# Recent Developments in the use of Acoustic Sensors and Signal Processing Tools to Target Early Infestations of Red Palm Weevil in Agricultural Environments 1

Author: Mankin, Richard W.

Source: Florida Entomologist, 94(4) : 761-765

Published By: Florida Entomological Society

URL: https://doi.org/10.1653/024.094.0405

# RECENT DEVELOPMENTS IN THE USE OF ACOUSTIC SENSORS AND SIGNAL PROCESSING TOOLS TO TARGET EARLY INFESTATIONS OF RED PALM WEEVIL IN AGRICULTURAL ENVIRONMENTS[1]

RICHARD W. MANKIN
U.S. Department of Agriculture, Agriculture Research Service,
Center for Medical, Agricultural, and Veterinary Entomology, Gainesville, FL, USA

[1]Presented verbally at The Challenge, Red Palm Weevil, Workshop, March 29-31, 2010, Riyadh, Saudi Arabia

ABSTRACT

Much of the damage caused by red palm weevil larvae to date palms, ornamental palms, and palm offshoots could be mitigated by early detection and treatment of infestations. Acoustic technology has potential to enable early detection, but the short, high-frequency sound impulses produced by red palm weevil larvae can be difficult to distinguish from certain similar sounds produced by other insects or small animals, or by wind-induced tapping noises. Considerable research has been conducted to develop instruments and signal processing software that selectively amplify insect-produced sounds and identify signal features that distinguish sounds produced by a particular target insect from those produced by other causes. Progress has been made in identifying unique spectral and temporal patterns in the sounds produced by larvae during movement and feeding activities. This report describes some of the new instrumentation and signal analyses available for early, reliable detection of red palm weevil larvae in groves and greenhouses.

Key Words: *Rhynchophorus ferrugineus*, acoustic detection, invasive species

RESUMEN

Gran parte de los daños causados por las larvas del gorgojo rojo de las palmas a las palmeras dátiles, palmas ornamentales y los retoños de palmas podrían ser mitigados mediante la detección temprana y el tratamiento de las infestaciones. La tecnología acústica tiene el potencial de permitir la detección temprana, pero los impulsos cortos de alta frecuencia de sonido producidas por las larvas del gorgojo rojo de las palmas pueden ser difíciles de distinguir de ciertos sonidos similares producidos por otros insectos o animales pequeños o los toques de sonido producidos por el viento. Se han realizado muchas investigaciones para desarrollar instrumentos y software (programas de computadora) de procesamiento de señales que amplifican selectivamente los sonidos producidos por insectos e identificar las características de las señales que distingue a los sonidos producidos por el insecto clave en particular de los producidos por otras causas. Se ha avanzado en la identificación de patrones espectrales y temporales únicos de los sonidos producidos por las larvas durante las actividades de movimiento y la alimentación. Este informe describe algunos de los nuevos instrumentos y análisis de señales para la detección temprana y fiable de las larvas del gorgojo rojo de las palmas en las plantaciones e invernaderos.

The red palm weevil, *Rhynchophorus ferrugineus* (Olivier), has caused considerable economic loss to date palms, *Phoenix dactylifera* L., since the 1980s in the Middle East (Mukhtar et al. 2011). The larvae penetrate the palm tree trunks after hatching in soft, injured, or protected areas of the trees, creating cavities and tunnels that weaken its structure and reduce transfer of nutrients and water between the root system and crown. The hidden larvae usually remain undetected until they cause considerable damage. Undetected larvae can be transported within and between different agricultural regions inadvertently; consequently, improved methods of early detection would be greatly beneficial for control and reduction in the spread of these pests.

