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Estimation of Instantaneous Frequency from Empirical Mode Decomposition on Respiratory Sounds Analysis

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Abstract— **Instantaneous frequency (IF) calculated by empirical mode decomposition (EMD) provides a novel approach to analyze respiratory sounds (RS). Traditionally, RS have been analyzed using classical time-frequency distributions, such as short-time Fourier transform (STFT) or wavelet transform (WT). However, EMD has become a powerful tool for nonlinear and non-stationary data analysis. IF estimated by EMD has two major advantages: its high temporal resolution and the fact that a priori knowledge of the signal characteristics is not required. In this study, we have estimated IF by EMD on real RS signals in order to identify continuous adventitious sounds (CAS), such as wheezes, within inspiratory sounds cycles. We show that there are differences in IF distribution among frequency scales of RS signal when CAS are within RS. Therefore, a new method for RS analysis and classification may be developed by combining both EMD and IF.**

I. Introduction

Respiratory sounds (RS) from pulmonary auscultation contain useful information about some lung diseases in the respiratory system. It is well known that certain abnormal sounds are associated with particular pulmonary disorders. Therefore, in order to achieve a right diagnosis, it is necessary to analyze and interpret RS properly. In that sense, digital signal processing and analysis helps to overcome problems derived from physician's subjectivity.

As RS signals are non-stationary and nonlinear processes, they have to be analyzed in both time and frequency domains. Previous studies have proposed different analysis algorithms based on features extraction from classical time-frequency distributions (TFDs), such as short time Fourier transform (STFT) or wavelet transform (WT) [1, 2, 3]. Moreover, recent studies have used alternative tools for RS analysis, such as temporal-spectral dominance derived from STFT [4] or multi-scale principal component analysis (PCA) applied to Fourier transform (FT) of the signals [5]. However, it is well known that any technique which is based on FT or any integration-based transform is limited by the uncertainty principle, which limits the combined time-frequency resolution. Furthermore, STFT and WT are non-adaptive techniques and they require a priori choice of fixed analysis parameters based on signal characteristics.

In order to overcome these problems, we propose a new approach to analyze RS, based on instantaneous frequency (IF) estimated by empirical mode decomposition (EMD). The main advantage of the proposed method is that IF estimated by EMD provides information about the frequency content of the sound signals at each time instant, and thus both high time and frequency resolution are achieved. Moreover, since EMD is an adaptive and direct decomposition technique, it is not necessary a priori knowledge of signal characteristics. However, in order to calculate IF on multi-component signals a set of requirements have to be met [6, 7]. In that sense, the combination of both EMD and IF, called as Hilbert spectrum [8, 9], provides a physically meaningful IF, resulting in a useful tool for nonlinear and non-stationary data analysis.

In this study, we have developed a customized algorithm for IF estimation by EMD on RS signals. Since RS are multi-component signals and the IMFs obtained from the EMD are not entirely mono-component signals, we had to smooth their phase signals to avoid meaningless IF values. The proposed technique has been tested on real respiratory sound recordings from asthmatic patients. In these patients, continuous adventitious sounds (CAS), such as wheezes, are the most common abnormal sounds. CAS have a duration of more than 100 ms and are characterized by a pitch of over 100 Hz. These sounds are clinically relevant since they contribute to assessing the severity of asthma. In this study, we have checked whether IF distribution allows us to detect CAS within RS.

II. Materials and Methods

A. Data Acquisition

Respiratory sounds were recorded at the Pulmonary Function Tests Laboratory, Hospital Universitari Germans Trias i Pujol, Badalona, Spain. RS were recorded from asthmatic patients in sitting position using three piezoelectric contact microphones (TSD108, Biopac, Inc.) with a frequency response of 35-3500 Hz. Two microphones were placed on the back surface: right/left bases of the lungs, and one more microphone was placed over the right side of the trachea. All microphones were attached to the skin using adhesive rings. Moreover, respiratory airflow signal was recorded using a pneumotachograph (TSD107B, Biopac, Inc.). All signals were recorded at a sample rate of 12500 samples/second using a 16-bit analogue-to-digital converter

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(MP150, Biopac, Inc.). After digitalization, sound signals were band pass filtered (70-2000 Hz). Automatic respiratory phase segmentation was achieved from the airflow reference signal. RS signals from 21 asthmatic subjects were recorded and signal segmentation was applied to extract inspiratory sounds cycles. All cycles were manually classified by a senior physician by listening to them, thus separating those cycles which had wheezing from normal sounds cycles.

