical signal. Emile Berliner invented the first microphone on March 4, 1877, but the first useful microphone was invented by Alexander Graham Bell. Many early developments in microphone design took place in Bell Laboratories.

All microphones capture sound waves with a thin, flexible diaphragm (or ribbon in the case of ribbon microphones). The vibrations of this element are then converted by various methods into an electrical signal that is an analog of the original sound.

Most microphones in use today use electromagnetic generation (dynamic microphones), capacitance change (condenser microphones) or piezoelectric generation to produce the signal from mechanical vibration.

In a capacitor microphone, also known as a condenser microphone, the diaphragm acts as one plate of a capacitor, and the vibrations produce changes in the distance between the plates. Since the plates are biased with a fixed charge (Q), the voltage maintained across the capacitor plates changes with the vibrations in the air, according to the capacitance equation:

$$Q = C.V$$

where Q = charge in coulombs, C = capacitance in farads and V = potential difference in volts. The capacitance of the plates is inversely proportional to the distance between them for a parallel-plate capacitor

$$C \alpha \frac{A}{d}$$

Capacitor microphones can be expensive and require a power supply, commonly provided from mic inputs as phantom power (Invented in the mid-1960s and standardized shortly thereafter, phantom power is a widely-used method for supplying current to devices over signalling cables, especially audio), but give a high-quality sound signal and are now the preferred choice in laboratory and studio recording. An electret microphone is a relatively new type of condenser microphone invented at Bell laboratories in 1962 by Gerhard Sessler and Jim West, and often simply called an electret microphone. An electret is a dielectric material that has been permanently electrically charged or polarised. The name comes from electrostatic and magnet; a static charge is embedded in an electret by alignment of the static charges in the material, much the way a magnet is made by aligning the magnetic domains in a piece of iron. They are used in many applications, from high-quality recording and lavalier use to built-in microphones in small sound recording devices and telephones. Though electret mikes were once considered low-cost and low quality, the best ones can now rival capacitor mikes in every respect (apart from low noise) and can even have the long-term stability and ultra-flat response needed for a measuring microphone. Unlike other condenser microphones, they require no polarising voltage, but normally contain an integrated preamplifier which does require power (often incorrectly called polarizing power or bias). This preamp is frequently phantom powered in sound reinforcement and studio applications. While few electret microphones rival the best DC-polarized units in terms of noise level, this is not due to any inherent limitation of the electret. Rather, mass production techniques needed to produce electrets cheaply don't lend themselves to the precision needed to produce the highest quality microphones applications.

Because of differences in their construction, microphones have their own characteristic responses to sound. This difference in response produces non-uniform phase and frequency responses. In addition, mics are not uniformly sensitive to sound pressure, and can accept differing levels without distorting. Although for scientific applications microphones with a more uniform response are desirable, this is often not the case for music recording, as the non-uniform response of a microphone can produce a desirable coloration of the sound. There is an international standard for microphone specifications (IEC 60268-4), but very few manufacturers adhere to it.

A frequency response diagram plots the microphone sensitivity in decibels over a range of frequencies (typically at least 0–20 kHz), generally for perfectly on-axis sound (sound arriving at 0° to the capsule). Frequency response may be less informatively stated textually like so: "20 Hz–20 kHz ±3 dB". This is interpreted as a (mostly) linear plot between the stated frequencies, with variations in amplitude of no more than 3 dB plus or minus. However, one cannot determine from this information how smooth the variations are, nor in what parts of the spectrum they occur. Note that commonly-made statements such as "20 Hz–20 kHz" are meaningless without a decibel measure.

The self-noise or equivalent noise level is the sound level that creates the same output voltage as the inherent noise of the microphone. This represents the lowest point of the microphone's dynamic range, and is particularly important should you wish to record sounds that are quiet. The measure is often stated in dBA, which is the equivalent loudness of the noise on a decibel scale frequency-weighted for how the ear hears, for example: "15 dBA SPL" (SPL means sound pressure level relative to 20 micropascals). The lower the number the better. Some microphone manufacturers state the noise level using ITU-R 468 noise weighting, which more accurately represents the way we hear noise, but gives a figure some 11 to 14 dB higher. A quiet microphone will measure typically 20 dBA SPL or 32 dB SPL 468-weighted.

The maximum SPL (sound pressure level) the microphone can accept is measured for particular values of total harmonic distortion (THD), typically 1%. This is generally inaudible, so one can safely use the mic at this level without harming the recording. Example: "142 dB SPL peak (<1% THD)". The higher the value, the better. The clipping level is perhaps a better indicator of maximum useable level as the 1% THD figure usually quoted under max SPL is really a very mild level of distortion, quite inaudible especially on brief high peaks. Harmonic distortion from microphones is usually of low-order (mostly third harmonic) type, and hence not very audible even at 3-5%. Clipping, on the other hand, usually caused by the diaphram reaching its absolute displacement limit (or by the preamplifier), will produce a very harsh sound on peaks, and should be avoided if at all possible. For some mikes the clipping level may be much higher than the max SPL. The dynamic range of a mike is the difference in SPL between the noise floor and the maximum SPL. If stated on its own, for example "120 dB", it conveys significantly less information than having the self-noise and maximum SPL figures individually.

Sensitivity indicates how well the mike converts acoustic pressure to output voltage. A high sensitivity mike creates more voltage and so will need less amplification at the mixer or recording device. This is a practical concern but not directly an indication of the mike's quality, and in fact the term sensitivity is something of a misnomer, 'transduction gain' being perhaps more meaningful, (or just "output level") because true sensitivity will generally be set by the noise floor, and too much "sensitivity" in terms of output level will compromise the clipping level. There are two common measures. The (preferred) international standard is made in mV per pascal at 1 kHz. A higher value indicates greater sensitivity. The older American method is referred to a 1 V/Pa standard and measured in plain dB, resulting in a negative value. Again, a higher value indicates greater sensitivity, so −60 dB is more sensitive than −70 dB.

1.7.1 Used Equipments in this study

Respiratory sounds were recorded by a microphone. Electret condenser type (ECM) microphone (Sony ECM T-150), which was used in literature is also used in this study. Working method of the microphone can be one or all directions. We used microphone in one direction for sound recording by using of stethoscope head. Microphone was mounted onto stethoscope head to get standard and valuable sound. Its impedance is 2.2 kΩ. Response bandwidth is between 30-15000 Hz. This bandwidth also includes heart, muscle and other sounds at the recordings. Therefore, recorded sounds have to be filtered before analyzing the signals. We have to prevent sounds coming from sliding of the microphone at the chest wall. Besides, sounds coming from ambient have to be filtered. For that reason, we have to record sounds at the lowest sound intensity laboratories. Climate, announce, traffic, patient parents noises affect recordings. Therefore, recordings at the hospital laboratories have to be made silently at the weekend. Nevertheless, obtaining of the patients is also problem at the weekend without some volunteers. Smokers and/or COPD students are the volunteers of this study.

1.8 Processing System

The system used for analyzing the sound recordings is given below.

Computer: AMD 3500+, 64 bit, 2GB DDR-Ram, 160 GB HD.
Program: MATLAB.

1.9 Method

Control groups are arranged to record respiratory sounds from normal people, who are the volunteers. To make the control groups, we take care of the age ranging between 20-60 years old as in equal distributions. Patient sound records during normal breathing. Advising measurement distance from chest to device is the 6mm. Working groups are arranged from respiratory patient, who visit lung disease clinic. Pulmonary patient sounds are directly recorded before clinical treatment. Recording sound is taken between 4^{th} and 5^{th} intercostals space under the scapula. These recorded sounds include also heart and muscle sounds. Recorded sounds are taken from varying sex, age, height, and weight people. Sounds were recorded together with breath sounds. Heart sounds are below the 100 Hz. The help of varied digital low pass filters can filter this type of sounds. After filtering of the sounds, we have digital respiratory sounds without muscle and heart sounds. Above the 2000 Hz, is not belonging to respiratory disease according to literature survey, which can be filtered by high pass filters. Pneumonia disease sound frequencies are between 300 to 600Hz. The patients, who have pneumonia can be examined by their respiratory signal by the help of band pass filters as in determined range with some searching signal characteristics.

Frequency of wheezing sounds is about 400 Hz. Vesicular breath sound frequency of the healthy people is going over to 1000Hz. Some using filters are; infinite impulse filter (IIR), finite impulse filter (FIR), Yule walker, ellip and etc.

Recording sounds at the normal people are taken because of the meaning and shape of the normal sound. Thus, we want to have some standards related to quantities of normal sounds. On the other hand, how the each people have different fingerprint, and also have different own sound characteristics. For that reason, we want to get new way to our project. We decided that determining of the disease sounds is going together with personal database to get personally disease sounds. In our opinion, until now, to get sound characteristics, difficulties of the all project have been came from that reason. We take pay attention to this to our project. That may be beneficial to good approach. Healthy and patient people are classified according to age, sex, height, weight and etc.

1.10 AN AUSCULTATION DEVICE

An auscultation device, which can be seen in figure, may be consist of following parts to use easily by the clinicians:

- **Computer** to analyze signals and turns to usable diagnosis information.
- **Microphones** to get signals as in digital from valuable measuring place that may be consist of stethoscope head to isolate air and sound from human body surface.
- The Spirometer and attached flow head function together as a **Pneumotachometer**, with an output signal proportional to airflow.
- **Software program**, that may be improve from signal anaylsing and stattical analyzing technicque, which consist of old information relations.

Sound was recorded as a digital signal with simultaneously breath recording to understand where/when the disease distinction takes place. Sound is directly related to lung volume and its dynamic properties.

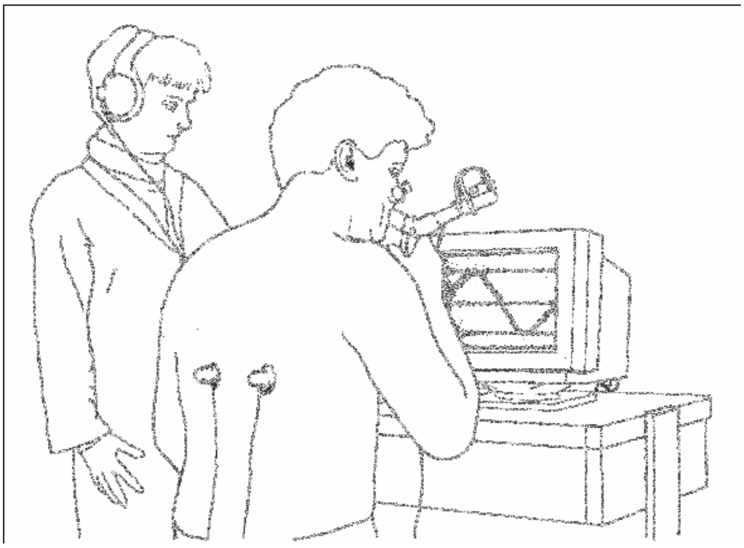


Figure 1.2 Measuring technique of the Respiratory sounds

CHAPTER 2

LITERATURE SURVEY

During the last two decades, much research has been carried out on computer-based respiratory sound analysis systems. However, respiratory sounds are highly non-stationary stochastic signals due to changing airflow rate, heart sounds and change in lung volume during a respiration cycle. This makes the analysis of the respiratory sounds a difficult task.

Over recent years, the scientific activity within the field of respiratory acoustics has increased markedly. However, a lack of guidelines for data acquisition, storage, signal processing and analysis of the lung sound signal has made it difficult to compare results from different laboratories and has hampered the commercial development of respiratory sound analysis equipment. Several efforts have been undertaken to solve these problems [12,14,15]. With the use of modern digital signal processing techniques, the analysis of waveforms by computer has become an established research technique for the investigation of respiratory sounds [12,16].

Bibliographies reviewing the overall literature may be found in the following papers on snoring [17,18], cough [17-21], stridor [22], and wheeze [23,24]. Studies involving an objective analysis of respiratory sounds show that lower respiratory sound analysis accounted for 55% of the total and snoring for the remaining 45%.

Overall, 50% of the papers were written by CORSA participants.
Good bibliographies on breath sound analysis may be found in papers by Malmberg et al. [25], Gavriely et al. [26] and Schreur et al. [27].

2.1 Signal Acquisition Methods

In all applications, sounds recorded from the respiratory system were captured by microphones or contact sensors situated at the mouth, on the chest or elsewhere. Typically, one chest-wall sound channel was used, but in many papers, two and occasionally multiple channels were used [28, 29]. Respiratory sound data through five microphones placed at proper locations on the chest wall along with a flow signal for synchronization [3].

Upper airways sounds such as snoring and cough were often captured by microphones used in free field at a set distance from the patient's mouth [21].
Adventitious and breath sounds originating from the lower airways were captured from the chest wall using two types of microphone: 1) electret air-coupled microphones and 2) contact sensors (accelerometers) [12,30].

Air-coupled microphones were used in all European Centres, but the size, shape and dimensions of the air cavity between the microphone and chest varied from centre to centre [30]. Microphone housings were generally designed and custom-made by individual centres according to particular theories and ideas. In North America and Israel, a variety of commercially available and custom-made contact sensors and accelerometers, attached on to the chest wall with either adhesive rings or a rubber belt, were employed [15].

Respiratory sounds can be recorded continuously, and analyzed on-line to monitor sleep apnea, nocturnal changes of bronchial obstruction in asthma (*e.g.* wheezing time) [31], ventilation during anesthesia [32] and regional distribution of ventilation [33]. Respiratory sounds recording and analysis can be used when assessing the response to bronchodilators and to bronchoconstrictors [34, 35] or the variations of airflow obstruction during acute bronchial challenge tests in children. Respiratory sounds can also be applied to monitoring and analyzing the bronchial response to inhaled nonspecific bronchoconstrictive agents like methacholine or histamine both in children [36] and in adults [37–39]. Changes in breath sound frequency distribution, in terms of the median frequency, have been shown to reflect the airway changes during histamine challenge tests in adults and children with asthma [25, 35]. Other authors have studied the behavior of breath sounds during exercise- induced airway obstruction in children with asthma [40]. In some cases, it could be useful to use methods for long-term recording of cough using filtered acoustic signals [41, 25]. Body movements related to the cough can be recorded by a static charge sensitive bed or by sensors giving similar information. The patient can be studied lying or sitting with no transducers or electrodes attached [19].

2.2 Analogue pre-filtering and storage

The most commonly used bandwidth for breath sounds is from 60–100 Hz to 2 kHz when recorded on the chest (lung sounds) and from 60–100 Hz to 4 kHz when recorded over the trachea. For adventitious sounds on the chest, it is from 60–100 Hz to 6 kHz. The analogue filtering applied to the captured sound signal varied from centre to centre according to established practice, available technology and the particular application. Most researchers employed a high-pass filter [15, 42] with a cut-off frequency chosen somewhere in the range from 30–150 Hz, the norm being around 50–60 Hz [41, 43, 44].

A low-pass filter was always used in the capture of lower airway sounds with the cut-off frequency set between ~1600 and 3000 Hz [23, 42, 44]. Upper airway sounds were generally processed with higher cut-off frequencies [21]. Until 1990, normal practice was to store sound and flow signals on analogue magnetic recording tape, for subsequent digitization off line (flow signals were usually recorded using FM tape recorders). In recent years, DAT tape recorders have been used for both sound and flow, though normal practice is now direct digitization and acquisition by computer [43, 45].

2.3 Digitization protocols

Analogue-to-digital converters are used with word lengths of nominally 12, 14 or 16 bits per sample [23, 27, 43]. A wide range of different sampling rates are in common use, the lowest being around 4 kHz and the highest being 22.05 kHz. Three centres used standard multi-media sound cards *e.g.* "SoundBlaster" cards [45], and several others used other commercial multi-channel signal acquisition cards.

2.4 Signal processing

The spectral analysis of respiratory sounds using the discrete Fourier transform (DFT), invariably making use of a Fast Fourier Transform (FFT) algorithm.[15, 26, 46, 47] was universal. A version of the Fourier transform (FT) applicable to a discrete time series (finite sequence of signal samples) [46,47]. A series of number usually proportional to the values of an analogue signal at a series of times (normally equally spaced) [48].

The fast Fourier transform (FFT) is a very efficient algorithm (numerical process) used for calculating the discrete FTs [49–51]. The duration of each analysis segment was typically between 20 and 50 ms, which means that with a sampling rate of around 10 kHz, signal block lengths of 256, 512 or 1024 samples were commonly used. Zero padding and overlapping of analysis segments techniques were commonly used [23,43,52], and windowing was usually by a Hamming, Hann or other universally accepted type nonrectangular window.

The survey revealed that newer highly advanced spectral analysis and digital signal processing techniques were being increasingly used, these included autoregressive analysis [53,54] wavelets[55], Pronys method [56], neural networks [57] and higher-order spectra [58]. The analysis of the signal usually involved some of the following elements [15,46,47] short-term power and power spectral density, spectrographs; averaged power spectra; estimation of spectral energy distribution(*e.g.* quartiles); flow representation (sometime flow gating or flow-standardized spectra) [46,47,59,60]; wheeze detection [15,23,61-63]; crackle detection [29,64-67]; cough detection [19-21]; snoring detection [17,18,68,69], and a variety of other techniques [30,46,57,59,61,70,71].

Short time Fourier transform representation is well known in speech processing [72] and in respiratory sound analysis [73]. The consecutive spectra can be computed with or without an overlap. The advantage of such a representation is the ability to reintroduce the notion of time. The signal is no longer characterized by a mean spectrum. The evolution of its "instantaneous" and successive spectra is observed [74,75]. The methodology of the proposed WT-FD filter is the subject of this paper

[76]. The results from the application of the WT-FD filter to real bioacoustics data are described and discussed in the accompanying paper [77], also including performance evaluation, noise robustness testing, and comparison of the proposed method with previous works. A wavelet packet (WP) based analysis of short-term heart rate variability signal could provide a useful criterion for the detection of sleep apnea [78].

Three techniques for waveform fractal dimension (FD) calculation were applied, based on: (1) signal variance; (2) non-normalized signal morphology; and (3) signal morphology normalized along both axes within the windows. Hence, this method may prove useful in the measurement of true changes in LS fractality and deciphering differences between LS in health and disease [79].

The spectral characteristics of healthy and pathological respiratory sound signals for inspiration and expiration phases were investigated. They have observed noticeable differences between healthy and pathological spectra and power spectral densities of sound recorded from pathological subjects are observed to contain high frequency components compared to those of healthy sound waveforms. It is concluded that spectral features can be used to develop a respiratory-sound classifier [80]. The Cepstral analysis is proposed with Gaussian Mixture Models (GMM) method to classify respiratory sounds in two categories: normal and wheezing. The proposed schema is compared with other classifiers: Vector Quantization (VQ) and Multi-Layer Perceptron (MLP) neural networks. A post processing is proposed to improve the classification results [81].

The classification process is done using two classifiers: k-Nearest Neighbor (k-NN) classifier with Itakura and Euclidian distance measures, and Minimum distance classifier with the Mahalanobis distance measures [82].

A novel decision fusion scheme for the classification of respiratory sounds is proposed [83]. Neural network classification of lung sounds using wavelet coefficients [84] and classification of coughs using Fourier power spectra have been used as features [85]. Respiration sounds of individual asthmatic patients were analyzed in the scope of the development of a method for computerized recognition of the degree of airways obstruction. The technique of artificial neural networks was applied for relating sound spectra and simultaneously measured lung function values [86].

Performance of the relatively new constructive probabilistic neural network (CPNN) against the more common classifiers, namely the multilayer perceptron (MLP) and radial basis function network (RBFN), in classifying a broad range of tracheal—bronchial breath sounds were also searched [87]. Genetic algorithms is to search for optimal structure and training parameters of neural network for a better predicting of lung sounds. This application resulted in designing of optimum network structure and, hence reducing the processing load and time [88].

Lung sounds (LS) of children after bronchoconstriction should differ from baseline LS in terms of amplitude and pattern characteristics [89]. Mobile phone recordings clearly discriminate tracheal breath sounds in asthma and could be a noninvasive method of monitoring airway diseases [90]. To predict the characteristics of tracheal sounds the first use of a dynamic and distributed acoustic model of the respiratory tract. The model incorporates sound sources due to turbulent flow and allows for glottal aperture variation [91]. Assessing a blind data-based classification between 'spontaneous' and 'voluntary' human cough on individual sound samples [92]. To develop an automated and objective method to separate swallowing sounds from breath sounds [93] and nonlinear analysis as a promising tool for quantitative analysis of swallowing sounds and swallowing disorders [94].

A simple system for the measurement and analysis of lung sound has been implemented with custom made electronic stethoscope, DasyLAB, and a sound blaster card inserted in a portable computer [95].

The application of signal coherence method for parametric representation and automatic classification of the respiratory sounds is investigated [96]. A comparison is made between the performances of k-NN classifiers with different feature sets derived from respiratory sound data acquired from four different fixed locations on the posterior chest area [97]. The design of a novel non-linear mapping method for visual classification based on multilayer perceptrons (MLP) and assigned class target values [98]. A new regularization scheme is applied to the data to stabilize training and consultation [99].

To characterize the frequency spectrum, earlier studies have used the following parameters: median frequency [43,100], selected frequency with the highest power [43], quantile frequencies [101] and in addition to this Artificial Neural Network (ANN) [101-102]. In some studies, Wavelet analysis [103,104] and constructive probabilistic neural network [105] are used to compare these methods.

In subjects with healthy lungs, the frequency range of the vesicular breathing sounds extends to 1000 Hz, where as majority of the power within this range is found between 60 Hz and 600 Hz [12,106]. Heart and respiratory sounds graphics for various stethoscope depth have been given in references [107]. Other sounds, such as wheezing or stridor, can sometimes appear at frequencies above 2000 Hz [12]. The normal classification of lung sounds in frequency bands involves: low (100-300 Hz), middle (300-600 Hz), high (600-1,200 Hz) frequency bands [108].

The normal lung sounds were analyzed according to age, sex, and smoking habit. Measurement of two frequency bands of 330 to 600 Hz and 60 to 330 Hz are considered. For both men and women, a slight increase of the relative power in the frequency band of 330 to 600 Hz was recorded with increasing age. However, on the basis of large individual variations, these small changes have no clinical significance and need not to be considered in automatic detection of lung diseases by analyzing lung sounds [109]. The images support the concept that inspiratory sounds are produced dominantly in the periphery of the lung while expiratory sounds are generated more centrally [107]. Standardized description and evaluation methods for normal and abnormal lung sounds do not currently exist, and the descriptive parameters of the frequency spectrum used in investigations must therefore still be tested [109,110,111]. The effects of breathing pathways are investigated. The spectra of sounds recorded over the trachea of adults typically reveal peaks near 700 and 1500 Hz [112].

2.5 Displays

Graphical representations of results were usually custom written. Some of the commoner forms of display were power plots in the time-domain, three-dimensional spectrographs and airflow, plot of averaged power spectra and time expanded waveforms [64-66,113]. Many other more specialized types of display including real-time spectrographs were employed specific to individual centres [114]. The graphics and programming software used to produce such displays were very variable but there is increasing usage of the graphic facilities offered by versions of C++ and MATLAB.

2.6. Abnormal breath sounds

Breath sounds may be abnormal in certain pathological conditions of the airways or lungs. Bronchial obstruction, *e.g.* in asthma, induces an increase of higher frequency components of the sound spectrum without the appearance of wheezing [25,35]; during bronchodilatation, the sound energy moves back to lower frequencies. In asthma, a significant association was found between the level of bronchoconstriction assessed in spirometric variables and the median frequency of breath sounds recorded over the trachea or on the chest in bronchial challenge tests [35]. Even in asthmatic patients with a normal ventilatory function, the median frequency of the breath sounds may be elevated [114]. Thus, it is probable that the allergic inflammation in the airways in asthma may induce certain changes in the mucosal or the submucosal part of the bronchi, which can induce changes in the airflow dynamics, including turbulence, during breathing. Breath sounds with abnormally high frequencies and intensity, and with a prolonged and loud expiratory phase are typical in many diseases with airway obstruction, like in asthma and in chronic bronchitis. These abnormal breath sounds have also been called bronchial sounds. They have frequency components up to 600–1,000 Hz recorded over the posterior chest wall. In chronic obstructive lung disease (COPD) with an emphysematic component, two phenomena are often observed. Firstly, the breath sound intensity is often reduced, which has been attributed to a reduced airflow [115]. Secondly, the, values of frequency variables may be within normal limits or lowered [35], which has been attributed to an increase in the low-pass filtering effect of the damaged pulmonary tissue in pulmonary emphysema.

Somewhat varying frequency bands have been obtained in studies on normal breath sounds. Averaged spectra computed on tracheal sounds (inspiration and expiration phases) have shown that the log amplitude response curve remained approximately flat in the range 75–~900 Hz, before rapidly falling away at higher frequencies [86, 90]. Several other authors measured spectra of lung sounds on a linear plot with maximum amplitudes of 140 –200 Hz, followed by an exponential decay to insignificant levels at ~400 Hz [4]. Such differences are partly the result of using different representation of data, a linear scale being more likely to over accentuate high-amplitude responses and underestimate weaker signals. However, even though some investigators have measured an upper limit frequency as high as 3,000 Hz for tracheal sounds [112], it is commonly admitted that normal respiratory sounds contain components among which the most significant have a frequency of 50–1,200 Hz. The frequency spectra of tracheal sounds decline rapidly at >850–900 Hz. Due to muscle sounds and heart sounds [117], respiratory sounds are not usually studied at <50–60 Hz and the range 0–60 Hz should be filtered by a high pass filter. Due to the dependence of breath sounds on airflow rate, respiratory sound spectra should be reported at a known airflow. Moreover, the frequency spectra at zero flow should be given in order to determine the background noise [15].

2.7. Adventitious sounds

2.7.1 Crackles

Crackles are discontinuous adventitious lung sounds [118,119] explosive and transient in character, and occur frequently in cardio respiratory diseases [65]. Their duration is less than 20 ms, and their frequency content typically is wide, ranging from 100 to 2000 Hz or even higher [15,120]. Two types of crackles may be distinguished: coarse and fine.

The acoustical basis for this classification is well presented in the literature [119]. Crackles are assumed to originate from the acoustic energy generated by pressure equalization [121] or a change in elastic stress [122] after a sudden opening of abnormally closed airways. Crackles may sometimes occur in healthy subjects, during a deep inspiration [123], as a result of segmental reopening of dependent lung units. In those cardio respiratory disorders where crackles are frequently found, abnormal closure of the small airways may result from increased elastic recoil pressure (*e.g.* in pulmonary fibrosis) or from a stiffening of small airways caused by accumulation of exudated fluid (*e.g.* in heart failure) or infiltrative cells (*e.g.* pneumonitis, alveolitis). The mechanisms of generation of the crackling sounds in chronic bronchitis and emphysema are incompletely understood, but, a source in the large airways has been suggested [124]. Bubbling of air through secretions is one possible mechanism but does not account for all the crackling phenomena in these patients. In patients with chronic obstructive lung disease, the loss of elastic recoil and bronchial support [125] may predispose to collapse and subsequent reopening of the lobar bronchi [126–128]. When present, crackling sounds in patients with lung fibrosis are typically fine, repetitive, and end inspiratory, whereas those associated with chronic airways obstruction *(e.g.*COPD, emphysema or bronchiectasis) are coarse, less repeatable, and occur early in inspiration [13, 128]. Patients with airways obstruction may also have expiratory crackles, and, unlike in patients with pulmonary fibrosis, the crackles may be audible at the mouth; in addition, these crackles may change or disappear after coughing [5]. In heart failure, the crackles tend to occur from the mid to late inspiratory cycle, and they are coarse in character [128]. Mathematical models and experiments predict that crackles originating from smaller airways are shorter in duration (fine in character), and those originating from larger airways are more coarse [122]. The appearance of crackles may be an early sign of respiratory disease, *e.g.* in asbestosis [65, 129]. Since the closure of small airways is gravity-dependent, crackles tend to occur first in the basal areas of the lungs, and later, when the disease progresses, also in the upper zones of the lungs. When present, the number of crackles per breath is associated with the severity of the disease in patients with interstitial lung disorders [130]. Moreover, the waveform and timing of crackles may have clinical significance in differential diagnosis of cardio respiratory disorders [5, 65].

Since the bandwidth of the commonly encountered crackles is 100–2,000 Hz, a sampling rate of 5,512 Hz provides a sufficient frequency range (*i.e.* 0–2,700 Hz).

However, the study of several fine crackles may require a wider range of analysis as they exhibit high frequency components. Therefore, in this case, the use of a sampling rate of ≥11,025 Hz is recommended [131]. Visually, the timing of crackles in relation to the respiratory phase is conveniently illustrated using a condensed time-domain presentation "phonopneumogram" [13, 127]. Quantitatively, this relationship may be characterized by calculating the start and end point of crackles as a percentage of the respiratory phase [128].
By using the timing and waveform characteristics of crackles, a two-dimensional discriminate analysis has been applied [132]. This approach may be useful when different lung diseases presenting with crackles are to be distinguished from each other. Examples of parameter estimation based methods used in crackle detection include adaptive nonlinear filters [71] and wavelet transformation [133].

An instrument for separating crackles from stationary lung sounds and quantifying their characteristics is realized with adaptive filtering and implementing nonlinear operators to wavelet based decomposed lung sounds [134]. Effective classification of respiratory sounds for various pathologies can be achieved if a large database is formed [135].

2.7.2 Squawks

Occasionally, in patients with interstitial lung diseases, crackles may be followed by short inspiratory musical sounds; these are called squawks [124,136,137]. In extrinsic allergic alveolitis, squawks have been found to be shorter in duration and higher in pitch than in pulmonary fibroses due to other causes [137]. Their duration rarely exceeds 400 ms. Squawks are assumed to originate from oscillation of small airways after sudden opening, and their timing seems to depend on the trans pulmonary pressure in a similar manner as in crackles. Thus, the basic mechanisms of their origin probably differ from that of wheezes in asthma. Therefore, we suggest that the term "squawk" should be limited to inspiratory short wheezes in patients with interstitial lung disorders that involve small airways; otherwise, short musical sounds may be called simply "short wheezes". The basic methods of respiratory sound analysis for squawks are the same as for wheezes.

2.7.3. Wheezes

Wheezes are continuous adventitious lung sounds, which are superimposed on the normal breath sounds. According to the earlier definition of the American Thoracic Society (ATS), the word "continuous" means that the duration of a wheeze is longer than 250 ms. The ATS also defines wheezes as high-pitched continuous sounds and qualifies low-pitched continuous sounds as rhonchi. The ATS nomenclature specifies that a wheeze contains a dominant frequency of 400 Hz or more, while rhonchi are characterized as low-pitched continuous sounds with a dominant frequency of about 200 Hz or less. However, investigators have not always agreed with those features. For instance, wheezes produce highly variable frequencies ranging from 80 to 1600 Hz according to GAVRIELY *et al.* [138] and from 350 to 950 Hz according to PASTERKAMP and co-workers [139]. According to the new definitions of the present CORSA guidelines, the dominant frequency of a wheeze is usually >100 Hz and the duration >100 ms [140].

Wheezes, which are louder than the underlying breath sounds, are often audible at the patient's open mouth or by auscultation by the larynx. They can be monophonic, when only one pitch is heard, or polyphonic when multiple frequencies are simultaneously perceived. The transmission of wheezing sound through the airways is better than transmission through the lung to the surface of the chest wall. The higher-frequency sounds are more clearly detected over the trachea than at the chest [62,141]. The high-frequency components of breath sounds are absorbed mainly by the lung tissue [142]. The highest frequency of wheezes observed by BAUGHMAN and LOUDON [31,61], who recorded lung sounds over the chest wall, was 710 Hz. FENTON *et al.* [62] have studied the frequency spectra of wheezy lung sounds recorded simultaneously over the neck and the chest. Peaks at 870 and 940 Hz detected over the trachea were almost absent on the chest, as a result of the low-pass filtering effect of the lungs. These observations emphasize the importance of tracheal auscultation and sound recording in asthma [143,144].

According to recent definitions [10] and the present CORSA definitions, the dominant frequency of a wheeze is ≥80–100 Hz, and that of a rhonchus is ≤300 Hz.

There is no reason to try to set an upper limit for the pitch. So far, no wheeze has been reported with a pitch of >1600 Hz [138]. It is recommended, however, when studying wheezes, to use a sampling rate of ≥5,000 Hz [131].

Novel proposed technique can be quite useful in clinical diagnostics, mainly when the analysis can be made continually, using many respiratory cycles from patient. However, in this application the algorithm still needs to automatically detect the beginning and the ending of the respiratory cycle [145].

2.7.4. Snores

Snores are noises commonly heard during the sleep. It is suggested that a snore is produced by vibrations in the walls of the oropharynx [146]. However, it is possible that also other structures could be put in vibration and participates to the snores. Snoring is frequently associated with the obstructive sleep apnoea syndrome and with cardiovascular diseases [147]. The snore is an inspiratory sound, although expiratory components can appear in obstructive sleep apnea. It can occur during the whole inspiration or at the end of the inspiration. Snores are loud sounds with an intensity higher than 50 dB(A). This intensity depends on the recording technique, but mean energies as high as 85–90 dB have been reported [97,148-150]. The snore contains periodic components, having a fundamental frequency between 30 and 250 Hz [69,151]. The fundamental frequency varies during the same snore or from a snore to another [152]. The snore is associated with an inspiratory flow limitation, as well as an increase in airways resistance.

The fundamental has been reported to be as low as 30 Hz and may be >250 Hz in some cases [153]. In nasal snoring, the upper limit of the spectrum defined as the last peak maximum frequency (Fmax) with a power >3% of the peak power is reported to be ~550 Hz [151]. For oronasal snoring, the same peak Fmax is ~850 Hz. These limits can be increased in the case of obstructive sleep apnea. When studying frequency spectra of snoring sounds, it is recommended that the range 30–2,000 Hz be considered, even if there is only a small amount of energy >1,200 Hz.

They present a novel algorithm to extract Speech and Voiced-Snore segments from corrupted SRS measurements. The algorithm utilizes Higher Order Statistics (HOS) due to its insensitivity to Gaussian noise and the ability to reconstruct a system preserving true phase characteristics [154].

Sleep nasendoscopy, when palate and tongue are seen to vibrate, they are indeed characterized by low (137 Hz) and high (1243 Hz) frequency sounds respectively. In addition, we have characterized epiglottic snores to occur at 490 Hz and tonsillar snores at 170 Hz [155]. Differences between snores and Obstructive Sleep Apnea Syndrome (OSAS) patients, and suggest that snore variability could be higher in OSAS patients [156].

2.7.5. Stridors

Stridors are very loud wheezes, which are the consequence of a morphologic or dynamic obstruction in larynx or trachea. This sound can be heard near the patient without a stethoscope. The ear of a trained examiner may recognize the source of the noises: supraglottic, glottic, subglottic or tracheal [157]. Different terms are used to compare them to known noises: "cluck of turkey", "whistle of snake", "foghorn". The stridor usually occurs during inspiration when it is extrathoracic and during expiration when it is intrathoracic unless the obstruction is fixed, in which case, stridor may appear in both phases of respiration. The principal etiology of the supraglottic stridor is suctioning of ary-epiglottic folds onto the lumen of the airways during inspiration. These phenomena occur because of an excess of supraglottic tissue (anatomic hypothesis). In the glottic area, the main aetiology of stridor is vocal cord paralysis. Stridor is common in infants and in babies, since the dimensions of the supraglottic area are small. However, the obstruction in babies is most often due to a subglottic viral inflammation (laryngitis). Stridor is usually characterized by a prominent peak at about 1,000 Hz in its frequency spectrum. This component is called the pitch. The envelope of the pitch and the complexity of the spectrum (*i.e.* number of peaks or harmonics) is dependent on the disease, the site of obstruction, the airflow and the volume. Moreover, the elasticity of the obstruction and the surrounding tissues influence the sound generation. A fixed obstruction will generate a constant pitch, and a dynamic obstruction will modulate the pitch in frequency as in the case of a laryngomalacia.

The commonly observed range for the pitch is 600–1,300 Hz [158,159], usually ~1,000 Hz. In adults, the pitch of the stridor is usually much lower and is <200 Hz. Although it is quite difficult to provide information on the other peaks, it seems that they are much more flow/volume-dependent than the main peak. Thus, a sampling frequency of ≥5,512 Hz is recommended when studying the main peak of the stridor. In addition, if the interest is in the estimation of obstruction parameters, this frequency should be ≥11,025 Hz, according to the CORSA recommendation [131].

2.8. Asthma

So far, few studies have been carried out in asthmatic patients and normal subjects [160]. Lung sounds are recorded before and after the inhalation of a β-stimulant bronchodilator drug (terbutaline) to understand the effect of terbutaline [160]. To validate asthma monitoring system based on wheezing detection in phonopneumograms are also studied [161]. Wheezes have been reported as adventitious respiratory sounds in asthmatic or obstructive patients, during forced exhalation maneuvers [12].

Not only asthmatic patients but also other diseases are important to analyze the respiratory sounds. Patients with sleep apnea, Pneumothorax, upper airway obstruction, chronic obstructive pulmonary disease (COPD) are of some examples of the clinical cases [163-166].

The lung sounds in a patient with pulmonary fibrosis, asthma and chronic obstructive pulmonary disease (COPD) that take place in which frequency bands are also shown [103,104]. A wheeze in a patient with asthma, frequency 420 Hz and in addition, harmonics of higher pitch can also be depicted. Toward the end of first inhalation, a weak high frequency wheeze of approximately frequency 900 Hz is visible. Such a sound can be difficult to hear with an acoustic stethoscope.

Not only asthmatic patients but also other diseases are important to analyze the respiratory sounds. Patients with sleep apnea, Pneumothorax, upper airway obstruction, chronic obstructive pulmonary disease (COPD) are of some examples of the clinical cases [24,161].

2.9 Aliasing

The effect that, after sampling a harmonic function appears to manifest another frequency. This occurs if the frequency of the original continuous harmonic signal is higher than half the sampling rate. The apparent frequency is equal to the smallest distance of the original frequency to any integer multiple of the sampling rate. For example, if the sampling rate is 1 kHz, a sampled harmonic signal of 800 Hz will appear to have a frequency of 200 Hz; a sampled harmonic signal of 1,000 Hz will appear to have a frequency of 0 Hz (a constant value); a sampled harmonic signal of 5,100 Hz will appear to have a frequency of 100 Hz. In general, for arbitrary signals, the spectrum should be zero above half the sampling rate. All frequency components above this frequency (the Nyquist frequency) will be "aliased", and this corrupts the actual original components in the base band [167].

2.10 Filtering Methods

It is a device that transforms a signal at its input into a signal at its output. Usually, the transformation aims to remove unwanted components [46]. Filters can be classified in analogue filters (*e.g.* implemented by operational amplifiers, resistors and capacitors) and digital filters (*e.g.* implemented by programmable digital hardware).

Many methods have been proposed to eliminate environmental noises. Most of the environmental noises can be avoided by using a soundproof room. An acoustic chamber can reduce ambient background noise by up to 30 dB [168], but most frequently, it is not available for clinical respiratory sound recordings. Shielding of the sensors with sound isolation materials can be helpful to eliminate environmental noise [169]. The noise at zero airflow (breath holding) picked up on the chest wall for assessing background noise in the frequency domain [15] should be measured in order to assess the quality of the recording. In spectral analysis, it can even be used to subtract the noise spectrum.

For real time auscultation, an automated gain control (AGC) with adaptive algorithm has been implemented for electronic stethoscopes application. The overall heart sound reduction by this method ranges from 75% to 83% at different chest location. As a result, a convenient and effective heart sounds reduction electronic stethoscope has been proposed [170]. Performance of an automatic method for structural decomposition, noise removal and enhancement of bowel sounds (BS), based on the wavelet transform were studied [171]. Heart sounds are the main unavoidable interference in lung sound recording and analysis. Hence, several techniques have been developed to reduce or cancel heart sounds (HS) from lung sound records. The use of a wavelet transform domain filtering technique as an adaptive de-noising tool, implemented in lung sounds analysis [172-173]. Adaptive Noise Cancellation with Recursive Least Square (Higher Order Statistics) method is used to filter out the heart sound from lung sound [174].

This paper proposes a novel method for HS localization using entropy of the lung sounds [175] and a robust and novel method for estimating flow using entropy of the band pass filtered tracheal sounds is proposed [176].

In the range of lower frequencies (<100 Hz), heart and muscle sounds overlap; this range must therefore be filtered out for the assessment of lung sounds [4]. The current problem of lung sounds recording is noise from sources such as heart and muscle sounds, noise from contact between the recording device and the skin and the environmental noise that corrupt the lung sound signal. To reduce the effect of these sounds, all sound signals should be filtered [4,43,107]. Changes in lung function with age have long been well known and studied. The frequency spectrum of lung sounds below 300 Hz in infants and children is also age dependent. In adults an age dependence of lung sounds has been assumed [4]. To improve the convergence speed, transform domain adaptive filter (TDAF) with Walsh-Hadamard transform (WHT) are used [177]. This structure would cancel the ambient noise more efficiently.

CHAPTER 3

SIGNAL PROCESSING and SOUND WAVE

3.1 Signals, Systems, and Signal Processing

To be able to understand what the meaning of the sound wave is, mathematical explanation of signal and wave will be given. A study summarizes [180] sounds analysis as follows.

A signal is defined as any physical quantity that varies with time, space or any other independent variable or variables. Mathematically we describe a signal as a function of one or more independent variables.

For example, a segment of speech may be represented to a high degree of accuracy as a sum of several sinusoids of different amplitudes and frequencies, that is, as

$$\sum_{i=1}^{N} A_i(t) \sin[\ 2 * \Pi F_i(t)t + \theta_i(t)] \qquad (3.1)$$

where $\{A_i(t)\}$, $\{F_i(t)\}$ and $\{\theta_i(t)\}$ are the sets of (possibly time varying) amplitudes, frequencies, and phases, respectively, of the sinusoids. In fact, one way to interpret the information content or message conveyed by any short time segment of the speech signal is to measure the amplitudes, frequencies, and phases contained in the short time segment of the signal.

Another example of natural signal is an electrocardiogram (ECG), such a signal provides a doctor with information about the condition of the patient's heart. Similarly, an electroencephalogram (EEG) signal provides about the activity of the brain.

Speech, electrocardiogram, and electroencephalogram signals are examples of information bearing signals that evolve as a function of a single independent variable, namely time.

A system may also be defined as a physical device that performs on operation on a signal. For example, a filter used to reduce the noise and interference corrupting a desired information- bearing signal is called a “system”. In this case the filter performs some operations on the signal, which has the effect of reducing (filtering) the noise and interference from the desired information-bearing signal. In general, the system is characterized by the type of operation that is performs on the signal. For example is the operation is stationary, the system is called stationary. If the operation on the signal is nonstationary, the system is said to be nonstationary, and so forth. Such operations are usually referred to a signal processing.

For our purposes, it is convenient to broaden the definition of a system to include not only physical devices, but also software realizations of operations on a signal. In digital processing a signal of a digital computer, the operation performed on a signal consists of a number of mathematical operations, that is, we have a digital signal processing system realized in software. For example, a digital computer can be programmed to perform digital filtering.

3.1.1 Analog-to-digital Conversion

Most signals of practical interest such as speech, biological signals, seismic signals, radar signals, sonar signals and various communication signals such as audio and video signals are analog. To process analog signals by digital means (Fig. 3.1) it is first necessary to convert them into digital form, that is, to convert them into a sequence of numbers having finite precision. This procedure is called analog-to-digital (A/D) conversion, and the corresponding devices are called A/D converters (ADC’s). The process of converting signal into an analog signal is known as digital-to-analog (D/A) conversion.

There are two parameters in this conversion process, the frequency at which the waveform should be sampled, and the accuracy (number of bits) with which the samples should be represented. The sampling theorem, due to Nyquist, states that in order not to lose information, a waveform should be sampled at a frequency of at least twice the highest frequency in the waveform.

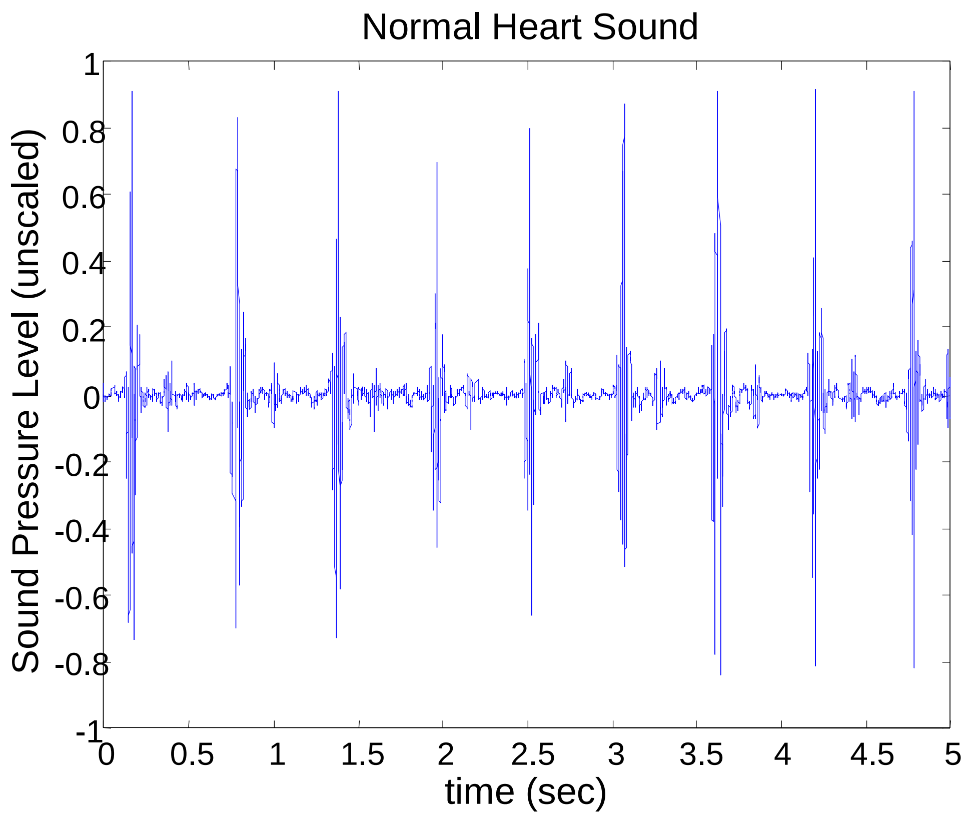


Figure 3.1 Digitization of a heart sound waveform (5 sec) segment and sampled with 8 kHz.

