A SURVEY ON AUDIO BIOLOGICAL SIGNAL PROCESSING

[1]Ayappan G, [2]Anila S
[1} Assistant Professor G, [2] Associate Professor
[1][2]Department of Electronics and Communication Engineering
[1][2]Sri Ramakrishna Institute of Technology , Coimbatore

Abstract: Biomedical signals plays a pivotal role in the detection of future disease and technology scaling has resulted in the development of novel applications in the medical fields. In the past decade, rapid advancements in the development of low power design methodologies have resulted in feasible designs for various wearable and implantable medical systems. These systems monitor various internal as well as external parameters related to the human health, such as temperature, heart rate and so on. Apart from these parameters, it is well known that acoustic symptoms such as cough, sneeze, belching and so on, are early markers of serious health issues such as influenza, diarrhea, and whooping cough, especially among children. A different algorithm is used to detect symptomatic patterns in human acoustic nonspeech signals. These include audio recordings of cough, sneeze, belch, wheeze and vomit patterns. These five human nonspeech audio tracks are selected, because they are the most commonly observed signals. In this paper different algorithms and acoustic nonspeech signals are explained.

***Index Terms:* Acoustic nonspeech signals, short-time fourier transform, wavelet, resolution, signal processing, discrete wavelet**

I INTRODUCTION

The design and development of wearable biosensor systems for health monitoring has garnered lots of attention in the scientific community and the industry during the last years[2]. Mainly motivated by increasing healthcare costs and propelled by recent technological advances in miniature biosensing devices, smart textiles, microelectronics, and wireless communications, the continuous advance of wearable sensor-based systems will potentially transform the future of healthcare by enabling proactive personal health management and ubiquitous monitoring of a patient's health condition. These systems monitor various internal as well as external parameters related to the human health, such as temperature, heart rate, and so on. Apart from these parameters, it is well known that acoustic symptoms, such as cough, sneeze, belching, and so on, are early markers of serious health issues, such as influenza, diarrhea, and whooping cough, especially among children [3], [4]. If repetitive occurrence of these symptoms is detected in advance, it is possible for the patient or the healthcare personnel to commence remedial action prior to aggravation of the problem. Various algorithms have been proposed to classify the nonspeech signals. Here the various nonspeech signals, properties and the related algorithm have been discussed.

II TYPE OF DISEASES AND SIGNALS

2.1 Asthma

Asthma is a common long term inflammatory disease of the airways of the lungs. It is characterized by variable and recurring symptoms, reversible airflow obstruction and bronchospasm. Symptoms include episodes of wheezing, coughing, chest tightness, and shortness of breath. These episodes may occur a few times a day or a few times per week. Depending on the person, they may become worse at night or with exercise.

Symptoms:

Asthma is characterized by recurrent episodes of wheezing, shortness of breath, chest tightness, and coughing. Fig.1 shows the asthma signal.

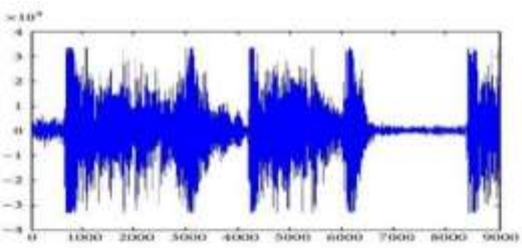

Fig.1 asthma signal

2.2 Wheezing

A wheeze is a continuous, coarse, whistling sound produced in the respiratory airways during breathing for wheezes to occur, some part of the respiratory tree must be narrowed or obstructed, or airflow velocity within the respiratory tree must be heightened. Wheezing is commonly experienced by persons with a lung disease; the most common cause of recurrent wheezing is asthma attacks, though it can also be a symptom of lung cancer, congestive heart failure, and certain types of heart diseases. Fig.2 shows the wheezing signal.

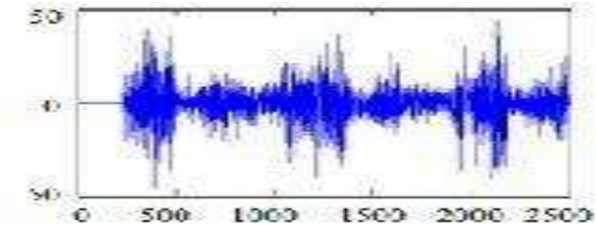

Fig.2 wheezing signal

2.3 Cold cough

The common cold and the flu may seem very similar at first. They are indeed both respiratory illnesses and can cause similar symptoms. However, different viruses cause these two conditions, and the symptoms will gradually help to differentiate between the two. Fig.1 shows the cold cough signal.

