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Automatic acoustic detection of the red palm weevil

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ABSTRACT

The red palm weevil (RPW) is a key pest of horticultural and ornamental palm species in Asia, the Middle East and the Mediterranean region, currently dispersing in Mediterranean European countries, endangering the landscape. The RPW larvae bore deep into palm crowns, trunks and offshoots, concealed from visual inspection until the palms are nearly dead. Traded palm trees are intensively transported between and within countries, spreading the pest worldwide. Consequently, an urgent need exists to identify and monitor concealed RPW larvae. Acoustic signals of boring RPW larvae can be recorded from the infested palms using off-the-shelf recording devices, but the resolution of the signals emitted by healthy palms is often difficult to discriminate. The purpose of this research was to develop a mathematical method to automatically detect acoustic activity of RPW in offshoots and implement it in a prototype setup. The methodology applied was similar to techniques used in the field of speech recognition, utilizing Vector quantization (VQ) or Gaussian mixture modeling (GMM). The algorithm successfully achieved detection ratios as high as 98.9%. The study shows that it is feasible to detect RPW sounds using the mathematical method of speech recognition and commercial recording devices, which could be utilized to monitor trade and transportation of offshoots.

1. Introduction

A red palm weevil, *Rhynchophorus ferrugineus* (RPW), is a key pest of horticultural and ornamental palm species in Asia, the Middle East and the Mediterranean region. The RPW is currently spreading in Mediterranean European countries, endangering picturesque landscapes that are very attractive to tourists (Ferry and Gómez, 1998; Khalid, 2007; Murphy and Briscoe, 1999; Soroker et al., 2006, 2005). The female RPW lays eggs in injuries in the trunks of established trees, at the base of the palm leaves, at tree crowns and adjacent to offshoots. The RPW larvae bore deep into palm crowns, trunks, and offshoots, generally concealed from visual inspection until the palms are nearly dead. Several weevil generations may develop within a single tree. Infested trees suffer from reduced productivity. Heavy infestations often result in collapsed trees and thus, total loss of crops (Blumberg et al., 2001). Young palm trees (and in the case of date palms, their offshoots) are intensively traded and transported between and within countries, therefore the pest is spread worldwide (Giblin-Davis, 2001).

There is an urgent need to monitor and identify concealed RPW larvae that might otherwise spread rapidly through

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commercial channels. Distinct acoustic signs of RPW larvae activities are produced while the larvae are chewing and moving. However, it is known that plants can produce sounds in various cases, e.g., in a drought-stricken situation (Fukuda et al., 2007; Jolivet, 1998). Thus sounds emerging from a tree do not directly indicate the presence of larvae. Sound produced by heavy infestations can even be picked up by the human ear (Al-Manie and Alkanhal, 2004; Giblin-Davis, 2001), but when the sounds are that loud it indicates that severe damage to palm tissue has already occurred (Soroker et al., 2006).

Previously, acoustic detection of chewing and locomotion sounds has been used to monitor and detect termites in wood (Scheffrahn et al., 1993), adult insects and larvae in stored products (Mankin et al., 1997), grubs in soil (Mankin et al., 2000; Zhang et al., 2003), pink boll worm larvae in cotton (Hickling et al., 1994; Ingram, 1994), and wheat pests in stems (Mankin et al., 2004). These studies were either fully based on human capabilities (Ingram, 1994; Soroker et al., 2004; Al-Manie and Alkanhal, 2004), or based on human analysis of a software output (Mankin et al., 2002; Zhang et al., 2003). Attempts have been made to automatically detect damage and infestation in wheat and hazelnuts based on impact acoustics analysis and voice verification methods (Cetin et al., 2004; Pearson et al., 2007; Ince et al., 2007) and attempts have been made to automatically identify and classify singing insects based on a speaker recognition paradigm (Potamitis et al., 2006; Ganchev et al., 2007). These sensitive automatic detection systems utilized state-of-the-art speaker recognition methods, however, they were not found applicable to the palm agro-system. The problem of discriminating RPW larvae sounds from plant and background sounds can be compared to the problem of 'text-independent speaker identification', which associates an unknown voice with one from a set of enrolled speakers based on unheard sentences (Bimbot et al., 2004). We hypothesized that the discrimination of RPW larvae sounds from plant sounds and background noise is similar to recognition of a certain speaker among several, and that the RPW larvae discriminating problem can be solved using the same tools as in the case of the speaker recognition problem; the common ground to these two discrimination problems is that in both we try to capture the spectral characteristics of a subject in order to identify it later on. There is extensive and well-documented literature in the field of speaker recognition, including Rabiner and Juang (1993), Reynolds and Rose (1995), Campbell (1997), Bilmes (1997), Duda et al. (2001), Bimbot et al. (2004) and Petrovska-Delacretaz et al. (2007). We used several recognition elements from these studies for the RPW detection algorithm in this study.

