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# An Analysis of Sounds for Lungs with Excessive Water

Kah Jun Hong, *Member IEEE*, Wee Ser, *Senior Member, IEEE*, David Chee-Guan Foo

**Abstract**— Excessive lung water occurs when too much water accumulates in the lung, causing breathing difficulty. Current diagnosis methods include X-rays and CT-scans. However, because of their bulk and the need for trained professionals to operate, physicians rely on auscultation for preliminary diagnosis. Recent attempts have been made to automate the auscultation process and some degree of success has been reported. Thus, it would be useful to provide more analysis of such lung sounds. This paper attempts to study the characteristics of breathing sounds from lungs with excessive water and compare them with breathing sounds from healthy lungs. Using a modified empirical mode decomposition to split the signals, the root-mean-squared energy (RMS) and kurtosis were used as characteristics. These characteristics were extracted from the intrinsic mode functions (IMF) and were analyzed. Results showed that certain IMF were effective in characterizing both kinds of sounds due to their small spread in RMS or kurtosis. Results also (using  $p$ -values from statistical tests) showed that for certain intrinsic mode functions, lung sounds with excessive lung water exhibit different medians from sounds of healthy lungs. There was strong linear independence between each IMF of the two sounds. Empirical mode decomposition was shown to be able to extract useful information for analyses.

## I. INTRODUCTION

There has been research on the acoustic classification of adventitious lung sounds. Many techniques have been proposed to classify both discontinuous and continuous adventitious lung sounds (DAS and CAS). Techniques such as lacunarity [1], frequency ratio from power spectral density [2], and wavelet transform [3] have been used to more than 90% accuracy with different classifiers such as k-Nearest Neighbor (k-NN) and Support Vector Machine (SVM).

[4] used Empirical Mode Decomposition (EMD) to analyze fine and coarse crackles. Using EMD, there was better discrimination for both fine and soft crackles. Hilbert Huang Transform (HHT), an application of EMD for instantaneous frequency (IF), was used to analyze fine and coarse crackles in [5]. [6] used average IF and thresholding to classify fine and coarse crackles, with “almost 100% correct detection and total accurate classification.”

However, most literature tend to focus on analysis of DAS and CAS, and not specific diseases. This paper attempts to analyze sounds of lungs with excessive lung water. Excessive lung water happens when too much water accumulates in the lung and causes breathing difficulty [7].

To detect excessive lung water, some techniques have been developed, such as dilution techniques, X-ray machines and CT-scans. Due to their bulk and requirement for trained personnel to operate, these machines can only be found in hospitals. As a result, physicians rely on the use of auscultation for preliminary diagnosis.

Yang and Wee first proposed a signal processing approach for detecting excessive lung water using sound based sensing [8]. Different features and classifiers were explored, and Mel-Frequency Cepstral Coefficients (MFCC) together with k-NN produced the best result, with a reported 95.7% accuracy. [9] proposed a sub-band feature extractor that segmented the frequencies of lung sound recordings into sub-bands. These sub-bands were used as features that were ranked using Principle Component Analysis (PCA) and Support Vector Machine Recursive Feature Elimination (SVMRFE). Classification was done using k-NN and SVM. Accuracy was reported to have an F-measure of up to 99%.

Since these recent attempts to automate the process of auscultation for excessive lung water have been successful, it would then be useful to provide more detailed analysis of lung sounds containing excessive water.

This paper attempts to study the characteristics of lung sounds with excessive water and lung sounds with healthy lungs. The study utilizes empirical mode decomposition (EMD), which allows for dealing with nonlinear and nonstationary signals. Proposed by Huang et al. [10], EMD was claimed to be an adaptive and automatic time-varying filter.

Using a modified EMD, the proposed method splits the signal into “intrinsic mode functions (IMF)”-like signals, and analyzes the root-mean-squared (RMS) energy and kurtosis as features of these IMF-like signals. The analysis includes a study of the similarities and characteristics of these IMFs. Differences are also investigated for breathe sounds from lungs with excessive water and healthy lungs using statistical testing. The Mann-Whitney U Test is used for statistical significance. The null hypothesis is tested at  $p < 0.05$ .

