

# Experimental Studies for Effective Analysis of the Upper and Lower Respiratory Tract Infections

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**ABSTRACT:** Examines in biomedical Engineering have come up with successful apparatuses for the study, examination and analysis of Human Anatomy and related issue. Gigantic measure of research spotlights on the investigation and analysis of Respiratory tract Infection Diseases. The Respiratory tract is isolated as upper respiratory tract and lower respiratory tract. The present paper has talked about through experimentation and scientific investigation that the utilization of equalizer enhances the extraction of components from the crackle sounds. The principle center is around a fuzzy neural model that was tried for throat illness recognition utilizing sound examination. This uses Mel frequency Cepstral Coefficient(MFCC) as highlight extraction, ANN-Fuzzy as highlight mapping and the Least mean square (LMS) calculation for versatile separating. Working over the lower respiratory tract, a fuzzy model for finding of respiratory diseases utilizing Respiratory Inductance Plethysmography (RIP) information, has been proposed.

**KEYWORDS:** Equalization of crackles, Respiratory sound analysis, Fuzzy-based expert system, Neuro-fuzzy Approach, respiratory inductance plethysmography(RIP), Mel frequency Cepstral Coefficient(MFCC).

## I. INTRODUCTION

Artificial Neural Network and Fuzzy Logic have been broadly utilized for finding of various ailments of human body [1-3]. Neuro-fuzzy alludes to blends of artificial neural networks and fuzzy logic. Neuro-fuzzy hybridization brings about a half breed savvy framework that synergizes these two strategies by consolidating the human-like thinking style of fuzzy frameworks with the learning and connectionist structure of neural networks. The paper underscores on the Neuro-Fuzzy approach for examination and determination of respiratory contamination maladies. Experimentations for grouping of respiratory ailments utilizing respiratory sound examination has enhanced the concentration of the work. Respiratory illnesses might be researched by performing at least one of the accompanying tests [15-18].

- Chest x-ray
- Pulmonary function test
- Computed tomography scan
- Culture of microorganisms from secretions such as sputum
- Bronchoscopy
- Biopsy of the lung or pleura
- Ventilation - perfusion scan

Ultrasound scanning can be useful to detect fluid such as pleural effusion. Respiratory diseases [19-21] can be classified in many ways: by the organ involved, by the pattern of symptoms or by the cause of the disease.

Obstructive lung diseases

Obstructive lung diseases [20-23] are diseases of the lung where the bronchial tubes become narrowed making it hard to move air in and especially out of the lung.

- Chronic Obstructive Pulmonary Disease (COPD)

- Asthma
- Restrictive lung diseases
- Respiratory tract infections
- Upper respiratory tract infection
- Lower respiratory tract infection
- Malignant tumors

The major types of respiratory system cancer are:

- Small cell lung cancer
- Non-small cell lung cancer
- Adenocarcinoma
- Large cell undifferentiated carcinoma
- Other lung cancers (carcinoid, Kaposi's sarcoma, melanoma)
- Lymphoma
- Head and neck cancer
- Mesothelioma (usually caused by exposure to asbestos dust)

Present work is done for analysis and diagnosis of respiratory tract infection diseases and asthma detection. The paper has been organized to discuss crackle sound equalization, followed by a fuzzy neural model that was tested for throat disease detection (asthma) using sound analysis and a fuzzy model for diagnosis of respiratory infections using Respiratory Inductance Plethysmography (RIP) data. Finally, conclusions are stated based on experimental observations.

## II. DISCRETE TIME EQUALIZATION FOR RESPIRATORY SOUND ANALYSIS AND RECOVERY

Crackles, crepitation, or rales are the clicking, rattling, or crackling noises that may be made by one or both lungs of a human with a respiratory disease during inhalation. They are often heard only with a stethoscope. Crackles can be heard in patients with pneumonia, atelectasis, pulmonary fibrosis, acute bronchitis, bronchiectasis, and interstitial lung disease or post thoracotomy or metastasis ablation.

