A SIGNAL PROCESSING MODULE FOR NON-DESTRUCTIVE TARGETING OF TERMITE ACTIVITY USING THE SPECTRAL KURTOSIS AND THE DISCRETE WAVELET TRANSFORM

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ABSTRACT

In this paper we present the operation results of a portable computer-based measurement equipment conceived to perform non-destructive testing of suspicious termite infestations. Its signal processing module is based in the Spectral Kurtosis (SK), with the de-noising complement of the Discrete Wavelet Transform (DWT). The SK pattern allows the targeting of alarms and activity signals. The DWT complements the SK, by keeping the successive approximations of the termite emissions, supposed more non-gaussian (less noisy) and with less entropy than the detail approximations. For a given mother wavelet, the maximum acceptable level, in the wavelet decomposition tree, which preserves the insects' emissions features, depends on the comparative evolution of the approximations details' entropies, and the value of the global spectral kurtosis associated to the approximation of the separated signals. The paper explains the detection criterion by showing real-life recordings.

1. INTRODUCTION

This paper deals with the performance of a final-version equipment for termite detection, whose previous prototype's performance was described in [1]. The measurement method is mainly based in the interpretation of the spectral kurtosis graph, along with the wavelet analysis. We use the sound card, which simplifies the hardware and the criterion of detection.

The instruments for plague detection are thought with the objective of decreasing subjectiveness of the field operator. At the same time, they should be conceived to perform an early targeting of the plague, in order to treat the infestation before serious economic damage occurs. On-site monitoring implies reproducing the natural phenomenon of insect emissions with high accuracy. As a consequence it is imperative the use of a deep storage device, and high sensitive probes. These features make the price paid very high, and still do not guarantee the success of the detection. Besides, the expert's subjectiveness plays a crucial role.

The methods in which the instruments are based are very much dependent on the detection of excess of power in the signals; these are the so-called second-order methods, e.g. the RMS calculation, which does not provide information regarding the time fluctuations of the amplitudes. Another handicap of the second-order principle, e.g. the classical power spectrum, attends to the preservation of the energy during data processing. Consequently, the eradication of additive noise lies in filter design and sub-band decomposition.

As an alternative to improve noise rejection and complete characterization of the signals, in the past ten years, a myriad of higher-order methods are being applied, in scenarios which involve signal separation and characterization of non-Gaussian signals. The main handicap of applying higher-order statistics is the amount of data which they generate, and that have to be stored in the measurement unit. An examination of the multi-dimensional data structures (tensors) reveals redundant (symmetrical) information; so relevant directions have to be selected within the tensor data structure. Secondly, the interpretation of higher-order cumulants and poly-spectra are reduced to a set of catalogued noise processes, and only a few attempts have been made in order to characterize the processes via HOS.

This paper describes a method based in the spectral kurtosis (a modification of the method described in [2] and [1]) to detect infestations of subterranean termites in a real-life scenario (Southern Spain). Wavelet decomposition is used as an extra tool to aid detection from the preservation of the approximation of the signal, which is thought to be more Gaussian than the details.

The measurement site was selected by our partner plague eradication company, to be a suspicious location. Speech and the typical urban background sounds clearly bury the termites' emissions, which came from the soil, under all of us. Sounds were not audible, except from alarms signals, only produced when termites are clearly disturbed.

The interpretation of the results is focussed on the peakedness of the statistical probability distribution associated to each frequency component of the signal, to measure the distance from the Gaussian distribution. The spectral kurtosis serves as a twofold tool. First, it enhances non-Gaussian signals over the background. Secondly, it offers a more complete characterization of the transients emitted by the insects.

The paper is structured as follows: in Section 2 a review on termite detection and relevant HOS experiences sets the foundations. In Section 3 we make a brief report on the definition of kurtosis; we use an unbiased estimator of the spectral kurtosis, successfully used in [1], using a higher measurement bandwidth. Results are presented in Section 5. Wavelets are summarized in Section 4. Finally, conclusions are drawn in Section 6.