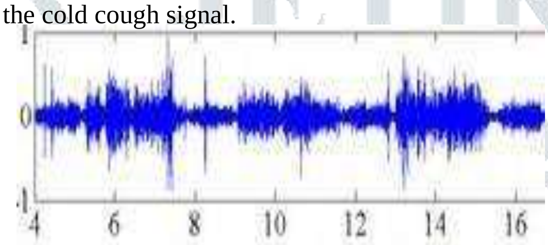

Fig.3 Cold cough signal

2.4 Obstructive Sleep Apnea(OSA)

Obstructive sleep apnea is the most common type of sleep apnea. It occurs when the soft tissue in the back of the throat relaxes during sleep and blocks the airway, often causing to snore loudly. Snoring may be a sign of a more serious condition known as Obstructive Sleep Apnea(OSA). OSA is characterized by multiple episodes of breathing pauses greater than 10 seconds at a time, due to upper airway narrowing or collapse. This results in lower amounts of oxygen in the blood, which causes the heart to work harder. It also causes disruption of the natural sleep cycle, which makes people feel poorly rested despite adequate time in bed.

OSA symptoms:

The various symptoms of OSA are, Loud or frequent snoring, silent pauses in breathing, Choking or gasping sounds, daytime sleepiness or fatigue, unrefreshing sleep and insomnia. The representation of OSA signal is shown in Fig.4.

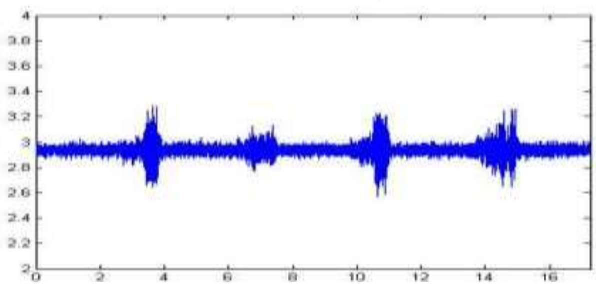

Fig.4 OSA snore signal

2.5 Sneezing

A sneeze, is an expulsion of air from the lungs through the nose and mouth, usually caused by particles irritating or itching the nasal muscles. A sneeze expels air heavily from the mouth and nose in an explosive action resulting chiefly from irritation of the nasal muscles. Sneezing is possibly linked to sudden exposure to bright light, sudden change (fall) in temperature, breeze of cold air, a particularly full stomach, or viral infection, and can lead to the spread of disease. Fig.5 shows the sneezing signal.

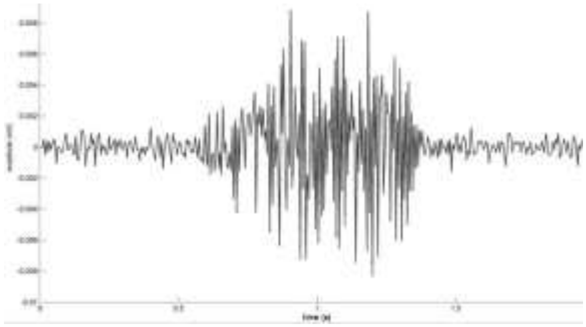

Fig.5 Sneezing signal

III ALGORITHMS

Several algorithms have been presented in order to process human acoustic signals. These algorithms are used primarily for speech recognition or for the classification of limited patterns viz., cough, sneeze, techniques, which are expensive in terms of hardware power consumption. In order to design a system for a wearable product, it is necessary to optimize power consumption with functional efficacy. Hence, optimal signal processing techniques need to be selected depending on signal analyzed, hardware cost, and computational efficiency. Several mathematical tools, such as Fast Fourier transform (FFT), Short-Time Fourier transform (STFT), wavelet transform, and so on, can be used to spectrally analyze the acoustic signals. Another technique that can be used to analyze audio signals is the S-transform [10]. This is an extension of continuous wavelet transform, where the STFT is calculated over a window of varying width[1].

3.1 Short-Time Fourier Transform

The DFT is not very well suited for the analysis of in stationary signals when applied to the entire signal. Practical signals, for instance an antenna signal, cannot be analyzed in an on-line manner by the DFT. This motivates to split a long signal into segments and compute the DFT on these segments. This transformation is known as the Short-Time Fourier transformation (STFT).