### A. IMPROVEMENT IN CRACKLE SOUND USING MODIFIED EQUATION

A discrete time equalizer [23-28] can be used to recover sounds with characteristics closer to the ones generated by the lungs, after measuring the attenuation of the transmission channel. It can be accepted that the thorax and the thorax-receiver interface act as a straight and time invariant framework with the separate unit impulsive response  $t[n]$  and  $c[n]$ , the output signal  $x[n]$  gained with the mouthpiece on the chest is given by,

$$x[n] = d[n] * t[n] * c[n] = d[n] * g[n] \quad (1)$$

where  $*$  is the convolution operator and  $d[n]$  stands for the respiratory sound.

The purpose of the equalizer is to cancel the effect of  $g[n]$  in order to recover  $d[n]$ , such that

$$y[n] \approx d[n], \quad y[n] = d[n] * g[n] * h[n] \quad (2)$$

where  $h[n]$  is the equalizer's unit impulse response. To cancel this effect, the convolution of the unit impulse responses of the equalizer and channel must approximate to the unit sample

$$h[n] * g[n] \approx \delta[n] \text{ which gives } y[n] \approx d[n]. \quad (3)$$

Thus, the input signal  $d[n]$  can be recovered by a linear inverse filtering operation which is also referred as equalization, also called de convolution.

**B. THE CRACKLE SOUND EQUALIZER**

MATLAB is utilized to test the size reaction of a FIR channel that mimics the deliberate weakening bend ( $G(e^{j\omega})$ ). The inverse of FIR channel ( $H(e^{j\omega})$ ) contained posts outside the hover of unit range. FIR slightest square inverse (FLSI) technique [21] is an option way to deal with and acquire a stable  $h[n]$ . The execution of the  $h[n]$  got with the FLSI technique relies on upon the selection of its number of coefficients (N). The impact of N on the equalizer reaction can be evaluated by applying  $h[n]$  of various sizes to crackles gained from stable walking fibrosis patients. Keeping in mind the end goal to contrast the leveled crackle with the connected one, they were standardized by their individual extreme amplitudes. The normal weakening qualities and its standard deviation are got from different respiratory sounds. The transmission channel goes about as a LPF. Subsequently, the channel will misshape information on lung sounds with expansive spectra. In this way, the utilization of an equalizer may recoup information from the lung sounds permitting the extraction of better quantitative analysis files. To discover the most reasonable channel length (N) for the proposed equalizer, crackle waveforms connected to the subjects' mouths were standardized by their separate greatest amplitudes; similar crackles were recorded on the mid-section, evened out by channels planned with various number of coefficients, and standardized by their most extreme amplitudes. A short time later, the mean absolute error (MAE) and the root mean square error (RMSE) of the diverse equalized crackles were figured,

$$MAE = 1/M \sum_{i=1}^M |y_i - \bar{y}| \tag{4}$$

$$RMSE = 1/M \sum_{i=1}^M (y_i - \bar{y})^2 \tag{5}$$

where  $y_i$  is the normalized sample value of the crackle recorded at the mouth;  $\bar{y}$  is the normalized sample value of the equalized crackle recorded on the chest, and  $M$  is the number of crackle samples. The crackles recorded on the chest of each individual were reasonably corrupted by the channel. The table 2.1 below shows the MAE and RMSE values before after equalization.

Classification	MAE <sub>BE</sub>	RMSE <sub>BE</sub>	MAE <sub>AE</sub>	RMSE <sub>BE</sub>
Corrupted crackle	0.18	0.23	0.12	0.15
Very Corrupted crackle	0.28	0.34	0.13	0.18

TABLE 2.1: MAE and RMSE Values Calculated between the Crackle Waveforms Sampled in the Mouth and on the Chest

**III. THE FUZZY NEURAL APPROACH FOR AUTOMATIC SPEECH RECOGNITION (ASR) USING MFCC**

**A. Asthma Detection by ASR**

Asthma is a lung disease that affects airflow back and forth from lungs. A whistling sound comes when asthmatic patient breathes. A feature extraction technique is applied for extracting similar features in asthmatic patients and normal human being. Mel – frequency Cepstral Coefficient technique is used for feature extraction process. We used ANN-Fuzzy as feature mapping and the least mean square (LMS) algorithm for adaptive filtering [29, 30]. The results obtained were compared with parallel approaches.