B. Empirical Mode Decomposition of RS

The major requirement for IF estimation is to have a mono-component signal or at least a narrowband signal. RS are multi-component signals and therefore they have to be decomposed into mono-component signals in order to achieve a physically meaningful IF. In that sense, a new class of functions, designated as intrinsic mode functions (IMF), was defined by Huang N. E. [8] as a practical way to decompose a signal into a set of components for which the IF can be defined at any point. An IMF is a function that represents the oscillation mode embedded in the data signal. The method to decompose non-stationary and nonlinear signals into IMF components was called empirical mode decomposition (EMD). The main advantage of EMD is that its decomposition base is derived from the original data themselves, in contrast to WT. Moreover, it has been proved that EMD acts as a 'wavelet-like' filter bank and its benefits are similar to those of WT [10]. However, EMD has not been widely used to RS signal analysis. Even though explosive lung sounds detection by EMD was proposed in a recent study [11], combination of EMD and IF has not been previously applied to RS processing.

In this study, EMD has been applied to each inspiratory sound cycle as a step prior to the IF estimation. IMFs are obtained in decreasing order of frequency, where IMF 1 includes the highest frequency components in the RS. Therefore, for each cycle, IMFs from 1 to 4 are obtained in order to cover the frequency range of interest for RS analysis. Matlab algorithms reported by Rilling and Flandrin [12] are used in this study. An example of EMD method applied to a RS cycle, with a wheezing, is shown in Fig. 1. This cycle was previously classified by a physician as a wheezing cycle, and its pitch around 300 Hz was graphically corroborated by examining the spectrogram. As shown, most of the wheezing components are within IMF 1 and IMF 2.

C. Instantaneous Frequency

In order to calculate the IF, a complex signal has to be obtained from each IMF for which envelope and phase signals can be defined. From a practical point of view, the analytic signal defined by Gabor [13] is the appropriate method for generating a unique complex signal from a real one. Equation (1) is the time expression for an analytic signal, z(t):

$$z(t) = s(t) + jH[s(t)] = a(t)e^{j\Phi(t)} \tag{1}$$

where s(t) is the real signal (an IMF in the present work), H[•] is the Hilbert transform, a(t) is the absolute value of z(t), and Φ(t) is the phase of z(t). Then, an instantaneous frequency (f_i) and envelope (e_i) can be defined as the phase derivative (2) and envelope (3) of the analytic signal, respectively [6, 7]:

$$f_i(t) = \frac{1}{2\pi}\frac{d\Phi}{dt} \tag{2}$$

$$e_i(t) = \left|z(t)\right| = a(t) \tag{3}$$

According to the definition in (2), positive IF values will only result if the phase of the analytic signal is monotonically increasing. As IMFs of RS are not entirely mono-component signals, their phase signals may contain decreasing value segments. It would result in negative IF episodes, which lack of physical meaning and are away from real values.

In order to avoid negative IF values in RS, we have proposed a smoothing function to the IF computation algorithm. It consist of applying a shape-preserving

