CLASSIFICATION OF RESPIRATORY PATHOLOGY FROM PULMONARY ACOUSTIC BASED ON RESPIRATORY CYCLE SEGMENTATION AND TWO – STAGE CLASSIFICATION

©This item is protected by original copyright

by

Rajkumar Palaniappan

(1140610743)

A thesis submitted in fulfillment of the requirements for the degree of

Doctor of Philosophy in Mechatronic Engineering

School of Mechatronic Engineering

UNIVERSITI MALAYSIA PERLIS

2015

UNIVERSITI MALAYSIA PERLIS

DECLARATION OF THESIS

Author's full name : Rajkumar Palaniappan

Date of birth : 24.12.1986

Title : CLASSIFICATION OF RESPIRATORY PATHOLOGY FROM PULMONARY ACOUSTIC SIGNALS BASED ON RESPIRATORY CYCLE SEGMENTATION AND TWO – STAGE CLASSIFCATION

Academic Session : 2015-2016

I hereby declare that the thesis becomes the property of Universiti Malaysia Perlis (UniMAP) and to be placed at the library of UniMAP. This thesis is classified as:

☐ **CONFIDENTIAL** (Contains confidential information under the Official Secret Act 1972)*

☐ **RESTRICTED** (Contains restricted information as specified by the organization where research was done)*

☐ **OPEN ACCESS** I agree that my thesis is to be made immediately available as hard copy or on-line open access (full text)

I, the author, give permission to the UniMAP to reproduce this thesis in whole or in part for the purpose of research or academic exchange only (except during a period of _____ years, if so requested above).

Certified by:

_____ _____

SIGNATURE **SIGNATURE OF SUPERVISOR**

H1433351 DR.KENNETH SUNDARAJ

(NEW IC NO. / PASSPORT NO.) **NAME OF SUPERVISOR**

Date :_____ Date : _____

©This item is protected by original copyright

ACKNOWLEDGMENT

The successful completion of this thesis work relies on the influence of many people who have generously given their time and energy in specific ways. I take this opportunity to express my gratitude and thanks to each of you who have been a part of this PhD journey.

First and foremost I would like to express my sincere gratitude to the support and supervision of Assoc. Prof. Dr. Kenneth Sundaraj, who brought in this opportunity, for his suggestions, guidance, encouragement and challenges throughout this work from its beginning. Indeed, his inputs and ideas were of immense help in the making of this thesis.

I gratefully thank Prof. Dr. M. K. Sudarshan MD (Principal - Kempegowda Institute of Medical Sciences (KIMS)), and Assoc. Prof. Dr. D. H. Aswath Narayana MD (Head Department of Community Medicine - KIMS) for permitting the data collection process for this research to be conducted in KIMS campus and also their cooperation and guidance. I extend my thanks to Dr. S. Sebastian MD (Klang General Hospital) for the valuable comments, discussions, ideas and suggestions that helped me through this work.

I would like to express my unlimited appreciation to Prof. Dr. N. Huliraj MD (Head Department of Pulmonary Medicine - KIMS), Assoc. Prof. Dr. S. S. Revadi MD and Assoc. Prof. Dr. B. Archana MD for their valuable supervision and guidance in the data collection processes for this thesis. Their patience and positive attitude foster me in completing my data collection for this research work. I would like to express my thanks to all the members in Department of Pulmonary Medicine – KIMS for their cooperation and encouragement.

I take this time to thank the Dean, School of Mechatronic Engineering Assoc. Prof. Dr. Abu Hassan bin Abdullah and the program chairman Dr. Ruslizam bin Daud for their cooperation and administrative assistance through this course of study.

I would like to express my gratitude and thanks to the vice chancellor of UniMAP, Yang Berbahagia Brigedier Jeneral Datuk Prof. Dr. Kamarudin Hussin, for providing me an

© This item is protected by original copyright

opportunity in this university and the financial support through research assistantship and graduate assistantship.

It is an honor to thank my fellow colleagues, members of AI- rehab research group who supported me in this research work. At this junction, I would like to appreciate my parents, Mr. C. Palaniappan and Mrs. P. Sridevi, brother, Mr. P. Kathir Kaman, sister-in-law Mrs. K. Anu Shankari and my niece Aishwarya for always being there for me in this solitary research journey, still being 2500 miles away from me. I also thank all my friends for their support and encouragement throughout this PhD journey.

