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Nonlinear characteristics of wheezes as seen in the wavelet higher-order spectra domain

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Abstract—**The aim of this study was to capture and analyze the nonlinear characteristics of asthmatic wheezes, reflected in the quadrature phase coupling of their harmonics, as they evolve over time within the breathing cycle. To achieve this, the continuous wavelet transform was combined with third-order statistics/spectra. Wheezes from diagnosed asthmatic patients were drawn from a lung sound database and analyzed in the time-bi-frequency domain. The analysis results justified the efficient performance of this combinatory approach to reveal and quantify the evolution of wheeze nonlinearities with time.**

I. INTRODUCTION

FROM the variety of abnormal breath sounds, wheezes are frequently met, as they are related with obstructive airways diseases, such as asthma and chronic obstructive pulmonary disease (COPD) [1]. Wheezes are continuous lung sounds with time duration greater than 150 ms [2], which discriminates them from other abnormal sounds, such as crackles, which typically last less than 20 ms [3]. The waveform of a wheeze in time domain resembles that of a sinusoidal sound, justifying its musicality; hence, wheezes appear as distinct peaks in the frequency domain (>100 Hz) [3].

Although the pathophysiologic mechanisms that generate wheezes are not entirely clear [4], they are believed to be produced by periodic oscillations of the air and airway wall and are categorized into monophonic and polyphonic wheezes [5]. To this end, analysis of the harmonic interaction of wheezes becomes important.

Automatic wheeze detection was based on methodologies that combined spectra with criteria or rules concerning the amplitude, duration and pitch range of wheezes [5]-[8]. Although significant scientific effort was placed on the detection of wheezes, a limited number of works [5], [9], dealt with the nonlinear interactions of their harmonic content.

In the present study, wheeze analysis is performed combining continuous wavelet transform (CWT) with third-order statistics/spectra. More precisely, quadrature phase-coupling between wheeze harmonics is investigated, based on wavelet bispectrum (WBS) and wavelet bicoherence (WBC) as a means to track and quantify the evolution of the nonlinear characteristics of wheezes within the breathing cycle. The combination of wavelet transform with third-order statistics/spectra introduces the nonlinear analysis of wheezes in the time-bi-frequency domain. The proposed analysis was tested on breath sounds with wheezes recorded from asthmatic patients and attempts to shed light to wheeze nonlinear characteristics associated with underlying pathologies. Differences in the degree of these nonlinearities and phase coupling of wheezes could form a new tool towards the characterization and feature extraction of the associated pulmonary pathologies.

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II. METHODOLOGY

A. Continuous Wavelet Transform (CWT)

The continuous wavelet transform (CWT) is defined as [10]

$$W_x(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t)\psi^*\left(\frac{t-b}{a}\right)dt , \tag{1}$$

where $x(t)$ is the signal in time-domain, ($x(t) \in L^2(\Re)$), * is the complex conjugate and $\psi(t)$ is the mother wavelet scaled by a factor a , $a > 0$, and dilated by a factor b . In the CWT, the time and scale parameters (a,b) are continuous. Due to its direct analogy to the Fourier transform, the complex Morlet wavelet is chosen for the realization of the CWT, which is given by [11]

$$\psi(t) = \frac{1}{\sqrt{\pi f_b}} e^{-t^2/f_b} e^{j2\pi f_c t} , \tag{2}$$

where f_b is a bandwidth parameter and f_c is the wavelet center frequency.

B. Higher-Order Spectra (HOS)

The bispectrum (BS) $B(\omega_1,\omega_2)$ of a process $\{X(k)\}$ is defined as [12]:

$$B(\omega_1,\omega_2) = E\{X(\omega_1)X(\omega_2)X^*(\omega_1+\omega_2)\} , \tag{3}$$

where $E\{\cdot\}$ is the expectation value, $X(\omega_i), i = 1,2$ is the complex Fourier coefficient of the process $\{X(k)\}$ at frequencies ω_i and $X^*(\omega_i)$ is its complex conjugate. The bicoherence (BC), or normalized BS, is defined as [12]:

$$b(\omega_1,\omega_2) = \frac{B(\omega_1,\omega_2)}{[P(\omega_1)P(\omega_2)P(\omega_1+\omega_2)]^{1/2}} , \tag{4}$$

where $P(\omega_i), i = 1,2$ is the power spectrum at frequencies ω_i of the process. The magnitude of BC, $|b(\omega_1,\omega_2)|$, or bicoherency index, constitutes a measure of the amount of quadrature phase-coupling that occurs in a signal between any two of its frequency components, due to their non-linear interactions. The bicoherence index is bounded between 0 and 1; when $|b(\omega_1,\omega_2)|$ is equal to

