WAVELETS TRANSFORMS APPLIED TO TERMITE DETECTION

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Abstract: In this paper we present an study which shows the possibility of using wavelets to detect transients produced by termites. Identification has been developed by means of analyzing the impulse response of three sensors undergoing natural excitations. De-noising by wavelets exhibits good performance up to SNR=-30 dB, in the presence of white gaussian noise. The test can be extended to similar vibratory or acoustic signals resulting from impulse responses.

1 INTRODUCTION

In acoustic emission (AE) signal processing a customary problem is to extract some physical parameters of interest in situations which involve join variations of time and frequency. This situation can be found in almost every nondestructive AE tests for characterization of defects in materials, or detection of spurious transients which reveals machinery faults (Lou and Loparo, 2004). The problem of termite detection lies in this set of applications involving non-stationary signals (de la Rosa et al., 2004b).

When wood fibers are broken by termites they produce acoustic signals which can be monitored using *ad hoc* resonant acoustic emission (AE) piezoelectric sensors which include microphones and accelerometers, targeting subterranean infestations by means of spectral and temporal analysis. The drawback is the relative high cost and their practical limitations (de la Rosa et al., 2004b).

The usefulness of acoustic techniques for detection depends 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). Furthermore, soil and wood are far from being ideal acoustic propagation media because of their high anisotropy and frequency dependent attenuation characteristics (Mankin and Fisher, 2002). This is the reason whereby signal processing techniques emerged as an alternative.

Second order methods (spectra) failure in low SNR conditions even with *ad hoc* piezoelectric sensors. Bispectrum have proven to be a useful tool for characterization of termites in relative noisy environments using low-cost sensors (de la Rosa et al., 2004a),(de la Rosa et al., 2004c). The computational cost could be pointed out as the main drawback of the technique. This is the reason whereby diagonal bispectrum have to be used.

Numerous wavelet-theory-based techniques have evolved independently in different signal processing applications, like wavelets series expansions, multiresolution analysis, subband coding, etc. The wavelet transform is a well-suited technique to detect and analyze events occurring to different scales (Mallat, 1999). The idea of decomposing a signal into frequency bands conveys the possibility of extracting subband information which could characterize the physical phenomenon under study (Angrisani et al., 1999).

In this paper we show an application of wavelets' de-noising possibilities for the characterization and detection of termite emissions in low SNR conditions. Signals have been buried in gaussian white noise. Working with three different sensors we find

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that the estimated signals' spectra match the spectra of the acoustic emission whereby termites are identified.

The paper is structured as follows: Section 2 summarizes the problem of acoustic detection of termites; Section 3 remembers the theoretical background of wavelets; Section 4 describes the experiments carried out. Conclusions are drawn in Section 5.

2 ACOUSTIC DETECTION OF TERMITES

2.1 Characteristics Of The AE Signals

Acoustic Emission(AE) is defined as the class of phenomena whereby transient elastic waves are generated by the rapid (and spontaneous) release of energy from a localized source or sources within a material, or the transient elastic wave(s) so generated (ASTM, F2174-02, E750-04, F914-03 [1]). This energy travels through the material as a stress or strain wave and is typically detected using a piezoelectric transducer, which converts the surface displacement (vibrations) to an electrical signal.

Termites use a sophisticated system of vibratory long distance alarm. When disturbed in their nests and in their extended gallery systems, soldiers produce vibratory signals by drumming their heads against the substratum (R*ö*hrig et al., 1999). The drumming signals consist of pulse trains which propagate through the substrate (substrate vibrations), with pulse repetition rates (beats) in the range of 10-25 Hz, with burst rates around 500-1000 ms, depending on the species (Connétable et al., 1999). Soldiers produce such vibratory signals in response to disturbance (1-2 nm by drumming themselves) by drumming their head against the substratum. Workers can perceive these vibrations, become alert and tend to escape.

Figure 1 shows one of the impulses in a burst and its associated power spectrum is depicted in figure 2. Significant drumming responses are produced over the range 200 Hz-10 kHz. The carrier (main component) frequency of the drumming signal is around 2600 Hz.

The spectrum is not flat as a function of frequency as one would expect for a pulse-like event. This is due to the frequency response of the sensor (its selective characteristics) and also to the frequency-dependent attenuation coefficient of the wood and the air.

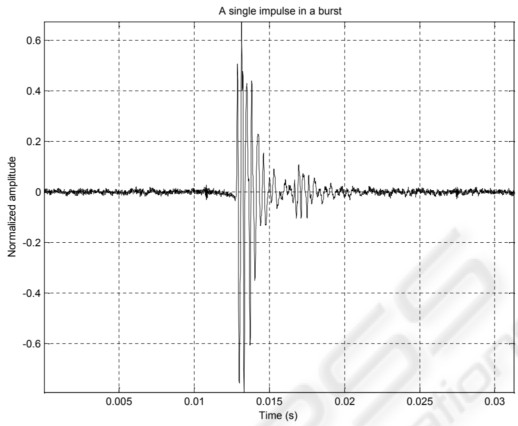

Figure 1: A single pulse of a four-pulse burst.

