CRACKLE DETECTION AND EXTEND ESTIMATION FROM LUNG SOUNDS

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Abstract:

Auscultation of the respiratory system with a stethoscope remains a very important part of the clinical exam. It provides a wealth of diagnostically useful information that includes normal breath sounds and adventitious or "added" sounds such as crackles. The development of computerized lung sound analysis enhances the possibility for clinical utilization of the information on crackles both in diagnosis and in follow-up of pulmonary diseases and possibly also in critical care units. In this work, we propose that simultaneously recording crackles using two, spatially separated, stethoscopes could allow not only the detection of the sounds but also an assessment of the severity of the disease and the extent of lung involvement. These findings could lead to a respiratory system auscultation tool that can be used by untrained personnel and even the patient himself to evaluate diseases.

Contents

1. Introduction

1.1 Respiratory sounds

Respiratory sounds are produced by turbulent and vertical flow within the airways during the functions of air inspiration and expiration. Auscultation of the chest wall, permits listening of the generated sounds in the lung airways, but also the effects of thoracic tissues. Lung sounds are divided in normal and abnormal (adventitious).

Respiratory sounds contain frequencies and intensities that are abnormal, or crackles and wheezes and therefore respiratory diseases may be diagnosed. The correct and precise interpretation of these sounds is highly dependent on the experience and hearing skill of the physician and also their knowledge about the range of frequencies and intensities found in normal and abnormal respiratory sounds. Moreover, the properties of the stethoscope are significant variables in the accurate application of auscultation [1].

The stethoscope is still the most widely used instrument in clinical medicine. For a lot of years, it has been an effective tool for the diagnosis of respiratory diseases. In general, a stethoscope comprises a sound-receiving member, such as the members conventionally referred to as a bell or diaphragm, which in use is placed in contact with the part of the body nearest the place where a sound may originate. The bell or diaphragm is connected by suitable conduit means, such as a rubber tubing, to conventional ear tips or aurals designed to fit into the ears of the operator whereby the sound vibrations are carried or piped from the bell or diaphragm to the physician's ears. The car tips are frequently mounted at the ends of metal tubes, a pair of such tubes and the accompanying tips generally being referred to as binaurals. Often two or more sound-receiving elements are associated with the head [10].

Several respiratory sounds, normal and abnormal, will be examined and analysed in order to understand the importance of auscultation and lung sound analysis. A synopsis of several sound characteristics is found in table 1 [2].

Table 1. CATEGORIES OF RESPIRATORY SOUNDS*

Respiratory Sound	Mechanisms	Origin	Acoustics	Relevance
Basic sounds				
Normal lung sound	Turbulent flow vortices, unknown mechanisms	Central airways (expiration), lobar to segmental airway (inspiration)	Low-pass filtered noise (range < 100 to > 1,000 Hz)	Regional ventil-ation, airway caliber
Normal tracheal sound	Turbulent flow, flow impinging on airway walls	Pharynx, larynx, trachea, large airways	Noise with resonances (range < 100 to > 3,000 Hz)	Upper airway configuration
Adventitious sounds				
Wheeze	Airway wall flutter, vortex shedding	Central and lower airways	Sinusoid (range ~ 100 to > 1,000 HZ; duration, typically > 80 ms)	Airway obstruc-tion, flow limitation
Rhonchus	Rupture of fluid films, airway wall vibrations	Larger airways	Series of rapidly dampened sinusoids (typically < 300 Hz and duration > 100 ms)	Secretions, ab- normal airway collapsiblility
Crackle	Airway wall stress-relaxation	Central and lower airways	Rapidly dampened wave deflection (duration typically < 20 ms)	Airway closure, secretions

Table 1: Categories of respiratory sounds [2]

1.2 Normal sounds

Lung sounds transmit a power spectral density that is broadband with power decreasing as frequency increases. In the case that the signals are free of adventitious sounds, the logarithms of amplitude and frequency are linearly related in healthy subjects. It should be noted that inspiratory and expiratory sounds have different amplitudes and frequency ranges. When the flows are comparable, inspiratory lung sounds are more intense than expiratory sounds [3].

Due to technical advances in sound recording and analysis, more accurate measurements and comparisons of sound intensity and frequency content have become possible. The spectrum of sound recorded over the trachea is different than the one over the chest wall. Power declines exponentially as frequency increases for vesicular sounds, but sounds recorded over the trachea exhibit a different power spectrum. This power spectrum remains fairly constant up to a frequency averaging 920 Hz, and then falls rapidly. Moreover, there are similarities in the frequency content of the sounds recorded simultaneously over the thorax, the trachea and the open mouth. Higher peak frequencies have been observed in sounds recorded over the lung apex than over the base, but that could be due to different sound filtration or

different sound characteristics. During expiration the surface sounds are derived from tracheal sound, but during inspiration surface sounds are generated closer to the lung surface.

The tracheal or bronchial breath sounds are the ones heard by listening over the large airways. These sounds differ in character from vesicular sounds with a hollow or tubular sound. Bronchial sounds heard over consolidated lung almost certainly represent improved transmission to the periphery of sound produced in the large airways.

Breath sounds with characteristics that are somewhere between vesicular and bronchial sounds are called Broncho-vesicular. In healthy subjects, these sounds are most likely to represent an acoustic combination arriving at the site of auscultation from different sources [3].

1.3 Adventitious lung sounds

Adventitious or abnormal lung sounds are directly linked and able to provide useful information regarding lung disorders. The adventitious respiratory sounds are classified into the following two categories: continuous and discontinuous respiratory sounds. Continuous breath sounds contain wheezes and rhonchi's. On the other hand, discontinuous sounds are fine and course crackles, which are the major area of interest of this work [4].

1.3.1 Continuous Adventitious Lung sounds

Continuous adventitious sounds usually are indicators of disease. The context of the term "continuous" is a duration of more than 250ms, rather than a sound that continues throughout a respiratory circle. These sounds, usually called wheezes, are most of the time louder than underlying breath sounds. They can often be heard over the patient's open mouth or by auscultation over the larynx. They can be heard by the unaided ear at a small distance in an asthma patient [4].

Wheezing sounds are the aftermath of airway walls interaction with the gas moving through them. These sounds are produced when the calibre of the walls is narrowed down to a point where the opposite walls touch each other, due to bronchospasm, mucosal thickening or edema. Mass, elasticity and flow velocity of the airway to the point of closure, can be determined by the pitch of the wheeze [4].

The musical sound of wheezing can be easily recognized by ear since it differs from normal lung sounds. Medium to loud intensity wheezes are also easy to notice as sharp peaks in the power spectrum of respiratory sounds. Computer-based detection of wheeze is possible with algorithms that relate the amplitude of these spectral peaks to the average lung sound amplitude. When wheezing is audible but faint, the automated computer recognition becomes less reliable. Digital sonography translates the acoustic information into graphic images, which allows the visual identification of wheezes even at low intensities [5].

1.3.2 Discontinuous lung sounds

Discontinuous Adventitious Lung Sounds are defined by individual components lasting for less than 20ms. These sounds are heard as a series of brief explosive sounds and are called crackles. Of the adventitious lung sounds, crackles are perhaps the most useful for clinical diagnosis. There are two mechanisms that are considered the most probable sources of crackle generation [4].

The first is a sudden opening of a succession of small airways with fast equalisation of pressures. This causes a sequence of implosive sound waves and it is often the cause of crackles heard in patients with interstitial lung disease, such as fibrosing alveolitis or asbestosis. Other than that, these crackles could also be heard in subjects with congestive heart failure [4].

The second mechanism responsible for these sounds is the bubbling of air through secretions. These sounds range from the coarse bubbling sounds heard in patients who have copious secretions in their larger airways, to the sounds heard in patients with pulmonary edema or with obstructive lung disease. Studies have been made on the acoustic waveform of these crackles, by recording sounds simultaneously at more than one site [4].

Crackles often occur when the elastic recoil pressure of the lungs is increased, or there is inflammation or edema in the lungs. The characteristics of the crackling sounds possibly depend on the diameter of the airways which are closing and opening, and this in turn depends on the pathophysiology of the surrounding tissue [6]. The characteristics of crackles produced in airway models change with the size of the airways. Smaller airways produce crackles of shorter duration. Early inspiratory crackles are probably generated in more proximal airways than late inspiratory crackles. In chronic bronchitis and emphysema,

collapse of the lobar bronchi may occur at end-expiration due to loss of elastic recoil and bronchial support. In fibrosis, the process usually involves peripheral airways, the distribution of airway closure being gravity-dependent. The count and distribution of crackles also depend on the disease process and its severity [6].

The following types of crackles were described by Laennec [13] through his wooden cylinder stethoscope:

- humid or crepitous crackles
- mucous or gurgling crackles
- dry sonorous crackles
- dry sibilous or hissing crackles.

This type of crackle characterization in relation to the "dryness" or "humidity" of the sounds is no longer recommended [6]. The modern classification is based on the pitch and duration of the crackling sounds. The term fine crackles is used to characterize crackles with high frequency components and short duration, while coarse crackles is used for crackles with lower frequency and longer duration are recommended by the American Thoracic Society [14]. Furthermore, the timing of crackles in the respiratory cycles is characterized, as they may appear in early, mid- or end-inspiration or expiration [6].

Because of the very short duration and often low intensity of the crackles, their discrimination and characterization by normal auscultation is difficult [6]. Moreover, the linguistic descriptions of crackle sounds by different physicians are various. There are differences in physicians hearing properties as well as in the stethoscopes. The ideal sensitivity of the ear is normally at the frequency range of 1–2 kHz. Below 1000 Hz, the sensitivity of the ear decreases dramatically [6].

Apart from that, the frequency response of stethoscopes varies greatly depending on the type of stethoscope, and there are also great individual differences between them [6]. Stethoscopes have been shown to considerably attenuate all sound frequencies not in a uniform way using both the diaphragm and bell chest [15]. Other factors which also influence the hearing of crackling sounds are the sensitivity of the ear to different sound frequencies that depends on the relative loudness of the sound and the poor ability of the ear in recognizing a tone of very short duration [16]. There are also difficulties in hearing short

sounds separated from each other by very short intervals. Lastly, the minimum audible time interval for the separation of sounds also depend on the frequency composition and intensity of the sounds to be separated [17].

Crackles are classified as coarse or fine by the analysis of their waveform. Their various characteristics related to duration, pitch and amplitude, can be found in table 2. There is a wider distribution for coarse than for fine crackles. It should me mentioned that coarse crackles may originate in larger airways than fine crackles [4].

Fine crackles	**Coarse Crackles**
Short duration (<5ms)	Long duration (>10ms)
High frequency (>800Hz)	Lower pitch(<800Hz)
Low amplitude	High amplitude

Table 2: Fine and coarse crackle characteristics

Crackling at the beginning of inspiration is a common sign of chronic obstructive pulmonary diseases, particularly chronic bronchitis [19]. These sounds are low pitched, scanty, audible at the mouth, and cannot be extinguished by changes of posture, in contrast to late inspiratory crackles. Moreover, early inspiratory crackles are often associated with late expiratory crackles that are similar. Furthermore, unlike the random sequence of inspiratory crackling in deflated lungs, these early inspiratory cracklings are often defined by short sequences of equal loudness and spacing [18].

The crackling heard towards the end of inspiration in diffuse pulmonary fibrosis and other diseases characterized by pulmonary deflation is generated by late inspiratory crackling [18]. In deflated territories of the lung, the peripheral airways remain closed until a late stage of inspiration. By then the gas contained in the alveoli supplied by these airways is considerably below atmospheric pressure. When the airway opens again, the sudden equalization of pressure is followed by an explosive sound. The profuse late inspiratory crackling over the base of these lungs is the noise of miniature explosions coinciding with the sequential reopening of many peripheral airways [18].

Crackle sounds in the lungs indicate various lung diseases, therefore their analysis is of great significance. The most common way for a physician to analyse crackles, is auscultation through the stethoscope. The correct and precise interpretation of these sounds though, is

highly dependent on the experience and hearing skill of the physician and also their knowledge about the range of frequencies and intensities found in normal and abnormal respiratory sounds.

1.4 Literature review on automated crackle analysis

The interest in analysing crackles to interpret lung diseases, has fuelled various studies based on automated crackle analysis. By automatically analysing crackles physicians are able to come to conclusions faster and more accurately, without relying solely on their auscultating skills. Several methods have been developed and the most important will be briefly examined.

1.4.1 Automated Lung Sound Analysis in Pneumonia Patients

Computer-based technology has been developed, allowing objective measurement, quantification, and display of auscultation findings. A computerized multi-channel lung sound analyser was used, in order to determine whether objectively measured lung sounds differed significantly in patients with pneumonia versus asymptomatic subjects. A secondary goal, was the quantification of pneumonia sounds of patients for educational purposes [7]. The inspiratory crackles in the pneumonia patients were classified by the algorithm as coarse in 63% and both coarse and fine in 99%. Fifty percent of the expiratory crackles were classified as coarse and only one pneumonia patient had expiratory fine crackles. The remaining population had a combination of fine and coarse crackles. The presence of crackles in the control group was age-related, since the controls who had crackles were at least 60 years old. Wheezing was more common in the pneumonia patients. More specifically, it was present in 14% of patients during inspiration and in 21% during expiration. Three controls had inspiratory wheezing and one had expiratory wheezing. All pneumonia patients in this study had chest radiograph opacifications consistent with pneumonia. Right-sided pneumonia was more common than left-sided pneumonia. Lastly, upper-lobe involvement in the absence of lower-lobe involvement was uncommon [7].

1.4.2 Automated Analysis of Crackles in Patients with Interstitial Pulmonary Fibrosis

Crackles are a common finding in patients with interstitial pulmonary fibrosis (IPF). Their presence in a patient is often the first clue that the disease is present. Unfortunately, they can be misinterpreted as being due to congestive heart failure (CHF) or pneumonia (PN), and as a consequence patients may receive inappropriate therapy. On occasion, this can lead to

serious, unwanted side effects such as dehydration due to the inappropriate administration of diuretics or an adverse reaction to an antibiotic that was not indicated in the first place. In an attempt to reduce these complications, we studied the sound patterns of patients with these diseases using a multichannel lung sound analyser (STG16) to determine if such analysis could help differentiate IPF from CHF and PN. While crackle pitch can be assessed by a clinician using an acoustic stethoscope, other crackle features that are significantly different between IPF and CHF/PN can only be gained with the use of a computerized stethoscope. And some crackle features such as crackle transmission coefficient can only be calculated with the use of a multichannel lung sound analyser [8].