Larvae produce sounds as they move and feed within the palm tree trunk and stem. Several researchers, including von Laar (2002), Hetzroni et al. (2004a, b), Al-Manie & Alkanhal (2005), and Siriwardena et al. (2010) have determined that currently available insect detection instrumentation, including the Laar TCE 1 detector (Benedikt von Laar; Inc., Klein Gornow, Germany), the Larven Lauscher (NIR-Service, Bad Vilbel, Germany), the AED-2000 (AEC, Inc., Fair Oaks, California), as well as customized devices and general-purpose accelerometers can provide early detection of larvae in palm shoots and trees (Mankin et al. 2011). However, acoustic technology has not yet come into general use for detection of *R. ferrugineus* larvae, partly because of instrumentation costs, training needs, and traditional agricultural practices. In addition, background noise (Mankin et al. 2008b; Potamitis et al. 2009; Mankin & Moore 2010), as well as internal sounds within the tree itself (e.g., Fukuda et al. 2007), can interfere with precise identification of insect larval signals in trees. However, although other methods of early detection have been tested, some of which including pheromone traps have come into general use (Faleiro & Kumar 2008), each of these also has suffered from logistic and implementation issues (Mukhtar et al. 2011). Consequently developmental efforts to overcome the known deficiencies of insect acoustic detection technology have continued. Here we consider some of the signal processing analyses that have been developed to improve the reliability of detecting insect pests in groves and greenhouses, and which have potential for use in automated detection instruments.

### Spectral and Spatial Filtering

Much of the unwanted background noise in agricultural environments occurs over periods of 10 s or longer. Typically the background noise has peak energy at relatively low frequencies, below 1 kHz, and its source usually is somewhat distant from the tree to which the sensor is attached. In contrast, *R. ferrugineus* larval sound impulses are 3 to 50 ms in duration and have peak frequencies in the range of 1 to 3.8 kHz (Fig. 1, and see also Al-Manie & Alkanhal 2005; Mankin et al. 2008a; Potamitis et al. 2009). The signals in Fig. 1, for example, were recorded from a 4th-instar (ca. 90 mg) larva in a palm tree using a Larven Lauscher sensor by procedures described in Mankin et al. (2008a). The spectrogram was constructed in Raven (Charif et al. 2008) from 1024-point (23.2-ms) time slices with 50% overlap. Computers can be trained to discard low-frequency, long-duration signals, and to focus instead on groups (bursts) of short impulses (Mankin et al. 2011). The extent of filtering necessary in a given agricultural environment depends on the nature and intensity of the background noise. Filtering has been effective at frequencies as low as 200 Hz (Mankin et al. 2008b), and as high as 2000 Hz (Potamitis et al. 2009). After filtering, signals that remain above a background amplitude threshold for longer than 50-100 ms typically are discarded.

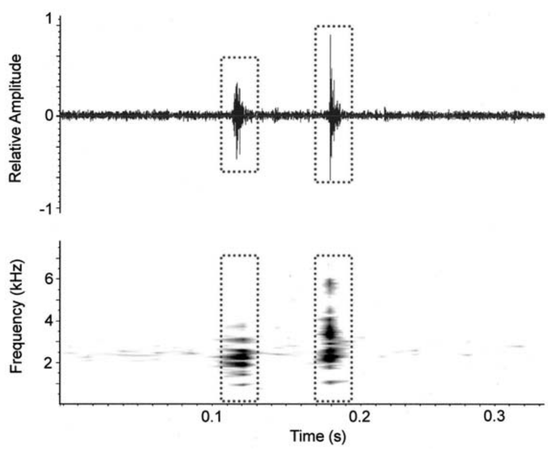


Fig. 1. Oscillogram and spectrogram of red palm weevil (RPW) sound-impulses (impulses in dotted boxes).