Last but not least, I am deeply thankful to different divinities existing in the universe by the principal concept of faith for successfully completing the research.

©This item is protected by original copyright

TABLE OF CONTENTS

		PAGE
DECLARATION OF THESIS		**i**
ACKNOWLEDGEMENT		**ii**
TABLE OF CONTENTS		**iv**
LIST OF TABLES		**ix**
LIST OF FIGURES		**xii**
LIST OF ABBREVIATIONS		**xiv**
LIST OF SYMBOLS		**xvii**
ABSTRAK		**xviii**
ABSTRACT		**xix**
CHAPTER 1	**INTRODUCTION**	**9**
1.1	Research Background	9
1.2	Motivations of the Work	10
1.3	Problem Statement	11
1.4	Research Objectives	12
1.5	Scope of the Thesis	15
1.6	Thesis Organization	16
CHAPTER 2	**LITERATURE REVIEW**	**18**
2.1	Physiology of Human Respiratory system	18

©This item is protected by original copyright

2.2 Respiratory Pathology and the Causes 19

2.3 Computerized Respiratory Sound Analysis 20

2.3.1 Types and Characteristics of Respiratory Sounds 20

2.3.2 Respiratory Sounds Data Acquisition 22

2.3.3 Respiratory Sounds Pre-processing 24

2.3.4 Respiratory Sounds Cycle Segmentation 25

2.3.5 Feature Extraction Techniques in Respiratory Sound Analysis 28

2.4 Machine Learning techniques in Respiratory Sound Analysis 31

2.5 Research Gap 34

2.6 Summary 35

CHAPTER 3 METHODOLOGY 37

3.1 Methodology 37

3.2 Respiratory Sound Acquisition Protocol 40

3.2.1 Ethics Statement 41

3.2.2 Subject Inclusion and Exclusion Criteria 42

3.2.3 Data Set 42

3.3 Pre-processing 45

3.3.1 Data Validation 45

3.3.2 Filtering 47

3.3.3 Respiratory Cycle Segmentation 47

3.4 Feature Extraction, Feature Reduction and Statistical Analysis 56

3.4.1 Parametric Representation 57

©This item is protected by original copyright

3.4.1.1 AR-Coefficients 57

3.4.1.2 Mel-Frequency Cepstral Coefficients 58

3.4.2 Non-Parametric Representation 59

3.4.2.1 Wavelet Packet Transform 60

3.4.2.2 Stockwell Transform 61

3.4.3 Dimensionality Reduction 64

3.4.4 Feature Vector 65

3.4.5 Statistical Analysis 67

3.5 Machine learning 67

3.5.1 K-Nearest Neighbour (*k*-nn) 68

3.5.2 Support Vector Machine (SVM) 68

3.5.3 Extreme Learning Machine (ELM) 72

3.6 Classifier Validation and Performance Evaluation 74

3.6.1 Conventional validation 74

3.6.2 Ten-fold Cross validation 74

3.6.3 Confusion Matrix 75

3.7 Summary 75

CHAPTER 4 RESULTS AND DISCUSSION 76

4.1 Introduction 76

4.2 Performance of Fuzzy Inference System 76

4.3 Results of Statistical Analysis (ANOVA) 78

4.4 Performance of Parametric Feature Representation 80

©This item is protected by original copyright

4.4.1 Performance of AR Coefficient Features with *k*-nn Classifier 80

4.4.2 Performance of AR Coefficients Features with SVM Classifier 83

4.4.3 Performance of AR Coefficients Features with ELM Classifier 88

4.4.4 Performance of MFCC Features with *k*-nn Classifier 91

4.4.5 Performance of MFCC Feature with SVM Classifier 94

4.4.6 Performance of MFCC Features with ELM Classifier 99

4.5 Performance of Non-parametric Feature Representation 102

4.5.1 Performance of WPT based features with *k*-nn Classifier 102

4.5.2 Performance of WPT based features with SVM Classifier 107

4.5.3 Performance of WPT based features with ELM Classifier 110

4.5.4 Performance of ST based feature with *k*-nn Classifier 113

4.5.5 Performance of ST based feature with SVM Classifier 118

4.5.6 Performance of ST based feature with ELM Classifier 121

4.6 Comparison between Feature Extraction Algorithms 124

4.7 Comparison between Machine Learning Algorithms 125

4.8 Comparison between Frameworks 126

4.9 Validation 127

4.10 Comparison with Previous Works 129

4.11 Application Development 133

4.12 Summary 136

CHAPTER 5 CONCLUSION AND RECOMENDATIONS 138

5.1 Summary of Findings 138

©This item is protected by original copyright

5.2 Research Contributions 139

5.3 Limitations 141

5.4 Recommendations for Future Works 141

REFERENCES **143**

APPENDIX A **153**

