An Application of HOS and ICA to Detect and Characterize Noisy Signals Generated by Termites

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Abstract—**This paper is concerned with the detection and characterization of termite signals in additive stationary noise for the purpose of recognition. A seismic accelerometer is used for a preliminary characterization of the acoustic emissions (AE) by means of standard second-order methods. An independent components analysis (ICA) algorithm based on fourth-order cross-cumulants is applied to detect vibrational alarm signals generated by soldier termites (*reticulitermes grassei*) from background noise. Vibrational signals from a low cost microphone, masked by uniform and gaussian noise, were taken as sensors outputs. Bispectrum is proposed as a higher order statistic to characterize vibratory time series. The results of the numerical experiments have proven that characterization and detection can be performed even with low signal-to-noise ratio signals.**

I. Introduction

The costs of the harm caused by termites and other insects could be significantly reduced through earlier detection. Detection is also important because environmental laws are becoming more restrictive with termiticides due to their health threats. Besides, only about 25 percent of the affected structure is accessible, and the conclusions depend very much on subjectiveness [1]. Thus, new techniques have been developed to gain accessibility. But at best they are considered useful only as supplements. Acoustic methods have emerged as an alternative.

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

Modern signal processing techniques can be used to distinguish insect sounds from background noise with good reliability in soil, because sound insulating properties of soil help reduce interference. Besides, such techniques have been successfully used in relatively noisy urban environments [2], [3].

The aim of the present paper consists of using higher order statistics (HOS) for a twofold purpose. First, a robust ICA cumulant-based algorithm is used to separate termite alarm signals from additive stationary noise. This could be the basis of separating low-level termite signals from urban noise using cheap equipment with non-invasive sensors. Second, the bispectrum have been applied to get a better characterization of the emissions in the frequency domain.

A previous estimation of the power spectrum (second-order characterization) of termite emissions was developed using a seismic accelerometer, with the aim of getting a biological reference. Data were acquired in the "Costa del Sol" (Málaga, Spain), in subterranean wood structures and roots. Emissions were recorded using a low cost microphone.

The paper is structured as follows. Section 2 summarizes the methods for acoustic detection of termites. Section 3 defines the ICA model and section 4 deals with the mathematical HOS tools employed. The ICA method is described in section 5. Section 6 describes the experiments carried out. Conclusions are drawn in Section 7.

II. Acoustic Detection of Termites: Characteristics and Devices

Acoustic emission (AE) is the elastic energy that is spontaneously released by materials undergoing deformation. This energy travels through the material as a stress and can be detected using a piezoelectric transducer.

When disturbed in their extended galleries, soldiers produce vibratory signals by drumming their heads against the substratum [4]. The signals consist of pulse trains which propagate through the substrate with pulse repetition rates (beats) in the range of 10-25 Hz, with burst rates around 500-1000 ms, depending on the species [2]. Workers perceive the vibrations, become alert and tend to escape.

Figure 1 shows a typical drumming signal produced by a soldier by taping its jaws against a chip of wood. It comprises two four-impulse bursts. Each of the pulses arises from a single, brief tap of the jaw. Signal's amplitudes are highly variable and depend on the wood and strength of the taps.

AE sensors have been used primarily for detection of termites in wood [5], but there is also the need of detecting

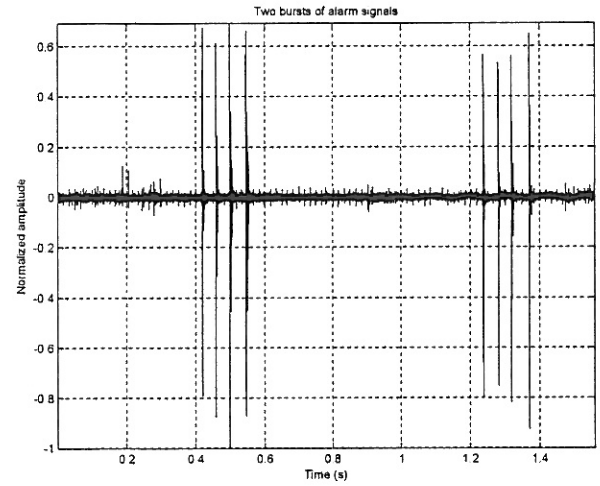

Fig. 1. Two bursts of a typical AE alarm signal produced by a soldier.

termites in trees and soil surrounding building perimeters. Soil and wood have a much longer coefficient of sound attenuation and distortion than air($\sim$600 dB m^{-1}, compared with 0.008 dB m^{-1} in the air), and the coefficient increases with frequency [3]. This attenuation reduces the detection range of the 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 [5].

