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Wavelets' filters and higher-order frequency analysis of acoustic emission signals from termite activity ☆

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ABSTRACT

A comparative analysis between two higher-order statistics in the frequency domain, combined with wavelets' filters, confirms the existence of three frequency sub-bands that characterize the species emission. De-noising via wavelet eliminates the symmetrical noise and reveals non-Gaussian features. Here, we show that the spectral kurtosis enhances the low and high-frequency components with high power variability, once the filter banks are applied, revealing new zones in the spectrum that are associated to high variability in the amplitudes. Despite de-noising via wavelets, the bi-spectrum is attenuated, but it confirms the frequency pattern of the emission, denoting at the same time the non-zero skewness of these components. Complementarily, it is observed that high bi-frequencies are attenuated more severely, suggesting the idea that certain frequencies content more information regarding symmetry than others. Results have been confirmed using three common wavelet families.

1. Introduction

Subterranean termites' emissions comprise complex sequences of low-level impulses.[1] Focussing on the acoustic (and near acoustic) emissions, we can distinguish between activity signals (associated to feeding and excavating) and the alarms (burst of 4 or 5 impulses depending on the species), which are produced in presence of a threaten, produced by the so-called "head banging", and with a frequency content below 4 kHz [1–8].

The key of detection resides in being capable of measure the chaotic low-level acoustic sequences that denote activity before the community of insects adopt the state of alarm (complete silence). Depending on the media and the species, characterization of the acoustical tracks may vary drastically both in time and frequency domains, because the impulses trains propagate through nonlinear media, making detection very sensitive to noise and false positives [6,8].

Inside this nonlinear scenario, numerous of works have demonstrated that Higher-Order Statistics (HOS) provide essential information regarding statistical parameters beyond the Gaussian model [8], managing to model impulsiveness and non stationary phenomena. Additionally, wavelet-based methods have been extensively used for removing additive noise; subtracting a threshold from the wavelet coefficients of noisy data. In a former work, the research team has proposed a method that uses wavelets, entropy and the Spectral Kurtosis (SK) in a preliminary stage, working over a concrete set of real-life signals [9]. In that study, it was proven that wavelets filters banks, working up to the fourth decomposition level, are capable of enhancing the fourth-order spectrum of the carrier frequencies. However, the detection rate was not still satisfactory due to the residual of false positives impulses that cannot be erased via the mirror filters. The present work confirms that the bi-spectrum can be employed to optimize the detection process, as it provides extra information associated with the carrier frequencies. It aims to compare the bi and tri-spectra performance in the following sense.

An average spectrum of the emission (feeding and excavating) is organized around carriers or principal zones in the bandwidth (e.g., 5–6 and 15–16 kHz in [9]). The spectral kurtosis enhances these bumps, attending only to the time variability of the amplitudes; and this happens despite the fact that time-domain power (amplitude) has been weakened after the application of the

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[1] In Europe, only two genus are common: *Kalotermes* and *Reticulitermes*. This work involves the species *Reticulitermes Grassei*.

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discrete filter banks. What is more, these filters maintain only the shapes (waveforms) which match the emission; so eventually this fact can help to confirm new singular frequencies (20 kHz in the present work).

Complementarily, the bi-spectrum confirms the former carriers (or bumps around the carriers) once the Discrete Wavelet Transform (DWT) is applied. Expectedly, as the bi-spectrum is a measure of the emissions' asymmetry, when removing details that contributed to asymmetry (rapid variations in the signal), the bi-spectrum value decreases globally. While the two first bumps are attenuated similarly, the very high-frequency components (the bump around 20 kHz) are significatively attenuated. As an additional consequence, this may arise the fact that discrete wavelets act like symmetry filters over the highest frequencies, offering a branch of possibilities to entomologists, as this interval of frequencies can be easily extracted using easy-to-handle equipment.

After presenting the background context of the wavelets applied to de-noising, in Section 2, the experimental results in Section 3 show that the main diagonal slices in the bi-spectrum tensorial data structure are enough to provide the skewness information of each frequency component. This is the main conclusion in Section 4, that draws a balance of the research and future works.

2. Theory background

The orthonormal bases $\{\psi\}_{j,k\in\mathbb{Z}}$ and $\{\phi\}_{j,k\in\mathbb{Z}}$ of the wavelet and scaling orthogonal subspaces ($\mathbf{W}_j$ and its orthogonal complement $\mathbf{V}_j$, respectively) in Eq. (1), allow the decomposition of any finite-energy signal $s(t)$ according to Eq. (2), for a given decomposition level J, and a maximum time shift τ_{max}:

$$\left\{[\psi,\phi]_{j,k}(t) = \frac{1}{\sqrt{2^j}}\cdot[\psi,\phi]\left(\frac{t-2^jk}{2^j}\right)\right\}_{(j,k)\in\mathbb{Z}^2}, \tag{1}$$

where k denotes the time-shifting index and j indicates the level in the decomposition tree [10]:

$$s(t) = \sum_{k=-\tau_{max}}^{\tau_{max}} a_J[k]\phi_{J,k}(t) + \sum_{j=1}^{J}\sum_{k=-\tau_{max}}^{\tau_{max}} d_j[k]\psi_{j,k}(t), \tag{2}$$

where $a_J[k] = \langle s, \phi_{J,k}\rangle\phi_{J,k}$, is the coarser resolution (low variations) of $s(t)$ at the level J, and $d_j[k] = \langle s, \psi_{j,k}\rangle\psi_{j,k},\ j = 1,\ldots,J$, with $k \in \mathbb{Z}$, are the detail coefficients (associated to rapid changes). The former projections are the so-called detail and approximation coefficients, cA_J and cD_j respectively.

