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High Frequency Analysis of Cough Sounds in Pediatric Patients with Respiratory Diseases

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***Abstract*— Cough is a common symptom in a range of respiratory diseases and is considered a natural defense mechanism of the body. Despite its critical importance in the diagnosis of illness, there are no golden methods to objectively assess cough. In a typical consultation session, a physician may briefly listen to the cough sounds using a stethoscope placed against the chest. The physician may also listen to spontaneous cough sounds via naked ears, as they naturally propagate through air. Cough sounds carry vital information on the state of the respiratory system but the field of cough analysis in clinical medicine is in its infancy. All existing cough analysis approaches are severely handicapped by the limitations of the human hearing range and simplified analysis techniques. In this paper, we address these problems, and explore the use of frequencies covering a range well beyond the human perception (up to 90 kHz) and use wavelet analysis to extract diagnostically important information from coughs. Our data set comes from a pediatric respiratory ward in Indonesia, from subjects diagnosed with asthma, pneumonia and rhinopharyngitis . We analyzed over 90 cough samples from 4 patients and explored if high frequencies carried useful information in separating these disease groups. Multiple regression analysis resulted in coefficients of determination (R^2) of 77-82% at high frequencies (15 kHz-90 kHz) indicating that they carry useful information. When the high frequencies were combined with frequencies below 15kHz, the R^2 performance increased to 85-90%.**

I. Introduction

Involuntary cough is a natural reflex and a defense mechanism for ejecting foreign material out of the respiratory system [1]. Cough is the most common reason in new medical consultations [2]. It is a common symptom in a range of respiratory illnesses such as pneumonia, bronchiolitis, bronchitis and asthma. Despite its critical importance in the diagnosis of illness, there are no golden methods to objectively assess cough. Objective parameters that can characterize cough remain elusive [3] and physicians rely on the subjective assessment of cough in clinical practice.

Cough sound is characteristic and easily identifiable with human hearing. Analyzing it, even subjectively, though, is a different matter altogether. In a study by *Smith et al.* [4], a group of 22 doctors and 31 staffs were asked to diagnose 9 patients based on cough sound alone. Gender and mucus were correctly identified 93% and 76% of the time, but wheezing and clinical diagnosis were poor at 39% and 34%, respectively. The bandwidth of the sounds was below 8 kHz and thus well within human hearing range (20Hz-20 kHz).

Other studies similarly adopted sampling frequencies that produced sounds within the human hearing range. These include diagnosing mucus [5,6] at 8 kHz and 44 kHz sampling frequencies, classifying healthy, asthma, and COPD patients at 11 kHz sampling frequency [7], and using combined cough sounds (digitally filtered to 50 Hz - 25 kHz frequency range) and airflow characteristics to classify normal subjects and patients with lung disorders [8]. None of the studies so far explored frequencies truly beyond human hearing, even though as early as 1998, Murata *et al.* [6] had noted that the frequencies of cough were widely spread up to 20kHz, the limit of their equipment at the time.

Some of the major problems in objective cough analysis are: (1) listening to cough sounds, as practiced over the unknown millennia, is severely handicapped by the limitations of the human hearing range. Sounds coming through a stethoscope are further degraded due to the substantial low-pass filtering effects of the lung and chest wall musculatures. The small bandwidth (up to 4kHz) of the stethoscope further aggravates this problem; (2) cough sounds are rich in structure, and the subjective listening is not an efficient mechanism to consistently draw important diagnostic features. Mathematical analysis of cough is in its infancy, and it too is limited to the low frequencies.

Apart from the sampling frequency, feature extraction is another significant challenge in cough characterization. Descriptions by health professionals are unreliable [4], but digital features have shown some early promise [5-9]. Cough is a non-stationary signal. Hence, a method that captures both the time and frequency changes simultaneously will be ideally suited for cough analysis. Short time Fourier transform (STFT) and wavelet have been used for the purpose, but STFT applies a fixed window size in the analysis, which is more suitable for signals with a single centre frequency.