**B. Neuro Fuzzy System Developed for Asthma Detection**

The following procedure was adopted for the development of the system,

1. Create database (DB) saved all the entries as given by the user at input.
2. Once DB is created, the ANFIS is trained.
3. After training is completed, Evaluate DB was applied to ANFIS classifier to get the required class

The graphical User Interface developed and the corresponding input audio wave file and the MFCC plot, for asthmatic and non-asthmatic samples appears as shown in Figure 3.1 and Figure 3.2 respectively.

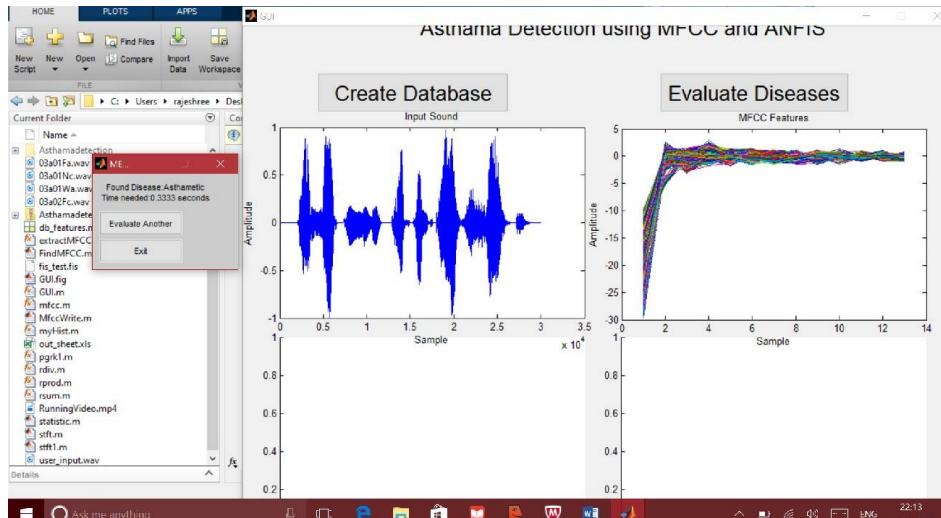


Figure 3.1. GUI, Audio Wave File and MFCC Plot for sample Asthmatic Data

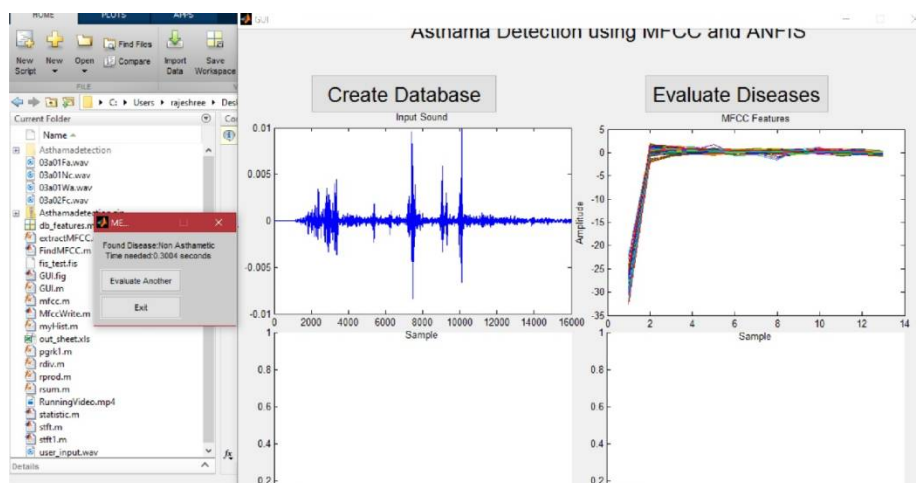


Figure 3.2 : GUI, Audio wave file and MFCC plot for sample non- asthmatic data

Results were formulated as follows:

1. Database for training was updated with 10 entries, and then evaluated using 12 entries (10 train + 2 new), tabulated the mean delay time and accuracy Accuracy = Number of correct results / Number of entries evaluated
2. Repeated step 1 with 20 entries in DB, and 24 entries for testing, Tabulated mean delay time and accuracy
3. Repeated step 2 with 40 entries in DB, and 48 entries for testing  
Tabulate mean delay time and accuracy
4. Repeated this till 100 entries, and then used the obtained table for result analysis

The System consistency of ANFIS system using MFCC as feature extraction is clear from the accuracy and mean delay values depicted in Table 3.1.

Number of entries in DB	Entries Tested	Mean Delay	Accuracy
10	12	0.045	91.66667
20	24	0.048	95.83333
50	60	0.044	93.33333
100	120	0.042	95.83333
200	240	0.053	97.5
400	480	0.044	98.125
500	600	0.041	98.16667

TABLE 3.1: Mean Delay and Accuracy Values for the Developed Neuro Fuzzy System.

#### IV. RIP DATA ANALYSIS

##### A. METHODOLOGY FOR RIP DATA ANALYSIS

The created framework contains a simple to utilize design, executing a progression of edit boxes, pushbuttons, and tomahawks, each having its own individual capacity. All together for the program to work legitimately, the client should first import crude data to be analyzed; this can be refined by tapping the "Import Raw Data" pushbutton in the upper right hand corner, appeared in figure 4.1.

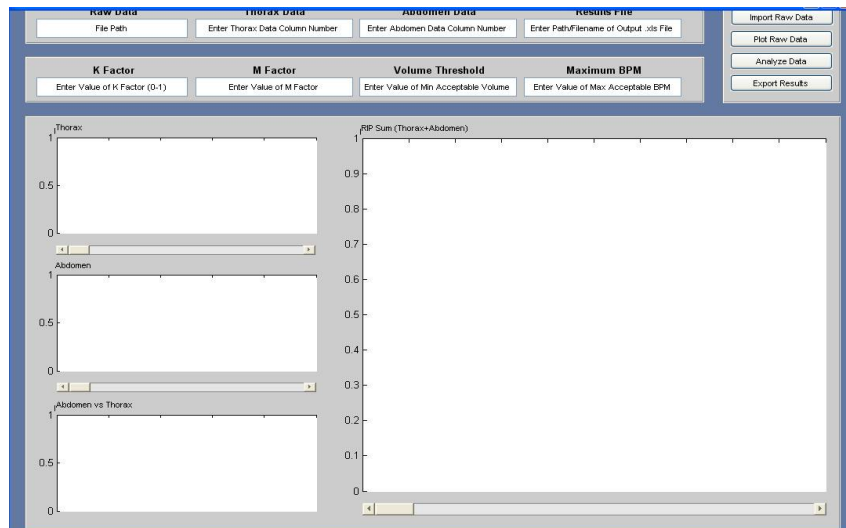


Figure 4.1 Designed System for RIP data Analysis

The callback for the import crude data button utilizes the get record order with a ".xls" Filter Spec to open a document program window for the client to choose an exceed expectations record to import. The document name is returned in the principal edit box situated at the highest point of the page marked "File Path" utilizing the set handles charge. Once the crude data is imported, the client is then required to enter the thorax and abdomen data segment numbers (the section numbers from the crude data spreadsheet) in two separate edit boxes. The thorax and abdomen segment numbers are called utilizing the get handles summon. After the crude data is plotted, the client is then incited to enter the alignment coefficients K and M in initial two edit boxes in the second line of boxes, marked "K Factor" and "M Factor", separately. Utilizing an "If" statement, the program is intended to show an appear cautioning for the situation that a K Factor not somewhere around 0 and 1 is entered. When the greater part of the sources of info are entered by the client, the "Analyze Data" button can be pushed to at the same time plot the aligned volume, stream and crude RIP sum.