1.4.3 An integrated automated system for crackles extraction and classification

Individual crackle waveforms have a general characteristic: the signal begins with a small initial deflection followed by deflections with greater amplitude, the span of the deflections also increases gradually until it reaches a constant. An integrated system for crackle recognition was proposed, in which three principal procedures are involved: crackles separation using a wavelet packet filter, crackles detection by fractal dimension and crackles classification based on Gaussian mixture models. Individual crackles are extracted and classified into fine crackles and coarse crackles automatically, by processing the respiratory signal [9].

The filter incorporates a multi-resolution decomposition of the original respiratory signal and an entropy-based best basis selection of the coefficients. Two thresholds are defined, in time and frequency domains respectively, to separate the crackles from the respiratory sounds. Then, a de-noising filter is applied to the discontinuous output of the previous filter and a crackle-peak-detector localizes the individual crackles by means of their fractal dimension. After that, three feature parameters, including the Gaussian bandwidth, the peak frequency and the maximal deflection width, of the crackles are extracted. Finally, crackles are classified into fine and coarse crackles using Gaussian mixture models [9].

1.5 Separating lung sounds from heart sounds

When applying respiratory auscultation, heart sounds interfere with lung sounds in a way that downgrades the validity of respiratory sounds analysis and potential disease diagnosis. Normal heart and lung sounds overlap in the low frequency range. Normal heart sounds are

in the field of 20 to 150 Hz while normal lung sounds are found between 40 and 600 Hz. Adventitious sounds, resulting from a structural abnormality or pathology, are present at higher frequencies. Adventitious heart sounds occur at up to 1200 Hz and adventitious lung sounds occur at up to 2000 Hz. However, there are ways to filter out heart sounds from lung sound recordings. There are those that require a separate noise reference such as linear adaptive filters, and those that don't such as filters employing time-frequency methods [20].

Sounds produced by the cardiac cycle are basic tones and murmurs. Physicians can detect these sounds from the chest surface, since the last ones travel there through the internal tissues. Human and nonhuman detection of heart sounds is not always valid due to physiological variables such as air trapping in lungs, thickness of adipose tissue and chest muscle mass that can change the amplitude and phase of the sound signal [21].

Heart sounds are produced by the blood flow in and out of heart and by the structure movement involved in the mechanism of this flow. Normal heart sounds can be divided into two components, called first tone and second tone or S1 and S2. The first one is associated with the beginning of ventricular contraction, closing of atrio-ventricular valves and opening of the ejecting valves (aortic and pulmonary). During the latter half of the cardiac cycle, the blood is pumped from the heart to the rest of the body and therefore, the first heart sound results. This sound is produced by the rise and release of pressure within the left ventricle, combined with the increase in ascending aortic pressure. Acoustically, the first heart sound S1 is a low, slightly prolonged lub and has a duration and frequency of about 0.15s and 25‑45 Hz respectively [22].

The second tone is produced by the closure of the aortic and pulmonary valves at the end of the ventricular systole and the reverberation of blood pushing against the closed valves. S2 is a shorter, high-pitched 'dup', caused when the ventricles stop the ejection, relax and allow the aortic and pulmonary valves to close right after the end of the ventricular systole. It lasts about 0.12 s, with a frequency of 50 Hz [22]. These two auscultatory events establish a framework within which further heart sounds (third and fourth tones) and murmurs can be placed and timed. The occurrence of extra sounds and murmurs with respect to the first two can be related to a variety of physiological or pathological conditions [21].

A method to remove heart interferences from lung sounds is linear adaptive filtering. The two main classes of linear adaptive filters that have been applied to lung sound recordings in order to reduce heart sounds are noise cancellation and linear prediction. In noise cancellation, the primary input contains both the noise to be removed and the desired signal. In linear prediction, a model of a signal is developed based on its past or future values, or on white noise. In ideal scenarios, a linear relationship and minimal correlation exists between the two. The reference signal represents the noise part of the primary input and filter output is a signal that models the noise in the input. The signal of interest is calculated by subtracting the filter output from the primary input. Examples of linear adaptive filters are least mean squares (LMS), fourth order statistics (FOS), recursive least squares (RLS), block fast transversal (BFT) and reduced order Kalman (ROK) [23].

A second method used to filter out heart sounds is time-frequency based filtering. Short-time Fourier Transform (STFT) and Wavelet Transform Analysis (WT), have been used for noise cancellation in heart and lung sounds. Using these methods, one can examine signals in both time and frequency domains. STFT presents intensity of data within segments of constant time and frequency resolution. In the case that data are non-stationary, window sizes must be chosen in a way that data within the windows are at least wide-sense stationary. Due to that, window size and spectral resolution is limited. Wavelet transform analysis is a more flexible method in terms of resolution and therefore does not demand stationary data. Finding the WT of a signal requires a mother wavelet function. This function is a waveform with morphological features that remain constant in terms of amplitude because it is dilated or compressed in time [23].

1.6 Crackles severity evaluation-proposal

In several respiratory diseases such as pneumonia, the alveoli inside the lungs pop at random times and places, thus creating crackle sounds. Using a stethoscope device, a physician can auscultate these crackling sounds and diagnose the condition. As it has been stated before, the correct and precise interpretation of respiratory sounds via stethoscopes, is highly dependent on the experience and hearing skill of the physician and also their knowledge about the range of frequencies and intensities found in normal and abnormal respiratory sounds.

Although diseases such as pneumonia can be detected and identified by a stethoscope, the disease extend inside the lung area is a different story. Unless a physician is a trained pulmonologist, it is actually very hard to distinguish the crackle extension inside the lungs and therefore the severity of the situation. A paediatric physician for example, could find difficulties diagnosing the severity of pneumonia in a child using a stethoscope. The only scientifically accepted method of investigating this, is an x-ray which should be used as rarely as possible. Apart from that, this device could be proven useful for home use and use in underdeveloped countries where physicians are not always available.

In this thesis, the simultaneous recording of lung crackles, using a dual head stethoscope-microphone device is proposed. This could allow not only the detection crackling sounds but also an assessment of the severity of the disease and the extent of lung involvement.

1.7 Contents of thesis

In the following chapters of this thesis, the structure of the proposed dual-head stethoscope device will be thoroughly analysed in terms of hardware and software. Several calibrations and measurements were performed in order to ensure that the two microphones have the signal characteristics, such as similar amplitude and low phase difference.

In order to assess the validity of this hypothesis, a series of simulations was performed. Initially, the sound corresponding to a single crackle was extracted from actual crackle sounds recorded and available online. The estimated shape and duration of this single crackle is very similar with those in the literature. Using the individual crackle sound and a model of the distribution of the collapsed alveoli in a lung region, the crackle sounds as would be heard by two microphones, placed at a known distance apart, were simulated. This model included a random distribution of alveoli with random popping times during an inspiratory period. The cross-correlation of the simulated recordings from the two microphones was investigated as a measure of the severity of the disease.

The next step was patient measurements. In vivo data collection was performed in order to collect:

- Data from healthy individuals
- Data from crackles

These data were analysed in terms of artefact reading detection, crackle detection and cross correlation of the two input channels. Apart from that, an estimation of the disease's severity was extracted from the data.

2. Methodology-Device hardware and setup

2.1 Stethoscope auscultation introduction

There is a great variation in modern stethoscopes and despite the high cost of many of them, these instruments in their simplest form, remain means for sound conduction between the body surface and the ears. Stethoscopes devices are rarely tested, rated, or compared. Factor that are taken into consideration when choosing one are often [5]:

- appearance
- reputation
- claims of performance

Stethoscopes are definitely not ideal acoustic instruments and the reason is they do not provide a frequency-independent, noise-free transmission of sounds. On the contrary, they can selectively amplify or attenuate sounds within the spectrum of clinical interest. Specifically, amplification usually occurs below 112 Hz and attenuation at higher frequencies [12].

When designing a stethoscope, convenience and clinical utility are often more important than acoustic fidelity. Amplification at low frequencies is appreciated by cardiologists since heart sounds are in this frequency range, which is poorly perceived by the human ear. Lung auscultation on the other hand, is not that simple and is highly dependent on the physician's skillset [5]. Intensity of the sound reaching the stethoscope earpiece at a given frequency depends on a number of factors. The physical factors which affect sound transmission are [12]:

- Size and volume of the bell
- Surface hardness of the bell cavity
- Diaphragm thickness
- Size
- Interior surface smoothness of the tube
- Length of the tube between chest and earpiece
- Inside diameter of the tube
- Air leaks between components of the stethoscope

Moreover, anatomical, physiological, and environmental factors affect stethoscope performance [12]:

- degree of mechanical contact between the bell or diaphragm and the body surface
- air leaks between the body surface and bell or diaphragm
- air leaks between the earpiece and the auditory meatus
- acoustical characteristics of the human ear
- interference by room noise

These factors are not all equally important, but they can definitely be significant and greatly vary from user to user. The typical acoustical transfer function of a stethoscope shows a decreasing transmission of sound (at the earpiece) as frequency increases. Superimposed on this pattern are a series of maxima and minima that are controlled by some of the above-mentioned factors [12]. When the bell is used as the chestpiece at frequencies below approximately 100 Hz, the sound received at the earpiece is actually louder than that at the chestpiece because of the amplification that takes place. On the other hand, use of the diaphragm as the chestpiece results in less amplification, or depending on the diaphragm's attenuation. Increasing tautness of the diaphragm membrane produces decreasing transmission of low-frequency sound. The decreasing efficiency of sound transmission to the earpiece with increasing frequency is dependent to a major degree on tube length, inside diameter, the tube's smoothness and the roughness of the bore surface. Small diameter, long tubes, and interior roughness result in greater sound reduction as the frequency increases [12].

The subject of this thesis is lung sound recording and certain sensors can be used in order to achieve the best results. Two types of transducers are in common use for lung sound recording and research: the electret microphone with coupling chamber and the accelerometer. Small sized electret microphones are widely available for speech and music recording and when coupled to the skin by a sealed chamber, in our case a stethoscope bell, this sensor is a sensitive lung sound transducer [5]. The overall frequency response of this coupling is affected by different sizes and shapes of coupling chambers. Those arrangements with smaller, conically shaped chambers are more sensitive to higher lung sound frequencies, but at the same time susceptible to ambient noise. Also, contact accelerometers are popular

in lung sound research and can be calibrated on a vibration table so their output is quantified. However, they are typically more expensive than electret microphones, are often fragile, and may exhibit internal resonances near the lung sound frequencies of interest [5].

Auscultation influences, such as the stethoscope's response and psychoacoustic phenomena, have contributed to widely taught concepts in the health care department. Although these concepts have proven useful in many clinical circumstances, recent acoustic investigations with high-fidelity measurements indicate that considerably more information of clinical utility can be gathered from respiratory sounds. This information often cannot be obtained by auscultation, and some of the new findings can only be interpreted by taking an acoustical perspective and extending or even breaking down a few traditional concepts. For instance, it has become clear that inspiratory sounds measured simultaneously over the extrathoracic trachea and at the chest surface contain highly unique regional information that can only be reproducibly extracted with a knowledge of the breathing flow rate. Such realizations are fuelling the investigation of the acoustic properties of the respiratory system to improve their use for diagnostic, screening, and monitoring purposes [5].

2.2 Dual-head microphone-stethoscope components

In this part, the experimental hardware setup and the dual-head microphone stethoscope device (DSM) will be presented and thoroughly analysed. Moreover, the device's calibration procedures and tests will be in-depth explained.

The DSM device consists of two Littmann type stethoscope heads, two mini microphones that are attached to a preamp and a wireless transmitter and receiver. The stethoscope heads were cut off from the complete stethoscope devices maintaining a tube piece of 5cm length. These heads were attached into two mini microphones whose output was sent into a preamp, in order to amplify the input signals and lastly, into a wireless signal transmitter. These hardware parts were fit inside a case that is clipped in the patient's belt.

The amplified signal was then transmitted, using a wireless transmitter into a receiver and a dual channel recording soundcard. The algorithm responsible for the recording and processing of the signal was developed in MATLAB environment. The schematics of the device is presented in figure 2.1.

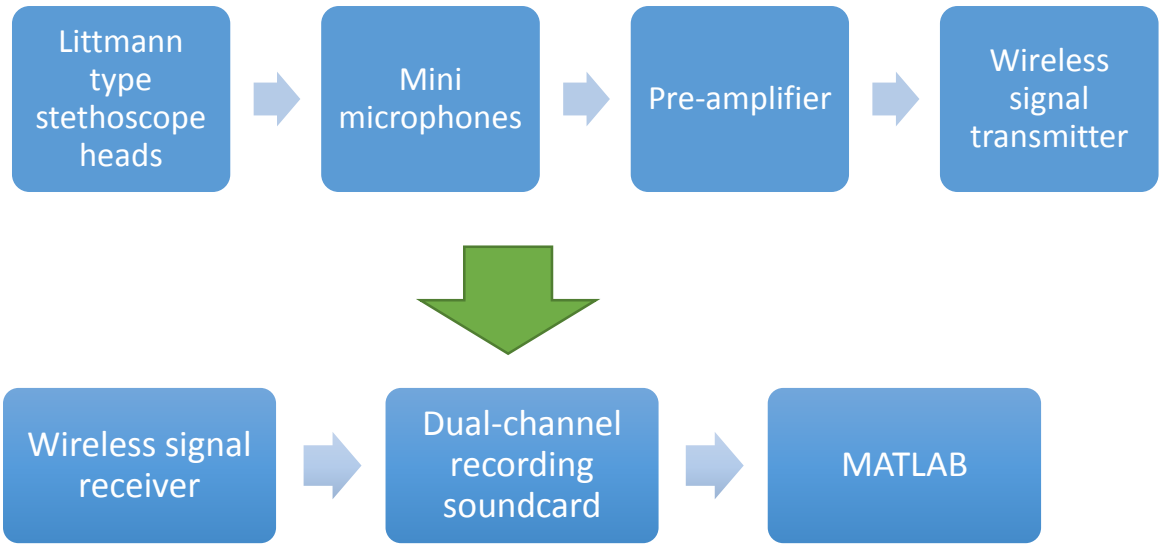

Figure 2.1: Hardware setup and signal transmission

Littmann type stethoscope heads: These types of Stethoscopes provide reliable acoustic performance for taking blood pressure readings and making limited physical assessments of adult patients. Weighing just 118 grams, it's the lightest of all Littmann adult stethoscopes, and is ideal for this particular device's portable design. The Lightweight II S.E. stethoscope offers a number of beyond-the-basics features such as a tuneable diaphragm, dual-sided chestpiece, and adjustable headset. It's a good choice for medical professionals such as LPNs, licensed vocational nurses, certified nursing assistants, and nursing students. Tuneable diaphragm technology lets clinicians hear different frequency sounds by simply adjusting the pressure on the chestpiece. Hold the chestpiece with light pressure to hear low frequency sounds; press a little more to hear higher frequency sounds. This feature allows efficient lung sound recording, as the pressure can be increased or decreased depending on the patient's crackle condition [24].