2. TERMITE DETECTION AND HIGHER-ORDER STATISTICS

Subterranean termites nest in the soil to obtain moisture, but they also nest in wood that is often wet. They can also build mud tunnels to reach wood several meters above the ground. These tunnels can extend for 15-20 meters to reach wood and often enter a structure through expansion joints in concrete slabs or where utilities enter the house. Termites are able to travel up to 40 meters from the colony and, once they discover a food source, they leave a *chemical track* for others to follow.

Termite detection has been gaining importance within the research community in the last two decades, due to the urgent necessity of avoiding the use of harming termiticides, and to the joint use of new emerging techniques of detection and hormonal treatments (IGR[1] products), with the aim of performing an early treatment of the infestation. A partial infestation can be exterminated after two or three generations of the colony's members with the aid of these hormones, which stop chitin synthesis [1].

The primary method of termite detection consists of looking for evidence of activity. But only about 25 percent of the building structure is accessible, and the conclusions depend very much on the level of expertise and the criteria of the inspector [3]. As a consequence, new techniques have been developed to remove subjectiveness and gain accessibility.

User-friendly equipment is being currently used in targeting subterranean insect infestations by means of temporal analysis of the vibratory data sequences. An acoustic-emission (AE) sensor or an accelerometer is fixed to the suspicious structure. The hits are captured by the transducer and registered by the counting assembly inside the hand-held instrument. This class of instruments is based on the calculation of the root mean square (RMS) value of the vibratory waveform. The RMS value comprises information of the AE raw signal power during each time-interval of measurement (averaging time). This measurement strategy coveys a loss of potentially valuable information both in the time and in the frequency domain. In fact, the events are averaged over time and the instantaneous occurrence of the impulses is omitted. Looking at the frequency content of the signals, the only possible action for the field operator is the option of pre-filtering, which allows the suppression of low-frequency audio signals which mask termites' emissions.

A more sophisticated family of instruments makes use of spectral analysis and digital filtering to detect and characterize vibratory signals [1]. Both classes of systems (counting-assemblies and spectrum-based) have the drawback of the relative high cost and their practical limitations.

From the practical point of view, the utility of the above acoustic techniques and equipment for detection depends very much on several biophysical factors. The main one is the amount of distortion and attenuation as the sound travels through the soil ($\sim$600 dB m^{-1}, compared with 0.008 dB m^{-1} in the air). This is the reason whereby digital signal processing techniques emerged as an alternative.

On the other hand, second-order statistics (i.e. correlation) and power spectra estimation (the second-order spectrum) fail in low SNR conditions even with *ad hoc* piezoelectric sensors. Spectrum estimation and spectrogram extract time-frequency features, but ignoring phase properties of the signals. Besides, second-order algorithms are very sensitive to noise, which makes the users' identification criteria (mainly based on frequency-pattern recognition) being difficult to apply without great uncertainty. Complementary second-order tools, like wavelets and wavelet packets (time-dependent technique) concentrate on transients and non-stationary movements, making possible the detection of singularities and sharp transitions, by means of sub-band decomposition [4].

Higher-order statistics, are being widely used in several fields. In the field of termite detection, a cumulant-based independent component analysis algorithm has proven to separate termites' alarm signals from synthetics noise backgrounds in a blind source separation scenario.The information contained in the diagonal of the bi-spectrum data structure has proven to enhance the frequency pattern of the termites' emissions [5].

3. CUMULANTS AND THE SPECTRAL KURTOSIS

Higher-order cumulants are polynomial functions of the moments, and they are related each other via a recursive formula, described in Eq. (1):

$$\kappa_r = \mu'_r - \sum_{k=1}^{r-1} \binom{r-1}{k-1} \kappa_k \mu'_{r-k} \quad (1)$$

In multiple-signal processing it is very common to define the combinational relationship among the cumulants of r stochastic signals, $\{x_i\}_{i\in[1,r]}$, and their moments of order $p, p \le r$, given by using the *Leonov-Shiryaev* formula [6]

$$\begin{aligned} Cum(x_1,...,x_r) = \sum(-1)^{p-1}\cdot(p-1)!\cdot E\{\prod_{i\in s_1} x_i\} \\ \cdot E\{\prod_{i\in s_2} x_j\}\cdots E\{\prod_{i\in s_p} x_k\}, \end{aligned} \quad (2)$$

where the addition operator is extended over all the partitions, like one of the form $(s_1, s_2, \ldots, s_p)$, $p = 1, 2, \cdots, r$; and $(1 \le i \le p \le r)$; being s_i a set belonging to a partition of order p, of the set of integers $1,\ldots,r$.

