Feature Extraction for the Differentiation of Dry and Wet Cough Sounds

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Abstract— **Differentiating dry and wet cough is an important factor in respiratory disease. The main objective of this paper is to analyze cough sounds and extract features that can be used in differentiation of dry and wet cough sounds. This paper proposes two features to achieve this goal. The first feature is the number of peaks of the energy envelope of the cough signal. The second feature is the power ratio of two frequency bands of the second phase of the cough signal. A set of eight highly dry and eight highly wet cough sound recordings were used. Using these two features, a clear separation was observed among the dry and wet cough sound recordings.**

Keywords-feature extraction; cough analysis; wet cough; dry cough; biomedical signal processing; signal processing algorithms;

I. INTRODUCTION

Cough is one of the most common symptoms among all respiratory diseases. The main purpose of the cough is to clear the breathing airways from foreign objects, secretions and mucus [1]. Depending on how often it occurs and its severity, cough may persist and become chronic in nature [2].

Cough sounds can be classified by nature into two types: dry and wet [3]. The nature of the cough is important in pathological studies and for diagnostic purposes. Differentiation of dry and wet cough sounds however, is very subjective. Sometimes it is difficult for patients to describe their cough sounds to healthcare professionals and this could make the diagnosis of disease and optimal prescription more difficult. Work on automated cough monitoring systems has therefore increased in recent years especially in the context of smart home monitoring [4] - [8] .

In previous studies, automated cough detection systems for the monitoring of cough frequency were designed using different digital signal processing (DSP) algorithms. These DSP algorithms were used to extract features such as Linear Predictive Coding (LPC) coefficients, Mel Frequency Cepstral Coefficients (MFCC) and spectral characteristics of sound events to detect cough from non-cough events [4] [7] [9]. Another study used Power Spectrum Density (PSD) frequency band ratio to detect cough sounds with phlegm [10]. To differentiate between different types of cough sounds, additional studies such as Murata et al. examined the waveforms and spectrograms of dry and wet cough sounds to extract features associated with mucus in the airways [3]. In addition, Hashimoto et al. investigated the influence of the rheological properties of airway mucus on cough sound generation [11]. In a recent study, various features from both cough airflow and acoustic characteristics were extracted, in order to distinguish normal subjects and subjects with lung disease [12].

This paper analyzes cough sounds in both the time and frequency domains in order to extract features to differentiate the dry and wet cough sounds.

II. COUGH SOUND CHARACTERISTICS

A typical cough sound signal, depicted in Figure 1a, consists of three phases. Phase 1: initial opening burst, Phase 2: noisy airflow and Phase 3: glottal closure [13]. There are some cases in which Phase 3 is not visible in the cough signal [15][16]. Figure 1b shows a sound spectrogram of a cough signal. The vertical axis shows the frequency distribution and the horizontal axis shows time. Each color shows the power of each frequency at a specific time, where red represents more power and blue represents less power.

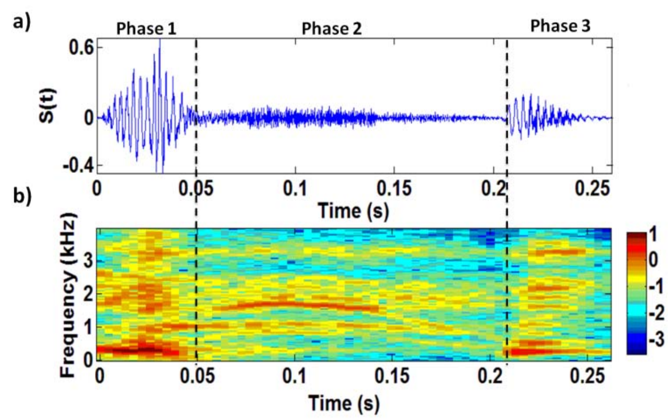

Figure 1. a) Dry cough signal with 3 phases: Phase 1, Phase 2, and Phase 3, b) Spectrogram of dry cough signal.

