An Overview of Breath Phase Detection – Techniques & Applications

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***Abstract*— The main aim of this study is to provide an overview on the state of the art techniques (acoustic and non-acoustic approaches) involved in breath phase detection and to highlight applications where breath phase detection is vital. Both acoustic and non-acoustic approaches are summarized in detail. The non-acoustic approach involves placement of sensors or flow measurement devices to estimate the breath phases, whereas the acoustic approach involves the use of sophisticated signal processing methods on respiratory sounds to detect breath phases. This article also briefly discusses the advantages and disadvantages of the acoustic and non-acoustic approaches of breath phase detection. The literature reveals that recent advancements in computing technology open avenues for researchers to apply sophisticated signal processing techniques and artificial intelligence algorithms to detect the breath phases in a non-invasive way. Future works that can be implemented after detecting the breath phases are also highlighted in this article.**

***Index Terms*— Breath Phase; Breath Sounds Detection; Respiratory Rate; Respiratory Sounds.**

I. INTRODUCTION

Auscultation is the process of listening to human body sounds. It started with the invention of stethoscope [1]. Chest auscultation is an essential practice for physical examination of lung patients. Lung sounds have information about underlying pathologies. These sounds can be divided into normal and abnormal sounds. Abnormal lung sounds are further divided into adventitious and non-adventitious sounds [2-5].

Computerized respiratory sound analysis is also an active field of research [6]. In this field most of the researchers are dealing with adventurous sounds detection and classification [2, 3]. Researchers are also focusing on respiratory sound analysis. Furthermore, researchers are also paying attention to the behavior of respiratory sounds in expiratory and inspiratory phase [4, 7].

Determining respiratory flow towards subsequently detecting breath phases has been of interest in the field of respiratory research for many years [8]. There are several applications for which determining respiratory flow and detecting breath phases could be considered important [9]. They have been found to be used in applications such as, early detection of sleep apnea, computing respiratory rate, computerized decision support systems (CDSS) for respiratory sound analysis, and in many other clinical tests where it is either mandatory or vital [10]. There are several instruments currently used by practitioners and researchers alike for respiratory flow estimation such as phonopneumographs, spirometers etc. Once the respiratory flow is recorded, the corresponding breath phases can be segmented using flow estimation. The estimated flow in the various breath phases can be used in many applications to detect respiratory related illness [11, 12]. The methods for detecting breath phases can be broadly classified into two main approaches namely the non-acoustic approach and the acoustic approach. The following sections will discuss in detail about these two approaches for detecting breath phases and the applications which rely on breath phase detection. We are going to discuss in more details acoustic approach which depends on properties of signal and it is our main focus.

II. NON-ACOUSTIC APPROACH

The non-acoustic approach is otherwise called a sensor-based method [13]. The commonly used sensor-based methods are impedance plethysmography (IPG), the fibre optic-based method, respiratory inductive plethysmography (RIPG) and flow measurement based methods.

In IPG, electrodes are placed on the surface of the body, and the changes in tissue volume are measured based on variations in electrical impedances [14]. The placement of the IPG electrodes over the chest wall allows measurement of the change in respiratory volume [15]. Because the electrodes are placed on the human body, the measured electrical impedance is highly sensitive to movements [8].

In 1994, Vegfors et al. proposed a respiratory rate monitoring system developed using fibre optic technology [16]. In this approach, optical fibres are placed near the nose and mouth of the subject, and the variation in light reflection is measured. The fibre optic tips become condensed as warm air is expired during respiration, which changes the reflectivity of the light. However, this fibre optic technique can cause discomfort to the subjects due to the placement of fibre optic tips near the nose and mouth, which affects the natural breathing pattern [8].

RIPG is another technique for measuring the respiratory rate [17] that includes the use of two wire-insulated elastic bands positioned around the abdomen and the rib cage under each armpit. During the respiration process, the cross-sectional area of the abdomen and the rib cage increases and decreases, resulting in changes in the self-inductance and frequency of the coils within the elastic bands [18]. These changes are then converted into a waveform to measure the respiratory rate. In 2015, one researcher [19] used a wireless type respiratory rate detection system. Respiratory rate was measured by bending type sensor which is a long and thin sheet with variable resistance. The sensor was placed longitudinally on the center of the abdomen to measure the change in expansion and contraction. Resistance of sensors varies according to the degree of bending [19]. Similar to the fibre optic technique, RIPG also causes discomfort to the subjects due to the placement of the elastic bands, which affects the natural breathing pattern [20].