Ideally, the spectral kurtosis is a representation of the kurtosis of each frequency component of a process. For estimation issues we will consider M realizations of the process; each realization containing N points; i.d. we consider M measurement sweeps, each sweep with N points. The time spacing between points is the sampling period, T_s, of the data acquisition unit.

An unbiased estimator for the spectral kurtosis for M N-point realizations at the frequency index m is given by:

$$\hat{G}_{2,X}^{N,M}(m) = \frac{M}{M-1}\left[\frac{(M+1)\sum_{i=1}^{M}|X_N^i(m)|^4}{\left(\sum_{i=1}^{M}|X_N^i(m)|^2\right)^2} - 2\right]. \quad (3)$$

This estimator is the one we have implemented and it was also used successfully in [2]. To show its performance we have tested it with a synthetics matrix consisting of M=500 realizations or signals, each register containing N=1921 data. The sampling frequency is F_s=64,000 Hz. One realization is the linear combination of 5 signals. Two sine waves with constant amplitude values, at frequencies of 5 kHz and 15

[1]**I**nhibitor **G**rowth **R**egulators

kHz. One sine at 25 kHz with amplitude varying according to a Gaussian distribution. A white Gaussian process and, finally, a colored Gaussian process filtered between 10 and 11 kHz, by a 5th-order Butterworth digital bandpass filter. Fig. 1 shows the performance of the spectral kurtosis estimator over the synthetics. The kurtosis is negative for each frequency component with constant amplitude value, positive for the component with Gaussian-law amplitude, and null for the colored Gaussian noise. The spectral kurtosis is obviously zero for all the components of the white Gaussian noise.

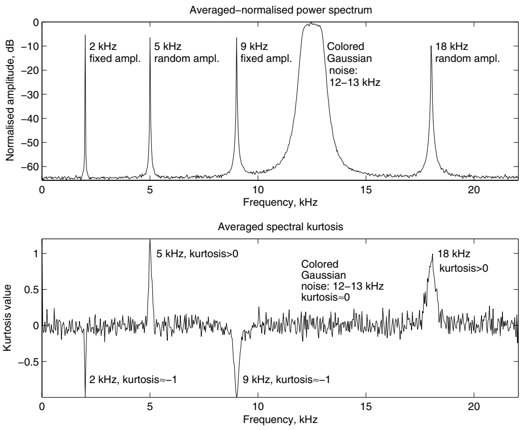

Figure 1: Performance of the spectral kurtosis estimator over a synthetics.

Regarding the experimental signals, we expect to detect positive peaks in the kurtosis's spectrum, which may be associated to termite emissions, characterized by random-amplitude impulse-like events. We assume, as a starting point, that non-Gaussian behavior of termite emissions is more acute than in speech. As a final remark, we expect that constant amplitude interferences are clearly differentiate due to their negative peaks in the SK graphs.

4. THE WAVELET TRANSFORM

A *mother wavelet* is a function ψ with finite energy[2], and zero average. This function is normalized[3], $\|\psi\| = 1$, and is centered in the neighborhood of t=0.