Although the above vibratory signals have distinctive time instances it is difficult to detect them in a noisy environment. A variety of signal processing methods have been used in similar situations in other fields of Science and Technology [6], [7], [8]. They include statistical analysis, spectral analysis, time-frequency analysis and wavelet transforms. As such methods are all based on energy conservation, they are useful for finding predominant information, such as peaks.

Low signal-to-noise ratio sources cannot be identified successfully, using the methods mentioned above. This is because the algorithms in the measurement process retain energy information from one domain to another. As a consequence, spurious signals of interest, like pulse-like events, are buried in the environment.

HOS and ICA bring a different strategy in dealing with source separation and identification of non-Gaussian random processes.

III. The ICA Model and its Properties

Blind source separation (BSS) by ICA is receiving attention because of its numerous applications in many fields such as speech recognition, medicine and telecommunications [9], [10], [11]. Statistical methods in BSS are based in the probability distributions and the cumulants of the mixtures. The recovered signals (the source estimators) have to satisfy a condition which is modelled by a contrast function. The underlying assumptions are the mutual independence among sources and the non-singularity of the mixing matrix [9], [12], [13].

Let $\mathbf{s}(t) = [s_1(t), s_2(t), \ldots, s_m(t)]^T$ be the vector of unknown sources (statistically independent), where the superscript represents transpose. Independence means one source provides no further information about any other [14]. The mixture of the sources is modelled by

$$\mathbf{x}(t) = \mathbf{A} \cdot \mathbf{s}(t) \tag{1}$$

where $\mathbf{x}(t) = [x_1(t), x_2(t), \ldots, x_m(t)]^T$ is the available vector of observations and $\mathbf{A} = [a_{ij}] \in \Re^{m \times n}$ is the unknown mixing matrix, modelling the environment in which signals are mixed, transmitted and measured [15]. We assume that $\mathbf{A}$ is a non-singular n$\times$n square matrix. The goal of ICA is to find a non-singular n$\times$m separating matrix $\mathbf{B}$ such that extracts sources via

$$\hat{\mathbf{s}}(t) = \mathbf{y}(t) = \mathbf{B} \cdot \mathbf{x}(t) = \mathbf{B} \cdot \mathbf{A} \cdot \mathbf{s}(t) \tag{2}$$

where vector $\mathbf{y}(t) = [y_1(t), y_2(t), \ldots, y_m(t)]^T$ is an estimator of the original sources [16], [17], [18]. The separating matrix has a scaling freedom on each of its rows because the relative amplitudes of sources in $\mathbf{s}(t)$ and columns of $\mathbf{A}$ are unknown [9], [13], [17]. The final transfer matrix $\mathbf{G} \equiv \mathbf{BA}$ relates the vector of independent original signals to its estimators [19].

IV. Higher Order Statistics for Termite Signals Characterization

A. Cumulants

High order statistics, known as cumulants, are used to infer new properties about the data of non-Gaussian processes [6], [20], [21]. Before cumulants, such processes had to be treated as if they were Gaussian. Cumulants and polyspectra reveal information about amplitude and phase, whereas second order statistics are phase-blind [21], [22]. The relationship among the cumulant of *r* stochastic signals and their moments of order $p, p \leq r$, can be calculated by using the *Leonov-Shiryayev* formula [20], [21]

$$\begin{aligned} Cum(x_1, ..., x_r) = \sum (-1)^k \cdot (k-1)! \cdot E\{\prod_{i \in v_1} x_i\} \\ \cdot E\{\prod_{j \in v_2} x_j\} \cdots E\{\prod_{k \in v_p} x_k\} \end{aligned} \tag{3}$$

where the addition operator is extended over all the set of v_i $(1 \leq i \leq p \leq r)$ and v_i compose a partition of *1,…,r*.

