A Novel Method for Wet/Dry Cough Classification in Pediatric Population

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***Abstract*— Cough is one of the early symptoms of the respiratory tract infections. Cough can be classified into wet and dry classes based on the mucus. In pediatric population, knowing the type of cough is useful for diagnosis as well as treatment. Currently, the classification of coughs is carried manually during the physical examination. Manual classification is tedious and subjective. The results depend heavily on the experiences and the skills of the physicians. In this paper, we propose a novel feature set called intra-cough shimmer jump (ICSJ) and intra-cough Teager energy operator jump (ICTeJ) to discriminate dry/wet coughs. The proposed method achieved 76% of accuracy, 77% of sensitivity and 75% of sensitivity. The Kappa agreement was 0.52, indicated a moderate agreement with the classification from the pediatricians. Our method can be developed into a non-invasive tool for assessing cough in the resource limited-settings.**

Keywords—respiratory diseases, cough, wavelet, shimmer, Teager energy

I. Introduction

Respiratory diseases are characterized by the present of coughs as one of their symptoms. Cough is the natural mechanism to protect the respiratory system. It forces the mucus or the foreign materials out of the respiratory airways. Cough is one of the common motivations to visit clinicians for medical consultation. According to [1, 2], the prevalence of cough in both adults and children is around 5% - 10%.

In a typical consultation session, clinician may listen to several episodes of natural or voluntary coughs and then classify them into wet and dry (non-wet) categories. The wet coughs are associated with the existence of mucus in the airways. Such information is extremely important in the diagnosis as well as the treatment. In children, chronic wet coughs (defined as coughs existing beyond 4 weeks) may indicate the infection of serious respiratory diseases such as pneumonia [3], requiring a quick medication. However, the manual wet/dry cough classification is very subjective, depends heavily on the skills and experiences of the physicians.

A few attempts have been proposed to develop systems for classifying wet and dry coughs. These attempts were carried out by dividing the coughs into three phases (initial opening burst, noise airflow, glottal closure) and then measuring the phase of each duration [4], finding the number of peaks of the cough signal envelopes and computing power ratio between two frequency bands [5]. However, these studies only included a few cough samples (<31) made the results difficult to be interpreted. Their defined phases are not always present in the cough signal from the pediatric population as well. The methods used the durations and the magnitudes of the coughs that vary widely in the larger samples.

In this paper, we propose a novel feature set called intra-cough shimmer jump (ICSJ) and intra-cough Teager energy operator jump (ICTeJ). These features are independent from the magnitude and the phases of the cough signal. The development of the feature set is described the following sections.

II. Methods

A. Recording protocol and data set preparation

We recorded coughs from pediatric patients admitted with respiratory complaints at Sardjito Hospital, Yogyakarta, Indonesia. We acquired data in the natural hospital environment, by simply placing our recording system by the bed. The ethical clearance for this work had been received from Sardjito Hospital.

The recording system consisted of a low-noise microphone (Model NT3, RODE®, Sidney, Australia), a pre-amplifier, and A/D converter (Model Mobile Pre-USB, M-Audio®, CA, USA). The output of the A/D converter was connected to the USB port of a laptop computer. The nominal distance could vary from 40 cm to 100 cm due to subject movement. The sampling rate was set at 44.1 k samples/s and 16-bit resolution to obtain the best sound quality.

The cough samples obtained from the recording were classified manually by two pediatricians having experience more than 15 years into wet and dry classes. The results were then constructed as dataset for developing a method for wet/dry cough classification.

Our proposed method comprises of four processes: (i) noise reduction, (ii) decomposition of cough signal into several frequency bands using wavelet, (iii) feature extraction, and (iv) classification of cough episodes into wet/dry classes using fuzzy c-mean clustering. The description of each process is described in the following sections.

B. Noise reduction

The discrete sound signal can be denoted as the summation of cough sound $s(n)$ and the background noise $b(n)$ (Eq.1). To reduce the background noise, we processed the signal into a power spectral subtraction filter (PSS). The PSS estimates the clean sound signal via the power subtraction spectral of *s(n)* with estimated *b(n)* [7]. The noise *b(n)* was estimated by tracking spectra minima in each frequency band without any distinction of voice activity and silent. Details of the method can be found in [7]. The sound signal after filtering is given in (2).

$$s[n] = s_C[n] + b[n] \tag{1}$$

$$\hat{s}[n] = s_c[n] \tag{2}$$

C. Signal decomposition

The generation of cough sound is influenced by the rheological properties of the airway mucus [8]. The mucus may contribute to the amplitude and energy perturbation in a specific frequency band. To obtain these features; we decomposed the cough signal into several frequency bands using discrete wavelet transform (DWT). In DWT, the cough signal is processed to low pass and high pass filter having impulse responses of g and h, respectively. To obtain finer resolution, the decomposition is repeated in several levels of successive low and high pass filtering.