A particular case of decomposition is de-noising. The wavelet-based detection procedure consists of applying a couple of mirror filters for each decomposition level. The procedure of noise reduction for a given signal $s(t)$ is based on decreasing the noise content of its high frequency components (detail coefficients), preserving at the same time the characteristic shape of the signal. The threshold values for the detail coefficients (cD_j) at every level of decomposition are determined according to the relationship in Eq. (3):

$$thr_j = \sqrt{2\cdot log\|cD_j(t)\|}, \tag{3}$$

and the soft (in this work) thresholding procedure is accomplished according to Eq. (4):

$$cD_j(t) = \begin{cases} (|s| - thr_j), & cDj > thr_j \\ 0, & cDj \leqslant thr_j \end{cases} \tag{4}$$

Filter banks are second-order statistical estimators. Therefore, the role of the bi-spectrum is to add information, e.g. regarding the phase of the signals and the interdependency of its frequency components, this arises symmetry properties associated to the probability density function. The discrete bi-spectrum of $s(t)$ is defined using the *Fourier* convolution theorem as the double transform, according to Eq. (5):

$$B(f_1,f_2) = \sum_{\tau_1=-\tau_{1,max}}^{\tau_1=\tau_{1,max}}\ \sum_{\tau_2=-\tau_{2,max}}^{\tau_2=\tau_{2,max}} w(\tau_1,\tau_2)C_{3,s}(\tau_1,\tau_2) \times \exp\left[-j2\pi(f_1\tau_1+f_2\tau_2)\right], \tag{5}$$

where $w(\tau_1,\tau_2)$ is a 2D window function (*Hamming*-type in the work), and $C_{3,x}(\tau_1,\tau_2)$ is the third-order cumulant of the signal under test, i.e. $C_{3,s}(\tau_1,\tau_2) = E\{s(t)s(t+\tau_1)s(t+\tau_2)\}$, being $E\{\}$ the expectation operator, τ_1 and τ_2 the time shifting variables, and (f_1,f_2) the bi-frequency [11]. Eq. (5) is an indirect estimation of the bi-spectrum, since it is based in the cumulants.

The bi-spectrum is intended to confirm the asymmetrical frequency components that have been enhanced by the fourth-order spectrum, which enhances the impulsiveness in the time domain. While the second order-filters banks act decisively over the performance of the spectral kurtosis preserving the transients with the same shape as the mother wavelet, they should attenuate the third-order spectrum because it eliminates noise, and adjust the symmetry of the measurement time-series. Therefore, bi-spectrum will corroborate detection and, at the same time it shows the second order nature of the wavelets. Additionally, not all frequencies are equally attenuated, as they exhibit different symmetry properties, inherited from the time-domain measurements.

3. Results

Wavelets are applied to the data and then the higher-order statistics performance is compared over filtered and non-filtered time-series of measurements. The wavelet analysis (de-noising) has been performed with the following adjustment parameters. Mother wavelets: Daubechies 9 (*db9*), *sym8* (of the *symlets* family), and the B-spline bi-orthogonal wavelet (3 vanishing moments in the synthesis wavelet and 5 vanishing moments in the analysis wavelet, *bior3.5*).

The three families are common and serve as high-valuable test tools to compare results. Daubechies are compactly supported orthonormal wavelets. The *symlets* are nearly symmetrical wavelets. The bi-orthogonal family of wavelets exhibits the property of linear phase, which is needed for signal and image reconstruction. We present results for the *sym8* performance.

The soft and global threshold have been chosen for the four decomposition levels, and the approximation coefficients are not thresholded. Beyond level 4, the reconstructed version does not reproduce with fidelity the original emission (the spectra are definitively distorted).

The measurement session took place in a garden in Southern Spain (Malaga, Andalusia), using the sensor SP-1L (*Acoustic Emission Testing*) and the sound card of the portable computer. A number of 100 recordings, each containing 220,000 data, were captured using the sound card of a portable computer, and the audio input, which was attached to the transducer charge-to-volt modulus.

Fig. 1 shows a comparative example of a second and fourth-order analysis. While the power spectral density (PSD in the two top graphs) after applying wavelets is clearly reduced (70% on average), the Spectral Kurtosis (SK in the two lower graphs) operates the other way round, enhancing the whole spectrum, but specially the frequency bumps corresponding to alarms (left to 5 kHz) and feeding and excavating emissions (to the right of 5 kHz, and around 15.5 kHz and 20 kHz carriers). This is due to the fact that the SK accounts for the peakedness of the probability curve associated to each frequency and is enhanced once the *noise floor* is