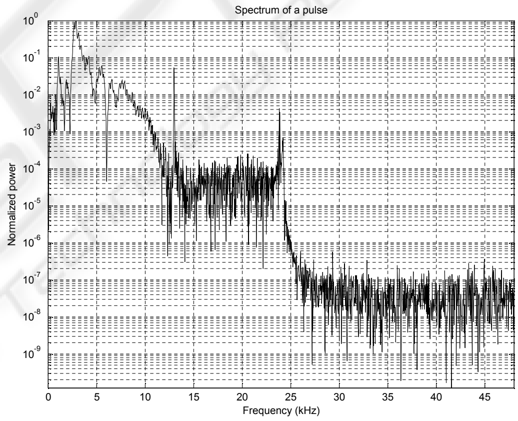

Figure 2: Normalized power spectrum of a single pulse.

2.2 Devices, Ranges Of Measurement And HOS Techniques

Acoustic measurement devices have been used primarily for detection of termites (feeding and excavating) in wood, but there is also the need of detecting termites in trees and soil surrounding building perimeters. Soil and wood have a much longer coefficient of sound attenuation than air and the coefficient increases with frequency. This attenuation reduces the detection range of acoustic emission to 2-5 cm in soil and 2-3 m in wood, as long as the sensor is in the same piece of material (Mankin et al., 2002). The range of acoustic detection is much greater at frequencies $<$10 kHz, and low frequency accelerometers

[1] American Society for Testing and Materials. F2174-02: Standard Practice for Verifying Acoustic Emission Sensor Response. E750-04: Standard Practice for Characterizing Acoustic Emission Instrumentation. F914-03: Standard Test Method for Acoustic Emission for Insulated and Non-Insulated Aerial Personnel Devices Without Supplemental Load Handling Attachments.

have been used to detect insect larvae over 1-2 m in grain and 10-30 cm in soil (Robbins et al., 1991).

It has been shown that ICA success in separating termite emissions with small energy levels in comparison to the background noise. This is explained away by statistical independence basis of ICA, regardless of the energy associated to each frequency component in the spectra (de la Rosa et al., 2004c). The same authors have proven that the diagonal bispectrum can be used as a tool for characterization purposes (de la Rosa et al., 2004a). With the aim of reducing computational complexity wavelets transforms have been used in this paper to de-noise corrupted impulse trains.

3 THE WAVELET TRANSFORM

3.1 Continuous Wavelet Transform (CWT)

A *mother wavelet* is a function ψ with finite energy [2], and zero average:

$$\int_{-\infty}^{+\infty} \psi(t)dt = 0, \qquad (1)$$

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:

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right); \qquad (2)$$

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:

$$CWTs(a,b) = \frac{1}{\sqrt{a}}\int_{-\infty}^{+\infty} s(t)\psi^*\left(\frac{t-b}{a}\right)dt; \quad (3)$$

where $\psi^*(t)$ is the complex conjugate of the mother wavelet $\psi(t)$, $s(t)$ is the signal under study, 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 frequency.

The expression for the modulus of CWT is:

$$|CWTs(a,b)| = k(a)^{\alpha}; \qquad (4)$$

where α is the so-called Lipschitz exponent and k is a constant. Looking at equation 4 one can discriminate the signal from the noise by analyzing the local maxima of $|CWTs(a,b)|$ across the scales.

Any finite energy signal $s(t)$ can be decomposed over a wavelet orthogonal basis [4] of $\mathbf{L}^2(\Re)$ according to:

$$s(t) = \sum_{j=-\infty}^{+\infty}\sum_{n=-\infty}^{+\infty}\langle s,\psi_{j,n}\rangle\psi_{j,n} \qquad (5)$$

Each partial sum can be interpreted as the details variations at the scale $a = 2^j$:

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

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 5 at the scale $a = 2^J$:

$$s_J(t) = \sum_{j=J}^{+\infty} d_j(t) \qquad (7)$$

3.2 Discrete Time Wavelet Transform (DTWT)

In the DTWT the original signal passes through two complementary filters and two signals are obtained as a result of a downsampling process, corresponding to the approximation and detail coefficients. The lengths of the detail and approximation coefficient vectors are slightly more than half the length of the original signal, $s(t)$. This is the result of the digital filtering process (convolution) (Angrisani et al., 1999). The approximations are the high-scale, low-frequency components of the signal. The details are the low-scale, high-frequency components.