Mini microphones and pre-amp (EAGLE G157B): This unusual miniature Stereo/Mono microphone type ALEM 106 finds hundreds of applications. The microphone body is just 10mm in diameter and houses two condenser elements. It is therefore a perfect match for

the stethoscope heads. Mic cable length is 1m and output cable length 3m to a Jack plug. The set is powered by a single AA battery with a life exceeding 1000 hours.

Wireless transmitter and receiver: The output of the microphone pre-amp is connected to the input of a wireless signal transmitter. The signal is transmitted into a receiver that is connected to the soundcard. Both the wireless transmitter and receiver are small sized and rechargeable.

Stereo recording soundcard: An external soundcard (DIAMOND XSTU21) was used, in order to simultaneously record the separate signals of the microphone set. The need of this component lies in the fact that stereo recording is not default in most computers.

Figure 2.2: Dual head stethoscope-microphone

2.3 Device calibration

A crucial step in calibrating the DMS device, was to ensure that there was no amplitude level difference nor phase shift between the two microphones. The importance of this step lies into the fact that the two microphones must record the exact same levels and phase, in order to function properly as respiratory sound recorders. An experiment was setup in order to make sure that the input devices were calibrated equally.

A function generator produced sinusoid signals of constant amplitude, in various frequencies. The first output was sent into an oscilloscope in order to monitor the signals, and the second was sent into a passive speaker. The soundwaves produced were recorded using the device's

microphones, kept at a standard distance. Various frequencies from 50 to 5000Hz were dialled in the function generator. The reasoning behind these frequency choices was to match the frequencies produced by respiratory system normal and abnormal sounds.

Using a MATLAB script, the signals were recorded and the amplitude difference and phase shift between the two microphone inputs were calculated. The device's calibration equipment setup is illustrated in figure 2.3.

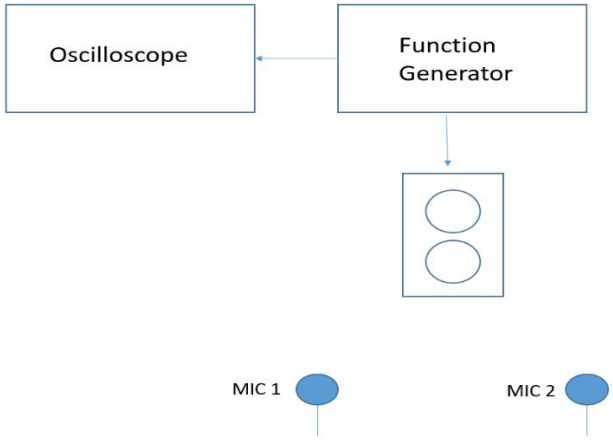

Figure 2.3: Calibration equipment setup

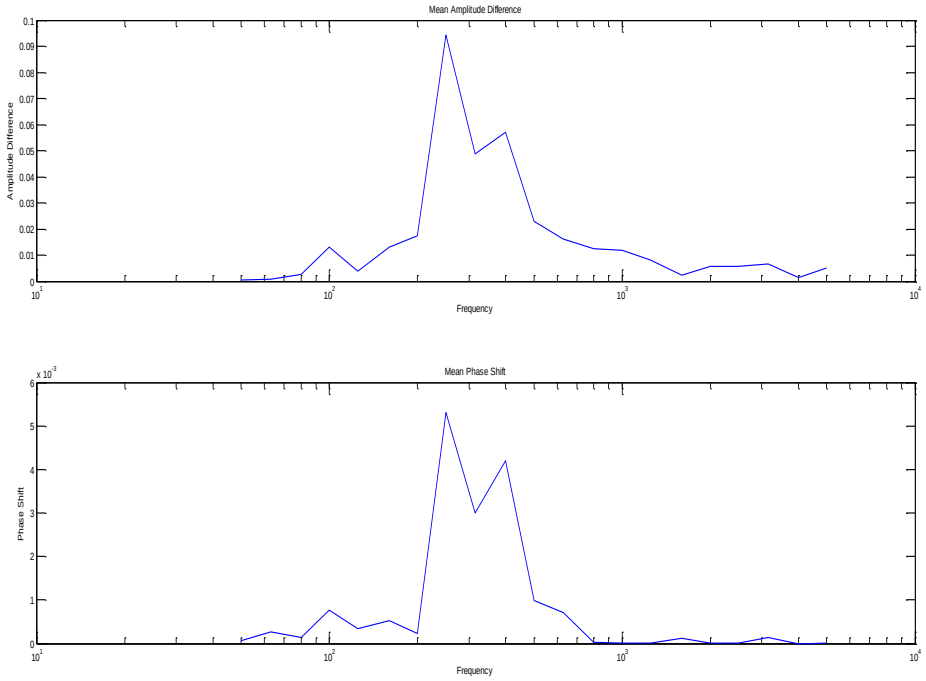

Figure 2.4: Mean amplitude difference and phase shift between the two mics

The results were plotted in the graph presented in figure 2.4, where a semi-log scale was applied. Both mean amplitude difference and phase shift between the two inputs are kept at low values. The maximum values are found in frequencies near 300-400Hz, but these values are so low that are not consider a problem anyhow.

3. Simulations

3.1 Crackle simulations

In order to theoretically validate the proposal, certain simulations were performed in MATLAB. The first step was to simulate the crackles inside the lung area, and the stethoscope-microphones set at specific distance apart [b]. The crackles were generated at random places and popping times inside the radius of a circle, during an inspiratory period of 1000ms. As it is shown in figure 3.1, the mics were placed 6cm away in the y-axis and at the beginning and ending of the x-axis in a known distance that can be used as a variable. The last part will be better explained later.

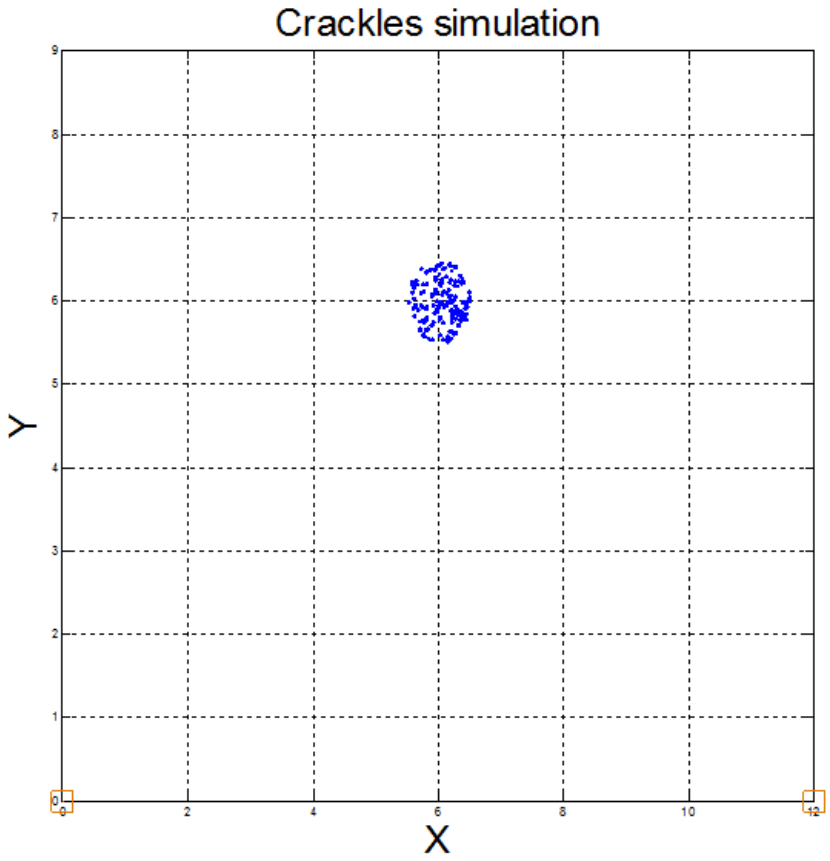

Figure 3.1: Simulation of crackles inside the lungs

The next step was to calculate the time-delay of each crackle's sound arrival at each of the microphones. These time-delays were calculated on a loop, using the distance of each crackle to each microphone. The sound velocity inside the lungs was found to be 2.4 cm/ms [11] and the time-delays were calculated via the general velocity formula. This procedure is illustrated in figure 3.2.

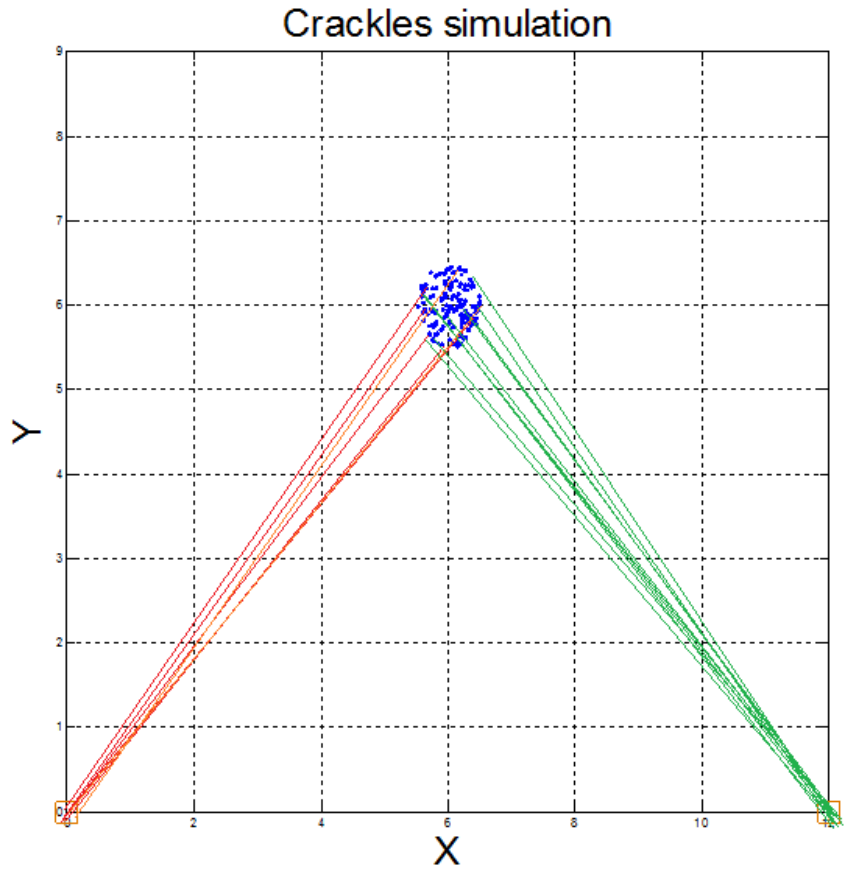

Figure 3.2: Distances of each crackle to each of the mics for calculation of time-delays

Next, the sound corresponding to a single crackle was extracted from actual crackle sounds recorded and available online. This waveform was derived by the point-to-point multiplication of a chirp waveform (sinusoid whose frequency is not constant) and a gamma function. The estimated shape and duration of this single crackle that is illustrated in figure 3.4, corresponded well with those in the literature.

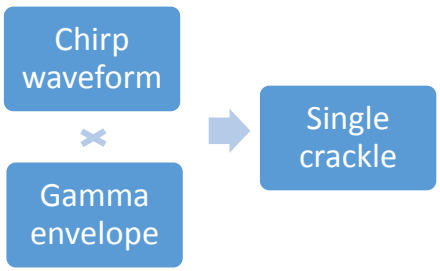

Figure 3.3: Single crackle extraction

Using the individual crackle sound and a model of the distribution of the collapsed alveoli in the lung region, the crackle sounds as would be heard by two microphones, placed at a known distance apart, were simulated. The simulated crackles waveform in two channels, left and right, was generated by cross-correlation of the single crackle waveform and the calculated time-delays of each microphone.

The resulting left and right crackle waveforms are found in figure 3.4. The cross-correlation of the two channels was investigated, as a measure of the disease severity. The logic diagram of the algorithm used to get to the severity measurement is presented step-by-step in figure 3.5.

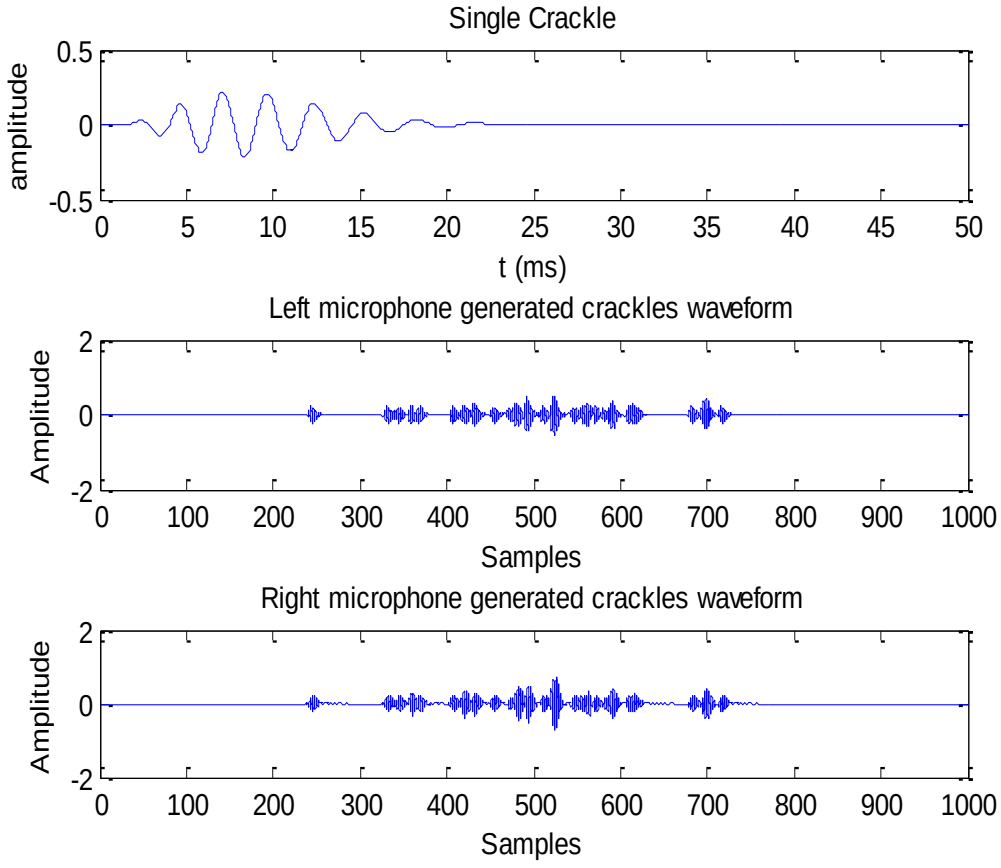

Figure 3.4: Single crackle waveform and left and right channel crackle sounds.