APPENDIX B **161**

APPENDIX C **170**

LIST OF PUBLICATIONS **182**

LIST OF AWARDS **184**

©This item is protected by original copyright

LIST OF TABLES

NO		PAGE
2.1	Previous works on Respiratory Phase detection	27
3.1	Subject Details	44
3.2	ANOVA Results for Raw Respiratory Sound Signals	46
3.3	Fuzzy Rules	53
3.4	Constant output for Sugeno FIS	54
3.5	Feature Vector Dimension	66
4.1	Feature Significance Results for Framework 1	79
4.2	Feature Significance Results for Framework 2	79
4.3	Feature Significance Results for Framework 3	80
4.4	Performance Outcome of AR Coefficients Features and *k*-nn Classifier with Framework 1	81
4.5	Performance Outcome of AR Coefficients Features and *k*-nn Classifier with Framework 2	82
4.6	Performance Outcome of AR Coefficients features and *k*-nn Classifier with Framework 3	84
4.7	Performance Outcome of the AR Coefficients Features and SVM Classifier with Framework 1	85
4.8	Performance Outcome of the AR Coefficients Features and SVM Classifier with Framework 2	86
4.9	Performance Outcome of the AR Coefficients Features and SVM Classifier with Framework 3	87
4.10	Performance outcome of the AR Coefficients and ELM Classifier with Framework 1	88
4.11	Performance outcome of the AR Coefficients and ELM Classifier with Framework 2	89
4.12	Performance outcome of the AR Coefficients and ELM Classifier with Framework 3	91
4.13	Performance Outcome of MFCC Features and *k*-nn Classifier with Framework 1	92
4.14	Performance Outcome of MFCC Features and *k*-nn Classifier with Framework 2	93
4.15	Performance Outcome of MFCC Features and *k*-nn Classifier with Framework 3	96
4.16	Performance Outcome of MFCC features and SVM Classifier with Framework 1	97
4.17	Performance Outcome of MFCC features and SVM Classifier with Framework 2	98
4.18	Performance Outcome of MFCC features and SVM Classifier with Framework 3	98

©This item is protected by original copyright

4.19	Performance Outcome of MFCC Features and ELM Classifier with Framework 1	99
4.20	Performance Outcome of MFCC Features and ELM Classifier with Framework 2	100
4.21	Performance Outcome of MFCC Features and ELM Classifier with Framework 3	101
4.22	Performance Outcome of WPT based Features and *k*-nn Classifier with Framework 1	103
4.23	Performance Outcome of WPT based Features and *k*-nn Classifier with Framework 2	104
4.24	Performance Outcome of WPT based Features and *k*-nn Classifier with Framework 3	106
4.25	Performance Outcome of WPT based Features and SVM Classifier with Framework 1	107
4.26	Performance Outcome of WPT based Features and SVM Classifier with Framework 2	107
4.27	Performance Outcome of WPT based Features and SVM Classifier with Framework 3	109
4.28	Performance Outcome of WPT based Features and ELM Classifier with Framework 1	110
4.29	Performance Outcome of WPT based Features and ELM Classifier with Framework 2	111
4.30	Performance Outcome of WPT based Features and ELM Classifier with Framework 3	112
4.31	Performance Outcome of ST based Features and *k*-nn Classifier with Framework 1	114
4.32	Performance Outcome of ST based Features and *k*-nn Classifier with Framework 2	115
4.33	Performance Outcome of ST based Features and *k*-nn Classifier with Framework 3	117
4.34	Performance Outcome of ST based Features and SVM Classifier with Framework 1	118
4.35	Performance Outcome of ST based Features and SVM Classifier with Framework 2	118
4.36	Performance Outcome of ST based Features and SVM Classifier with Framework 3	120
4.37	Performance Outcome of ST based Features and ELM Classifier with Framework 1	122
4.38	Performance Outcome of ST based Features and ELM Classifier with Framework 2	123
4.39	Performance Outcome of the ST based Features and ELM Classifier with Framework 3	124
4.40	Validation Results using ELM classifier and ST based features with Framework 3 (Dataset 2)	128
4.41	Validation Results using ELM classifier and ST based features with	129