The time interval T between successive samples is called the sampling period or sample interval and its reciprocal $1/T = F_s$ is called the sampling rate (samples per second) or the sampling frequency (Hertz). Unit frequency is the Nyquist frequency defined as the half the sampling frequency.

If a signal contains no frequency components over the frequency $f_{\max}$, the signal can be uniquely represented by equally spaced samples if the sampling frequency f_s is greater than twice $f_{\max}$. That is, sampling frequency must satisfy the inequality $f_s \rangle 2 f_{\max}$. The other aspect of the sampling theorem is that the original analog signal can be recovered by performing the appropriate operations on the sample values.

Aliasing, a phenomenon associated with the digitization of continuous signals, is closely related to the sampling rate and the Nyquist frequency, which is one half the sampling rates. Specifically, when digitized at a too low rate, a signal's high frequency components are said to fold about Nyquist frequency and appear low frequencies. If stated in the reverse way, you must sample data at twice its highest frequency component or else components higher than Nyquist frequency fold into low frequencies, and this distortion called as aliasing.

3.1.2 Fourier Analysis

Frequency is closely related to a specific type of periodic motion called harmonic oscillation, which is described by sinusoidal functions. The concept of frequency is directly related to the concept of time [181, 182].

Frequency analysis is useful for characterizing a signal; for seeing order where there appears to be none. Fourier analysis is also very useful as a means of filtering a signal.

Any continuous signal (i.e. a signal that only has one value at any one instant in time) can be represented by the sum of sine waves of varying frequency, amplitude and phase.

We can describe a pure sinusoidal function of time by the equation:

$$f(t) = \cos(\omega t) \qquad \omega = 2\pi f \tag{3.2}$$

This function has maximum positive and negative amplitude at time zero and at integer multiples of half the period, i.e. 0, T/2, T, 3T/2… The function can have maximum at other times by the introduction of a phase term:

$$f(t) = \cos(\omega t \pm \phi) \tag{3.3}$$

The cosine and sine harmonics can have different amplitudes, so we can write down a complete expression for the signal:

$$f(t) = a_n \cos n\omega t + b_n \sin n\omega t \tag{3.4}$$

where n is the harmonic number, 1,2,3…etc.

At present our sinusoidal function of time is symmetric about zero. Real signals can have 0 Hz or DC offsets. So we need one more term as:

$$f(t) = a_0 + \sum_{n=1}^{\infty} a_n \cos n\omega t + \sum_{n=1}^{\infty} b_n \sin n\omega t \qquad (3.5)$$

ω = the fundamental frequency

a_0 = DC offset

a_n, b_n = the Fourier coefficients

As a first step we will find the coefficient a_0 which represents the average DC (0 Hz) level of the signal. We can find the mean level of a function by calculating the area under the curve and dividing by the length of the base. For a function of time *f(t),* we calculate the area under the curve by taking the integral between t = 0 and t = the period T. The length of the base of the curve is the period T. Mathematically we write this as:

$$a_0 = \frac{1}{T}\int_{t=0}^{t=T} f(t)\, dt \qquad (3.6)$$

The next step is to find the cosine and sine coefficients a_n and b_n by finding the average of the function multiplied by sine waves of frequencies that are multiples of the fundamental.

$$a_n = \frac{2}{T}\int_0^T f(t)\cos(n\omega t)\, dt \qquad (3.7)$$

$$b_n = \frac{2}{T}\int_0^T f(t)\sin(n\omega t)\, dt \qquad (3.8)$$

The equations for finding the Fourier coefficients can be combined into a single equation:

$$a_n = \frac{2}{T}\int_0^T f(t)e^{-jn\omega t} dt \qquad (n \geq 1) \qquad (3.9)$$

A mathematical process called a Fourier Transform (FT) is used to decompose a signal into its component sine waves. An inverse FT reconstructs a signal from its Fourier components. The transform derives its name from Jean Baptiste de Fourier who was a scientist on Napoleons 1799 expedition to Egypt (During which time to Rosetta stone was discovered).

Following is an example to illustrate the use of Fourier series expansion. In the example the triangular periodic wave having a period of 0.24 sec and peak to peak value of 12 is examined. Infinite sum at the integrals are replaced by finite sums towards a numerical method to determine the Fourier series coefficients.

Analysis is done for seven harmonics with 6 and 24 intervals.

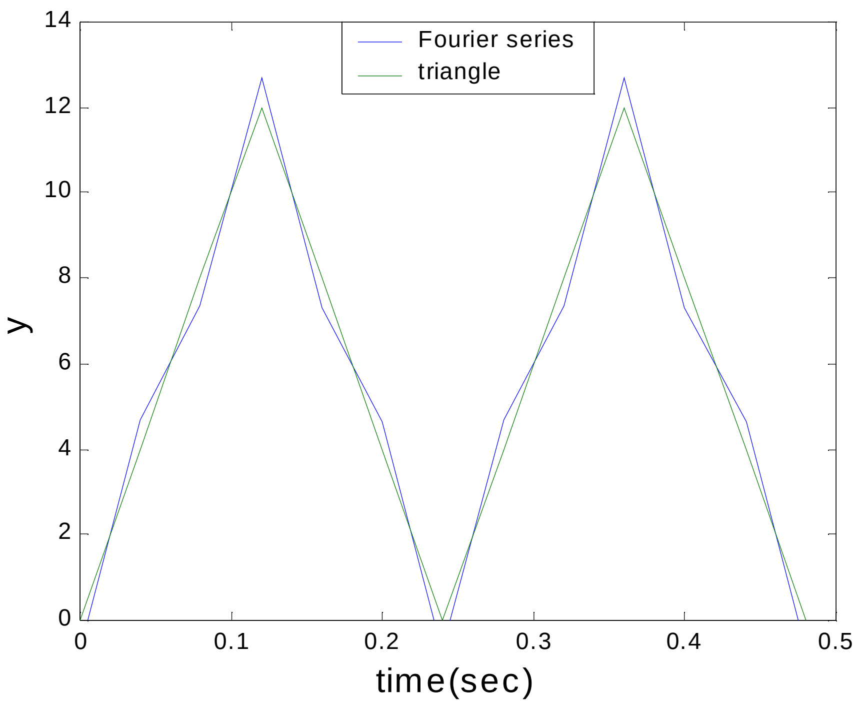


Figure 3.2   The triangular periodic wave having for seven harmonics with 6 intervals.

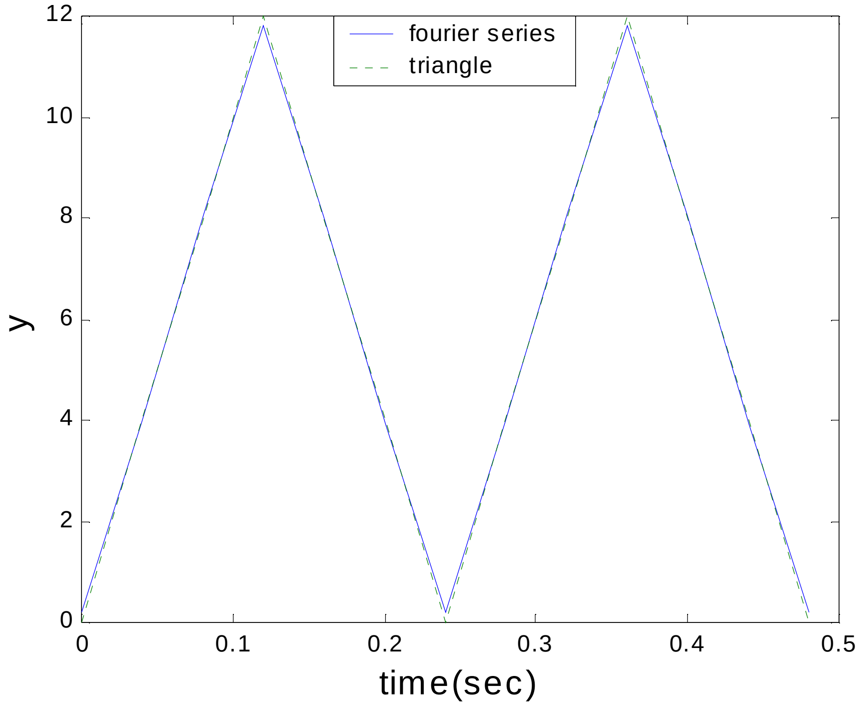


Figure 3.3 The triangular periodic wave having for seven harmonics with 24 intervals.

As seen in the Figure (3.2) and (3.3), increasing the harmonic number the Fourier series can fit very best with the periodic signal.

3.1.3 Discrete Fourier Transform

Performing a Fourier transform by hand, although possible, would be extremely time consuming, and error prone. Therefore, to get anywhere we need to perform a Fourier transform (FT) by computer. This is done using a Discreet Fourier Transform (DFT), which in effect is what we were doing by hand anyway. A DFT is performed on a *sampled* signal (using an ADC).

If a waveform has been digitized a frequency analysis can be performed by means of a technique known as the discrete Fourier transform or DFT. Suppose that the waveform is represented by

$$x(t) = x(nT) \qquad t = nT \qquad n=1, 2, 3\ldots\ldots\ldots\ldots\ldots, N \qquad (3.10)$$

There are N consecutive sampled values so that the sampling interval is T. To make things simpler, let us also suppose that N is even. If the function $x(t)$ is nonzero only in a finite interval of time, then that whole interval of time is supposed to be contained in the range of the N points given. Alternatively, if the function $x(t)$ goes on forever, then the sampled points are supposed to be at least 'typical' of what $x(t)$ looks like at all other times.

With N number of inputs, we will evidently be able to produce no more than N independent numbers of output.

A finite duration sequence $x(n)$ of length N has a Fourier transform:

$$X(w) = \sum_{n=0}^{N-1} x(n) e^{-jwn} \qquad 0 \le w \le 2\pi \qquad (3.11)$$

When we sample $X(w)$ at equally spaced frequencies

$$w = \frac{2\pi k}{N} \qquad \text{k=1, 2, 3………., N} \qquad (3.12)$$

the resultant samples are

$$X(k) = \sum_{n=0}^{N-1} x(n) e^{-j2\pi kn/N} \qquad \text{k=1, 2, 3………., N} \qquad (3.13)$$

Here equations (3.10) and (3.12) have been used in the final equality. The final summation in equation 12 is called the discrete Fourier transform of the N points $x(n)$.

The discrete Fourier transform has symmetry properties almost exactly the same as the continuous Fourier transform.

The formula for the discrete inverse Fourier transform, which recovers the set of $x(n)$'s exactly from the $X(k)$'s is:

$$x(n) = \frac{1}{N} \sum_{k=0}^{N-1} X(k) e^{j2\pi kn/N} \qquad \text{n=1, 2, 3 ………, N} \qquad (3.14)$$

Notice that the only differences between eqn13 and eqn14 are changing the sign in the exponential and dividing the answers by N.

3.1.4 Fast Fourier Transform

Two American mathematicians, Cooley and Tukey, noted that a very large fraction of the calculations performed as part of a DFT are repeated and therefore are redundant. Cooley and Tukey devised a means of stripping out the redundant calculations thus greatly speeding up the transform.

How much computations involved in computing the discrete Fourier transform (Equation 4.13) of N points, is important in practical considerations. Analysis may be required on line at a reasonable duration. To get an appreciation about the amount of computational mathematics required, define W as the complex number.

$$W = e^{-2j\pi/N} \tag{3.15}$$

Then equation (3.13) can be rewritten as:

$$X(k) = \sum_{n=0}^{N-1} x(n) W^{-kn} \tag{3.16}$$

In other words, the vector of $x(n)$'s is multiplied by a matrix whose $(n,k)^{th}$ element is the constant W to the power n*k. The matrix multiplication produces a vector result whose components are the $X(k)$'s. The matrix multiplication evidently requires N^2 complex multiplications plus a smaller number of operations to generate the required powers of W.

The discrete Fourier transform can be computed $N\log_2 N$ operations with an algorithm called the fast Fourier transform or FFT. In this algorithm the operations are divided into two sets, and then each set is itself subdivided. This process is repeated until each set contains only one term. This technique required only $N\log_2 N$ operations. Also N must be a power of 2.

Following is an example to illustrate the use of fast Fourier transform from the MATLAB. In the example the pure sinusoidal periodic wave having a frequency of 5 Hz is examined and is depicted in Figure (3.4) and (3.5).

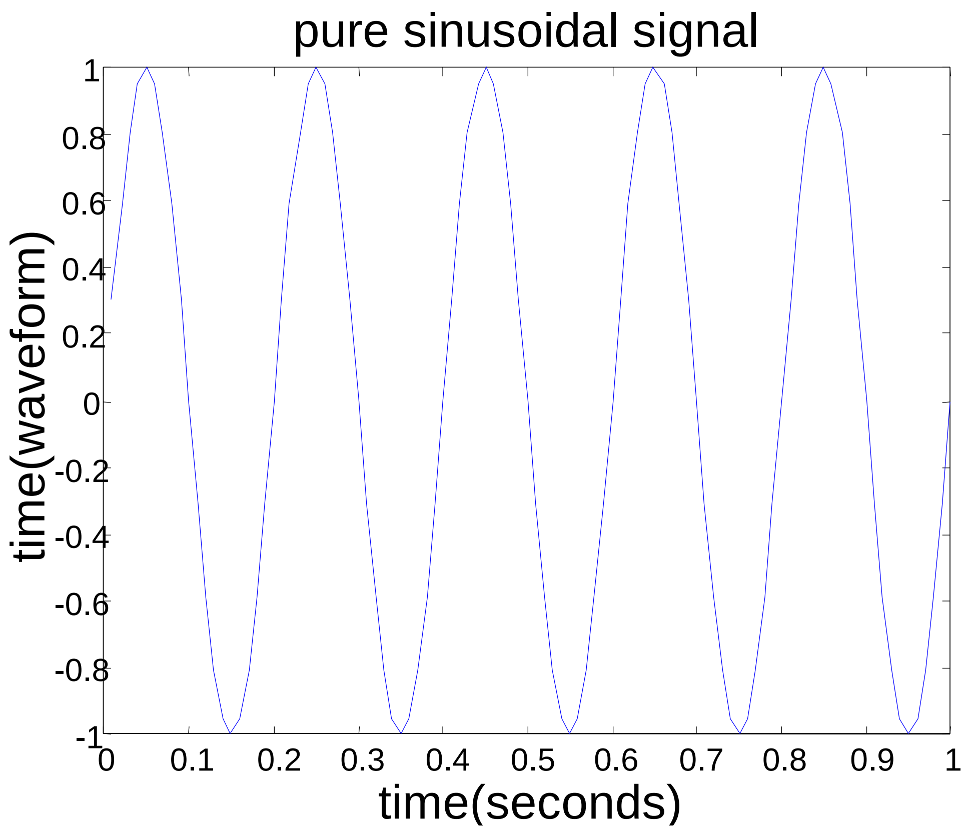


Figure 3.4 Pure sinusoidal signals having a 5 Hz frequency.

3.1.5 Power Spectrum Estimation Using the FFT

The first detail is power spectrum (also called a power spectral density or PSD) normalization. In general, there is some relation of proportionality between a measure of the squared amplitude of the function and a measure of the amplitude of the PSD. Unfortunately there are several different conventions for describing the normalization in each domain, and many opportunities for getting wrong the relationship between the two domains. Suppose that our function $x(t)$ is sampled at N points to produce values $x_1, \ldots\ldots\ldots\ldots x_N$, and that these points span a range of time t, that is $t = (N-1)T$, where T is the sampling interval. Then there are several different descriptions of the total power:

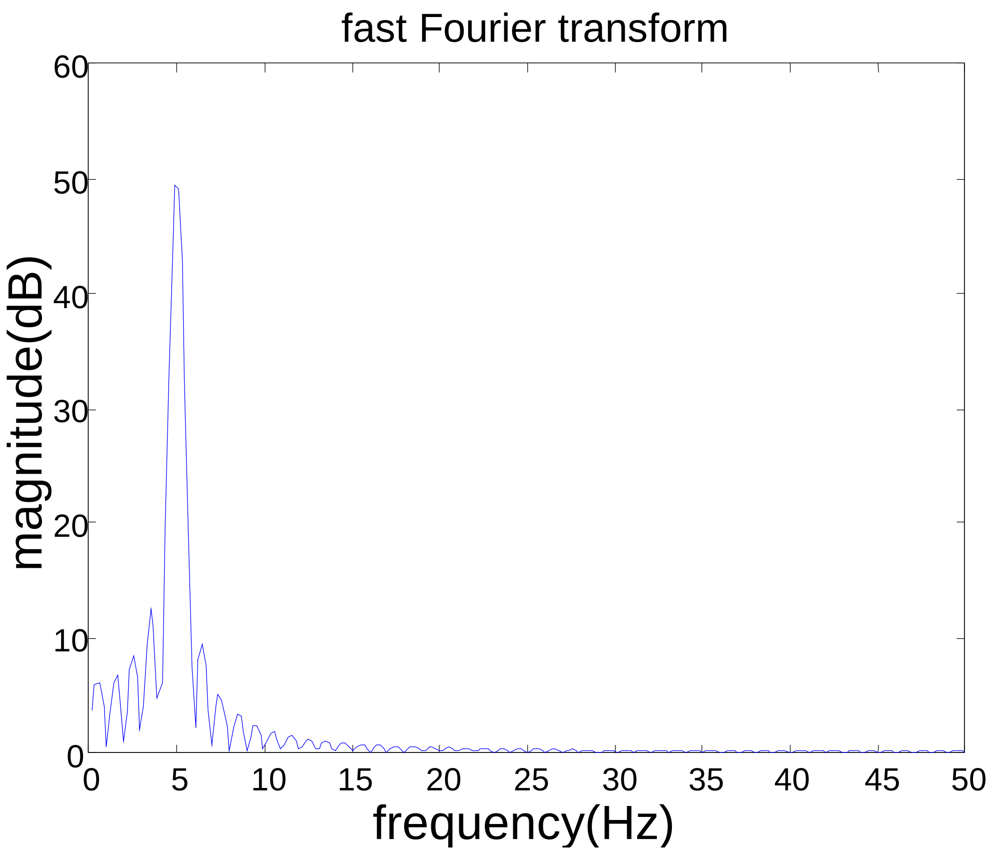


Figure 3.5 Taking a FFT by using a Matlab gives a signal frequency.

$$\sum_{j=0}^{N-1} |c_j|^2 \equiv \text{“sum squared amplitude”} \tag{3.17}$$

$$\frac{1}{T}\int_0^T |c(t)|^2\, dt \approx \frac{1}{N}\sum_{j=0}^{N-1} |c_j|^2 \equiv \text{“mean squared amplitude”} \tag{3.18}$$

$$\int_0^T |c(t)|^2\, dt \approx T\sum_{j=0}^{N-1} |c_j|^2 \equiv \text{“time-integral squared amplitude”} \tag{3.19}$$

The power spectral density is:

1. defined for discrete positive, zero and negative frequencies, and its sum over these is the function mean squared amplitude;
2. defined for zero and discrete positive frequencies only, and its sum over these is the function mean squared amplitude;

3. defined in the Nyquist interval from $-f_c$ and f_c, and its integral is the function mean squared amplitude;
4. defined from 0 to f_c, and its integral over this range is the function mean squared amplitude,[181]

It never makes sense to integrate the PSD of a sampled function outside of the Nyquist interval $-f_c$ and f_c since, according to the sampling theorem, power there will have been aliased into the Nyquist interval.

If we take an N-point sample of the function $c(t)$ at equal intervals and use the FFT to compute its discrete Fourier transform:

$$C_k = \sum_{j=0}^{N-1} c_j e^{-j2\pi k/N} \qquad \text{k=1, 2, 3……….., N} \qquad (3.20)$$

The power spectrum is defined at N/2+1 frequencies as:

$$P(0) = P(f_0) = \frac{1}{N^2}\left|C_0\right|^2$$

$$P(f_k) = \frac{1}{N^2}\left[\left|C_k\right|^2 + \left|C_{N-k}\right|^2\right] \qquad \text{k=1, 2 ……….., } \left(\frac{N}{2}-1\right) \qquad (3.21)$$

$$P(f_c) = P(f_{N/2}) = \frac{1}{N^2}\left|C_{N/2}\right|^2 \qquad (3.22)$$

where f_k is defined only for the zero and positive frequencies

$$f_k = \frac{k}{NT} = 2f_c\frac{k}{N} \qquad \text{k=0, 1, 2,……….., } \frac{N}{2} \qquad (3.23)$$

A heart sound signal is not exactly periodic, but it does not change much from period to period. If the start of each period could be determined, it would be possible to take N equal to the number of points in a glottal period and perform FFT at this period.

This is sometimes done, but it is difficult to locate the beginning of each period in practice.

Normally an arbitrary sequence of N points is taken. This is equivalent to multiplying the signal by a rectangular window which is zero everywhere except during the period to be analyzed. This introduces discontinuities at the edges which distort the spectrum by adding spurious high frequency components.

A better technique is to multiply the signal by a smooth window function. Triangular, Gaussian and cosine shaped windows have been used, but the effects are much the same. A common technique is to use a Hamming window,[181,182]. The Hamming window coefficient is:

$$w[n+1] = 0.54 - 0.46\cos(2\pi \frac{n}{N-1}) \qquad \text{n =1, 2, 3…………., N} \qquad (3.24)$$

The effect of this is shown in Figures (3.6), (3.7) and (3.8).

The equations given above express the DFT in terms of complex numbers. Usually in analysis it is the energy at each harmonic number (or frequency) which is required. This is given by power spectrum:

$$D_k \equiv \sum_{n=0}^{N-1} c_n w_n e^{-j2\pi kn/N} \qquad \text{k =1, 2, 3,…………, N} \qquad (3.25)$$

where c_n is sampled data and w_n is window function.

$$P(0) = P(f_0) = \frac{1}{W_{ss}^{\ 2}} |D_0|^2$$

$$P(f_k) = \frac{1}{W_{ss}^{\ 2}} \left[|D_k|^2 + |D_{N-k}|^2 \right] \qquad \text{k=1, 2 …………,} \ (\frac{N}{2}-1) \qquad (3.26)$$

$$P(f_c) = P(f_{N/2}) = \frac{1}{W_{ss}^{\ 2}} \left| D_{N/2} \right|^2$$

where W_{ss} stands for "window squared and summed",

$$W_{ss} \equiv N \sum_{n=0}^{N} w_n^{\ 2} \tag{3.27}$$

and f_k is given by Eqn 3.23

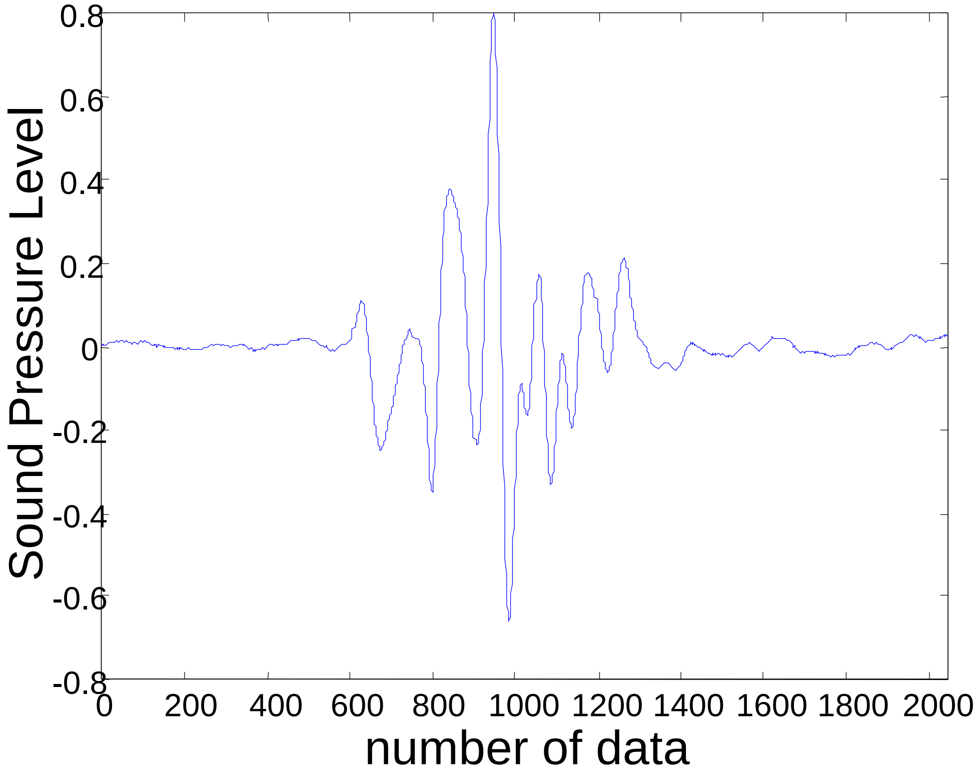


Figure 3.6 0.256 sec waveform segment of S1 and sampled with 8 kHz

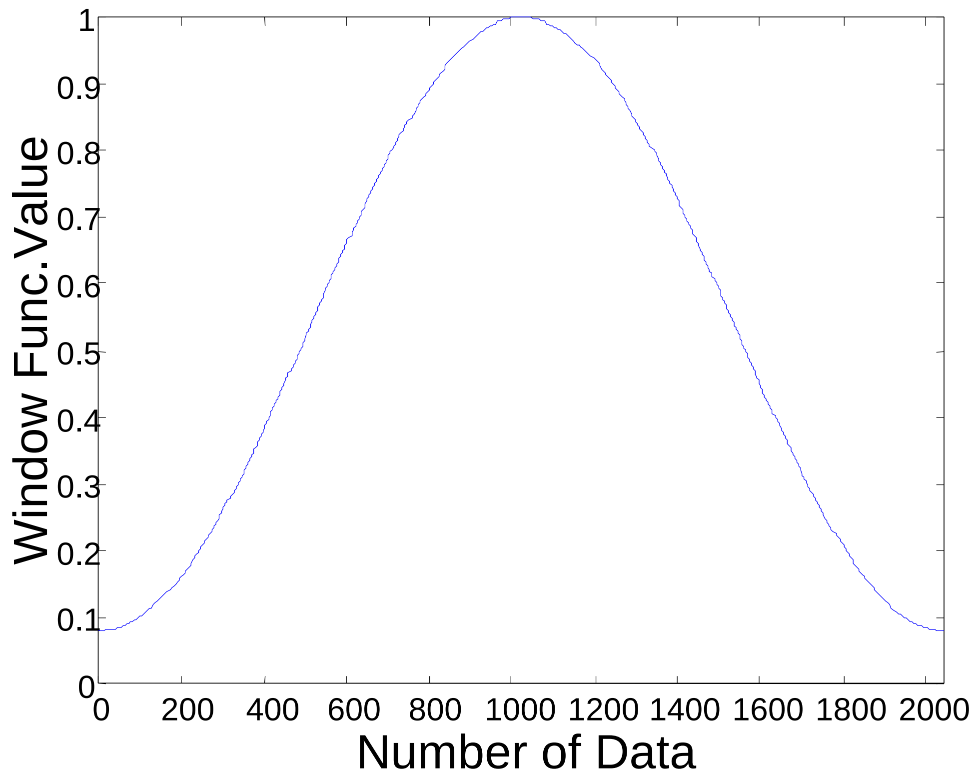


Figure 3.7 Hamming window

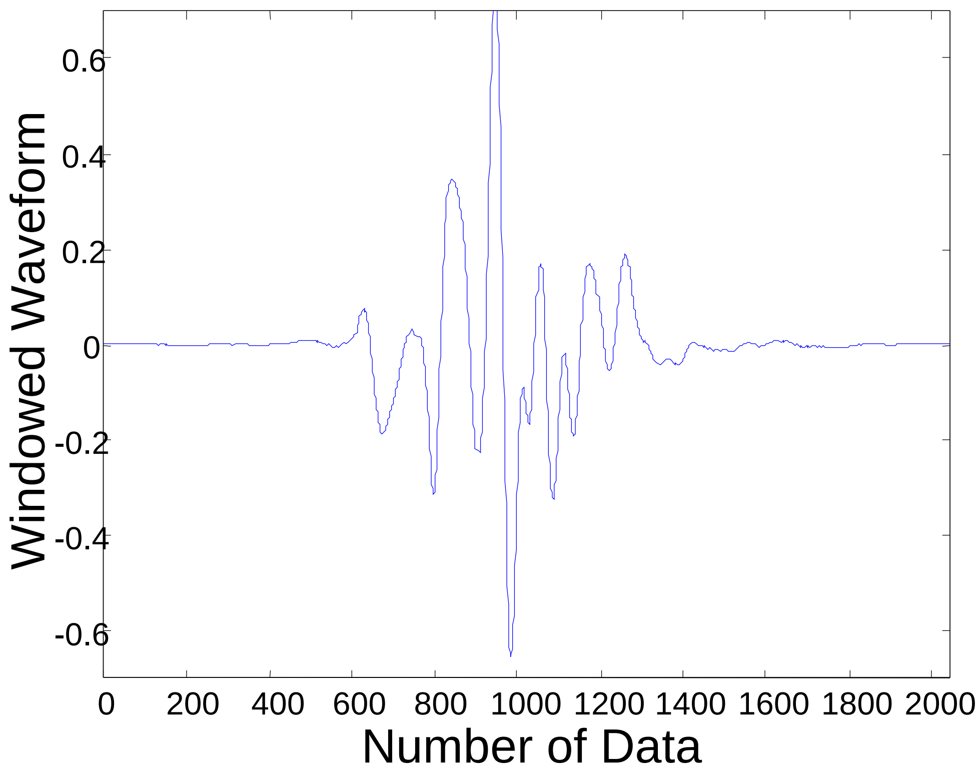


Figure 3.8 Windowed form of Fig. 3.6, by Hamming window of Fig 3.7

3.2 Design of Digital Filters

In the design of frequency-selective filters, the desired filter characteristics are specified in the frequency domain in terms of the desired magnitude and phase response of the filter. In the filter design process, we determine the coefficients of a casual FIR (Finite Impulse Response) or IIR (Infinite Impulse Response) filter that closely approximates the desired frequency response specifications. The issue of which type of filter to design, FIR or IIR, depends on the nature of the problem and on the specifications of the desired frequency response.

In practice, FIR filters are employed in filtering problems where there is a requirement for a linear phase characteristic within the bandpass of the filter. If there is no requirement for a linear phase characteristic, either an IIR or an FIR filter may be employed. Today, FIR and IIR digital filter design is greatly facilitated by the availability of numerous computer software programs.

In conjunction with our discussion of digital filter design, we describe frequency transformations in both the analog and digital domains for transforming a low-pass prototype filter into another low-pass, band-pass, band-stop, or high-pass filter.

The goal of filter design is to perform frequency dependent alteration of a data sequence. Filter design methods differ primarily in how performance is specified. How to apply the filter design tools to IIR and FIR filter design problems.

3.2.1 IIR Filter Design

The primary advantage of IIR filters over FIR filters is that they typically meet a given set of specifications with a much lower filter order than a corresponding FIR filter.

The classical IIR filters, Butterworth, Chebyshew types I and II, elliptic and Bessel, all approximate the ideal ‘brickwall’ filter in different ways. Signal processing toolbox in Matlab provides functions to create all these types of classical IIR filters in both analog and digital domains. For most filter types, you can also find the lowest filter order that fits a given filter specification in terms of pass-band and stop-band attenuation, and transition width.

The principal IIR digital filter design technique this toolbox provides is based on the conversion of classical low-pass filters to their digital equivalents. All classical IIR low-pass filters are ill conditioned for extremely low cut-of frequencies. Therefore, instead of designing a low-pass IIR filter with a very narrow pass-band, it can be better to design a wider pass-band and decimate the input signal. The toolbox provides five different types of classical IIR filter, each optimal in some way.

3.2.2 FIR Filter Design

Digital filters with finite duration impulse response (FIR) response have both advantages and disadvantages compared to infinite duration impulse response (IIR) filters.

FIR filters have the following primary advantages:

- They can have exactly following primary advantages.
- They are always stable.
- The design methods are generally linear
- They can be realized efficiently in hardware
- The filter start-up transients have finite duration.

The primary disadvantages of FIR filters are that they often require a much higher filter order than IIR filters to achieve a given level of performance.

The functions fir1, fir2, firls, remez, fircls, and fircls1 all design type I and II linear phase FIR filter by default.

3.2.3 Advantages of Digital versus Analogue Filtering

There are many advantages to digitizing signals from an instrumentation point of view. Some of these are:

- Permanent storage of digitized signal
- No electronic noise is associated with digital processing
- Digital analysis using a computer may well be cheaper than an analogue circuit
- A ‘virtual’ instrument can be built using a PC.
- Easy frequency analysis

3.2.4 Relations and General Properties Signal Processing Method

Raw signals are generally represented that time axis (independent variables), amplitude (dependent variables). When we plot time-domain signals, we obtain a time-amplitude representation of the signal. This representation is not always the best representation of the signal for most signal processing related applications. Therefore, Robi Polikar [178] talk about signal and mathematical representation as briefly as follow:

In many cases, the most distinguished information is hidden in the frequency content of the signal. Frequency changing in time (where/when) is also important in our search to get valuable information from respiratory signal. The frequency SPECTRUM of a signal is basically the frequency components (spectral components) of that signal. The frequency spectrum of a signal shows what frequencies exist in the signal. The frequency is measured in cycles/second, or with a more common name, in "Hertz". For example the electric power we use in our daily life in the Turkey is 50 Hz (60 Hz elsewhere in the world). Signals have own characteristics related to some mathematical representations. Therefore, each signal has cosine and sine components. So how do we measure frequency, or how do we find the frequency content of a signal? The answer is FOURIER TRANSFORM (FT). If the FT of a signal in time domain is taken, the frequency-amplitude representation of that signal is obtained. In other words, we now have a plot with one axis being the frequency and the other being the amplitude. This plot tells us how much of each frequency exists in our signal.

Often times, the information that cannot be readily seen in the time-domain can be seen in the frequency domain. Every transformation technique has its own area of application, with advantages and disadvantages, and the wavelet transform (WT) is no exception. For a better understanding of the need for the WT let's look at the FT more closely. FT (as well as WT) is a reversible transform, that is, it allows going back and forward between the raw and processed (transformed) signals. However, only either of them is available at any given time. That is, no frequency information is available in the time-domain signal, and no time information is available in the Fourier transformed signal. The natural question that comes to mind is that is it necessary to have both the time and the frequency information at the same time? Recall that the FT gives the frequency information of the signal, which means that it tells us how much of each frequency exists in the signal, but it does not tell us when in time these frequency components exist. This information is not required when the signal is so-called stationary. Signals whose frequency content does not change in time are called stationary signals. In other words, the frequencies content of stationary signals do not change in time. In this case, one does not need to know at what times frequency components exist, since all frequency components exist at all times! FT gives the spectral content of the signal, but it gives no information regarding where in time those spectral components appear. Therefore, FT is not a suitable technique for non-stationary signal, with one exception:

FT can be used for non-stationary signals, if we are only interested in what spectral components exist in the signal, but not interested where these occur. However, if this information is needed, i.e., if we want to know, what spectral component occur at what time (interval), then Fourier transform is not the right transform to use. For practical purposes it is difficult to make the separation, since there are a lot of practical stationary signals, as well as non-stationary ones. Almost all biological signals, for example, are non-stationary. Some of the most famous ones are ECG (electrical activity of the heart, electrocardiograph), EEG (electrical activity of the brain, electroencephalograph), and EMG (electrical activity of the muscles, electromyogram). When the time points of the spectral components are needed, a transform giving the TIME-FREQUENCY REPRESENTATION of the signal is needed. Wavelet transform is capable of providing the time and frequency information simultaneously, hence giving a time-frequency representation of the signal. How wavelet transform works is completely a different fun story, and should be explained after short time Fourier Transform (STFT). The WT was developed as an alternative to the STFT.

To make a real long story short, we pass the time-domain signal from various high pass and low pass filters, which filters out either high frequency or low frequency portions of the signal. This procedure is repeated, every time some portion of the signal corresponding to some frequencies being removed from the signal.

Here is how this works: Suppose we have a signal, which has frequencies up to 1000 Hz. In the first stage we split up the signal in to two parts by passing the signal from a high pass and a low pass filter (filters should satisfy some certain conditions, so-called admissibility condition) which results in two different versions of the same signal: portion of the signal corresponding to 0-500 Hz (low pass portion), and 500-1000 Hz (high pass portion). Then, we take either portion (usually low pass portion) or both, and do the same thing again. This operation is called decomposition.

Assuming that we have taken the low pass portion, we now have 3 sets of data, each corresponding to the same signal at frequencies 0-250 Hz, 250-500 Hz, 500-1000 Hz.

Then we take the low pass portion again and pass it through low and high pass filters; we now have 4 sets of signals corresponding to 0-125 Hz, 125-250 Hz,250-500 Hz, and 500-1000 Hz. We continue like this until we have decomposed the signal to a pre-defined certain level. Then we have a bunch of signals, which actually represent the same signal, but all corresponding to different frequency bands. We know which signal corresponds to which frequency band, and if we put all of them together and plot them on a 3-D graph, we will have time in one axis, frequency in the second and amplitude in the third axis. This will show us, which frequencies exist at which time (there is an issue, called "uncertainty principle", which states that, we cannot exactly know what frequency exists at what time instance, but we can only know what frequency bands exist at what time intervals)

The uncertainty principle, originally found and formulated by Heisenberg, states that, the momentum and the position of a moving particle cannot be known simultaneously. This applies to our subject as follows:

The frequency and time information of a signal at some certain point in the time-frequency plane cannot be known. In other words: We cannot know what spectral component exists at any given time instant. The best we can do is to investigate what spectral components exist at any given interval of time. This is a problem of resolution, and it is the main reason why researchers have switched to WT from STFT. STFT gives a fixed resolution at all times, whereas WT gives a variable resolution as follows :

Higher frequencies are better resolved in time, and lower frequencies are better resolved in frequency. This means that, a certain high frequency component can be located better in time (with less relative error) than a low frequency component. On the contrary, a low frequency component can be located better in frequency compared to high frequency component. FT decomposes a signal to complex exponential functions of different frequencies. The way it does this, is defined by the following two equations:

$$X(f) = \int_{-\infty}^{\infty} x(t).e^{-2j\pi ft}\,dt \tag{3.28}$$

$$x(t) = \int_{-\infty}^{\infty} X(f).e^{2j\pi ft}\,df \tag{3.29}$$

At the STFT, We not only know what frequency components are present in the signal, but we also know where they are located in time. The short-time Fourier transform (STFT), or alternatively short-term Fourier transform, is a Fourier-related transform used to determine the sinusoidal frequency and phase content of local sections of a signal as it changes over time. Simply described, in the continuous-time case, the function to be transformed is multiplied by a window function which is nonzero for only a short period of time. The Fourier transform (a one-dimensional function) of the resulting signal is taken as the window is slid along the time axis, resulting in a two-dimensional representation of the signal. Mathematically, this is written as:

$$STFT\{x(\ )\} \equiv X(\tau,\omega) = \int_{-\infty}^{\infty} x(t)\omega(t-\tau)e^{-j\omega t}\,dt \tag{3.30}$$

where w(t) is the window function, commonly a Hann window or gaussian "hill" centered around zero, and x(t) is the signal to be transformed. $X(\tau,\omega)$ is essentially the Fourier Transform of x(t)w(t-τ), a complex function representing the phase and magnitude of the signal over time and frequency. Often phase unwrapping is employed along either or both the time axis, τ and frequency axis, ω, to suppress any jump discontinuity of the phase result of the STFT. The time index τ is normally considered to be "slow" time and usually not expressed in as high resolution as time t. In the discrete time case, the data to be transformed could be broken up into chunks or frames (which usually overlap each other). Each chunk is Fourier transformed, and the complex result is added to a matrix, which records magnitude and phase for each point in time and frequency. This can be written as:

$$STFT\{x[\;]\} \equiv X(m,\omega) = \sum_{-\infty}^{\infty} x[n]\omega[n-m]e^{-j\omega n} \quad (3.31)$$

Likewise, with signal x[n] and window w[n]. In this case, m is discrete and ω is continuous, but in most typical applications the STFT is performed on a computer using the Fast Fourier Transform, so both variables are discrete and quantized. Again, the discrete-time index m is normally considered to be "slow" time and usually not expressed in as high resolution as time n.

The continuous wavelet transform was developed as an alternative approach to the short time Fourier transform to overcome the resolution problem. Unlike the STFT which has a constant resolution at all times and frequencies, the WT has a good time and poor frequency resolution at high frequencies, and good frequency and poor time resolution at low frequencies.

3.3 Sound wave

In this part sound and physical properties will be explained [179]. A wave is a disturbance that propagates through space, often transferring energy. While a mechanical wave exists in a medium (which on deformation is capable of producing elastic restoring forces), waves of electromagnetic radiation, and probably gravitational radiation can travel through vacuum, that is, without a medium. Waves travel and transfer energy from one point to another, with little or no permanent displacement of the particles of the medium (there is little or no associated mass transport); instead there are oscillations around fixed positions.

Sound is a disturbance of mechanical energy that propagates through matter as a wave. Sound is characterized by the properties of sound waves, which are frequency, wavelength, period, amplitude and velocity or speed. Noise and sound often mean the same thing; when they differ, a noise is an unwanted sound. In science and engineering, noise is an undesirable component that obscures a signal. What is noise and what is signal depends on your point of view. Humans perceive sound by the sense of hearing. By sound, we commonly mean the vibrations that travel through air and can be heard by humans. However, scientists and engineers use a wider definition of sound that includes low and high frequency vibrations in air that cannot be heard, and vibrations that travel through all forms of matter, gases, liquids and solids. The matter that supports the sound is called the medium. Sound propagates as waves of alternating pressure, causing local regions of compression and rarefaction. Particles in the medium are displaced by the wave and oscillate. The scientific study of sound is called acoustics. Sound is perceived through the sense of hearing. Humans and many animals use their ears to hear sound, but loud sounds and low frequency sounds can be perceived by other parts of the body through the sense of touch. Sounds are used in several ways, most notably for communication through speech or, for example, music. Sound can also be used to acquire information about properties of the surrounding environment such as spatial characteristics and presence of other animals or objects. For example, bats use echolocation, ships and submarines use sonar, and humans can determine spatial information by the way in which they perceive sounds.

The range of frequencies that humans can hear is approximately between 20 Hz and 20,000 Hz. This range is by definition the audible spectrum, but some people (particularly women) can hear above 20,000 Hz. This range varies by individual and generally shrinks with age, mostly in the upper part of the spectrum. The ear is most sensitive to frequencies around 3,500 Hz. Sound above 20,000 Hz is known as ultrasound; sound below 20 Hz as infrasound.

The amplitude of a sound wave is specified in terms of its pressure. The human ear can detect sounds with a very wide range of amplitudes and a logarithmic decibel amplitude scale is used. The quietest sounds that humans can hear have an amplitude of approximately 20 μPa (micropascals) or a sound pressure level (SPL) of 0 dB re

20 μPa (often incorrectly abbreviated as 0 dB SPL). Prolonged exposure to a sound pressure level exceeding 85 dB can permanently damage the ear, sometimes resulting in tinnitus and hearing impairment. Sound levels in excess of 130 dB are considered above of what the human ear can withstand and may result in serious pain and permanent damage. At very high amplitudes, sound waves exhibit non-linear effects including shock.

The speed of sound is a term used to describe the speed of sound waves passing through an elastic medium. The speed varies with the medium employed (for example, sound waves move faster through water than through air), as well as with the properties of the medium, especially temperature. It is sometimes used in describing the nature of substances. In conventional use and in scientific literature sound velocity, v, and sound speed, c, are used synonymously and should not be confused with sound particle velocity (also symbolized as v), which is the velocity of the individual particles. The term is commonly used to refer specifically to the speed of sound in air. The speed varies depending on atmospheric conditions; the most important factor is the temperature. Humidity has little effect on the speed of sound, nor does air pressure per se. (Pressure has no effect at all in an ideal gas approximation. This is because pressure and density both contribute to sound velocity equally, and in an ideal gas the two effects cancel out, leaving only the effect of temperature.) Sound usually travels more slowly with greater altitude, due to reduced temperature. An approximate speed of sound in air (in meters per second) can be calculated from:

$$c_{air} = (331.5 + (0.6\vartheta))ms^{-1} \qquad (3.32)$$

where ϑ (theta) is the temperature in degrees Celsius (°C).

In general, the speed of sound c is given by

$$c = \sqrt{\frac{C}{\rho}} \qquad (3.33)$$

where

C is a coefficient of stiffness

ρ is the density

Thus the speed of sound increases with the stiffness of the material, and decreases with the density. For general equations of state, if classical mechanics is used, the speed of sound *c* is given by

$$c^2 = \frac{\partial p}{\partial \rho} \tag{3.33}$$

where differentiation is taken with respect to adiabatic change.

If relativistic effects are important, the speed of sound may be calculated from the relativistic Euler equations. In a Non-Dispersive Medium – Sound speed is independent of frequency, so the speeds of energy transport and sound propagation are the same. For audio sound range air is a non-dispersive medium. We should also note that air contains CO_2 which *is* a dispersive medium, and it introduces dispersion to air at ultrasound frequencies (> 28 kHz).

In a Dispersive Medium – Sound speed is a function of frequency. The spatial and temporal distribution of a propagating disturbance will continually change. Each frequency component propagates at its own phase speed, while the energy of the disturbance propagates at the group velocity. A suspension of small particles in a fluid is an example of a dispersive medium.

Speed in solids

In a solid, there is a non-zero stiffness both for volumetric and shear deformations. Hence, in a solid it is possible to generate sound waves with different velocities dependent on the deformation mode.

In a solid rod (with thickness much smaller than the wavelength) the speed of sound is given by:

$$c_{solids} = \sqrt{\frac{E}{\rho}} \tag{3.34}$$

where

E is Young's modules

ρ (rho) is density

Thus, in steel the speed of sound is approximately 5100 $m \cdot s^{-1}$.

In a solid with lateral dimensions much larger than the wavelength, the sound velocity is higher. It is found by replacing Young's modulus with the plane wave modulus, which can be expressed in terms of the Young's modulus and Poisson's ratio as:

$$M = E\frac{1-\nu}{1-\nu-2\nu^2} \tag{3.35}$$

Speed in a fluid

In a fluid the only non-zero stiffness is to volumetric deformation (a fluid does not sustain shear forces).