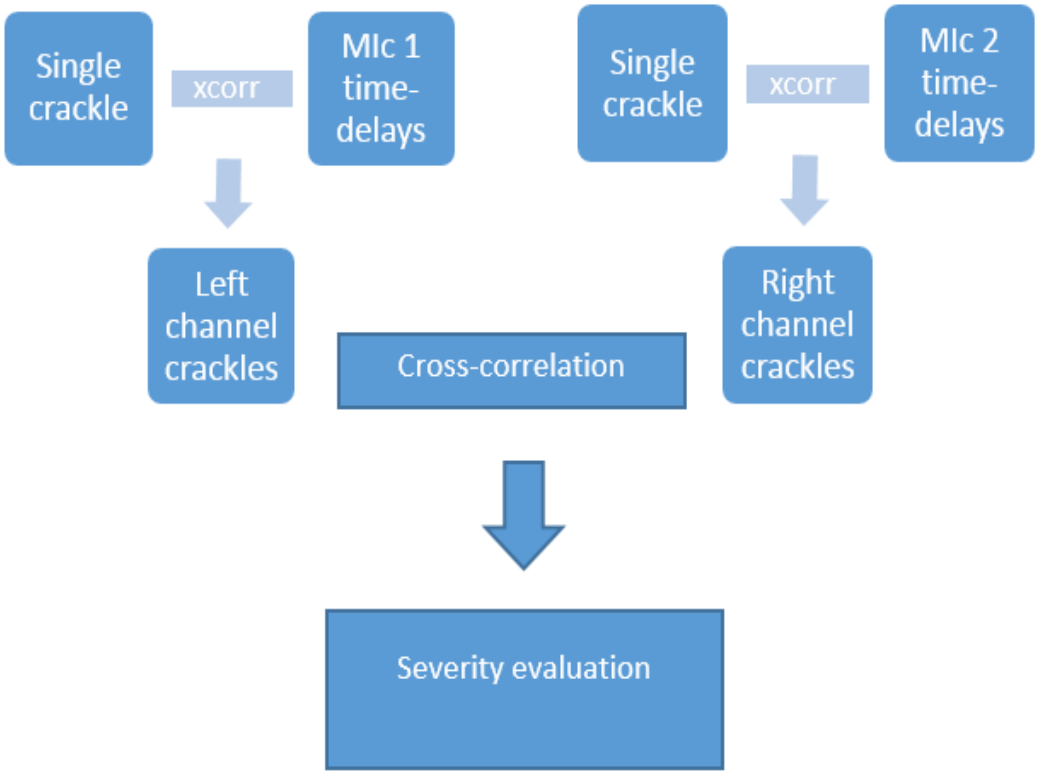

Figure 3.5: Algorithm diagram

3.2 Simulation models

In order to investigate the proposition that the maximum cross-correlation of the two channels could be a crackles severity estimation, two simulation scenarios were performed: first, the algorithm simulates the lung area involvement while keeping the alveoli population constant in contrast to the second scenario, where the alveoli population increases.

3.2.1 Model A: Constant alveoli population

In the first case, the algorithm performed a simulation of the “infected” lung area by keeping the popping alveoli population constant. The involved lung area was simulated by a circle whose radius varied, thus increasing the infected area.

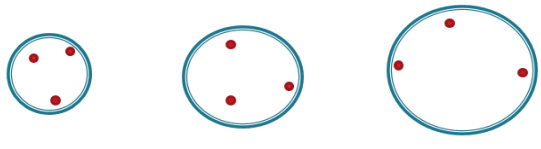

Figure 3.6: Model A

The radius values that were chosen were from 0.5cm to 4cm in steps of 0.5. The simulation was performed several times for each value and the maximum cross-correlation of the two simulated recording channels was calculated [c]. As it is illustrated in the box plot in figure 3.7, the maximum cross-correlation value presented a downward trend as the area radius increased.

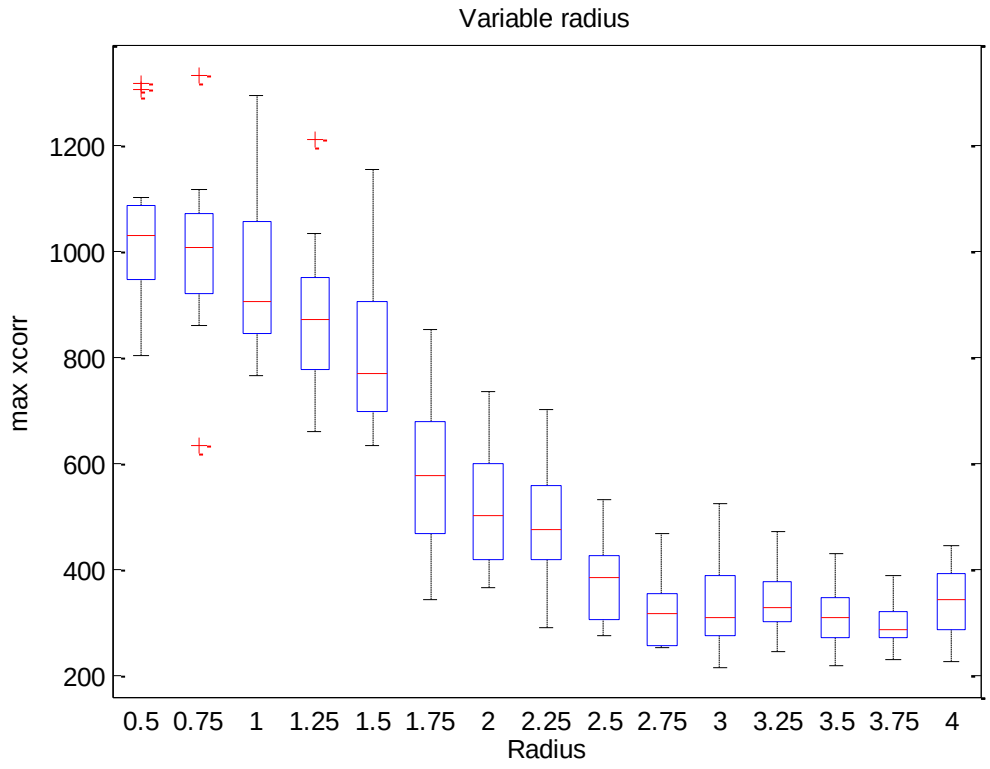

Figure 3.7: Box plot of the first model

In order to test the hardware's response to the model, a lab setup was created. Three speakers were put in a triangular setup and the two mics were set at distances according to the simulation, but in scale. The setup is illustrated in figure 3.8.

Lung crackle sounds were found online and used as input to the speakers. Next, the speaker "radius" opened up in order to simulate the crackle area increase just like the software simulation. Recordings for several radius values were performed. Specifically, four recordings were made for each distance value. The results are shown in figure 3.9 and it is clear that the downward trend, more or less agrees with the software simulation in figure 3.7.

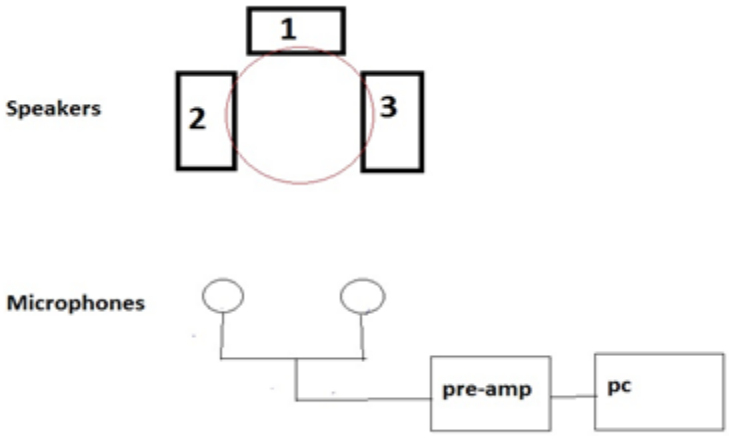

Figure 3.8: Hardware setup

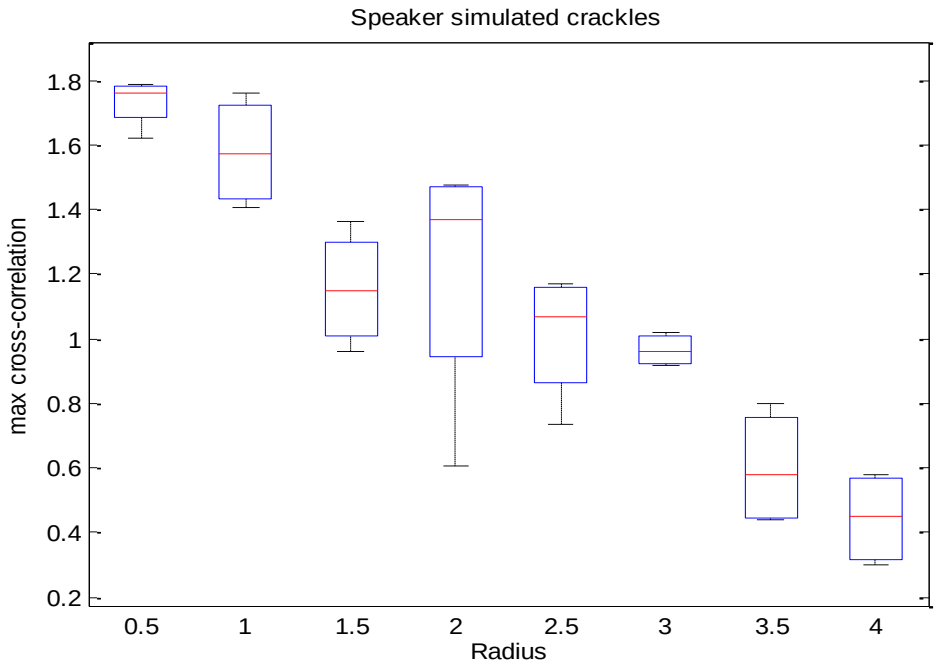

Figure 3.9: Speaker simulated crackles

3.2.2: Model B: Variable alveoli population

Secondly, the algorithm performed a simulation of the lung area suffering from crackles, by using the popping alveoli population as a variable. The involved lung area was again illustrated by a circle whose radius varied, simulating the increase of the infected area and at the same time exponentially increasing the crackle population.

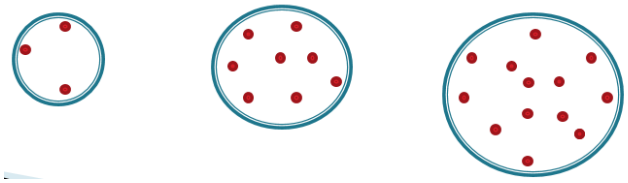

Figure 3.10: Scenario B

The radius values again, were from 0.5cm to 4cm in steps of 0.5. The simulation was performed several times for each value and the maximum cross-correlation of the two simulated recording channels was calculated. As illustrated in the box plot in figure 3.11, the maximum cross-correlation value presented an upward trend as the area radius increased.

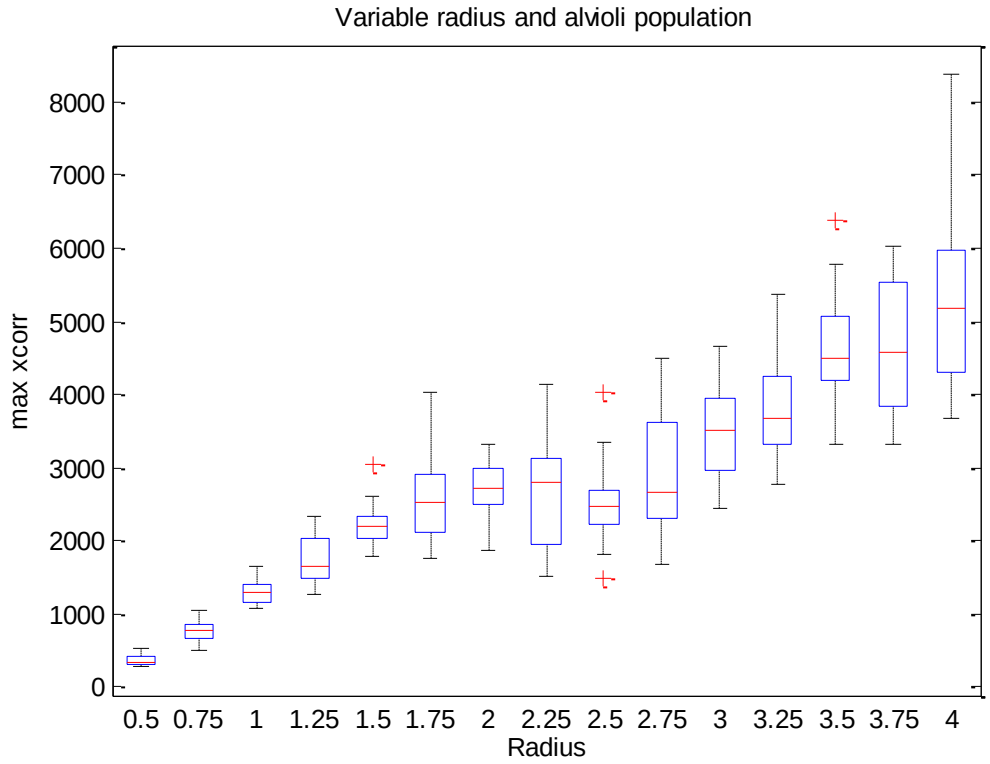

Figure 3.11: Box plot of the second model

The question is which of these two models is closer to reality, a crackle-infected lung area. The first estimation leans towards the second model where the alveoli that “pop” increase with the lung area involved. In vivo examinations were performed in order to prove this, but this is explained in later chapters.