$\psi(t)$ can be expanded with a scale parameter a, and translated by b, resulting the *daughter functions* or *wavelet atoms*, which remain normalized:

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right); \tag{4}$$

The CWT can be considered as a correlation between the signal under study $s(t)$ and the wavelets (*daughters*). For a real signal $s(t)$, the definition of CWT is:

$$CWTs(a,b) = \frac{1}{\sqrt{a}}\int_{-\infty}^{+\infty} s(t)\psi^{*}\left(\frac{t-b}{a}\right)dt; \tag{5}$$

[2] $f \in \mathbf{L}^2(\Re)$, the space of the finite energy functions, verifying $\int_{-\infty}^{+\infty}|f(t)|^2\,dt < +\infty$.

[3] $\|f\| = \left(\int_{-\infty}^{+\infty}|f(t)|^2\,dt\right)^{1/2} = 1$.

where $\psi^{*}(t)$ is the complex conjugate of the mother wavelet $\psi(t)$, $s(t)$ is the signal under study, and a and b are the scale and the position respectively ($a \in \Re^{+} - 0, b \in \Re$). The scale parameter is proportional to the reciprocal of the frequency. Eq. (5) establishes that each coefficient provide numerical information about the similarity between the signal under study and the time-shifted frequency-scaled wavelet daughter.

In the Discrete Time Wavelet Transform (DTWT) only a subset of scale and time shifts are chosen. A tree-structure arrangement of filters allows the sub-band decomposition of the signal. The original signal passes through two complementary filters (*quadrature mirror filters*), and two signals are obtained as a result of a down-sampling process, corresponding to the approximation and detail coefficients. In each stage of the filtering process the same two digital filters are used: a high-pass and its mirror filter (low-pass). All these filters have the same relative bandwidth (ratio between frequency bandwidth and center frequency).

Any finite energy signal $s(t)$ can be decomposed over a wavelet orthogonal basis according to:

$$s(t) = \sum_{j=-\infty}^{+\infty}\sum_{k=-\infty}^{+\infty}\langle s, \psi_{j,k}\rangle \psi_{j,k} \tag{6}$$

Each partial sum, indexed by k, in Eq. (6) can be interpreted as the details variations at the scale $a = 2^j$ (at each level j of analysis, the scale is increased by a factor of two.):

$$d_j(t) = \sum_{k=-\infty}^{+\infty}\langle s, \psi_{j,k}\rangle \psi_{j,k} \qquad s(t) = \sum_{j=-\infty}^{+\infty} d_j(t) \tag{7}$$

The approximation of the signal $s(t)$ can be progressively improved by obtaining more layers or levels, with the aim of recovering the signal selectively. For example, if $s(t)$ varies smoothly we can obtain an acceptable approximation by means of removing fine scale details, which contain information regarding higher frequencies or rapid variations of the signal. This is done by truncating the sum in equation 6 at the scale $a = 2^J$:

$$s_J(t) = \sum_{j=J}^{+\infty} d_j(t) \tag{8}$$

Details corresponding to indexes $j < J$ are not gathered in Eq. (8).

Daubechies 5 has been selected as most similar wavelet mother, because of the highest coefficients in the decomposition tree. Given the wavelet mother, to show the process of selecting the maximum decomposition level in the wavelet tree, we have adopted a criterion based on the calculation of Shannon's entropy (information entropy), which is a measure of the uncertainty associated with a random variable X; this entropy denoted by $H(X)$, and defined by:

$$H(X) := -\sum_{i=1}^{N} p(x_i)\log_{10} p(x_i), \tag{9}$$

where X is an N-outcome measurement process $\{x_i, i = 1, \cdots, N\}$, and $p(x_i)$ is the probability density function of the outcome x_i.

We show this strategy via the following example, based on real-life data, which contain activity signals from termites, presented in Fig. 5 (without de-noising) and in Fig. 6

(once, the signal has been de-noised). The lower sub-figure in Fig. 6 is the result of the de-noising performance at the *4*th-decomposition level; using the global thresholding we keep the approximation signal. The entropy of the approximations and the details are compared for each level of comparison and shown in Fig. 2.

By looking at the graph of Fig. 2, at level 4, the entropy of the approximations is less than the entropy of the details. So level 4 is in a sense, a point of inversion. No improvement is obtained for level 5, where the entropies are very similar.