©This item is protected by original copyright

Framework 3 (R.A.L.E Dataset)

©This item is protected by original copyright

LIST OF FIGURES

NO		PAGE
2.1	Human Respiratory System	19
2.2	General Block Diagram for Respiratory Sound Analysis	20
2.3	Types and Characteristics of Respiratory sounds	23
3.1	Block Diagram of the Methodology used in Framework 1	38
3.2	Block Diagram of the Methodology used in Framework 2	38
3.3	Block Diagram of the Methodology used in Framework 3	39
3.4	WISE Digital Stethoscope	41
3.5	Illustration of Auscultation Points	41
3.6	Raw Respiratory Sound Signals	43
3.7	(a) Original Signal Plot and (b) Spectrogram of the Original Signal	46
3.8	Respiratory Cycle Illustration	49
3.9	Fuzzy Inference System	51
3.10	Input Membership Function Plot for NPSD	52
3.11	Input Membership Function Plot for CNPSD	52
3.12	Output Membership Function Plot of Mamdani-type FIS	53
3.13	Input/Output Surface of the Mamdani-type FIS	53
3.14	Input/Output Surface of the Sugeno-type FIS	54
3.15	Respiratory Cycles after Segmentation	55
3.16	Flowchart for Respiratory Cycle Segmentation Algorithm	56
3.17	Block Diagram of the Process Used to Obtain the MFCC Feature Vector	59
3.18	Tree Representation of Wavelet	61
3.19	Tree Representation of Wavelet Packet Transform	61
3.20	Separating Hyperplane for a Simple Two-Class Problem	69
4.1	Correlation Coefficient plot for Mamdani method	77
4.2	Correlation Coefficient plot for Sugeno method	77
4.3	Classification Accuracy for the Three Frameworks using Ten Fold Cross Validation	131
4.4	Classification Accuracy for the Three Frameworks using Conventional Validation	132

© This item is protected by original copyright

4.5 CDSS Tool Front End 133
4.6 Patients Information Panel 134

©This item is protected by original copyright

LIST OF ABBREVIATIONS

ANFIS	-	Adaptive Neuro-Fuzzy Inference System
ANN	-	Artificial Neural Network
ANOVA	-	Analysis of Variance
AR	-	Auto Regressive
API	-	Application Programming Interface
CC	-	Coarse Crackles
CD	-	Compact Disc
CDSS	-	Computerized Decision Support System
CHF	-	Congestive Heart Failure
CLS	-	Continuous Lung Sounds
COG	-	Center of Gravity
COPD	-	Chronic Obstructive Pulmonary Disease
CORSA	-	Computerized Respiratory Sound Analysis
CRF	-	Case Report Form
CT	-	Computer Tomography
DFT	-	Discrete Fourier Transform
DLS	-	Discontinuous Lung Sounds
F	-	Female
FC	-	Fine Crackles
FEV	-	Forced Expiratory Volume

©This item is protected by original copyright

FFT	-	Fast Fourier Transform
FIS	-	Fuzzy Inference System
GAL	-	Grow and Learn
GMM	-	Gaussian Mixture Model
HMM	-	Hidden Markov Model
ILD	-	Interstitial Lung Disease
IPF	-	Idiopathic Pulmonary Fibrosis
IPG	-	Impedance Plethysmography
k -nn	-	*k* -Nearest Neighbor
LVQ	-	Linear Vector Quantization
MARS	-	Marburg Respiratory Sounds
M	-	Male
MFCC	-	Mel Frequency Cepstral Coefficients
MLP	-	Multilayer Perceptron
N	-	Normal/Control
OP	-	Obstructive Pathology
PCA	-	Principal Component Analysis
R	-	Rhonchi
RBF	-	Radial Basis Function
RIP	-	Respiratory Inductive Plethysmography
RP	-	Restrictive Pathology
SD	-	Standard Deviation
SDK	-	Software Development Kits