Wavelets utilize different window sizes to represent different frequencies, resulting in a better representation of various features in cough sounds. Knocikova *et al.* [7] demonstrated this in their classification of three groups (healthy, asthma, COPD) of adult voluntary cough sounds using continuous (CWT) and discrete (DWT) wavelet transform for cough feature extraction.

The aim of this study is to determine whether frequencies beyond human hearing capability contain useful cough sound information, which is unprecedented. Involuntary pediatric

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cough sounds with underlying respiratory diseases were chosen, as this study is inspired by the severity of global child mortality due to acute respiratory infections (ARI) alone [10].

II. Methods

A. Subjects

In this study, 96 cough events from 4 subjects identified with frequent cough and underlying respiratory diseases were recorded from patients in Sardjito Hospital, Yogyakarta, Indonesia. Parental consents were sought prior to recording and participation is voluntary. Table 1 details the clinical parameters of the patients. Each subject is unique in terms of combination of age, gender, and clinical diagnosis.

TABLE 1
DEMOGRAPHIC AND CLINICAL FEATURES OF SUBJECTS

	P 1	P 2	P 3	P 4
Age	7m	9m	11y1m	14y4m
Gender	M	F	F	F
Weight	7.2	7.5	42	46
Height	71	80	150	160
Breath rate	58	40	48	32
Heart rate	180	140	151	150
Diagnosis	Asthma	Rhinopharyngitis	Pneumonia	Asthma

B. Signal Acquisition

The signal acquisition is performed by a research assistant (RA) who is a nurse specifically recruited for this work. The RA was trained on how to operate the recording system. The system has two microphones: a free-field prepolarised condenser microphone (Model 40BE, GRAS, Holte, Denmark) aimed at the patient and a second condenser microphone (Model NT3, RODE, Sydney, Australia) directed away from patient. The second microphone allows distinction of coughs originating from the subjects from others in the room, such as relatives or other patients. The GRAS microphone has a ±3dB cut-off at 100 kHz. Only recordings from GRAS are used for the analysis.

Both microphones connect to an audio interface (Model Tracker Pre USB2.0, E-MU, California, US) that converts the analog signal to digital. Recordings were made using Adobe Audition software, running on a Windows XP laptop connected to the audio interface, with sampling frequency set to 192 kHz, stereo, 16-bit, and saved in WAV format. The gain for the recording system was carefully selected such that the cough sounds were recorded in the best intensity yet without clipping. Inevitably, there were samples which are clipped due to the spontaneous nature of cough and had to be discarded.

C. Cough Analysis

Figure 1 shows the processes undertaken in this study. To analyze the cough, samples were studied in several domains. Figures were created in each domain, with intensity in time, FFT in frequency, STFT in time-frequency, and wavelet in time-scale. STFT analysis was performed using a 250 sample Hamming window. Wavelet representations were created using several wavelets commonly used, namely Haar, Daubechies, and Morlet. The Daubechies wavelet family (of which Haar is a part) was used successfully in a study on classification based on cough sounds by Knocikova *et al.* [7], whereas Morlet wavelet has been used extensively for feature extraction in signal processing field.

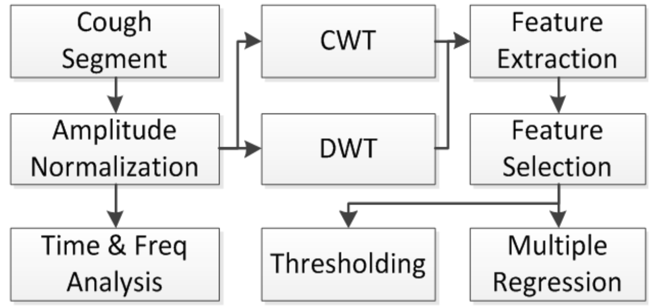

Fig 1. Processes involved in the study. Cough segments were manually extracted, normalized and transformed. Time and frequency analysis were compared with wavelets. Coefficients from CWT and DWT were used as features and a selection process is carried out using thresholds and multiple regressions.