The STFT $X[\mu,n]$ of a signal $x[k]$ is defined as

$$X[\mu,n] = \sum_{k=n}^{n+N-1} x[k]w[k-n]w_N^{k\mu}$$

where $w_N = e^{-j2\pi N}$ denotes the kernel of the DFT and $w[k]$ a window function of length N which is normalized by one. Starting from $k = n$, the signal $x[k]$ is windowed by $w[k]$ to a segment of length N. This windowed segment is then transformed by a DFT of length N. The STFT has many applications in digital signal processing. For instance in the spectral analysis of signals or the processing of non-stationary signals. The resulting spectrum $X[\mu,n]$ depends on the frequency index μ and the time index n. It is therefore also termed as time-frequency domain and techniques using the STFT as time-frequency processing. This gives a better resolution of the signal.

3.2 Discrete Wavelet Transform

Discrete wavelet transform (DWT) is a common signal processing tool used for multiresolution analysis of various types of signals. DWT decomposes the input signal into narrow bands of its component frequencies. This decomposition is represented in the form of approximate and detail coefficients. While the approximate coefficients correspond to the low-frequency/coarser variations of the signal, the detail coefficients are the high frequency/finer variations. DWT uses various types of wavelet and scaling function as the basis for signal decomposition. Choosing an appropriate wavelet function is essential for an accurate resolution of the signal. Due to multiresolution property, DWT helps in preserving both spectral and temporal information in the signal unlike FFT. It also has a better resolution as compared with STFT due to dyadic scaling [6]. Traditionally, wavelet transform has been used extensively in image processing, especially for applications requiring data compression. In recent times, it has also been used in analyzing biological signals in field of bioinformatics and neuroscience [7], [9]. Apart from the above-mentioned advantages of using DWT, the hardware implementation of DWT using techniques, such as Mallat's algorithm or lifting facilitates low-power design.

IV CONCLUSION

In the field of biomedical, number of algorithms have been developed for analyzing biomedical signals, and also number of transformations have been proposed for extracting feature from the biomedical signal. The discrete wavelet transform has to distinguish and segregate the five acoustic signals efficiently. Due to this requirement and the advantages over FFT/STFT. DWT can be used for the spectral resolution of input signals. It is observed that the five types of symptomatic patterns being detected occur in frequency band specific DWT coefficients. The multiresolution property of DWT also filters out the unwanted noise from the signal of interest effectively. The Mallat's algorithm, used to implement the wavelet transform, uses lower order filters in combination with subsampling operation to resolve the signal into very narrow frequency bands. This is advantageous in implementing the hardware.

REFERENCES

[1] Himanshu S. Markandeya and Kaushik Roy, "Low-power system for detection of symptomatic patterns in audio biological signals," *IEEE Trans. Very Large Scale Integr. (VLSI) Syst.*, vol. 24, no. 8, pp. 2679-2687, Aug. 2016

[2] A. Pantelopoulos and N. G. Bourbakis, "A survey on wearable sensor-based systems for health monitoring and prognosis," *IEEE Trans. Syst., Man, Cybern. C, Appl. Rev.*, vol. 40, no. 1, pp. 1–12, Jan. 2010.

[3] A. Basak, S. Narasimhan, and S. Bhunia, "KiMS: Kids' health monitoring system at day-care centers using wearable sensors and vocabulary-based acoustic signal processing," in *Proc. 13th IEEE Int. Conf. e-Health Netw. Appl. Services (Healthcom)*, Jun. 2011, pp. 1–8.

[4] J. Hogan and M. Mintchev, "Manometry-based cough identification algorithm," *Int. J. Inf. Theories Appl.*, vol. 14, no. 2, pp. 127–132, 2007.

[5] S. Matos, S. S. Birring, I. D. Pavord, and D. H. Evans, "Detection of cough signals in continuous audio recordings using hidden Markov models," *IEEE Trans. Biomed. Eng.*, vol. 53, no. 6, pp. 1078–1083, Jun. 2006.

[6] S. Mallat, *A Wavelet Tour of Signal Processing*. San Diego, CA, USA: Academic, 1999.

[7] H. S. Markandeya, G. Karakonstantis, S. Raghunathan, P. P. Irazoqui, and K. Roy, "Low-power DWT-based quasi-averaging algorithm and architecture for epileptic seizure detection," in *Proc. 16th ACM/IEEE Int. Symp. Low Power Electron. Design (ISLPED)*, Aug. 2010, pp. 301–306.

[8] *Audio Micro Stock Audio Library*. [Online]. Available: http://www.audiomicro.com, accessed Oct. 2014.

[9] P. Lio, "Wavelets in bioinformatics and computational biology: State of art and perspectives," *Bioinformatics*, vol. 19, no. 1, pp. 2–9, 2003.