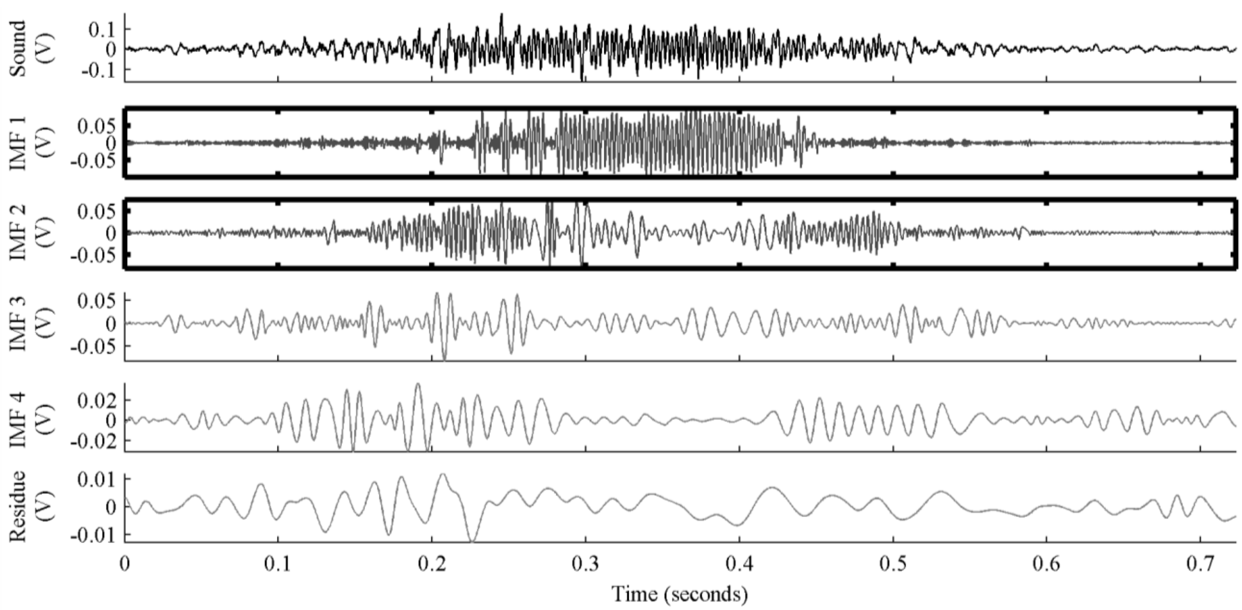

Figure 1. Empirical mode decomposition of a RS with a wheezing segment. The major components of the wheeze appear in IMF 1 and IMF 2.

piecewise cubic interpolation to the phase signal in order to keep out those segments where the phase decreases.

The complete algorithm to estimate IF comprises the following steps:

Step 1: generate IMFs from 1 to 4 by EMD on each inspiratory sounds cycle.

Step 2: calculate the analytic signal for each IMF by Hilbert transform.

Step 3: extract the phase signal from each analytic signal.

Step 4: smooth the phase signals. The smooth function prevents IF from taking negative values when the method is applied to RS analysis.

Step 5: estimate IFs by differentiating the smoothed phase signals.

Time derivative is generated using a 5-point least squares polynomial approximation, which transfer function is in (4).

$$H(z) = 0.2 + 0.1z^{-1} - 0.1z^{-3} - 0.2z^{-4} \quad (4)$$

III. Results and Discussion

In order to test the performance of the proposed method on normal and wheezing RS, two inspiratory sounds cycles have been chosen from the dataset. Figs. 2-A and 2-C correspond to IFs and IEs from the wheezing cycle in Fig. 1. As shown in C, most of the energy is concentrated in IE 1 and IE 2 due to a low pitch wheeze that is within the inspiratory sounds cycle. Furthermore, looking at IF 1 and IF 2, we found an almost constant IF value around 300 Hz, which corresponds to the tracked pitch of the wheeze. On the other hand, Figs. 2-B and 2-D show IFs and IEs from a normal sounds cycle. As shown in D, energy is scattered over time in normal inspiratory sounds. IE 1 and IE 2 show that energy is uniformly distributed over cycle duration. With respect to the IF distribution, there is not a fixed IF value over cycle duration, but a mean IF value that decrease from IF 1 to IF 4, as shown in B. It indicates that energy spreads over time and frequency in normal inspiratory sounds.