A. Dry Cough Characteristics

A dry cough, as the name indicates, is dry and without any mucus or sputum [3]. Normally all three phases are visible in a dry cough signal as shown in Figure 1a. After initial burst

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(Phase 1), less energy is observed in Phase 2 at higher frequencies, as shown in Figure 1b.

B. *Wet Cough Characteristics*

Typically wet cough is produced by foreign bodies (e.g. bacteria, virus) causing inflammation and secretion in the lower airways: bronchi (bronchitis), bronchiole (asthma), alveolae (pneumonia). Occasionally it can be triggered by upper respiratory tract inflammation, e.g. nasal infection with post-nasal drip; therefore, a wet cough produces mucus and sputum [3]. Figure 2a shows a typical wet cough sound signal and Figure 2b shows the corresponding spectrogram. Unlike dry cough sounds, more energy is observed in Phase 2 at higher frequencies for wet cough sounds.

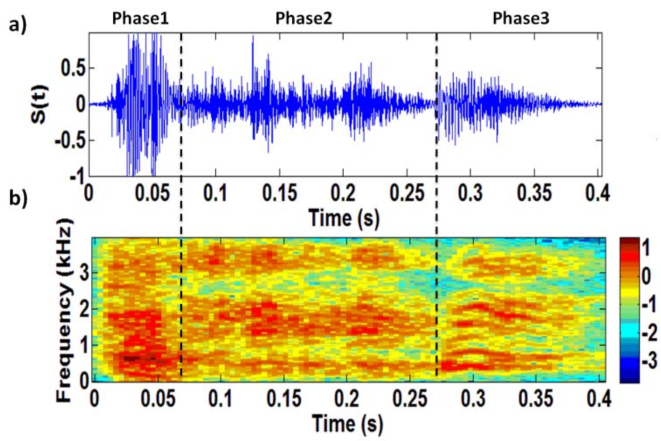

Figure 2. a) Wet cough signal with 3 phases: Phase 1, Phase 2, and Phase 3, b) Spectrogram of wet cough signal.

C. *Data Acquisition and Pre-processing*

1) *Data Acquisition*

A cough sound database was created from cough sound recordings obtained from the following three sources: sound-effect.com, the freesound project website (www.freesound.org), and the online cough recordings provided by Smith et al. [14]. Eight highly dry and eight highly wet cough sounds were selected and verified by medical professionals for the purpose of this research. All of the cough recordings were recorded in the daytime and this is an important factor in analyzing cough signals [17].

2) *Pre-processing*

Each cough recording was resampled to 8 kHz, since the frequency content is known to be contained under 4 kHz [7]. An anti-aliasing filter along with a resampling procedure was performed in Matlab.

III. ENERGY ENVELOPE PEAK DETECTION

In this section, the algorithm for extracting a time domain feature, which is the number of peaks in the energy envelope of the cough signal, will be explained and referred to as Feature 1. In order to extract this feature, the algorithm depicted in Figure 3 was used.

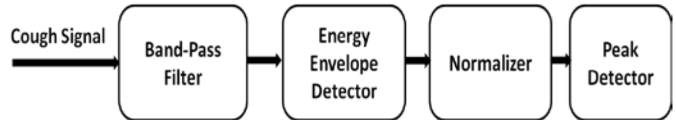

Figure 3. Spectral energy feature extraction algorithm.

A. *Band-Pass Filter*

Resampled cough signals were passed through a band-pass filter with cut-off frequencies at 50 Hz intervals, in order to determine the most significant frequency bands. The band-pass filtered of a dry and a wet cough recording at 200-250 Hz, are shown in Figure 4 and Figure 7 respectively.

B. *Energy Envelope Detector*

The energy envelope was determined by squaring the input signal to obtain $S^2(t)$, depicted in Figure 5 and Figure 8. Afterwards, $S^2(t)$ was passed through a second order butterworth low-pass filter with a cut-off frequency of 10 Hz to determine its energy envelope $E(t)$. The cut-off frequency of the low-pass filter was chosen experimentally.