Hence the speed of sound in a fluid is given by

$$c_{fluid} = \sqrt{\frac{K}{\rho}} \tag{3.36}$$

where

K is the adiabatic bulk modulus

The speed of sound in water is of interest to those mapping the ocean floor. In saltwater, sound travels at about 1500 m·s-1 and in freshwater 1435 m·s-1. These speeds vary due to pressure, depth, temperature, salinity and other factors.

Speed in ideal gases and in air

For a gas, K is approximately given by

$$K = \kappa.p \tag{3.37}$$

where

κ is the adiabatic index also known as the isentropic expansion factor and sometimes-called γ (Greek letter gamma). It is the ratio of constant-pressure to constant-volume heat capacities of the gas (Cp / Cv), and arises because a classical sound wave induces an adiabatic compression, in which the heat of the compression does not have enough time to escape the pressure pulse, and thus contributes to the pressure induced by the compression.

p is the pressure.

Using the ideal gas law the speed of sound is identical to:

$$c_{gas} = \sqrt{\kappa.\frac{p}{\rho}} = \sqrt{\kappa.\frac{R.T}{M}} \quad (3.38)$$

where

R (287.05 $J \cdot kg^{-1} \cdot K^{-1}$ for air) is the gas constant for air: the universal gas constant R, with units of $J \cdot mol^{-1} \cdot K^{-1}$, is divided by the molar mass of air, as is common practice in aerodynamics.

κ (kappa) is the adiabatic index (1.402 for air), sometimes noted γ

T is the absolute temperature in kelvins.

In the standard atmosphere:

T_0 is 273.15 K (= 0 °C), giving a value of 331.5 $m \cdot s^{-1}$ (=1193 $km \cdot h^{-1}$).

T_{20} is 293.15 K (= 20 °C), giving a value of 343.4 m·s-1 (= 1236 $km \cdot h^{-1}$)

T_{25} is 298.15 K (= 25 °C), giving a value of 346.3 m·s-1 (= 1246 $km \cdot h^{-1}$).

In fact, assuming an, the speed of sound c depends on temperature only, not on the pressure or density (since these change in lockstep for a given temperature and cancel out). Air is almost an ideal gas. The temperature of the air varies with altitude, giving the following variations in the speed of sound using the standard atmosphere - *actual conditions may vary*.

Effect of temperature

ϑ In ˚C	c in $m.s^{-1}$	ρ in $kg.m^{-3}$	Z in $N.s.m^{-3}$
−10	325.4	1.341	436.5
−5	328.5	1.316	432.4
0	331.5	1.293	428.3
5	334.5	1.269	424.5
10	337.5	1.247	420.7
15	340.5	1.225	417.0
20	343.4	1.204	413.5
25	346.3	1.184	410.0
30	349.2	1.164	406.6

Table 3.1 Effect of Temperature

ϑ is the temperature in °C

c is the speed of sound in $m\cdot s^{-1}$

ρ is the density in $kg\cdot m^{-3}$

Z is the acoustic impedance in $N\cdot s\cdot m^{-3}$ ($Z=\rho\cdot c$)

Given normal atmospheric conditions, the temperature, and thus speed of sound, varies with altitude:

Effect of frequency and gas composition

With increasing frequency the sound wave compression approaches a perfect adiabatic because there is less and less time for heat to escape in the compression process. For this reason, sound waves in air, particularly ultrasound, approach the theoretical relation given above very closely, as frequency rises.

The molecular composition of the gas contributes both as the mass (M) of the molecules, and their heat capacities, and so both have an influence on speed of sound. In general, at the same molecular mass, monatomic gases have slightly higher sound speeds (over 9% higher) due to the fact that they have a higher gamma (5/3 = 1.6) than diatomics do (7/5 = 1.4). Thus, at the same molecular mass, the sound speed of a monatomic gas goes up by a factor of

$$c_{gas} = \sqrt{\frac{1.6}{1.4}} \approx 1.09 \qquad (3.39)$$

This gives the 9% difference, and would be a typical ratio for sound speeds at room temperature in helium vs. deuterium, each with a molecular weight of 4. Sound travels faster in helium than deuterium because adiabatic compression heats helium more, since the helium molecules can store heat energy from compression only in translation, but not rotation. Thus helium molecules (monatomic molecules) travel faster in a soundwave and transmit sound faster. (Sound generally travels at about 70% of the mean molecular velocity in gases).

Note that in this example we have assumed that temperature is low enough that heat capacities are not influenced by molecular vibration. However, vibrational modes simply cause gammas which decrease toward 1, since vibration modes in a polyatomic gas gives the gas additional ways to store heat which do not affect temperature, and thus do not affect molecular velocity and sound velocity. Thus, the effect of higher temperatures and vibrational heat capacity acts to increase the difference between sound speed in monatomic vs. polyatomic molecules, with the speed remaining greater in monatomics.

3.4 Acoustical Natural Frequencies

The sound in human body travels through trachea, larynx, etc. They can be considered as pipes. It is necessary to see the change in frequencies in these systems approximately. An acoustic wave is a longitudinal pressure wave, which it propagates. The amplitude disturbance is thus parallel to the direction of propagation.

Consider the pipe in the figure, where the length is much greater than the diameter. The cross-section may have an arbitrary shape. Assume that the pipe is filled with some gas or liquid.

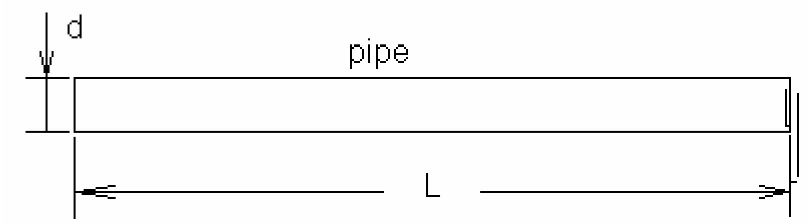


Figure 3.9 Pipe

L is the length

c is the speed of sound

The acoustic pressure p(x,t) is governed by the equation

$$\frac{\partial^2 p}{\partial x^2} = \frac{1}{c^2}\frac{\partial^2 p}{\partial t^2} \qquad (3.40)$$

Note that this equation has the same form as the equation for the longitudinal vibration of a rod. Note that the speed of sound is given by equation 3.34 for solids. If we change equation following format,

$$c = \sqrt{\frac{E}{\rho_0}} \qquad (3.41)$$

where E is the modulus of elasticity,

ρ_0 is the equilibrium density.

Separate the variables in equation. Let

$$p(x,t) = P(x)T(t) \tag{3.42}$$

Substitute the equation in to previous equation and apply the following boundary conditions, one can obtain frequencies.

Case I: Both Ends Open

$$\omega_n = n\pi\frac{c}{L}, n = 1,2,3,....$$

Case II: Open-Closed

$$\omega_n = \left(\frac{2n-1}{2}\right)\pi\frac{c}{L}, n = 1,2,3,...$$

Case III: Both Ends Closed

$$\omega_n = n\pi\frac{c}{L}, \quad n = 1,2,3,...$$

Infinite number of frequencies is obtained for different pipe lengths, pipe material, speed of sound, and different boundary conditions. Thus sound frequency in a disease can change human to human, age to age, and weight to weight. The shape of the lung is different in everybody. The structural properties of the organ also changes with age and weight.

CHAPTER 4

SOUND RECORDING

ECM T-150 Sony Microphone is used to get sound signals directly to the computer as in digital signals. Sound was recorded in noiseless clinical ambient at the hospital. But, there is no special sound isolation at the hospital room. Patients were classified related to some parameters such as age, gender, smoker/non-smoker, weight, passed patient knowledge and etc. Recorded sound signals were stored with patient data at the computer.

Some of measuring restriction can affect searches: Some of these;

- Measuring time period for each patient
- How many times measured each respiratory signal during patient treatment
- Position of the patient sit/ supine
- Run or staying patient
- Ambient effects and Seasons (Rel.Humidty)
- Recorded data restriction (Signal Sampling rate and Computer Restriction)

Sound analysis coming from measuring data as digital signal can be at least Nyquist's frequency or more. Therefore, sampling rate of the sound was investigated 8000 Hz. The sound signal was high-pass filtered at 7.5 Hz to remove DC offset (1st order Butterworth filter) and low-pass filtered at 2.5 kHz to avoid aliasing (8th order Butterworth filter). The original sampling rate was 8 kHz. The sound signal was again high-pass filter filtered at 100 Hz to remove heart and muscle sound (1^{st} order Butterworth filter) and low-pass filtered at 2.5 kHz to avoid aliasing (8^{th} order Butterworth filter).

Lung sounds from the chest were recorded from 22 patients (12 men and 10 women) with different pulmonary diseases which are 8 healthy subjects and 14 different pulmonary diseases. Types of recorded diseases are: rhonchus, wheezing, pneumonia, asthma, bilateral rhonchus, current wheezing, wheezing at expirium, wheezing at left, hypersensitive pneumonia, interstitial pulmonary fibrosis, bronchiectasis, rhomatoid artrit. The frequency of the recorded wheezing and rhonchus sounds are like as in literature about 400 Hz. And patient with pneumonia, frequency range is between 300- 600 Hz.

The sounds recorded are given in Appendix A. All the subjects were asked to breath spontaneously in the sitting position and sounds were recorded over the right scapula. In all figures, there are 4 graphs. The first one (a), shows time domain of the original signal. The second one (b), shows the diagram filtered to remove DC offset and aliasing. The third one (c), shows the diagram filtered to remove heart sound. The last one (d), shows FFT of the final signal which is without muscle and hearth signals, and high frequency aliasing.

In Figure A. 1, normal vesicular sounds recorded over the right scapula of a 21 year old, 1.75 m height, 79 kg weight, and no smokers’ man are shown. After 500 Hz there is no considerable frequency component.

In Figure A. 2, normal vesicular sounds recorded over the right scapula of a 24 year old, 1.75 m height, 75 kg weight, and no smokers’ man are shown.

In Figure A. 3, normal vesicular sounds recorded over the right scapula of a 24 year old, 1.70 m height, 75 kg weight, and no smokers’ man are shown.

In Figure A. 4, normal vesicular sounds recorded over the right scapula of a 21 year old, 1.80 m height, 72 kg weight, and quit smoking man are shown.

In Figure A. 5; normal vesicular sounds recorded over the right scapula of a 25 year old, 1.74 m height, 90 kg weight, and quit smoking man are shown.

In Figure A. 6; normal vesicular sounds recorded over the right scapula of a 50 year old, 1.58 m height, 76 kg weight, and no smoker’s woman are shown.

In Figure A. 7; normal vesicular sounds recorded over the right scapula of a 53 year old, 1.58 m height, 81 kg weight, and no smoker’s woman are shown.

In Figure A. 8; normal vesicular sounds recorded over the right scapula of a 29 year old, 1.61 m height, 63 kg weight, and no smoker's woman are shown.

In Figure A. 9; a patient with asthma were recorded over the right scapula of a 54 year old, 1.75 m height, 93 kg weight, and quit smoking man are shown. In Figure A. 10; a patient with asthma and bilateral rhonchus were recorded over the right scapula of a 59 year old, 1.61 m height, 96 kg weight, and no smoker's woman. Information about a patient with asthma has rhonchus sounds in both lungs that are given above. As the severities of sounds are increased so rhonchus sounds turns to wheezing. High frequency wheezes of approximately 400 Hz is visible. This region are seen in Figure A.10b

In Figure A. 11; a patient with current wheezing recorded over the right scapula of a 66 year old, 1.53 m height, 72 kg weight, and no smoker's woman are shown. Current wheezing sounds had higher amplitude at 300 Hz and in addition, frequencies around the 400 are visible.

In Figure A. 12; a patient with wheezing sounds at expirium recorded over the right scapula of a 73 year old, 1.73 m height, 91 kg weight, and smoker's man are shown. Spectrum of wheezing sounds at expirium are seen above and frequency range are visible. In Figure A. 13; a patient with wheezing sounds were recorded over the right scapula of a 23 year old, 1.72 m height, 62kg weight, and quit smoking man.

In Figure A. 14; a patient with pneumonia were recorded over the right scapula of a 72 year old, 1.72 m height, 64 kg weight, and no smoker's man. In literature, frequency bands of pneumonia sounds are known as 300-600 Hz.

In Figure A. 15; a patient with pneumonia were recorded over the right scapula of a 34 year old, 1.76 m height, 80 kg weight, and no smoker's man. In this Figure A. range of pneumonia is more definite.

In Figure A. 16; a patient with hypersensitive pneumonia were recorded over the right scapula of a 66 year old, 1.61m height, 72 kg weight, and no smoker's woman. In subjects with hypersensitive pneumonia, majority of the power is found at 400 Hz.

In Figure A. 17; a patient with interstitial pulmonary fibrosis were recorded over the right scapula of a 59 year old, 1.49 m height, 35 kg weight, and no smoker's woman. Spectrum of intersiyel pulmonary fibrosis extends to 500 Hz.

In Figure A. 18; a patient with rhonchus were recorded over the right scapula of a 56 year old, 1.69 m height, 117 kg weight, and smoker's man. Majority of the power of this sound is found 150 Hz and quadratic majority of the power is found between 300 and 350 Hz.

In Figure A. 19; a patient with bilateral rhonchus were recorded over the right scapula of a 41 year old, 1.54 m height, 77 kg weight, and smoker's woman. A patient with rhonchus in lung, frequency of wheezing is same as in literature.

In Figure A. 20; a patient with bronchiectasis were recorded over the right scapula of a 66 year old, 1.57 m height, 65 kg weight, and no smoker's woman.

In Figure A. 21; a patient with romatoid artrit were recorded over the right scapula of a 49 year old, 1.67 m height, 66 kg weight, and quit smoking man.

In Figure A. 22; a patient with extended expirium sound were recorded over the right scapula of a 37 year old, 1.61 m height, 71 kg weight, and no smoker's woman.

Also R.A.L.E sounds are given in Appendix B. We obtained respiratory sound signals from internet web site "http://www.rale.ca" Recorded sounds are analyzed using FFT and STFT with hamming window.

In Figure B.1 R.A.L.E. Normal vesicular sounds were recorded over the left anterior upper chest of a 15 year old male adolescent

In Figure B.2, R.A.L.E. Tracheal sounds were recorded over the trachea of a healthy 26 year old man

In Figure B.3 R.A.L.E. Bronchial sounds were recorded over the right anterior upper chest of a 12 year old boy

In Figure B.4 R.A.L.E. Bronchovesicular sounds were recorded over the right posterior lower chest of a 2 day old baby girl.

In Figure B.5 R.A.L.E. Crackles sounds were recorded over the right posterior lower chest of a 9 year old boy with pneumonia.

In Figure B.6 R.A.L.E. Crackles and bronchial breathing were recorded posteriorly over the consolidated left lower lung of a 16 year old boy with tuberculosis.

In Figure B. 7 R.A.L.E. Late inspiratory fine crackles were recorded over the right posterior lower lung of a 55 year old woman with rheumatoid lung disease.

In Figure B.8 R.A.L.E. Grunting was recorded with a microphone in front of the mouth of a premature baby girl with respiratory distress 7 hours after birth.

In Figure B.9 R.A.L.E. Inspiratory squawk and crackles were recorded over the right posterior upper chest of a 78 year old woman with interstitial pulmonary fibrosis.

In Figure B.10 R.A.L.E. Stridor was recorded over the trachea of a 15 month old girl with croup.

In Figure B.11 R.A.L.E. Expiratory wheezing was recorded over the right anterior upper chest of an 8 year old boy with asthma. There is a slight frequency component between 400-500 Hz.

In Figure B.12 R.A.L.E. Wheezing and coarse crackles were recorded over the right posterior lower lung of an 8 month old boy with viral bronchiolitis. There is a powerful frequency component between 400-500 Hz

In Figure B.13 R.A.L.E. Wheezing over trachea and right lower lung was recorded from an 11-year old girl with acute asthma.

CONCLUSION

This thesis has presented a study on respiratory sound signal with using digital signal processing method. Respiratory diseases can rapidly be handle using signal processing tools and analyzed. The relation between disease and sound can be found in frequency domain. This can be accomplished by using FFT. In this thesis FFT is used for that reason. The figures obtained from sound recordings in University hospital are presented in Appendix A. But this is not enough, because some sound signals have time dependent frequencies. Therefore, STFT is the good approach for this case. But, this is not enough to understand whole signals during breathing cycle. Windowing is used to concentrate on the desired part of the signal .We used STFT with hamming window and presented in Appendix B. Our search and literature survey indicates that wheezing sound frequencies are about 400 Hz. Also pneumonia disease has frequency between 300 and 600 Hz. Therefore, other respiratory diseases also can be found in different frequency ranges. But, there are many difficulties affecting the analysis such as number of patient for each respiratory disease.

Clinicians will be able to use some packet and standard software program to get efficient and rapid diagnosis. However, it will be aimed to prepare user interfaced software in the future studies. This special software program will be used together with pneumotachometer measuring values and also may include database parts related to patient and diseases to get statistical information. After, each instrument and parts have international standard use; an auscultation device can be found as in standard packet to use easily by clinicians.

APPENDIX A

RESPIRATORY DISEASE SOUND GRAPHICS

Normal breath sound

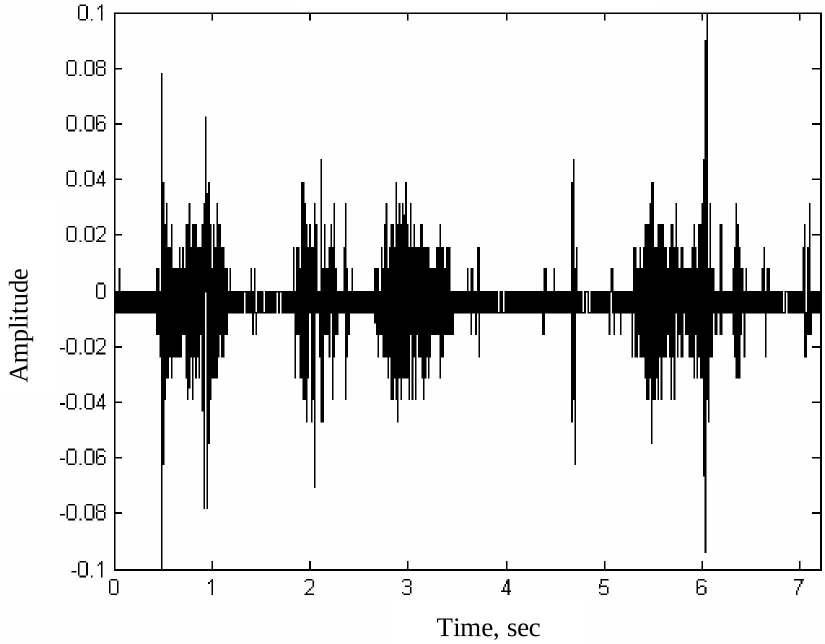


Figure A. 1a

Power spectrum density

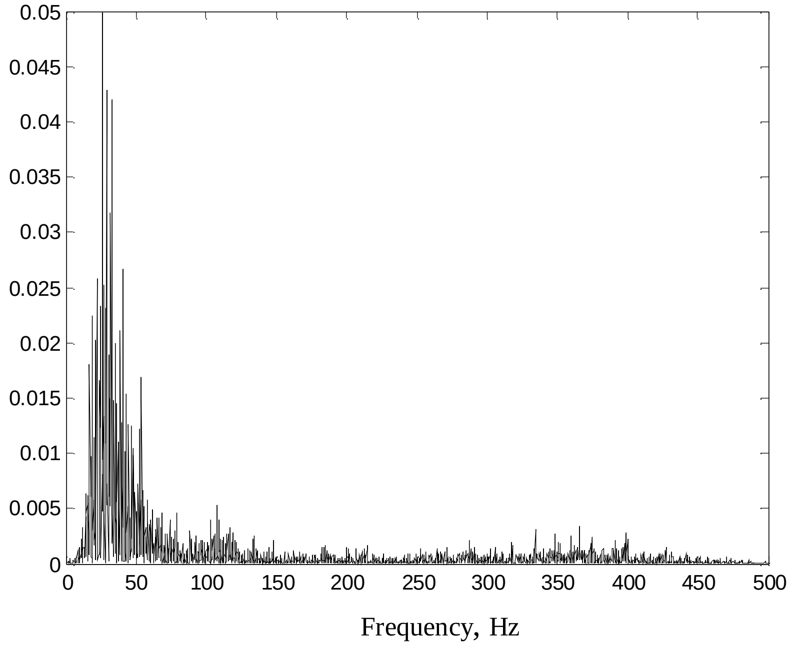


Figure A. 1b

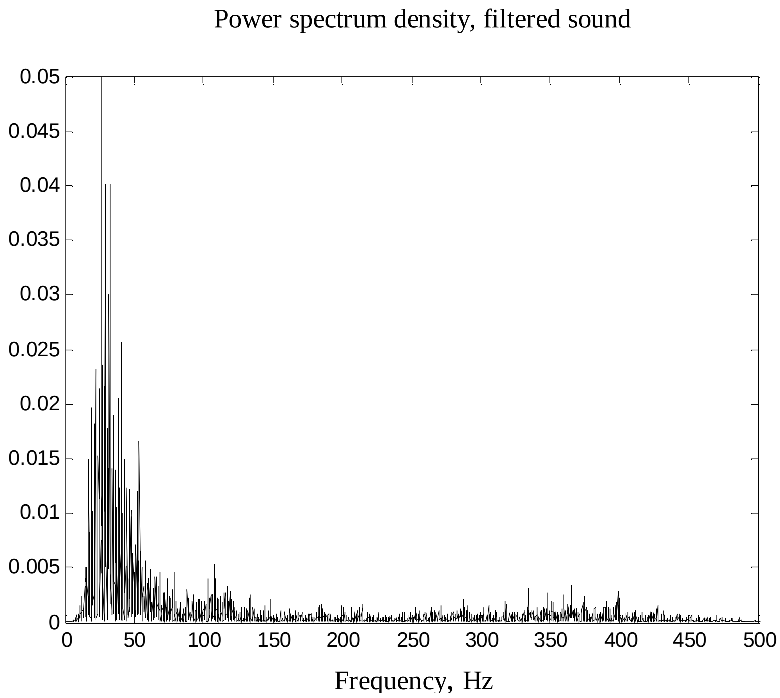


Figure A.1c

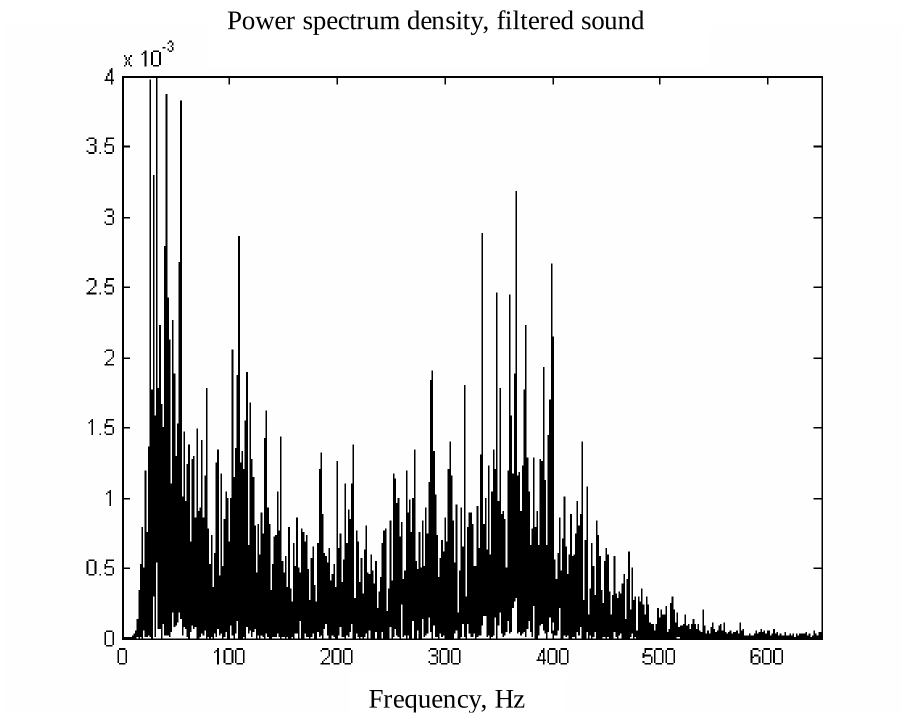


Figure A.1d

Figure A. 1. Normal breath sounds in time-domain signal (a) FFT's (b) filtered to remove DC offset and aliasing (c) and filtered to remove heart sound (d) FFT's.

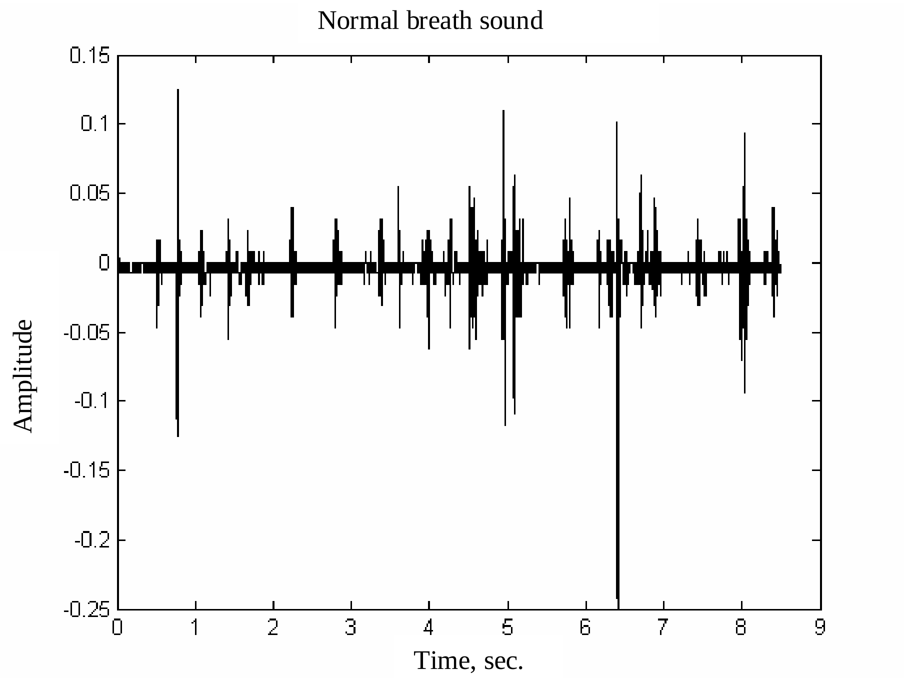


Figure A.2a

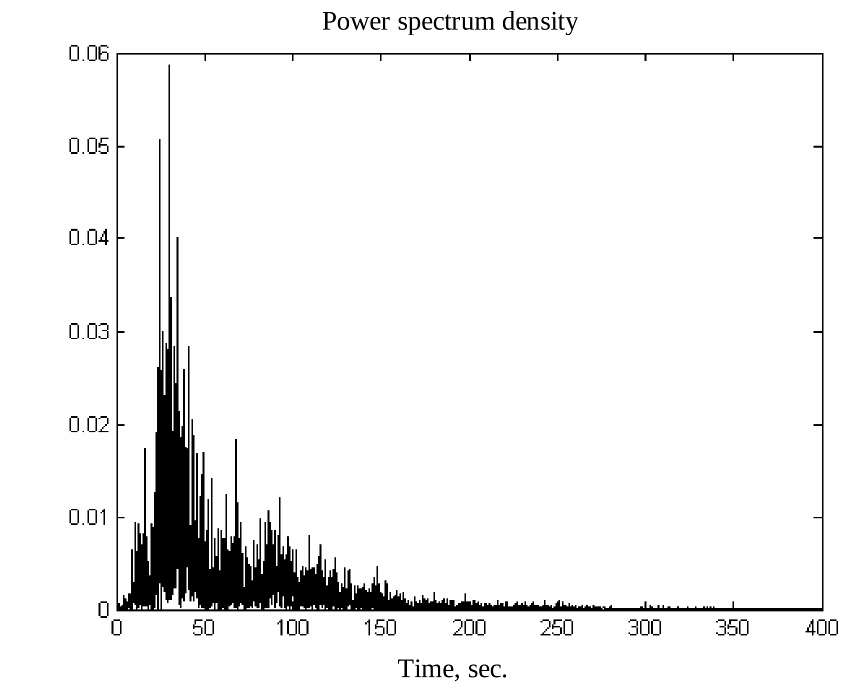


Figure A.2b

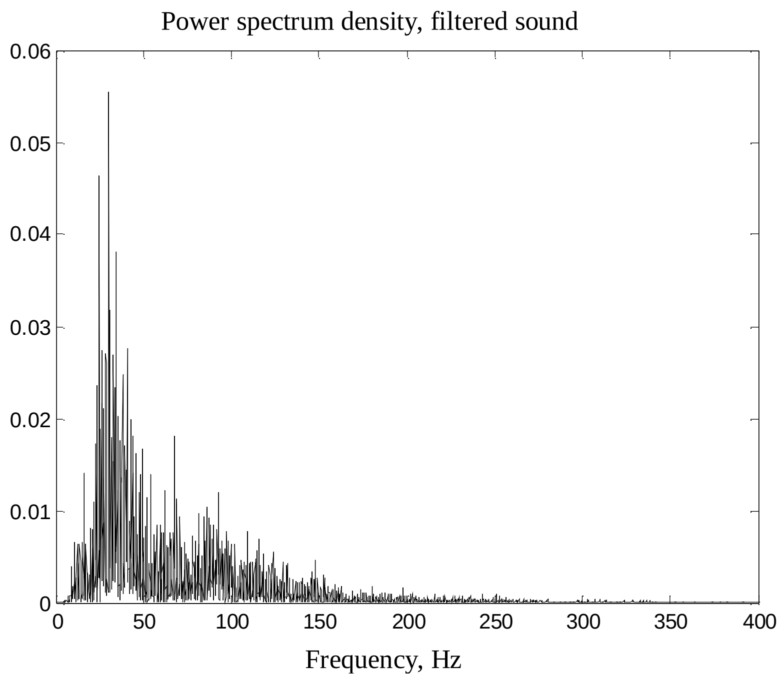


Figure A.2c

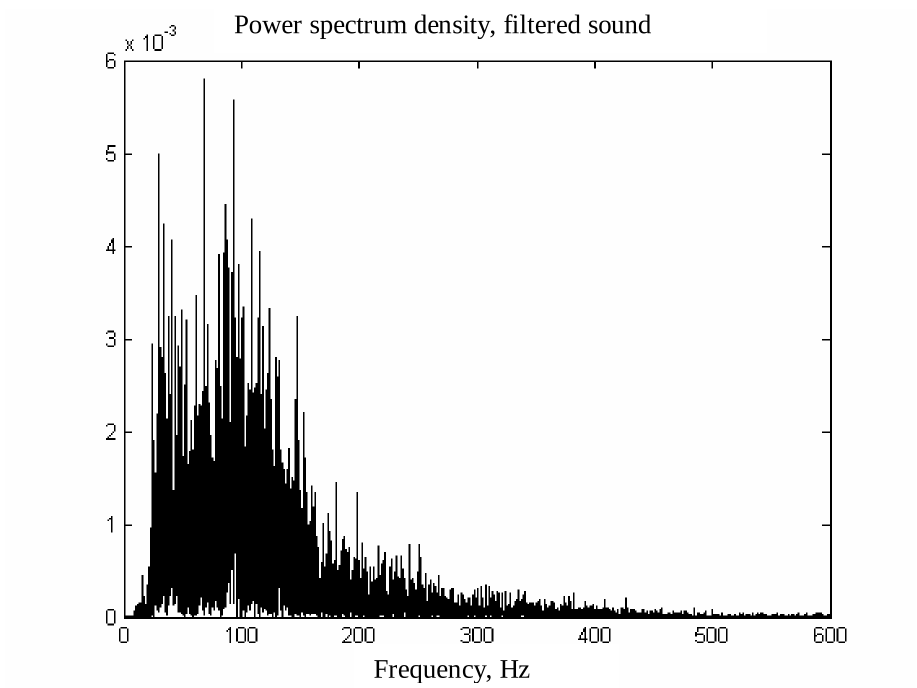


Figure A.2d

Figure A. 2. Normal breath sounds in time-domain signal (a) FFT's (b) filtered to remove DC offset and aliasing (c) and filtered to remove heart sound (d) FFT's.

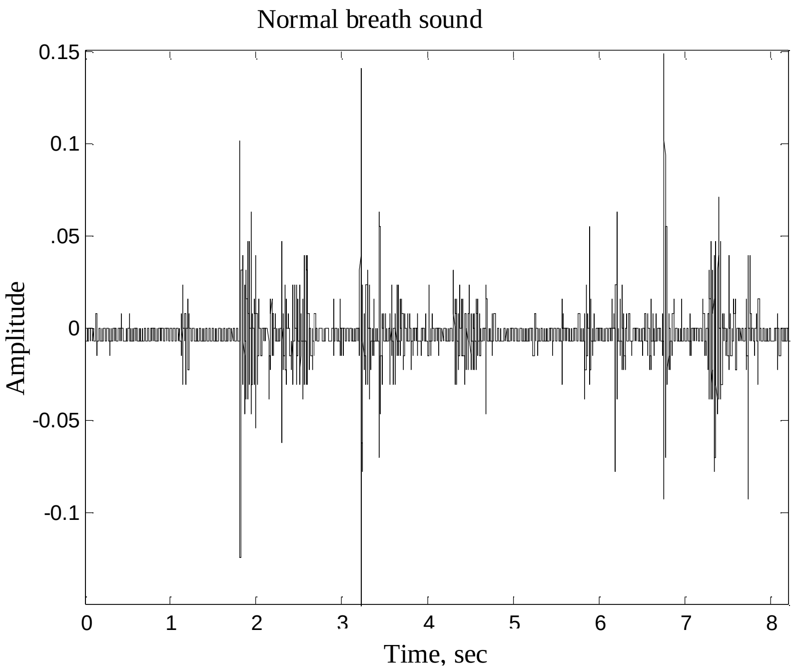


Figure A.3a

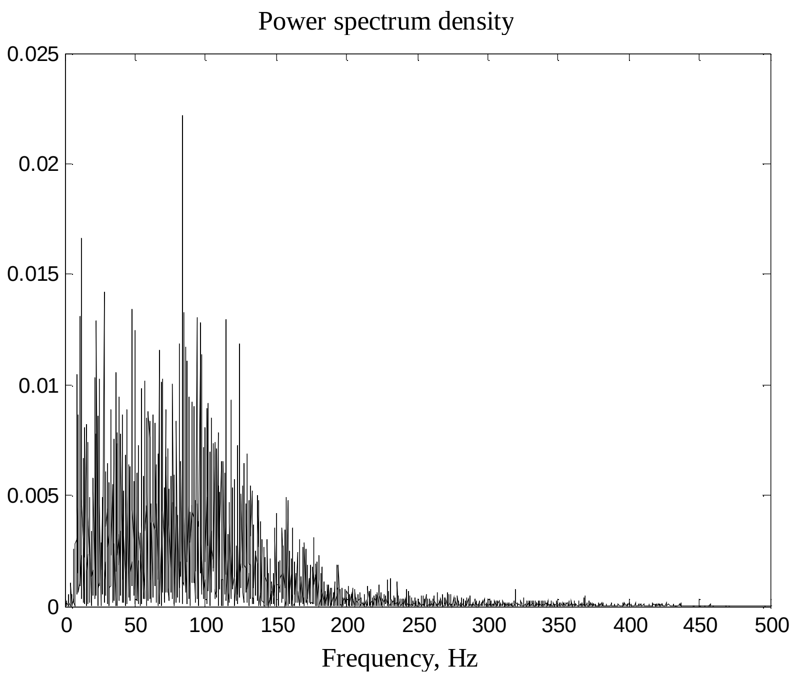


Figure A.3b

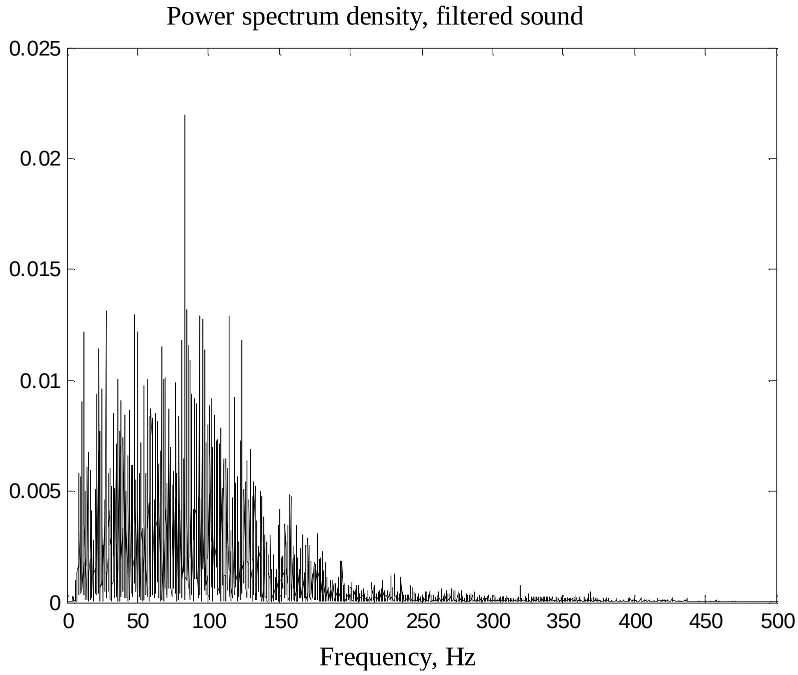


Figure A.3c

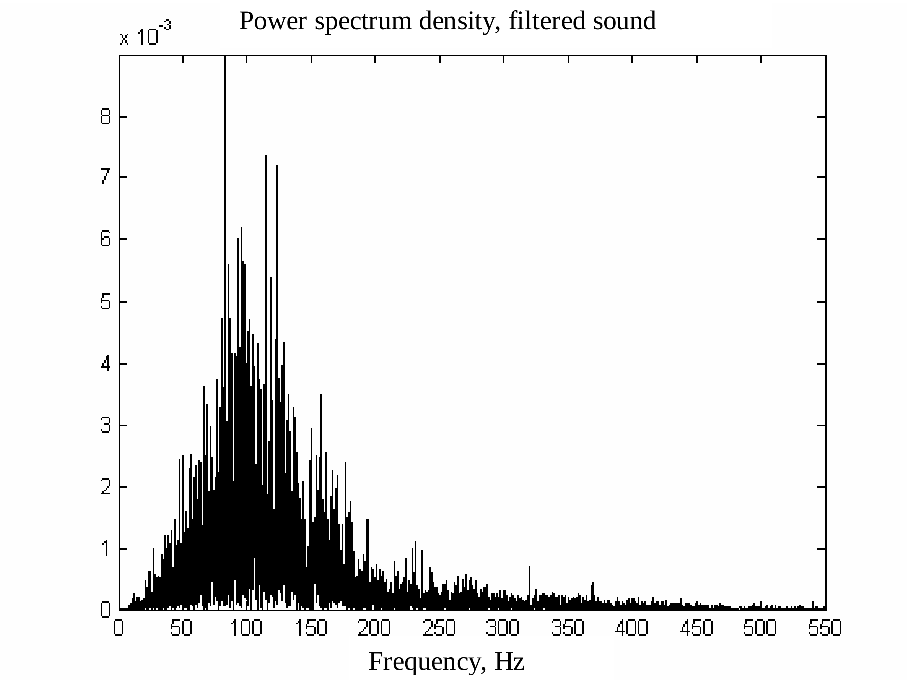


Figure A.3d

Figure A. 3. Normal breath sounds in time-domain signal (a) FFT's (b) filtered to remove DC offset and aliasing (c) and filtered to remove heart sound (d) FFT's.

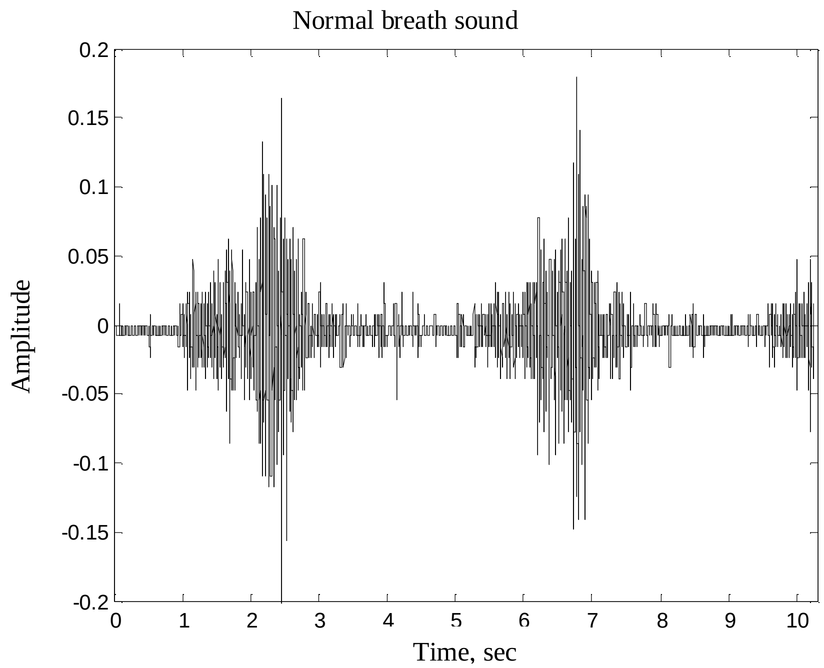


Figure A.4a

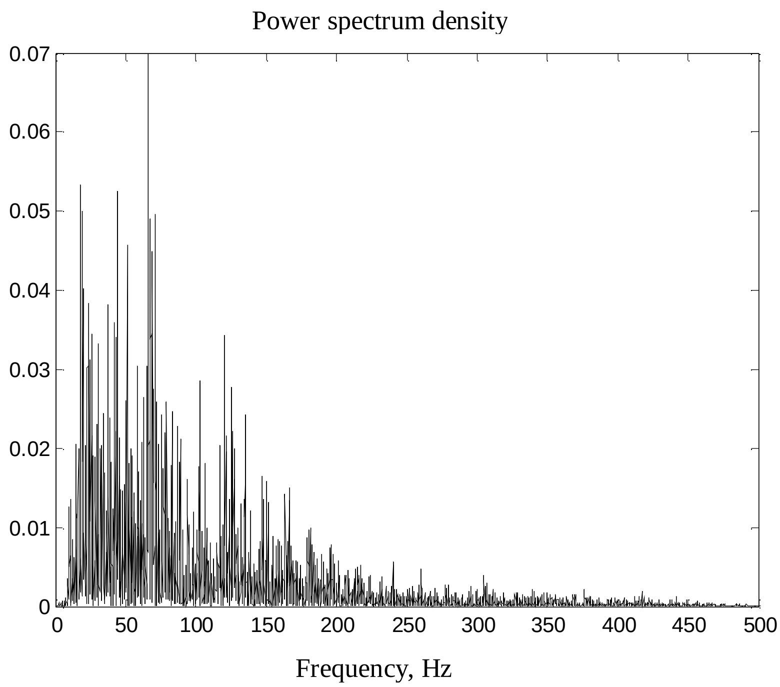


Figure A.4b

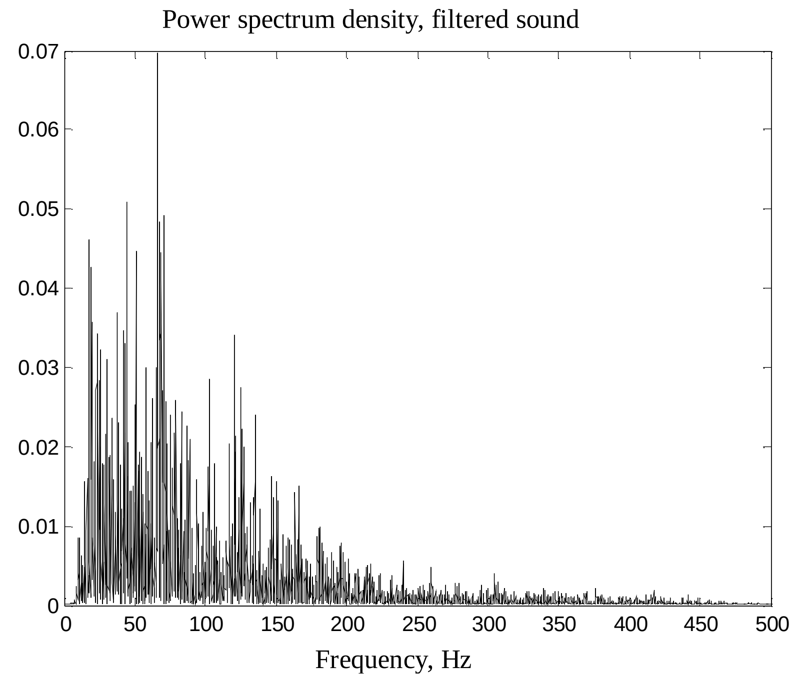


Figure A.4c

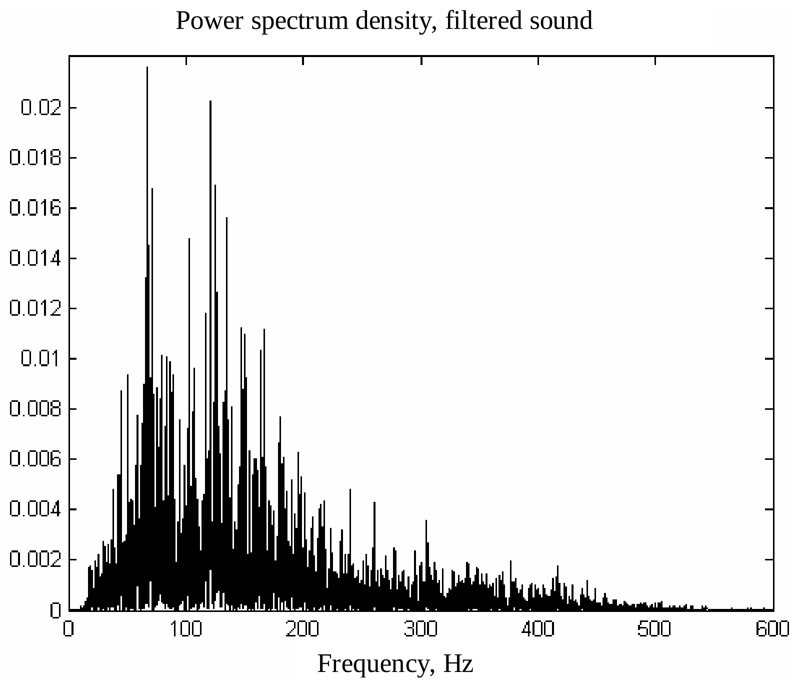


Figure A.4d

Figure A. 4. Normal breath sounds in time-domain signal (a) FFT's (b) filtered to remove DC offset and aliasing (c) and filtered to remove heart sound (d) FFT's.