A tree-structure arrangement of filters allows the subband decomposition of the signal. In each stage of the filtering process the same two digital filters are used: a highpass $h_a(\cdot)$, the discrete mother, and its mirror (lowpass) $g_a(\cdot)$. All these filters have the same relative bandwidth (ratio between frequency bandwidth and center frequency). The results of the decomposition can be expressed as:

$$DTWTs(j,n) = \sum_{k=0}^{N-1} h_j(2^{j+1}n-k)s(k), \qquad (8)$$

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

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

[4] $\left\{\psi_{j,n}(t) = \frac{1}{\sqrt{2^j}}\psi\left(\frac{t-2^jn}{2^j}\right)\right\}_{(j,n)\in\mathbb{Z}^2}$

where N is the number of samples in the signal, j is the decomposition level, n is the time shifting. The same arguments are valid for the process of reconstruction.

3.3 Wavelet Packets (WP)

The WP method is a generalization of wavelet decomposition that offers more possibilities of reconstructing the signal from the decomposition tree. If n is the number of levels in the tree, WP methods yields more than $2^{2^{n-1}}$ ways to encode the signal. The wavelet decomposition tree is a part of the complete binary tree.

When performing a split we have to look at each node of the decomposition tree and quantify the information to be gained as a result of a split. An entropy based criterion is used herein to select the optimal decomposition of a given signal. We use an adaptative filtering algorithm, based on the work by Coifman and Wickerhauser (Coifman and Wickerhauser, 1992).

Functions that verify additivity-type property are suitable for efficient searching of the tree structures and node splitting. The criteria based on the entropy match these conditions, providing a degree of randomness in an information-theory frame. In this work we used the entropy criteria based on the p-norm:

$$E(s) = \sum_{i}^{N} \|s_i\|^p; \qquad (9)$$

with p≤1, and where $s(t) = [s_1(t), s_2(t), \ldots, s_N(t)]$ in the signal of length N.

The results are accompanied by entropy calculations based on Shannon's criterion:

$$E(s) = -\sum_{i}^{N} s_i^2 log(s_i^2); \qquad (10)$$

with the convention $0 \times log(0) = 0$.

4 EXPERIMENTS AND CONCLUSIONS

Two accelerometers (KB12V, seismic accelerometer; KD42V, industrial accelerometer, MMF) and a standard microphone have been used to collect data from termites in different places (basements, subterranean wood structures and roots) using the sound card of a portable computer and a sampling frequency of 96000 (Hz). These sensors have different sensibilities and impulse response. This is the reason whereby we normalize spectra.

The de-noising procedure was developed using a $sym8$, belonging to the family *Symlets* (order 8), which are compactly supported wavelets with least asymmetry and highest number of vanishing moments for a given support width. We also choose a soft heuristic thresholding.

We used 15 registers (from *reticulitermes grassei*), each of them comprises a 4-impulse burst buried in white gaussian noise. De-noising performs successfully up to an SNR=-30 dB. Figure 3 shows a de-noising result in one of the registers. Figure 4 shows

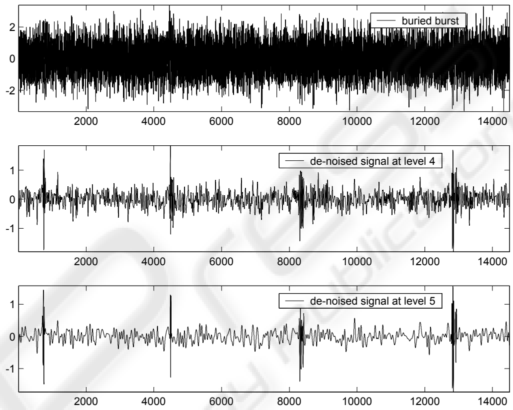

Figure 3: Limit situation of the de-noising procedure (SNR=-30 dB). From top to bottom: a buried 4-impulse burst, estimated signal at level 4, estimated signal at level 5. Time resolution: 1/96000 (s)

a comparison between the spectrum of the estimated signal at level 4 and the spectrum of the signal to be de-noised, taking a register as an example. Significant

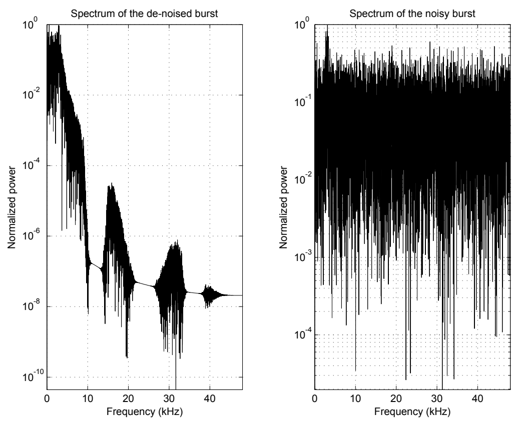

Figure 4: Spectra of the estimated signal and the buried burst.

components in the spectrum of the recovered signal are found to be proper of termite emissions.

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