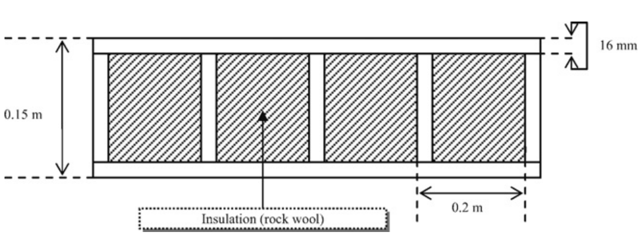

Fig. 1 – Sound-isolated box wall section. Each wall was 0.15 m thick, constructed from two layers of 16-mm plywood, braced with orthogonal braces.

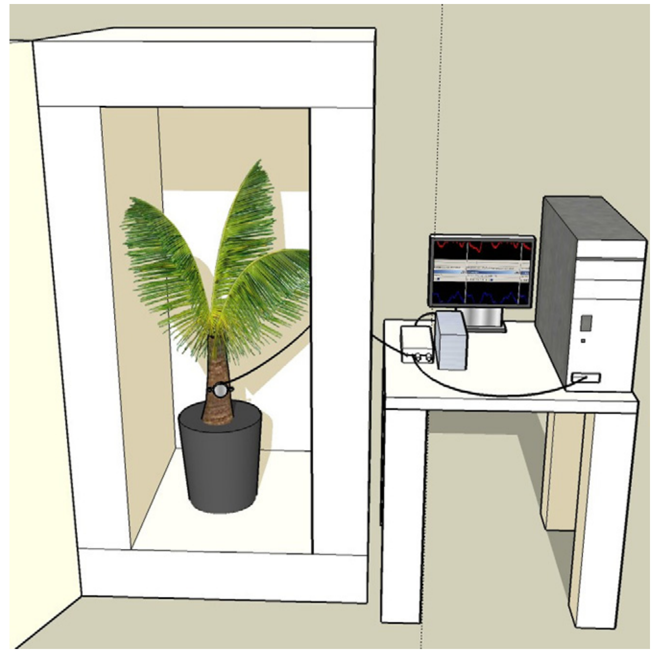

Fig. 2 – Recording equipment diagram.

Our purpose was to develop an automatic, robust and computationally light algorithm for detection of acoustic activity of RPW larvae in offshoots that would enable us to build a prototype setup for non-invasive inspection of suspected offshoots. This technique could determine RPW infestation, thus offering a solution to monitoring and control of the spread of the RPW infestation in offshoots.

2. Materials and methods

2.1. *Recordings*

Young date palms (*Phoenix dactylifera*) and offshoots, trunk diameter ranged between 60 and 100 mm, were grown in 10 L buckets inside isolated greenhouse under quarantine conditions. The plants were visually and acoustically inspected to ensure they did not host any insects. The insects occasionally found were ants; these however were not acoustically detectable. The offshoots were infested with one or two young RPW larvae weighing 32 ± 5 mg each; 22 were infected with one RPW larva, three were infected with two RPW larvae, and four offshoots were used as a control group. The RPW larva was inserted through a 3 mm in diameter hole drilled in the offshoot trunk (Soroker et al., 2004). We recorded 377 wav files of infected offshoots and 55 wave files of uninfected offshoots (control group). The length of each file varied between 55 and 60 s. During the data acquisition, only files containing sounds were saved, blank recordings were discarded. All recordings were conducted with the offshoots placed inside the sound-isolated recording box in a greenhouse. Each offshoot was recorded three times per week over a period of about 4 weeks.

Recording box outer dimensions were: 1.5 m high, 0.8 m wide and 0.8 m deep. The walls and door were 0.15 m thick,

Fig. 3 – (a) Amplifier and a 12 V, 7 Ah battery. (b) An offshoot inside the sound-isolated box. (c) Piezoelectric microphone. (d) Microphone attached to offshoot's stem with a rubber band.

constructed from a 16-mm plywood frame (Fig. 1). The walls were filled with rock wool. The back inner wall of the box was coated with Sonex sound-absorbing foam (www.sonex-online.com/, Seattle, Washington, US. PO Box 967, 455 First St., Langley, WA 98260) to reduce the humming effect.

