An Application of ICA to Identify Vibratory Low-Level Signals Generated by Termites

Juan Jose G. de la Rosa[1], Carlos G. Puntonet[2], Juan Manuel Górriz, and Isidro Lloret

[1] University of Cádiz, EPS-Electronics Instrumentation Group, Av. Ramón Puyol S/N, 11202 Algeciras-Cádiz, Spain
juanjose.delarosa@uca.es
http://www2.uca.es/grup-invest/instrument_electro/ppjjgdr/jjgdr.htm
[2] University of Granada, Department of Architecture and Computers Technology, ESII, C/Periodista Daniel Saucedo, 18071 Granada, Spain

Abstract. An extended robust independent components analysis algorithm based on cumulants is applied to identify vibrational alarm signals generated by soldier termites (*reticulitermes grassei*) from background noise. A seismic accelerometer is employed to characterize acoustic emissions. To support the proposed technique, vibrational signals from a low cost microphone were masked by white uniform noise. Results confirm the validity of the method, taken as the basis for the development of a low cost, non-invasive, termite detection system.

1 Introduction

Termites damage structures world-wide irreparably. The costs of this harm 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 building 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 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 (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 particular contribution of this study is to show that a robust ICA cumulant-based algorithm is capable of separating termite alarm signals, generated in wood and recorded using a low cost microphone, from background

C.G. Puntonet and A. Prieto (Eds.): ICA 2004, LNCS 3195, pp. 1126–1133, 2004.

noise. This could be the basis of separating low-level termite activity signals from background urban noise using cheap equipment with non-invasive sensors. A seismic accelerometer was used to characterize the frequency contents. Data were acquired in the "Costa del Sol" (Malaga, Spain), in subterranean wood structures and roots.

The paper is structured as follows: Section 2 summarizes the methods for acoustic detection of termites; Section 3 defines the ICA model and outlines the characteristics of emissions in wood; Section 4 describes the experiments carried out. Conclusions are drawn in Section 5.

2 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.

Termites use a sophisticated system of vibratory long distance alarm. 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 [3]. 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.

Signals' amplitudes were highly variable and depend on the wood and strength of the taps. Power spectrum of a single impulse shows that significant drumming responses are produced over the range 200 Hz-10 kHz and the carrier frequency is around 2600 Hz. The spectrum is not flat as a function of frequency as one

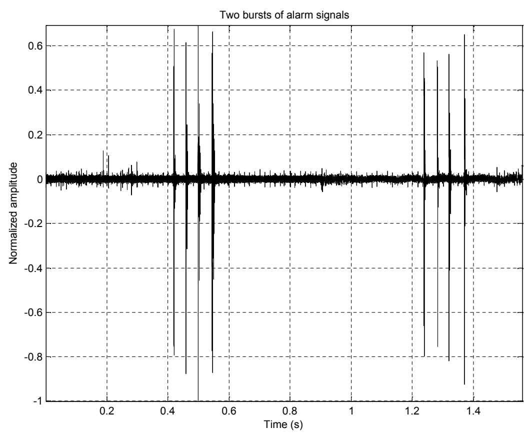

Fig. 1. Two bursts of a typical AE alarm signal produced by a soldier.

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.

AE sensors have been used primarily for detection of termites in wood [5], 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 and distortion than air(∼600 dB m^{-1}, compared with 0.008 dB m^{-1} in the air), and the coefficient increases with frequency [2].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].

3 The ICA Model and Its Properties

3.1 Outline of ICA

Blind source separation (BSS) by ICA is receiving attention because of its applications in many fields such as speech recognition, medicine and telecommunications [6],[7],[8]. 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 [6],[9],[10].

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 [11]. 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 [12]. We assume that $\mathbf{A}$ is a non-singular n×n square matrix. The goal of ICA is to find a non-singular n×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 sources [13],[14]. 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 [6],[10],[14]. The transfer matrix $\mathbf{G} \equiv \mathbf{BA}$ relates the vector of independent original signals to its estimators [15].

3.2 The Implementation of the Algorithm

High order statistics, known as cumulants, are used to infer new properties about the data of non-Gaussian processes [16],[17]. 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 [18],[19]. 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 [17],[18]

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

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.*

It has been proved that a set of random variables are statistically independent if their cross-cumulants are zero [14]. This property can be used to define a contrast function. A criteria to obtain this 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. Separation of the sources can be developed using the following contrast function based on the entropy of the outputs [9],[14]

$$H(\mathbf{z}) = H(\mathbf{s}) + log[det(\mathbf{G})] - \sum \frac{\mathbf{C}_{1+\beta, y_i}}{1+\beta} \quad (4)$$

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 [14] that the separating matrix can be obtained by means of the following recurrent equation

$$\mathbf{B}^{(h+1)} = [\mathbf{I} + \mu^{(h)}(\mathbf{C}^{1,\beta}_{y,y}\mathbf{S}^{\beta}_{y} - I)]\mathbf{B}^{(h)} \quad (5)$$

where $\mathbf{S}^{\beta}_{y}$ is the matrix of the signs of the output cumulants. Equation (5) 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

$$\mu^{(h)} = \min(\frac{2\eta}{1+\eta\beta}, \frac{\eta}{1+\eta\|\mathbf{C}^{1,\beta}_{y,y}\|_p}) \quad (6)$$

with $\eta < 1$ to avoid $\mathbf{B}^{(h+1)}$ being singular; $\|.\|_p$ denotes de p-norm of a matrix. The adaptative equation (5) converges, if the matrix $\mathbf{C}^{1,\beta}_{y,y}\mathbf{S}^{\beta}_{y}$ tends to the identity.