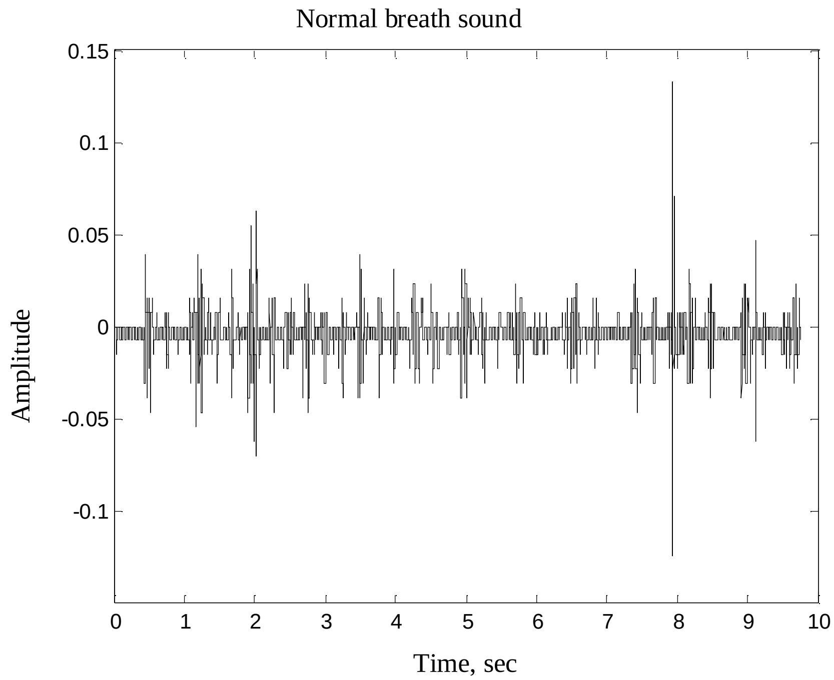


Figure A.5a

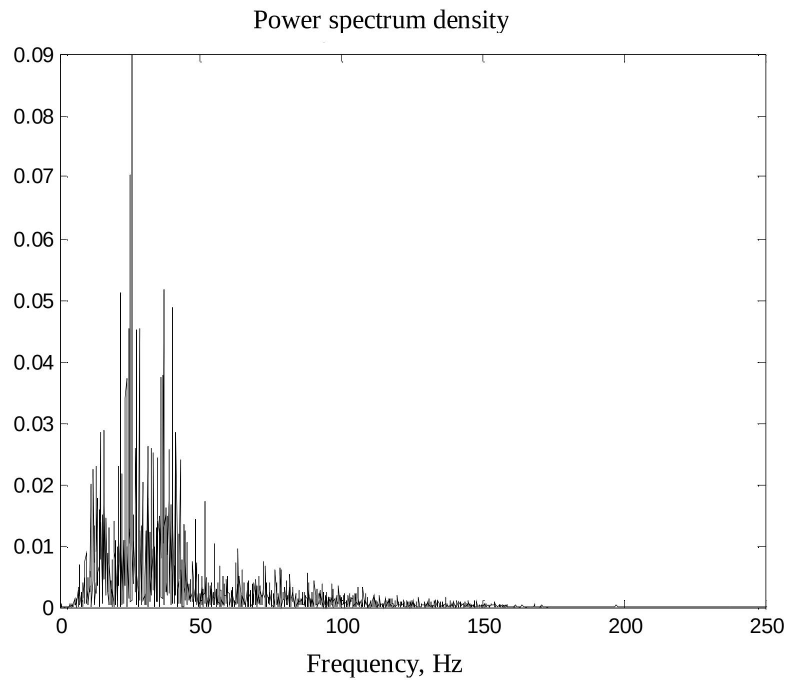


Figure A.5b

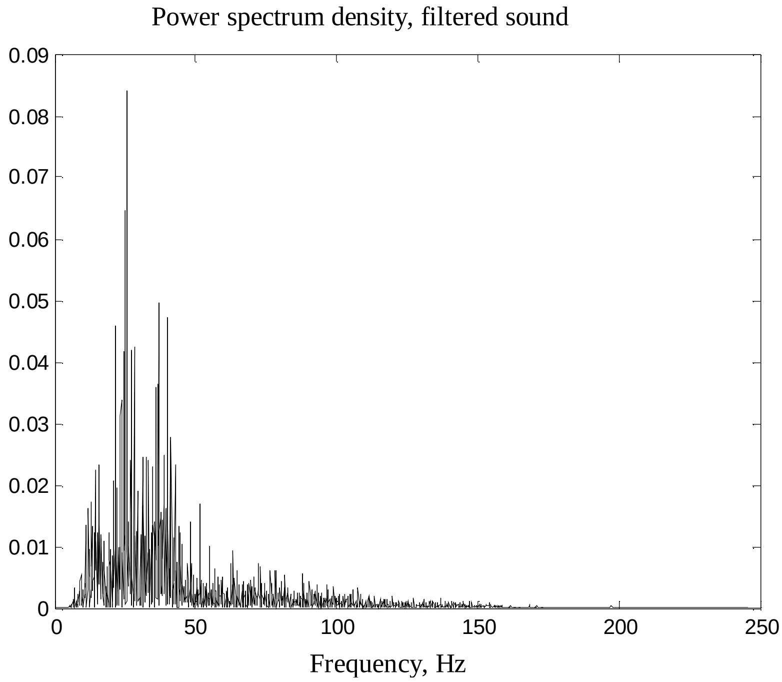


Figure A.5 c

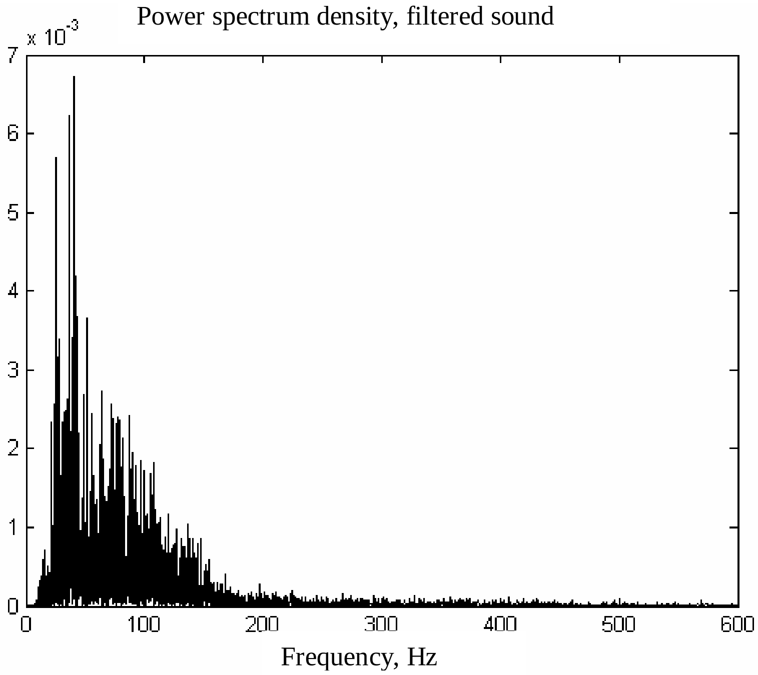


Figure A.5d

Figure A. 5. Normal breath sounds in time-domain signal (a) FFT's (b) filtered to remove DC offset and aliasing (c) and filtered to remove heart sound (d) FFT's.

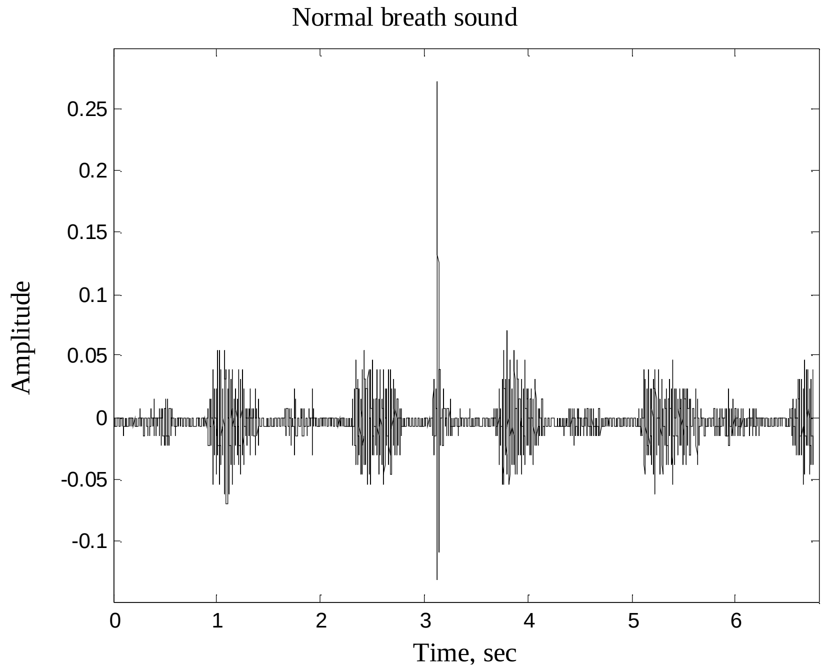


Figure A.6a

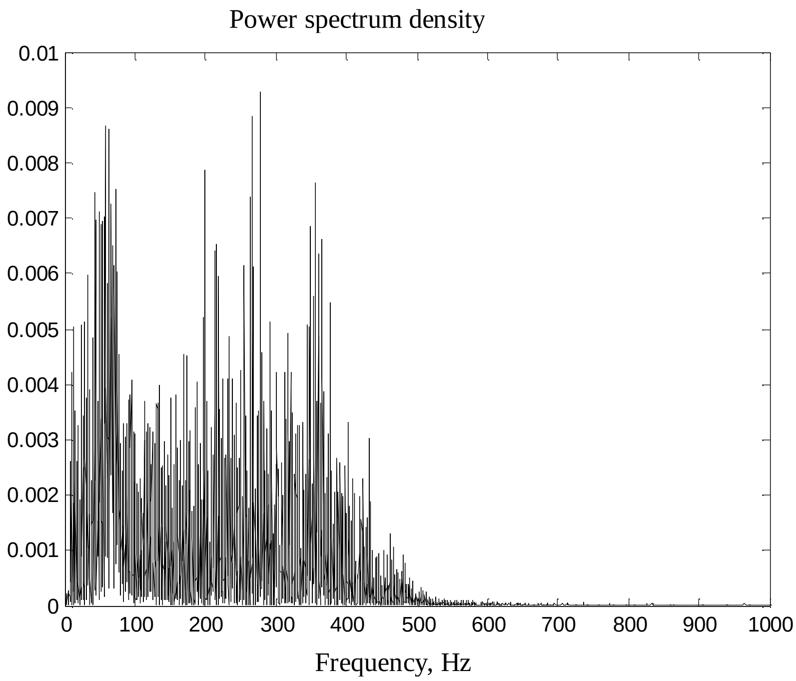


Figure A.6b

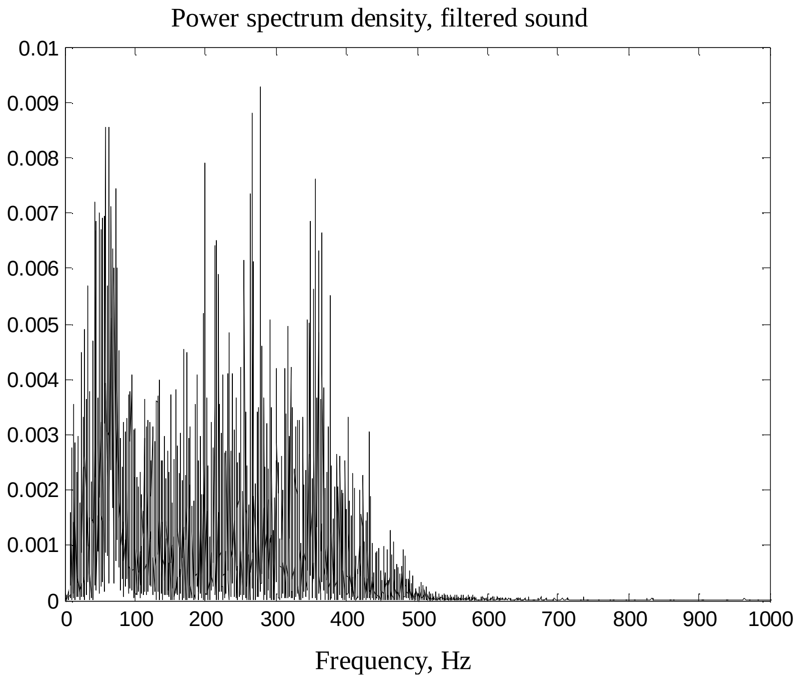


Figure A.6c

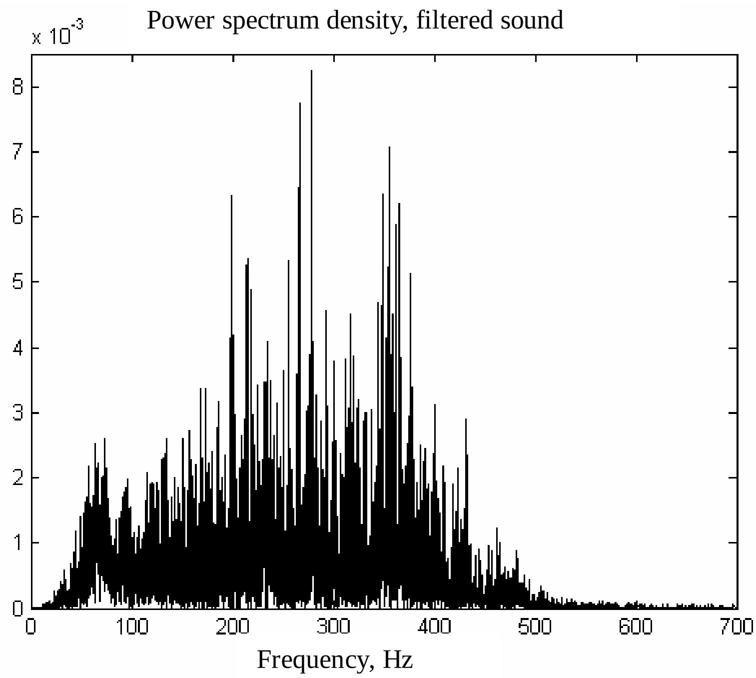


Figure A.6d

Figure A. 6. Normal breath sounds in time-domain signal (a) FFT's (b) filtered to remove DC offset and aliasing (c) and filtered to remove heart sound (d) FFT's.

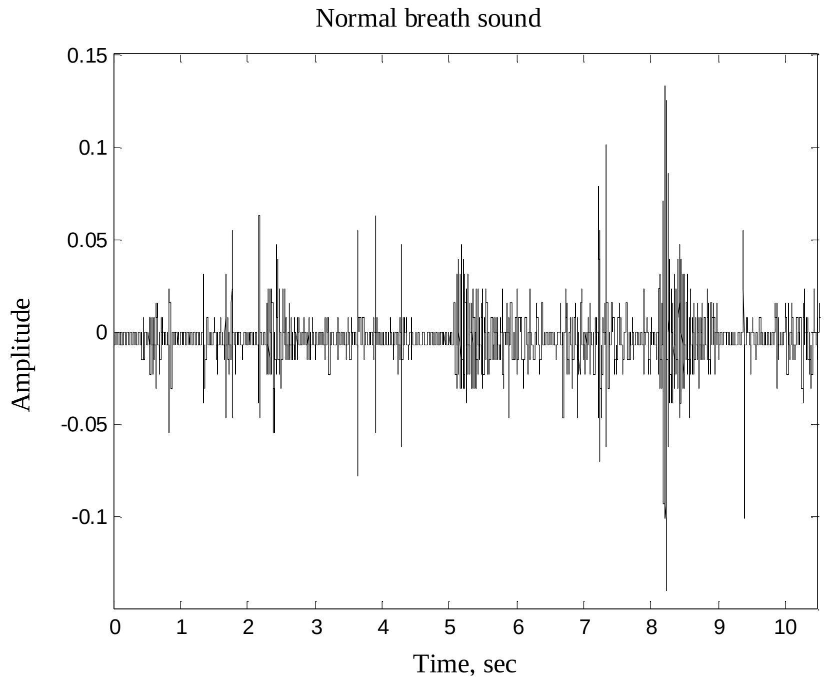


Figure A.7a

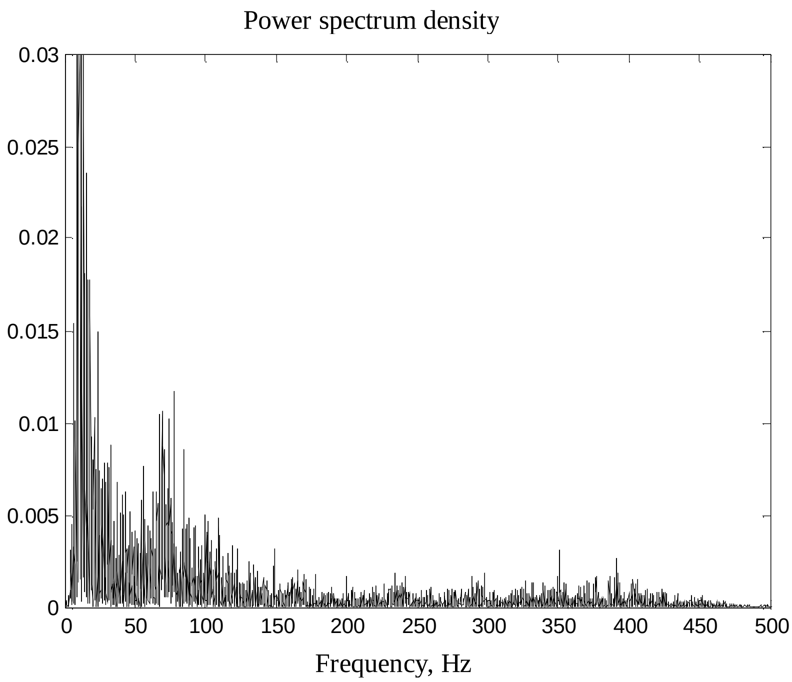


Figure A.7b

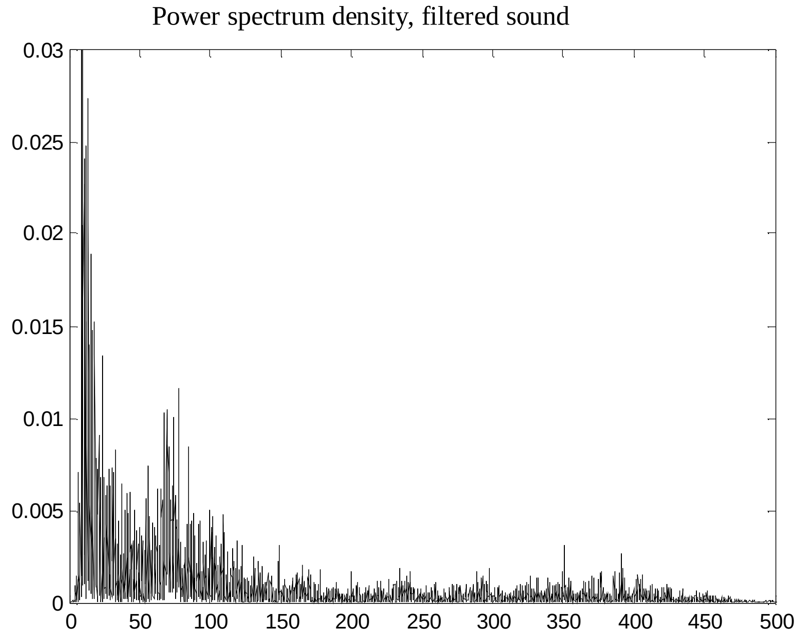


Figure A.7c

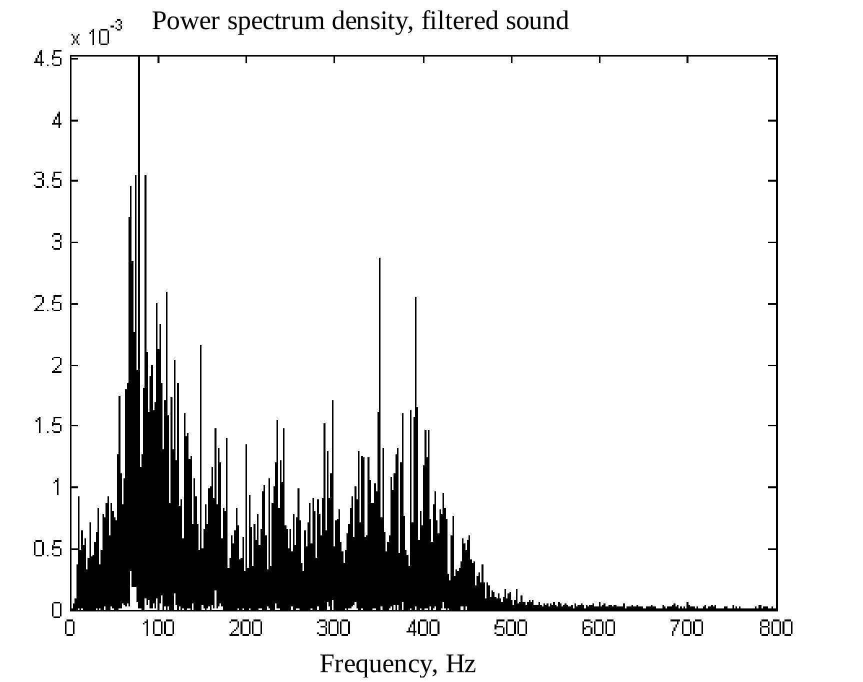


Figure A.7d

Figure A. 7. Normal breath sounds in time-domain signal (a) FFT's (b) filtered to remove DC offset and aliasing (c) and filtered to remove heart sound (d) FFT's.

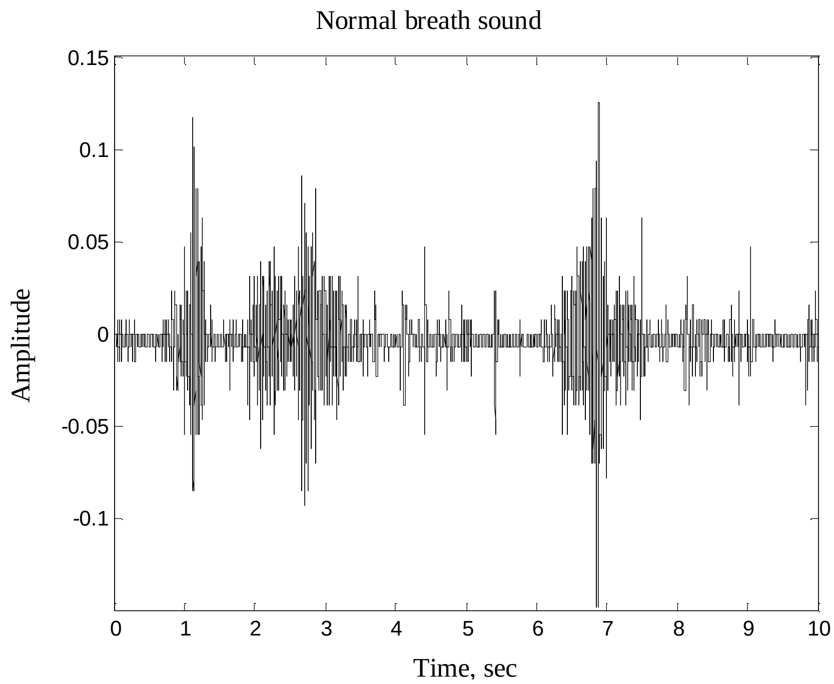


Figure A.8a

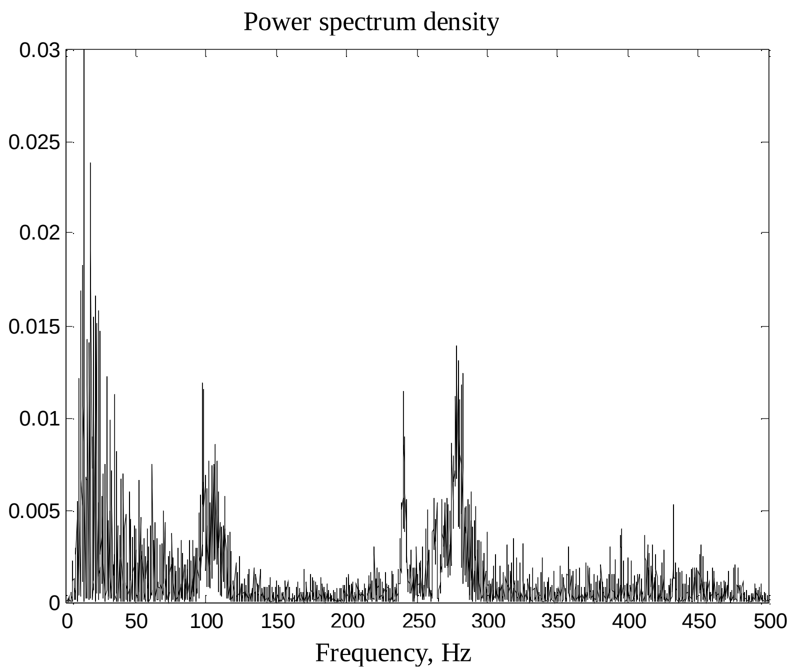


Figure A.8b

Power spectrum density, filtered sound

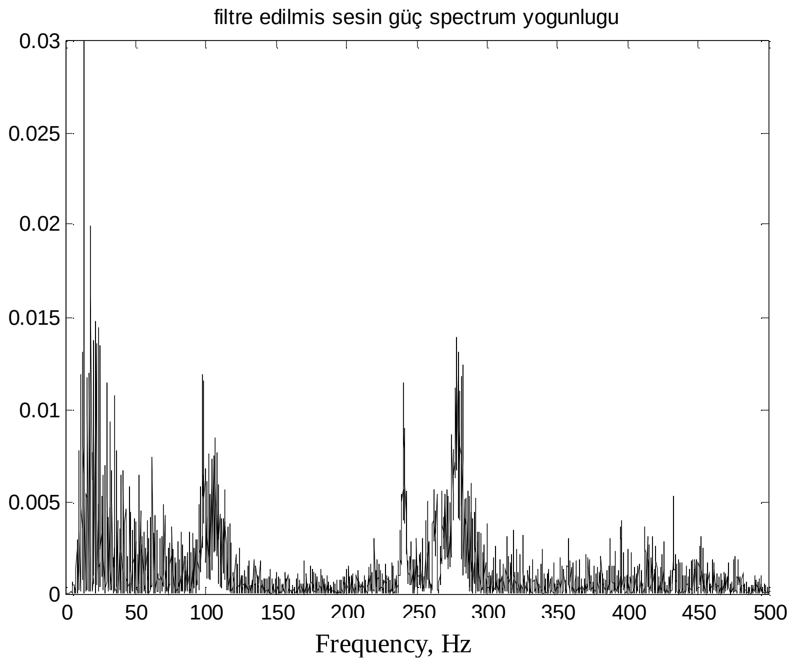


Figure A.8c

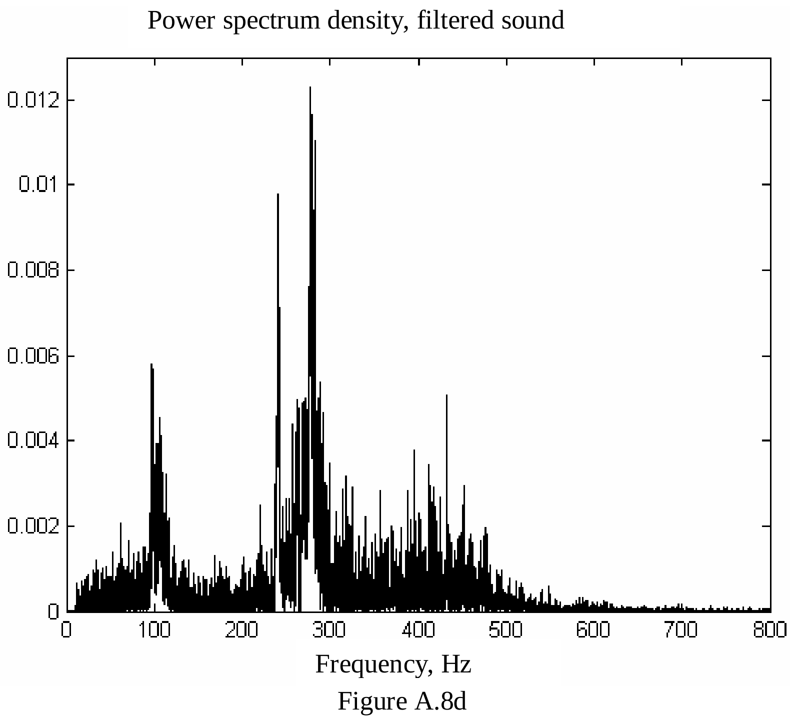


Figure A.8d

Figure A. 8. Normal breath sounds in time-domain signal (a) FFT's (b) filtered to remove DC offset and aliasing (c) and filtered to remove heart sound (d) FFT's.

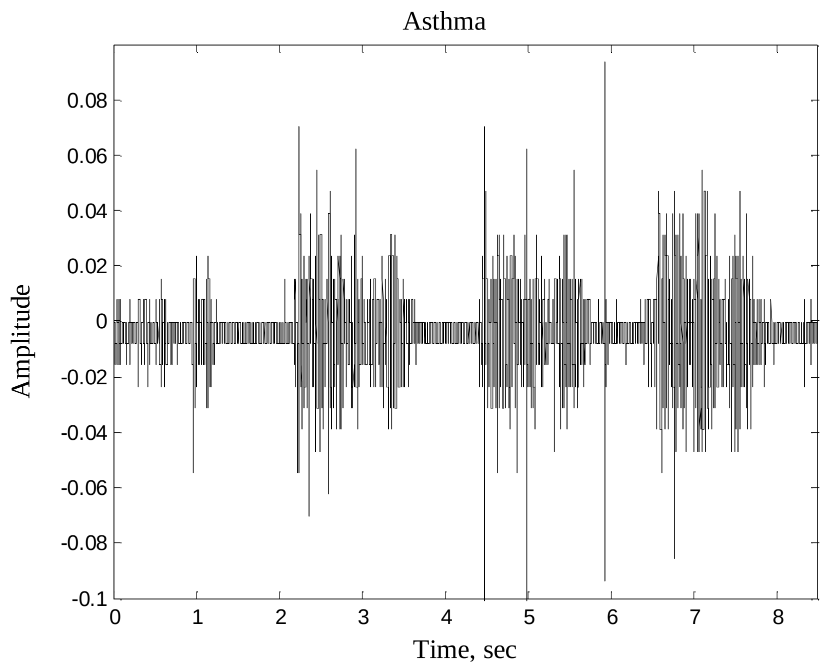


Figure A.9a

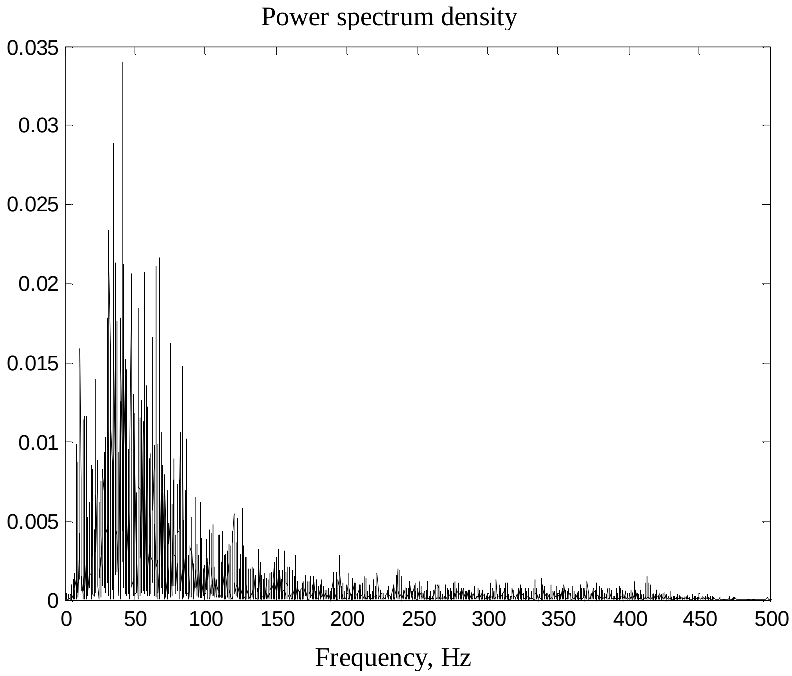


Figure A.9b

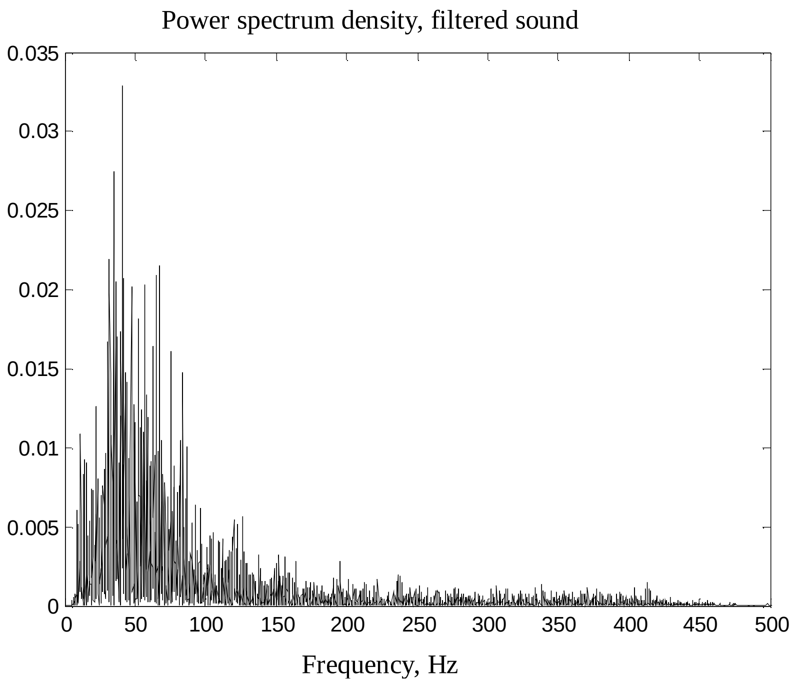


Figure A.9c

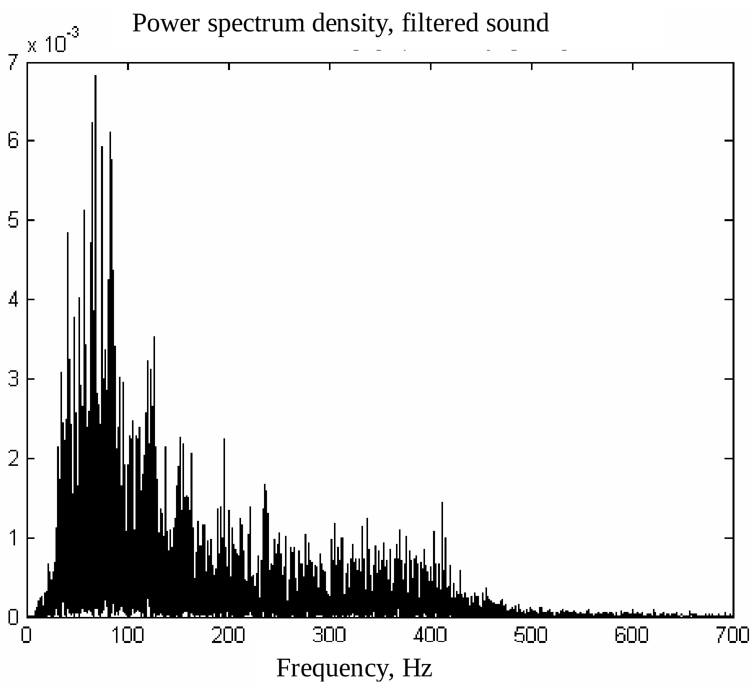


Figure A.9d

Figure A. 9. A patient with asthma in time-domain signal (a) FFT's (b) filtered to remove DC offset and aliasing (c) and filtered to remove heart sound (d) FFT's.

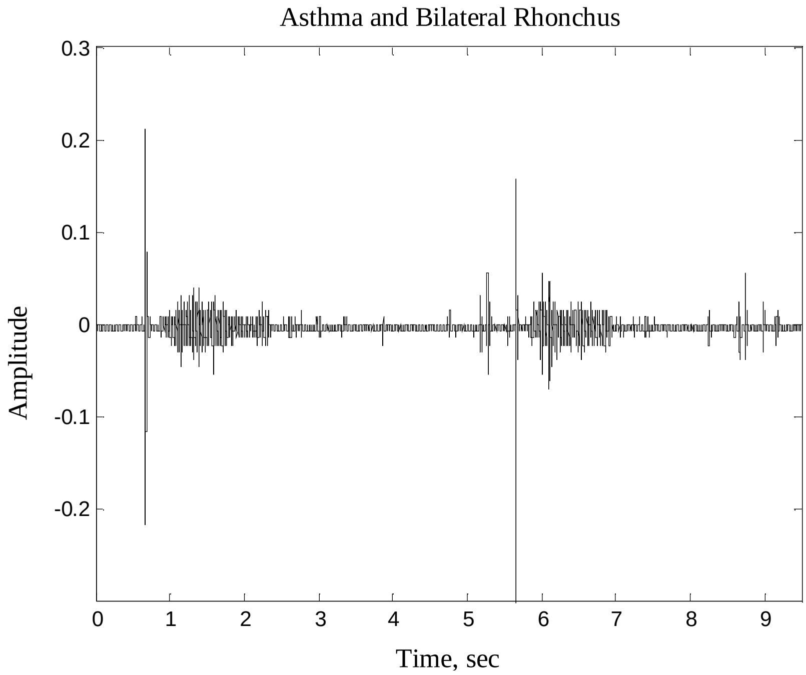


Figure A.10a

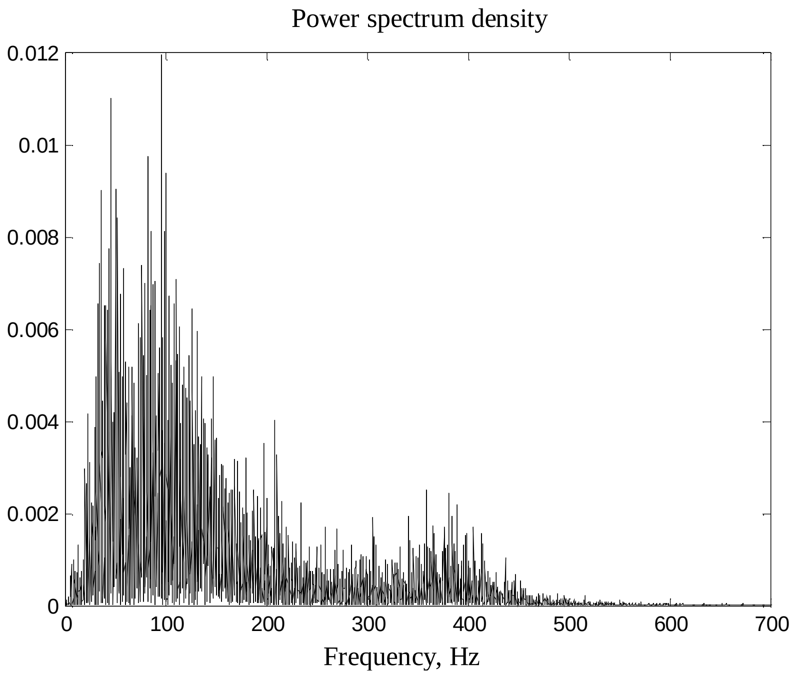


Figure A.10b

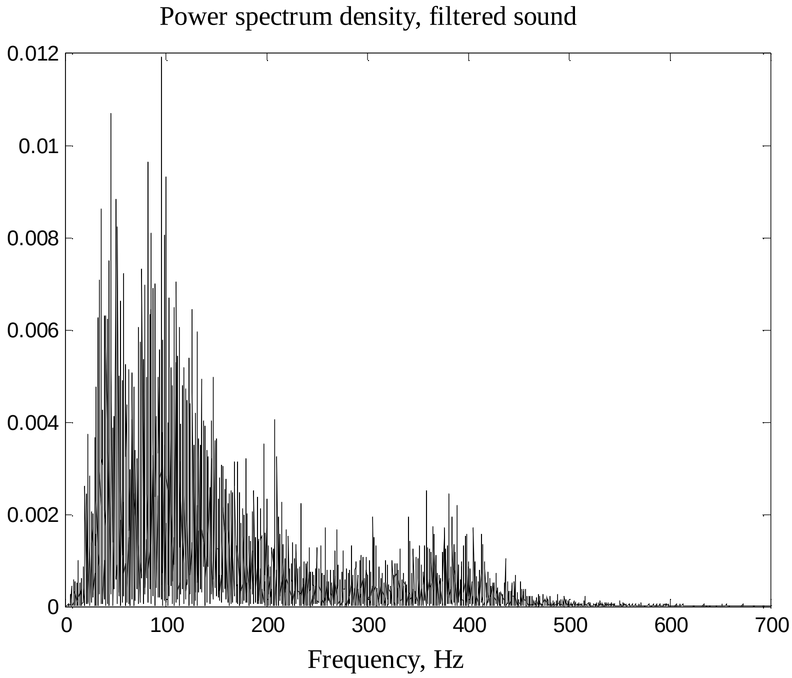


Figure A.10c

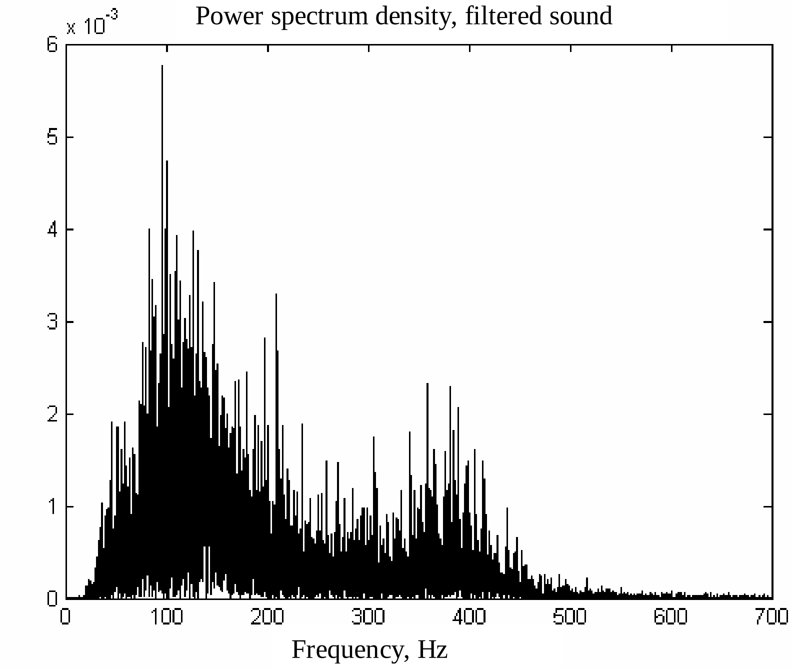


Figure A.10d

Figure A. 10. A patient with asthma and bilateral rhonchus in time-domain signal (a) FFT's (b) filtered to remove DC offset and aliasing (c) and filtered to remove heart sound (d) FFT's.