©This item is protected by original copyright

SOM	-	Self Organization Maps
ST	-	Stockwell Transform
STFT	-	Short-Time Fourier Transform
SVM	-	Support Vector Machine
W	-	Wheeze
WA	-	Weighted Average
WHO	-	World Health Organization
WPT	-	Wavelet Packet Transform
WT	-	Wavelet Transform

©This item is protected by original copyright

LIST OF SYMBOLS

Hz	-	Hertz (Unit of frequency)
%	-	Percentage
±	-	Plus/minus
dB	-	Decibel (Unit of amplitude loss)
F - Value	-	Critical value for F - distribution
p - value	-	Probability of obtaining test statistical result

©This item is protected by original copyright

Pengelasan Patologi Pernafasan daripada Isyarat Akustik Pulmonari Menggunakan Representasi berparameter dan bukan berparameter

ABSTRAK

Auskultasi adalah proses mendengar bunyi dalam badan dengan menggunakan stetoskop. Proses ini memberi maklumat penting mengenai keadaan semasa bagi organ-organ dalaman seperti jantung, paru-paru dan sistem pencernaan. Auskultasi adalah kaedah yang subjektif dan cenderung untuk menjadi kurang dipercayai. Analisis bunyi pernafasan berkomputer bagaimanapun adalah lebih berkesan dan boleh dipercayai. Tesis ini membincangkan pembangunan sistem sokongan keputusan berkomputer (CDSS) untuk mengesan patologi pernafasan menggunakan isyarat akustik paru-paru. Isyarat akustik pulmonari dikumpulkan daripada 72 subjek untuk membangunkan CDSS. Dalam usaha untuk membangunkan alat CDSS, tiga kerangka metodologi yang berbeza telah dicadangkan untuk menentukan klasifikasi patologi pernafasan yang paling berkesan. Isyarat akustik paru-paru telah ditapis untuk menyingkirkan bunyi dan artifak lain diikuti oleh segmentasi kitaran pernafasan. Dalam tesis ini, segmentasi kitaran pernafasan dilakukan dengan menggunakan sistem kesimpulan Fuzzy. Ciri-ciri representasi parametrik (Mel frekuensi pekali cepstral (MFCC) dan model Auto-regresif (AR)) dan representasi bukan parametrik (paket wavelet mengubah (WPT) dan transformasi Stockwell (ST)) kemudiannya diekstrak keluar. Ciri-ciri yang diekstrak telah dikurangkan dimensinya dengan menggunakan analisis komponen utama dan analisis statistik telah dilakukan untuk menentukan tahap kepentingan vektor ciri-ciri yang diekstrak dengan menggunakan analisa ANOVA sehala. Pemerhatian menunjukkan bahawa ciri-ciri yang diekstrak secara statistik signifikan dengan $p < 0.05$. Dalam peringkat kasifikasi pelbagai pengelas bukan linear seperti k-jiran terdekat (k-nn), mesin vektor sokongan (SVM) dan mesin pembelajaran melampau (ELM) telah dilaksanakan untuk mengklasifikasikan patologi pernafasan daripada bunyi pernafasan. Dalam peringkat klasifikasi, pengelas ELM menunjukkan prestasi yang terbaik daripada pengelas k-nn dan SVM untuk semua kerangka. Keputusan eksperimen menunjukkan bahawa pengekstrakan ciri-ciri berasaskan ST dengan pengelas ELM menunjukkan prestasi yang terbaik dengan kerangka ketiga. Penggunaan ciri-ciri berasaskan ST dan pengelas ELM dengan kerangka ketiga telah disahkan menggunakan satu set data yang terdiri daripada 48 subjek dan sistem itu didapati boleh dipercayai dengan purata ketepatan klasifikasi 96.63%, 97.57% dan 98.48% dalam mengklasifikasikan (bunyi normal, bunyi paru-paru berterusan dan bunyi paru-paru tidak berterusan), (bubar dan ronchi) dan (gemercik halus dan gemercik kasar). Selepas pengesahan berjaya dibuat alat CDSS dibangunkan menggunakan ciri-ciri berasaskan ST dan pengelas ELM dengan kerangka ketiga.