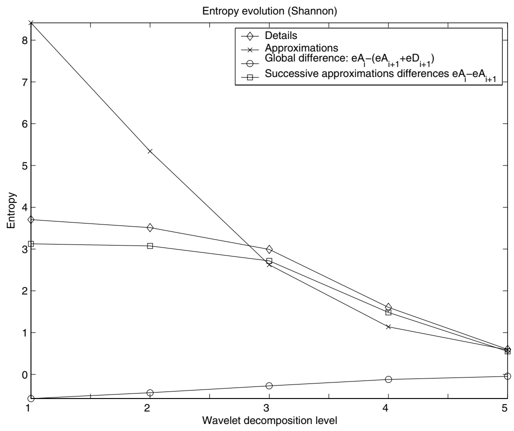

Figure 2: Evolution of the entropy.

We can also see that the global difference of entropies increases towards zero, at level 5, as a complementary indication that further decomposition will not suppose progress in de-noising.

5. EXPERIMENTS AND RESULTS

5.1 The instrument and the measurement procedure

A piezoelectric probe-sensor (model SP-1L from *Acoustic Emission Consulting*) is used in the final version of the instrument, and was described in detail in [1]. The sensor is connected to the sound card of a lap-top computer and the acquisition is driven by MATLAB, via the Graphical User Interface (GUI) (not shown in this paper).

The transducer SP-1L was used to record the data registers in the field experience, and the ICP unit (**I**ntegrated **C**ircuit **P**iezoelectric; ICP interface) was connected to the sound card of a lap-top computer, configuring an autonomous measurement unit (the sampling frequency was F_s=44,100 Hz). The recording stage took place in a garden with evidence of infestation, and the bare waveguide of the sensor was introduced in the lawn, over the suspicious zone.

Termite sounds from feeding are like sharp pops and crackles in the audio output. The key of the spectral kurtosis detection strategy used in this work lies in the potential enhancement of this non-Gaussian behavior of the emissions. If this happens, i.e. if an increase of the non-Gaussian activity (increase in the kurtosis, peakedness of the probability distribution) is observed-measured in the spectral kurtosis graph, there may be infestation in the surrounding subterranean perimeter, where the transducer is attached.

Termite emissions are non-stationary, so the instrument treats data by ensemble averaging of the sample registers, following the indications in [7] (pp. 463-465). Each spectrum and spectral kurtosis graph presented in this section is the result of averaging the spectra of the sample registers, or realizations. As a final remark, acquired data is normalized according to the norm: $\|s\| = \left(\sum_{i=1}^{N} |s_i|^2\right)^{1/2}$.

5.2 Operating cases

In this subsection we present two possible situations associated to the measurement cases. We present the signals out of the instrument display in order to be analyzed more precisely. A data acquisition time of 5 seconds and a sample frequency of 44,100 Hz have been selected. So every time the user performs an acquisition (pressing the button "Go") 220,500 points are stored. The software-engine is adjusted to calculate the averaged spectral kurtosis (SK) over a set of 220 realizations, each of them containing 1,000 points.

Two couples of data registers have been selected as significant examples, corresponding to typical measurements situations. For a given couple, first we present the results without applying wavelets. Then we explain the information wavelets add.

Fig. 3 presents a clear detection case, characterized by termite activity signals without termites' alarms. Two peaks are clearly enhanced in the SK graph (near 5 kHz, and near 15 kHz).

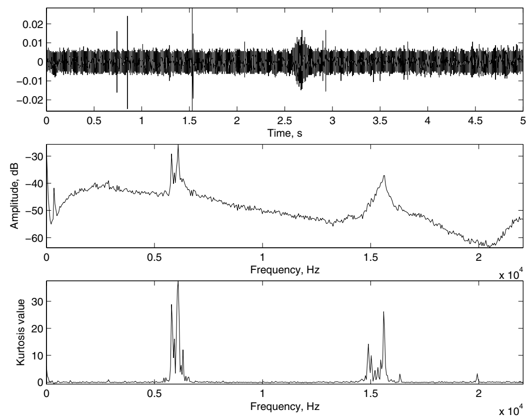

Figure 3: A clear measurement of activity detection.