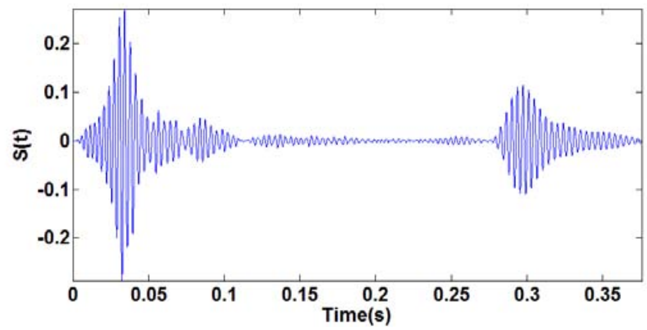

Figure 4. Band-pass filtered dry cough recording at 200-250 Hz.

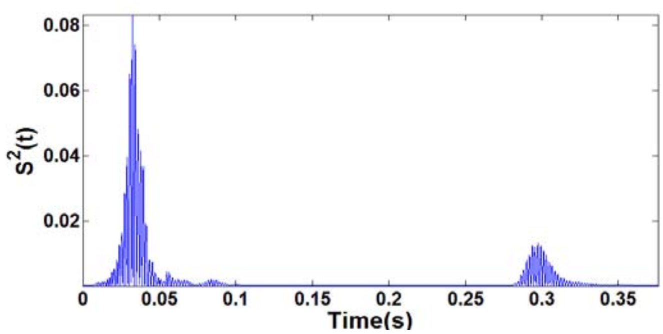

Figure 5. Signal squared of band-pass filtered dry cough recording.

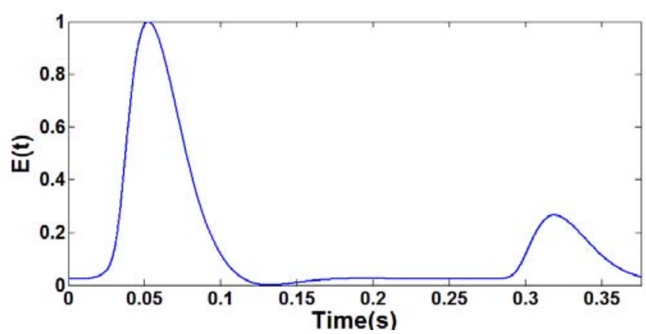

Figure 6. Energy envelope of band-pass filtered dry cough recording.

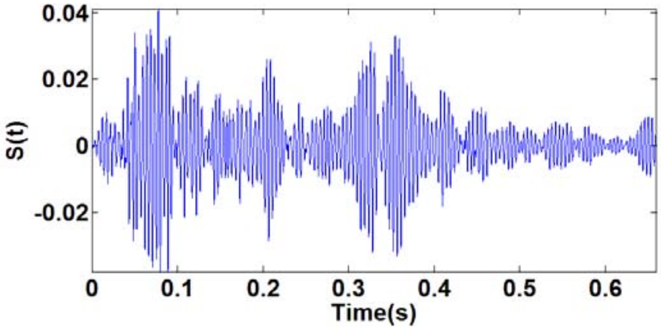

Figure 7. Band-pass filtered wet cough recording at 200-250 Hz.

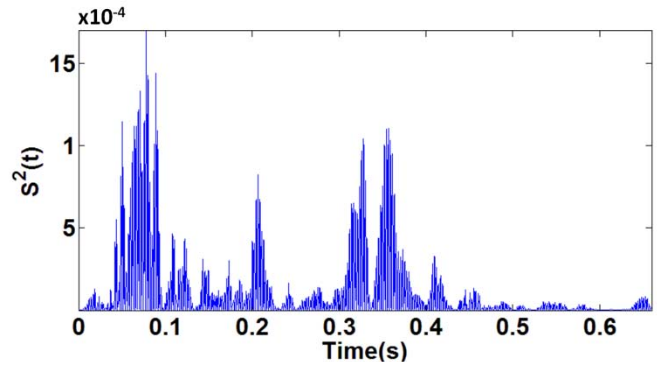

Figure 8. Signal squared of band-pass filtered wet cough recording.