Let i denote the level of the decomposition. The decomposed signal at level i is given by (3) and (4).

$$A_i[n] = \sum_{k=-\infty}^{\infty} \hat{s}[n] g[2n-k] \tag{3}$$

$$D_i[n] = \sum_{k=-\infty}^{\infty} \hat{s}[n] h[2n-k] \tag{4}$$

where (A_i) and (D_i) are the approximation and details of the low and high frequency components, respectively. In this work, we particularly used the details (D_i).

D. Feature computation

To compute the feature of the cough signal, we apply sliding window $w_r[n]$ with length N and β overlapping to $D_i[n]$, generating j data sub-blocks. Let $D_{ij}[n]$ denotes j^{th} sub- block of the i^{th} decomposed signal. In each sub-block of $D_{ij}[n]$, we computed the following features:

i. Temporal amplitude perturbation (shimmer)

In wet coughs, the vibration and dislocation of mucus may contribute to the changes of temporal amplitude of cough in the time domain. To capture this feature, we computed the 11 points of the temporal amplitude perturbation in sub-block $D_{ij}[n]$ as given in (5). In Eq. 5, P is the magnitude of peaks (P_m, $m = 1, 2, \ldots, M$) within the sub-block j of the signal while m is the peaks number and M is the total number of peaks.

$$Sh_{ij} = \frac{(1/(M-10)\sum_{m=6}^{M-5}\left|P_m - \left(\sum_{o=m-5}^{m+5} P_o/11\right)\right|}{1/M\sum_{m=1}^{M} P_m} \tag{5}$$

ii. Teager energy operator perturbation

The use of Teager energy operator (TEO) has found success in the speech processing [9] as well as the detection of high frequency oscillation [10]. In this work, we used Teager energy to capture the influences of mucus vibration and dislocation in a specific frequency band.

Let $x^t_{ij}[n]$, $t = 1, 2, \ldots, T$, represents the frames in the sub-blocks of decomposed cough signal with length L ($L < N$). The discrete TEO can be obtained using (6) [11]. We computed the mean of TEO (ψ_t) in each frame and the absolute TEO perturbation (E_{ij}) in each cough episode. Equations to compute ψ_t and E_{ij} are given in (7) an (8) respectively.

$$\psi[x^t_{ij}[n]] = x^t_{ij}[n]^2 - (x^t_{ij}[n-1]x^t_{ij}[n+1]) \tag{6}$$

$$\psi_t = -20\log\sum_{n=1}^{L}\psi[x^t_{ij}[n]]/L \tag{7}$$

$$E_{ij} = \frac{1/(T-1)\sum_{t=1}^{T-1}|\psi_t - \psi_{t+1}|}{1/T\sum_{t=1}^{T}\psi_t} \tag{8}$$

E. Measurement of intra-cough feature variation

To quantify the wetness of the cough episodes, we investigate the characteristic of features discontinuities between j sub-blocks. This method was inspired by the use of pitch discontinuities feature in the snore analysis [12].

Let F_p, $F_p = \{[Sh_{ij}\, E_{ij}]\}$ is a feature set of p^{th} arbitrary cough episode comprised of J data sub-blocks. We define a new quantity, called intra-cough shimmer jump (*ICSJ*) and intra-cough TEO jump (*ICTeJ*), to represent the occurrence of shimmer and TEO perturbation in a cough episode higher than a threshold q, $q = \{[q_S\, q_E]\}$. The probability of *ICSJ* and *ICTeJ* are denoted as G_{pq} ($G_{pq} = \{[G_{Sq}\, G_{Eq}]\}$ and computed using Eq. 9.

$$G_{pq}(J) = \frac{n_{pq}(J)}{J} \tag{9}$$

where n_{pq} is the number of sub-blocks within signal of total J sub-blocks having feature lower than a threshold q.