3.3 Microphone distance

The distance separating the two microphones, was investigated by simulation in order to achieve the best results. The values chosen to be investigated were 6, 8 and 10cm. Cross-correlations for multiple simulations of both models were collected. The following figures illustrate the results of multiple simulations for each radius value.

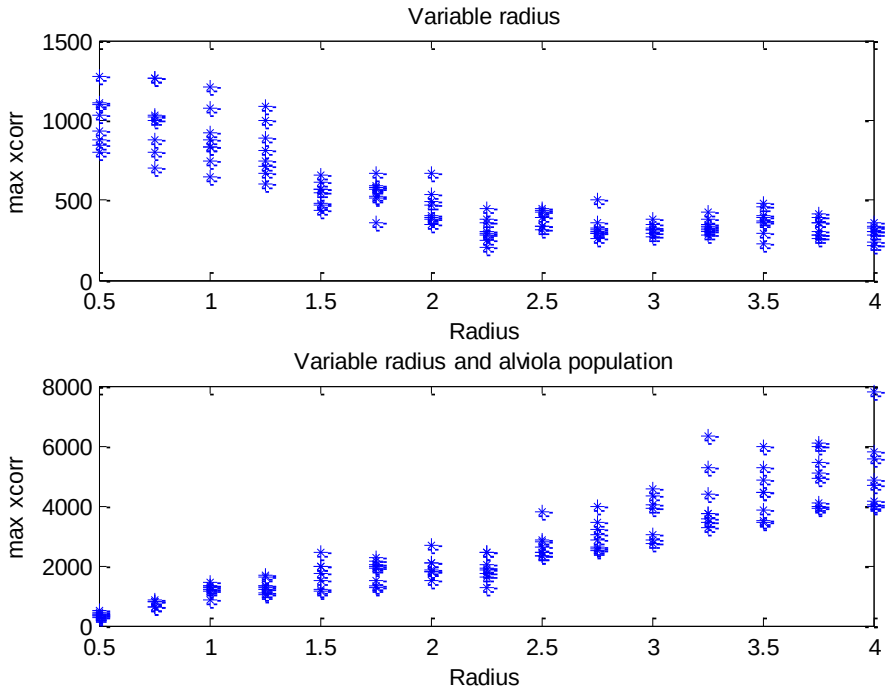

Figure 3.12: 6cm microphone distance simulations

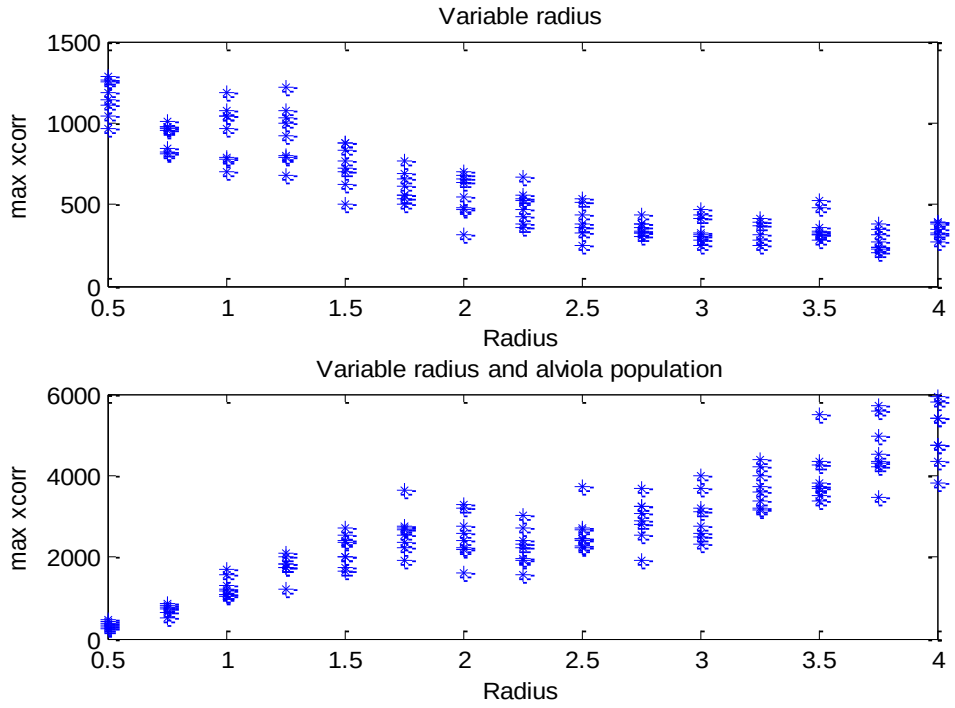

Figure 3.13: 8cm microphone distance simulations

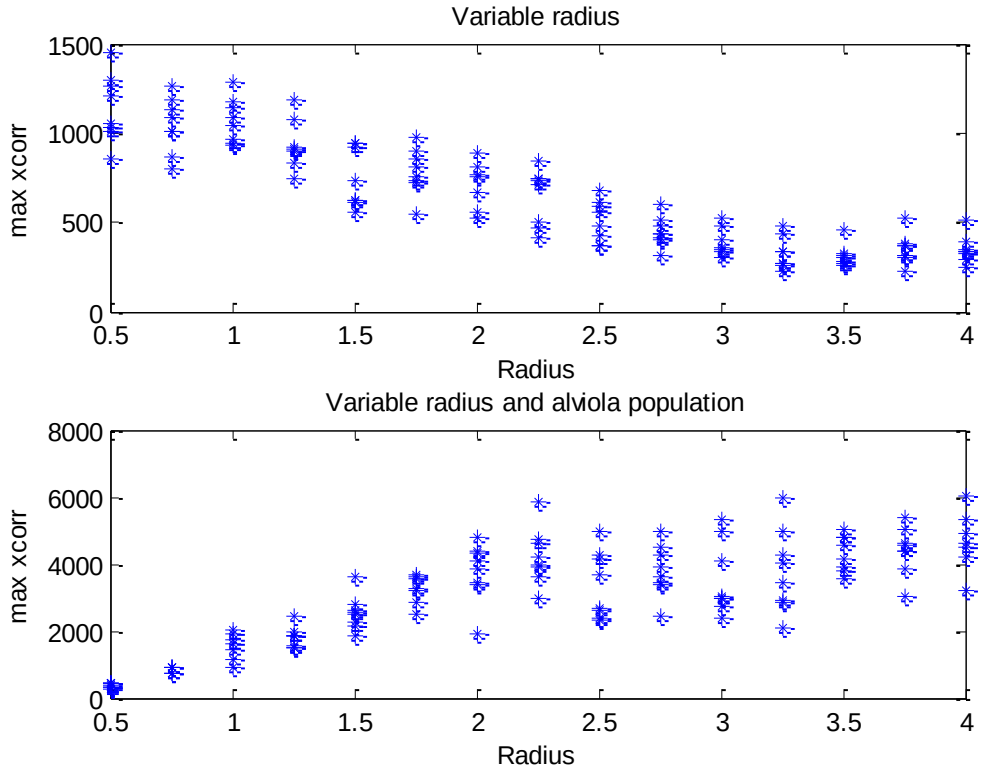

Figure 3.14: 10cm microphone distance simulations

Next, the mean values and standard deviations of the simulation iterations were calculated and plotted. Figure 3.15 is based on the first model that was previously discussed. The mean value of the maximum cross-correlations in relation to the lung area radius is plotted and a decreasing trend is observed. The 6cm curve is the closest to linearity, so this mic distance gives the best results in this case.

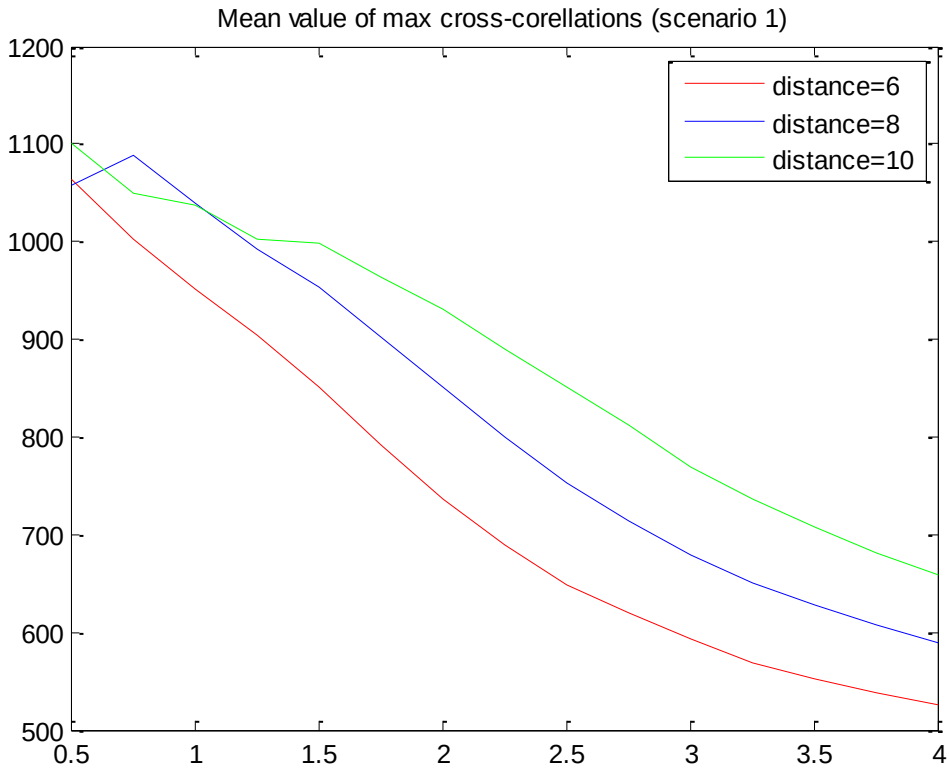

Figure 3.15: Mean value of cross-correlations in scenario 1

Likewise, the standard deviation of the maximum cross-correlation of each simulation was calculated and is illustrated in figure 3.16. As the lung area increases, so does the standard deviation which is something to be expected. The most linear curve appears to be the 8cm one.

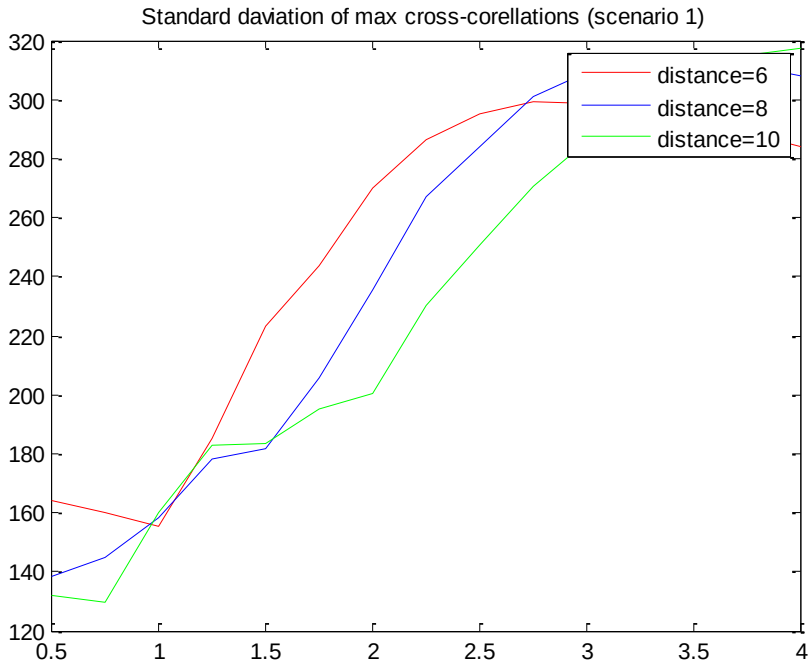

Figure 3.16: Standard deviation of cross-correlations in scenario 1

The same calculations and plots were performed for the second model under the same conditions but with the previously mentioned difference, which is the number of collapsed alveoli taken into account when increasing the infected lung area.

In figure 3.17, the cross-correlations mean value is plotted in relation to the increasing radius and collapsed alveoli number. It is observed that the mean cross correlation increases with the widening of the area involved.

Likewise, the cross-correlations standard deviation rises as the lung area radius and alveoli increase as it is shown in figure 3.18. In both figures of the second model, the 6and 8cm mic distances present a more linear behaviour, while the 10cm distance contains more extreme values. Based on these simulations the 8cm microphone distance will be chosen for in-vivo experiments.