Fig. 3 shows an example of a variable pitch wheeze. Looking at IF 1, we found that IF has an almost fixed decreasing value from about 1350 to 950 Hz during the

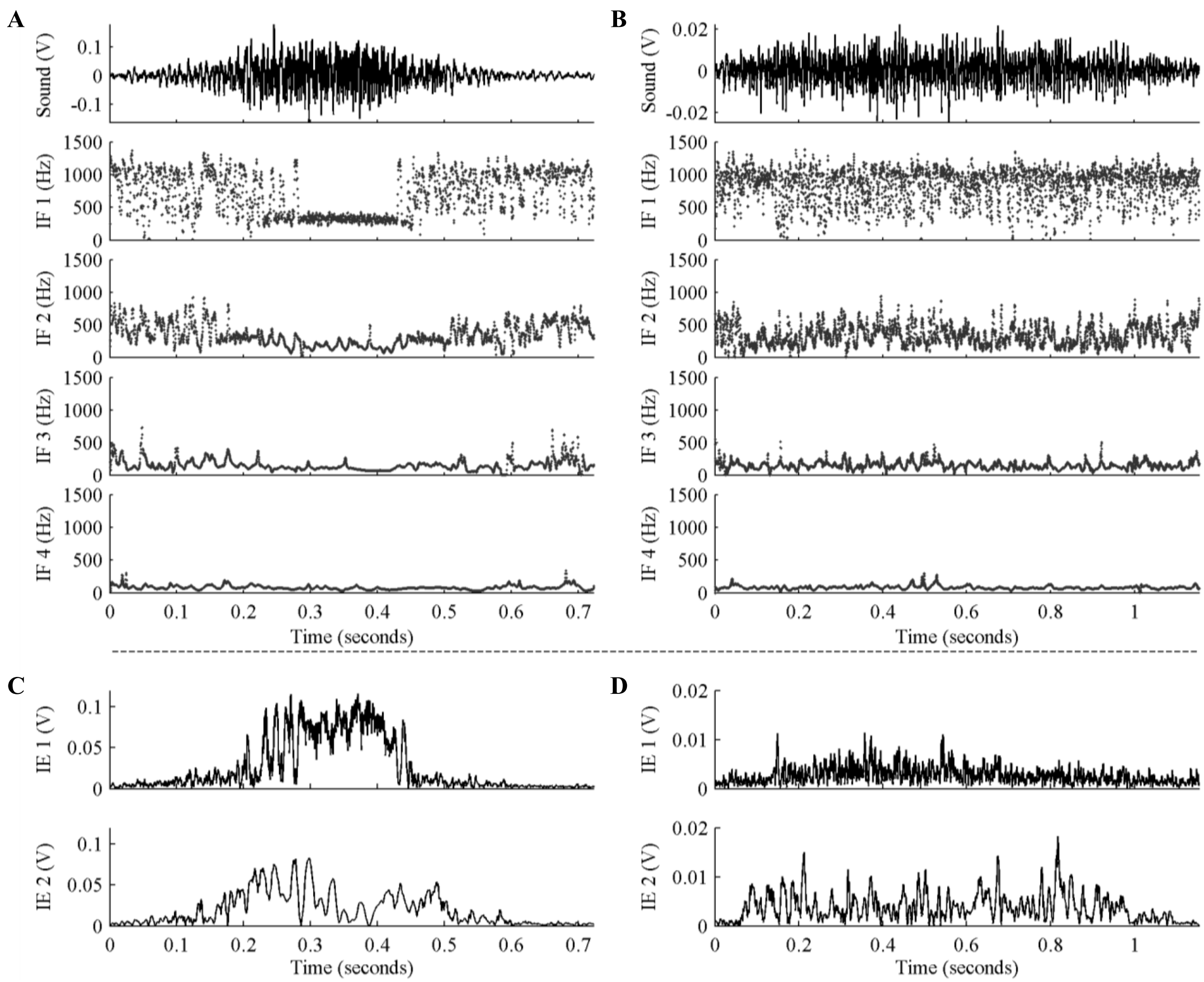

Figure 2. Instantaneous frequencies (IF) for IMFs from 1 to 4: wheezing cycle (A) and normal sounds cycle (B). Instantaneous envelopes (IE) for IMFs 1 and 2: wheezing cycle (C) and normal sounds cycle (D).