F. Fuzzy c-mean clustering

Cough sounds can be discriminated into wet or dry. However, in human perception, the coughs sounds may be categorized into finer classes such as slightly wet or very wet depend on the quantity of mucus in the airways. In this work we infer how human discriminate cough sounds into wet/dry classes by using fuzzy c-mean clustering (FCM). The fuzzy logic uses linguistic approach to define an imprecise condition [13]. In this work, we used the fuzzy logic as a classifier to estimate the wetness degree of coughs. In this process, *ICSJ* and *ICTeJ* were used as input for the FCM. The Mamdani's [14] inference system was used in this work. We varied the number of cluster in FCM to get the best wet/dry cough separation. The classification results using FCM were then compared with the manual classification from the professional pediatricians. The performance of our method was computed using parameters such as Cohen's Kappa, Positive Prediction Value (PPV), Negative Prediction Value (NPV), accuracy, sensitivity and specificity were computed.

III. Discussion and Results

A. Manual cough classification

We developed a graphical user interface (GUI) software to visualize and to play the cough sounds signals. Two professional pediatricians used the GUI to manually classify our cough data

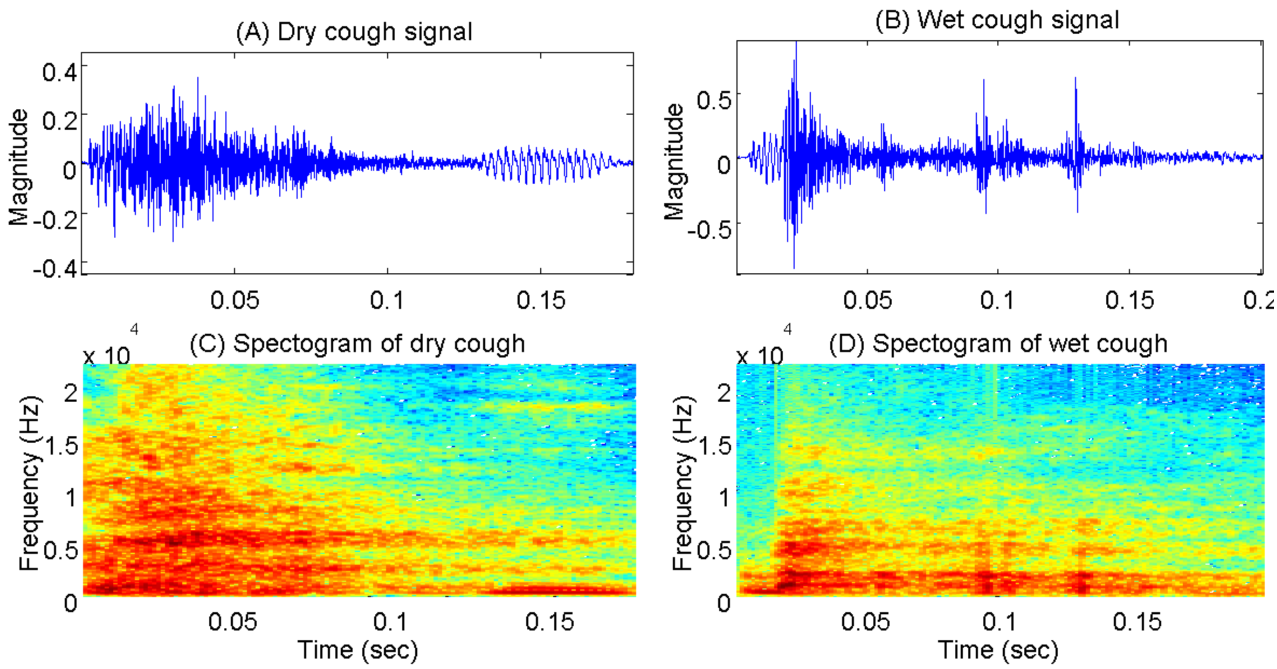

Fig. 1. (A) and (B) respectively are the dry cough and wet cough signal in time domain while (C) and (D) respectively are the spectrogram of dry cough and wet cough signal. It can be seen that the vibration and dislocation of the mucus can been seen in the time domain as well as frequency domain.

into wet and dry classes. In this work, we used 185 cough episodes from 39 pediatrics subjects (age range 0.1 – 15 years). From these samples, 100 classified as dry and 85 classified as wet.