By using (3) the second-, third-, and fourth-order cumulants are given by:

$$Cum(x_1, x_2) = E\{x_1 \cdot x_2\} \tag{4a}$$

$$Cum(x_1, x_2, x_3) = E\{x_1 \cdot x_2 \cdot x_3\} \tag{4b}$$

$$\begin{aligned} Cum(x_1, x_2, x_3, x_4) = E\{x_1 \cdot x_2 \cdot x_3 \cdot x_4\} \\ - E\{x_1 \cdot x_2\} E\{x_3 \cdot x_4\} \\ - E\{x_1 \cdot x_3\} E\{x_2 \cdot x_4\} \\ - E\{x_1 \cdot x_4\} E\{x_2 \cdot x_3\} \end{aligned} \tag{4c}$$

In the case of nonzero mean variables x_i have to be replaced by x_i-$E\{x_i\}$.

Let $\{x(t)\}$ be a rth-order stationary random process. The rth-order cumulant is defined as the joint rth-order cumulant of the random variables $x(t)$, $x(t+\tau_1)$,..., $x(t+\tau_{r-1})$,

$$\begin{aligned} &C_{r,x}(\tau_1, \tau_2, \ldots, \tau_{r-1}) \\ &\quad = Cum[x(t), x(t+\tau_1), \ldots, x(t+\tau_{r-1})] \end{aligned} \tag{5}$$

The second-, third- and fourth-order cumulants of zero-mean $x(t)$ can be expressed using (4) and (5)

$$C_{2,x}(\tau) = E\{x(t) \cdot x(t+\tau)\} \tag{6a}$$

$$C_{3,x}(\tau_1, \tau_2) = E\{x(t) \cdot x(t+\tau_1) \cdot x(t+\tau_2)\} \tag{6b}$$

$$\begin{aligned} &C_{4,x}(\tau_1, \tau_2, \tau_3) \\ &= E\{x(t) \cdot x(t+\tau_1) \cdot x(t+\tau_2) \cdot x(t+\tau_3)\} \\ &= C_{2,x}(\tau_1) - C_{2,x}(\tau_2 - \tau_3) \\ &= C_{2,x}(\tau_2) - C_{2,x}(\tau_3 - \tau_1) \\ &= C_{2,x}(\tau_3) - C_{2,x}(\tau_1 - \tau_2) \end{aligned} \tag{6c}$$

By putting $\tau_1 = \tau_2 = \tau_3 = 0$ in (6), we obtain

$$\gamma_{2,x} = E\{x^2(t)\} = C_{2,x}(0) \tag{7a}$$

$$\gamma_{3,x} = E\{x^3(t)\} = C_{3,x}(0,0) \tag{7b}$$

$$\gamma_{4,x} = E\{x^4(t)\} - 3(\gamma_{2,x})^2 = C_{4,x}(0,0,0) \tag{7c}$$

Equations (7) are the measures of the variance, skewness and kurtosis of the distribution in terms of cumulants at zero lags. Normalized kurtosis and skewness are defined as $\gamma_{4,x}/(\gamma_{2,x})^2$ and $\gamma_{3,x}/(\gamma_{2,x})^{3/2}$, respectively. We will use and refer to normalized quantities because they are shift and scale invariant. If $x(t)$ is symmetric distributed, its skewness is necessarily zero (but not *vice versa*); if $x(t)$ is Gaussian distributed, its kurtosis is necessarily zero (but not *vice versa*).

B. Polyspectra

We will assume in the following that the cumulant sequences satisfies the condition

$$\sum_{\tau_1=-\infty}^{\tau_1=+\infty} \cdots \sum_{\tau_{r-1}=-\infty}^{\tau_{r-1}=+\infty} |C_{r,x}(\tau_1, \tau_2, \ldots, \tau_{r-1})| < \infty \tag{8}$$

Under this assumption, the higher order spectra are usually defined in terms of the rth-order cumulants as their (r-1)-dimensional Fourier transforms

$$\begin{aligned} &S_{r,x}(f_1, f_2, \ldots, f_{r-1}) \\ &= \sum_{\tau_1=-\infty}^{\tau_1=+\infty} \cdots \sum_{\tau_{r-1}=-\infty}^{\tau_{r-1}=+\infty} C_{r,x}(\tau_1, \tau_2, \ldots, \tau_{r-1}) \\ &\cdot \exp[-j2\pi(f_1\tau_1 + f_2\tau_2 + \cdots + f_{r-1}\tau_{r-1})] \end{aligned} \tag{9}$$

The special polyspectra derived from (9) are power spectrum (r=2), bispectrum (r=3) and trispectrum (r=4). Only power spectrum is real, the others are complex magnitudes.