The sample results for minute volume and tidal volume are shown in table 4.1.

Breaths /Minutes	Minute Volume	Tidal Volume
0	0	207.1128
37.5	7681.851	204.8494
37.5	7582.648	202.2039

TABLE 4.1: Analyzed Result from the RIP Data

### B. NEURO FUZZY SYSTEM FOR RIP DATA ANALYSIS

Once the raw data is imported, the client is then required to enter the thorax and abdomen data section Fig numbers. At the point when the "Plot Raw Data" pushbutton is enacted, the program peruses the imported exceed expectations record utilizing the xlsread work. The framework then plots the thorax and abdomen data as an element of time in the first and second, individually, of three similarly estimated tomahawks situated on the left half of the interface. The third tomahawks plots abdomen versus thorax, picturing the stage relationship between the two compartments. The biggest tomahawks, plots the aggregate of thorax and abdomen data (add up to lung volume) . After the raw data is plotted, the client is then provoked to enter the alignment coefficients K and M in initial two edit boxes in the second column of boxes, marked "K Factor" and "M Factor", individually.

When all the input part of the sources of info are entered by the client, the "Analyze Data" button can be pushed to at the same time plot the aligned volume, flow and raw RIP entirety. The button likewise figures the respiratory parameters: Tidal Volume (TV), Breaths Per Minute (BPM), and Minute Volume (MV) utilizing the "zero\_crossing.m" and "derive\_data.m" capacities. These ascertained parameters can be sent out utilizing the "Export Data" push button. The client is provoked to include the filepath and filename of the exceed expectations record to spare the yield to. The xlswrite capacity was utilized to compose the yield data to a spreadsheet with segment headers BPM, TV and MV and their individual values in every segment .The reason for the "Volume Threshold" input box is to permit the client to enter the estimation of least satisfactory volume, and the "Maximum BPM" input box permits the client to include the estimation of most extreme worthy breaths every moment, these two factors are actualized to help the client sift through and kill clamor in the data.

The other interface that has been designed for the analysis of sound files is shown in figure 4.2. User can input a sound file and view a plot of the sound wave. User can use menu to perform functions such as increasing speed at which sound is played, selecting for certain frequencies and wavelengths, and outputting file. User can provide respiratory or lung sound files as an input to this interface. These file can be represented or can be exported to excel spreadsheet.

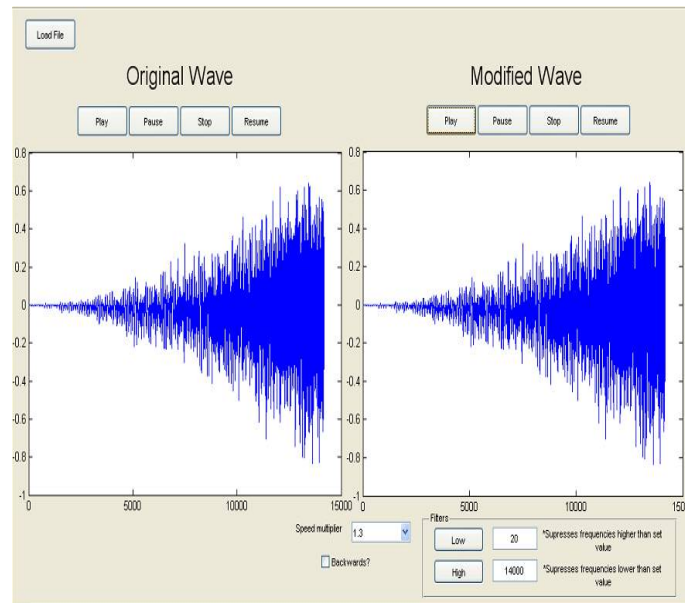


Figure 4.2. Screenshot of Interface for Analyzing Respiratory or Lung Sounds.