## II. DATA AND METHODS

### A. Data Collection

The data was collected from 17 volunteers. 7 volunteers had excessive lung water due to pulmonary edema while 10 volunteers had healthy lungs. Respiratory sounds were recorded from the back of the test subjects using a stethoscope sensor (Addest Technovation) connected to a laptop. The ground truth was determined by an expert physician. The sampling rate was 8000Hz. The recordings were normalized to have the same RMS energy. The recordings were validated by specialists. The majority of the recordings ranged from 30 seconds to a minute and were divided into 181 four-second long samples. They were then

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categorized into either lung sounds with excessive lung water (ELW) or healthy lungs (HL).

## B. Analysis Method

### 1) Empirical Mode Decomposition

The original EMD empirically identifies the intrinsic oscillatory modes of the signal by particular time scales [10]. These modes are called IMF, and they characterize the data through oscillating waves with zero local mean. Because of the sifting process, EMD is a decomposition that is complete, orthogonal, local and adaptive [10].

Each IMF satisfies two conditions. The first condition states that the number of extrema and the number of zero crossings can only differ by at most one. The second condition states that the local mean of the IMF must be zero. The locality of the mean can be defined by the problem. The signal can be represented by the sum of its IMF by

$$s(t) = \sum_{i=1}^N IMF_i(t) + r_N(t) \quad (1)$$

Where  $N$  is the total number of IMF, and  $r_N(t)$  is the residue signal that is constant or monotonic.

The sifting process is as follows:

1. Generate an upper envelope of the given signal  $s(t)$  by a cubic spline using the local maximums.
2. Generate a lower envelope of the given signal  $s(t)$  by a cubic spline using the local minimums.
3. Find the average of the envelopes to attain the mean envelope,  $m(t)$ .
4. Compute the difference  $h(t) = s(t) - m(t)$ . This is regarded as one sift.
5. Check if  $h(t)$  is an IMF, then
  - a. if  $h(t)$  is an IMF, calculate the remainder,  $w(t) = s(t) - h(t)$
  - b. if  $h(t)$  is not an IMF, replace  $s(t)$  with  $h(t)$  and repeat step 1-5.

Once the first IMF is generated, the second IMF can be generated by using the sifting procedure on the first residue  $r_1(t) = s(t) - IMF_1(t)$ . IMF stop generating when the  $n^{th}$  residue  $r_N(t)$  is either monotonic or constant.

It is known that for real signals, it is sometimes difficult for the sifting process to meet the criteria for IMF. Thus for the proposed algorithm, two modifications are made.

1. Instead of checking if  $h(t)$  is an IMF after every sift, an IMF was generated after  $M$  sifts. This was decided after analyzing each sifting. Two analyses were made.

For all the samples, the difference between extrema and zero crossing dropped exponentially and stabilized after less than 100 siftings. Fig. 1 shows the difference between extrema and zero crossing for each IMF up to the 14<sup>th</sup> IMF for one sample.

The standard deviation between each sifting was also determined. The standard deviation was calculated with the formula:

$$SD = \frac{\sum_{i=0}^T [h_i(t) - h_{i-1}(t)]^2}{\sum_{i=0}^T h_{i-1}^2} \quad (2)$$

Where  $h_i(t)$  is the signal one sifting after  $h_{i-1}(t)$ .

The standard deviation also dropped exponentially and stabilized after 200 siftings. Thus there were insignificant change between each sifting after 200 sifts.  $M$  was chosen in this paper to be 250.

2. The number of IMFs are fixed to be  $N$  unless before  $N$  IMFs are generated, the latest IMF is monotonic or constant, which then  $N'$  number of IMFs are generated, with the residue  $r_N$  being the monotonic or constant IMF.

### 2) Statistical Analysis

The root-mean-squared (RMS) energy and kurtosis of the IMFs were studied as proposed features. The RMS energy was calculated with the formula

$$RMS = \sqrt{\frac{1}{N} \sum_{i=1}^N |s(t)|^2} \quad (3)$$

and kurtosis was calculated using

$$k = \frac{\frac{1}{N} \sum_{i=1}^N [s(t) - \bar{s}]^4}{\left\{ \frac{1}{N} \sum_{i=1}^N [s(t) - \bar{s}]^2 \right\}^2} \quad (4)$$

where  $N$  is the length of signal.