Polyspectra are multidimensional functions which comprise a lot of information. As a consequence, their computation may be impractical in some cases. To extract useful information one-dimensional slices of cumulant sequences and spectra are employed in non-Gaussian stationary processes.

V. The Implementation of the ICA Algorithm

It has been proved that a set of random variables are statistically independent if their cross-cumulants are zero [17]. This property can be used to define contrast functions. The contrast function, $\Phi[y]$, verifies

$$\Phi[y] = \Phi[BAs] \geq \Phi[s] \tag{10}$$

in order to be minimized. A criteria to obtain the contrast function is to minimize the distance between the cumulants of the sources $\mathbf{s}(t)$ and the outputs $\mathbf{y}(t)$. But in a real situation sources are unknown, so it is necessary to involve the observed signals. We use an entropic function in the terms described as follows [12], [17]. Separation of the sources can be developed using the following contrast function based on the entropy of the outputs

$$H(\mathbf{z}) = H(\mathbf{s}) + log[det(\mathbf{G})] - \sum \frac{\mathbf{C}_{1+\beta,y_i}}{1+\beta} \tag{11}$$

where $\mathbf{C}_{1+\beta,y_i}$ is the $1+\beta$th-order cumulant of the ith output, $\mathbf{z}$ is a non-linear function of the outputs y_i, $\mathbf{s}$ is the source vector, $\mathbf{G}$ is the global transfer matrix of the ICA model and $\beta > 1$ is an integer verifying that $\beta + 1$-order cumulants are non-zero.

Using this contrast function it has been demonstrated [17] that the separating matrix can be obtained by means of the following recurrent equation

$$\mathbf{B}^{(h+1)} = [\mathbf{I} + \mu^{(h)}(\mathbf{C}^{1,\beta}_{y,y}\mathbf{S}^{\beta}_{y} - I)]\mathbf{B}^{(h)} \tag{12}$$

where $\mathbf{S}^{\beta}_{y}$ is the matrix of the signs of the output cumulants. Equation (12) can be interpreted as a quasi-Newton algorithm of the cumulant matrix $\mathbf{C}^{1,\beta}_{y,y}$. The learning rate parameters $\mu^{(h)}$ and η are related by

$$\mu^{(h)} = \min\left(\frac{2\eta}{1+\eta\beta}, \frac{\eta}{1+\eta\|\mathbf{C}^{1,\beta}_{y,y}\|_p}\right) \tag{13}$$

with $\eta < 1$ to avoid $\mathbf{B}^{(h+1)}$ being singular; $\|.\|_p$ denotes de p-norm of a matrix. The adaptative equation (12) converges, if the matrix $\mathbf{C}^{1,\beta}_{y,y}\mathbf{S}^{\beta}_{y}$ tends to the identity.

VI. Results and Discussions

Data acquisition took place in a basement, using a low-cost microphone, *Ariston* CME6 model, with a sensibility of 62±3 dB and a bandwidth of 100 Hz-8 kHz, connected to the sound card of a portable computer (96000 Hz, sample frequency).

Sources 1 and 2 consist of two zero-mean normalized bursts. Normalized kurtosis are 212.93, and 211.09, respectively; which shows that ICA is expected to work. The third and forth sources consist of two uniform distributed noise signals with enough amplitude to mask the burst. The elements of the 4×4 mixing matrix are chosen from uniformly distributed random numbers within 0 and 1. No pre-whitened was applied in order to manipulate four mixtures.

In order to compare this method with traditional ones, based on energy conservation, we compared the power spectra of the separated signals to the original sources of *reticulitermes grassei*.

AE methods work under the hypothesis of considering the vibratory signals as pulse trains. A previous characterization of the emissions was developed using a seismic accelerometer (KB12V, MMF). Figure 2 shows a comparison between the impulse response of the accelerometer (upper graph) and the spectrum of one impulse in a burst. We conclude, from this power spectrum of a single pulse, that significant drumming responses are produced over the range 200 Hz-4 kHz and the carrier frequency is around 2600 Hz [1], [2].