4 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).

High-pass filtering suppresses non-relevant low-frequency coupling from the sensor and the environment, obtaining two zero-mean normalized bursts (sources 1 and 2). 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 mixing matrix is a 4×4 matrix whose elements 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 power spectrum comparisons, 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. Characterization was developed using a seismic accelerometer (KB12V, MMF). Figure 2 shows a comparison between the impulse response (upper graph) of the accelerometer and the spectrum of the drumming signals, which let us conclude the 2600 Hz peak corresponding to the carrier [1],[3].

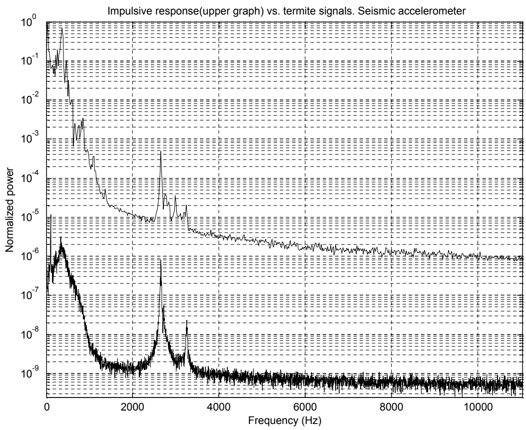

Fig. 2. Comparison between impulsive response and spectrum of vibratory alarm signals.

Figure 3 shows the original filtered sources and the mixtures, which give very little information about the original sources. Comparing the separated results, in figure 4, with the source signals 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. Three, the sequences are arranged as the same way as the original, although this can be changed.

Figure 5 show 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,

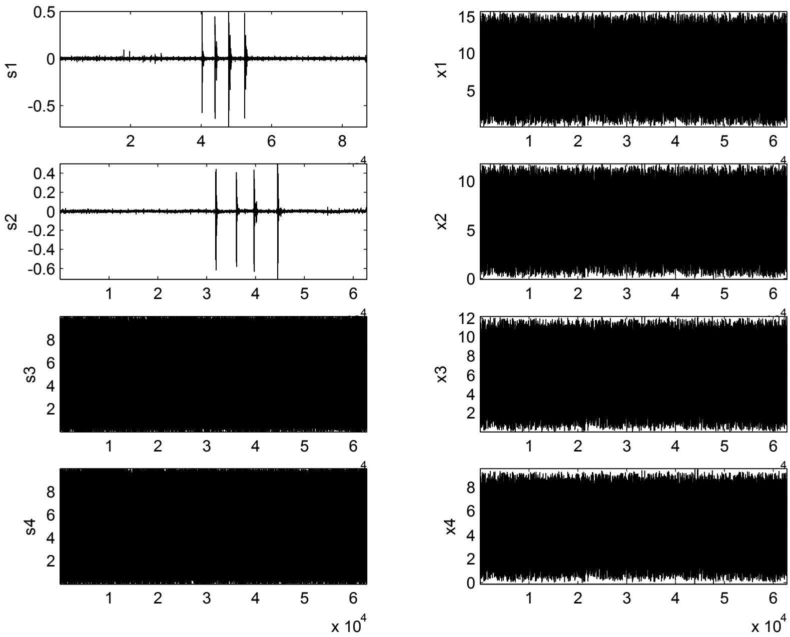

Fig. 3. The sources and their mixtures. Horizontal units: 1/96000 (s).

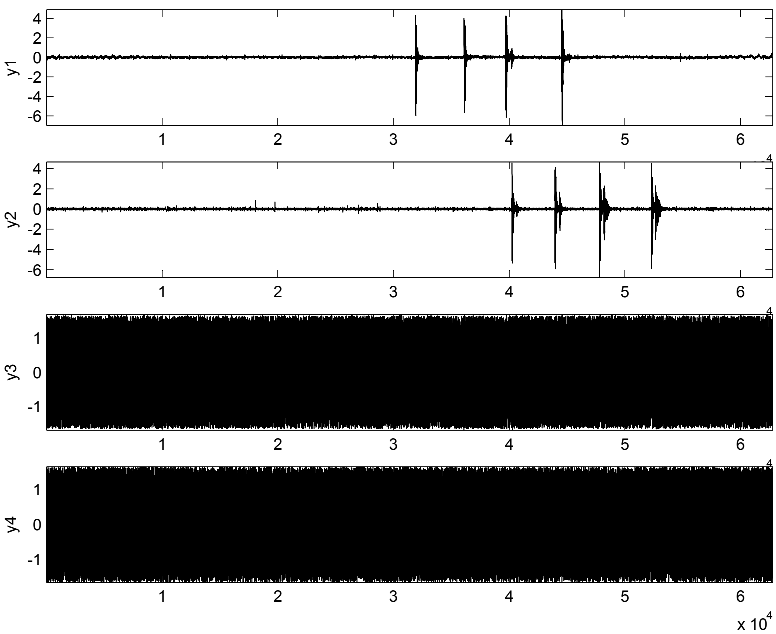

Fig. 4. The separation results by the ICA algorithm. Horizontal units: 1/96000 (s).

confirming the validity of the proposed method based on the traditional spectra-based method.