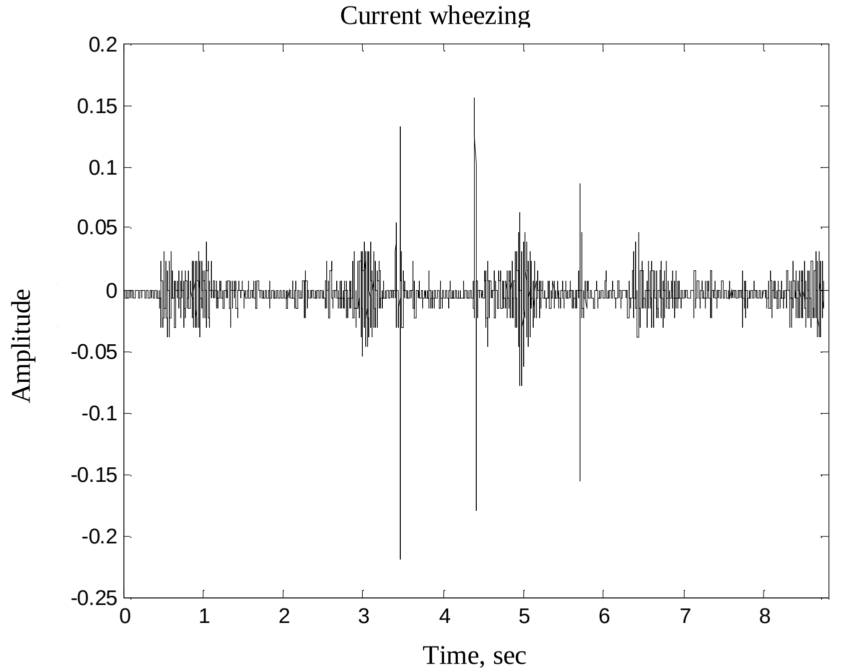


Figure A.11a

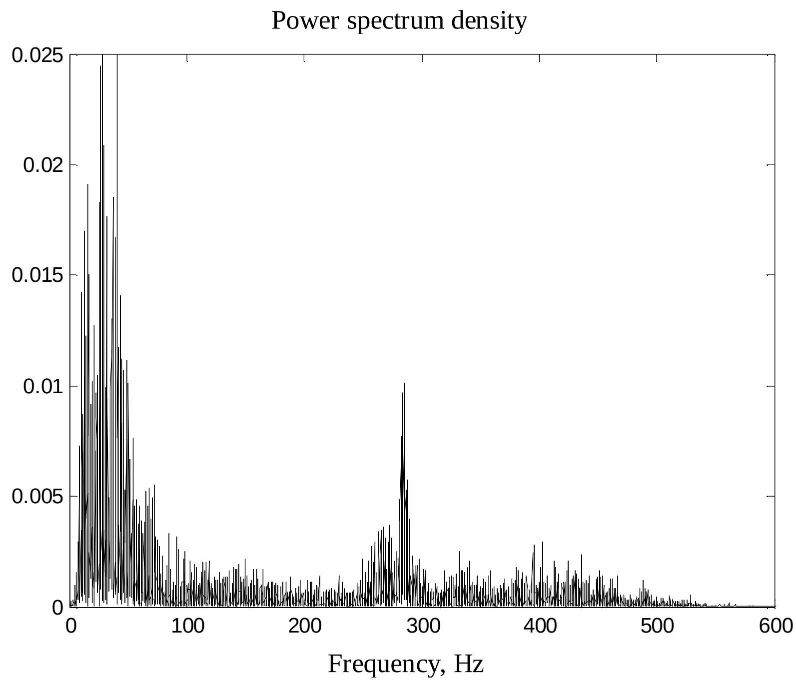


Figure A.11b

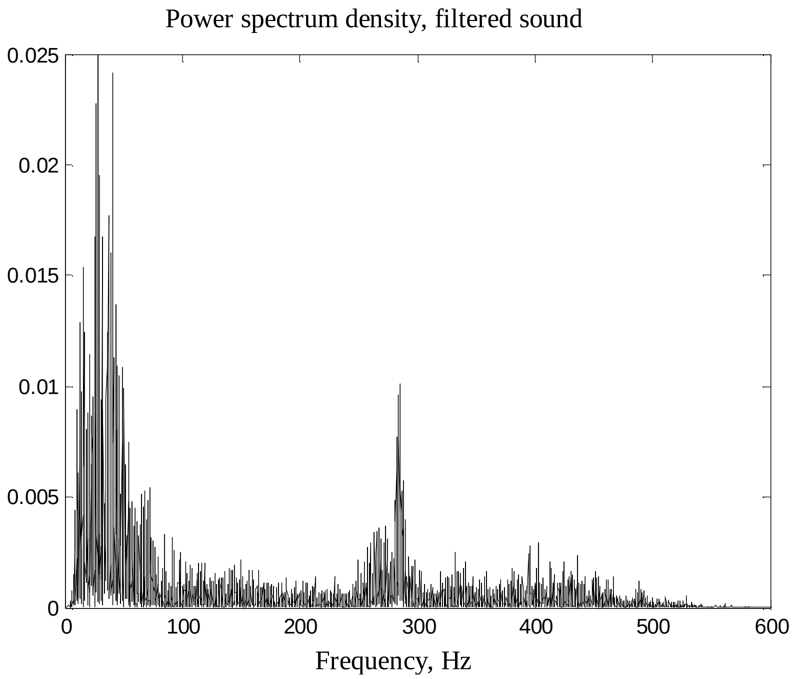


Figure A.11c

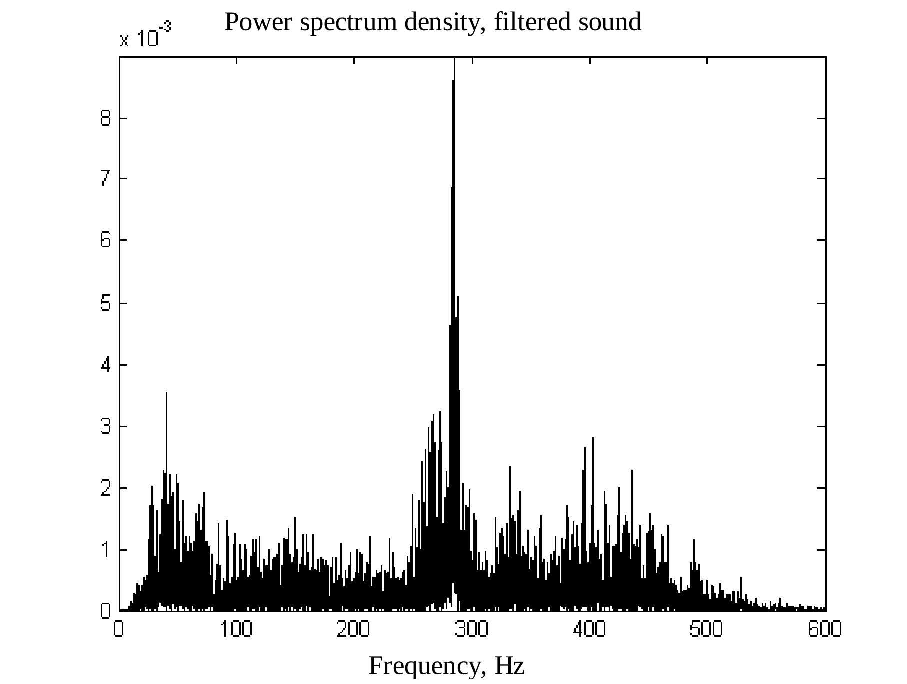


Figure A.11d

Figure A. 11. Current wheezing sound in time-domain signal (a) FFT's (b) filtered to remove DC offset and aliasing (c) and filtered to remove heart sound (d) FFT's.

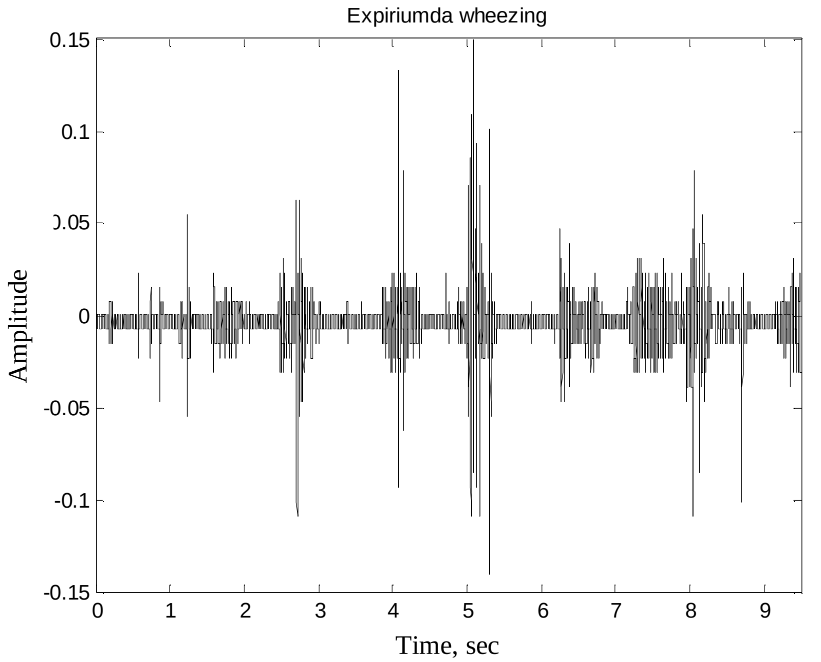


Figure A.12a

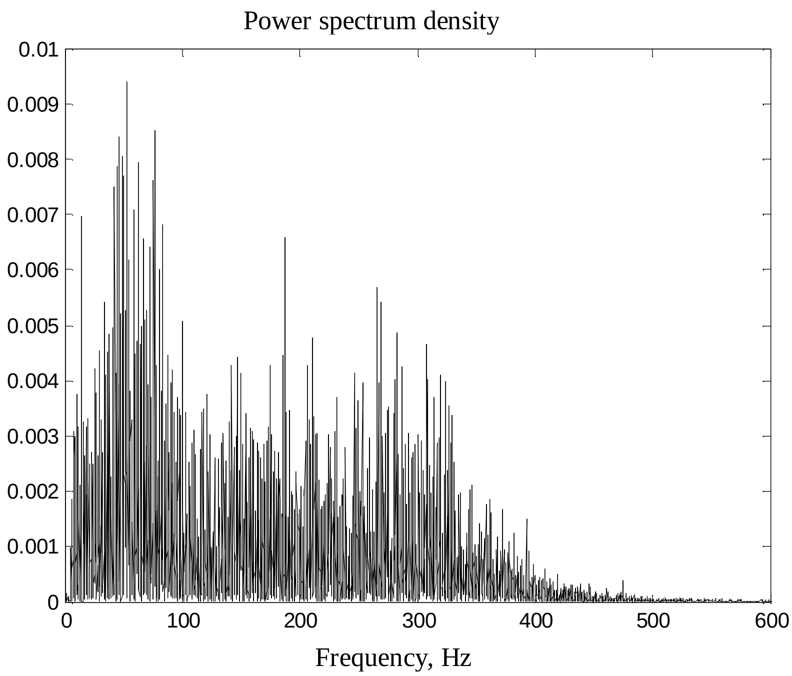


Figure A.12b

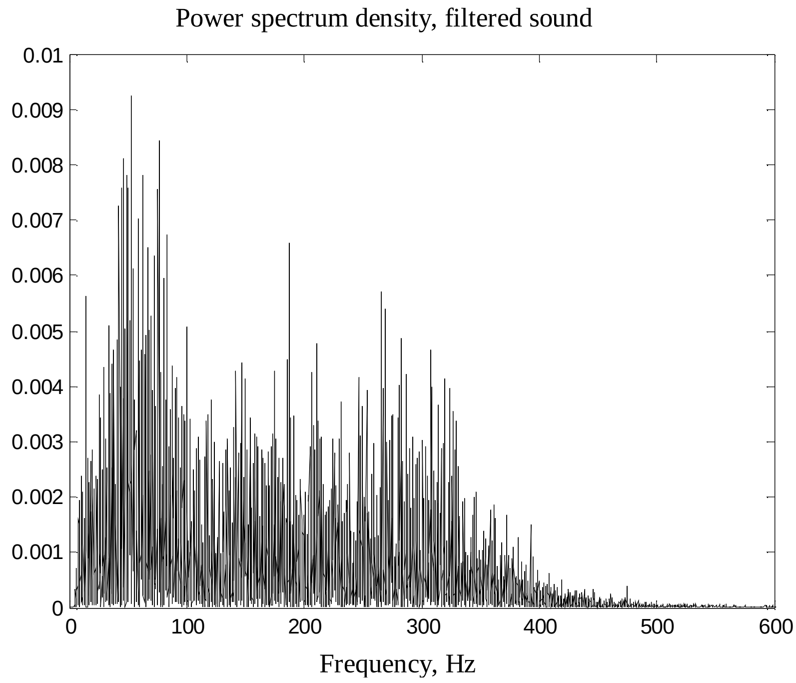


Figure A.12c

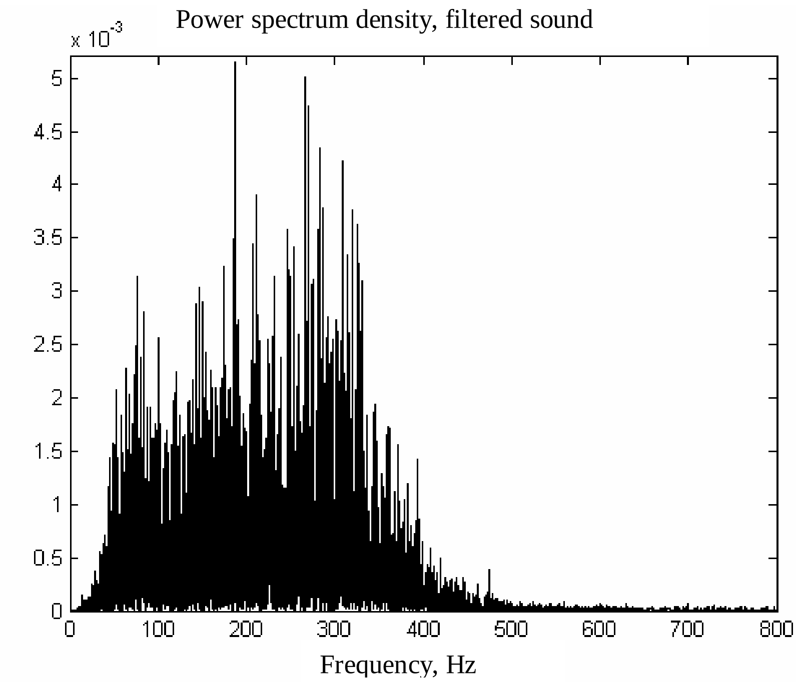


Figure A.12d

Figure A. 12. Wheezing sound at expirium in time-domain signal (a) FFT's (b) filtered to remove DC offset and aliasing (c) and filtered to remove heart sound (d) FFT's.

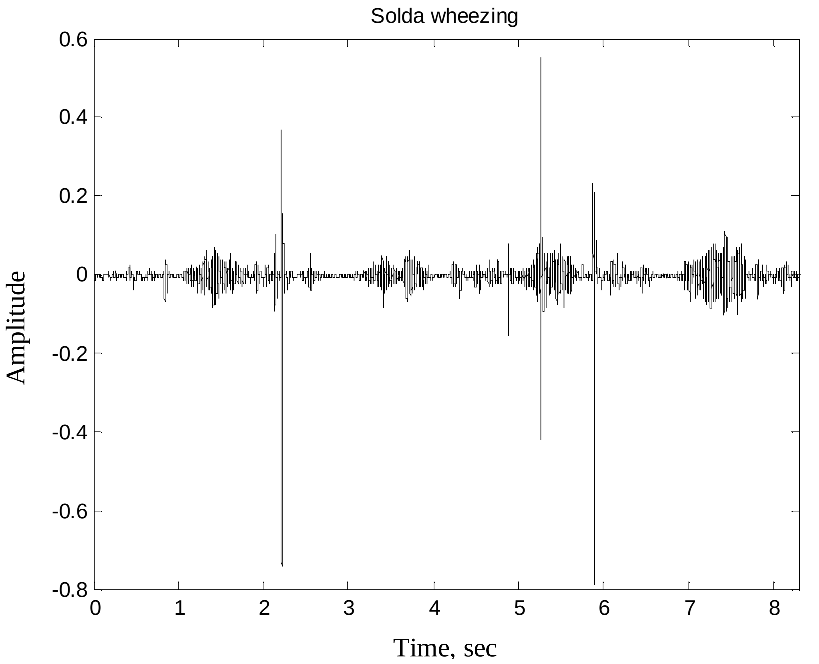


Figure A.13a

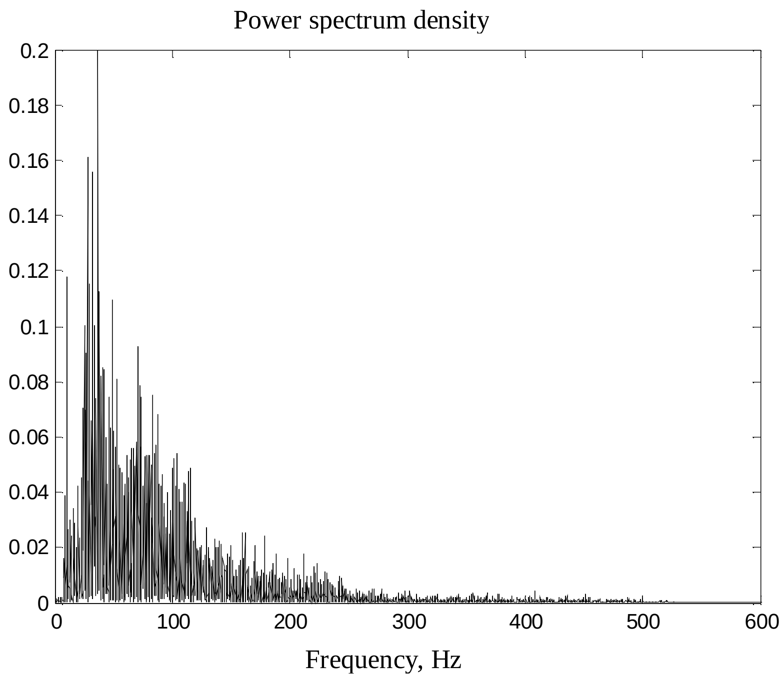


Figure A.13b

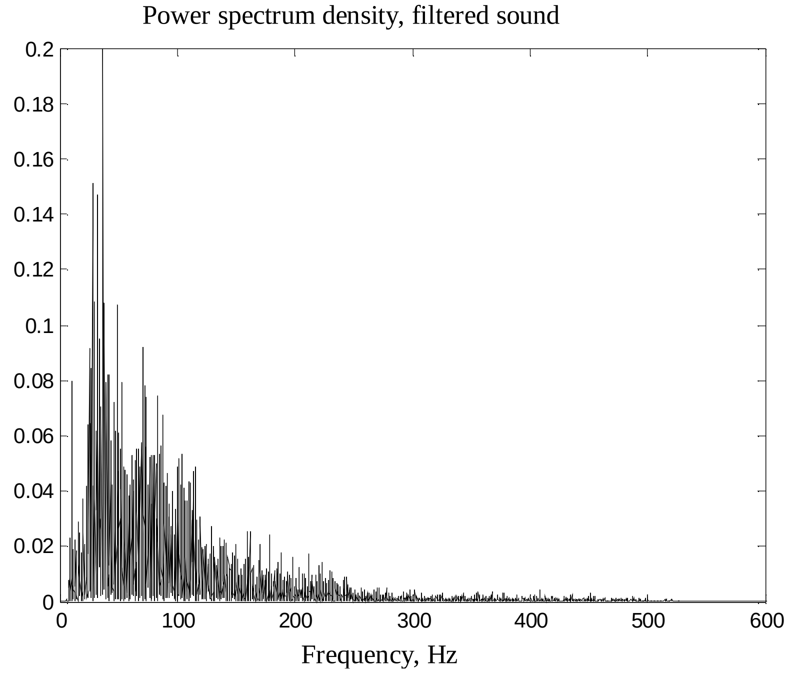


Figure A.13c

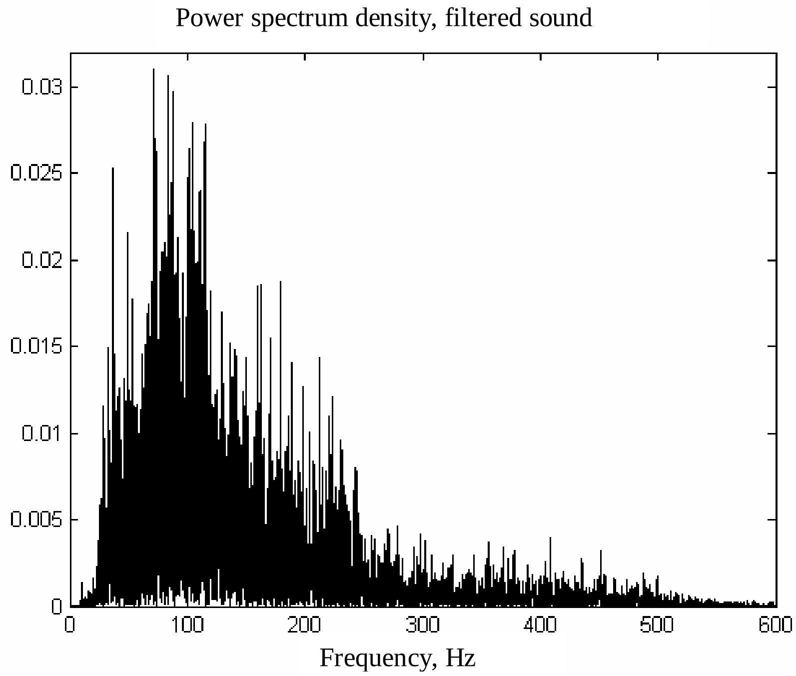


Figure A.13d

Figure A. 13. Wheezing sound in time-domain signal (a) FFT's (b) filtered to remove DC offset and aliasing (c) and filtered to remove heart sound (d) FFT's.

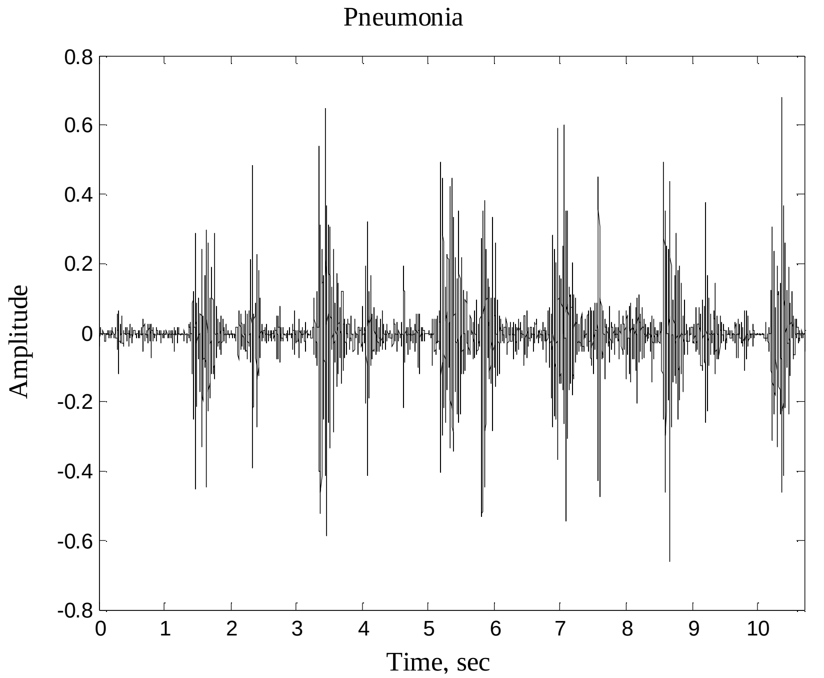


Figure A.14a

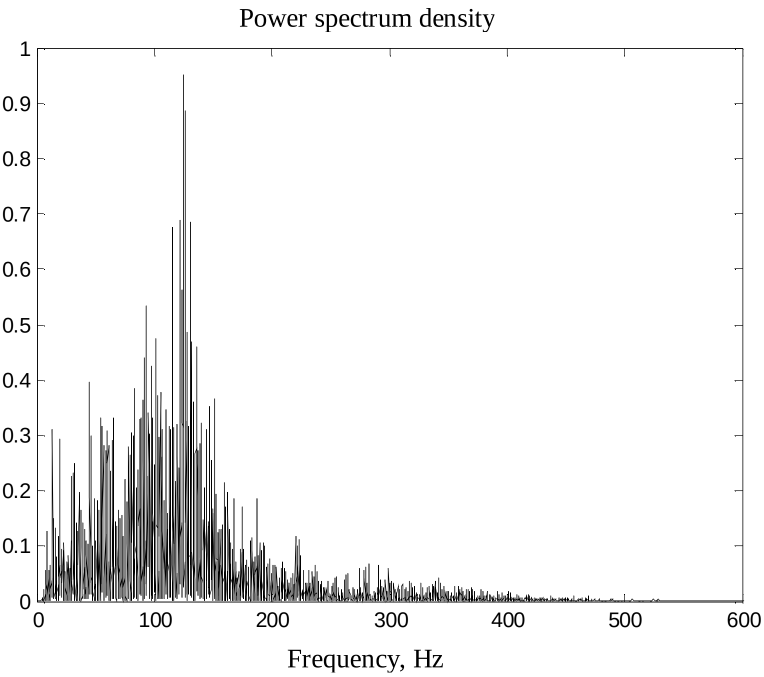


Figure A.14b

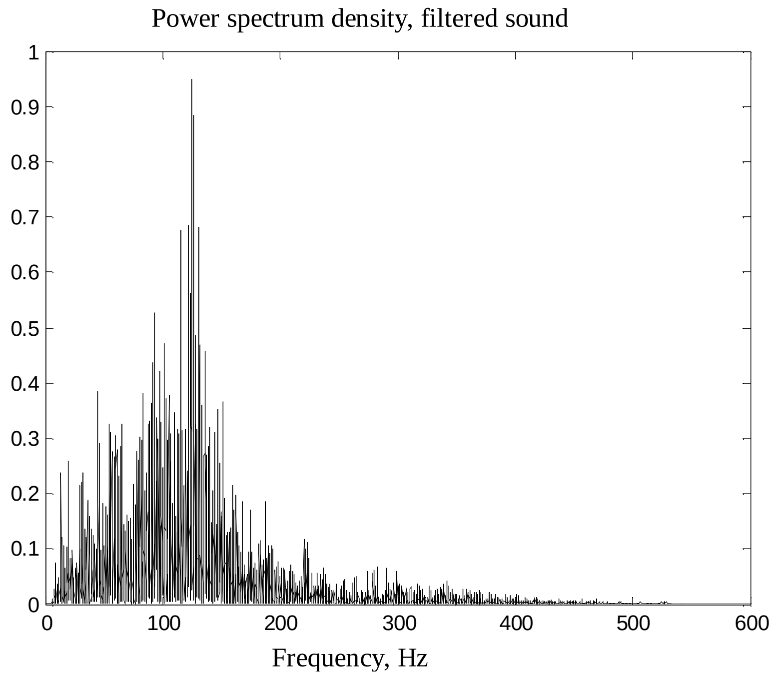


Figure A.14c

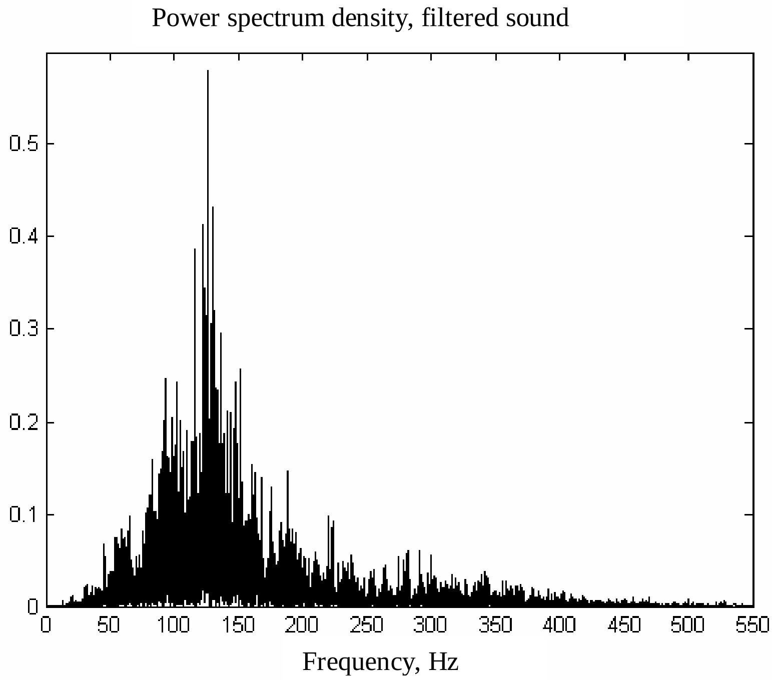


Figure A.14d

Figure A. 14. Pneumonia sound in time-domain signal (a) FFT's (b) filtered to remove DC offset and aliasing (c) and filtered to remove heart sound (d) FFT's.

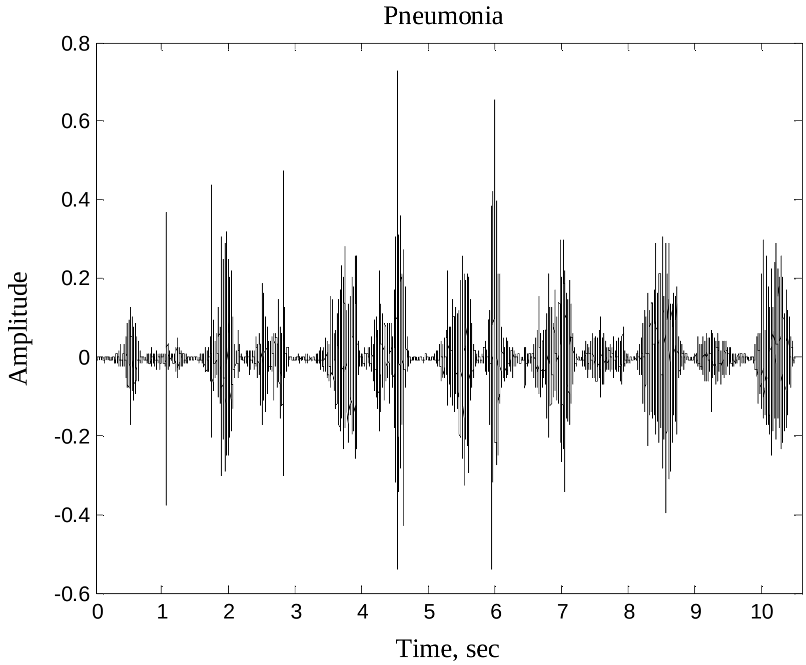


Figure A.15a

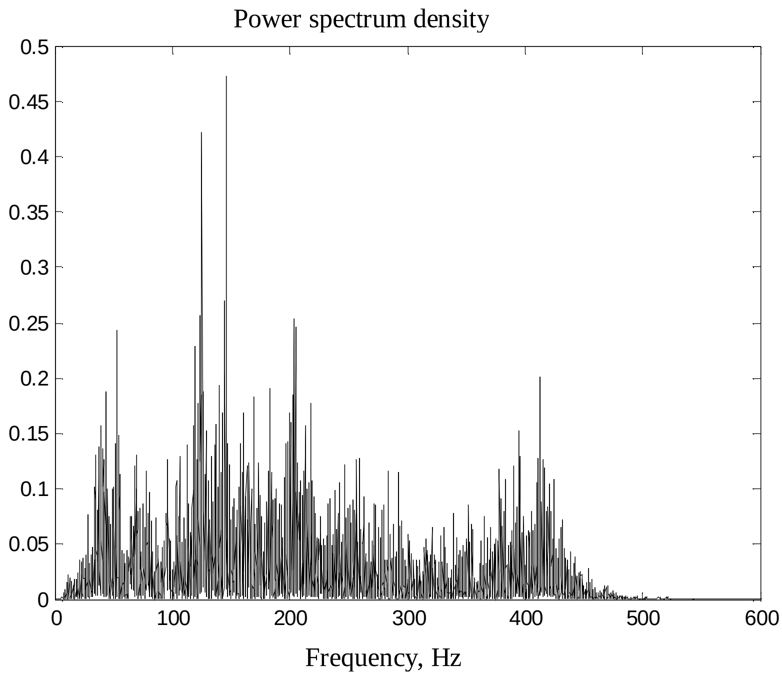


Figure A.15b

Power spectrum density, filtered sound

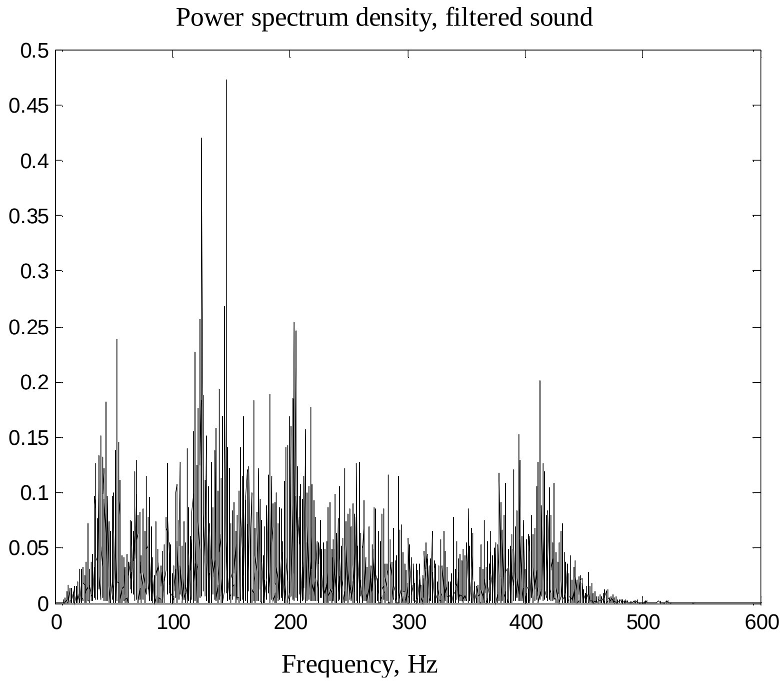


Figure A.15c

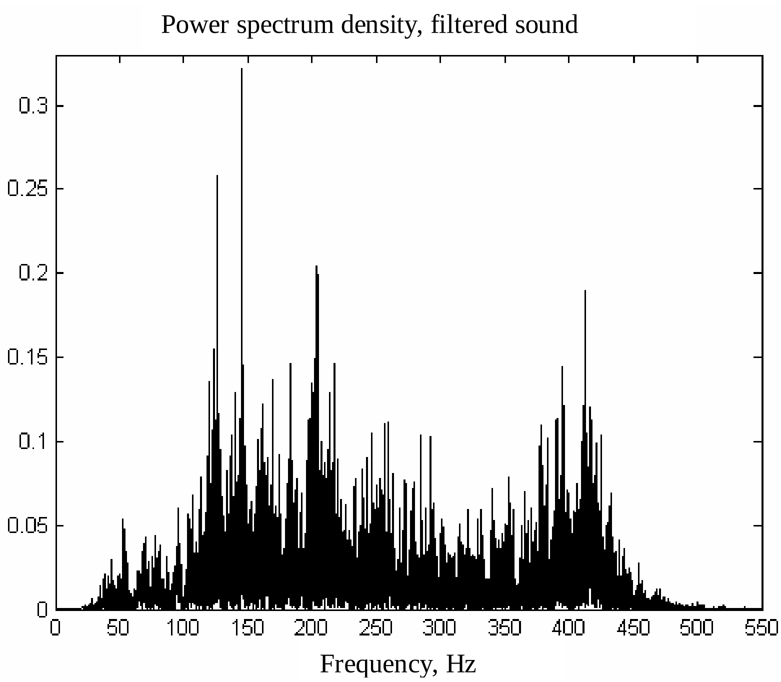


Figure A.15d

Figure A. 15. Pneumonia sound in time-domain signal (a) FFT's (b) filtered to remove DC offset and aliasing (c) and filtered to remove heart sound (d) FFT's.

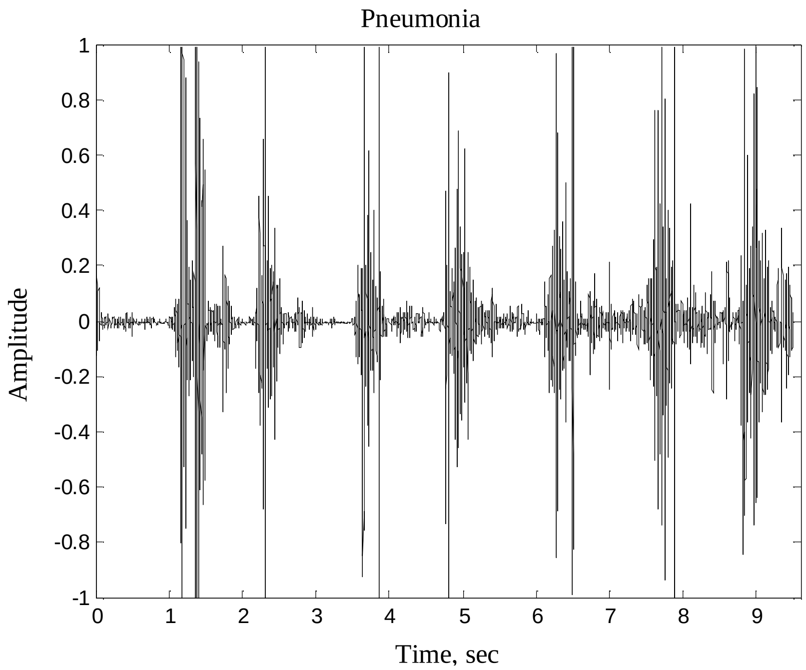


Figure A.16a

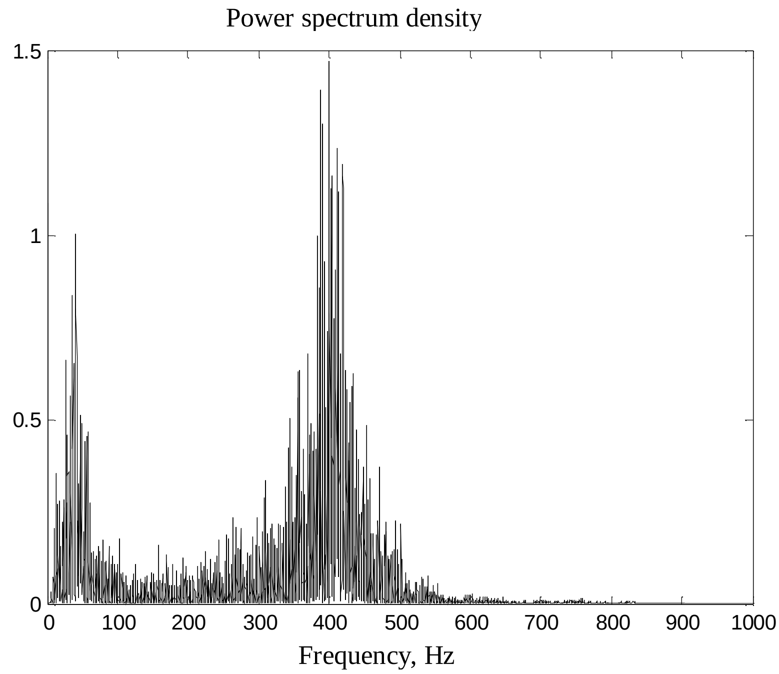


Figure A.16b

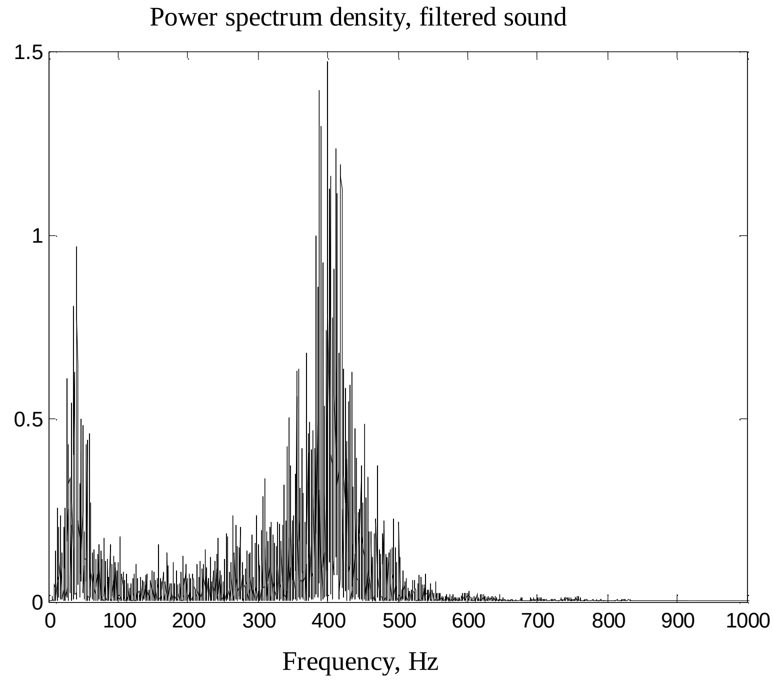


Figure A.16c

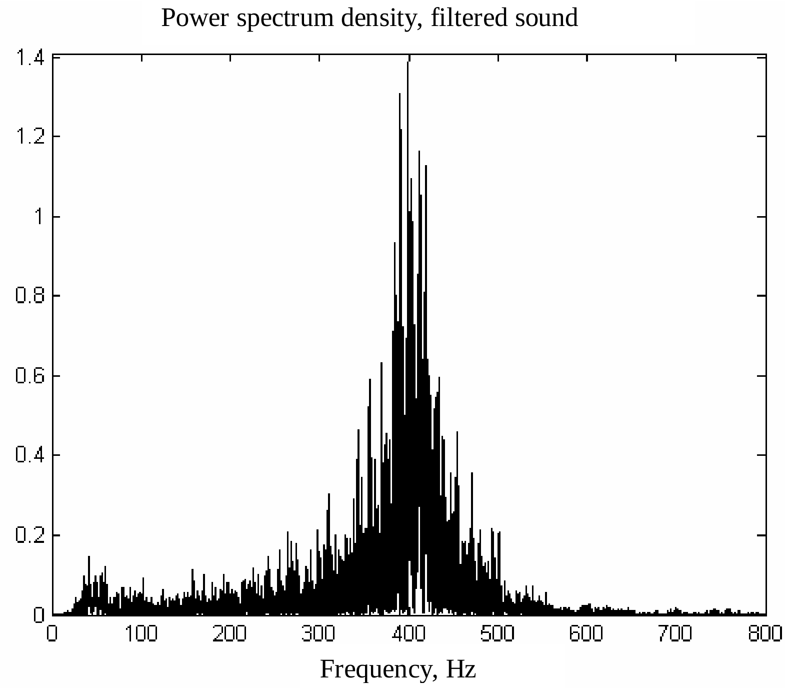


Figure A.16d

Figure A. 16. Hypersensitive pneumonia sound in time-domain signal (a) FFT's (b) filtered to remove DC offset and aliasing (c) and filtered to remove heart sound (d) FFT's.

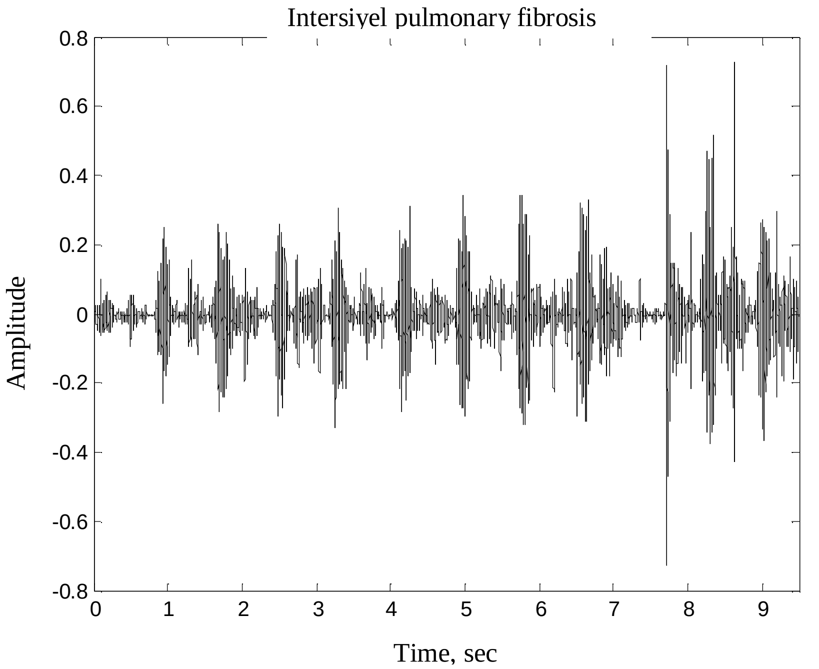


Figure A.17a

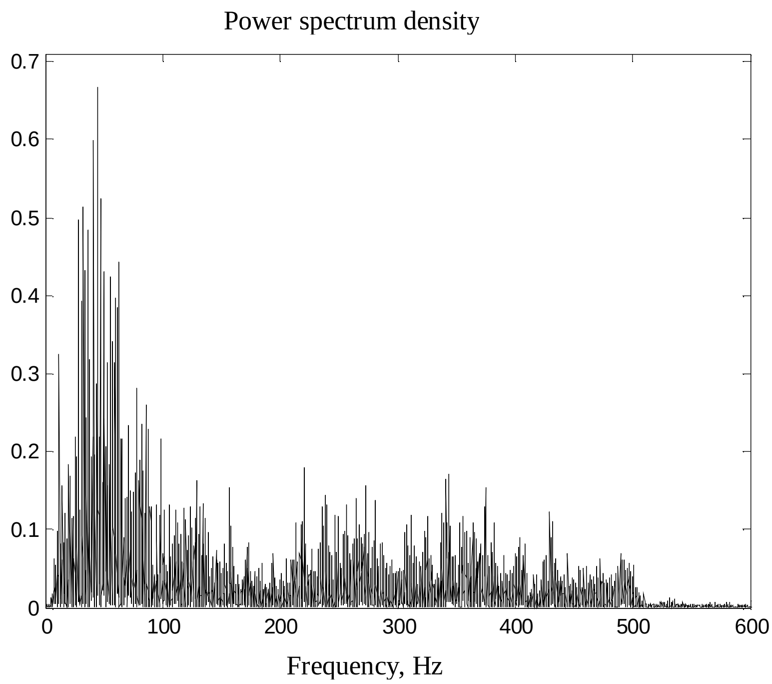


Figure A.17b

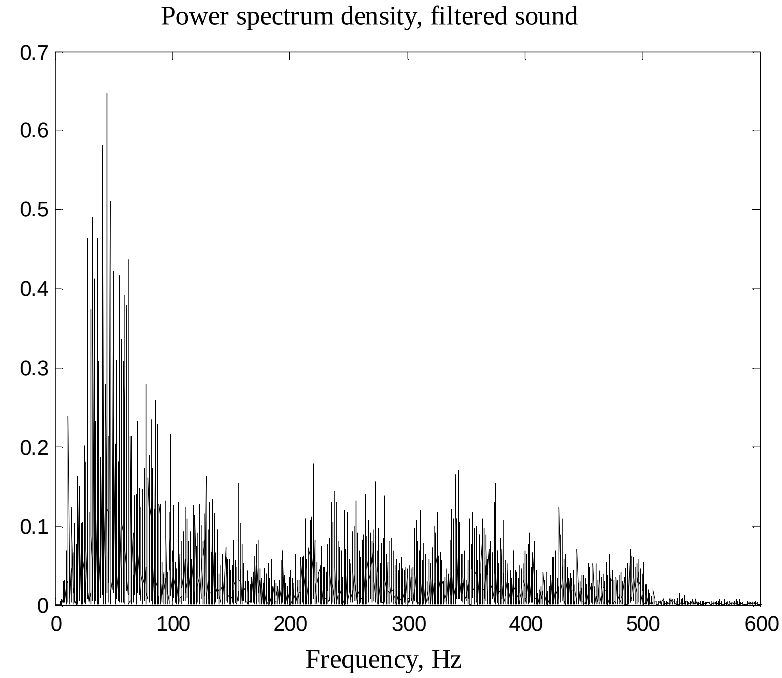


Figure A.17c

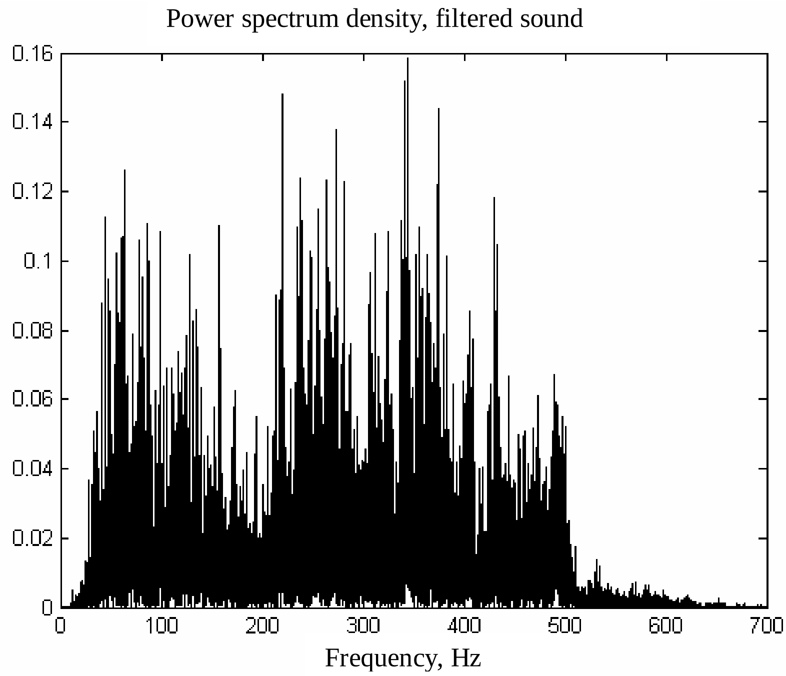


Figure A.17d

Figure A. 17. Interstitial pulmonary fibrosis sound in time-domain signal (a) FFT's (b) filtered to remove DC offset and aliasing (c) and filtered to remove heart sound (d) FFT's.