© This item is protected by original copyright

Classification of Respiratory Pathology from Pulmonary Acoustic Signals Using Parametric and Non-Parametric Representations

ABSRACT

Auscultation is the process of listening to the internal sounds of the body using a stethoscope. This process provides vital information on the present state of the internal organs, such as the heart, lungs and the gastrointestinal system. Auscultation is subjective and prone to be not reliable. However computerized respiratory sound analysis is more effective and reliable. This thesis discusses the development of a computerized decision support system (CDSS) to detect respiratory pathology using pulmonary acoustic signals. The pulmonary acoustics signals were collected from 72 subjects to develop the CDSS. In order to develop the CDSS tool, three different methodological frameworks were proposed to determine the most effective classification of respiratory pathology. The recorded pulmonary acoustics signals were filtered to remove noise and other artifacts followed by respiratory cycle segmentation. In this work, the respiratory cycle segmentation is performed by using Fuzzy Inference system. Parametric (Mel-frequency cepstral coefficients (MFCC) and Auto-regressive model (AR)) and Non-parametric (wavelet packet transform (WPT) and Stockwell transform (ST)) representations of features were extracted. The features extracted were dimensionally reduced using principal component analysis and a statistical analysis was performed to determine the significance level of the feature vector using One-way ANOVA. Observations showed that the extracted features were statistically significant with $p < 0.05$. In the classification stage various non-linear classifiers such as *k*-nearest neighbor (*k*-nn), support vector machines (SVM) and extreme learning machine (ELM) were implemented to classify the respiratory pathology from respiratory sounds. In the classification, extreme learning machine performed better than *k*-nn and support vector machine classifier for all the frameworks. Experimental results showed that ST based feature extraction performed well with ELM classifier with third framework. The ST based features and ELM classifier with third framework was validated using a new set of data comprising of 48 subjects and the system was found to be reliable with mean classification accuracy of 96.63%, 97.57% and 98.48% for classifying (normal, continuous lung sounds and discontinuous lung sounds), (wheeze and rhonchi) and (fine crackles and coarse crackles) respectively. After successful validation a CDSS tool was developed using the ST based features and ELM classifier with third framework.

©This item is protected by original copyright

CHAPTER 1

INTRODCTION

This chapter presents an introduction to respiratory pathology, discussion on conventional methods used for the diagnosis of respiratory pathology, drawbacks of the existing methods and the advantages of using computerized respiratory sound analysis. The main objectives of the proposed research and the organization of the thesis are also described in the following section.

©This item is protected by original copyright

1.1 Research Background

Auscultation is the process of listening to the internal sounds of the body using a stethoscope. This process provides vital information on the present state of the internal organs, such as the heart, lungs and the gastrointestinal system (Chauhan et al., 2008; J. Earis, 1992). The stethoscope, which was invented by a French physician named René Théophile Hyacinth Laennec in 1816, has been used to perform auscultation for several years now (Welsby et al., 2003). The medical professionals auscultate the heart to indentify presence of heart murmurs, gallop and also to monitor the heart rate (Leatham, 1958). When listening to the lung sounds, medical professional listen for vital signs such as wheeze, rhonchi and crackles (Murphy, 1981). In auscultating the gastrointestinal system, medical professional listen for signs of bowel sounds (Craine et al., 1999). The stethoscope remains the most widely used instrument in clinical medicine. In addition, it has been an effective tool for the diagnosis of respiratory pathology for a number of years now. The auscultation process using stethoscope is inexpensive, non-invasive, and less time-consuming. This process mainly relies on the medical professional and hence requires

well-trained medical professional to recognise respiratory pathology from sounds. In addition, it also depends on the hearing perception of the medical professionals for accurate diagnosis. To overcome these drawbacks computerized respiratory sound analysis was proposed in the early 1980's (Nissan et al., 1993). Computerized respiratory sound analysis deals with the analysis of respiratory sounds by applying various signal processing and machine learning algorithms.