In some cases, flow measurement devices are used to determine the respiratory rate. The commonly used flow measurement devices include phonopneumographs, spirometers and other devices used for testing pulmonary functions. Using this approach, flow measurements are used to measure the forced expiratory volume (FEV), which is then used to determine the respiratory rate [21] and also used for phase detection [22-25]. This technique cannot be used for patients with very severe respiratory illness [26] or onto children [27]. Further, this technique may not be suitable for continuous monitoring [28].

III. ACOUSTIC APPROACH

The acoustic approach is otherwise called a direct measurement technique [13]. Direct measurement techniques are prone to drawbacks, and hence, researchers have started developing indirect techniques to measure the respiratory rate using pulmonary acoustic signals. These indirect measurements involve the analysis of pulmonary acoustic signals in the time or frequency domain or time and frequency domain to detect the breath phases [10]. The indirect technique involves the auscultation of pulmonary acoustic signals, in a manner which does not affect the natural breathing pattern of subjects. Such a technique allows the recording of pulmonary acoustic signals from patients with severe respiratory illness [3].

In 2009, Jin et al. proposed a genetic algorithm-based technique for detecting the breath phases and subsequently segmenting the respiratory cycles from pulmonary acoustic signals [29]. The number of respiratory cycles is estimated through noise estimation and non-linear mapping followed by the application of a genetic algorithm to identify the breath phases. In 2004, Hult et al. [8] proposed a novel technique for detecting and segmenting breath phases using the Fast Fourier Transform (FFT)-based summation method, which is applied to the windowed pulmonary acoustic signals to calculate an index that can be used to detect the respiratory phases. This technique provides sufficient evidence regarding the use of spectral changes for detecting breath phases.

In 2016, Palaniappan et al. [10] recorded pulmonary acoustic signals from 69 subjects using an electronic stethoscope placed over three different locations, namely the trachea and the posterior left and right lung bases. The averaged normalized power spectral density and changes in the normalized power spectral density were extracted from the pulmonary acoustic signals to develop a fuzzy model for the detection of breath phases. The system developed by Palaniappan et al. exhibited an accuracy of 98% in detecting the respiratory phases.

Subsequently, a year later in 2017, Palaniappan et al. [9] again recorded pulmonary acoustic signals from a different set of 72 subjects using an electronic stethoscope placed over the same three different locations. This time, only the averaged normalized power spectral density was extracted from the pulmonary acoustic signals and it was fed into an adaptive neuro fuzzy model for the detection of breath phases. This modified system developed by Palaniappan et al. exhibited an accuracy of 99% in detecting the breath phases.

The previously used indirect methods for detecting breath phases and segmenting the breath cycle are listed in Table 1. These works are from the year 2000 onwards and taken only from reliable sources with accurate reporting (clear methodology and results).

Table 1
Previous studies on Indirect methods for Breath Phase detection

Reference	Number of Subjects	Acoustical Method	Auscultation Points	Results
[30]	11 children (Group 1) and 10 adults (Group 2); all healthy	Spectral analysis	Trachea (suprasternal notch), Left midclavicular area (2nd intercostal space), Left parasternum (2nd interspace), Right midclavicular area (2nd intercostal space), Right parasternum (2nd interspace), Right midclavicular area (3rd interspace)	Overall accuracies of 76% and 67.6% for the 1st and 2nd groups were reported
[8]	20 subjects with various respiratory pathologies	FFT-based Summation method	Trachea	An overall accuracy of 98.5% was reported
[13]	6 healthy subjects	Area and shape of the sound envelope	Trachea	An overall accuracy of 93% was reported
[31]	7 controls and 14 subjects with airway obstruction	Phase-shift difference information	Trachea	An overall accuracy of 98.07% was reported
[32]	7 controls and 14 subjects with airway obstruction	Sample entropy and Genetic algorithm	Trachea	An overall accuracy of about 98% was reported
[29]	7 controls and 14 subjects with airway obstruction	Sample entropy and a heterogeneity measure	Trachea	An overall accuracy of 100% was reported
[33]	Normal subjects	Triplet Markov chains	Trachea	The developed system was reported as effective
[34]	10 controls	Entropy	Trachea	An overall accuracy of 94% was reported

