Optimum Features Computation Using Genetic Algorithm for Wet and Dry Cough Classification

Yusuf A Amrulloh, Ibnu H Priastomo, Elvira S Wahyuni
Department of Electrical Engineering
Univesitas Islam Indonesia
Yogyakarta, Indonesia
yusuf.amrulloh@uii.ac.id

Rina Triasih
Child Health Department
Gadjah Mada University
Yogyakarta, Indonesia

***Abstract*— The nature of cough sound has been considered as one of the important diagnostic tools. For example, wet cough in children may represent lower respiratory tract infections. However, cough classification is not an easy task. It cannot be done easily by community health workers. Therefore, an automated method is needed to help them in classifying the types of cough. Several features extraction methods have been proposed for classifying wet/dry cough with different performances. Using all those features have consequences increasing the computational cost. In this work, we develop a method to select the optimum feature set for classifying wet and dry cough in children. We recorded cough sound from thirty children younger than four years diagnosed with respiratory tract infections. Then, sound features such as Mel-frequency cepstral coefficients, energy, non-Gausianity index, zero crossing, linear predictive coding and pitch were extracted. We implemented genetic algorithm to select the optimum features and artificial neural networks to classify wet/dry cough. The results show that our proposed method could reduce around twenty-five percent of the features used in the computation while keeping the accuracy, sensitivity and specificity higher than 96%. The results are much higher compared to the previous studies which involving pediatric subjects. This significant achievement supports the development of in situ respiratory disease screening in distant areas.**

Keywords—genetic algorithm, sound features, wet/dry cough, children

I. Introduction

Cough is one of the ultimate symptoms of respiratory diseases. Its sounds may represent the physiological condition of the respiratory tracts [1]. In children, it may represent the etiology of the diseases [2]. Cough sound has been used for screening purposes of respiratory diseases not only in children but also in adults [3][4][5]. One of the common category used by the physician to distinguish the type of cough is its wetness [6].

Wet/dry category of cough refers to the existence of mucus in the respiratory tracts. As part of the defends mechanism, the respiratory tracts will produce mucus against the infections agents such air virus or bacteria. During the expiratory phase of cough, the mucus vibrates and moves due to the fast air burst come from the sudden opening of the glottis. The vibration and movement of mucus creates the unique sound of wet cough [7]. In contrast, dry cough is defined as cough with lack of mucus.

Cough has been considered as an important symptom examined by physician during examination [8]. It also has been used by WHO as screen in criteria for dangerous respiratory diseases such as pneumonia [9]. In Indonesia, pneumonia is one of the prime cause of mortality in children younger than five years. Currently, most of cough examination in the health facilities in Indonesia are performed manually. To classify the cough sounds, physicians listen to several cough episodes during physical examination. Unfortunately, the results of the manual classification are very subjective. The experiences and the physical condition of the physicians heavily affect the classification results. Further, in the rural areas of developing countries, experienced physicians are very rare. This may make the diagnosis results less accurate. As examining cough is not an easy task, some community health workers even disregard this important symptom during the examination. Therefore, an automated method for classifying wet/dry cough will be very useful to handle the situation. It also can improve the diagnostic results done by community health workers.

Recently, several methods have been proposed to automate the classification of wet and dry cough. Study in [10] claimed a very high accuracy in separating wet/dry cough. However, it is only supported by very few episodes of cough from adults. In our previous studies, our methods and novel features were able to differentiate wet/dry cough from children with sensitivity from 77% to 87% and specificity from 75% to 88% [11][12]. Using a lot of sound features in the computation may increase the performance of the classification. However, it will also increase the computational load of the system. For standalone systems with limited computational resources, this pose problems during the deployment.

In this study, we address the issue of feature optimization for separating wet cough from dry cough in children diagnosed with respiratory diseases. We investigate the performance of features that have been used in cough processing such as Mel-frequency cepstral coefficients and linear predictive coding. We propose to implement genetic

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algorithm to obtain the optimum features and artificial neural networks to classify wet and dry cough. The proposed methods based on the facts that cough sounds can be modelled as stochastic processes. Therefore, instead of using linear algorithms, we choose to use evolutionary algorithms to obtain the optimum feature set. The contribution of our study is finding the optimum features for wet/dry cough classification. This allows portable system to reduce the time for computing the sound features as well as for processing them.