It is also remarkable that 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 microphone, and also to the frequency-dependent attenuation coefficient of the wood.

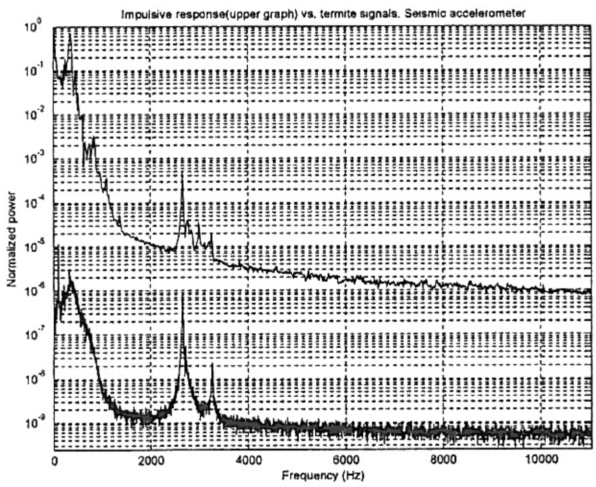

Fig. 2. Comparison between impulsive response and the spectrum of a tap.

Figure 3 shows the original sources and the mixtures, which give very little information about the original signals.

Comparing the separated results, in figure 4, with the sources in figure 3, a number of differences are found. First, the amplitudes are amplified to some extent due to the changes in the demixing matrix, implying that original amplitude information has lost. Second, there are time shifts between the original sources and the recovered signals. Third, the sequences are arranged as the same way as the originals, although this can be changed.

Figure 5 shows the normalized power spectrum of the second output. The spectra of the separated signals, $y_1(t)$ and $y_2(t)$, show the same carrier frequency as in the impulse response of the accelerometer. This helps us confirm the validity of the proposed method, because the carrier in the

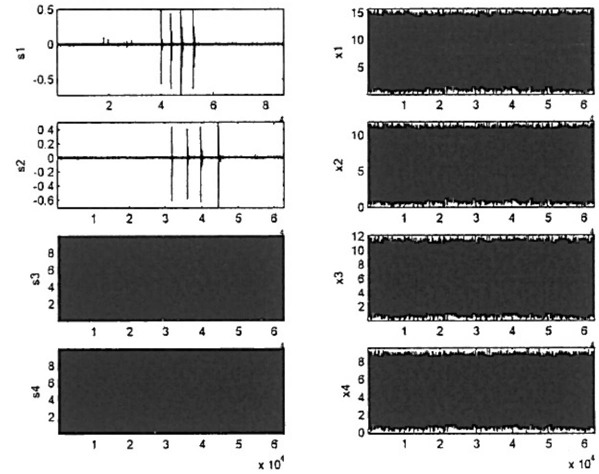

Fig. 3. The sources and their mixtures. Horizontal units: samples × 1/96000 (s).

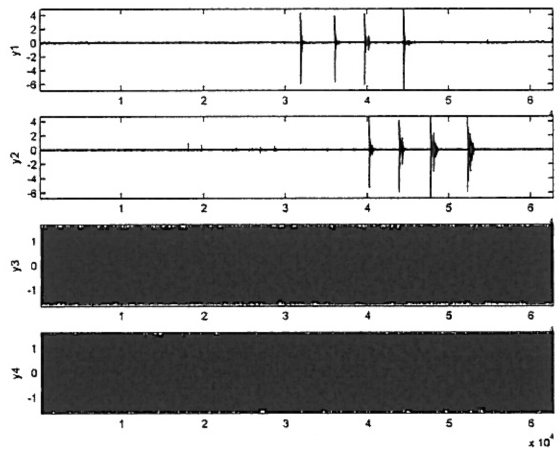

Fig. 4. The separation results by the ICA algorithm. Horizontal units: samples × 1/96000 (s).

spectra of the separated signals matches the carrier frequency in the spectra of the impulsive response of the accelerometer.