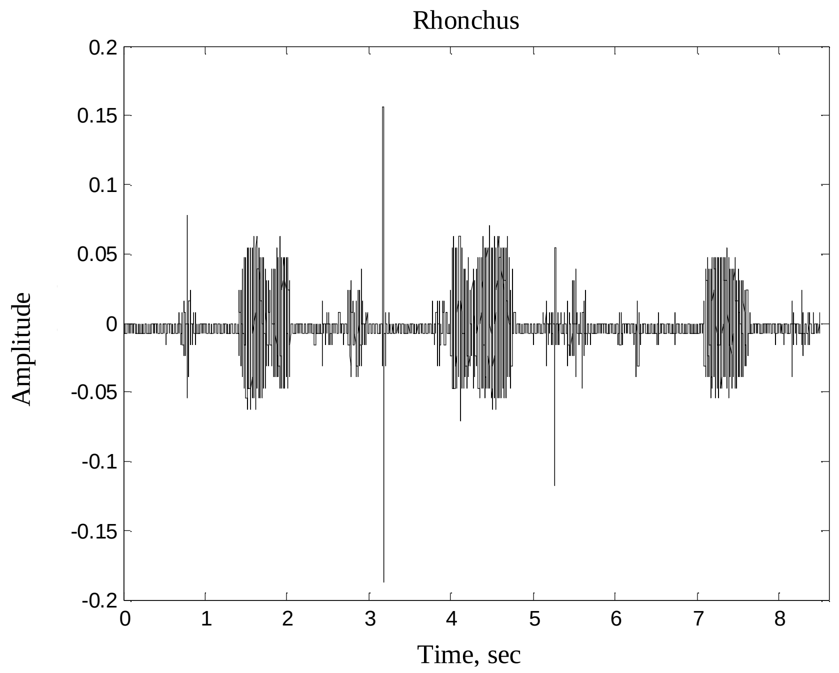


Figure A.18a

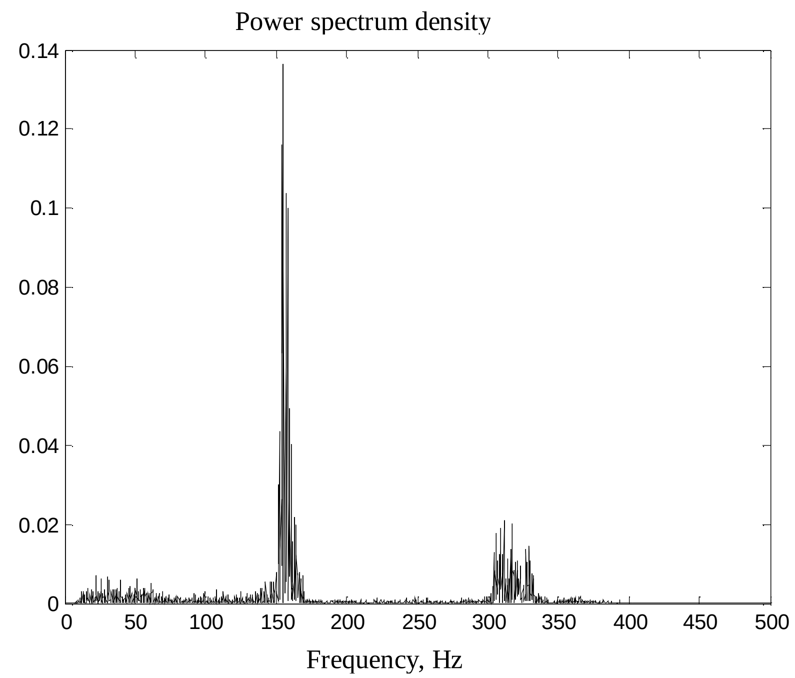


Figure A.18b

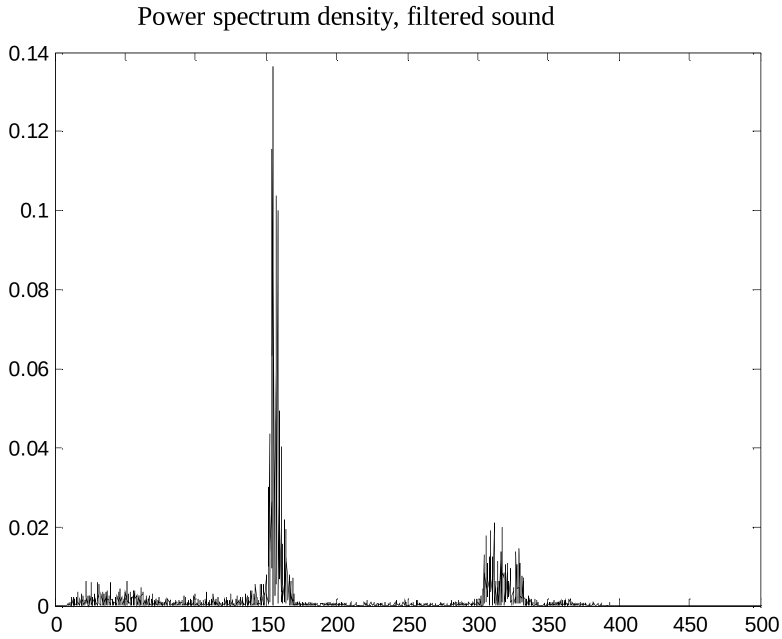


Figure A.18c

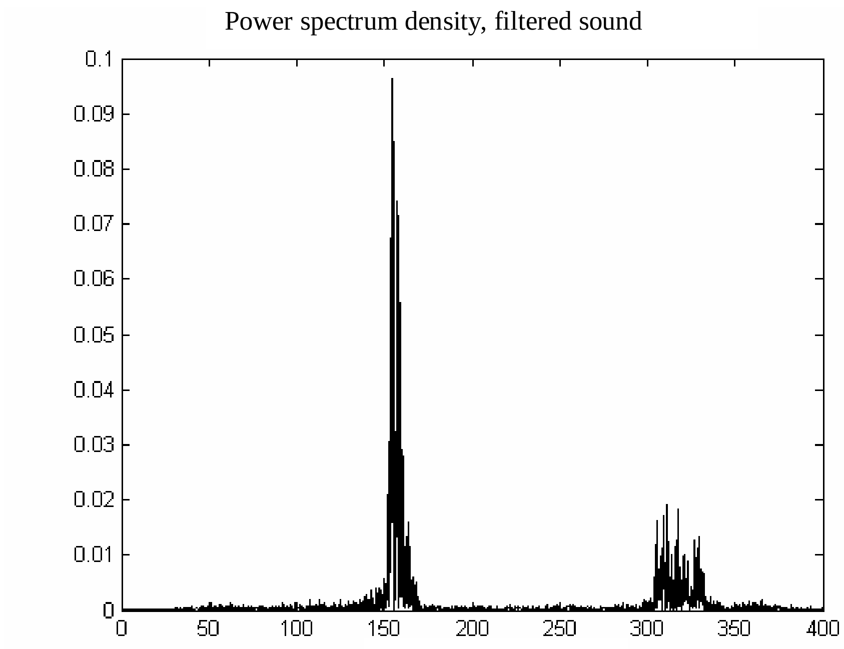


Figure A.18d

Figure A. 18. Rhonchus sound in time-domain signal (a) FFT's (b) filtered to remove DC offset and aliasing (c) and filtered to remove heart sound (d) FFT's.

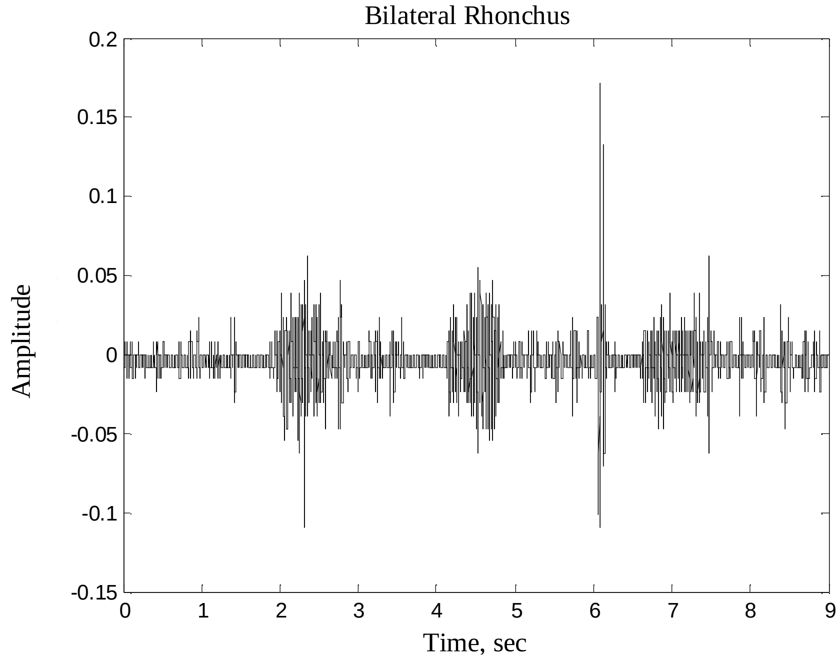


Figure A.19a

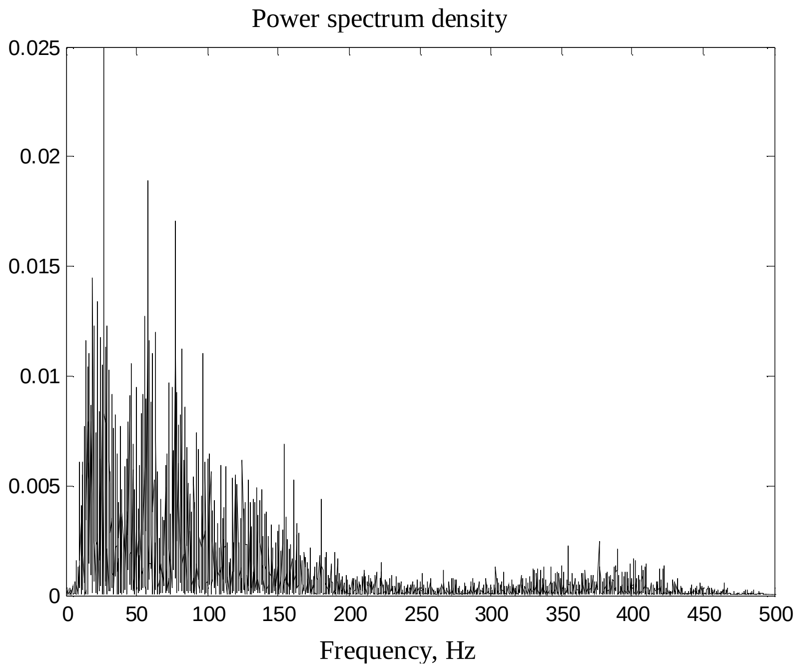


Figure A.19b

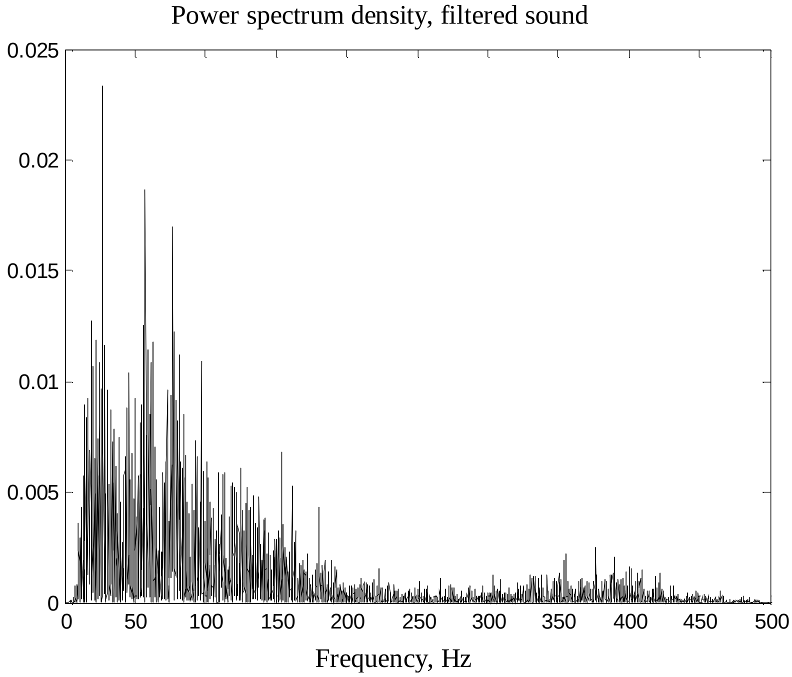


Figure A.19c

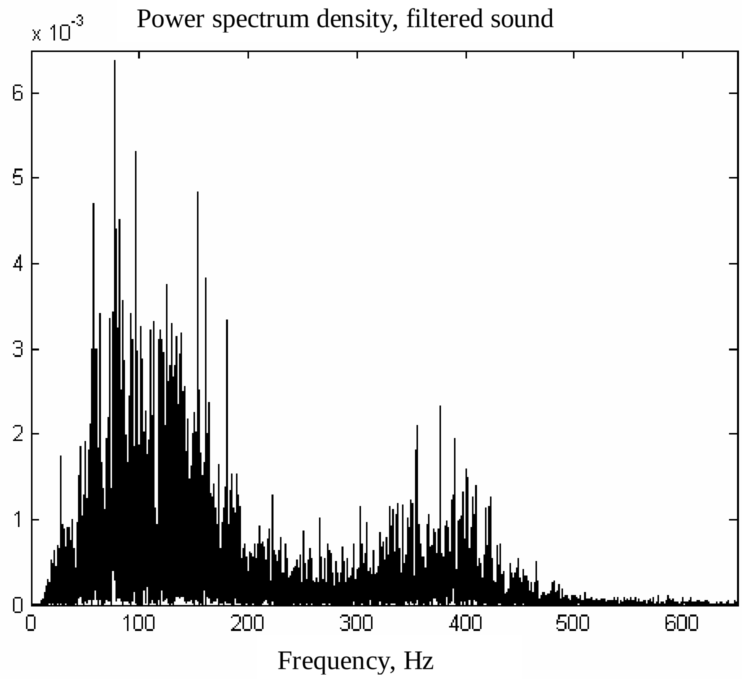


Figure A.19d

Figure A. 19. Rhonchus sound in time-domain signal (a) FFT's (b) filtered to remove DC offset and aliasing (c) and filtered to remove heart sound (d) FFT's.

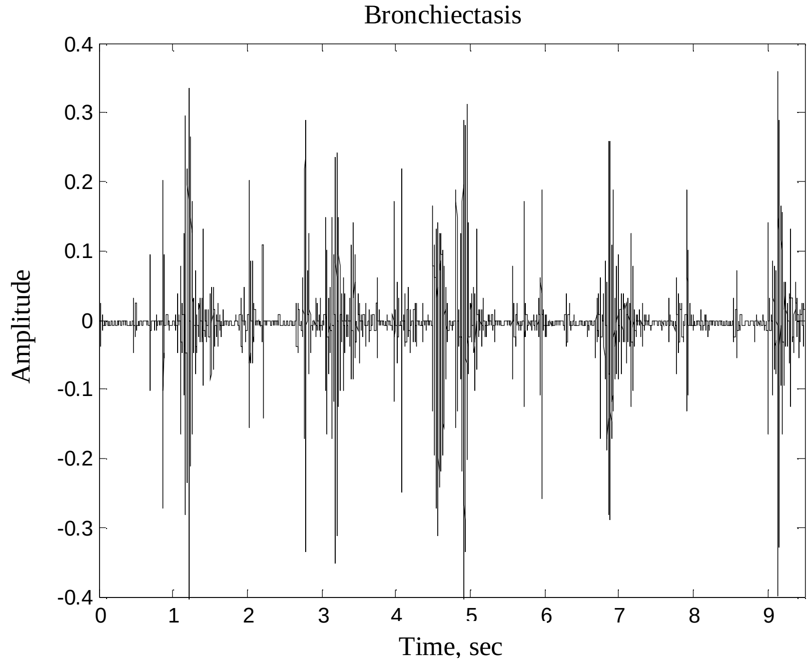


Figure A.20a

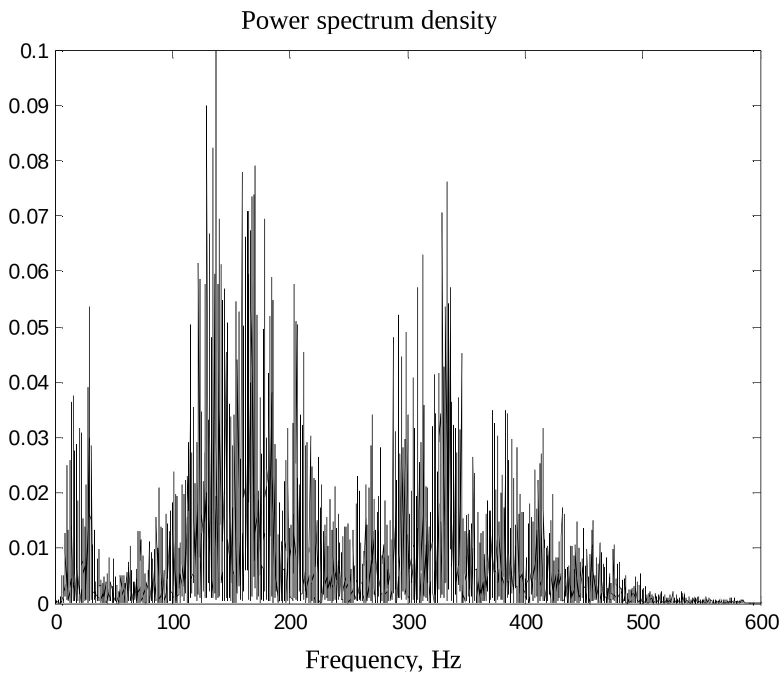
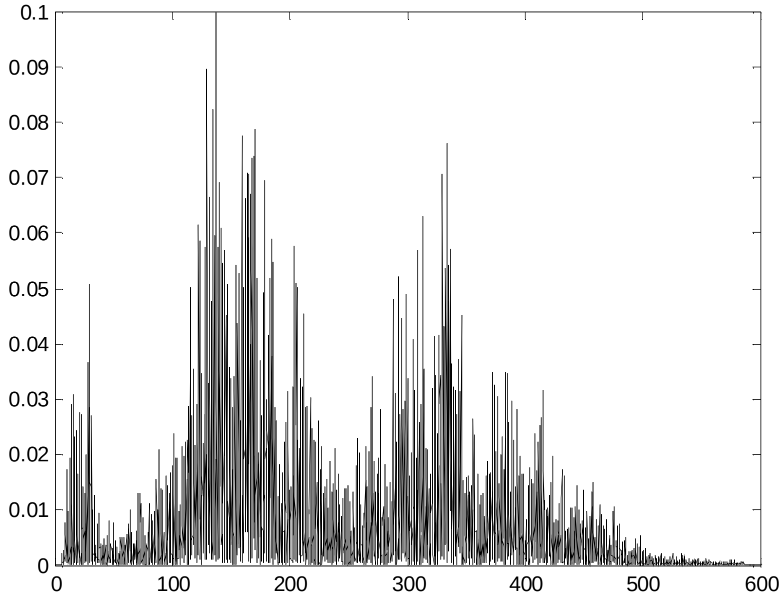


Figure A.20b

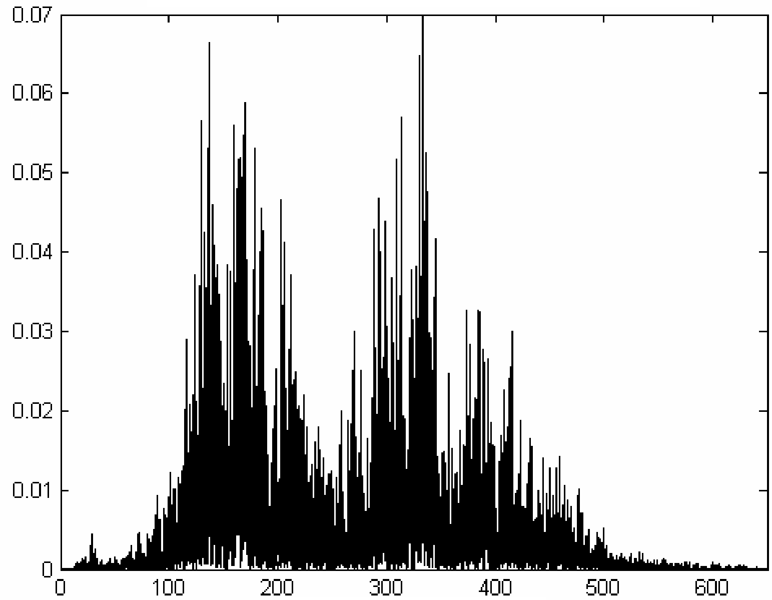
Power spectrum density, filtered sound



Frequency, Hz

Figure A.20c

Power spectrum density, filtered sound



Frequency, Hz

Figure A.20d

Figure A. 20. Bronchiectasis in time-domain signal (a) FFT's (b) filtered to remove DC offset and aliasing (c) and filtered to remove heart sound (d) FFT's.

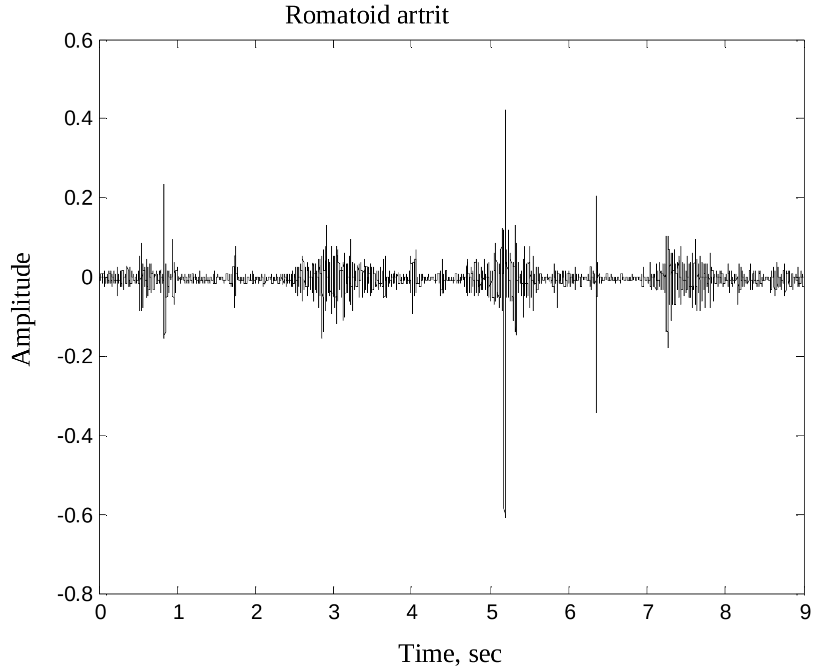


Figure A.21a

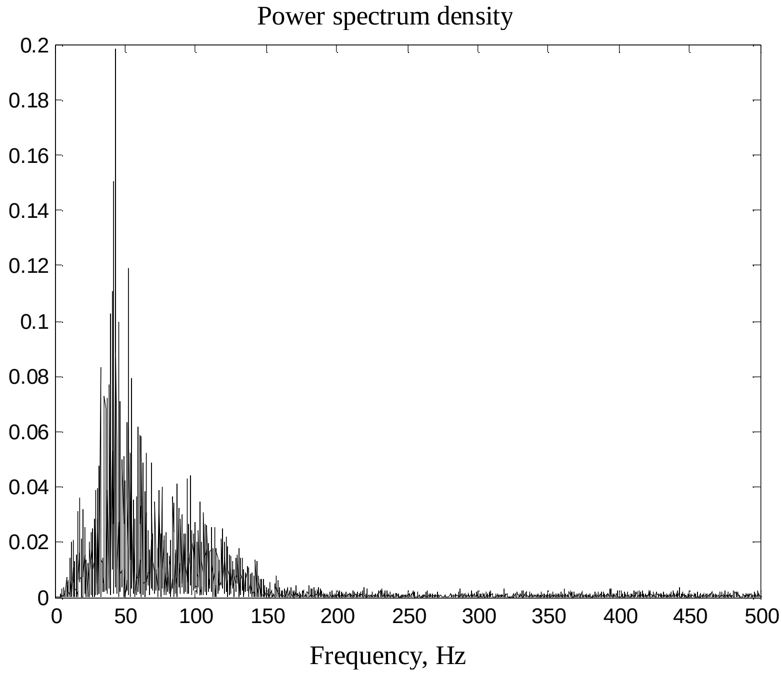


Figure A.21b

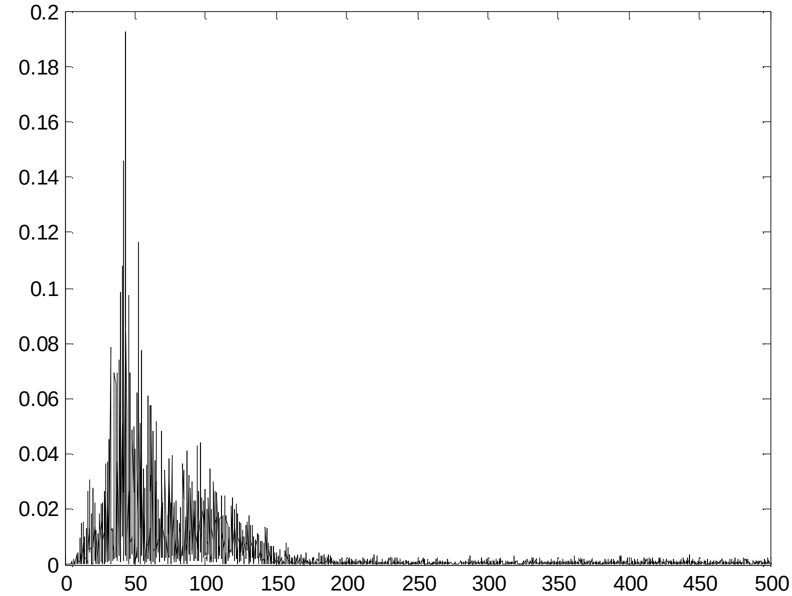


Figure A.21c

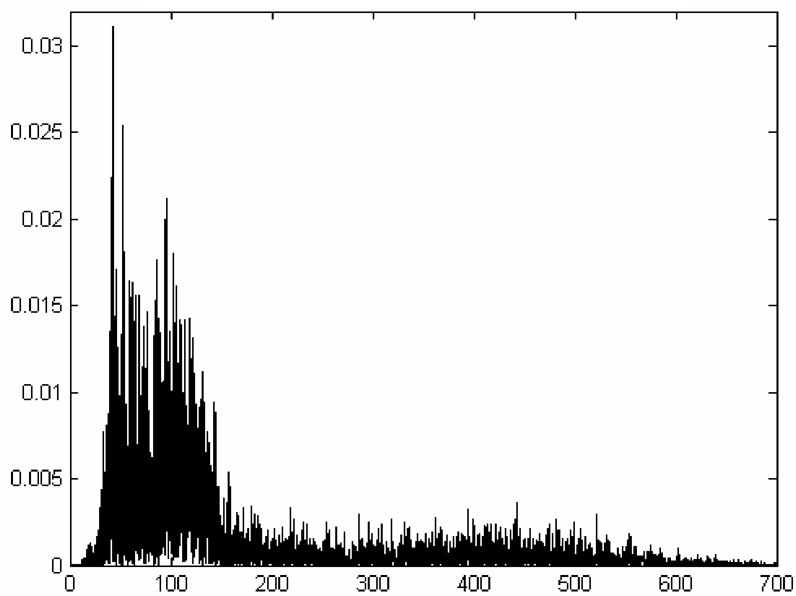


Figure A.21d

Figure A. 21. Rhomatoid artrit in time-domain signal (a) FFT's (b) filtered to remove DC offset and aliasing (c) and filtered to remove heart sound (d) FFT's.

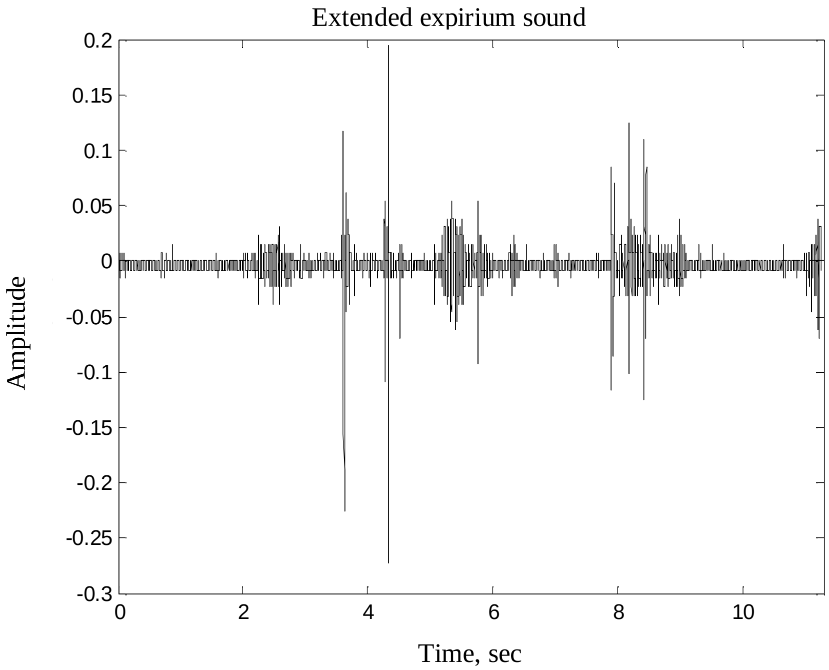


Figure A.22a

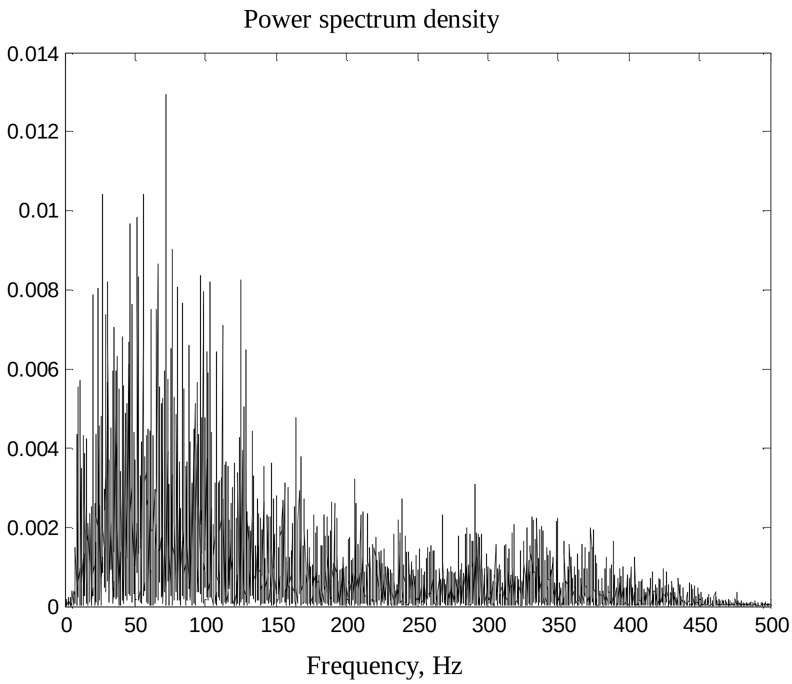
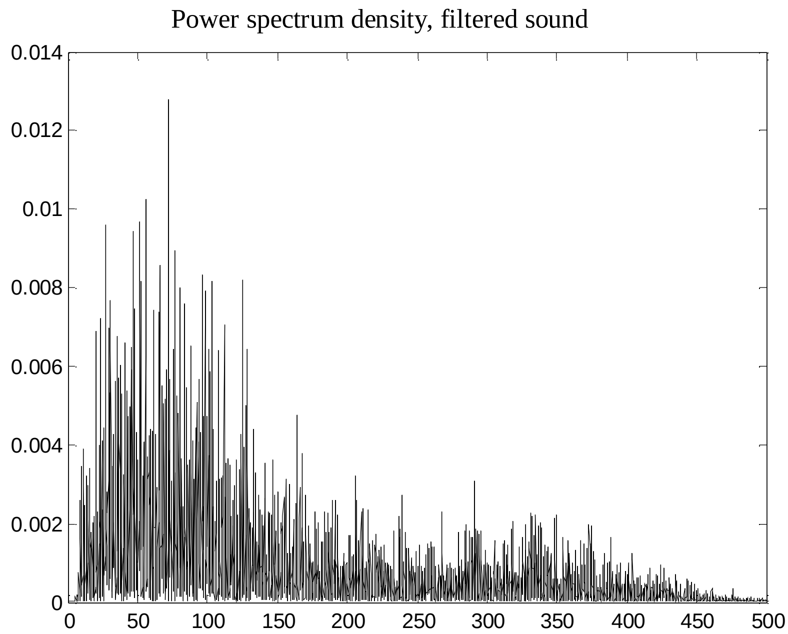


Figure A.22b



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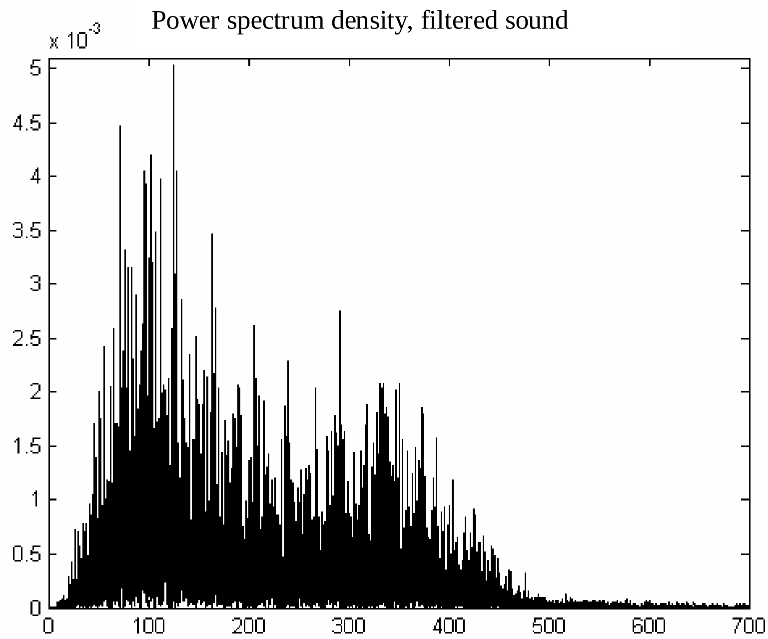


Figure A.22d

Figure A. 22. Extended expirium sound in time-domain signal (a) FFT's (b) filtered to remove DC offset and aliasing (c) and filtered to remove heart sound (d) FFT's.

APPENDIX B

R.AL.E. Repository

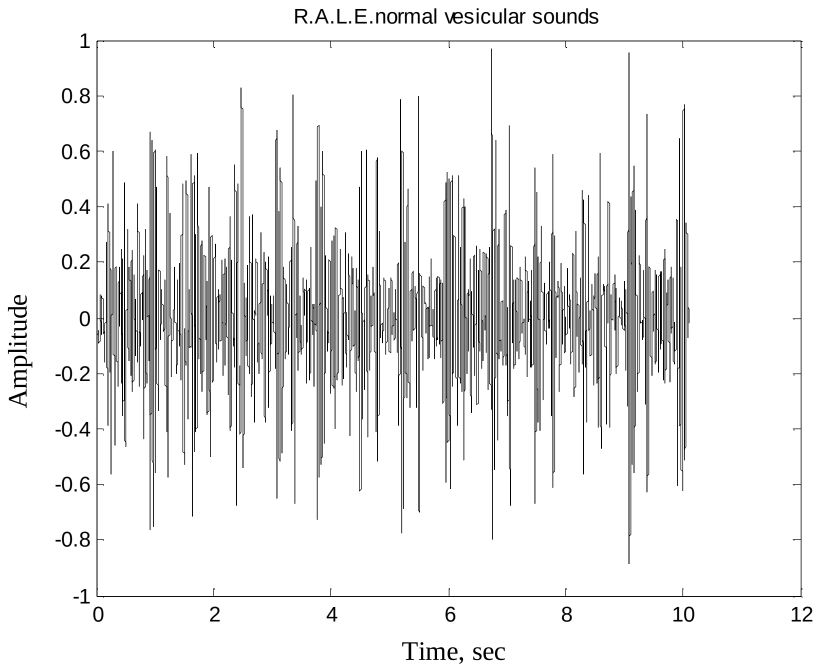


Figure B1a

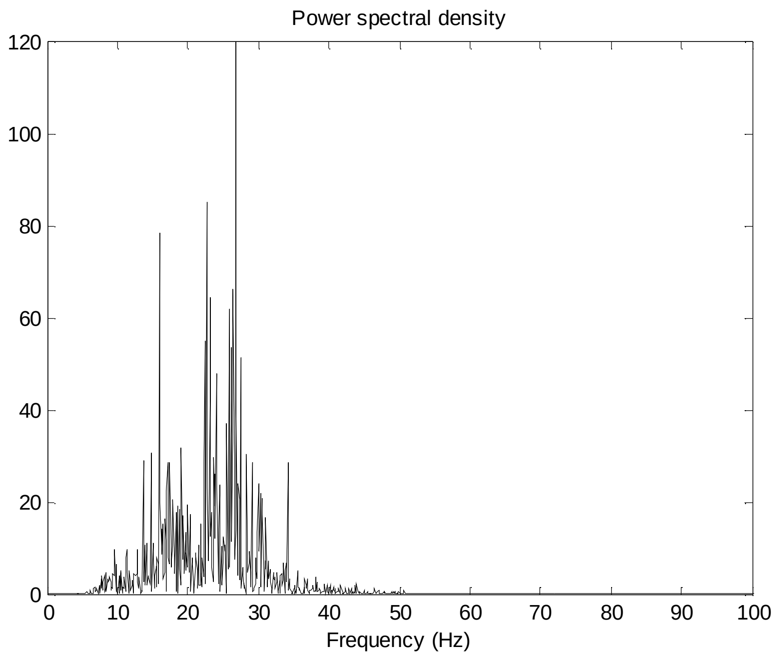


Figure B.1b

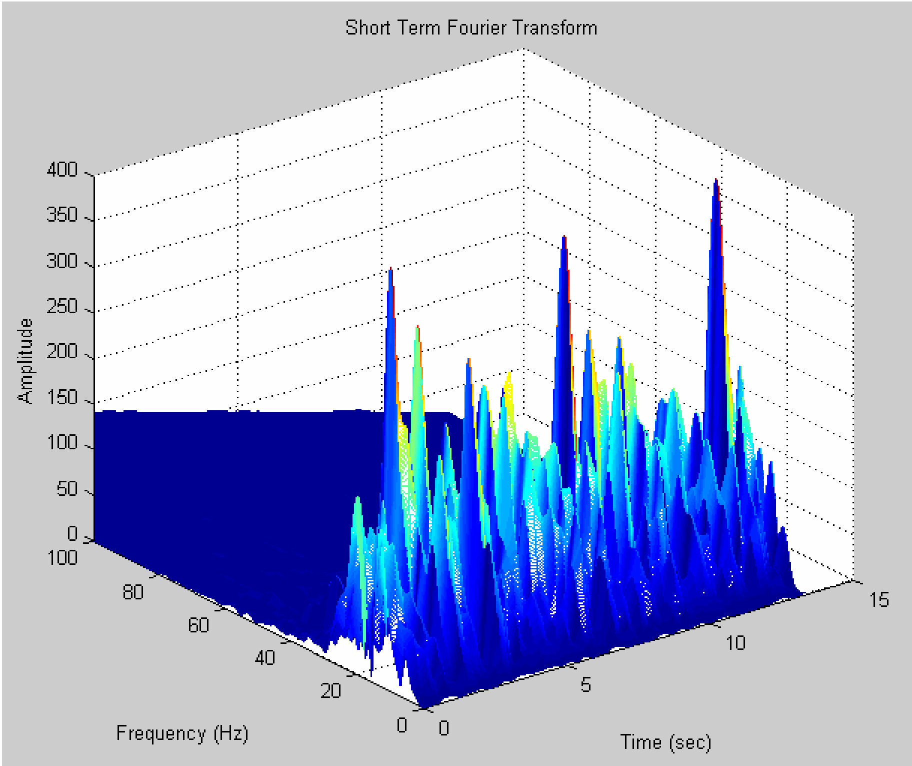


Figure B.1c

Figure B. 1. (a) R.A.L.E Normal vesicular sounds in time domain signal (b) FFT's.(c) 3D STFT, Using Hamming window

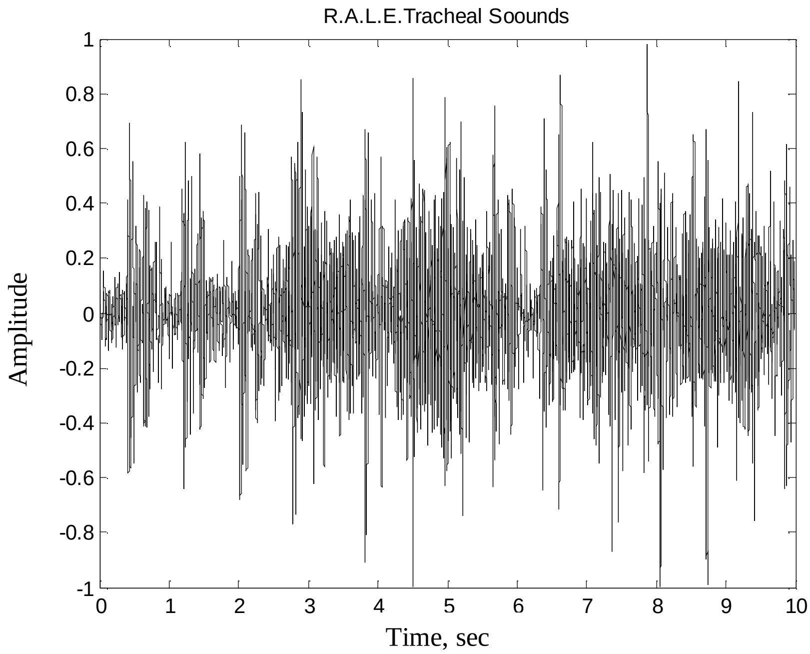


Figure B.2a

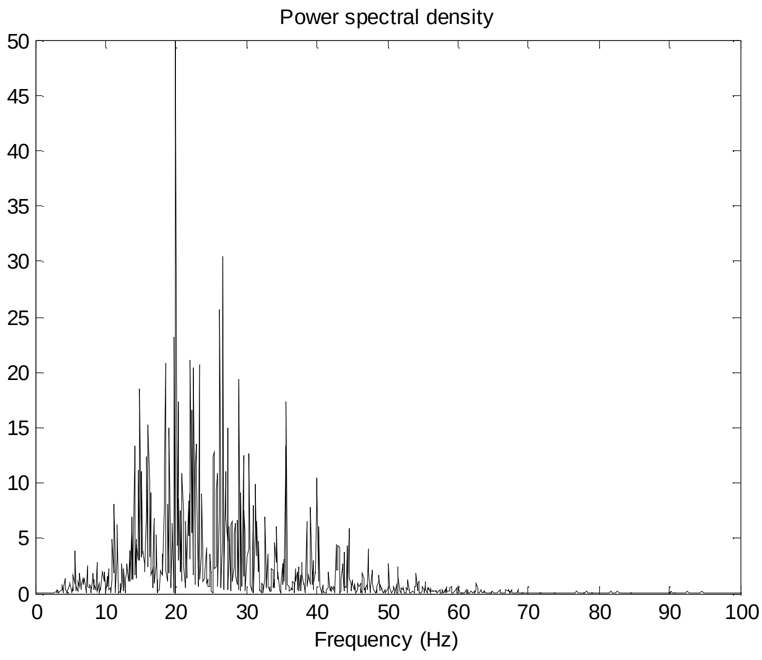
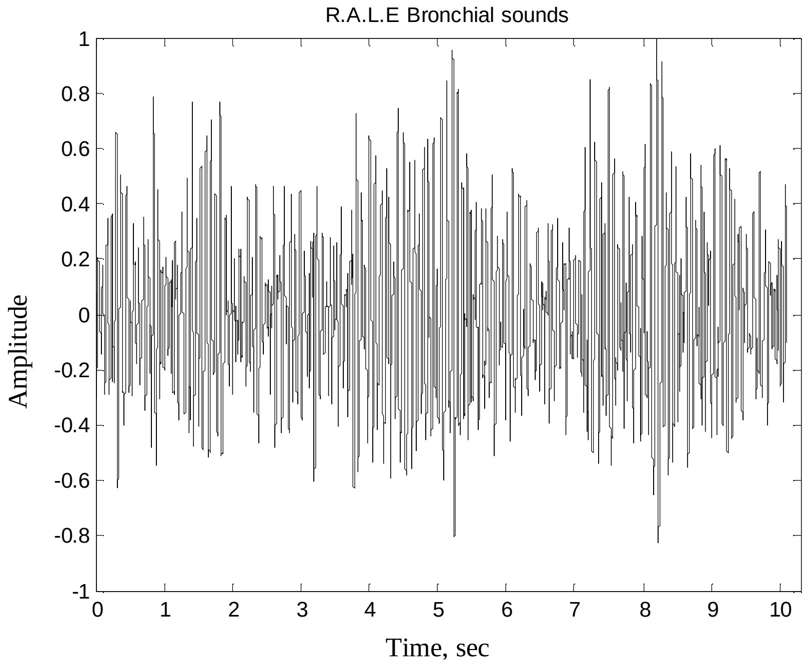