The remainder of the paper is divided into three sections which is consisted of material and methods, results and discussion, and conclusion. The way we designed and carried the study is described in the materials and methods section as follows.

II. Materials and Methods

A. Data Acquisition

In this section we described the recording environment, descriptions of participants and the recording set up.

1). Recording environment and description of participants.

This study took place at the Respiratory Medicine Unit of the Sardjito Hospital, Yogyakarta, Indonesia. The ethical clearance from the hospital had been completed before study was started. We recruited pediatric patients admitted to the hospital due to respiratory diseases. The recruitment of the patients followed the inclusion criteria of cough, breathlessness, and fever (defined as temperature greater than 37.5°C). Those who met at least two criteria were included in the study.

The physical examination was carried out by pediatrician shortly after the patients arrive at hospital. Chest x-ray and other laboratory test were performed to support the final diagnosis by following the recommendation of the pediatrician. Information such as demographic information, symptoms and the outcomes of the clinical assessment (e.g.: chest auscultation, breathing rate, temperature, oximetry) were collected by hospital's staff as routine task and used for further analysis.

2). Recording setup

In this study, RODE NT3 microphones, Mobile Pre-USB pre-amplifier and A/D converter and a laptop were used to record cough sound from the recruited subjects. The sound signal was sampled at 44.1kHz, 16-bit resolution. We set the position of the microphones at around 50cm, however it may change due to the movements of the patients. We simply put the recording set in the ward without modified the environments.

B. Construction of the dataset

We recorded cough sounds from thirty pediatric subjects. In each subject, ten cough sound episodes were extracted from the recording. Only cough free from artifact and clipping problems were used in this study. Two trained assistants then classified the cough into wet and dry classes. The constructed dataset consisted of 300 cough episodes with 150 coughs of wet and dry in each class.

In the following step, we passed the cough sound through the feature extraction process to obtain mathematical feature set that can be used to represent wet/dry cough.

C. Feature extraction

As part of pre-processing, we applied high pass filtering with cut-off of 10 Hz to remove noise due to the vibration of microphone stands and cables. Following the process, we extracted the features of the cough sounds in 20 milliseconds frame. Let y is the frame of cough sounds and N is total number of frame. Key features such as Linear Predictive Coding (LPC), Mel-frequency cepstral coefficients (MFCC), formant frequencies, zero crossing rate (ZCR), log energy, non-Gaussianity score (NGS), kurtosis and pitch were computed in each frame.

Our selection of those features based on the facts that cough sound generation has some similarities with speech. Cough initiated with inspiratory phase where air is taken into lungs and followed by the closing of glottis. The closed glottis increases the pressure in lungs. This is called compressive phase. In the next phase, sudden opening of glottis followed by the rushed flow of air from the lungs through the airways. The last process is called expiration wherein most of the cough sounds originate [13]. In this study, the resonance in the vocal, nasal and pharyngeal tracts of cough was modelled using formant frequencies (FF). We computed pitch to model the opening and closing of vocal cord. Further, inspiratory, compressive and expiratory was modelled using source-filter of Linear Predictive Coding. The feature of log energy was measured the loudness of cough sounds. The type of cough sounds such as wet and dry can be recognized by physician, hence we used MFCC to model the human's hearing.

To obtain the statistics information in the cough signal, we computed non-Gaussianity score (NGS) and Kurtosis [14]. Non-Gaussian process may occur during the sudden opening of glottis from the transition of compressive phase to expiratory phase. We computed NGS and kurtosis to represent those physiological conditions.

Let $f_i(y)$, $i = 1, 2, \ldots, 32$, denotes the feature vectors of LPC, MFCC, FF, ZCR, log energy, NGS, kurtosis and pitch respectively. The total number of the features are thirty-two consisted of eight LPC, fourteen MFCCs, five FF, and one feature each for ZCR log energy, NGS, kurtosis and pitch. We used all these features as input for classifier to separate wet cough from dry cough.

In this study we used two classifiers, linear regression model (LRM) and artificial neural networks (ANN). However, only in ANN, genetic algorithm was used to optimize the features. Details of the classification process is described in the following section.

D. Classification

In this process, feature vectors $f_i(y)$ were used as input for classifiers. Two classifiers were implemented in this study.