[10]	69 subjects with various respiratory pathologies	Normalised power spectral density and change in normalised power spectral density using fuzzy inference system (FIS)	Trachea, Posterior right lung base, Posterior left lung base	An overall accuracy of 98% was reported
[9]	72 subjects with various respiratory pathologies	Normalised power spectral density using adaptive neuro fuzzy inference system (ANFIS)	Trachea, Posterior right lung base, Posterior left lung base	An overall accuracy of 99% was reported

IV. APPLICATIONS

Knowledge on the characteristics of respiration is important in several clinical applications, especially for patients in the intensive care unit, patients anaesthetised, patients undergoing rehabilitation or physiotherapy, and for those patients subjected to cardiac and pulmonary investigations [8, 35]. In these patients, by monitoring their breathing cycles, we can identify the respiratory rate. An adult with a respiratory rate of over 20 breaths per minute is most likely seriously unwell. Similarly, an adult with a respiratory rate of over 24 breaths per minute is likely to be in a critical health condition [36]. Abnormal respiratory rates and changes in the respiratory rate are the earliest indicators of physiological instability.

For example, respiratory rate monitoring is vital in patients with sleep apnea. In these patients, the breathing cycle is either slowed or stopped. Very often, pauses in breathing, shallow breathing or infrequent breathing appear as symptoms. Hence, monitoring the respiratory rate which involves detecting the breathing phases is vital in these patients. Each respiratory cycle comprises of the inspiration phase, pause phase and the expiration phase. Vital information pertaining to the assessment of the respiratory system lies either in the inspiration or expiration phases or even both in some cases.

Respiratory phase detection is also vital in the pulmonary acoustic signal analysis to diagnose pathology. Pulmonary acoustic signal analysis has been an effective tool for assessing the respiratory system for the past three decades [2, 37]. The adventitious sounds in the pulmonary acoustic signals provide indications of respiratory related illness. These breath sounds can be clinically characterized by their duration within a respiratory cycle and their relationship to the phase of respiration. It was revealed that these developments in respiratory sound analysis drive the development of Electronic Health (e-health) care tools [26].

V. DISCUSSION

Our findings reveal that the acoustic approach is more advantages than the non-acoustic approach in detecting the respiratory phases. The acoustic approach is non-invasive, inexpensive, less time consuming, it does not affect the natural breathing manoeuvre of the subject and it can also be used in patients with the severe respiratory illness. There are numerous applications which require breath phase segmentations namely in early detection of sleep apnea. With all these benefits, an acoustic approach is more beneficial in many research areas related to the respiratory system. However, we find that the research works on the acoustic approach based detection of breath phases is still in its infancy stages. The research on breath phase detection should progress to an advanced level given the recent advancement in signal processing techniques and machine learning algorithms. The current and future advancement in technology may open up new questions or it may provide answers to a few questions about which researchers in the field of pulmonary acoustic signal analysis are looking for.

VI. CONCLUSIONS

This article gives an overview of the state of the art techniques (acoustic and non-acoustic approaches) involved in breath phase detection and provides evidence of applications where breath phase detection is vital. The non-acoustic approaches involve placement of sensors or flow measurement devices to estimate the breath phases, whereas the acoustic approaches involve the use of sophisticated signal processing methods on respiratory sounds to detect and identify breath phases. This article has also presented a brief discussion on the advantages and disadvantages of the acoustic and non-acoustic approaches of breath phase detection. The discussion clearly shows that the acoustic based approach is non-invasive, less expensive and does not affect the natural breathing pattern of the subjects. We believe the recent advancement in technology will allow researchers to apply sophisticated signal processing techniques and artificial intelligence algorithms to detect the breath phases in a non-invasive way. Future works that can be implemented after detecting the breath phases were also highlighted in this article.

ACKNOWLEDGMENT

The authors would like to thank UTeM for providing the research platform to conduct this work. We would like to thank the Ministry of Higher Education (MoHE), Malaysia for providing financial support through the FRGS (FRGS/1/2016/TK04/UTEM/01/1) research grant scheme. We extend our gratitude to the hospitals – Al-Mustafa Chest Clinic at Wazirabad, Pakistan and District Headquarters Teaching Hospital at Gujranwala, Pakistan. Authors would like to covey special thanks to the physicians – Dr Sebastian Sundaraj, Dr Muhammad Ghulam Abbas, Dr Asma Riaz and Dr Rabia Fatima for providing opinions in this study.

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