Signals from *R. ferrugineus* larvae attenuate rapidly within a palm tree and high-frequency signals attenuate more rapidly than low-frequency signals (Mankin et al. 2000); consequently, two sensors spaced several cm apart may detect signals of different frequencies and amplitudes from the same larval infestation. This enables the use of high-pass filters to eliminate much of the background noise, and if multiple sensors are used simultaneously, the signals from one can be subtracted from the other to extract distant noise before other signal processing is conducted (e.g., Aubin et al. 2000). In surveys of potential infestations in trees, experienced listeners often sample at multiple locations in the tree (Mankin & Moore 2010; Siriwardena et al. 2011; Mankin et al. 2011). Signals recorded from *R. ferrugineus* larvae at distances of 0.5, 1, and 4 m are notably different, for example, due to the reduction in detectability of high-frequency signals at greater distances from the larvae (Mankin et al. 2011), and instructive samples of such recordings have been copied onto IPods for use in training scouts to discriminate signals of the targeted larvae from other insects and general background noise. Similarly, small larvae are likely to produce lower-frequency and lower-amplitude signals than large larvae (Mankin et al. 2011).

### Acoustic Spectrum Features

Considerable improvement in signal-noise discrimination can be obtained by separating individual insect-produced impulses as independent events, computing several spectral features of each impulse, and then comparing the spectral features with expected values (Mankin et al. 2000; Potamitis et al. 2009; Hussein et al. 2009). Usually the spectral features are normalized before the comparisons are performed. Several spectral features have proven useful for purposes of discrimination, including the Fourier transform (Mankin et al. 2000; Hetzroni et al. 2004a, b), the dominant harmonic (Potamitis et al. 2009), and linear frequency cespstral coefficients (Pinhas et al. 2008; Potamitis et al. 2009). In Fig. 2, for example, a profile is constructed as a mean of three spectra of sound impulses produced by 0.36-mg