Recording equipment (Figs. 2 and 3) was composed of Pentium II 266 MHz PC, equipped with a high-definition audio card (any sound card capable of 24-bit 96 kHz recording), a sound-isolated recording box, an amplifier and a microphone (Larven Lauscher, NIR-Service W. Weinard., An den Banggarten 22a D-61118 Bad Vilbel., nir-service@gmx.de).

Algorithm analysis equipment was composed of AMD Athlon 64 3200+ based computer, which enabled real-time operation. The algorithm was implemented using Matlab (2007).

2.2. *Recording procedure*

An offshoot was placed inside the acoustically isolated box. The microphone was attached to the offshoot trunk with a rubber band (Fig. 3(d)), and box was sealed. The operator, equipped with headphones, monitored the acoustic activity inside the box and began the recording process each time any acoustic activity was heard for periods of 55–60 s. Silence was maintained in the room during the recording as a precaution to reduce environmental noises.

Table 1 – Three listeners labeled 404 sound file

Group	Files in group	Percentage	RPW larva age[a]
'Practical Full Agreement': files that where labeled (positive, positive, positive) or (negative, negative, negative)	193	48	$\mu = 10.54$; $\sigma^2 = 5.72$
'Practical Partial Agreement': files that where labeled (positive, positive, unknown) or (negative, negative, unknown)	85	21	$\mu = 8.95$; $\sigma^2 = 5.84$
'Impractical Full Agreement': files that where labeled (unknown, unknown, unknown)	4	1	$\mu = 3.75$; $\sigma^2 = 1.71$
'Impractical Partial Agreement': files that where labeled (positive, unknown, unknown) or (negative, unknown, unknown)	46	12	$\mu = 1.52$; $\sigma^2 = 5.05$
'No Agreement': files that where labeled with one positive label and one negative label	74	18	$\mu = 2.35$; $\sigma^2 = 5.28$

Possible labels were: positive, negative and unknown. The files were sorted into five groups according to labeling by three listeners.
[a] RPW larva age in days from infestation.

2.3. *Manual labeling*

Recordings of uninfested offshoots always result with sound files that we can undoubtfully label as 'noise'. This is not the case with recordings of infested offshoots, since sounds that emerge from an infested offshoot may be the result of plant activity, or, they may be the result of larvae activity. Since labeling of infested offshoots is not trivial, four experienced listeners were asked to examine 404 recorded files, in a single blind test. Each listener labeled each file as 'positive', 'negative' or 'unclear'. A 'positive' label indicated that the listener identified clear RPW larvae activity in the file. A 'negative' label indicated that the listener was certain that the recording did not contain any RPW larvae sounds. An 'unclear' label means that the listener was undecided.

The files where then sorted, based on their labels, into two groups: (1) 'Full Agreement', files that all four listeners labeled the same (either positive or negative) or (2) 'No Agreement', the remainder of the files. It was found that the four listeners fully agreed on 35.4% of the files. The agreement among three out of the four listeners was evaluated. Out of the four possible triplets, we found the following ratios: 44.55%, 41.34%, 38.86% and 48.27%. We therefore decided to take into account only the three listeners that gained higher correlation and to discard the fourth listener. A new refined grouping scheme was then introduced, where the files were sorted into five categories: (1) 'Practical Full Agreement': files that where all labeled 'positive' (positive, positive, positive) or all 'negative' (negative, negative, negative); (2) 'Practical Partial Agreement': files that where labeled (positive, positive, unknown) or (negative, negative, unknown); (3) 'Impractical Full Agreement': files that where labeled (unknown, unknown, unknown); (4) 'Impractical Partial Agreement': files that where labeled (positive, unknown, unknown) or (negative, unknown, unknown); (5) 'No Agreement': the rest of the files.

Our algorithm was evaluated against 278 files from the 'practical full agreement' and 'practical partial agreement' groups (Table 1) plus 28 additional files that contained plant activity sounds from the control group.