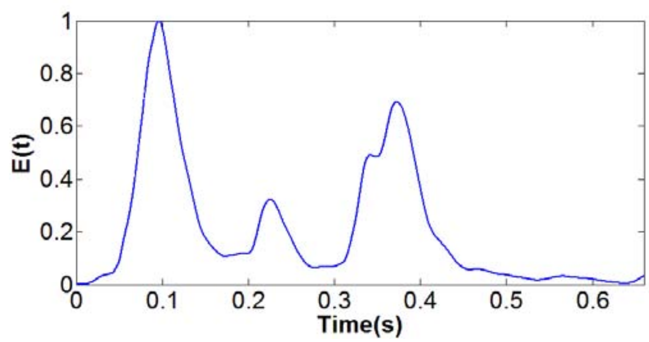

Figure 9. Energy envelope of band-pass filtered dry cough recording.

C. Normalization

The energy envelope, *E(t),* was normalized between 0 and 1 to compensate for the recording amplitude differences between the cough recordings. Figure 6 and Figure 9 show the normalized *E(t)* of a dry and wet cough recordings respectively.

D. Peak Detector

By comparing the shape of the energy envelope of both dry and wet cough signals, it was concluded that there is a significant difference between the two types of cough signals. In order to use this difference as a descriptive feature, a peak detection algorithm was used. The peak detection algorithm locates the local maxima of the signal and based on a threshold, considers them a significant peak. Figure 10 and Figure 11 show peaks of the energy envelope of two dry and two wet cough recordings respectively.

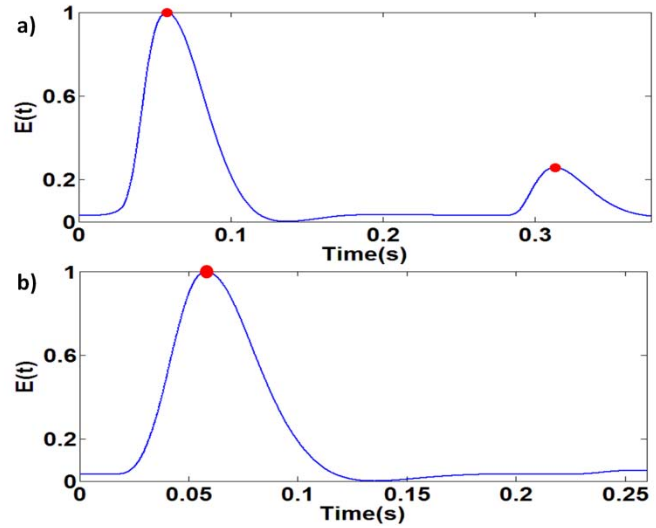

Figure 10. a) Normalized energy envelope and peaks of dry cough recording 1, b) Normalized energy envelope and peaks of dry cough recording 2.

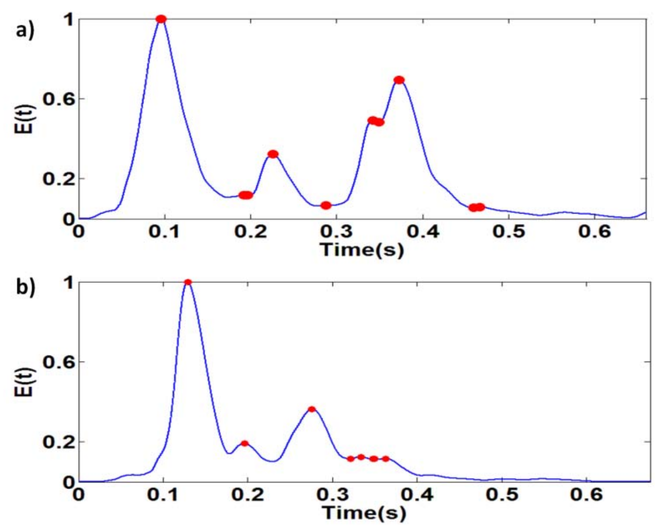

Figure 11. a) Normalized energy envelope and peaks of wet cough recording 1, b) Normalized energy envelope and peaks of wet cough recording 2.