The CWT of a cough function $c(t)$ is defined as the integral transform of $c(t)$ with window functions $\Psi_{a,b}(t)$:

$$W_{cough}(a,b) = \int_{-\infty}^{+\infty} c(t)\Psi_{a,b}^{*}(t)dt \tag{1}$$

The superscript * in equation (1) refers to the complex conjugate. The scale factor a represents the scaling of the function $\Psi(t)$ and the shift factor b represents the temporal translation of the function. In CWT, a and b are assumed to be continuous in value, but in DWT these are discretized. Done carefully, the process should only remove redundant signal representation without jeopardizing reconstruction. The resulting $W_{cough}(a,b)$ is a set of wavelet coefficients representing $c(t)$ in wavelet domain for a particular scale. A total of 64 scales were used for CWT and 5 for DWT. Each scale increments essentially halve the frequency bandwidth and transform only the lower band to wavelet coefficients. In this way, early scales produce wavelet coefficients containing high frequency signals whilst later scales represent only low frequency signals. The strength of wavelet transform lies in the use of different windows (scaling function) for each scale, thereby resulting in better representation of non-stationary signals such as cough.

D. Feature Extraction and Selection

Cough varies considerably intra and inter-personally. This is one of the major challenges in cough analysis. For this reason, features closely tied to cough intensity are likely to be affected. Instead, features that represent the distribution of cough signal within the time-frequency or time-scale domain should possess higher significance. Knocikova *et al.* [7] demonstrated this aspect in their voluntary cough classification study adult of patients with different respiratory conditions.

As many features as possible were gathered out of the available samples, followed by a feature selection process using simple classifiers such as thresholding on a single feature and multiple regression which uses combinations of features instead. The aim is to classify cough irrespective of the source. As the subject number is limited, we believe it is unnecessary at this stage to employ sophisticated techniques.

III. Results and Discussions

In our observation of coughs in various domains, we found that cough signal truly varies significantly in the time and frequency domain. No useful patterns were found in comparing all the cough samples. An example of information derived from each sample can be seen in Figure 2. Some pattern can be seen from STFT, though the nature of the fixed window distorts the true shape of cough signal. For this reason, no features were derived from these domains.

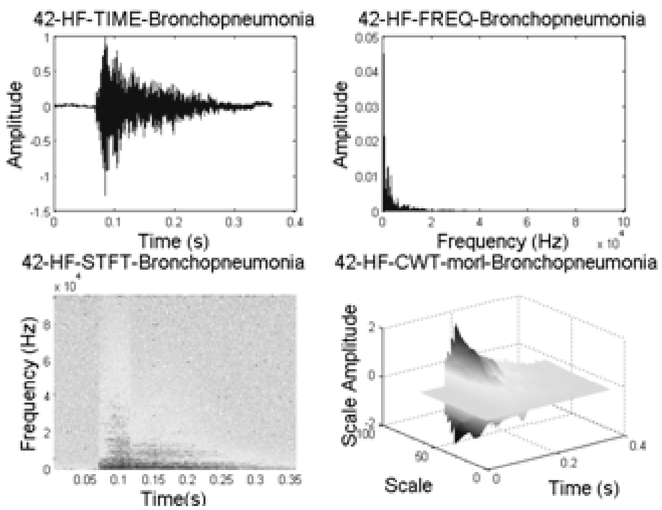

Fig 2. Cough signal (from top left clockwise): Time domain, Frequency domain, Time-Frequency domain and Wavelet domain. More details can be extracted from wavelet representation of the signal compared to all others.

In the time-scale or wavelet domain: Haar, Daubechies4, Daubechies8, and Morlet wavelets were utilized to create a set of wavelet coefficients representative of each sample. All four were compared in continuous and discrete form in all 96 cough samples with identifying features noted. Morlet was chosen for continuous wavelet transform (CWT) and Daubechies4 for discrete wavelet transform (DWT).