2.4. *Algorithm overview*

Given a new unknown sound stream (or file), our aim was to accurately detect RPW larvae activity within the stream. The stream was divided into a series of fixed-size segments, which were labeled separately. If, at least one of the segments was labeled as 'larva', the stream was also labeled as 'larva'; otherwise it was labeled as 'noise'. Segment length varies between 2 and 10 s. The detection algorithm (Fig. 4) included: (a) Preprocess—framing the segment into short fixed-size overlapping frames, filtering out null frames, extracting feature and normalizing, (b) Labeling frames—using a clustering algorithm to label each frame in the segment, and (c) Labeling segment—detecting larvae activity according to the frame labels in the segment and a segment score function.

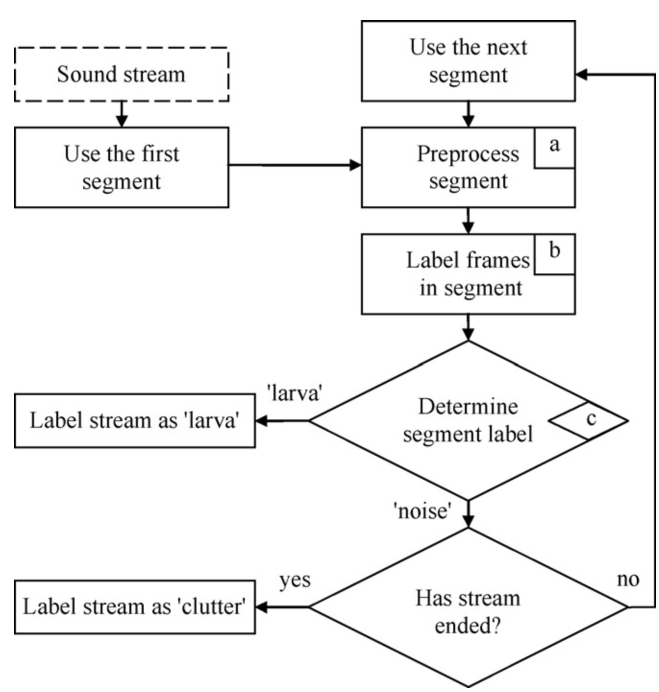

Fig. 4 – Flow diagram describing the detection algorithm used to analyze sound files.

2.5. Algorithm description

The preprocessing included the division of the file into several fixed-size frames with 50% overlap (Bimbot et al., 2004). The lengths of the frames used were: 128, 256, 512, 1024 and 2048 samples long (equivalent to 1.3, 2.7, 5.3, 11.7 and 23.3 ms in sampling rate of 96 kHz, respectively). These frame lengths allowed us to use the assumption of stationarity (Bimbot et al., 2004). The noise threshold was calculated using a 2 s silence recording that was manually selected. The threshold enabled us to separate all frames into two groups: 'null frames' which included frames with lower RMS amplitude than the noise threshold, and 'signal frames' which were all of the other frames. The null frames which did not carry any usable information were discarded (Bimbot et al., 2004). We calculated a log-spectral feature vector for each signal frame, using the Hamming window as suggested by Bimbot et al. (2004). The features where calculated according to the following band passes: 100–175, 175–325, 325–625, 625–1225, 1225–2425, 2425–4825, 4825–9625 and 9625–19,225 Hz. The power contained in the last band (9625–19,225 Hz) was used to normalize the feature vector by subtracting it from each of the other features.

We experimented with two clustering algorithms: Vector quantization (VQ) (Linde et al., 1980) and Gaussian mixture modeling (GMM) (Reynolds and Rose, 1995; Bilmes, 1997). We ran the clustering algorithm twice, once for the larvae sounds and a second run for the noise sounds. The resulting two centroids/Gaussian groups constituted a classifier for larvae and noise activity in a single frame. Using GMM, we calculated two mixtures, one for the larvae activity and a second for the noise. Each frame was labeled by utilizing the standard likelihood estimation function of the GMM algorithm. Using VQ, we calculated two cluster groups, one for larvae and the other for noise, and used them to label each frame by shortest distance (Euclidian), using the nearest neighbor classifier.

The sound stream was divided into fixed-size non-overlapping consecutive segments. Each Segment was divided into 50% overlapping frames; features were extracted, normalized and labeled. A decision rule was then used to label the whole segment (Eq. (5)). The segment length of 5 s was initially chosen arbitrarily. Potentially, a segment may contain hundreds of signal frames, but it may, as well, be sparse or even empty after all null frames were filtered out. Each segment was labeled either as 'larvae' or 'noise'. It was common to label sound segment with a score function (Bimbot et al., 2004). Our segment labeling function used the frame labels in the segment in addition to a score function.