Figure B.2 b

Figure B. 2. (a) R.A.L.E Tracheal sounds in time domain signal (b) FFT's.(c) 3D STFT, Using Hamming window



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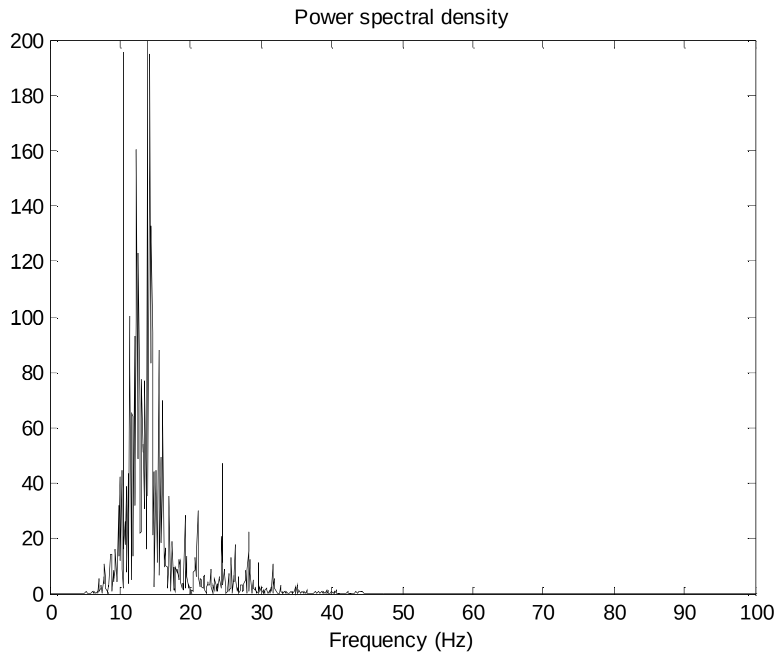


Figure B.3b

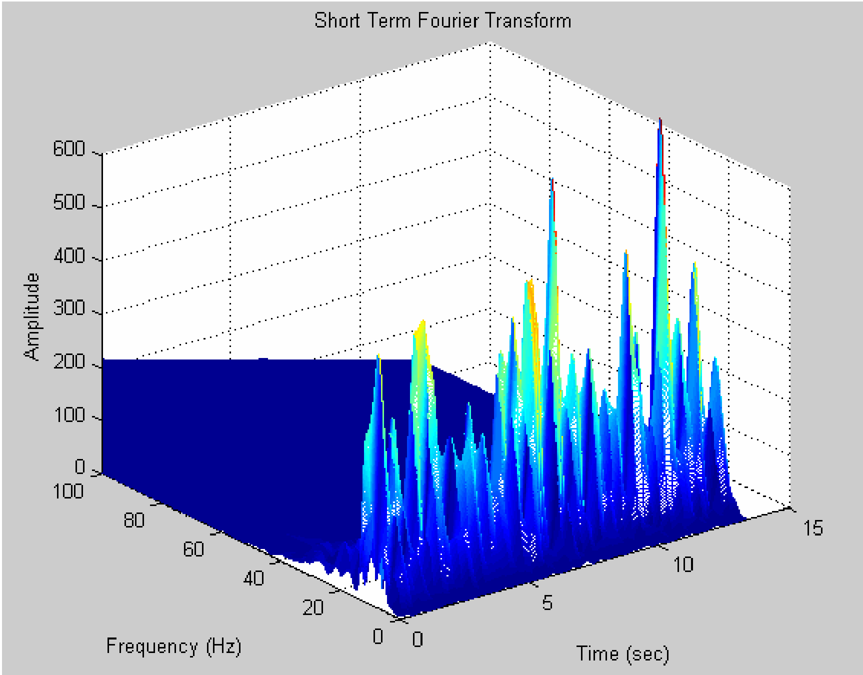
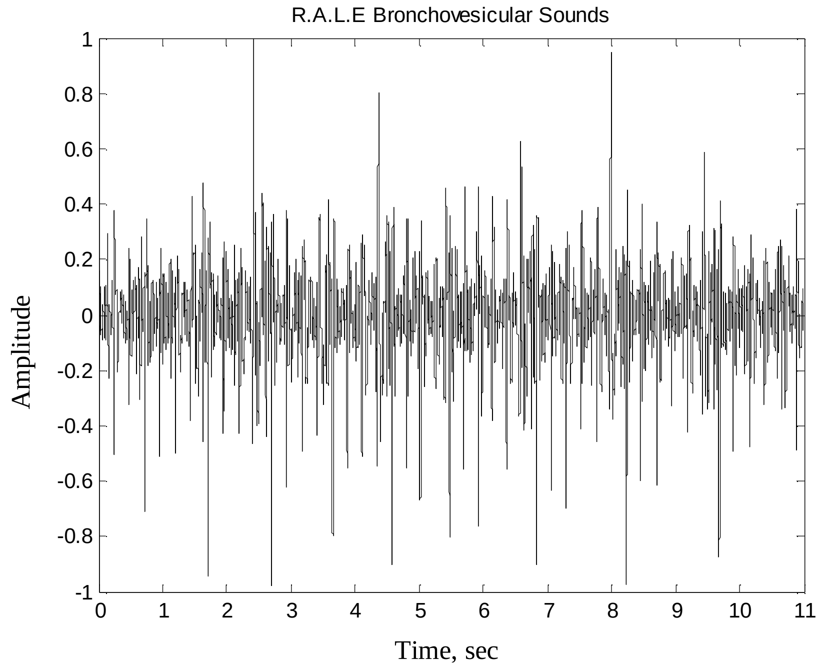


Figure B.3c

Figure B. 3. (a) R.A.L.E Bronchial sounds in time domain signal (b) FFT's.(c) 3D STFT, Using Hamming window



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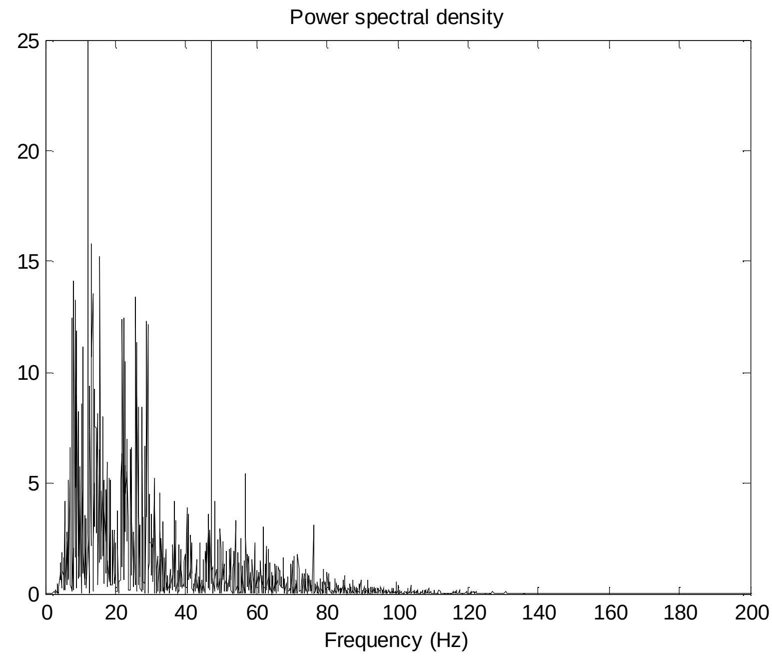


Figure B.4b

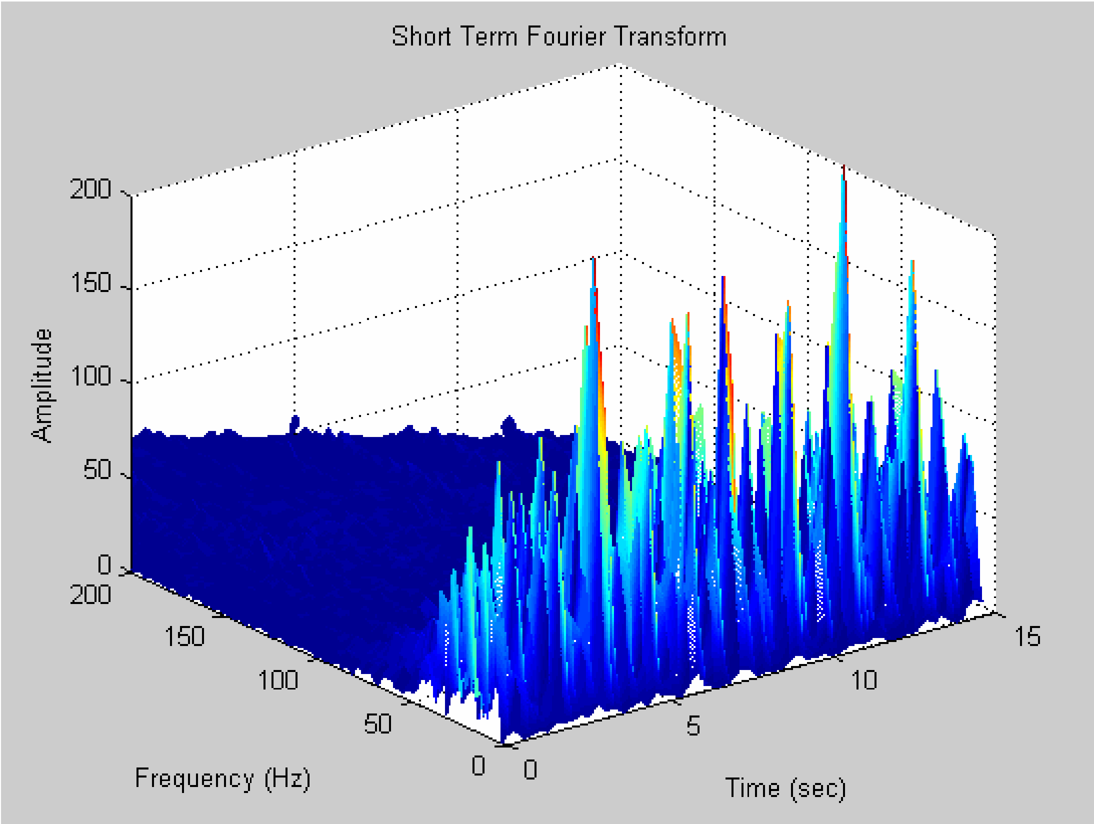
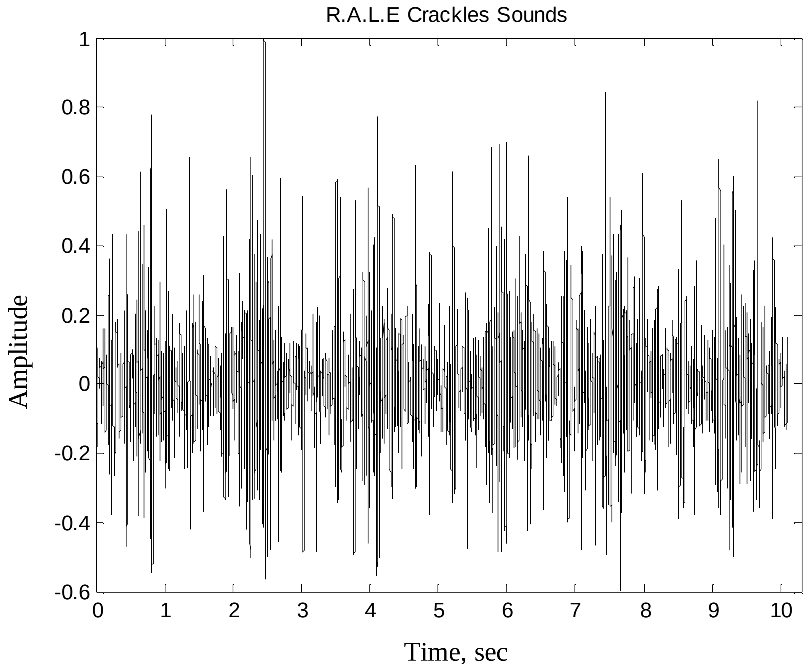


Figure B.4c

Figure B. 4. (a) R.A.L.E Bronchovesicular sounds in time domain signal (b) FFT's.(c) 3D STFT, Using Hamming window



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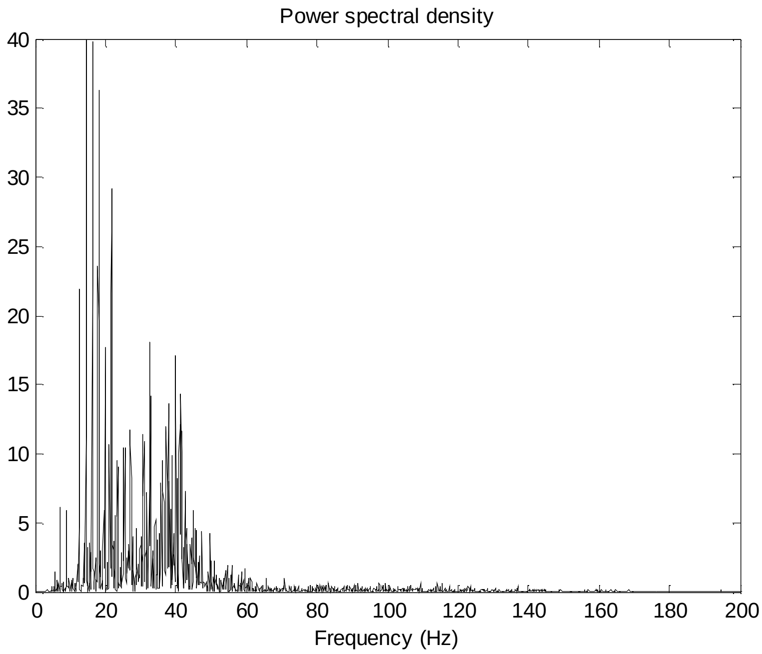


Figure B.5b

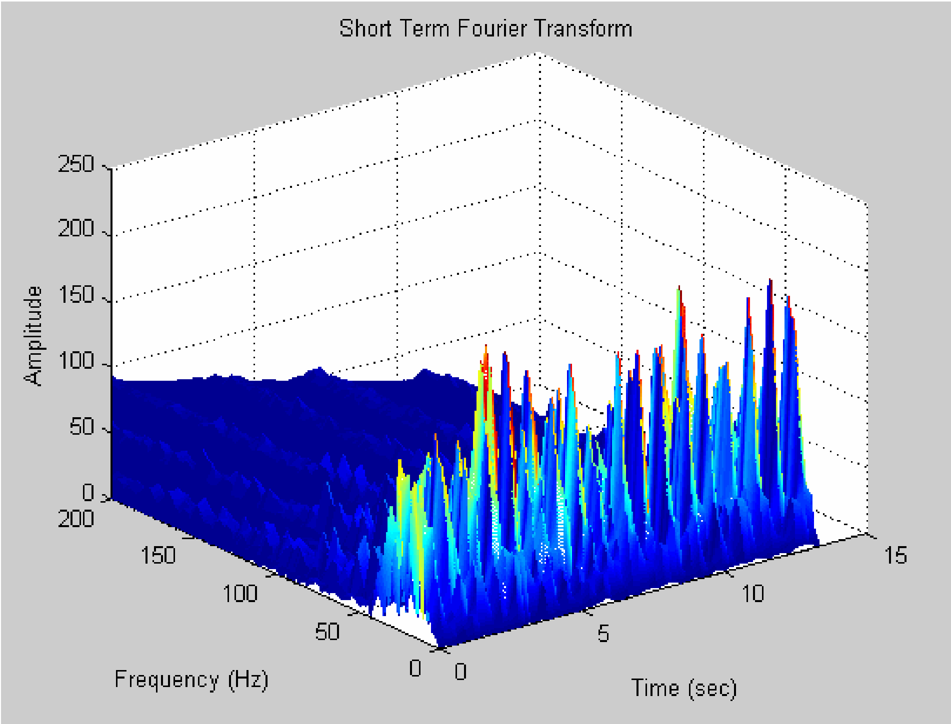
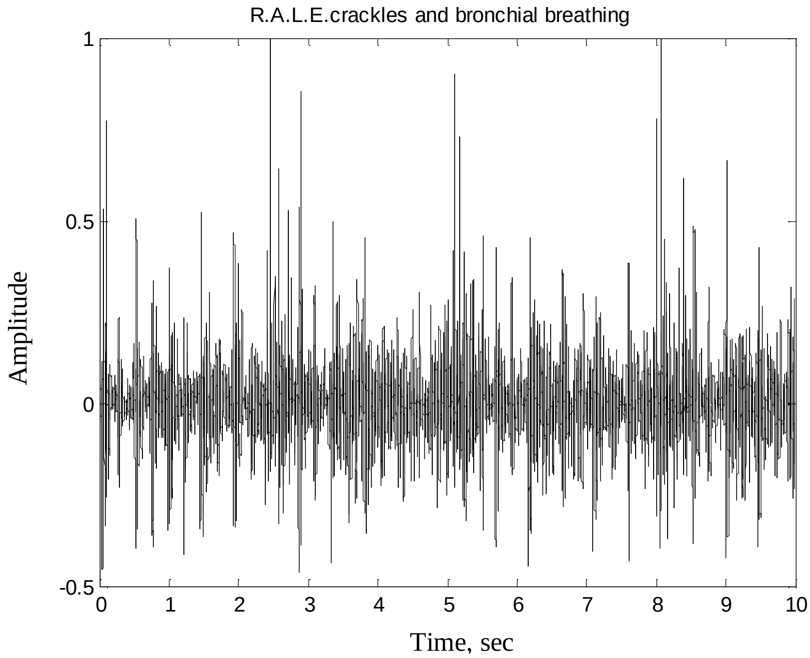


Figure B.5c

Figure B. 5. (a) R.A.L.E Crackles sounds with pneumonia in time domain signal (b) FFT's.(c) 3D STFT, Using Hamming window



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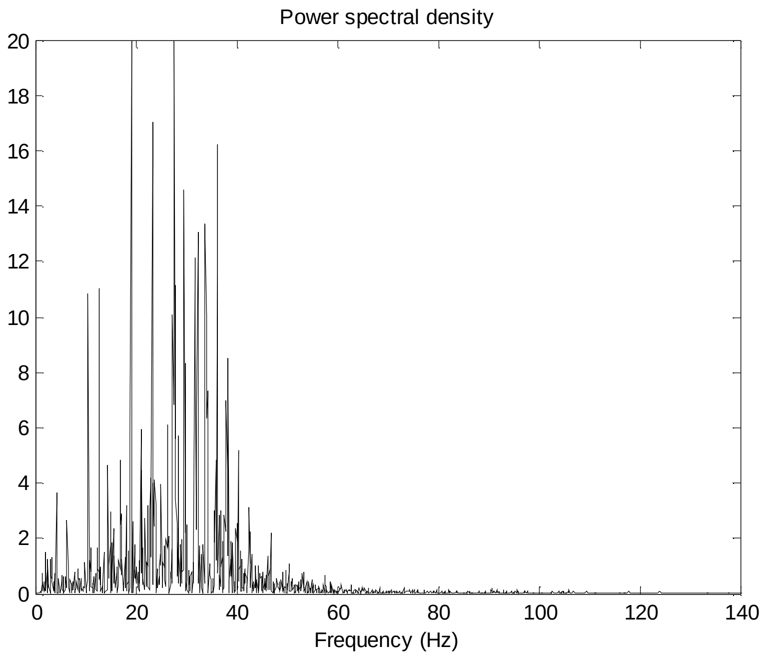
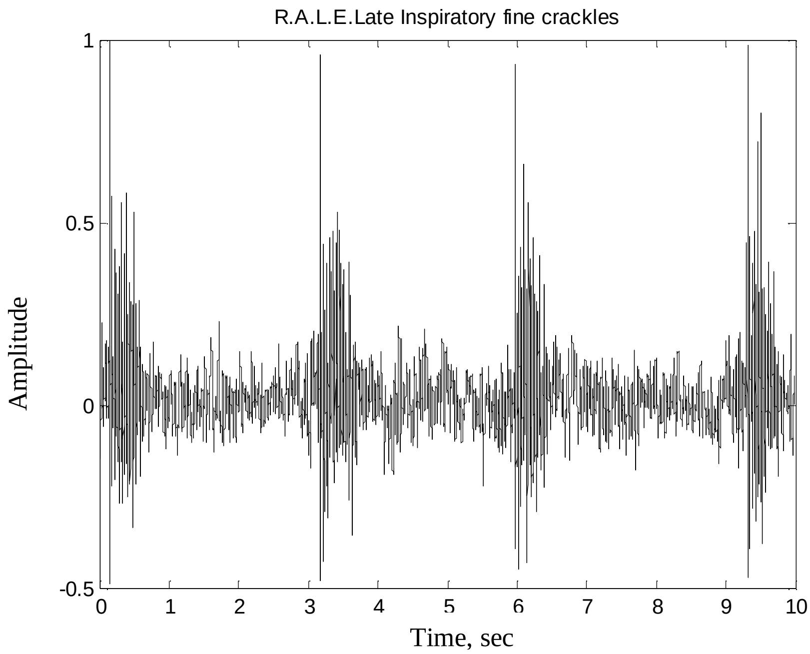


Figure B.6b

Figure B. 6. (a) R.A.L.E. crackles and bronchial breathing with tuberculosis. in time domain signal (b) FFT's



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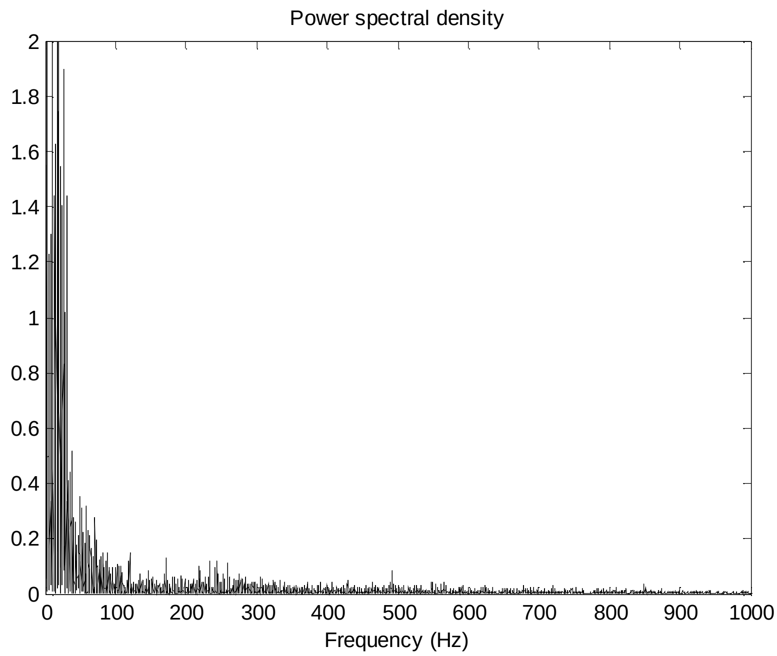

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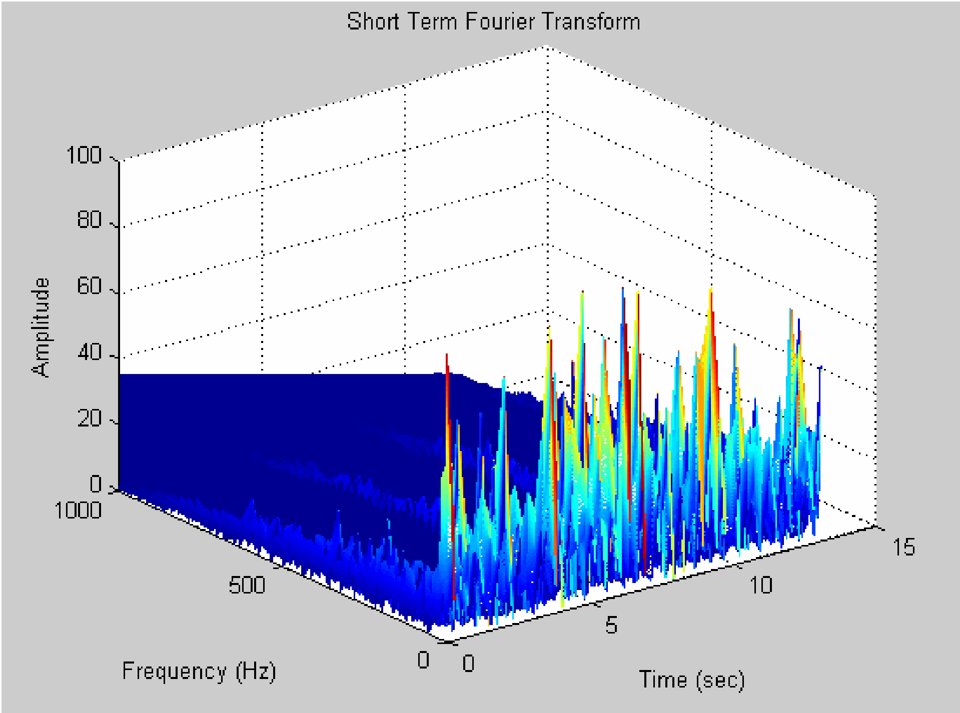
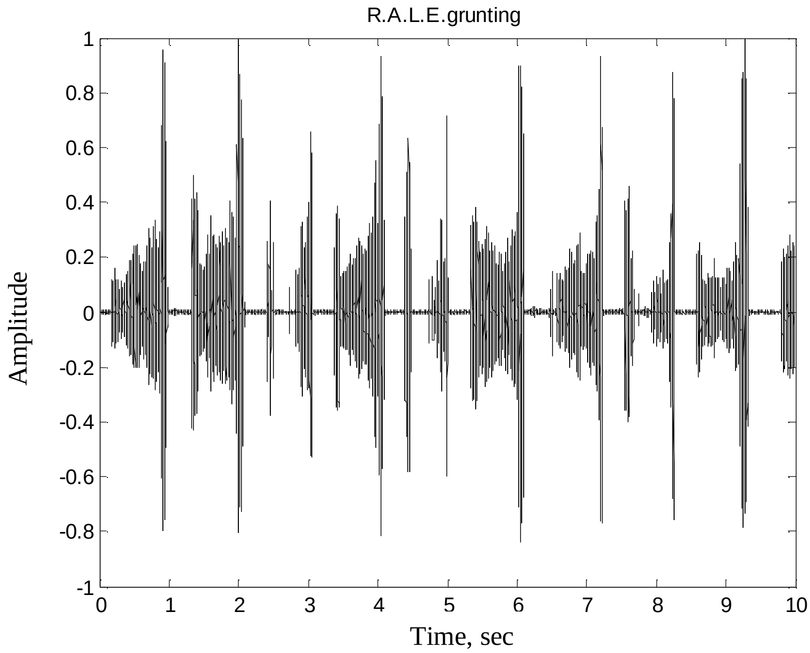


Figure B.7c

Figure B. 7. (a) R.A.L.E. late inspiratory fine crackles with rheumatoid lung disease. in time domain signal (b) FFT's.(c) 3D STFT, Using Hamming window



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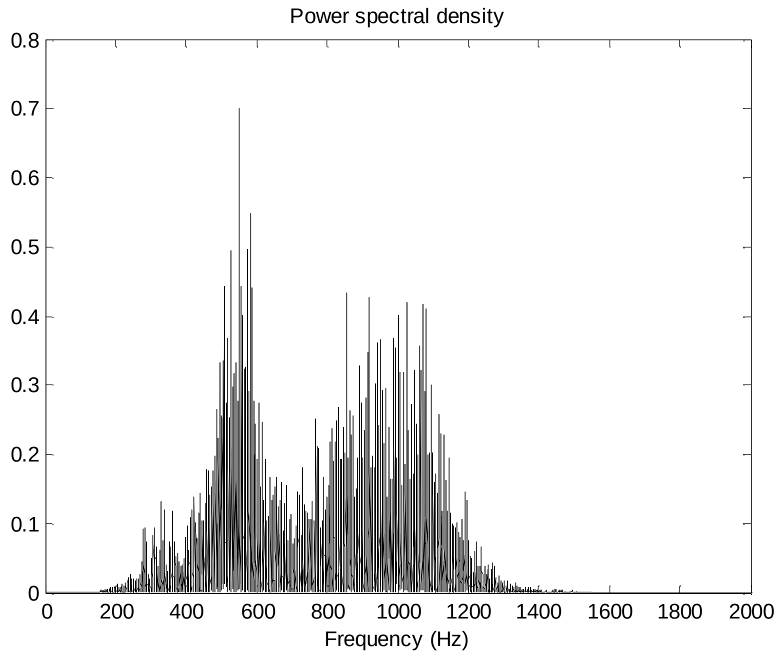

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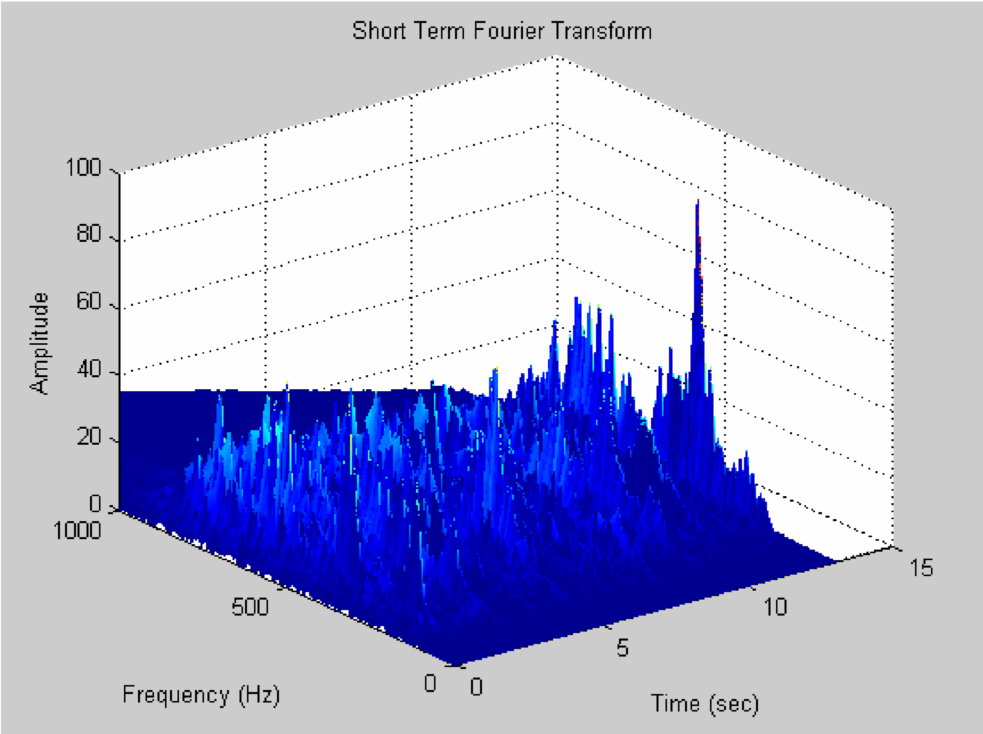
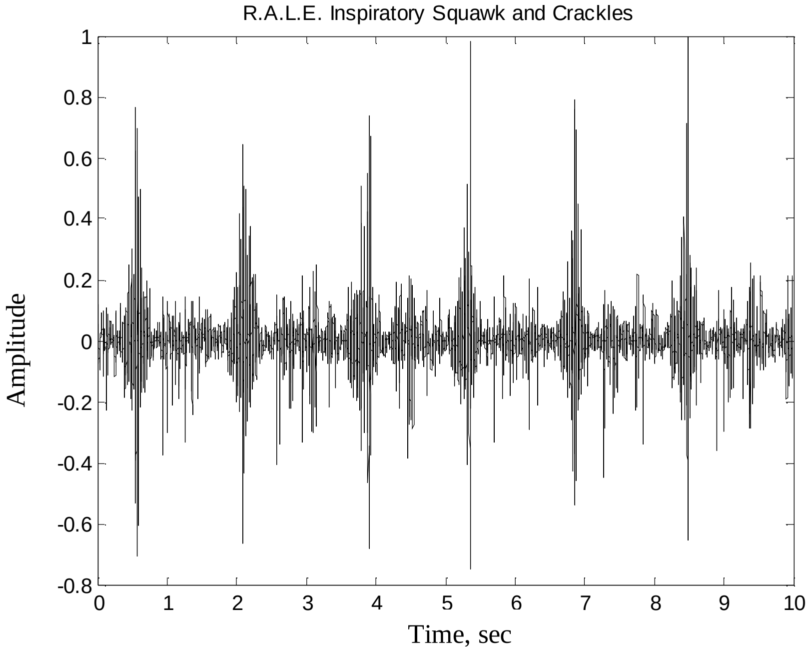


Figure B.8c

Figure B. 8. (a) R.A.L.E. Grunting with respiratory distress in time domain signal (b) FFT's.(c) 3D STFT, Using Hamming window



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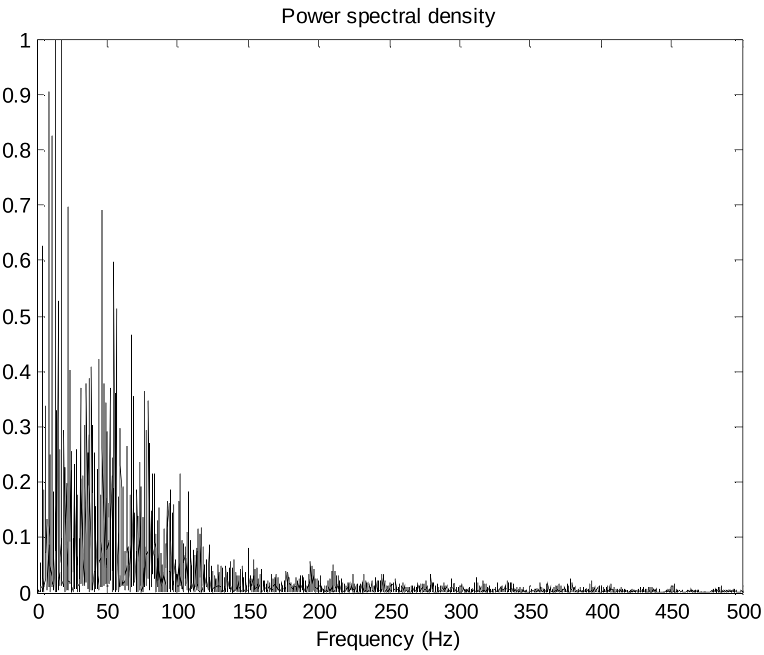
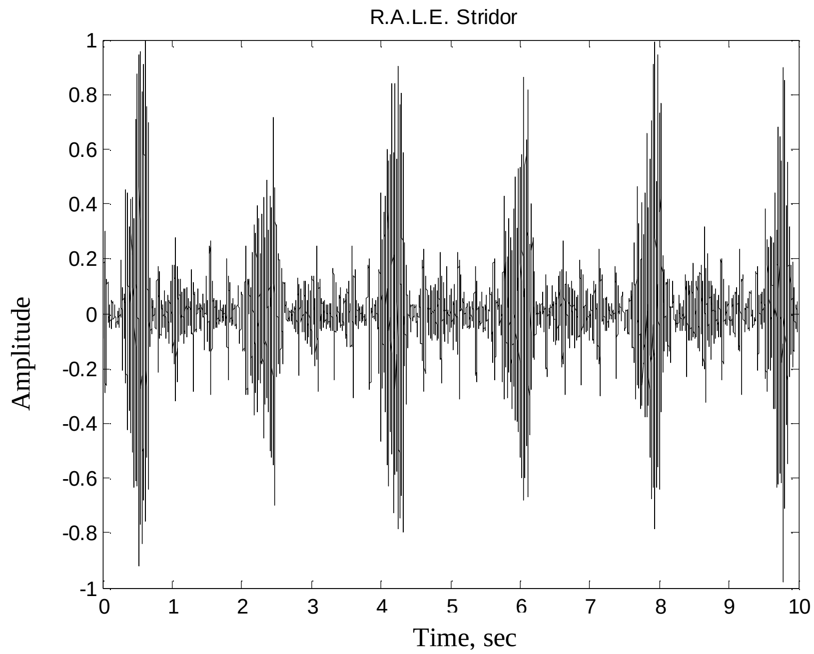


Figure B.9b

Figure B. 9. (a)R.A.L.E. Inspiratory squawk and crackles with interstitial pulmonary fibrosis in time domain signal (b) FFT’s



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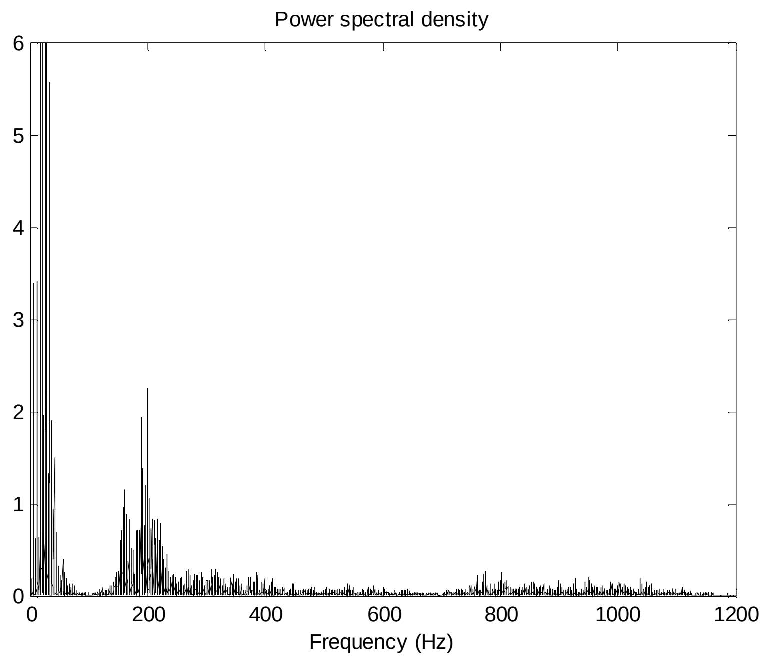


Figure B.10b

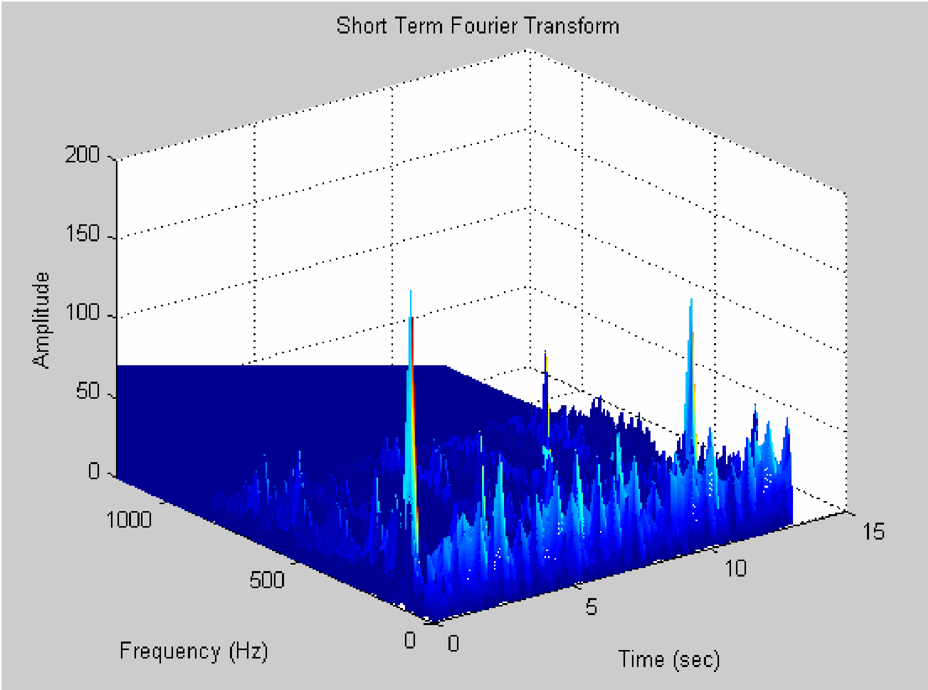
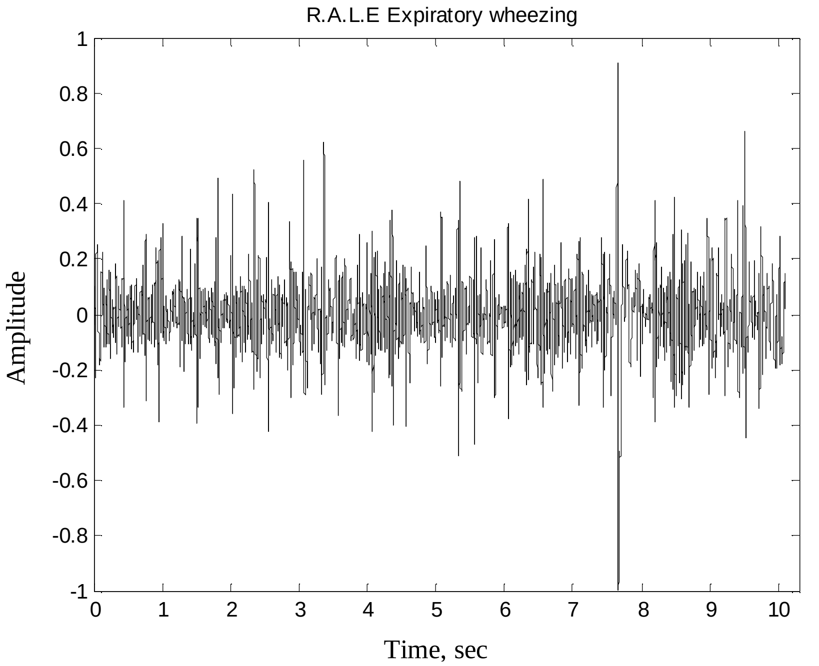


Figure B.10c

Figure B. 10. (a) R.A.L.E. Stridor with croup in time domain signal (b) FFT's.(c) 3D STFT, Using Hamming window



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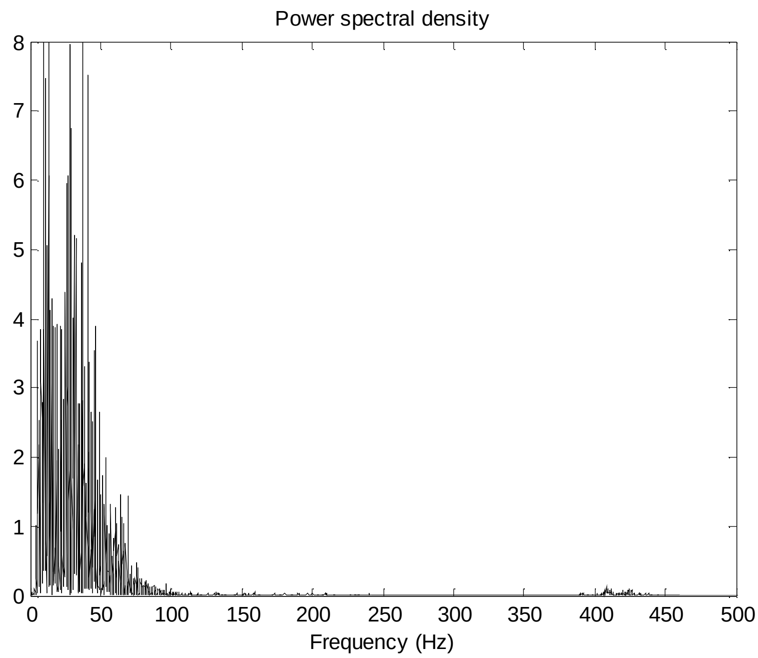