## V. CONCLUSION

The experimental results have confirmed the effectiveness of the proposed system to analyze the respiratory and lung sounds. The discrete equalization method to compensate sound attenuation is enforced by the thorax and thorax-microphone interface with a system based on the CORSA guidelines. The diseases are classified after analysing the recorded respiratory sounds. The disease classification is improved after respiratory sound equalization. The disease classification results can be further improved by using neuro fuzzy systems. Working over the lower respiratory tract, a fuzzy model for diagnosis of respiratory infections using Respiratory Inductance Plethysmography (RIP) data, has been proposed. Paper has also presented pure Adaptive Neuro Fuzzy Interference System (ANFIS) for classification, which is a better classifier than Support vector machines (SVM) for pattern recognition. MFCC for feature extraction has yielded better results as compared to Dynamic Time wrapping (DTW) in asthma detection using ASR.

## REFERENCES

- [1] Zhou Zhixiang Joseph K C Kwan, "A Respiratory Tract Infection Index for SARS and Avian Influenza Outbreaks", Proceedings of the 2005 IEEE Engineering in Medicine and Biology 27th Annual Conference Shanghai, China, September 1-4, 2005
- [2] Sheng-Ta Hsieh, Chih-Dao Chen, "An Expert System Application for Respiratory Infection Diagnostic", 9th International Conference on Ubiquitous Intelligence and Computing and 9th International Conference on Autonomic and Trusted Computing 2012.
- [3] Sandra Reichert, "Analysis of Respiratory Sounds: State of the Art," Clinical Medicine: Circulatory, Respiratory and Pulmonary Medicine 2008:2 45-58.
- [4] Ulas Bagic, "Automatic Detection of Tree-in-Bud Patterns for Computer Assisted Diagnosis of Respiratory Tract Infections", 33rd Annual International Conference of the IEEE EMBS Boston, Massachusetts USA, August 30 - September 3, 2011
- [5] K. Ho, N. Tsuchiya, H. Nakajima, K. Kuramoto, S. Kobashi and Y. Hata, "Fuzzy logic approach to respiration detection by air pressure sensor," in Proc. of IEEE International Conference on Fuzzy Systems, pp. 911-915, 2009.
- [6] S. H. Ling, Nuryani and H. T. Nguyen, "Evolved fuzzy reasoning model for hypoglycaemic detection," in Proc. of 2010 Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pp. 4662-4665, 2010.
- [7] S. H. Ling, H. T. Nguyen and F. H. F. Leung, "Hypoglycemia detection using fuzzy inference system with genetic algorithm," in Proc. of 2011 IEEE International Conference on Fuzzy Systems (FUZZ 2011), pp. 2225-2231, 2011.
- [8] Elpiniki I. Papageorgiou, "Medical decision making through fuzzy computational intelligent approaches", ISICA, CCIS 51, pp. 266-275, Springer-Verlag Berlin Heidelberg 2009.
- [9] Janikow C. Z., "Fuzzy Decision Trees Manual, free version for Fuzzy Decision Trees", 1998.
- [10] Janikow C. Z., "Fuzzy decision trees: issues and methods". IEEE Trans. Systems Man Cybernet. Part B (Cybernetics), 28(1), pp. 1-14, (1998)
- [11] Ahmad Taher Azar, "Expert System Based on Neural-Fuzzy Rules for Thyroid Diseases Diagnosis", MulGraB/BSBT/IurC 2012, CCIS 353, pp. 94-105 Springer-Verlag Berlin Heidelberg 2012.