For the GMM algorithm, we offered the following score function, which is the log likelihood function of the model (Bilmes, 1997):

$$\mathrm{Score}(C, X) = \log\left(\prod_{x\in X}\Pr(x|C)\right) = \sum_{x\in X}\log\left(\sum_{l=1}^{k}\omega_l \underbrace{N(\mu_l,\sigma_l,x)}_{\text{normal distribution}}\right) \quad (1)$$

where

X is an array of feature vectors from an unknown source.
C is a mixture model with k mixtures and the parameters ω, σ and μ.
k is the number of Gaussians in C.

For the VQ algorithm, we offered the following score function, which was a simplified case of the log likelihood (Eq. (1)), where all weights were equal and the probability of any vector x being classified as its nearest neighbor centroid, was 1 and 0 for all the other centroids:

$$\mathrm{Score}(C, X) = -\sum_{x\in X}\mathrm{Min}_{c\in C}(|c-x|) \quad (2)$$

where

X is an array of feature vectors from an unknown source.
C is an array of k centroids derived from the VQ algorithm.

Eq. (1) or (2) were used to evaluate the likelihood that each segment originated from larvae or noise activity. A higher score indicated greater similarity. The score function was a weighted sum of distances between each frame in the segment to the nearest centroid/Gaussian in the model. Based on the likelihood ratio between both scores, the segment was labeled using (Bimbot et al., 2004):

$$\mathrm{SL}_1(X) = \begin{cases} \text{'larva'}, & \mathrm{Score}(C_l, X) > \theta\cdot\mathrm{Score}(C_n, X) \\ \text{'noise'}, & \text{otherwise} \end{cases} \quad (3)$$

where

X is a sound segment.
Score(C,X) is (1) in case of GMM and (2) in case of VQ.
θ is the likelihood ratio threshold, varies between 1.5 and 3.5.
C_l is the k-centroids/Gaussians that were learned for the larvae sounds.
C_n is the k-centroids/Gaussians that were learned for the noise sounds.
The value of θ was fine tuned with a twofold cross-validation.

Utilizing a linear discrimination between the number of larvae labels and noise labels in the segment, we offer the following segment labeling function:

$$\mathrm{SL}_2(X) = \begin{cases} \text{'larva'}, & L(X) > \beta \text{ and } L(X) > \gamma\cdot N(X) \\ \text{'noise'}, & \text{otherwise} \end{cases} \quad (4)$$

where

X is a sound segment.
$L(X)$ is the number of 'larva' labels in segment X.
$N(X)$ is the number of 'noise' labels in segment X.
β is the minimum number of 'larva' labels in the segment, varies between 5 and 20 in a 1 s long segment, for longer segments multiply by the segment length.
γ is the ratio between the number of larvae and noise labels in a 'larva' segment, varies between 3 and 8.
We fine tuned β and γ with twofold cross-validation.

Table 2 – The median detection ratio over various sets of parameters, ordered by frame length, and sub-ordered by segment length

Learning set	Clustering algorithm	Segment length	k	Frame length	Type-1-error (%)	Type-2-error (%)	Correct (%)
All larvae	GMM	1,3,5	2,3,5,7,10	128	15	0	92.5
All larvae	VQ	1,3,5	3,5,10,20,40	128	15	0	92.5
All larvae	GMM	1	2,3,5,7,10	256	15	0	92.5
All larvae	GMM	3	2,3,5,7,10	256	8.6	0	95.7
All larvae	GMM	5	2,3,5,7,10	256	6.9	0	96.6
All larvae	VQ	1	3,5,10,20,40	256	15	0	92.5
All larvae	VQ	3	3,5,10,20,40	256	8.6	0	95.7
All larvae	VQ	5	3,5,10,20,40	256	6.9	0	96.6
All larvae	GMM	1	2,3,5,7,10	512	3.1	3.1	96.9%
All larvae	GMM	3	2,3,5,7,10	512	3.1	1.4	97.7
All larvae	GMM	5	2,3,5,7,10	512	3.1	3.8	96.5
All larvae	VQ	1	3,5,10,20,40	512	3.1	3.1	96.9
All larvae	VQ	3	3,5,10,20	512	1.4	1	98.8
All larvae	VQ	5	3,5,10,20,40	512	3.1	3.1	96.9
All larvae	GMM	1	5,7,10	1024	4.1	0	97.9
All larvae	GMM	3	5,7,10	1024	2.4	2.4	97.6
All larvae	GMM	5	2,3,5,7,10	1024	2	3.5	97.25
All larvae	VQ	1	3,5,10,20,40	1024	4.1	0	97.9
All larvae	VQ	3	3,5,10,20,40	1024	2.4	2	97.8
All larvae	VQ	5	3,5,10,20,40	1024	2	3.5	97.25
All larvae	GMM	5	2,3,5,7,10	2048	1.3	2.6	98.1
All larvae	VQ	1,3,5	20,40	2048	1.3	2.6	98.1
Single larva	GMM	5	2,3,5,7,10	512	3.1	3.1	96.9
Single larva	VQ	5	5,7,10	512	3.1	3.1	96.9
Single larva	GMM	5	2,3,5,7,10	1024	2	3.5	97.25
Single larva	VQ	5	5,10,20,40	1024	2	3.5	97.25
Single larva	VQ	5	5,10,20,40	2048	1.3	2.6	98.1