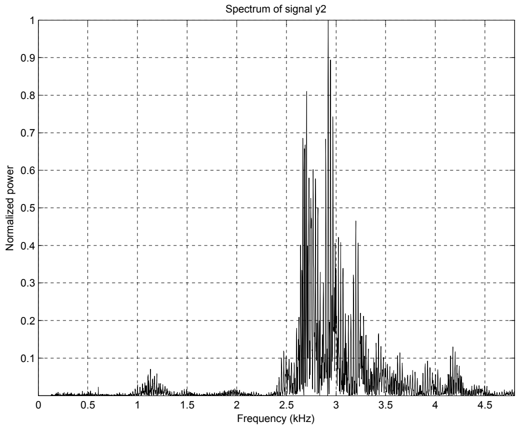

Fig. 5. Normalized power spectrum of the second output.

5 Conclusions

ICA has been presented as a novel method used to detect vibratory signals from termite activity. 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.

Acknowledgment

The authors would like to thank the *Spanish Ministry of Science and Technology* for funding the project DPI2003-00878, and the *Andalusian Autonomous Government Division* for funding the research with *Contraplagas Ambiental S.L.*

References

1. Robbins, W., Mueller, R., Schaal, T., Ebeling, T.: Characteristics of acoustic emission signals generated by termite activity in wood. In: Proceedings of the IEEE Ultrasonic Symposium. (1991) 1047–1051
2. Mankin, R., Fisher, J.: Current and potential uses of acoustic systems for detection of soil insects infestations. In: Proceedings of the Fourth Symposium on Agroacoustic. (2002) 152–158
3. Connétable, S., Robert, A., Bouffault, F., Bordereau, C.: Vibratory alarm signals in two sympatric higher termite species: Pseudacantotermes spiniger and p. militaris (termitidae, macrotermitinae). Journal of Insect Behaviour **12** (1999) 90–101
4. Röhrig, A., Kirchner, W., Leuthold, R.: Vibrational alarm communication in the african fungus-growing termite genus macrotermes (isoptera, termitidae). Insectes Sociaux **46** (1999) 71–77
5. Mankin, R., Osbrink, W., Oi, F., Anderson, J.: Acoustic detection of termite infestations in urban trees. Journal of Economic Entomology **95** (2002) 981–988
6. Puntonet, C.: New Algorithms of Source Separation in Linear Media. PhD thesis, University of Granada, Department of Architecture and Technology of Computers, Spain (1994)
7. Mansour, A., Barros, A., Onishi, N.: Comparison among three estimators for higher-order statistics. In: The Fifth International Conference on Neural Information Processing, Kitakyushu, Japan (1998)
8. A. Mansour, N. Ohnishi, C.P.: Blind multiuser separation of instantaneous mixture algorithm based on geometrical concepts. Signal Processing **82** (2002) 1155–1175
9. Puntonet, C., Mansour, A.: Blind separation of sources using density estimation and simulated annealing. IEICE Transactions on Fundamental of Electronics Communications and Computer Sciences **E84-A** (2001)
10. Hyvärinen, A., Oja, E.: Independent Components Analysis: A Tutorial. Helsinki University of Technology, Laboratory of Computer and Information Science (1999)
11. Lee, T., Girolami, M., Bell, A.: A unifying information-theoretic framework for independent component analysis. Computers and Mathematics with Applications **39** (2000) 1–21
12. Zhu, J., Cao, X.R., Ding, Z.: An algebraic principle for blind source separation of white non-gaussian sources. Signal Processing **79** (1999) 105–115
13. Cardoso, J.: Blind signal separation: statistical principles. Proceedings of the IEEE **9** (1988) 2009–2025
14. Górriz, J.: Hybrid Algorithms for Time-Series Modelling Using AR-ICA Tecniques. PhD thesis, University of Cádiz, Department of Systems' Engineering and Electronics, Spain (2003)
15. Ham, F., Faour, N.: Infrasound Signal Separation using Independent Component Analysis. Sponsored by the Boeing Company, Contract No. 7M210007 (2002)
16. Hinich, M.: Detecting a transient signal by biespectral analysis. IEEE Trans. Acoustics **38** (1990) 1277–1283
17. Nykias, C., Mendel, J.: Signal processing with higher-order spectra. IEEE Signal Processing Magazine (1993) 10–37
18. Mendel, J.: Tutorial on higher-order statistics (spectra) in signal processing and system theory: Theoretical results and some applications. Proceedings of the IEEE **79** (1991) 278–305
19. Swami, A., Mendel, J., Nikias, C.: Higher-Order Spectral Analysis Toolbox User's Guide. (2001)