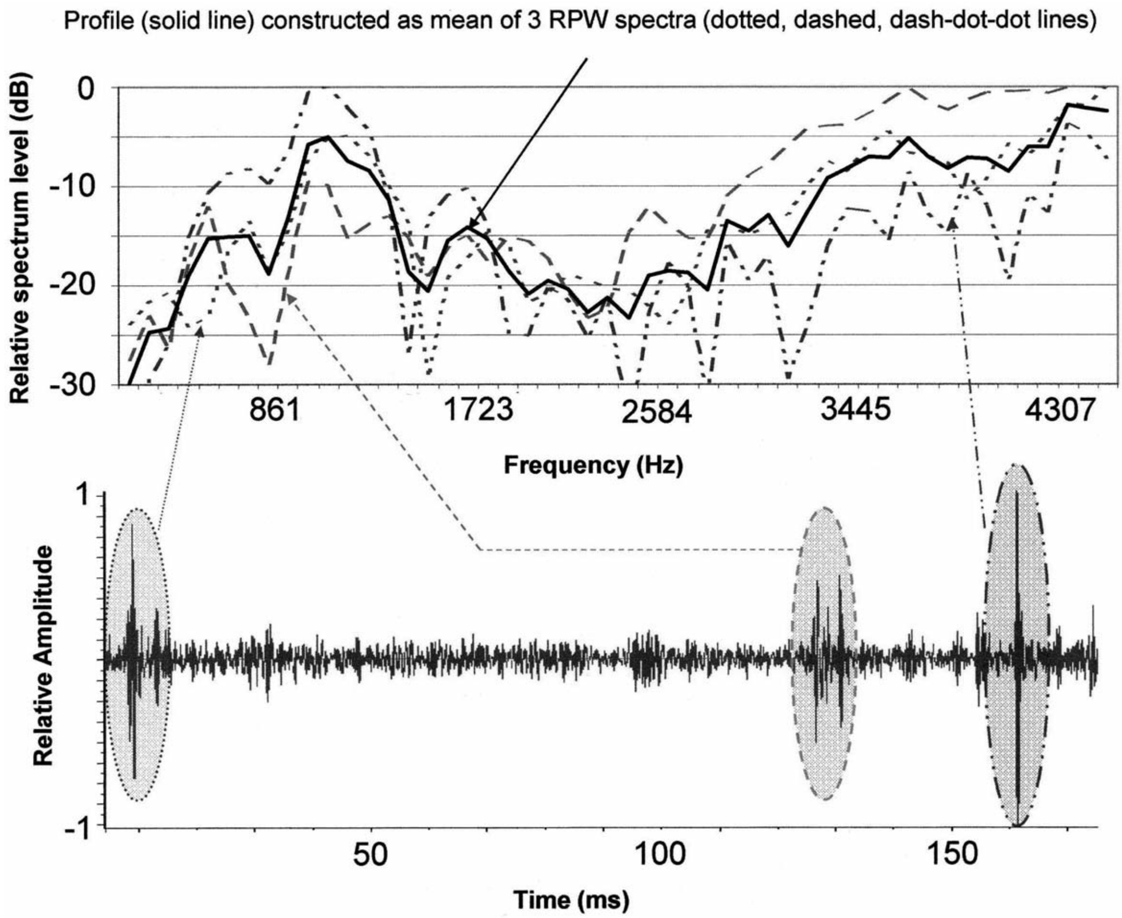


Fig. 2. Example of a spectral profile calculated as the mean spectrum from three individual red palm weevil (RPW) larval sounds (impulses marked in dotted, dashed, and dash-dot-dot ovals).

RPW larva in a sugarcane section and recorded using the Larven Lausher sensor by methods described in Mankin et al. (2008a). Using such profiles, it is possible to determine whether each individual impulse in a recording matches sufficiently with known insect sounds or if it should be discarded.

Various other methods have been used to cluster together features of insect-produced signals and discriminate them from background noise features, including several used in speech recognition (e.g., Bimbot et al. 2004), such as vector quantization (Pinhas et al. 2008) and Gaussian mixture modeling (Pinhas et al. 2008; Potamitis et al. 2009). It can be anticipated that signal processing programs will be available soon that enable researchers and scouts to choose among multiple signal discrimination methods to optimize the reliability of identifying their target insects. In addition, the reliability of detection can be improved by incorporating temporal pattern features in to the analyses (see below).

Acoustic Temporal Pattern Features

Many cryptic insects that move and feed in trees (von Laar 2002; Mankin et al. 2008a, b, 2010) or soil (Mankin et al. 2000; Mankin et al. 2009) have behavioral patterns with regularities that can be identified by listeners. The patterns usually do not have sufficient regularity to be characterized reliably by computer programs, but several studies have found that the insect-produced signals can be identified by computer as bursts of impulses separated by quiet intervals of 0.25 s or more (Mankin et al. 2008b; 2009). The number of sound impulses in a burst varies with the behavior, but a typical locomotory or feeding movement produces at least six impulses, and often can produce as many as 50-200 impulses. These regularities can be used as signal features to distinguish a target insect from other insects or background sounds. The temporal regularities are most easily identified when the insect is large and active, e.g., with *R. ferrugineus* larvae > 0.27

gm (Mankin et al. 2008a). The incorporation of bursts as a signal feature in signal processing enables discarding of wind-induced tapping noises and other background sounds that have the same spectral characteristics as insect-produced sounds but typically are very brief or very long in duration (Mankin et al. 2009; Mankin & Moore 2010). These features are somewhat independent of RPW larval size in that the correlation between the rate of bursts and larval weight is not significant, and neither is the correlation between the rate of impulses and larval weight (Mankin et al. 2008a). Similar results were found for larvae of another wood-boring insect, *Agrilus planipennis* Fairmaire (Ulyshen et al. 2011).