The de-noised data in the time domain are shown in the upper graph of Fig. 4. Applying the spectral kurtosis to the de-noised version, it is seen that all the frequency components are enhanced, specially those ones in the detection band. This fact confirms the presence of insects, and it is of special value in doubtful situations (e.g. low-level signals), when they are really needed.

In Fig. 5 a doubtful measurement case is presented. Activity evidence is outlined only near 5 kHz. Once again, the wavelets have been applied (shown in Fig. 6), and the enhancements near 5 kHz and 15 kHz confirm the detection.

Hereinafter, we present the conclusions.

6. CONCLUSIONS AND ACCOMPLISHMENTS

Assuming the starting hypothesis that the insect emissions may have a more peaked probability distribution than any other simultaneous source of emission in the measurement

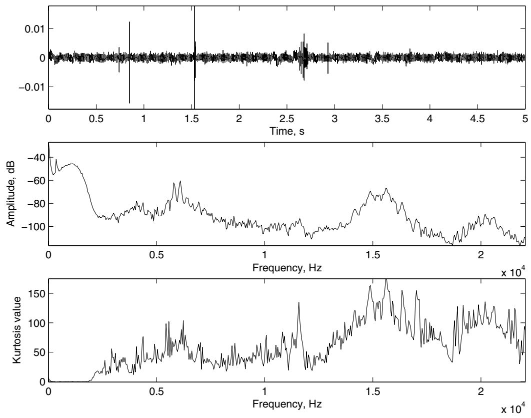

Figure 4: De-noising results for data in Fig. 3. A general enhancement of the spectral kurtosis occurs.

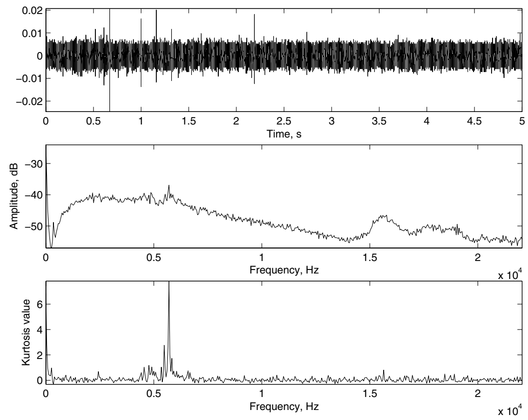

Figure 5: A doubtful measurement situation.

perimeter, we have design a termite detection strategy based in the calculation of the *4*th-order cumulants for zero time lags, which are indicative of the signals' kurtosis, and their corresponding spectra (the spectral kurtosis, SK).

An estimator of the SK has been used to perform a selective analysis of the peakedness of the signal. It has been shown that new frequency components gain in relevance in the spectral kurtosis graphs. This fact is specially noticeable when wavelets are applied in order to clarify detection in doubtful situations.

The main goal of this signal-processing method is to reduce subjectiveness due to visual or listening inspection of the registers. This means that in a noisy environment, it may be possible to ignore termite feeding activity even with an *ad hoc* sensor because, despite the fact that the sensor is capable of register these low-level emissions, the human ear can easily ignore them [1].

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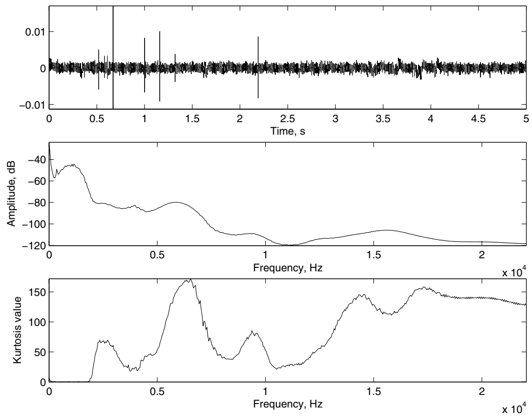

Figure 6: De-noising results of data in Fig. 5.

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