1, the frequency components at ω_1 and ω_2 are completely phase-coupled, whereas, when $|b(\omega_1,\omega_2)|$ is equal to 0, there is no quadrature phase-coupling between the harmonics at ω_1 and ω_2 [13].

C. Wavelet-based HOS

By analogy to the definition of the bispectrum in Fourier terms (see (3)), the wavelet bispectrum (WBS) is defined as [14]

$$B_w(a_1,a_2)=\int_T W_x^*(a,\tau)W_x(a_1,\tau)W_x(a_2,\tau)d\tau\,, \tag{5}$$

where the integration is done over a finite time interval $T:\tau_0\le\tau\le\tau_1$, and α,α_1,α_2 satisfy the following rule:

$$\frac{1}{a}=\frac{1}{a_1}+\frac{1}{a_2}\,. \tag{6}$$

WBS expresses the amount of quadrature phase-coupling in the interval T, which occurs between wavelet components of scale lengths a_1,a_2, and a of $x(t)$ such that the sum rule of (6) is satisfied. By interpreting the scales as inverse frequencies, $\omega=2\pi/a$, the WBS can be interpreted as the coupling between wavelet coefficients at frequencies that satisfy $\omega=\omega_1+\omega_2$, within the frequency resolution.

Similarly to the definition of BC (see (4)), the wavelet bicoherence (WBC) can be defined as the normalized WBS, i.e.,

$$b_w(a_1,a_2)=\frac{B_w(a_1,a_2)}{\left\{\left[\int_T\left|W_x(a_1,\tau)W_x(a_2,\tau)\right|^2d\tau\right]\left[\int_T\left|W_x(a,\tau)\right|^2d\tau\right]\right\}^{1/2}} \tag{7}$$

which magnitude $|b_w(a_1,a_2)|$ can attain values between 0 and 1. For ease of interpretation, the squared WBC plotted in the $(\omega_1,\omega_2)-$plane, i.e., $|b_w(\omega_1,\omega_2)|^2$, is preferred. Due to the symmetries in the definition and the limitation set by the Nyquist frequency ω_s [15], the estimation of WBC in the whole bi-frequency plane can be based on its values in the principal region $\{\Delta:\omega_1,\omega_2\le\omega_1,\omega_1+\omega_2\le\omega_s\}$.

For comparing cases computed under the same numerical conditions, the summed wavelet bicoherence (SWBC) could be introduced as

$$b_w^2(\omega)=\sum_\Delta b_w^2(\omega_1,\omega_2)\,. \tag{8}$$

In general, the numerical values of SWBC depend on the chosen calculation grid, thus they basically provide qualitative summarization of the underlying information.

As van Milligen *et al.* [14] note, the use of non-orthogonal wavelets, like Morlet, results in non statistically independent wavelet coefficients. This introduces a statistical noise level in the estimation of WBC, with an upper bound given by [14]

$$N_b(\omega_1,\omega_2)\approx\left[\frac{\pi}{\min\left(|\omega_1|,|\omega_2|,|\omega_1+\omega_2|\right)}\frac{1}{T}\right]^{1/2}. \tag{9}$$

From (9) it can be easily observed that the statistical noise affects the low frequencies of WBC, whereas, at higher ones it drops rapidly with T. This reveals the power of WBC to serve as a noise filter for coherent signals.