The medians and spread of features values were analyzed to determine the characteristics and similarities for sounds of lungs with ELW and HL.

Statistical analysis was also used to study the differences between lung sounds with excessive lung water and healthy lungs. First, the Lilliefors test was used to determine if the distribution of the proposed features of each IMF was from the normal family. The Lilliefors test uses the null hypothesis

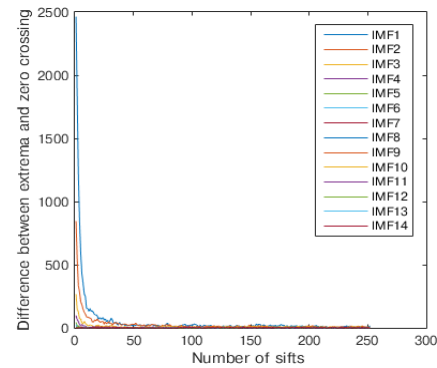


Figure 1. The difference between extrema and zero crossing decreases exponentially, then remains constant.

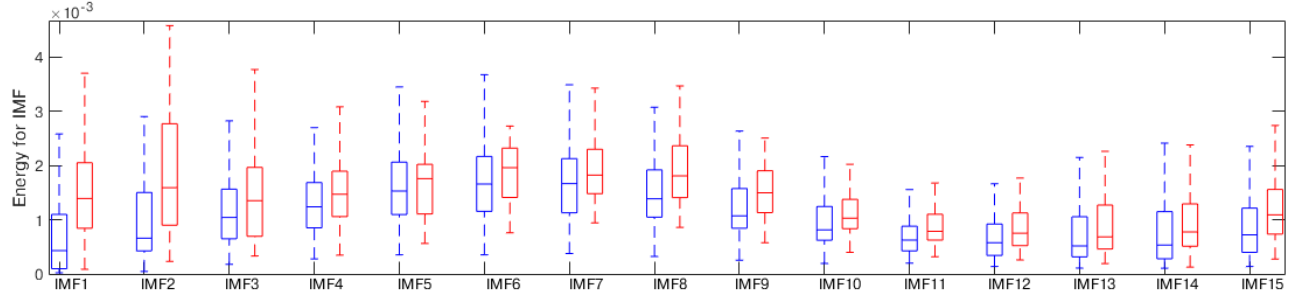


Figure 2. Box plots of RMS energy for IMF showing median, and 25th and 75th percentile. Outliers have been removed for presentation. Red: Plots for ELW. Blue: Plots for HL.

that the data comes from a distribution in the normal family, against the alternative that it does not come from such a distribution. It was tested at the 5% significance level. The results of the test showed that, for the data collected, both the RMS energy and kurtosis of each IMF were non-normal.

To analyze the differences between ELW and HL using IMF, the Mann-Whitney U test was used. The Mann-Whitney U test was chosen because of the non-normal distribution of the IMFs. It uses the null hypothesis that two sets of independent data have equal medians, against the alternative that they are not equal. In this case, it was used to test if the median of the proposed features within each IMF between ELW and HL were the same. The null hypothesis was tested at the 5% significant level. Thus if  $p < 0.05$ , the null hypothesis would be rejected, and one could conclude that the median of the tested feature value was equal between the two types of lung sounds. For the purpose of being succinct in Section III, a conclusion that feature values are equal would refer to their medians being equal.

Since sounds for both ELW and HL are breathe sounds, they will have independent as well as dependent characteristics. Thus, correlation between IMF of ELW and HL were also done to investigate linear independence.

### III. ANALYSIS RESULTS

The number of siftings to obtain each IMF was chosen to be  $M = 250$ . The number of IMFs obtained was chosen to be  $N = 14$ . Thus 15 separate signals were attained from each sample. EMD and feature extraction were applied on the whole four-second sample, and no windowing was implemented.

The proposed features of each IMF was calculated. For each IMF (and  $r_N$ ), two datasets for each feature was obtained. One dataset belonged to ELW sounds and the other dataset belonged to HL sounds. Each IMF was investigated with these two datasets. The Mann-Whitney U test was used on datasets for each IMF to test if the value of the proposed features between the two categories were different. If  $p < 0.05$ , the null hypothesis (described in Section B.2) would be rejected and one could conclude that the values for the proposed features extracted from the IMF between the two categories were different.