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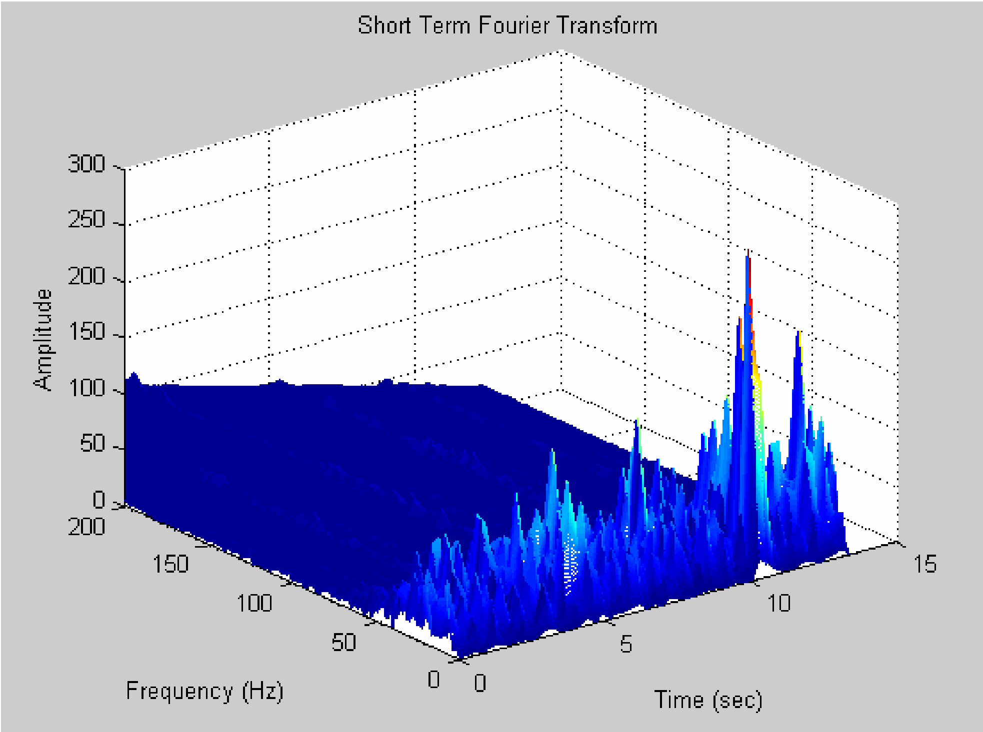
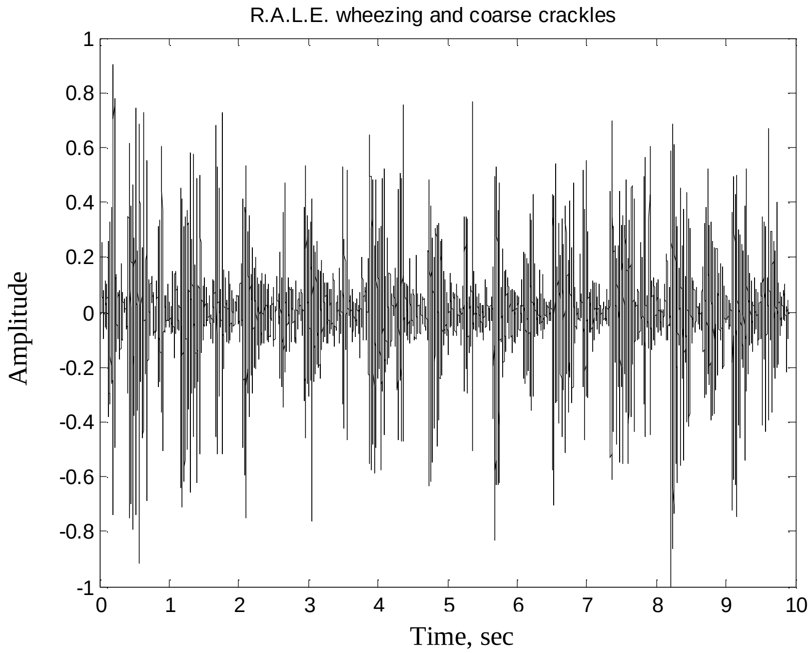


Figure B.11c

Figure B. 11. (a) R.A.L.E. Expiratory wheezing with asthma. in time domain signal (b) FFT's.(c) 3D STFT, Using Hamming window



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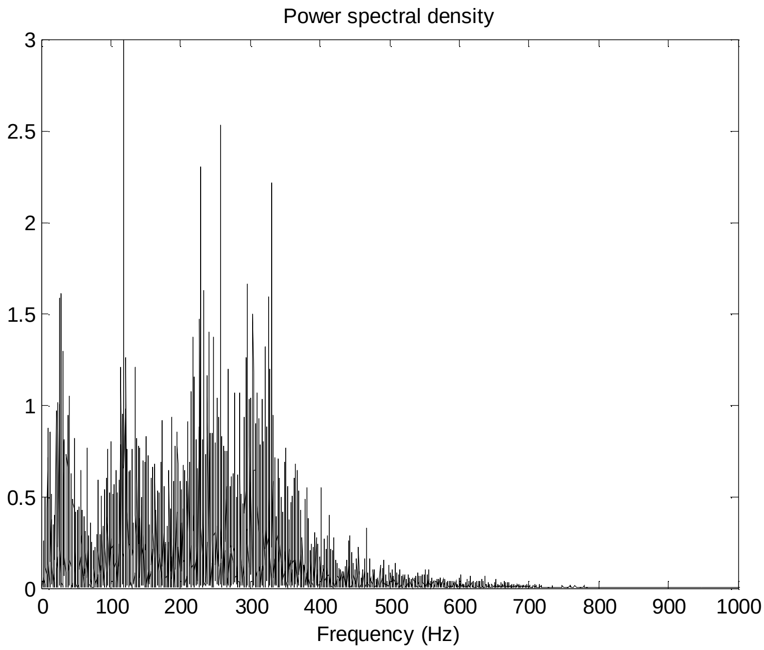

Figure B.12b

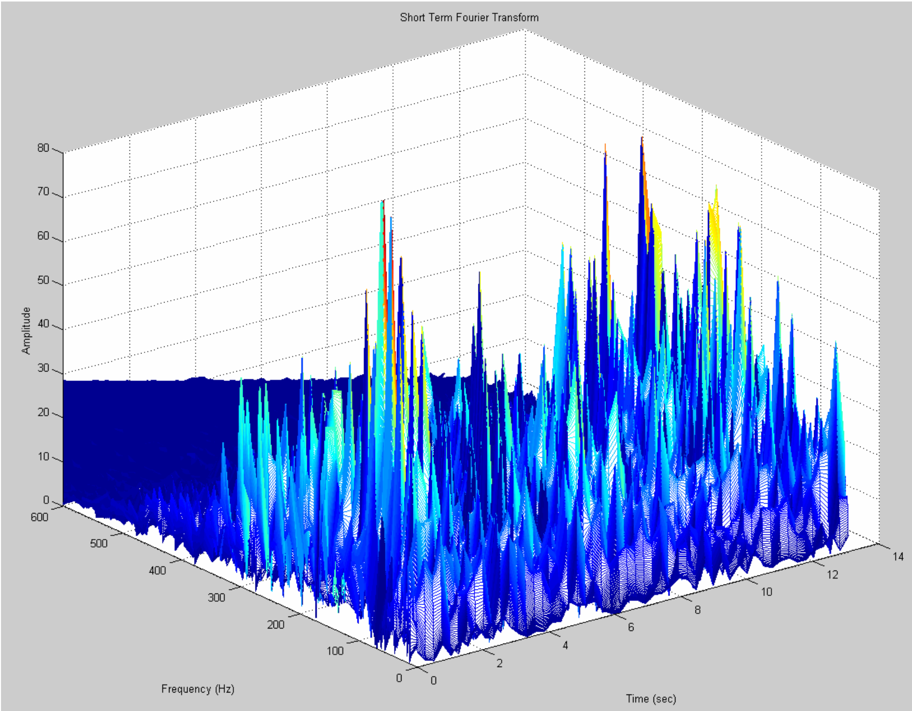

Figure B.12c

Figure B. 12. (a) R.A.L.E. Wheezing and coarse crackles with viral bronchiolitis in time domain signal (b) FFT's.(c) 3D STFT, Using Hamming window

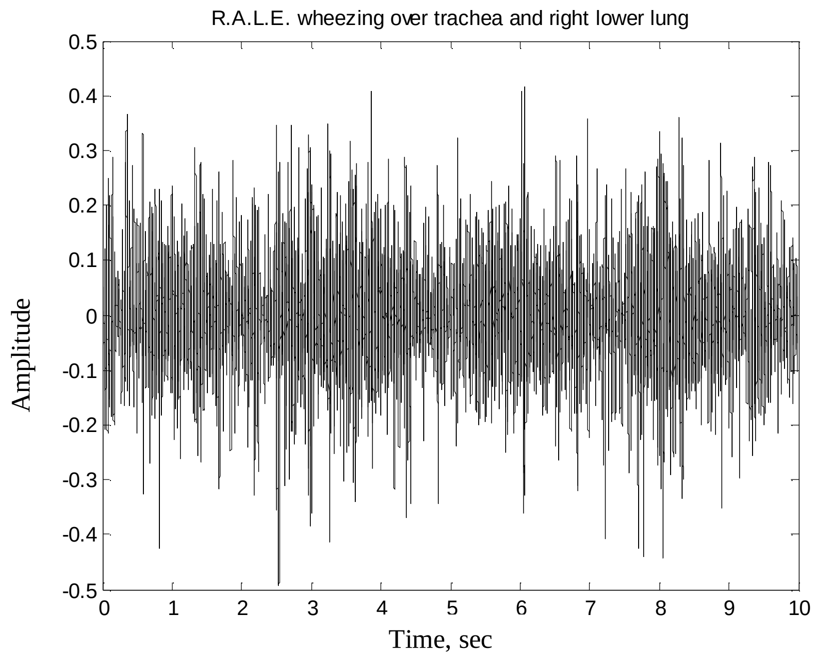

Figure B.13a

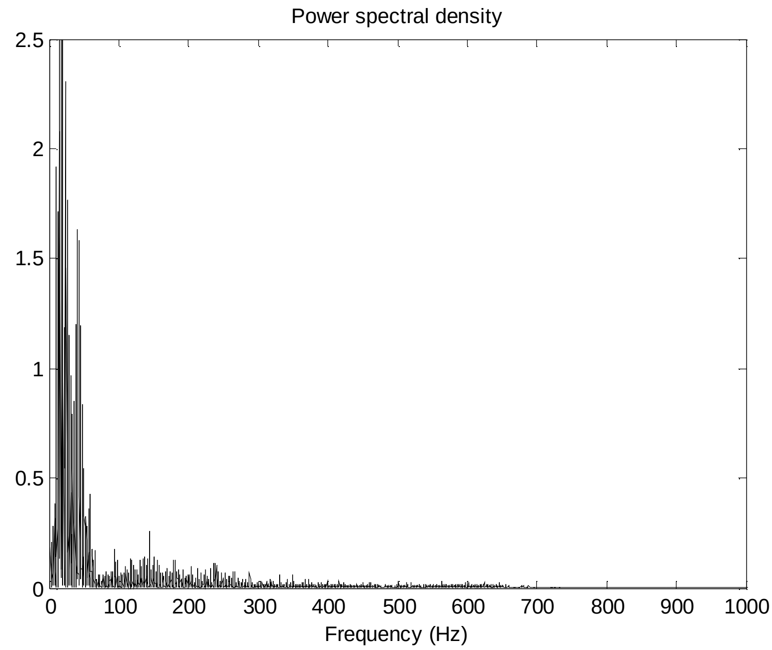

Figure B.13b

Figure B. 13. (a)R.A.L.E. Wheezing over trachea and right lower lung with acute asthma in time domain signal (b) FFT's

REFERENCES

1. Aka, L., Öz, H.R., Yıldırım C.A., Göksu, S., "Acil solunum yolu hastalıklarında solunum seslerinin dijital analizi ile hastalık teşhisi üzerine literatür taraması", 7. TÜRKİYE Acil Tıp Sempozyumu ve 3. Acil Hemşireliği ve Paramedik Sempozyum 24-27 Kasım 2004, Gaziantep, Türkiye.

2. Aka L., Öz H.R., Yıldırım C.A., Göksu S. Akpolat A. "Solunum yolları sesleri ile hastalık teşhisi üzerine literatür taraması", 12. Ulusal Makine Teorisi Sempozyumu Erciyes Üniversitesi, Kayseri 09 -11 Haziran 2005

3. Loudon, R.G., "The lung speaks out", *Am. Rev. Respir. Dis.*, 27, 1982, 411-412.

4. Charbonneau, G., Racineux, J.L., Sudraud, M., and Tuchais, E., "An accurate recording system and its use in breath sounds spectral analysis", *J. Appl. Physiol.*, 55, 1982, 1120–1127.

5. Forgacs, P. "Lung sounds", *Br. J. Dis. Chest*, 63, 1969, 1–14.

6. Loudon, R.G., and Murphy, R. "Lung sounds", *Am. Rev. Respir. Dis.* 130, 1984, 663–673.

7. Murphy, R.L., Holford, S.K., and Knowler, W.C., "Visual lung sound characterization by time-expanded wave-form analysis", *N. Engl. J. Med.*, 28, 1977, 968–971.

8. Murphy, R.L. "Auscultation of the lung—past lesson, future possibilities", *Thorax*, 36, 1981, 99–107.

9. Mori, M., "Lung sound analysis and pulmonary function studies", *Rinsho Byori. Apr.*, 42(4), 1994, 396-400.

10. Gavriely, N., Nissan, M., Rubin, A., and Cugell, D., "Spectral characteristics of chest wall breath sounds in normal subjects", *Thorax*, 50, 1995, 1292–1300.

11. Sovijärvi, A.R.A., Vanderschoot, J., Earis, J.E., "Standarization of computerized respiratory sound analysis", Eur. Respir. Rev., 10, 2000, 77-85.

12. Pasterkamp, H., Kraman, S.S, DeFrain, P., Wodicka, G., " Respiratory sounds (Advanced beyond the stethoscope)", *American Journal of Respiratory and Critical Care Medicine*, 156 (3), 1997, 974-987.

13. Nath, A.R, Cape1, L.H, "Inspiratory crackles-early and late", *Thorax*, 29, 1974, 223-227.

14. Mussel MJ., "The need for standards in recording and analyzing respiratory sounds", *Med Biol Eng Comput* ,30, 1992, 129–139.

15. Gavriely N., Cugell, D., “Breath Sounds Methodology”, Boca Raton, FL, CRC Press, 1995.

16. Earis J., “Lung sounds [editorial]”, *Thorax,* 47, 1992, 671-672.

17. Dalmasso, F., Benedetto, G., Pogolotti, R., Righini, G., Spagnolo, R., “Digital processing of snoring sounds”, *Eur Respir J* Suppl, 11, 1990, 528s–532s.

18. Dalmasso, F., Prota, R., “Snoring: analysis, measurement, clinical implications and applications”, *Eur Respir J*, 9, 1996, 146–159.

19. Salmi, T., Sovijärvi, A., Brander, P., Piirilä, P., “Long-term recording and automatic analysis of cough using filtered acoustic signals and movements on static charge sensitive bed”, *Chest,* 94, 1988, 970–975.

20. Piirilä, P., Sovijärvi, A., “Objective assessment of cough”, *Eur Respir J* , 8, 1995, 1949–1956.

21. Doherty, M., Wang, L., Donague, S., *et al.* “The acoustic properties of capsaicin-induced cough in healthy subjects”, *Eur Respir J*, 10, 1997, 202–207.

22. Slawinski, E., Jamieson, D., “Studies of respiratory stridor in young children: Acoustic analysis and tests of theoretical models”, *J Paediatr Otorhinolaryngol*, 19, 1990, 205–222.

23. Spence, D., Graham, D., Jamieson, G., Cheetham, B., Calverley, P., Earis, J.E., “The relationship between wheezing and lung mechanics during methacholine-induced bronchoconstriction in asthmatic subjects”, *Am J Respir Crit Care Med* ,154, 1996, 290–294.

24. Meslier, N., Charbonneau, G., Racineux, J., “Wheezes”, *Eur Respir J.* 8, 1995, 1942-1948.

25. Malmberg, L., Sorva, R., Sovijärvi, A., “Frequency distribution of breath sounds as an indicator of bronchoconstriction during histamine challenge test in asthmatic children”, *Pediatr Pulmonol*, 18, 1994, 170–177.

26. Gavriely, N., Nissan, M., Rubin, A., Cugell, D., “Spectral characteristics of chest wall breath sounds in normal subjects”, *Thorax*, 50, 1995, 1292–1300.

27. Schreur, H., Sterk, P., Vanderschoot, J., *et al.* “Lung sound intensity in patients with emphysema and in normal subjects at standardized airflows”, *Thorax,* 47, 1992, 674-679.

28. Şen, İ., Kahya, Y.P., “A multi-channel analog processing circuit for respiratory sound acquisition applications”, Proceedings of the 25th Annual lnternational Conference of the IEEE/EMBS, September 17-21, 2003, Cancun, Mexica.

29. Benedetto, G., Dalmasso, F., Spagnolo, R., "Surface distribution of crackling sounds", IEEE *Trans Biomed Eng,* 35, 1988, 406–412.
29. Pasterkamp, H., Consunji-Araneta, R., Oh, Y., Holbrow, J., "Chest surface mapping of lung sounds during methacholine challenge", *Pediatr Pulmonol*, 23, 1997, 21-30.
30. Pasterkamp, H., Kraman, S.S., DeFrain, P., Wodicka, G., "Measurement of respiratory acoustical signals. Comparison of Sensor", *Chest*, 104, 1993, 1518–1525.
31. Baughman, R.P., Loudon, R.G., "Lung sound analysis for continuous evaluation of airflow obstruction in asthma", *Chest*, 88, 1985, 364–368.
32. Hok, B., Bythell, V., Bengtsson, M., "Development of a wireless stethoscope for auscultatory monitoring during anaesthesia", *Med Biol Eng Comput,* 26, 1988, 317–320.
33. Ploy-Song-Sang, Y., Macklem, P.T., Ross, W.D.R., "Distribution of regional ventilation measured by breath sounds", *Am Rev Respir Dis,* 117, 1978, 657–664.
34. Anderson, K., Aitken, S., Carter, R., MacLeod, J.E.S., Moran, F., "Variation of breath sound and airway caliber induced by histamine challenge", *Am Rev Respir Dis,*141, 1990, 1147–1150.
35. Malmberg, P.L., Sovijärvi, A.R.A., Paajanen, E., Piirilä, P., Haahtela, T., Katila, T., "Changes in frequency spectra of breath sounds during histamine challenge test in adult asthmatics and healthy control subjects", *Chest,* 105, 1994, 122–131.
36. Tinkelman, D.G., Lutz, C., Conner, B., "Analysis of breath sounds in normal and asthmatic children and adults using computer digitized airway phonopneumography (CDAP)", *Respir Med*, 85, 1991, 125–131.
37. Beck, R., Dickson, U., Montgomery, M.D., Mitchell, I., "Histamine challenge in young children using computerized lung sounds analysis", *Chest,* 102, 1992, 759–763.
38. Spence, D.P.S., Bentley, S., Evans, D.H., Morgan, M.D.L., "Effect of methacholine induced bronchoconstrictive on the spectral characteristics of breath sounds in asthma", *Thorax*, 47, 1992, 680–683.
39. Sanchez, I., Avital, A., Wong, I., Tal, A., Pasterkamp, H., "Acoustic *versus* spirometric assessment of bronchial responsiveness to methacholine in children", *Pediatr Pulmonol*, 15, 1993, 28–35.

40. Rietveld, S., Dooijes, E.H., “Characteristics and diagnostic significance of wheezes during exercise-induced airway obstruction in children with asthma”, *Chest,* 110, 1996, 624–631.
41. Sestini, P., Panzardi, G., Rossi, M., Vagliasindi, M., “A new method for the objective evaluation of cough for long period of time”, Proc 15th Int Lung Sounds Conf, 1991, Veruno, Italy.
42. Pasterkamp, H., Carson, C., Daien, D., Oh, Y., “Digital respirosonography. New images of lung sounds”, *Chest*, 96, 1989, 1405–1412.
43. Sovijärvi, A., Malmberg, L., Paajanen, E., *et al.* “Averaged and time-gated spectral analysis of respiratory sounds. Repeatability of spectral parameters in healthy men and in patients with fibrosing alveolitis”, *Chest,* 109, 1996, 1283–1290.
44. Rossi, M., Pasquali, G., Barnabe, R., *et al.* “Pnonopneumography findings in patients with sarcoidosis and lung fibrosis”, *Sarcoidosis,* 10, 1993, 156–157.
45. Plante, F., Kessler, H., Cheetham, B.M.G., Earis, J.E., “Speech monitoring of infectious laryngitis”, Proc Int Conf for Spoken Language Processing”, ICLSP 1996; 1: 700-704.
46. Stearns, S.D., Hush, D.R., “Digital Signal Analysis”, *2nd Edn. Englewood Cliffs, NJ,* Prentice Hall, 1990.
47. Cooley, J.W., Lewis, P.A.W., Welch, P.D. “The finite Fourier transform”, *IEEE Trans Audio Electroacoust,* Au-17, 1969, 77.
48. Rabiner, L.R., Radar, C.M., “Digital Signal Processing”, *New York, IEEE Press,* 1972.
49. Cooley, J.W., Tukey, J.W., “An algorithm for the machine calculation of complex Fourier series”, *Math Comput,* 19, 1965, 297.
50. Yoganathan, A.P., Gupta, R., Corcoran, W.H., “Fast Fourier transform in the analysis of biomedical data”, *Med Biol Eng,* 14, 1976, 239–245.
51. Shabtai-Musih, Y., Grotberg, J.B., Gavriely, N., “Spectral content of forced expiratory wheezes during air, He, and SF6 breathing in normal humans”, *J Appl Physiol,* 72, 1992, 629-635.
52. Bohadana, R., Peslin, H., Uffholtz, H., Pauli, G., “Potential for lung sound monitoring during bronchial provication testing”, *Thorax,* 1995; 955–961.
53. Gavriely, N., Herzberg, M., “Parametric representation of normal breath sounds”, *J Appl Physiol*, 73, 1992, 1776–1784.

54. Vanderschoot, J., Schreur, H., "AR (q, v) modeling of normal lung sounds", *Meth Inf Med*, 33, 1994, 24–27.

55. Ademovic, E., Charbonneau, G., "Time scale segmentation of respiratory sounds", *Technol Health Care*, 6, 1998, 53–63.

56. Jamieson, G., Cheetham, B., Morruzzi, J., Earis, J., "Spectral analysis of pulmonary sounds", *Int J Modell Simul*, 14, 1994, 89–91.

57. Malmberg, L., Kallio, K., Haltsonen, S., Katila, T., Sovijärvi, A., "Classification of lung sounds in patients with asthma, emphysema, fibrosing alveolitis and healthy lungs by using
self-organizing maps", *Clin Physiol*, 16, 1996, 115–129.

58. Charbonneau, G., Sudraud, M., Soufflet, P., Attal, C., Gaultier, A., "Hierarchial clustering analysis of lung sound spectra", *EURSCOP 88 Signal Processing IV* , 1988, 1257–1297.

59. Rosqvist, T., Paajanen, E., Kallio, K., *et al.* "Toolkit for lung sound analysis", *Med Biol Eng Comput*, 33, 1995, 190–195.

60. Schreur, H., Diamant, Z., Vanderschoot, J., *et al.* "Lung sounds during allergen-induced asthmatic responses in patients with asthma", *Am J Respir Crit Care Med*, 153, 1996, 1474–1480.

61. Baughman, R., Loudon, R., "Quantitation of wheezing in acute asthma", *Chest*, 86, 1984, 718–722.

62. Fenton, T., Pasterkamp, H., Tal, A., Chernick, V., "Automated spectral characteristics of wheezing in asthmatic children", *IEEE Trans Biomed Eng*, 32, 1985, 50–55.

63. Shabtai-Musih, Y., Grotberg, J., Gavriely, N., "Spectral content of forced expiratory wheezes during air, He, and SF6 breathing in normal humans", *J Appl Physiol*, 72, 1992, 629–635.

64. Murphy, R., Holford, S., Knowle, W., "Visual lung-sound characterisation by time-expanded wave-form analysis", *N Eng J Med*, 296, 1977, 2968–2971.

65. Piirilä, P., Sovijärvi, A., "Crackles: recording, analysis and clinical significance", *Eur Respir J* , 8, 1995, 2139–2148.

66. Dalmasso, F., Guarene, M., Spagnolo, R., Benedetto, G., Righini, G., "A computer system for timing and acoustical analysis of crackles: a study in cryptogenic fibrosing alveolitis", *Bull Eur Physiopathol Respir*, 20, 1984, 139–144.

67. Al-Jerad, N., Strickland, B., Bothamle, G., *et al.* "Diagnosis of asbestosis by a time-expanded wave form analysis, auscultation and high resolution computer tomography: a comparative study", *Thorax,* 48, 1993, 347–353.

68. Murphy, R., Del-Bono, E., Davidson, F., "Validation of an automatic crackle (rale) counter", *Am Rev Respir Dis,* 140, 1989, 1017–1020.

69. Gavriely, N., Jensen, O., "Theory and measurements of snores", *J Appl Physiol,* 74, 1993, 2828–2837.

70. Beck, R., Odeh, M., Oliven, A., Gavriely, N., "The acoustic properties of snores", *Eur Respir J* , 8, 1995, 2120–2128.

71. Ono, M., Arakawa, K., Mori, M., Sugimoto, T., Harashima, H., "Separation of fine crackles from vesicular sounds by a non-linear digital filter", *IEEE Trans Biomed Eng,* 36, 1989, 386–395.

72. Boite, R., Kunt, M., "Traitement de la parole Presses polytechniques romandes" 1987.

73. Hirschberg, J., "Acoustic analysis of pathological cries, stridors and coughing sound in infancy", *Int J Pediatr Otorhinolaryngol,* 2, 1980, 287–300.

74. Cohen, L., "Time-frequency distribution - a review", *IEEE,* 77, 1989, 941–979.

75. Altes, R.A., "Detection, estimation, and classification with spectrograms", *J Acoust Soc Am,* 67, 1980, 1232–1246.

76. Hadjileontiadis, L.J., "Wavelet-Based enhancement of lung and bowel sounds using fractal dimension thresholding—Part I:Methodology", *IEEE transactions on biomedical engineering,* Vol. 52, no. 6, June 2005, 1143-1148.

77. Hadjileontiadis, L.J., "Wavelet-Based enhancement of lung and bowel sounds using fractal dimension thresholding—Part II: Application results," *IEEE Trans. Biomed. Eng.,* Vol. 52, no. 6, Jun. 2005, 1050–1064.

78. Kitsas, I.K., Hadjileontiadis, L.J., and Panas, S.M., "Short-term analysis of heart-rate variability using wavelet packets an efficient detector of sleep apnea episodes", *Proceedings of the second joint EMBS/BMES conference,* October 23-26, 2002, Houston, USA.

79. Gnitecki, J., Moussavi, Z., "The fractality of lung sounds: A comparison of three waveform fractal dimension algorithms", *Chaos, Solitons and Fractals,* 2005, Articles in Press.

80. Güler, E.Ç., Engin, T., Sankur, B., Kahya, Y.P., "Spectral analysis of respiratory sounds in healthy and pathological subjects", *IEEE International Biomedical Engineering Days*, 1992.

81. Bahoura, M., Pelletier, C., "Respiratory sounds classification using cepstral analysis and gaussian mixture models", *Proceedings of the 26th Annual International Conference of the IEEE/ EMBS*, September 1-5, 2004, San Francisco, CA. USA.

82. Alsmadi, S.S., Kahya, Y.P., "Online classification of lung sounds using DSP", *Proceedings of the second joint EMBS/BMES conference*, October 23-26, 2002, Houston, USA.

83. Kahya, Y.P., Güler, E.Ç., Sankur, B., Raudys, S., "Hiercarchical classifacition of respiratory sounds", *Proceedings of the 20th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, Vol. 20, No.3, 1998.

84. Kandaswamy, A., Kumar, C.S., Ramanathan, Rm. Pl., Malmurugan, J.N., "Neural classification of lung sounds using wavelet coefficients", Computers in Biology and Medicine, 34, 2004, 523–537.

85. Moshou, D., Chedad, A., Van Hirtum, A., De Baerdemaeker, J., Berckmans, D., Ramon, H., "Neural recognition system for swine cough", Mathematics and computers in simulation, 56, 2001, 475-487.

86. Oud, M., "Lung function interpolation by means of neural-network-supported analysis of respiration sounds", *Medical Engineering and Physics*, 25, 2003, 309-316.

87. Follanda, R., Hinesa, E., Duttaa, R., Boilota, P., Morgan, D., "Comparison of neural network predictors in the classification of tracheal bronchial breath sounds by respiratory auscultation", *Artificial Intelligence in Medicine*, 31, 2004, 211-220.

88. Güler, İ., Polat, H., 1 and Ergün, U., "Combining neural network and genetic algorithm for prediction of lung sounds", *Journal of Medical Systems*, Vol. 29, No. 3, June 2005, 217-231.

89. Gnitecki, J., Moussavi, Z., Pasterkamp, H., "Classification of lung sounds during bronchial provocation using waveform fractal dimensions", *Proceedings of the 26th Annual International Conference of the IEEE EMBS*, Semptember 1-5, 2004, San Franscisco, USA.

90. Anderson, K., Qiu, Y., Whittaker, A.R., Lucas, M., "Breath sounds, asthma, and the mobile phone", *Lancet*, 358, 2001, 1343-44.

91. Harper, V.P., Pasterkamp, H., Kiyokawa, H., and Wodicka, G.R., “Modelling and measurement of flow effects on tracheal sounds”, *IEEE Transactions On Biomedical Engineering,* Vol. 50, No. 1, January 2003.

92. Van Hirtum, A., Berckmans, D., “Automated recognition of spontaneous versus voluntary cough”, *Medical Engineering & Physics,* 24, 2002, 541–545.

93. Aboofazeli, M., Moussavi, Z., “Automated classification of swallowing and breath sounds”, *Proceedings of the 26th Annual International Conference of the IEEE/EMBS,* September 1-5, 2004, San Francisco, USA.

94. Aboofazeli, M., Moussavi, Z., “Analysis and classification of swallowing sounds using reconstructed phase space features”. 2005.

95. Polat, H., Güler, İ., “A simple computer-based measurement and analysis system of pulmonary auscultation sounds”, *Journal of Medical Systems,* Vol. 28, No. 6, December 2004, 665-672.

96. Baydar, K.S., Ertuzun, A., and Kahya, Y.P., “Analysis and classification of respiratory sounds by signal coherence method”, *Proceedings of the 25th Annual Intemational Conference of the IEEE EMBS,* September 17-21, 2003, , Cancun, Mexico.

97. Kahya, Y.P., Bayatli, E., Yeginer, M., Çiftci, K., Kilinc, G., “Comparison of different feature sets for respiratory sound classifiers”, *Proceedings of the 25th Annual Intemational Conference of the IEEE/EMBS,* September 17-21, 2003, Cancun, Mexico.

98. Güler, E.Ç., Sankur, B., Kahya, Y.P., Raudys, S., “Visual classification of medical data using MLP mapping”, *Computers in Biology and Medicine*, 28, 1998, 275-287.

99. Güler, E.Ç., Sankur, B., Kahya, Y.P., Raudys, S., “Two stage classification of respiratory sound patterns”, *Computers in Biology and Medicine,* 35, 2005, 67-83.

100. Sanchez, I., Pasterkamp, H., “Tracheal sound spectra depend on body height”, *Am. Rev. Respir, Dis.,* 148, 1993, 1083-1087.

101. Gross, V., Dittmar, A., Penzel, T., Schüttler, F., and Von Witchert, P., “ Classification of asthmatic breath sounds: Preliminary results of the classifying capacity of human examiners versus artificial neural networks”, *Am J Respir Crit Care Med,* Vol.162, 2000, 905-909.

102. Rietveld, S., Oud, m., and Dooijes, E.H., “Classification of asthmatic breath sounds: Preliminary results of the classifying capacity of human examiners versus

Artificial Neural Networks", *Computers and Biomedical Research*, 32, 1999, 440-448.

103. Melbye, H., "Lung sounds and lung function (video)", *Oslo: The Norwegian Medical Association,* 1999.

104. Melbye, H., "Auscultation of the lungs, still a useful examination?", *Tidsskr Nor Laegeforen,* 121, 2001, 451-4.

105. Folland, R., Hines, E., Dutta, R., Boilet, P., Morgan, D., "Comparison of neural networks predictors in the classification of tracheal-bronchial breath sounds by respiratory auscultation", Artificial Intelligence in Medicine (2004), Article in Press.

106. Manecke, G.R.Jr., Poppers, P.J., "Esophageal stethoscope placement depth: Its effect on heart and lung sound monitoring during general anesthesia.

107. Kompis, M., Pasterkamp, H., and Wodicka, G.R., "Acoustic imaging of the human chest", *Chest,* 120, 2001, 1309-1321.

108. Pasterkamp, H., Patel, S., and Wodicka, G.R., "Asymmetry of respiratory sounds and thoracic transmission", Med. Biol., Eng, Comput., 35, 1997, 103-106.

109. Gross, V., Dittmar, A., Penzel, T., Schüttler, F., and Von Witchert, P., " The relationship between normal lung sounds, age, and gender", Am J Respir Crit Care Med, 162, 2000, 905-909.

110. Sanchez, I., Vizcaya, C., " Tracheal and lung sounds repeatability in normal adults", Respir Med., Dec;97(12), 2003, 1257-60.

111. Rietveld, S., Rijssenbeek-Nonwens, L.H., "Diagnostics of spontaneous cough in childhood asthma: Results of continuous tracheal sound recording in the homes of children", Chest, Jan;113(1), 1998, 50-4.

112. Kraman, S.S., Pasterkam, H., Kompis, M., Takase, M., Wodicka, G.R., "Effects of brathing pathways on tracheal sound spectral features", Respiration Physiology, 111, 1998, 295-300.

113. Sovijärvi, A., Kallio, K., Paajanen, E., *et al.* "A new versatile PC-based lung sound analyser (HeLSA). Repetability of spectral parameters and sound amplitude in healthy subjects", *Technol Health Care*, 6, 1998, 11–22.

114. Cheetham BMG, Sun X, Earis JE. Real-time analysis of lung sounds *Technology and Health Care,* 6, 1998, 3-10.

115. Schreur, H.J., Vanderschoot, J., Zwinderman, A.H., Dijkman, J.H., Sterk, P.J., "Abnormal lung sounds in patients with asthma during episodes with normal lung function.", *Chest* ,106, 1994, 91–99.

116. Schreur, H.J., Sterk, P.J., Vanderschoot, J., Van Klink, H.C., Van Vollenhoven, E., Dijkman, J.H., "Lung sound intensity in patients with emphysema and in normal subjects at standardized airflows", Thorax, 47, 1992, 674-679.

117. Iyer, V.K., Ramamoorthy, P.A., Ploysongsang, Y., "Quantification of heart sounds interference with lung sounds", *J Biomed Eng,* 11, 1989, 164–165.

118. Robertson, A.J., Cooper, D., "Rales, rhonchi and Laënnec", *Lancet*,1, 1957, 417–423.

119. American Thoracic Society. Updated nomenclature for membership relation. *ATS News*, 3, 1977, 5–6.

120. Murphy, R.L., Jr, Sorensen, K., "Chest auscultation in the diagnosis of pulmonary asbestosis", *J Occup Med*, 15, 1973, 272–276.

121. Forgacs, P., "Crackles and wheezes", *Lancet*, 2, 1967, 203–205.

122. Fredberg, J.J., Holford, S.K., "Discrete lung sounds: crackles (rales) as stress-relaxation quadrupoles", *J Acoust Soc Am,* 73, 1983, 1036–1046.

123. Workum P, Holford SK, Delbono EA, Murphy RL. The prevalence and character of crackles (rales) in young women without significant lung disease. *Am Rev Respir Dis* 1982; 126: 921–923.

124. Forgacs, P., "Lung Sounds", London, Bailliere Tindall, 1978.

125. Malklem, P.T., Fraser, R.G., Brown, W.G., "Bronchial pressure measurements in emphysema and bronchitis", *J Clin Invest* , 44, 1965, 897–905.

126. Murphy, R.L., "Discontinuous adventitious lung sounds", *Semin Respir Med*, 6, 1985, 210–218.

127. Nath AR, Capel LH. Inspiratory crackles and mechanical events of breathing. *Thorax* 1974; 29: 695–698.

128. Piirilä P, Sovijärvi ARA, Kaisla T, Rajala HM, Katila T. Crackles in patients with fibrosing alveolitis, bronchiectasis, COPD, and heart failure. *Chest* 1991; 99: 1076–1083.

129. Al Jarad N, Strickland B, Bothamley G, Lock S, Logan-Sinclair R, Rudd RM. Diagnosis of asbestosis by a time expanded wave form analysis, auscultation and high resolution computed tomography: a comparative study. *Thorax* 1993; 48: 347–353.

130. Epler GR, Carrington CB, Gaensler EA. Crackles (rales) in the interstitial pulmonary

131. Cheetham BMG, Giordano A, Helistö P, Vanderschoot J. Digitisation of data for respiratory sound recordings. *Eur Respir Rev* 2000; 10: 77, 625–635.
132. Sovijärvi ARA, Piirilä P, Luukkonen R. Separation of pulmonary disorders with two-dimensional discriminant analysis of crackles. *Clin Physiol* 1996; 16: 171–181.
133. Sankur B, Guler E.C, Kahya Y.P. “Multiresolution biological transient extraction applied to respiratory crackles”. *Comput Biol Med* 1996; 26:
134. Kahya, Y.P., Yerer, S., Cerid, Ö., “A wavelet based instrument for detection of crackles in pulmonary sounds”, 2001 Proceedings of the 23rd Annual EMBS international conference, October 25-28, İstanbul, Turkey.
135. Kahya, Y.P., Güler, E.Ç., Özcan, C., Sankur, B., “Classifacation of respiratory sounds using crackle parameters”, 18th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Amsterdam 1996
136. Geddes DM, Corrin B, Brewerton DA, Davies RJ, Turner-Warwick M. Progressive airway obliteration in adults and its association with rheumatoid disease. *Q J Med* 1977; 46: 427–444.
137. Earis JE, Marsh K, Pearson MG, Ogilvie CM. The inspiratory "squawk" in extrinsic allergic alveolitis and other pulmonary fibroses. *Thorax* 1982; 37: 923
138. Gavriely N, Palti Y, Alroy G, Grotberg JB. Measurement and theory of wheezing breath sounds. *J Appl Physiol* 1984; 57: 481–492.
139. Pasterkamp H, Tal A, Leahy F, Fenton R, Chernick V. The effect of anticholinergic treatment on postexertional wheezing in asthma studied by phonopneumography and spirometry. *Am Rev Respir Dis* 1985; 132: 16–21.
140. Sovijärvi ARA, Dalmasso F, Vanderschoot J, Malmberg LP, Righini G, Stoneman SAT. Definition of terms for applications of respiratory sounds. *Eur Respir Rev* 2000: 10, 597–610.
141. Takezawa Y, Shirai F, Sawaki S, *et al*. Comparison of wheezes over the trachea and on the chest wall. *In*: Proc. 5th Int Conf Lung Sounds; London; 1980.
142. Wodicka GR, Stevens KN, Golub HL, Cravalho EG, Shannon DC. A model of acoustic transmission in the respiratory system. *IEEE Trans Biomed Eng* 1989; 36: 925–934.
143. Pasterkamp H, Fenton R, Tal A, Chernick V. Tracheal *vs* lung sounds in acute asthma. *Am Rev Respir Dis* 1984; 129: 256A.
144. Husodo HOS. Tracheal auscultation in the differentiation of whistling sounds heard at the chest. *In*: Proc. 7th Int Conf Lung Sounds, University of California;

145. Riella, R.J., Nohama, P., Borges, R.F., Stelle, A.L., “Automatic Wheezing Recognition in Recorded Lung Sounds”, Proceedings of the 25thAnnual Intemational Conference of the IEEE EMBS Cancun, Mexico, September 17-21,2003.
146. Robin IG. Snoring. *Proc R Med* 1948; 41: 151–153
147. Young T, Palta M, Dempsey J, Skatrud J, Weber S, Badr S. The occurrence of sleep-disordered breathing among middle-aged adults. *N Engl J Med* 1993; 328: 1230–1235.
148. Prazic M. Snoring and presbyacusis. *Acta Otolaryngol* 1973; 75: 216–219.
149. Hoffstein V. Blood pressure, snoring, obesity, and nocturnal hypoxaemia. *Lancet* 1994; 344: 643–645.
150. Series F, Marc I, Atton L. Comparison of snoring measured at home and during polysomnographic studies. *Chest* 1993; 103: 1769–1773.
151. Perez-Padilla JR, Slawinski E, Difrancesco LM, Feige RR, Remmers JE, Whitelaw WA. Characteristics of the snoring noise in patients with and without occlusive sleep apnoea. *Am Rev Respir Dis* 1993; 147: 635–644.
152. Meslier N, Auregan Y, Badatcheff A, Depollier C, Racineux J-L. Spectral analysis of snores in patients with obstructive sleep apnoea syndrome. *Am Rev Respir Dis* 1990; 141:
153. Sovijärvi ARA, Malmberg LP, Charbonneau G, Vanderschoot J, Dalmasso F, Earis JE. Characteristics of breath sounds and adventitious sounds. *Eur Respir Rev* 2000; 10:
77, 591–596.
154. Kumnajeewu, Asela S., Abeyratne, Udantha R., and Hukins, C., “Towards a home apnea monitor: a new method of extracting speech and voiced-snore segments from noisy respiratory sounds”, IEEE International Workshop on Biomedical Circuits & Systems, 2004.
155. Agrawal, S., Stone, P., Mcguinness, K., Morris, J., and Camilleri, A.E., “Sound frequency analysis and the site of snoring in natural and induced sleep”, Clin. Otolaryngol. 27, 2002,162-166.
156. Jank, R., Fiz, J.A., Sola-Soler, J., Blanch, S., Artis, P., Morera, J., “Automatic Snoring Signal Analysis in Sleep Studies”, Proceedings of the 25" Annual Intemational Conference of the IEEE EMBS, Cancun, Mexico, September 17-21.2003.

157. Cotton R, Reilly JS. Stridor and airway obstruction. *In*: Bluestone CD, Stool SE, eds. Pediatric Otolaryngology. Philadelphia PA; Saunders, 1983; 1190-1204.

158. Leiberman A, Cohen A, Tal A. Digital signal processing of stridor and snoring in children. *Int J Pediatr Otorhinolaryngol* 1986; 12: 173–185.

159. Slawinski EB, Jamieson DG. Studies of respiratory stridor in young children: acoustical analyses and tests of a theoretical model. *Int J Pediatr Otorhinolaryngol*

160. 8. Fiz, J.A., Jane, R., Salvatella, D., Izquierdo, J., Lores, L., Caminal, P., Morera, J., "Analysis of tracheal sounds during forced exhalation in asthma patients and normal subjects: bronchodilator response effect", Chest, Sep;116(3), 1990, 633-638.

161. Mazic, I., Sovilj, S., Magjarevic, R., "Analysis of respiratory sound in asthmatic infants", Measurement Science Review, 3, 2, 2003, 9-12.

162. Jané, R., Cortés, S., Fiz, J.A., Morera, J., "Analysis of Wheezes in Asthmatic Patients during spontaneous respiration", Proceedings of the 26th Annual International Conference of the IEEE EMBS San Francisco, CA, USA • September 1-5, 2004

163. Paterkamp, H., Schafer, J., Wodicka, G.R., "Posture-dependent change of tracheal sounds at standardized flows in patients with sleep apnea", *Chest,* De;110(6), 1996, 1493-8.

164. Mansy, H.A., Royston, T.J., Balk, R.A., Sandler, R.H., "Pneumothorax detection using computerized analysis of breath sounds", *Med Biol Eng Comput,* Sep;40(5), 2002, 526-532.

165. Shi, Y., "Lung sound analysis of upper airway obstruction", Zhonghua Jie He He Hu Xi Za Zhi, Aug;15(4), 1992, 228-30, 256.

166. Malmberg, L.P., Pesu, L., Sovijärvi A.R.A., "Significant differences in flow standardized breath sound spectra in patient with chronic obstructive pulmonary disease, stable asthma, and healthy lungs", Thorax, Dec;50(12), 1995, 1285-91.

167. Enochson L. Digital signal analysis and aliasing. *Sound Vibration* 1987; 3: 28-31.

168. Druzgalski C, Donnemberg RL, Campbell RM. Techniques of recording respiratory sounds. *J Clin Eng* 1980; 5: 321–330.

169. Kaisla T, Sovijärvi A, Piirilä P, Rajala HM, Haltsonen S, Rosqvist T. Validated method for automatic detection of lung sound crackles. *Med Biol Eng Comput* 1991; 29: 517–521.

170. Yip, L., Zhang, Y.T., “Reduction of heart sounds from lung sounds recordings by automated gain control and adaptive filtering techniques”, 2001 proceedings of the 23rd annual EMBS international conference, October 25-28, İstanbul, Turkey.
171. Hadjileontiadis, L.J., Liatsos, C.N., Mavrogiannis, C.C., Rokkas, T.A., and Panas, S.M., “Enhancement of bowel sounds by wavelet-based filtering”, IEEE Transactions On Biomedical Engineering, Vol. 47, No. 7, July 2000.
172. Hadjileontiadis, L.J., Panas, S.M., “A wavelet based reduction of heart sound noise from lung sounds”, International Journal of Medical Informatics 52 (1998) 183–190.
173. Hossain, I., and Moussavi, Z., “An overvıew of heart-noıse reductıon of lung sound using wavelet transform based filter”, Proceedings of the 25th Annual lnternational Conference of the IEEE EMBS Cancun, Mexico September 17-21, 2003.
174. Saatci, E., and Akan, A., “heart sound reduction in lung sounds by spectrogram”, The 3rd European Medical and Biological Engineering Conference November 20 – 25, 2005 EMBEC'05, Prague, Czech Republic
175. Azadeh Yadollahi, “A robust method for heart sounds localization using lung sounds entropy”, Ieee Transactıons On Bıomedıcal Engıneerıng, Vol. 53, No. 3, March 2006,497-502.
176. Azadeh Yadollahi, Zahra M. K. Moussavi, “A robust method for estimating respiratory flow using tracheal sounds entropy”, Ieee Transactıons On Bıomedıcal Engıneerıng, Vol. 53, No. 4, Aprıl 2006,662-668.
177. Liao, Wei-Shun, Lin, Bor-Shyh, Lin, Bor-Shing, Wu, Huey-Dong, Chong, Fok-Ching, “Ambient noise canceller in pulmonary sound using WHT transform domain adapitve filter”, Proceedings of the second joint EMBS/BMES conference Houston, USA, October 23-26, 2002.
178.Robi Polikar, 136 Rowan Hall Dept. of Electrical and Computer Engineering Rowan University, “THE WAVELET TUTORIAL”
179. Wikipedia® is a registered trademark of the Wikimedia Foundation, Inc., “http://en.wikipedia.org/wiki/Mathematical”
180. Necla KARA, (2004) University of Gaziantep M.Sc. Thesis, “Frequency Analysis of Heart Sounds For Diagnostic Purposes”, p.26-43
181. Press, W.H., Flannery, B.P., Teukolsky, S.A., Vetterling, W. T., 1986, *Numerical Recipes*, New York, USA.

182. Proakis, J. G., Monalakis, D. G., 1991, *Digital Signal Processing Principles, Algorithms and Applications,* Prentice Hall

183. Leung T.S. , White P.R. , Collis W.B. , Brown E. , Salmon A.P. 1998, Acoustic diagnosis of heart diseases, *Proceedings of the 3rd International Conference on Acoustical and Vibratory Surveillance Methods and Diagnostic Techniques*, Senlis, France, 389-398.

184) Turkoglu I., Arslan A. , Ilkay E. , 2002, A pattern recognition system for diagnose of the heart mtral valve diseases based on wavelet packet and neural network, *F.Ü. Fen ve Mühendislik Bilimleri Dergisi*, 14(1), 1-10.