Since the WBC defined in (7) refers to a certain time interval T, its value is corresponded to the center of this interval, i.e., $t_0=T/2$. Consequently, the evolutionary WBC (EWBC) can be defined as

$$\begin{aligned}&\mathbf{b}_w(\omega_1,\omega_2,t)=\{b_w(\omega_1,\omega_2)\,|_{t=t_0+k\Delta T_1}\},\\&k=0,1,2,3,...;(2\pi/\omega_s)\le\Delta T_1\wedge k\Delta T_1\le T_{total}-2t_0\end{aligned}\,, \tag{10}$$

where T_{total} is the total time duration of the analyzed signal $x(t)$. When using EWBC, the evolution of the nonlinearities across time can be represented, within a time-resolution controlled by the selection of the ΔT_1 value.

III. Data Set and Implementation Issues

The proposed analysis was tested on breath sound signals from asthmatic patients, drawn from the MaRS database (Philipps University of Marburg, Germany) [16]. Airflow signals (maximum flow 1.5 l/s) were recorded simultaneously to the breath sound recording, using a pneumotachograph. Signal conditioning, i.e., amplification and band pass filtration (60-2100 Hz at 48 dB/oct, Butterworth), was performed prior to analogue-to-digital conversion with a 12-bit resolution at a sampling frequency of $f_s=5512$ Hz. More details about the dataset can be found in [16]. Wheeze analysis was carried out using Matlab 7.0 (The Mathworks Inc., Natick, MA). The frequency range of analysis was selected as $f=100:10:1000$ Hz with corresponding scales calculated by $a=f_cf_s/f$, a central frequency of Morlet wavelet at $f_c=0.8125$ Hz and its bandwidth parameter equal to $f_b=128$. The window duration was selected as $T=1$ s, since it was found that the maximum magnitude of the squared WBC settles around some value for $T\ge0.8$ s, while the time resolution as $\Delta T_1=0.5$ s.

IV. Results and Discussion

Figure 1(a) depicts one breathing cycle of a breath sound signal along with the normalized airflow (superimposed with a dotted-line) recorded from an asthmatic patient. As it can be seen from Fig. 1(a), the breath sound signal exhibits a profound high amplitude section (~1.2-2.8 s) corresponding to inspiratory wheeze, whereas an extended expiratory wheeze (~3.7-6.3 s) with decaying amplitude dominates the expiratory phase (negative airflow).

Figure 1(b) shows the corresponding CWT. From this figure, the harmonic character of wheezes (both inspiratory and expiratory) is apparent. Clearly, there are coexisting distinct spectral peaks within the area of 150 to 500 Hz that emerge during the appearance of wheezes, revealing their polyphonic character (like a chord). In addition, a frequency sweep from low to high frequencies and vice versa can be noticed, mainly at the beginning and end of wheezes, due to the increase or decrease of the airflow signal, respectively.

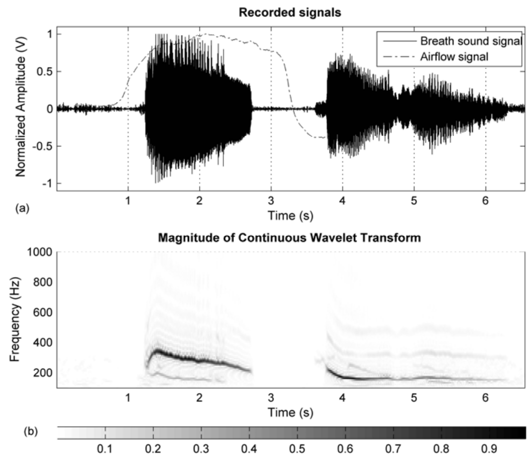

Fig. 1. An indicative example of the analyzed signal. (a) One breathing cycle of a breath sound recording from an asthmatic patient with two dominant wheezes (one inspiratory and one expiratory); (b) time-frequency (TF) representation of the analyzed signal using the continuous wavelet transform.

Moreover, the spectral peak within 200-400 Hz that sustains its high amplitude during the inspiratory wheeze is subsided in the expiratory one, where the spectral peak around 200 Hz seems to be the most evident one.