The first classifier is linear regression model (LRM). In this classifier, statistical model was implemented to find the linear relationship between independent variables and dependent variable as shown in Eq 1.

$$\gamma = a + Bx + \varepsilon_r \qquad (1)$$

where a is the intercept, B is the slope, γ is the wet/dry classes, x is the cough sound features and ε_r is the approximation error of the model. The best model was achieved whenever the error was minimized.

The classification using linear regression model was done in two steps: *i*) without feature selection and *ii*) with feature selection. To select the features, we computed the sensitivity and specificity of the model from each feature. Then we performed the hypothesis test to select the best feature from their sensitivity and specificity. We defined a p value threshold $p_{th} = 0.06$ [11]. Features having p value lower than p_{th} defined as optimal features set.

The second classifier is artificial neural networks (ANN). ANN is a mathematical model of neural system in the brain. It can model the relationship between the cough sound features and the wet/dry classes as a non-linear system. The sound features were used as input. They were connected to a set of neurons in input layer. In our models, wet set the number of neurons in the input layer, hidden layer and output layer as 155, 20 and 1, respectively. We used resilient backpropagation algorithm to train the network. In the training process, we implemented k-fold validation (k = 15). Then we computed the average and standard deviation of sensitivity, specificity and accuracy. Similar with LRM, we computed the performance of the system with and without feature selection. For ANN, the selection of features was carried using genetic algorithm (GA). The implementation of GA for feature selection is described in the following section.

E. Feature selection

In this process, we implemented genetic algorithm to optimize the feature vectors f_i. First, we developed population that consisted from feature subsets. The feature subsets were used as chromosome ψ in genetic algorithm. Each chromosome ψ was evaluated their fitness value using a fitness function. In this work, the fitness function was computed using the classification error of artificial neural network as given in Eq 2.

$$\psi = \varepsilon_a(f) \qquad (2)$$

where ε_a is the classification error of artificial neural network. For this work we used single point crossover and roulette wheel as selection operator [15].

III. Results and Discussion

A. Dataset

In this work, we involved thirty pediatrics subjects diagnosed with respiratory diseases such as pneumonia, bronchitis and asthma. The age range of study population was from three to seventy-two months. The total duration of dataset was 173 seconds, consisted of 96 seconds of wet cough samples and 77 seconds of dry cough samples.

TABLE 1. Results of classification using linear regression model: 1) without feature selection and 2) with feature selection.

	LRM	
	1	2
Accuracy (%)	49.0±6.9	54.30±5.2
Sensitivity (%)	49.1±6.7	49.40±2.9
Specificity (%)	49.1±6.7	49.40±2.9

B. Classification using LRM

As described in Section II.D, we computed the performance of linear regression model (LRM) with and without feature selection. The results of LRM classification is shown in Table 1. The result of classification with feature selection has accuracy around 5% higher compared to other ones. Meanwhile the specificity and sensitivity of the classification are relatively similar. The selected features with p lower than p_{th} were f_i, where i = 5, 8, 17, 18, 19, 20, 21, 22, 27. However, the overall results of LRM classification show a quite low performance (<55%).

TABLE 2. Results of classification using artificial neural network (ANN): 1) without feature selection and 2) with feature selection using genetic algorithm. n is the number of feature which were dropped.

	ANN without feature selection		
	Accuracy (%)	Sensitivity (%)	Specificity (%)
	96.4±0.8%	96.7±0.8%	96.8±0.8%
	ANN with feature selection		
n	Accuracy (%)	Sensitivity (%)	Specificity (%)
1	96,4 ± 0,7	96,2 ± 0,8	96,3 ± 0,8
2	96,7 ± 0,7	96,5 ± 0,7	96,6 ± 0,7
3	96,6 ± 0,7	96,5 ± 0,8	96,6 ± 0,8
4	96,5 ± 0,8	96,4 ± 1,0	96,5 ± 1,0
5	96,6 ± 1,0	96,2 ± 1,3	96,3 ± 1,3
6	96,4 ± 1,0	96,2 ± 1,1	96,3 ± 1,1
7	96,3 ± 0,9	96,3 ± 1,0	96,4 ± 1,0
8	96,1 ± 0,8	96,0 ± 0,8	96,1 ± 0,8
9	95,9 ± 1,2	95,7 ± 1,0	95,8 ± 1,0
10	95,5 ± 1,2	95,3 ± 1,2	95,4 ± 1,2
11	95,5 ± 1,2	95,5 ± 1,4	95,6 ± 1,3
12	94,7 ± 1,5	94,8 ± 1,5	94,9 ± 1,6
13	94,2 ± 1,5	94,2 ± 1,6	94,3 ± 1,6