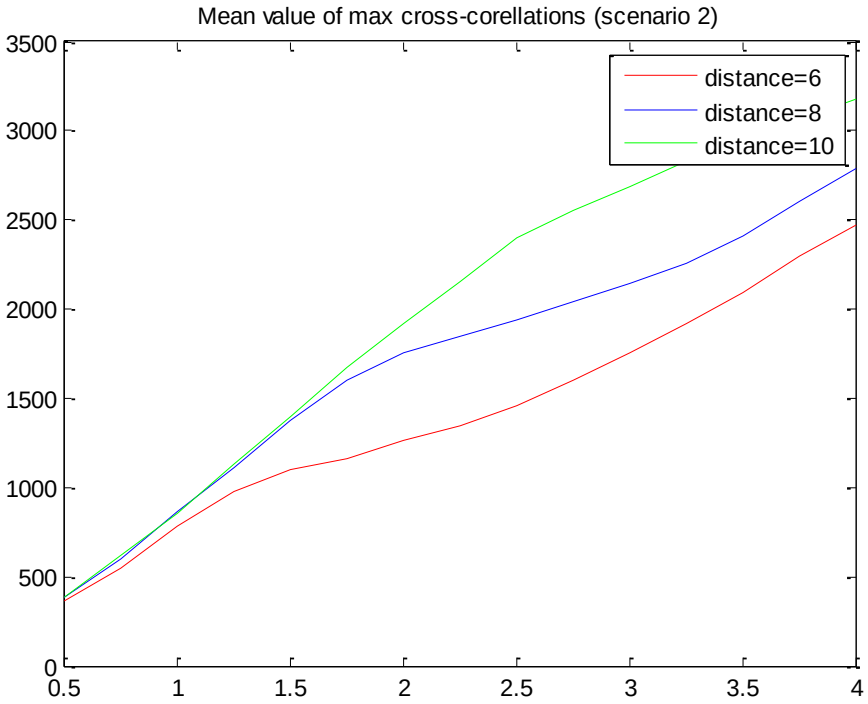

Figure 3.17: Mean value of cross-correlations

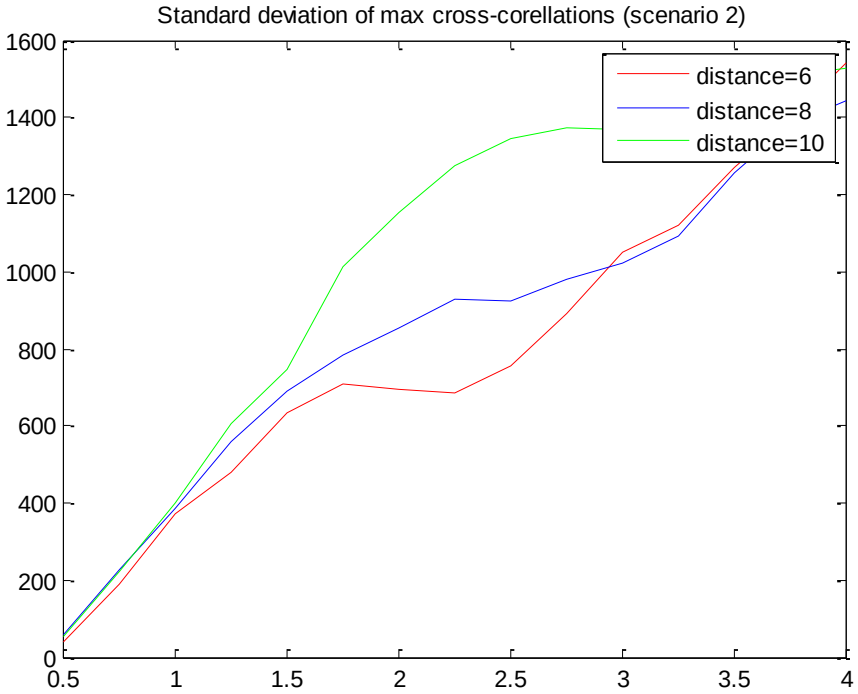

Figure 3.18: Standard deviation of cross-correlations

3.4 Discussion-importance

Several simulations were performed using the MATLAB environment in order to conclude in certain assumptions. A model of the lung area involved in pneumonia was simulated, along with the sound receivers. The alveoli that led to crackle sounds were simulated and maintained their random nature by popping in random places end times.

A single crackle waveform was extracted by following literature examples and combined with the microphone time delays of the constructed lung model. This procedure resulted in the simulated crackle sounds that were used as input to tests.

In the first simulated model, the alveoli number remained constant as the area grew. The simulations showed that maximum cross-correlation decreased as the area increased. This particular model was also tested physically by recording crackle sounds from three speakers that changed positions.

On the other hand, the second model follows the assumption that the alveoli number increases with the widening of the lung area involved. This model showed the exact opposite trend: the maximum cross-correlations of the two microphones increased. This second model seems closer to the real lung area-crackles system. In order to prove this, in vivo experiments were performed.

The importance of proving the relation of the microphones cross-correlation and the size of the crackle source area, lies in the potential diagnosing method of crackle severity using the DMS device.

4. Patient Measurements

In this chapter, in vivo experiments will be presented. Data were collected from healthy individuals and patients with crackles of various diseases. The DSM device was used in several subjects such as volunteers and hospital patients in collaboration with well-established pulmonologists.

Next a data analysis was achieved for various reasons. First, the device's algorithm was trained and tested in order to distinguish accurate readings from readings with artefacts, such as cloth rubbing. Next, it was tested for accurate crackle detection. Lastly, cross correlation of the two channels was used in order to get a measurement of the crackles expansion inside the lungs and therefore an assessment of the disease's severity. This process is illustrated in figure 4.1.

In the final step, these assessments were compared to actual lung x-rays, in order to validate the algorithm's accuracy and usability. Several results were analysed and conclusions were made.

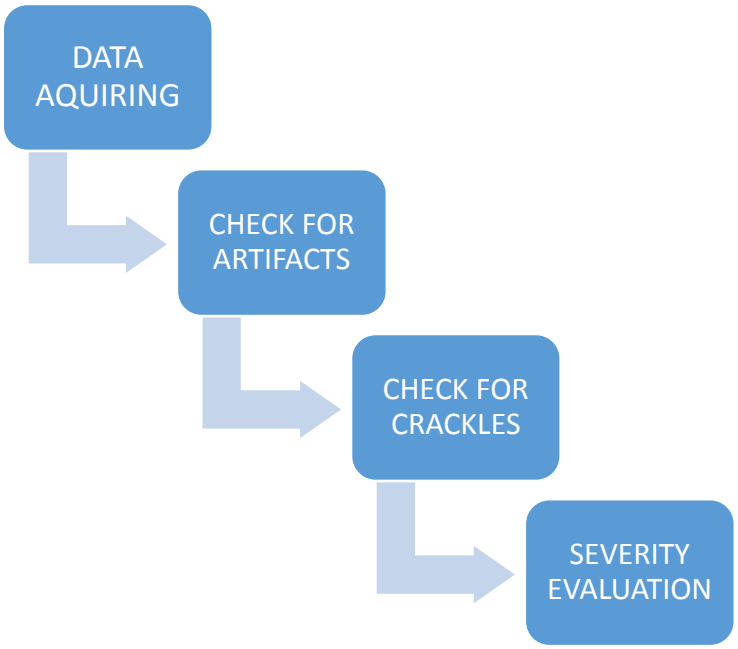

Figure 4.1: Data acquiring and analysis flowchart

4.1 In vivo data acquiring

In this first stage, it was crucial to develop a lung sound database in order to train the algorithm for a set of actions. These actions include the detection of artefacts in measurements, crackle detection and lung disease severity evaluation.

4.1.2 Data from healthy subjects and artefact detection

Lung sound data were attained from several volunteers. Two data sets were recorded from each volunteer.

In the first data set, the dual stethoscope device was placed in the upper chest and the subjects were instructed to take two deep breaths. These breath sounds were recorded and analysed in the MATLAB environment. The waveform of a volunteer is illustrated in figure 4.2.

In the second data set, each subject did the exact same thing with the difference that the operator purposely moved the stethoscope set in the second breath, thus inserting an artefact in the measurement. These artefacts were used to train the algorithm using the CLASSIFY function, to distinguish a valid reading from a false one. A waveform containing artefacts can be observed in figure 4.3. The artefacts begin at the 5th second.

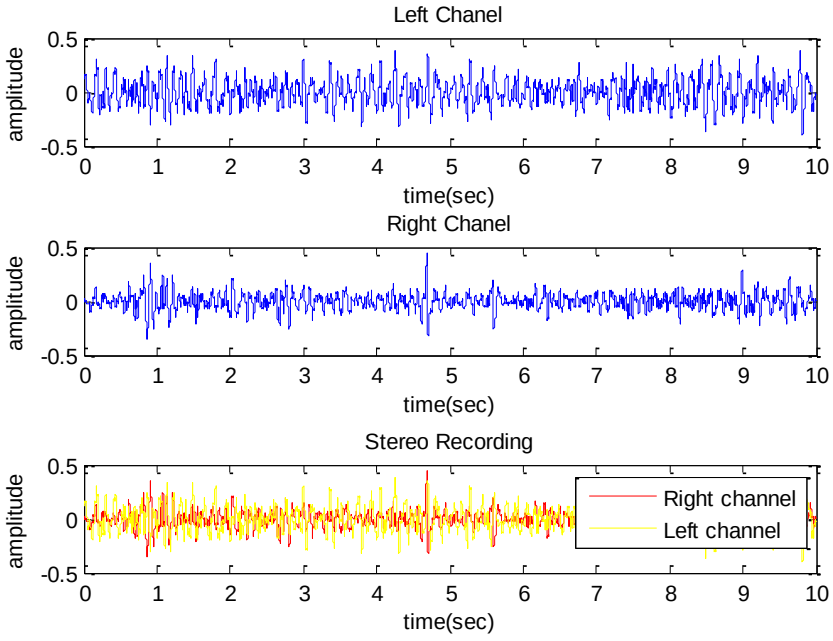

Figure 4.2: Lung sound waveform of a subject

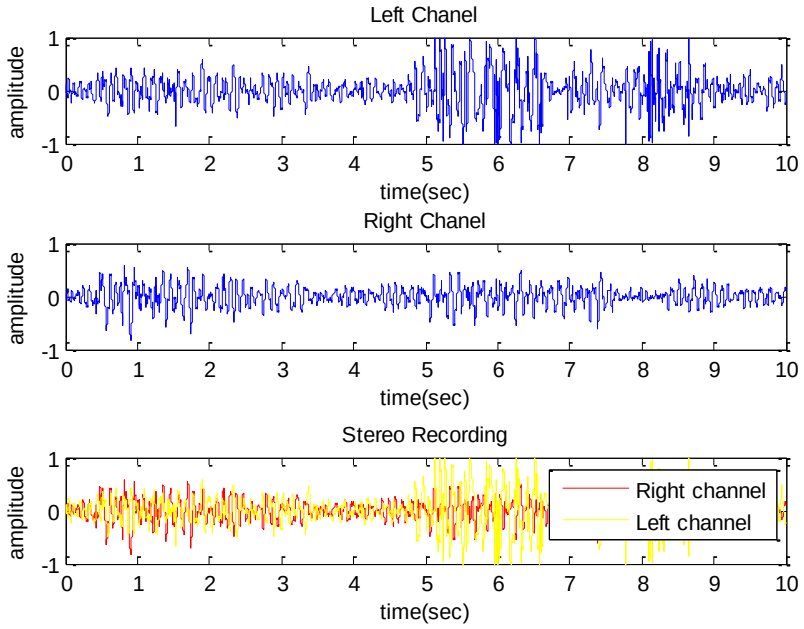

Figure 4.3: Lung sound recording with artefacts

The next step was to analyse the data and study the frequency spectrum. The spectrograms of both measurements of the lung sound data obtained were created and studied.

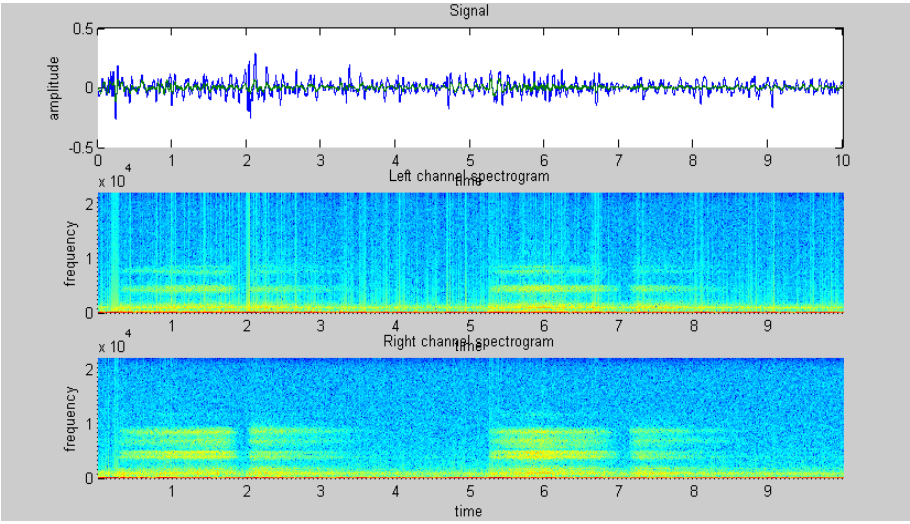

Figure 4.4: Lung sound spectrogram

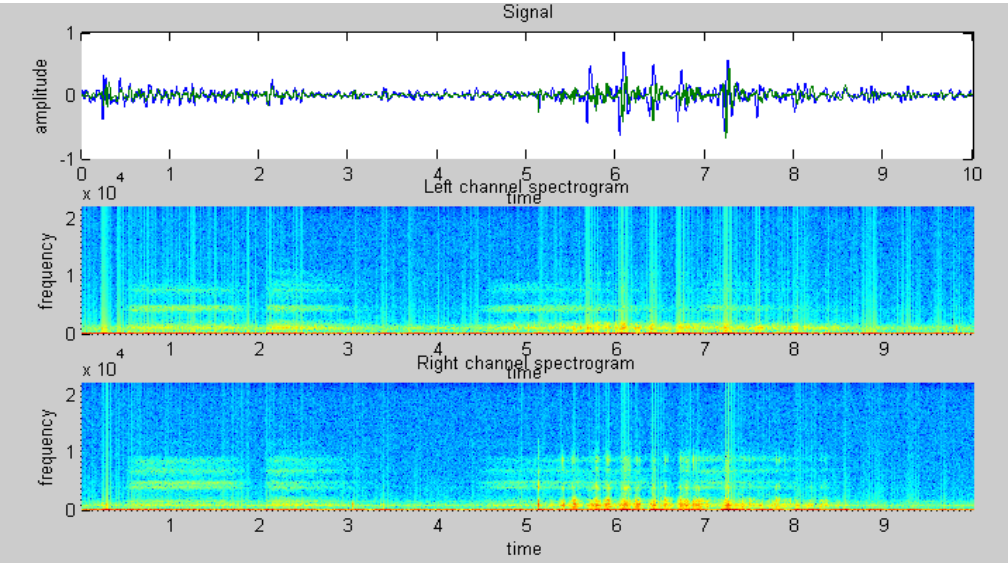

Figure 4.5: Lung sounds spectrogram with artefacts

The spectrograms in figures 4.4 and 4.5 illustrate the frequency spectrum of both measurements from a single subject-volunteer. In the second spectrogram, the one containing the artefact, an increase in certain frequencies seems to apply. This difference in the frequency spectrum was used in order to train the algorithm to automatically distinguish valid readings from ones with artefacts [d,e]. In figure 4.6, the waveform is displayed marking the artefact area, along with the spectrogram and image of the lung sound.