### Automated Machine Learning

Although signal processing programs have steadily improved in their capability to identify spectral and temporal patterns that distinguish targeted insect pests from other animals and general background noises, the human listener remains significantly better in successful discriminating pest insect sounds. Listeners can identify the sounds of larvae tearing wood fibers (Mankin et al. 2008b), the sounds of larvae moving in their feeding chambers (von Laar 2002; Mankin et al. 2009), and even occasional sounds of digestion (von Laar 2002), but signal processing tools are not yet available to perform such tasks. One potential approach is to train a computer program to teach itself the temporal patterns of typical insect scraping, feeding, or locomotory activities. Two approaches that appear particularly promising for insect detection include hierarchical temporal memory models (Hawkins 2004) and hierarchical sequential memory models (Jones 2009; Schwartz & Jones 2009). Both methods are under vigorous development and have a variety of potential applications above and beyond their insect detection applications. A rudimentary hierarchical sequential memory model was used to distinguish flying male and female Mediterranean fruit flies in an anechoic chamber, but until now, it has had only limited success in field environments (Mankin et al. 2006).

### Incorporation of Acoustic Technology into Quarantine, Eradication, and Management Programs

In regions where *R. ferrugineus* is well established, management is accomplished through mass-trapping of adults, sanitation, physical and chemical treatment of wounds, and chipping, burning, or otherwise disposing of palms observed to be infested with larvae (Faleiro & Kumar 2008). The use of acoustic technology enables improved detection of larvae (Siriwardena et al. 2010) and targeting of infested trees. This is even more important in the late stages of an eradication or quarantine program when the likelihood of adult trapping or visual observation of larvae is small. Once purchased or constructed, an acoustic instrument has a 5-10-year lifetime or more, based on experience with six systems used by the author, and is likely to pay back its original cost through improvements in timeliness and targeting capability.

## Acknowledgments

Saudi Arabia Basic Industries Corporation provided funding for the red palm weevil workshop. The use of trade, firm, or corporation names in this publication is for the information and convenience of the reader. Such use does not constitute an official endorsement or approval by the United States Department of Agriculture of any product or service to the exclusion of others that may be suitable.

## References Cited

Al-Manie, M. A., and Alkanhal, M. I. 2005. Acoustic detection of the red date palm weevil. World Academy of Science, Engineering and Technology 2: 160-163.

Aubin, T., Rybak, F., and Moulin, B. 2000. A simple method for recording low-amplitude sounds. Application to the study of the courtship song of the fruit fly *Drosophila melanogaster*. Bioacoustics 11: 51-67.

Bimbot, F., Bonastre, J. F., Fredouille, C., Gravier, G., Magrin-Chagnolleu, I., Meigneir, S., Merlin, T., Ortega-Garcia, J., Petrovska-Delacrétaz, D., and Reynolds, D. A. 2004. A tutorial on text-independent speaker verification. Eurasip. J.Appl. Signal Processing 2004, 430-451.

Charif, R. A., Waack, A. M., and Strickman, L. M. 2008. Raven Pro 1.3 user's manual. Cornell Laboratory of Ornithology, Ithaca, New York.

Faleiro, J. R., and Kumar, J. A. 2008. A rapid decision sampling plan for implementing area-wide management of the red palm weevil, *Rhynchophorus ferrugineus*, in coconut plantations of India. J. Insect Sci. 8: 15.

Fukuda, K., Utsuzawa, S., and Sakaue, D. 2007. Correlation between acoustic emission, water status and xylem embolism in pine wilt disease. Tree Physiol. 27: 969-976.

Hetzroni, A., Mizrach, A., Nakache, Y, and Soroker, V. 2004a. Developing spectral model to monitor activity of red palm weevil. Alon Hanotea 58: 466-469.

Hetzroni, A., Mizrach, A., Nakache, Y, and Soroker, V. 2004b. Spectral model for activity monitoring of red palm weevil. Paper No. 30-138A, Part III, p. 144 *In* 2004 CIGR International Conference, Beijing, China

Hussein, W. B., Hussein, M. A., and Becker 2009. Application of the signal processing technology in the detection of red palm weevil, pp. 1597-1601 *In* Proc. 17th European Signal Processing Conference, August 24-28, Glasgow, Scotland.

Jones, R. L. 2009. Hierarchical sequential memory model: pattern recognition and memorization. Internal Technical Memorandum. Sigma Space Corp.