- [12] Cetişli, B, "Development of an adaptive neuro-fuzzy classifier using linguistic hedges: Part 1, 2". Expert Systems with Applications 37(8), 6093–6101 (2010).
- [13] S.O. Olabiyisi, "A Decision Support System Model for Diagnosing Tropical Diseases Using Fuzzy Logic," African Journal of Computing & ICT September 2011.
- [14] D. F. Ponte, R. Moraes, D. C. Hizume, and A. M. Alencar, "Characterization of crackles from patients with fibrosis, heart failure and pneumonia," Med. Eng. Phys., vol. 35, no. 4, pp. 448–456, Apr. 2013.
- [15] S. Reichert, R. Gass, C. Brandt, & E. Andres, "Analysis of respiratory sounds: state of the art," Clinical Medicine: Circulatory, Respiratory, and Pulmonary Medicine, 2, 45-58, 2008.
- [16] D. F. Ponte, R. Moraes, L. J. M. Steidle, R. C. T. P. Viana, D. C. Hizume, and A. M. Alencar, "Equalization of Crackle Sounds to Compensate Thorax Attenuation," IEEE Trans on Instrumentation and Measurement, vol. 63, no. 8, Aug. 2014.
- [17] J. Mazic, S. Sovilj, and R. Magjarevic, "Analysis of respiratory sounds in asthmatic infants," Meas. Sci. Rev., vol. 3, no. 2, pp. 11–21, 2003.
- [18] A. Marques, A. Bruton, and A. Barney, "The reliability of lung crackle characteristics in cystic fibrosis and bronchiectasis patients in a clinical setting," Physiol. Meas., vol. 30, no. 9, pp. 903–912, Sep. 2009.
- [19] Hadjileontiadis, Leontios, "Lung Sounds: An Advanced Signal Processing Perspective. Synthesis Lectures on Biomedical Engineering., 2009.
- [20] D. F. Ponte, R. Moraes, L. J. M. Steidle, R. C. T. P. Viana, D. C. Hizume, and A. M. Alencar, Microcomputerized Respiratory Sound Recorder: A Low Cost Device, A. L. N. Fred, J. Filipe, and H. Gamboa, Eds. Palo Alto, CA, USA: Biodevices, Inc., 2010.
- [21] C. A. F. Rocha and M. G. Bellanger, "Sub-channel equalizer design based on geometric interpolation for FBMC/OQAM systems," in Proc. IEEE ISCAS, May 2011, pp. 1279–1282.
- [22] A. R. A. Sovijärvi, J. Vanderschoot, and J. E. Earis, "Standardization of computerized respiratory sound analysis," Eur. Respirat. Rev., vol. 10, no. 77, pp. 585–590, 2000.
- [23] R. A. Sovijärvi, L. P. Malmberg, G. Charbonneau, J. Vanderschoot, F. Dalmaso, C. Sacco, et al., "Characteristics of breath sounds and adventitious respiratory sounds," Eur. Respir Rev., vol. 10, pp. 591–596, 2000.
- [24] G. R. Wodicka, K. N. Stevens, H. L. Golub, and D. C. Shannon, "Spectral characteristics of sound transmission in the human respiratory system," IEEE Trans. Biomed. Eng., vol. 37, no. 12, pp. 1130–1135, Dec. 1990.
- [25] P. Piirilä, A. R. A. Sovijärvi, T. Kaisla, H. M. Rajala, and T. Katila, "Crackles in patients with fibrosing alveolitis, bronchiectasis, COPD and heart failure," CHEST J., vol. 99, no. 5, pp. 1076–1083, May 1991.
- [26] Kandaswamy, "Neural Classification of Lung Sounds Using Wavelet Coefficients", Computers in Biology and Medicine, 34, 523-537, 2004.
- [27] H Pasterkamp, S. Kramen, G. Wodicka, "Respiratory sounds: advances beyond the stethoscope. American Journal of Respiratory and Critical Care Medicine, 156, 975-987, 1997
- [28] A. Sovijärvi, J. Vanderschoot, J. Earis, "Standardization of computerized respiratory sound analysis. European Respiratory Review, 10, 585, 2000.
- [29] P. Piirilä, "Changes in crackle characteristics during the clinical course of pneumonia," Chest, vol. 102, no. 1, pp. 176–183, Jul. 1992.
- [30] M. P. Jones and D. W. Tomas, "Acoustic detection of physiological change within the thorax," in Proc. Int. Conf. Acoust. Sens. Imag., vol. 369. Mar. 1993, pp. 201–205.