TABLE 3. Least significant features obtain from iteration of feature selection using GA. n is the number of feature which were dropped, h is the number of how many times the features were dropped and i is the feature index.

n	h	i
1	7	32
2	4	31
3	7	32
4	9	32
5	9	32
6	7	3
7	13	24
8	11	32
9	11	32
10	11	29
11	12	24, 28, 32
12	12	25
13	13	27

C. Classification using ANN and Genetic Algorithm

Table 2 shows the classification results of artificial neural network (ANN) with and without feature selection using genetic algorithm (GA). The results of ANN classifier show that the accuracy, sensitivity and specificity are higher than 96%. The performances are much higher compared to LRM classification (<50%).

From the table it also can be seen that the performance of the classification relatively similar until eight features were excluded. The reduction of nine to eleven features made the performance dropped 1% while the reduction to thirteen features reduced the performance around 2%.

In this work, we also investigated the least significant features indicated by how many times (h) they were dropped in feature selection. The results are shown in Table 3. Feature f_i, for i = 3 represent the third feature of LPC, i = 24, 25, 27 represent the second, third and fifth feature of formant frequencies, i = 28 is zero crossing rate, i = 29 is log energy, i = 31 is the kurtosis and i = 32 is the pitch, were dropped in the feature selection. In the thirteen times of feature selection, f_{32} was dropped six times while f_{24} was dropped two times.

In the next process, we investigated the performance of the ANN in the absent of those least significant features. The results are shown in Table 4.

TABLE 4. Classification results without least significant features.

Dropped features	Accuracy (%)	Sensitivity (%)	Specificity (%)
f_{24}	96,1 ± 0,9	96,3 ± 0,8	96,4 ± 0,8
f_{32}	96,4 ± 0,8	96,5 ± 0,8	96,7 ± 0,8
$f_3, f_{25}, f_{27}, f_{28}, f_{29}, f_{31}$	95,9 ± 1,0	96,1 ± 1,1	96,2 ± 1,1
$f_3, f_{24}, f_{25}, f_{27}, f_{28}, f_{29}, f_{31}, f_{32}$	96,4 ± 0,6	96,5 ± 0,6	96,6 ± 0,6

In the testing using k-fold cross validation (k = 15), the results show that reduction of eight least significant features did not reduce the performance of the classification (around 96%). Therefore, the features can be dropped from the computation for selecting wet/dry cough in pediatric population.

The sound features such as log energy and zero crossing rate were categorized as non-significant features. It means that magnitude and the shape of cough sound signal may not carry essential information about the wetness of cough. Those features can be excluded in the next cough processing.

Cough sounds have non-linearity characteristics due to the airways conditions. Modelling cough sound using linear model is not the best approach. This is proved in our study that LRM produced very low accuracy, sensitivity and specificity as shown in Table 1. In contrast, the implementation of ANN and GA for classifying cough sound show outstanding results (Table 2). This because ANN able to model the relationship of cough features and wet/dry classes as nonlinear system. Further, GA through crossover and mutation can avoid local minima during feature set optimization. Therefore, the algorithm can select the optimum feature for wet/dry cough classification. The results also show that our proposed methods improved the achievement of our previous studies [11][12].

IV. Conclusion

In this work, we proposed the combination of artificial neural network and genetic algorithm for classifying wet and dry cough in pediatric population. Our results show that our methods achieved very high accuracy, sensitivity and specificity (>96%) when compared to the classification of the trained human operators. The results are also much higher compared to other studies. Using these results ones can directly computed the necessary features, hence, this will reduce the computational cost of the system. This approach is very beneficial for implementation in the embedded system for cough analysis. Despite the significant achievements, the classification of cough can be expanded into more specific classes as used in human language such as slightly wet, very wet, dry or very dry. Classifying in such way will give details about the characteristics cough.

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