The ability of WBS and WBC to capture the existence of nonlinearities in wheezes is shown in Fig. 2. In particular, the estimated magnitude of WBS (top), WBC (middle) and squared WBC (bottom) are illustrated in Figs. 2(i) and 2(ii), for a time section without wheeze (2.75-3.75 s) and with wheeze (3.75-4.75 s), respectively, corresponding to sections from the breath sound signal depicted in Fig. 1(a). From the comparison of the estimated WBS in Figs. 2(i) and (ii) it is apparent that the WBS of the section without wheeze (Fig. 2(i)-top) is spread in the area of low frequencies (100-150 Hz) and does not exhibit any distinct peak at a higher-frequency range; furthermore its values are significantly lower compared to those of the section with wheeze (Fig. 2(ii)-top). In the latter, the WBS reveals a concentration of its values around a peak located approximately at $(f_1, f_2) \approx (200{,}200)$ Hz. This implies that a possible quadrature self-phase-coupling exist at $(f_1, f_2) \approx$ (200,200) Hz related to the frequency located at $f_3 = f_1 + f_2 \approx 400$ Hz. Clearly, the inspection of CWT of Fig. 1(b) at the selected section justifies the existence of f_3.

The quantitative evaluation of the degree of quadrature phase-coupling is facilitated by the estimation of the magnitude of the corresponding WBC. Looking at the estimated magnitude of the squared WBC for both cases (Figs. 3(i)- and (ii)-middle) a more enhanced resolution of the bi-frequency content is provided. In Fig. 2(i)-middle, a wider spread is noticed, spanning from 100 Hz to 600 Hz, whereas in Fig. 2(ii)-middle, additional distinct peaks appear at higher frequencies. Comparing the values of the squared WBC of Figs. 3(i)- and (ii)-middle it can be seen that they are much lower in the time section that is without wheeze (maximum value of 0.15) than those of the time section that contains wheeze (maximum value of 0.8). This shows that practically there is no quadrature phase-coupling in the WBC content corresponding to the breath sound signal that does not contain wheeze; on the contrary, a strong quadrature phase-coupling exists between the harmonics revealed in the WBC content corresponding to the breath sound signal that contains wheeze. In particular, the distinct peaks at $(f_1, f_2) \approx (200{,}200)$ Hz and $(f_1, f_2) \approx (350{,}200)$ Hz correspond to squared WBC values of ~0.8 and ~0.7, respectively, justifying the quadrature self-phase-coupling at $(f_1, f_2) \approx (200{,}200)$ Hz related to the frequency located at $f_3 = f_1 + f_2 \approx 400$ Hz and the quadrature phase-coupling at $(f_1, f_2) \approx (350{,}200)$ Hz related to the frequency located at $f_4 = f_1 + f_2 \approx 550$ Hz. Moreover, in Fig. 2(ii)-middle, there are some peak formations whose frequency presents a constant increase, yet with smaller magnitude implying a smaller degree of quadrature phase-coupling. In particular, there is a peak starting from $(f_1, f_2) \approx (600{,}400)$ Hz and ending at $(f_1, f_2) \approx (800{,}400)$ Hz, which leads to the conclusion that there is one frequency component present whose frequency varies and is equal to $f_1 = 350:450$ Hz, another that has varying pitch equal to $f_2 = 600:800$ Hz and their sum $f_5 = f_1 + f_2 \approx 950:1250$ Hz or their difference $f_6 = |f_1 - f_2| \approx 250:350$ Hz. Figure 1(b) demonstrates that the difference frequency component f_6 is present, and its frequency actually demonstrates decrease.