E. Characteristic Differences

It was observed that the energy envelope of the dry cough signal followed a specific shape. It started with a peak, which represented the first phase of the dry cough signal. It followed by a flat region representing the second phase and finished with a small peak, if a third phase existed for that particular signal, as depicted in Figure 12a. The energy envelope of the wet cough signal, on the other hand, did not follow a specific shape. The shape was more random and multiple peaks were observed especially in the second phase, as depicted in Figure 12b.

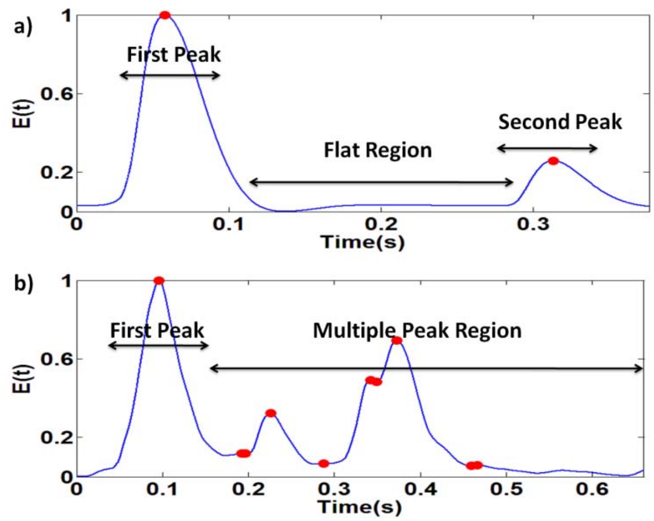

Figure 12. a) Energy envelope of a dry cough, b) Energy envelope of a wet cough.

The number of peaks for different frequency bands for both dry and wet cough signals were recorded and compared. The number of peaks for dry cough signals was observed to be between 1 and 3. On the other hand, the number of peaks for wet cough signals was observed to be more than 3 for most of the frequency bands. The frequency band 200-250 Hz was selected as the most descriptive, since the most separation between dry and wet cough signals were observed.

IV. Power Ratio Estimation

This section introduces an algorithm which extracts the power ratio of two frequency bands of the second phase of the cough signal. This will be referred to as Feature 2. The algorithm is depicted in Figure 13.

A. *Cough Phase Detection*

In this section, each cough recording was divided into 3 phases, by using the start and end point of each phase. The beginning of the cough sound was used as the start point of Phase 1. The start of the second phase was chosen when the sound amplitude had reduced significantly from its initial peak [13]. The start of Phase 3 was selected when there was a rise in the sound amplitude after the second phase.

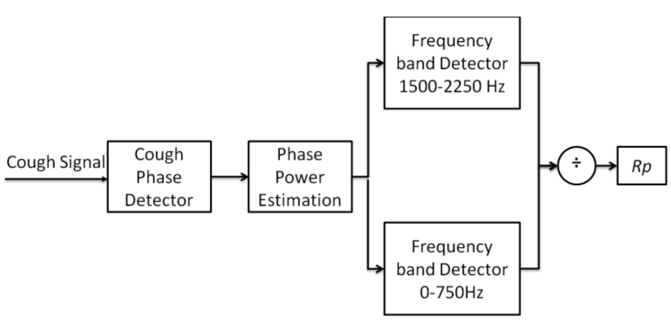

Figure 13. Power feature extraction algorithm.