In Fig 1, we illustrate the signal of dry and wet cough in the time domain (Fig 1.A and Fig 1.B) as well as in the frequency domain (Fig 1.C and Fig 1.D). In Fig 1.B (time axis 0.06s, 0.1s and 0.014), we can see the influence of mucus in the cough signal as the sudden changes of amplitudes during the exhalation stage. This represents the vibration and dislocation of the mucus. The event can be seen in the frequency domain as well (see Fig 1.D). In contrast, the contribution of mucus vibration and dislocation in dry cough signal is not obvious.

B. *Distribution of features*

In the feature extraction process, we applied a rectangular window with length of 100 ms (N=4410 samples), 90% overlapping (β=90) and six levels wavelet decomposition ($i = 6$) using Daubechies 4 (DB4) filter. For this work, we computed the features in the six level details of cough signal (D_6) spanning frequency band of 344 Hz – 689 Hz.

In Fig. 2, we show the probability density functions (*pdf*) of 11 points amplitude perturbation quotient (*Sh*) and the absolute Teager energy operator perturbation quotient (E). From the figure it could be seen that the *pdfs* of *Sh* and E have different distribution properties as such dry cough and wet cough can be discriminated.

C. *The probability of intra-cough shimmer and Teager energy operator jump*

Having *Sh* and E, now we can compute the probability of intra-cough shimmer jump (*ICSJ*) and Teager energy operator jump (*ICTeJ*) notated as ($G_{pq} = \{[G_{Sq}\, G_{Eq}]$) using Eq. 9. Suppose we select a threshold q_S = 0.48 and q_E = 0.03, hence we can compute *ICSJ* and *ICTeJ* then plot the distribution of these features (see in Fig. 3 (A) and Fig 3(B)). As can be seen, the distribution of *ICSJ* and *ICTeJ* in dry coughs and wet coughs are significantly different. Later, we used these features as input for the fuzzy c-mean clustering classifier to differentiate dry coughs from wet coughs.

In this paper, we tested several numbers of thresholds to obtain the best classification. We found that q_S = 0.36 and q_E = 0.07 showing the best separation between dry coughs and wet coughs.

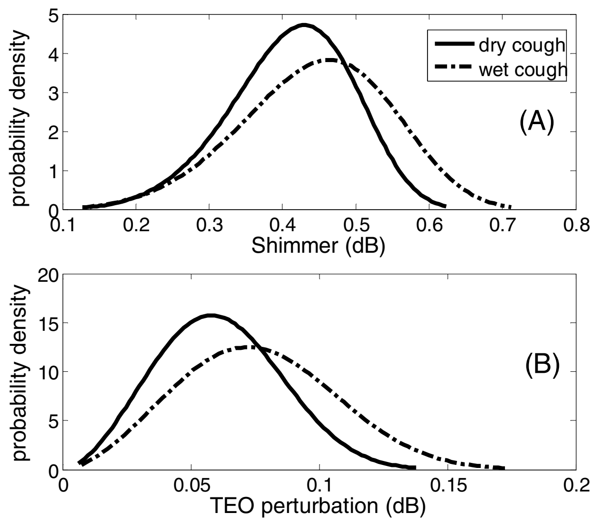

Fig. 2. (A) The probability density functions of the 11 points amplitude perturbation quotient (*Sh*), and (B) the absolute Teager energy operator perturbation quotient (E). Both features computed from the level 6 of details of cough signal (D_6). It shows that the *pdfs* of the features have non overlapping areas can be used in wet/non-wet classification.

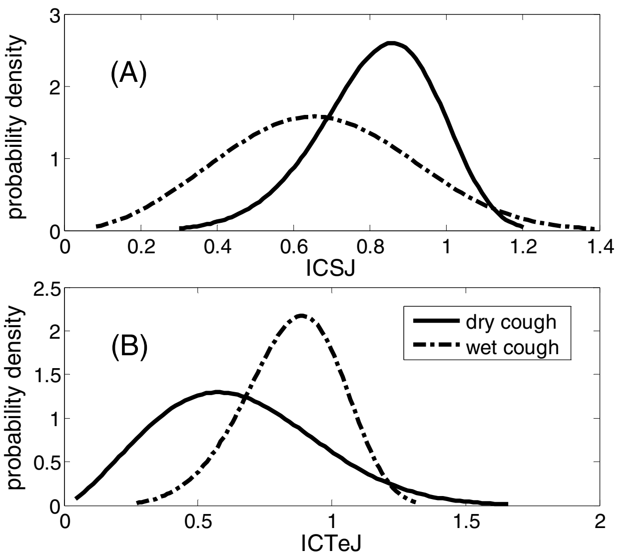

Fig. 3 The probability density function of intra-cough shimmer jump (*ICSJ*) feature and intra-cough teager energy jump (*ISTeJ*) feature computed from dry coughs and wet coughs.