First, the RMS energy of each IMF was calculated. IMF<sub>11</sub> and IMF<sub>12</sub> have the smallest spread of RMS energy for both lung sounds. Thus, among all the IMF, IMF<sub>11</sub> and IMF<sub>12</sub>

TABLE I. P-VALUES OF RMS FOR EACH IMF

IMF <sub>1</sub>	IMF <sub>2</sub>	IMF <sub>3</sub>	IMF <sub>4</sub>	IMF <sub>5</sub>
3.65E-7*	1.22E-5*	0.153	0.300	0.714
IMF <sub>6</sub>	IMF <sub>7</sub>	IMF <sub>8</sub>	IMF <sub>9</sub>	IMF <sub>10</sub>
0.102	0.0437*	5.84E-5*	1.46E-4*	9.65E-4*
IMF <sub>11</sub>	IMF <sub>12</sub>	IMF <sub>13</sub>	IMF <sub>14</sub>	$r_N$
1.20E-3*	1.90E-3*	1.64E-2*	7.40E-3*	1.10E-3*

Asterisks denotes statistical significance at 5% level

TABLE II. CORRELATION COEFFICIENTS OF RMS FOR EACH IMF

IMF <sub>1</sub>	IMF <sub>2</sub>	IMF <sub>3</sub>	IMF <sub>4</sub>	IMF <sub>5</sub>
-5.03E-2	8.40E-2	7.18E-2	-5.37E-2	7.33E-2
IMF <sub>6</sub>	IMF <sub>7</sub>	IMF <sub>8</sub>	IMF <sub>9</sub>	IMF <sub>10</sub>
-9.25E-2	-0.133	-0.111	4.60E-3	0.157
IMF <sub>11</sub>	IMF <sub>12</sub>	IMF <sub>13</sub>	IMF <sub>14</sub>	$r_N$
0.160	0.242	9.02E-2	0.129	1.97E-2

TABLE III. P-VALUES OF KURTOSIS FOR EACH IMF

IMF <sub>1</sub>	IMF <sub>2</sub>	IMF <sub>3</sub>	IMF <sub>4</sub>	IMF <sub>5</sub>
2.06E-6*	0.507	0.836	0.192	0.629
IMF <sub>6</sub>	IMF <sub>7</sub>	IMF <sub>8</sub>	IMF <sub>9</sub>	IMF <sub>10</sub>
1.74E-2*	3.80E-3*	1.31E-5*	6.42E-5*	2.50E-3*
IMF <sub>11</sub>	IMF <sub>12</sub>	IMF <sub>13</sub>	IMF <sub>14</sub>	$r_N$
2.80E-3*	4.90E-2*	9.10E-3*	8.50E-3*	5.570E-2

Asterisks denotes statistical significance at 5% level

TABLE IV. CORRELATION COEFFICIENTS OF KURTOSIS FOR EACH IMF

IMF <sub>1</sub>	IMF <sub>2</sub>	IMF <sub>3</sub>	IMF <sub>4</sub>	IMF <sub>5</sub>
8.76E-2	-0.222	0.245	0.371	0.174
IMF <sub>6</sub>	IMF <sub>7</sub>	IMF <sub>8</sub>	IMF <sub>9</sub>	IMF <sub>10</sub>
0.161	-6.90E-2	-2.82E-2	-0.147	-0.140
IMF <sub>11</sub>	IMF <sub>12</sub>	IMF <sub>13</sub>	IMF <sub>14</sub>	$r_N$
-6.01E-2	0.211	0.155	0.109	0.129