The information contained in the spectra would be enough for a complete statistical description of Gaussian processes only. To provide some insight about the power of the higher order statistics for characterization purposes of vibratory signals in Gaussian noise, 10 replications of signal-plus-white Gaussian noise were generated (SNR=0 dB). One of them is depicted in figure 6. The average spectrum of impulses in noise is showed in 7. As it is showed, the gap between maximum (carrier) and minimum is not big enough to establish a characterization criterion. Average bispectrum is showed in figure 8, a contour plot of figure 8 is showed in figure 9 and the average diagonal bispectrum in figure 10.

We observe very sharp peaks of the energy, concentrated in a narrow range of frequencies. This one-diagonal measures underlie information concerning the phase couplings of harmonics at integer multiplies of the fundamental one. Such information is based on non-linear combinations of classical Fourier transforms. For this reason, this method conveys a

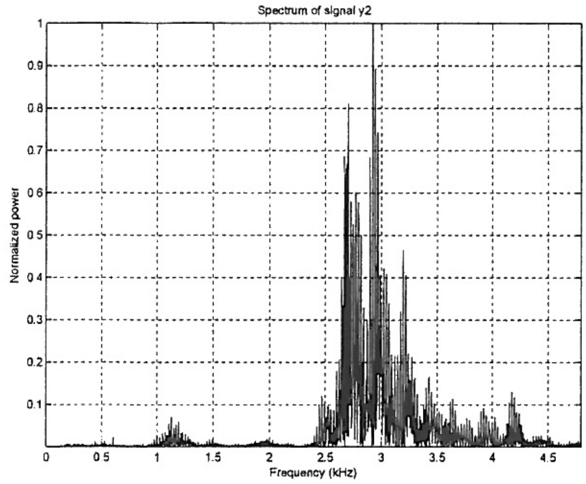

Fig. 5. Normalized frequency spectra of the second output.

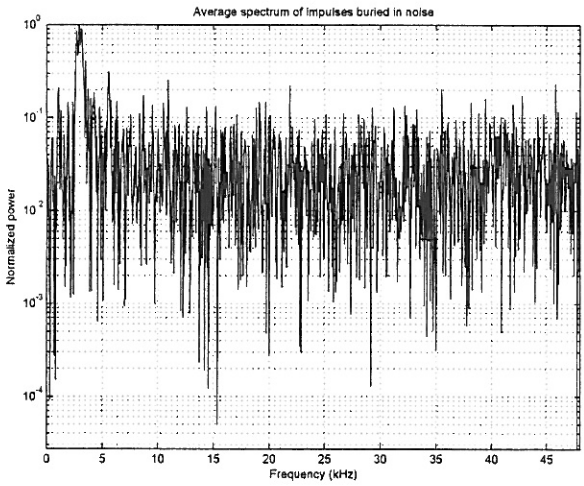

Fig. 7. Average spectrum of noisy bursts (Blackman's window used).

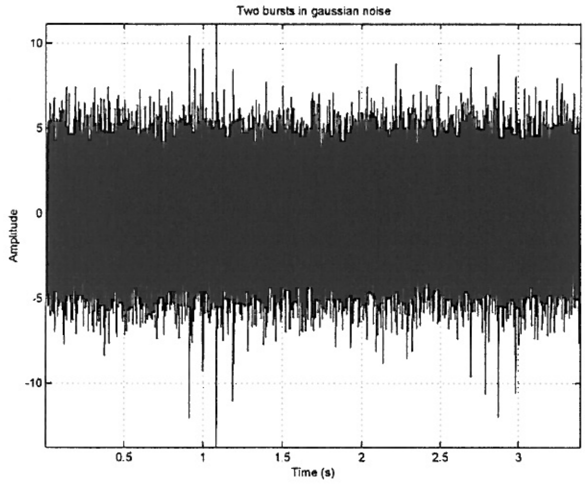

Fig. 6. Two noisy bursts; SNR=0 dB.

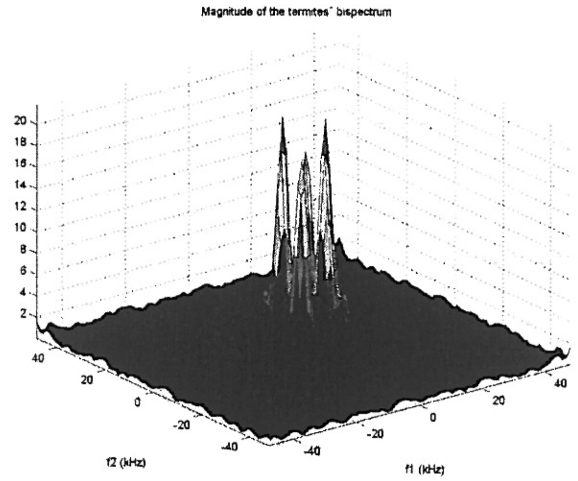

Fig. 8. Average bispectrum of the masked alarm signals.

useful higher order statistics measure.