1.2 Motivations of the Work

According to the World Health Organization (WHO), respiratory disorders such as chronic obstructive pulmonary disease (COPD), Asthma, pneumonia, pulmonary fibrosis and other respiratory related illness stands third as the cause of fatality throughout the world. WHO has reported 3 million fatalities due to COPD in the year 2012 (WHO, 2012). WHO also has reported that 235 million people were suffering from Asthma in 2011 (WHO, 2013a). In the case of pneumonia, 935,000 fatalities were reported by WHO in the year 2013 (WHO, 2013b). The major cause of respiratory related illness are smoking, prolonged exposure to certain toxic agents, air pollution and hereditary. Often, patients neglect consulting medical professionals at the early stages of the pathology and only seek medical attentions when the respiratory system is affected badly. By the time the respiratory abnormality is diagnosed, the damage might be irreversible. Early diagnosis and treatment can reduce the number of fatalities drastically and improve the patient's quality of life. Few major cause for fatalities due to respiratory related illness are the lack of treatment facilities and lack of medical professional in the rural areas. The methods for diagnosing respiratory related illness include auscultation, radiography techniques and pulmonary function test are very expensive and also time-consuming. Radiography techniques such as X-rays and Computer Tomography (CT) scans causes serious side effects on human body when exposed for a longer duration (Kandaswamy et al., 2004).

©This item is protected by original copyright

Obstructive pathology cannot be easily diagnosed using the radiography technique. The pulmonary function test does not cause any serious effects however it is time-consuming, expensive and the patients need to put extra effort in some tests such as spirometry and hence it is an invasive procedure. The pulmonary function test provides additional information's such as lung volume, respiratory flow estimation and also the severity level of the pathology (Shephard et al., 1959). In spite of its advantages, the drawbacks of pulmonary function test are invasive method, expensive and time consuming method. To overcome these drawbacks, an alternative method should be developed using respiratory sound analysis to recognize the respiratory pathology. The advantages of using the computerised respiratory sound analysis include non-invasive based approach, fast diagnosis, not expensive and are more accurate. It can additionally serve as a differential diagnosis tool for medical professionals. Differential diagnosis is a process to distinguish specific disease or condition suffered by a patient or to at least eliminate any other disease or condition. This research aims to develop a Computerized Decision Support System (CDSS) to detect respiratory pathology using the respiratory sounds.

©This item is protected by original copyright

1.3 Problem Statement

There are several issues related to the classification of respiratory pathology from respiratory sounds. The previous researchers have formulated unrecognized protocols and have not followed the standard computerized respiratory sound analysis (CORSA) guidelines in the data acquisition and filtering process. In the respiratory cycle segmentation, the researchers have implemented both non-acoustic approach and acoustic approach. However, the non-acoustic approaches are considered to affect the natural breathing process and hence the acoustic approaches have been implemented by the

previous researcher. In the acoustic approaches, researchers have focused on particular lung auscultation point and not developed a general method which can segment the respiratory cycles of any auscultation point. The accuracy reported by the previous researcher in segmenting the respiratory cycle was also found to be low which will have an effect on the classification of respiratory pathology. In the feature extraction stage, various parametric and non-parametric algorithms were implemented by previous researcher. However the sample size also comes into consideration and hence the reported accuracies are unreliable to predict the quality of features in categorizing the respiratory pathology. In the respiratory pathology classification stage, only few previous researchers have classified most of the respiratory pathology (Wheeze, Rhoinchi, Fine Crackles, and Coarse Crackles) categories. The previous research also shows that clinical validation was not performed in any study reported earlier. The development of CDSS tool is also not reported earlier.

©This item is protected by original copyright

1.4 Research Objectives

This research aims to develop a CDSS tool for respiratory pathology detection using respiratory sounds, signal processing algorithms and artificial intelligence techniques. Despite the presence of various studies in literature, this work focuses on various parametric and non-parametric characteristics of respiratory sound signals in an effort to identify suitable parameters to capture the minute and hidden information from the respiratory sounds for the detection of respiratory pathology. The objectives formulated for the successful implementation of the system are as follows.

i. **To design an experimental protocol for collecting respiratory sounds using Computerized Respiratory Sound Analysis (CORSA) standard.**

   One of the main challenges in computerized respiratory sound analysis research is the acquisition of proper respiratory sound data. To develop an effective