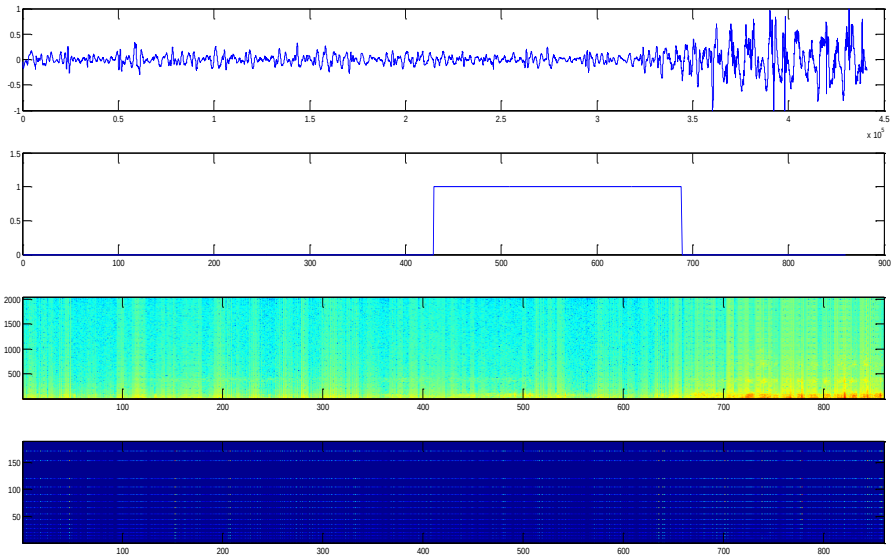

Figure 4.6: Waveform, area of artefacts, spectrogram and image of lung sound data

As stated before, these data were used for the purpose of training an algorithm to automatically detect artefacts in measurements. The method used to test the algorithm was to run several tests of lung data with artefacts, inserting each single subject as the one to be automatically checked for artefacts.

The algorithm contains a feature set that is used as training data for the classifier. Features used were:

- the spectrogram of the data
- the ratiogram of the data

The spectrogram of the data gives important information about the spectral content of the signal in relation to time. Areas with artefacts seem to have some extra frequency content in relation to normal areas. The classifier algorithm uses this fact as a feature used to classify.

The second feature, the ratiogram was calculated using the ratios of the peaks of the waveform. An array was created, containing ratios of each peak by all the others. As expected the diagonal of this array was filled with ones.

On top of that, principal component analysis (PCA) was performed in order to test which areas contain more important information. PCA is a way of identifying patterns in data, and expressing the data in such a way as to highlight their similarities and differences. Since patterns in data can be hard to find in data of high dimension, where the luxury of graphical representation is not available, it is a powerful tool for analysing data. The other main advantage of PCA is that once you have found these patterns in the data, and you compress the data, without much loss of information [25].

Lastly a median filter was applied in order to exclude extreme values. Through trial and error the best window lengths and Fast Fourier Transform samples were calculated. The ideal window used for the Fast Fourier Transform was 2048 samples per second, the points used were 2^13 and the filter window was 75 samples per second. The results were very good using these settings and the accuracy of the algorithm was near 90%.

```
Calculating features ......
Performing classification ......

corr =

    0.8907

fx >>
```

Figure 4.7: Accuracy of classification algorithm

4.1.3 Data from patients with crackles

The next step after obtaining data from healthy individuals was to record lung sounds with crackles. This was done in collaboration with two major hospitals and their pulmonologists. Patients affected with respiratory diseases containing crackles, were used as test subjects in order to train the algorithm to distinguish crackles from normal readings. A crackle recording waveform can be observed in figure 4.8.

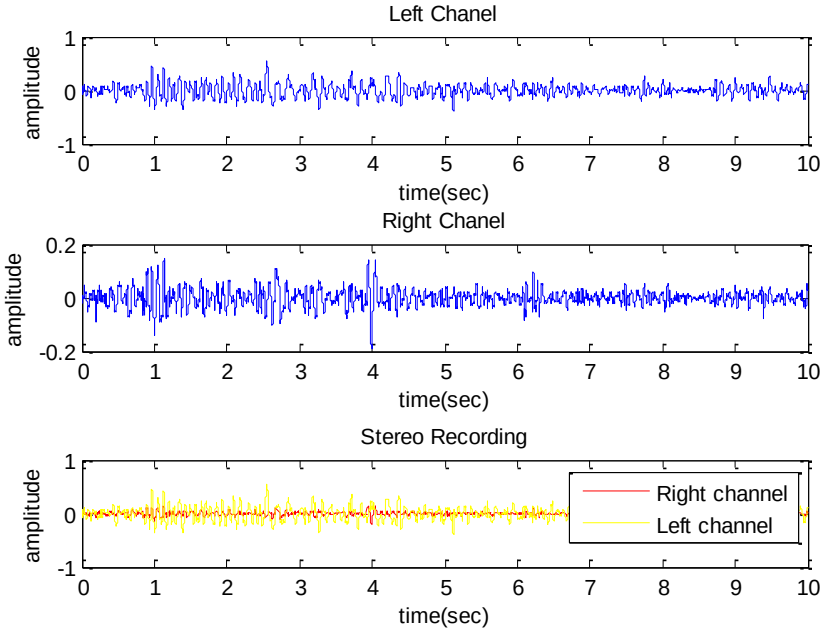

Figure 4.8: Crackles waveform

The methodology used was similar to the one used to identify readings with artefacts. The data from patients were acquired with the presence of their physician. The stethoscope heads were placed in the upper chest of the patient, which was instructed to breathe deeply. The

recordings were performed under the pressure of time and not in ideal conditions, so some noise was expected.

The first step into examining the lung crackles data was to perform Fourier transform and analyse the frequency spectrum. In figure 4.9 the spectrum of a crackle recording can be observed in logarithmic scaling.

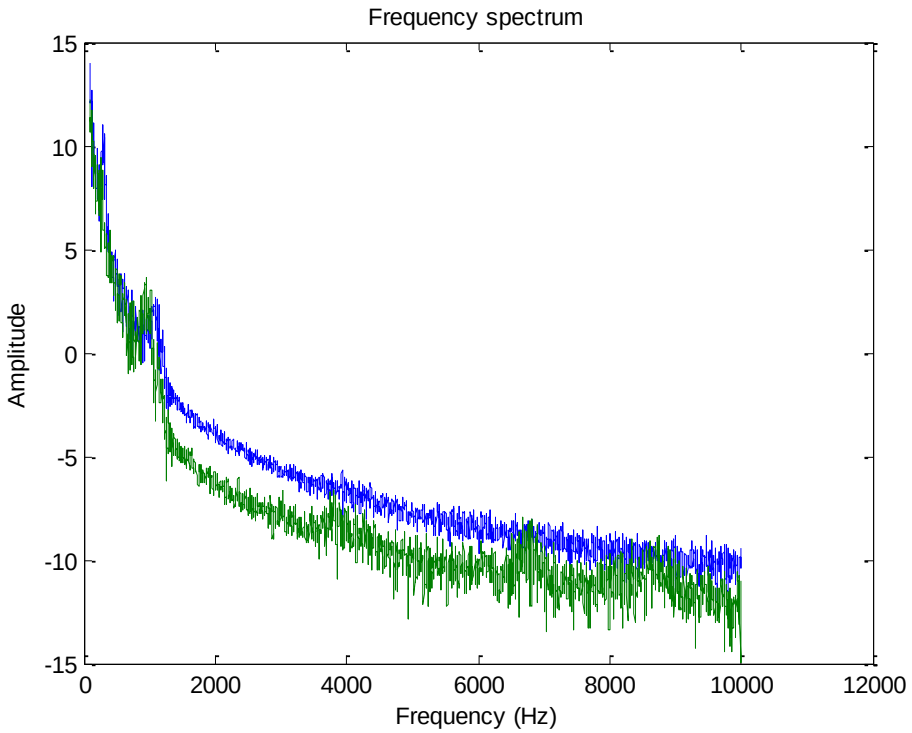

Figure 4.9: Crackles sound frequency spectrum

In order to distinguish respiratory sounds with artefacts, the classify function was utilized once again. First, the Fourier transforms of a series of crackle sounds were performed using the FFT MATLAB function.

The matrix with the ratios of the waveform peaks was calculated, resulting in the ratiograms of the two channels just like the methodology followed in the artefact detection. The only difference is that in this case, the ratiograms of the frequency spectrums were used instead of the ones of the time domain. These data were used as features and training data in the classification. These ratiograms were compared to the ones of healthy subjects in order for the algorithm to distinguish them and the percentage of successful classifications was 83%. This relatively low percentage is due to the low number of crackle subjects.

4.2 Data Analysis and results

The combination of the previously described steps, results in the general crackle-analysis algorithm. First the respiratory system data are acquired using the DSM device. Next the algorithm checks for artefacts such as cloth rubbing using the spectrogram and the ratiogram of the sound. If such artefacts exist, they are removed. If not, the process moves on to the next step.

Right up next, the algorithm checks for crackles by comparing the frequency spectrum of the recorded sound with a database of crackles. If crackles are absent, the examination is finished. On the other hand if crackles are identified, the algorithm proceeds to cross-correlate the left and right signals giving an estimation of the situation's severity. The logic diagram of the algorithm is illustrated in figure 4.10.

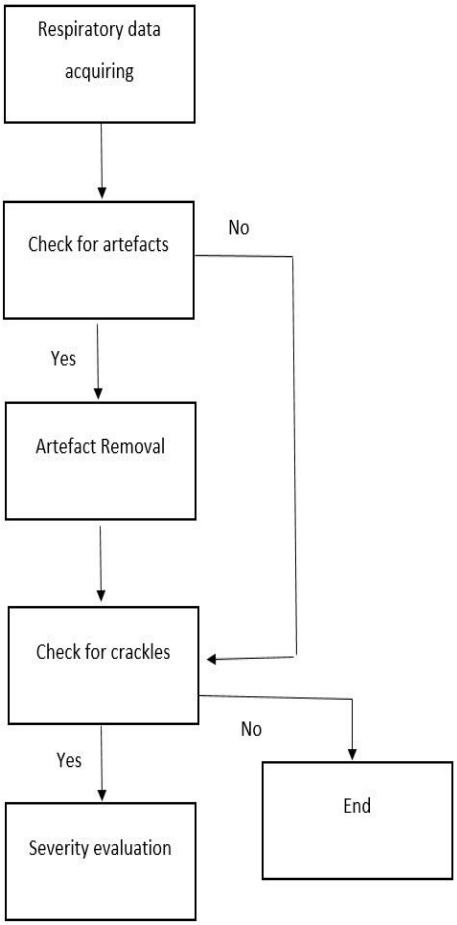

Figure 4.10: Algorithm methodology

In the final step of the methodology, severity evaluation of the crackles intensity and therefore the disease, was performed. The maximum cross-correlations of the two microphones were calculated in MATLAB using the acquired respiratory crackles data.

In digital signal processing, cross-correlation is used to measure the similarity of two series as a function of the lag of one relative to the other. Cross-correlations are useful for determining the time delay between two signals. After calculating the cross-correlation between the two signals, the maximum of the cross-correlation function indicates the point in time where the signals are best aligned [26].

The pulmonologists were asked to listen to these crackle data and give us a generic evaluation of the situation. They placed each sound file into 3 categories:

- Category 1: Low number of crackles-low severity
- Category 2: Medium number of crackles-medium severity
- Category 3: High number of crackles-high severity

As expected these evaluations were in agreement with the maximum cross-correlations of the two microphones of the DMS device. As it is illustrated in figure 4.11, there seems to be a linear relationship between the maximum cross-correlation and the severity category. As the number of crackles increases, so does the maximum cross-correlation. The lines indicate the maximum cross-correlation limits of the three groups.

In figure 4.12, Manova1 classification was performed using canonical coefficients. The ovals mark the groupings that were made in terms of low, medium and high severity estimations. As it can be observed only a single case was not classified correctly.

These findings agree with the simulations and specifically with the 2nd model where the maximum cross-correlation increases relatively linearly with the increase of crackles inside the lungs.

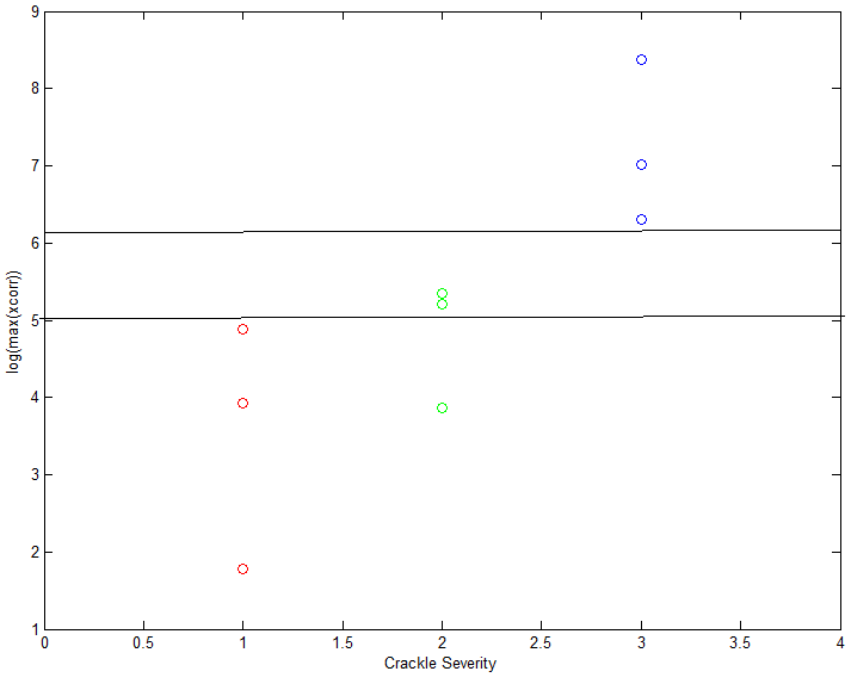

Figure 4.11: Severity evaluation

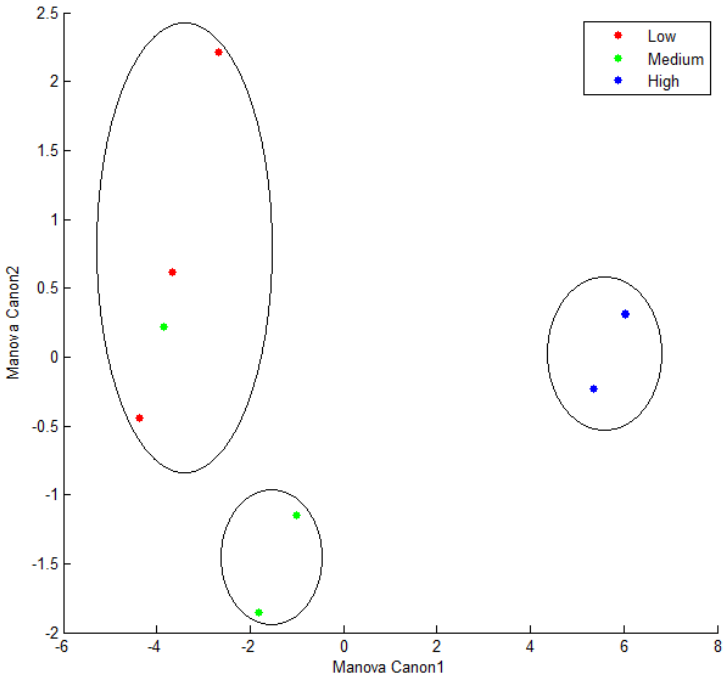

Figure 4.12: Manova1 Classification

It should be noted that the primary goal of this research was to compare these crackle severity estimations to x-rays in order to validate them. This could be applied in severe pneumonia patients where x-rays are performed to assess the situation's severity. The crackle area in relation to the lungs would be measured and matched to the cross-correlation of the two microphones. Due to the time of the year though, we weren't able to acquire any x-rays of pneumonia patients so this idea remains open for future work.