Mankin, R. W., Brandhorst-Hubbard, J., Flanders, K. L., Zhang, M., Crocker, R. L., Lapointe, S. L., McCoy, C. W., Fisher, J. R., and Weaver, D. K.

2000. Eavesdropping on insects hidden in soil and interior structures of plants. J. Econ. Entomol. 93: 1173-1182.

MANKIN, R. W., MACHAN, R., AND JONES, R. 2006. Field testing of a prototype acoustic device for detection of Mediterranean fruit flies flying into a trap, pp. 165-169 *In* Proc. 7th Int. Symp. Fruit Flies of Economic Importance, 10-15 Sep 2006, Salvador, Brazil.

MANKIN, R. W., MIZRACH, A. HETZRONI, A., LEVSKY, S., NAKACHE, Y., AND SOROKER, V. 2008a. Temporal and spectral features of sounds of wood-boring beetle larvae: identifiable patterns of activity enable improved discrimination from background noise. Florida Entomol. 91: 241-248.

MANKIN, R. W., SAMSON, P. R., AND CHANDLER, K. J. 2009. Acoustic detection of Melolonthine larvae in Australian sugarcane. J. Econ. Entomol. 102: 1523-1535.

MANKIN, R. W., SMITH, M. T., TROPP, J. M. ATKINSON, E. B., AND JONG, D. Y. 2008b. Detection of *Anoplophora glabripennis* (Coleoptera: Cerambycidae) larvae in different host trees and tissues by automated analyses of sound-impulse frequency and temporal patterns. J. Econ. Entomol. 101: 836-849.

MANKIN, R. W., AND MOORE, A. 2010. Acoustic detection of *Oryctes rhinoceros* (Coleoptera: Scarabaeidae: Dynastinae) and *Nasutitermes luzonicus* (Isoptera: Termitidae) in palm trees in urban Guam. J. Econ. Entomol. 103: 1135-1143.

MUKHTAR, M., RASOOL, K. G., PARRELLA, M. P., SHEIKH, Q. I., PAIN, A., LOPEZ-LLORCA, L. V., ALDRYHIM, Y. N., MANKIN, R. W., AND ALDAWOOD, A. S. 2011. Historical Arabian date palms threatened by weevils. Florida Entomol. (In Press)

PINHAS, J., SOROKER, V., HETZRONI, A., MIZRACH, A., TEICHER, M., AND GOLDBERGER, J. 2008. Automatic acoustic detection of the red palm weevil. Computers and Electronics in Agriculture. 63: 131-139.

POTAMITIS, I., GANCHEV, T., AND KONTODIMAS, D. 2009. On automatic bioacoustic detection of pests: The cases of *Rhynchophorus ferrugineus* and *Sitophilus oryzae*. J. Econ. Entomol. 102: 1681-1690.

SCHWARTZ, A. D., AND JONES, R. L. 2009. On the pattern classification of structured data using the neocortex-inspired memory-prediction framework. Technical Report 090612, Sigma Space Corp.

SIRIWARDENA, K. A. P., FERNANDO, L. C. P., NANAYAKKARA, N., PERERA, K. F. G, KUMARA, A. D. N. T., AND NANAYAKKARA, T. 2010. Portable acoustic device for detection of coconut palms infested by Ryncophorus ferrugineus (Coleoptera: Curculionidae). Crop Prot. 29: 25-29.

ULYSHEN, M. D., MANKIN, R. W., CHEN, Y., DUAN, J. J., POLAND, T. M., AND BAUER, L. S. 2011. Role of emerald ash borer (Coleoptera: Buprestidae) larval vibrations in host-quality assessment of *Tetrastichus planipennisi* (Hymenoptera: Eulophidae). J. Econ. Entomol. 104: 81-86.

VON LAAR, B. 2002. The bioacoustic detection of the red palm weevil. http://www.laartech.biz/data/pdf/Red Palm Weevil.pdf.