VII. Conclusions

ICA has been presented as a novel method used to detect vibratory signals from termite activity in wood. This method is far different from traditional ones, as power spectrum, which obtain an energy diagram of the different frequency components, with the risk that low-level sounds could be masked.

This experience shows that the algorithm is able to separate the sources 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. Results of the spectra let us conclude that the separation has been performed correctly, because the same spectral shape as the accelerometer response is outlined. In this stage we have proved the validity of ICA over a pre-processed set of signals. No frequency-domain comparison is made; a time-domain characterization is enough.

If we focus on the device, it has been proved that a low-cost microphone can be used for insect-detection purposes. This is so because in case of high-level background noise, even if it is white, as it has been proved, ICA is capable of extracting the burst of impulses. This means that accelerometers-based equipment could be displaced when it is not needed a high sensitive device. In the case of a high sensibility requirement, accelerometers can be used to extract distorted information which would be processed by ICA to extract the vibratory signals produced by insects.

The paper has also presented a method of higher order statistics characterization of the vibratory signals from termites. Application of the polyspectra of the third-order (bispectra) has enhanced the characterization of the data sequences in gaussian noise. Discriminative criteria is improved by means of the diagonal bispectrum.

The work carried out by Robbins *et al.* [1] have shown success in detecting infestations, by means of using electronics counters to compute the average of impulses in a measurement period (identification criteria was based in time domain analysis). This experiment was done in a lab, in low-noise

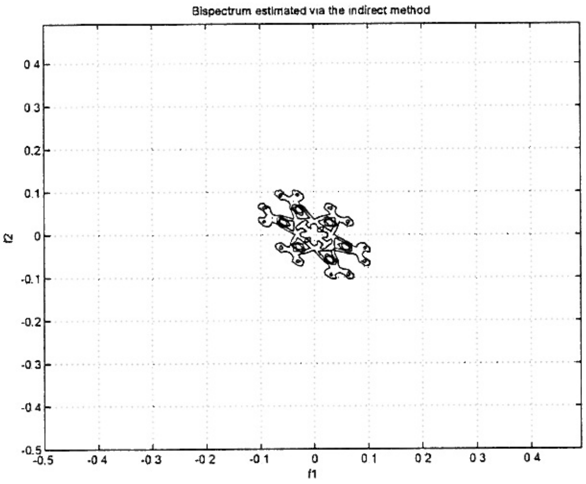

Fig. 9. Contour plot of the average bispectrum.

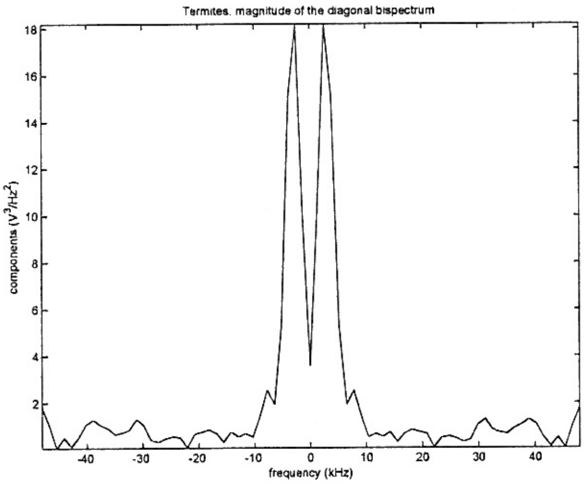

Fig. 10. Diagonal average bispectrum of the masked alarm signals.

conditions.

This paper presents a preliminary application of ICA and HOS for detection and characterization of termite emissions. Efforts have to be directed to analyze time series acquired in new scenarios. Signals in urban noise should be considered as one potential application, and measurements have to be developed in other media, like walls, where termites build galleries for the sake of linking their feeding locations.

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