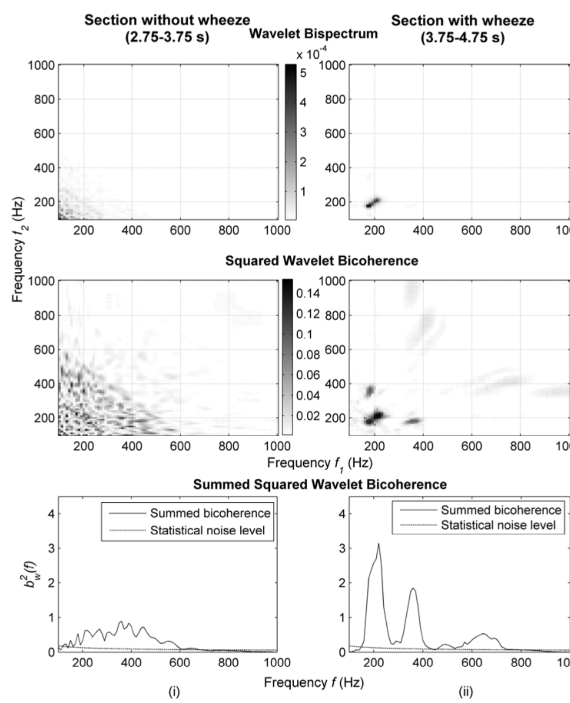

Fig. 2. Experimental results from the analysis of the breath sound signal shown in Fig. 1(a). (i): Section without wheeze (2.75-3.75 s) (ii): Section with wheeze (3.75-4.75 s). In both cases, the wavelet bispectrum (top subfigure), squared wavelet bicoherence (middle subfigure) and summed squared wavelet bicoherence along with statistical noise level (--) (bottom subfigure) are depicted, accordingly.

To further demonstrate the difference between the two sections in the degree of nonlinearity, the SWBC was estimated for both cases, shown in Figs. 2(i)- and (ii)-bottom, respectively. The SWBC is plotted along with the upper bound of the statistical noise level (dotted line) defined in (11). From the two subfigures it is apparent that the SWBC of the breath sound without wheeze (Fig. 2(i)-bottom) sustains a low value at a frequency range of 100-600 Hz, whereas the SWBC of the breath sound with wheeze (Fig. 2(ii)-bottom) demonstrates high peaks around 200 Hz and 350 Hz and a lower one around 650 Hz, showing a clear difference from the previous case. Note that in both cases, the estimated SWBC values overpass the noise level, justifying their reliability.

The evolution of the nonlinearities in breath sound signal that contains wheezes is demonstrated through the estimation of the ESWBC defined in (10). Its graphical representation for the whole breath sound signal shown in Fig. 2(a) with an isosurface $\left|b_w(f_1, f_2)\right|^2 = 0.2$ shown in Fig. 3. The vertical axis corresponds to time with a resolution of $\Delta T_1 = 0.5$ s. From this figure, it is apparent that quadrature phase-coupling occurs in both breathing phases only at the time instances where the wheezes exist. Moreover, the main frequency pair with quadrature self-phase-coupling [$(f_1, f_2) \approx (200,200)$ Hz] is sustained both in inspiratory and expiratory wheezes; however, additional pairs at higher frequencies with quadrature phase-coupling emerge during the expiratory wheeze. This relates to the pathology of asthma, as it affects more the expiratory phase than the inspiratory one of asthmatic patients [17].

From the above analysis it is clear that the introduction of time through the wavelet transform facilitates the dynamic identification of nonlinearities of the localized wheezes within the breathing cycle.

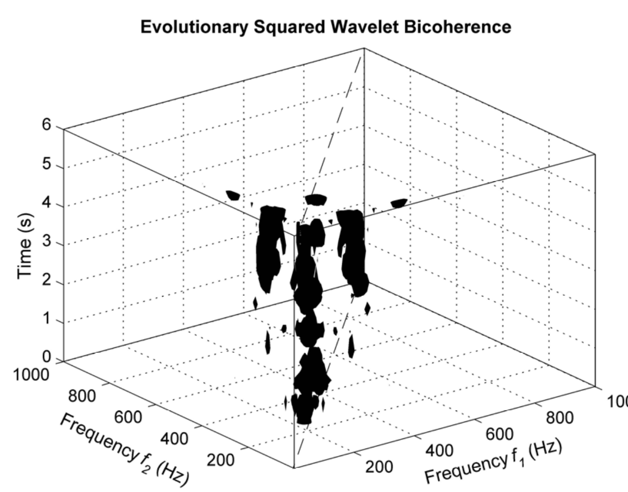

Fig. 3. Experimental Evolutionary squared wavelet bicoherence for isosurface $\boldsymbol{b}_w^2(f_1, f_2) = 0.2$.

V. Conclusion

A combination of wavelet transform with third-order statistics/spectra applied to nonlinear analysis of wheezes was presented in this study. This combinatory approach allowed for dynamic capturing of the nonlinear characteristics of wheezes, as they evolve during the breathing cycle. The promising results presented here allow the extension of this analysis to large-scale experiments, to further explore the association of these nonlinear characteristics of wheezes with the type and the severity of the related pathology.

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