5. Conclusions

5.1 Summary of work done

The subject of this thesis were respiratory sounds and their detection and analysis. Specifically the area of interest was crackling sounds inside the lung, their detection and severity estimation.

First, an introduction was made in normal and abnormal sounds. The characteristics of these sounds such as frequency and duration were analysed and their differences were made clear. Focus was given and adventitious sounds and specifically crackles. Crackles are discontinuous sounds that last around 5-10ms and are divided in two major groups.

- Fine crackles
- Coarse crackles

Fine crackles have a shorter duration and higher pitch, while coarse have a longer duration and lower pitch. The frequencies of crackles are found between 400 and 900Hz. Apart from that, a brief literature review was made on several automated crackle analysis methodologies.

Next, the methodology followed and the hardware setup was described. A general introduction was made in stethoscope auscultation and the characteristics of these devices. Then, the hardware setup that was used in this work was described. The DSM device consists of two stethoscope heads, two mini microphones that are attached to a preamp and a wireless transmitter and receiver. The stethoscope heads were cut off from the complete stethoscope devices maintaining a tube piece of 5cm length. These heads were attached into two mini microphones whose output was sent into a preamp, in order to amplify the input signals and lastly, into a wireless signal transmitter. These hardware parts were fit inside a case that is clipped in the patient's belt. Calibration tests were made using a function generator and an oscilloscope in order to ensure that the amplitude levels were even between the two microphones and there was no phase shift.

In the next chapter simulations were performed in the MATLAB environment. Crackles were simulated inside the lung area, and the stethoscope-microphones were set at specific distance apart. The crackles were generated at random places and popping times inside the

radius of a circle, during an inspiratory period of 1000ms. The time delays of each crackle sound arriving at each microphone were calculated. Using the individual crackle sound and a model of the distribution of the collapsed alveoli in the lung region, the crackle sounds as would be heard by two microphones, placed at a known distance apart, were simulated. The simulated crackles waveform in two channels, left and right, was generated by cross-correlation of the single crackle waveform and the calculated time-delays of each microphone.

Investigation of the proposition that the maximum cross-correlation of the two channels could be a crackles severity estimation, was made possible by simulating two scenarios:

- In the first model, the algorithm performed a simulation of the lung area by keeping the crackles population constant. The involved lung area was simulated by a circle whose radius varied, thus increasing the infected area. The maximum cross-correlation value presented a downward trend as the area radius increased.
- In the second model the algorithm performed a simulation of the lung area suffering from crackles, by using the popping alveoli population as a variable. The maximum cross-correlation value presented an upward trend as the area radius increased.

The distance separating the two microphones, was investigated by simulation in order to achieve the best results. The values chosen to be investigated were 6, 8 and 10cm. Cross-correlations for multiple simulations of both models were collected and the one that gave the best results was the distance of 8cm.

In the final chapter, data were collected from healthy individuals and patients with crackles of various diseases. The DSM device was used in several subjects such as:

- Healthy volunteers
- Hospital patients with crackles

First, the device's algorithm was trained and tested in order to distinguish accurate readings from readings with artefacts, such as cloth rubbing. Next, it was tested for accurate crackle detection. Lastly, cross correlation of the two channels was used in order to get a measurement of the crackles expansion inside the lungs and therefore an estimation of the disease's severity.

5.2 Important Results/ Major contributions

In vivo experiments showed that the crackles sound's intensity and therefore disease's severity was proportional to the left and right microphones cross-correlation. Cross-correlation's value was higher in more severe situations and lower in less severe. These findings agree with the second simulation model, where the number of crackles increased with the widening of the lung area involved.

A problem that was discovered during the patient measurements, was external sounds-artefacts. The algorithm of the DSM device was trained to trace artefacts such as cloth rubbing and remove them but in a live hospital environment there are much more external noises such as people talking, doors opening and closing, various medical devices sounds that were caught by the microphones and interfered with the measurements. A good example of this setback was the lung recording of an elder patient with heavy crackles that was on oxygen supply. The sound of the oxygen supply device heavily interfered with the lung sounds recording.

The DMS device could be ideal for home use-crackle detection and severity estimation. Moreover, it could be used in underdeveloped countries where health treatment is not always available and there is a lack of physicians.

5.3 Future work

It was stated before, the final goal of this research was to compare these crackle severity estimations to x-rays in order to validate them in cases of pneumonia. In severe pneumonia incidents, x-rays are performed to assess the situation's severity. The crackle area in relation to the lungs would be measured and matched to the cross-correlation of the two microphones. Due to the time of the year though, we weren't able to acquire any x-rays of pneumonia patients so this idea remains open for future work.

Apart from that, artefact detection could become more robust, detecting a wide range of artefacts such as medical devices sounds and background speech. Lastly, with a wider database of crackle sounds the algorithm could be trained to identify them with better accuracy.

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7. Appendix

a.
```
FS=44100;
r = audiorecorder(44100, 16, 2);
disp('Start speaking.')
recordblocking(r, 10);
disp('End of Recording.');
y=getaudiodata(r);
wavwrite(y,FS,'crackles_4')
left=y(:,1);
right=y(:,2);
time=(1/44100)*length(left);
t=linspace(0,time,length(left));
subplot(3,1,1), plot(t,left)
  title('Left Chanel');
  xlabel('time(sec)');
  ylabel('amplitude');
subplot(3,1,2), plot(t,right)
  title('Right Chanel');
  xlabel('time(sec)');
  ylabel('amplitude');
subplot(3,1,3), plot(t,right,'r')
  hold on;
  plot(t,left,'y')
  xlabel('time(sec)');
  ylabel('amplitude');
  title('Stereo Recording');
  l=legend('Right channel','Left channel');
  peak_amp=max(left)
  rmsleft=sqrt(mean(left.^2))
  rmsright=sqrt(mean(right.^2))
  amplitude_ratio=rmsleft/rmsright
```

b.
```
function [S1,S2] = cracklesim(n,R,doPlot)

if nargin<3
    doPlot=0;
end;

v=2.4; % Sound speed inside lungs (cm/ms)
Tb=1000; % Duration of inspiration (ms)


x0 = 8; % Center of the circle in the x direction.
y0 = 8; % Center of the circle in the y direction.
micp1=[0,0]; % Position of the left microphone
micp2=[16,0]; % Position of the right microphone


% Now create the set of points.
t = 2*pi*rand(n,1);
r = R*sqrt(rand(n,1));
x = x0 + r.*cos(t);
y = y0 + r.*sin(t);

if doPlot
% Now display our mic positions and random set of points in a figure.
    figure;
```

```
    plot(micp1(1),micp1(2),'Marker','sq','Color',[.88                    .48
0],'MarkerSize',20)
    hold on;
    plot(micp2(1),micp2(2),'Marker','sq','Color',[.88                    .48
0],'MarkerSize',20)
    plot(x,y, '.', 'MarkerSize', 5)
    axis square;
    axis([0 16 0 9]);
    grid on;
    % set(gcf, 'units','normalized','outerposition',[0 0 1 1]);
    fontSize = 30;
    xlabel('X', 'FontSize', fontSize);
    ylabel('Y', 'FontSize', fontSize);
    title('Crackles simulation', 'FontSize', fontSize);
end;

 for i=1:n
     d1(i)=sqrt(x(i)^2+y(i)^2);          % Distance from the left mic
     d2(i)=sqrt(((12-x(i))^2)+y(i)^2);   % Distance from the right mic
 end

 Ts = 500 + 100.*randn(n,1);

 for i=1:n
     td1(i)=Ts(i)+d1(i)/v;
     td2(i)=Ts(i)+d2(i)/v;
 end



fs=44000;    %sampling frequency
fc=300;      % crackle frequnecy (200Hz: coarse, 600Hz: fine)
tc=20;       % crackle duration (ms)
t0=0; tmax=50;
T=t0:(1/(fs/1000)):tmax;
x=T*44000/1000;
y =gampdf(x/100,5,tc*fs/1e6);
ym=chirp(T,1.5*fc/1000,tc,fc/1000);
sc=y.*ym;
if doPlot
    figure;
    subplot(3,1,1), plot(T,sc);
    xlabel('t (ms)');
    ylabel('amplitude')
    title('Single Crackle');
    hold on
end;

Tbsc=0:(1/(fs/1000)):1000;
S1=zeros([Tb*(fs/1000),1]);
S1(round(td1*(fs/1000)))=1;
S1=xcorr(sc,S1);
if doPlot
    subplot(3,1,2),  plot(Tbsc,S1(1:length(Tbsc))),  title('Left  microphone
generated  crackles  waveform'),  xlabel('Samples'),  ylabel('Amplitude'),
ylim([-2 2])
    soundsc(S1,fs);

end;
```

```
S2=zeros([Tb*(fs/1000),1]);
S2(round(td2*(fs/1000)))=1;
S2=xcorr(sc,S2);
if doPlot
    subplot(3,1,3), plot(Tbsc,S2(1:length(Tbsc))), title('Right microphone
generated crackles waveform'), xlabel('Samples'), ylabel('Amplitude'),
ylim([-2 2])
    soundsc(S2,fs);
end;

end
```

c.

```
step=0;
count=0;
for i=0.5:0.25:4
    for j=1:15
        count=count+1;
        [a,b]=cracklesim(150,i);
        C(count,1)=max(xcorr(a,b));
        R(count,1)=i;
    end
    step=step+1;
    V1(step,1)=std(C(:,1));
    r1(step,1)=i;
end

V1
figure;
boxplot(C,R), xlabel('Radius'), ylabel('max xcorr'), title('Variable
radius')

step=0;
count=0;
for i=0.5:0.25:4
    for k=50*(i/0.5)^2
        for j=1:15
            count=count+1;
           [a,b]=cracklesim(k,i);
           E(count,1)=max(xcorr(a,b));
           R(count,1)=i;
        end
    end
    step=step+1;
    V2(step,1)=std(E(:,1));
    r2(step,1)=i;
end
V2
figure;
boxplot(E,R), xlabel('Radius'), ylabel('max xcorr'), title('Variable radius
and alvioli population')
```

d.
```
Ws=1048;
Nfft=2^13;
Wr=200;
NPCA=1:25;
Wf=75;


data=[]; class=[]; subjects=[];
ResultsDirName='Subjects_results';
DataDirName='Subjects_wav';
dD=dir(DataDirName);
TimeDirName='Subjects_times';
dt=dir(TimeDirName);

fprintf('Calculating features ');
for p=3:length(dD)
    fprintf('.');
    [y,fs]=wavread(strcat(DataDirName,'\',dD(p).name));
    dtemp=cd;
    cd(TimeDirName);
    temp=dt(p).name;
    ind=strfind(temp,'.');
    eval(temp(1:ind-1));
    cd(dtemp);

    S1=spectrogram(y(:,1),Ws,Ws/2,Nfft);
    S2=spectrogram(y(:,2),Ws,Ws/2,Nfft);
    [m n]=size(S1);
    f=n/(length(y(:,1))/fs);
    C1=zeros([1 n]);
    C1(round(t1*f):round(t2*f))=1;
    R1 = Ratiogram(abs(S1),Wr);
    R2 = Ratiogram(abs(S2),Wr);

    data=[data; [ R1']; [ R2']];
    class=[class; C1'; C1'];

    subj=ones(size(C1'));
    subj=subj*(p-2);
    subjects=[subjects; subj; subj];
end
fprintf('\n');

SaveFile=sprintf('AllData_%d_%d_%d.mat',Ws,Nfft,Wr);
save(strcat(ResultsDirName,'/',SaveFile),'data','class','subjects');


fprintf('Performing classification ');
class_est=[];
Nsubj=length(unique(subjects));
for p=1:Nsubj
    fprintf('.');
    ind=find(subjects==p);
    Data_test=data(ind,:);
    ind=find(subjects~=p);
    Data_train=data(ind,:);
```

```
    Class_train=class(ind,:);

    coeff=princomp(Data_train);
    PCAData_train=Data_train*coeff(:,NPCA);
    PCAData_test=Data_test*coeff(:,NPCA);

   c=classify(PCAData_test,PCAData_train,Class_train);
   c=medfilt1(c,Wf);
   class_est=[class_est; c];
end
fprintf('\n');

   corr=1-sum(abs(class-class_est))/length(class)
```

e.

```
function rD = Ratiogram(S,Wsize)

[m, n]=size(S);
Temp=S(1:m-rem(m,Wsize),:);
[m, n]=size(Temp);
for q=1:n
    t=mean(reshape((Temp(:,q)'), Wsize, m/Wsize))';
    a(:,:,q)=(ones(length(t),1)*t')'/diag(t);
    t=triu(a(:,:,q),1);
    rD(:,q)= t(find(abs(t)));
end;
```