In total, there were 87 features derived from the wavelet coefficients: 67 features in CWT, and 20 features from DWT. Up to 64 scales were used for the former and 5 scales for the later. The first three features (Peak Coefficient, Peak Time, Peak Scale) correspond to the peak in the CWT coefficients: the magnitude, time when it happens, and the scale where it is located on, respectively. Vertical integration was carried out for each time sample of the CWT coefficients, and the maximum value out of all samples and the time where it happens are called Power (Time Domain) and PTD Position. Similarly, horizontal integration was used to calculate the Power (Freq Domain) and Maximum Scale, showing the most significant scale for each cough sample. In order to capture the cough shape, 64 features were calculated as ratio of energy contained in each scale and total energy from all scales. The energy is the sum of absolute values of coefficients in each scale, and the ratio for each scale is denoted as PFB1 up to PFB64.

From the DWT coefficients, again the cough shape is captured through calculating the ratio of the coefficients. There were 5 levels of detailed and approximate coefficients of each cough events, totaling to 10 sets. The energies were calculated as sum of squared values in each set, denoted as ED1 to ED5 for detailed coefficients and EA1 to EA5 for approximate coefficients. For the detailed coefficients, the ratio of each set (ED1 to ED5 against sum of ED1 to ED5) were calculated and defined as PED1 to PED5. In the same way, PEA1 to PEA5 were calculated for the approximate coefficients. Figures were generated to show the relationship among subjects based on single features. Figure 3 shows an example where feature 42 – PFB38 exhibits differences as well as considerable overlapping. Due to this fact,

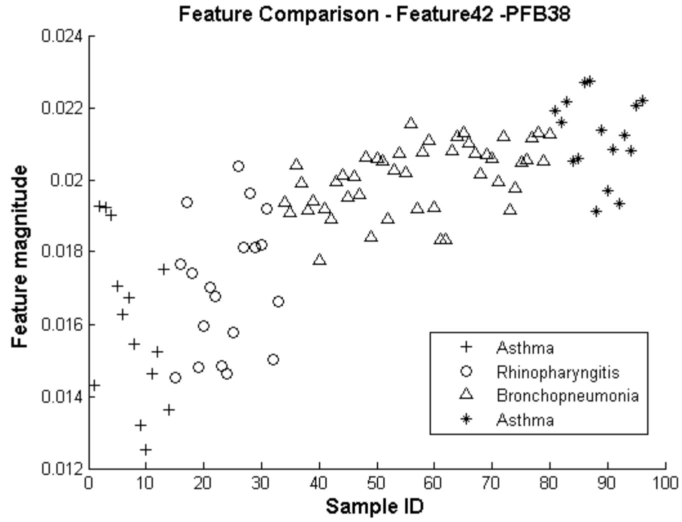

Fig 3. Feature comparison amongst four subjects. Clear separation between the first and last two patients can be seen here. Overlapping is evident in all patients. Cough sounds from the two asthma patient is totally opposite based on this feature alone.

thresholding method did not work effectively in classifying the groups. To link amongst features, linear and logarithmic multiple regressions were used. For each version, an iteration process was used to calculate the coefficient of each features and the least significant feature is dropped. This continues until only significant features ($p < 0.05$) were left in the final equation representing the actual values. Out of a matrix of 96 cough samples x 87 features, the multiple regression method seeks the best combination of features to draw a linear and a logarithmic line that would separate asthma, rhinopharyngitis and bronchopneumonia in a multidimensional space.

In the first selection, only features corresponding to frequencies lower than 15 kHz were included in the analysis. This value was used instead of 20 kHz as a more realistic representation of human hearing [11], [12].This was followed with analysis using only features corresponding to frequencies above 15 kHz, and then again with combined features from both groups. Due to the nature of scales in wavelet domain, there is no direct correlation with frequency, so the pseudo-frequencies were calculated as closest approximations for each scale instead.