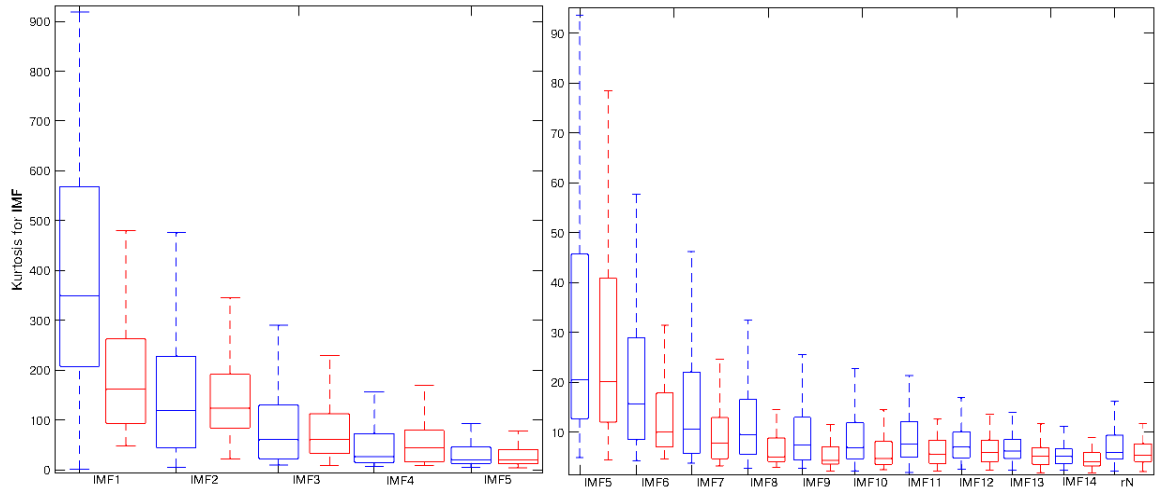


Figure 3. Box plots of kurtosis for IMF showing median, and 25th and 75th percentile. Outliers have been removed for presentation. Red: Plots for ELW. Blue: Plots for HL.

were the most effective in characterizing ELW or HL lungs sounds using RMS. IMF<sub>1</sub>-IMF<sub>3</sub> had the largest spreads thus were most ineffective in characterizing ELW or HL lung sounds using RMS. Comparisons between ELW and HL were also made. The  $p$ -values for each IMF showed that the RMS energy for IMF<sub>1</sub>, IMF<sub>2</sub>, IMF<sub>7</sub>, to IMF<sub>14</sub> and  $r_N$  between samples with ELW and samples with HL were different. Tests on IMF<sub>3</sub> to IMF<sub>6</sub> failed to reject the null hypothesis and thus the RMS energy of IMF<sub>3</sub> to IMF<sub>6</sub> were shown to be equal for the two types of lung sounds. Correlation coefficients for each IMF between the two datasets were generally close to zero, ranging from -0.111 to 0.242. Thus RMS of these datasets have strong linear independence. Fig. 2 shows the box plots for RMS energy. Table 1 shows the  $p$ -values for the RMS energy of each IMF. Table 2 shows the correlation coefficients for RMS energy.

Second, the kurtosis of each IMF was calculated. IMF<sub>13</sub> and IMF<sub>14</sub> had the smallest spread of kurtosis for both lung sounds. Thus these IMFs were the most effective in characterizing ELW or HL lung sounds. IMF<sub>1</sub>-IMF<sub>5</sub> had the largest spreads thus were most ineffective in characterizing ELW or HL lung sounds. The  $p$ -values for each IMF showed that kurtosis for IMF<sub>1</sub>, and IMF<sub>6</sub> to IMF<sub>14</sub> between samples for ELS and samples for HL were different. Tests for IMF<sub>2</sub> to IMF<sub>6</sub> and  $r_N$  failed to reject the null hypothesis and thus kurtosis of these IMFs (and  $r_N$ ) were shown to be equal for the two types of lung sounds. Correlation coefficients for each IMF between the two datasets were generally close to zero, ranging from -0.222 to 0.371. Thus kurtosis of these datasets have strong linear independence too. Fig. 3 shows the box plot for kurtosis. Table 3 shows the  $p$ -values for kurtosis. Table 4 shows the correlation coefficients for kurtosis.

Using the modified EMD to analyze lung sounds, the results show that some IMFs could be used to characterize lung sounds if RMS energy and kurtosis were used. The median of RMS energies and kurtosis for certain IMFs were revealed to be different and some were same between sounds from lungs with excessive water and healthy lungs. Using RMS energy and kurtosis, sounds of ELW and HL showed strong linear independence. EMD was shown to be an effective way for analysis. Further work include using these

features in a classifier and evaluating its accuracy. More investigations can be done with other features using EMD. Also, more data can be collected to increase the inter-patient variability.

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