B. *Phase Power Estimation*

The power of each phase was calculated in this step. P1, P2 and P3 are the power of Phase 1, Phase 2 and Phase 3 respectively. As mentioned previously, the recording method of each cough recording was different and since the power of a signal is dependant on the distance of the source to the microphone, P2 was normalized by dividing it by the total power of Phase 1, P1, as shown in (1).

$$P2_{norm}(f) = \frac{P2(f)}{\sum_{f=0}^{f=4k} P1(f)} \qquad (1)$$

where, $P1(f)$ and $P2(f)$ is the power of the Phase 1 and Phase 2 at frequency f respectively. $P2_{norm}(f)$ is the normalized power of Phase 2.

For dry cough recordings, a large peak was observed around 1500-2250 Hz, as depicted in Figure 14a. On the other hand, for wet cough signals, the peak was observed around 0-750 Hz, as depicted in Figure 14b.

C. *Power Ratio Estimation*

In this section, the power ratio, Rp was calculated as in (2)

$$Rp = \frac{\sum_{f=1500}^{f=2250} P2_{norm}(f)}{\sum_{f=0}^{f=750} P2_{norm}(f)} \qquad (2)$$

where, $P2_{norm}(f)$ is the normalized power of Phase 2.

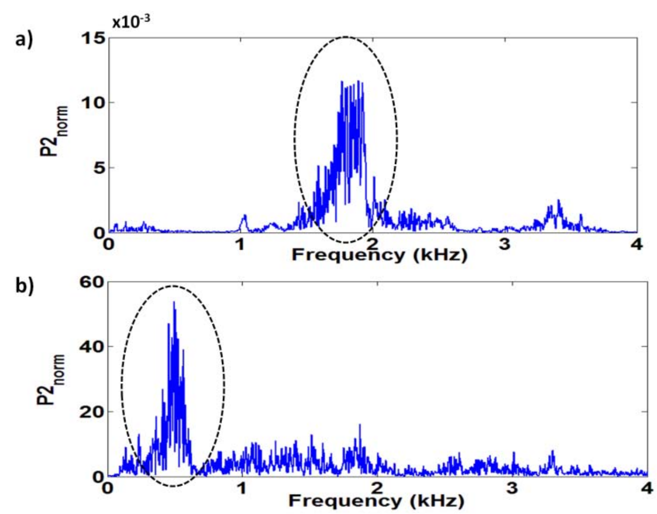

Figure 14. a) $P2_{norm}$ of a dry cough signal, b) $P2_{norm}$ of a wet cough signal.

The second feature extraction algorithm was run for the same dry and wet cough signals as the previous section. The Rp was calculated for both dry and wet cough signals. Figure 15 shows a plot of Feature 1 vs. Feature 2. As it can be seen from the plot, using these two features, a clear separation was observed between the two types of cough.

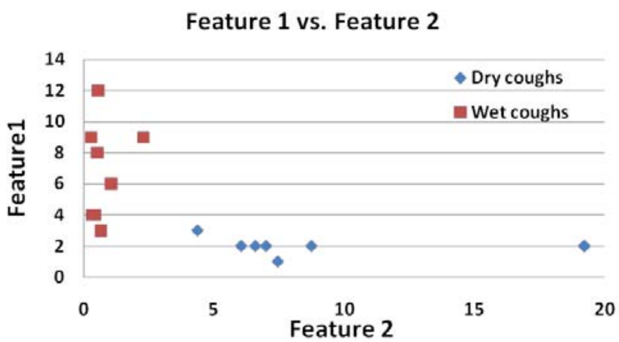

Figure 15. Separation of eight highly dry and eight highly wet cough sounds using Feature 1 and Feature 2.

V. Conclusions and Future Work

In this paper, two features, one in the time domain and one in the frequency domain, were extracted from both dry and wet cough sounds. Using these two features, a significant differentiation between highly dry and highly wet cough sounds was observed, as depicted in Figure 15. However, there is a wide spectrum between the two extremes and there are many coughs that could fall in between. Therefore, there will not be a definite line of separation between the two types of cough. The algorithms were run for more cough sounds and although there was still a visible separation, it was not as clear as Figure 15. Future work will focus on rating the cough sounds that fall between the ranges of wet and dry and also work toward detecting changes in cough sound from chronic cough to infected cough.

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