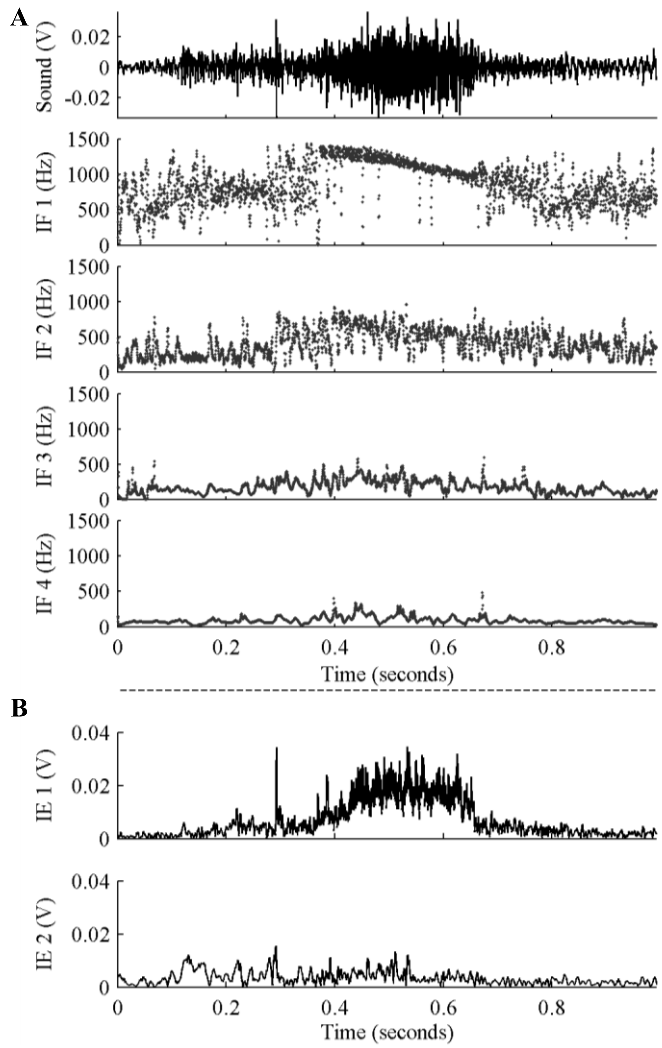

Figure 3. (A) Instantaneous frequencies (IF 1-4) of a wheezing segment with high variable pitch. (B) Instantaneous envelopes (IE 1-2) from IMFs 1-2.

whole wheeze duration. It was corroborated by inspection of the spectrogram. Therefore, it is clear that this decreasing pitch of the wheeze is properly tracked by IF.

As we have shown, IF from a certain IMF allows to identify constant and variable pitch wheezing sounds. However, due to the mode mixing effect of EMD, in the case shown in Fig. 2-A a wheeze with a pitch around 300 Hz is tracked as much by IF 1 as by IF 2. Nevertheless, changes in IF distribution are more obvious in IF 1, which IF scattering is usually higher than IF 2. Therefore, it makes easier identifying an almost constant IF value caused by a wheezing sound in IF 1 than in IF 2.

IV. Conclusion

This study demonstrates that IF, in combination with EMD, is a powerful tool to analyze RS. EMD allows us to analyze IF on RS at different frequency scales and at high temporal resolution. Continuous adventitious sounds, such as wheezes, cause changes in the distribution of the IF and IE over RS cycle duration. In particular, IF remains almost constant when a wheeze is within RS. Although some wheezes are tracked by IF from different IMFs, due to the mode mixing effect of EMD, there is always at least an IMF which IF allows the identification of the wheeze. In those cases, it is usually easier to identify wheezes at high frequency scales than at low scales. On the other hand, the major components of the signal energy (envelope squared) do not spread over time, but are concentrated throughout the course of the CAS. Therefore, the proposed method could be a step prior to the development of an algorithm for RS classification and wheeze detection.

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