TABLE 2
MULTIPLE REGRESSION – LOW FREQUENCY (f<15 kHz)

Feature	Linear	f (kHz)	Feature	Log	f (kHz)
Constant	13.02	n/a	Constant	-41.14	n/a
PFB11	-367.71	14	PFB11	-4.32	14
PFB25	-157.19	6.2	PFB27	-1.96	5.8
PFB51	-283.48	3	PFB50	-5.41	3.1
EA4	0.0006	7.8	EA5	-0.61	6.3
EA5	-0.0008	6.3	ED3	0.16	10.5
PED4	3.09	7.8	PED3	0.94	10.5
			PED4	-0.30	7.8
R^2	0.7694		R^2	0.8405	

The results in Table 2 shows that, with only low frequency (LF) features, the equation given achieved R^2 value of 76.94% and 84.05%, for linear and logarithmic, respectively. The R^2 value is a common measure of accuracy in statistics to show how close the representation against actual values is.

TABLE 3
MULTIPLE REGRESSION – HIGH FREQUENCY (*f* >15 kHz)

Feature	Linear	*f* (kHz)	Feature	Log	*f* (kHz)
Constant	1.08	n/a	Constant	3.59	n/a
PFB5	262.08	31.2	PFB5	-4.15	31.2
PFB7	551.15	22.2	PFB6	5.31	26
PFB9	-2028.46	17.3	PFB7	6.66	22.2
PFB10	1503.89	15.6	PFB8	-15.15	19.5
PED1	-17.65	31.5	PFB9	6.69	17.3
			EA1	-0.61	31.5
			ED2	0.25	15.7
R^2	0.7733		R^2	0.8232	

Table 3 shows the results of multiple regression analysis of the features using only high frequency (HF) features, with R^2 value of 77.33% and 82.32% for linear and logarithmic equations. It is very close to the performance of the LF features, and shows that there is information in both sides which can be used to classify between the disease groups.

Ultimately, one would expect the result to improve when features from both sides were taken into account. The third analysis undertaken utilizes features from LF and HF sides, but also features that do not only belong to each group (Peak Coefficient, Peak Time, Peak Scale, Power (Time Domain), PTD Position, Power (Freq Domain) and Maximum Scale).

TABLE 4
MULTIPLE REGRESSION RESULT - COMBINED

Feature	Linear	*f*	Feature	Logarithmic	*f*
Constant	-0.69	n/a	Constant	-27.38	n/a
Max Scale	0.03	n/a	PFB6	4.23	HF
PFB5	115.56	HF	PFB8	-4.05	HF
PFB7	1507.92	HF	PED2	-0.26	HF
PFB8	-2184.2	HF	PFB13	-2.11	LF
PFB10	808.36	HF	PFB27	-1.77	LF
PED1	-14.49	HF	PFB50	-4.58	LF
			EA5	-0.54	LF
			ED5	0.34	LF
			PED3	0.85	LF
			PED4	-0.19	LF
R^2	0.8513		R^2	0.9084	

The results in Table 4 reflected improved performances both in linear and logarithmic analysis, with R^2 value of 85.13% (linear) and 90.84% (logarithmic). Only HF features were deemed significant in the linear analysis, which further supports our hypothesis. LF features are still useful, however, on the logarithmic line. The contrast between features selected shows the difference in drawing a linear line in a multidimensional space versus a logarithmic line. The former is more restrictive, therefore has less optimized but more conservative classification result than the latter. The most important thing is that HF features proved significant in both methods, with LF features supplementing the classification results.

IV. CONCLUSION

We have shown that there is useful cough sound information in much higher frequency range than is traditionally used in cough sound analysis. Based on available data, we believe there is unique information in frequencies higher than is traditionally used in clinical settings, especially in frequencies beyond 15 kHz.

When it comes to diagnosis of the disease groups considered, however, the results of this study should be interpreted with due care as the number of subjects was limited four.

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