D. *Automated wet/dry cough classification using fuzzy c-mean clustering*

For classifying wet and dry cough, we used fuzzy c-mean clustering (FCM) algorithm. In this process, *ICSJ* and *ICTeJ* were used as input for FCM to discriminate each cough episodes into wet and dry classes. To achieve the best performance, we varied the number of cluster of the FCM. The best performance was indicated with Kappa agreement. Kappa value shows the agreement between the results from FCM with manual classification (professional pediatricians). Kappa value less than 0 means less than chance agreement, 0.01–0.20 is slight agreement, 0.21–0.40 is fair agreement, 0.41–0.60 is Moderate agreement, 0.61–0.80 is substantial agreement, and 0.81–1 is almost perfect agreement. The results of FCM classification is shown in Table 1.

The table shows that number of cluster 2 – 7 have low specificities and fair agreements with the pediatricians. In the nine clusters, the sensitivity increase to 84.5% but the specificity decline to 61.4%. The optimum results were achieved in 11 clusters showing a moderate agreement (κ = 0.52), high NPV (80%), sensitivity (77.4%) as well as specificity (75%). When the number of cluster was increased the NPV and the sensitivity declined. These results show that the too small numbers of clusters are not sufficient for discriminating wet/dry coughs. This may occur since the wetness of cough varies based on the quantity and position of the mucus in the airways. In the linguistic approach, human may classify the cough into finer categories such as very dry, dry, slightly wet, wet, and very wet. Therefore, the approach using fuzzy c-mean clustering is appropriate for this purpose.

Our proposed method shows that the low computational features such as amplitude perturbation and Teager energy operator perturbation can be used to discriminate dry coughs from wet coughs. The results are slightly lower compared with our previous work that used high computational features [15]. However, we believe that the performance of our method can be improved by optimizing all of the parameters. In this work, we involved pediatric subjects as such our results cannot directly compared to the study in [4] and [5]. Rather than using amplitude/magnitude of cough signal alone [4-5], we compute the changes of the amplitude and Teager energy over a cough episode in a specific frequency band. The classifier (FCM) presented in this paper was developed using cough signal that classified manually by the physicians. To improve the objectivity of the knowledge database used for FCM, the manual classification should be followed by clinical testing such as bronchoscopy test.

Table 1. Classification results using Fuzzy c-mean clustering. Nc = number of cluster, κ = Cohen's Kappa, PPV = Positive Prediction Value, NPV = Negative Prediction Value, Acc = Accuracy, Sens = Sensitivity, Spec = Specificity. The PPV, NPV, Accuracy, Sensitivity and Specificity are in percentage (%).

Nc	κ	PPV	NPV	Acc	Sens	Spec
2	0.17	88.2	58.9	61.6	17.9	98.0
3	0.32	83.8	64.2	68.1	36.9	94.1
4	0.37	83.7	66.2	70.3	42.9	93.1
5	0.39	85.7	66.4	70.8	42.9	94.1
7	0.41	77.2	68.8	71.4	52.4	87.1
9	0.45	64.5	82.7	71.9	84.5	61.4
11	0.52	72.2	80.0	76.2	77.4	75.2
13	0.52	73.8	78.2	76.2	73.8	78.2
15	0.51	75.3	75.9	75.7	69.0	81.2
17	0.52	76.3	76.1	76.2	69.0	82.2

IV. Conclusion

In this paper, we presented the development of a novel method for classifying cough sounds into wet and dry classes. We developed a set of novel features called intra-cough shimmer jump (*ICSJ*) and intra-cough Teager energy operator jump (*ICTeJ*). These features have been found useful for differentiating the wet and dry coughs. The linguistic approach in fuzzy is suitable to define the imprecise data/condition such as the wetness of cough. Our method achieved a moderate Kappa agreement with the professional pediatrics (0.52) and a significant accuracy, sensitivity and specificity (76.2%, 77.4% and 75.2% respectively). These initial results show the potential of the method to be developed as a non-invasive tool to assess cough in the pediatric population. Our method can be developed into a mobile phone application for field implementation. However, as our future work, we need to verify our method with the bronchoscopy and tested in larger data sets.

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