Using (3) and (4), we offer the combined decision rule:

$$\mathrm{SL}_3(X) = \begin{cases} \text{'larva'}, & L(X) > \beta \text{ and } L(X) > \gamma \cdot N(X) \\ & \text{and } \mathrm{Score}(C_l, X) > \theta \cdot \mathrm{Score}(C_n, X) \\ \text{'noise'}, & \text{otherwise} \end{cases} \tag{5}$$

3. Results

3.1. Sound description

Sounds that emerge from an infected offshoot might be a direct result of the RPW larvae activity or of the offshoots internal physiological processes, caused by factors such as drought (Jolivet, 1998). The acoustic activity of uninfested offshoots consists of a couple of distinct sounds: sharp quick click sounds or long continuous sounds that resemble paper being crushed. The acoustic activity of RPW larvae (inside an offshoot) consists of the following sounds: chewing, crawling, emission and quick oscillating sounds. We have visual confirmation of chewing, crawling and emission phenomena. The oscillating sound was observed only in infected offshoots, yet we do not know how it is produced.

3.2. Algorithm performance

We explored several sets of algorithm parameters aiming to improve the detection ratio and to test the algorithms sensitivity. We examined the following parameters: (1) clustering algorithm (VQ and GMM); (2) various learning sets; (3) the number of cluster/Gaussians (k); (4) various frame lengths (128, 256, 512, 1024 and 2048 samples long); (5) different segment lengths (varies from 1 to 5 s); (6) the three parameters that affect the segment score (β, γ and θ, Eq. (5)).

The algorithm performance was measured by counting the mismatched labels of the 55–60 s sound files, against the manual label. The null hypothesis H_0 is that the offshoot was not infected with RPW, and the alternative hypothesis H_1 is that the offshoot was infested. Therefore type-1-errors (false positive) occurred when the algorithm indicated RPW larvae activity that did not exist. Type-2-errors (false negative) occurred when the algorithm failed to detect existing RPW larvae activity. We identified several sets of parameters in which the detection result was stable, approximately 96–98% (Table 2) and collected the median error with respect to number of clusters. Both VQ and GMM algorithms demonstrated similar detection capabilities, including stability and consistency in detecting RPW larvae activity over various sets of parameters such as segment length and number of clusters. Throughout most of the study, we used the same learning set, which was randomly selected from the entire dataset of sound samples from active RPW larvae. After we found the optimal set of parameters, we evaluated the detection ratio of the same parameter set against a smaller learning set that was constructed from sound samples of a single RPW larva. We found one additional learning set, which was constructed from sound samples of only one larva, 10 times smaller, which

Table 3 – Detection ratios of the best sets of parameters

Method	Segment length	*k*	Frame length	Type-1-error (%)	Type-2-error (%)	Correct (%)
GMM	1	7	1024	3.8	0	98.1
GMM	1	10	1024	3.8	0	98.1
GMM	3	10	512	1.7	1	98.6
GMM	5	2	512	0.7	2	98.6
GMM	5	5	512	0.7	1.7	98.8
VQ	1	5	1024	1.7	1	98.6
VQ	1	20	1024	0.7	1.4	98.9
VQ	3	3	512	1.4	0.7	98.9
VQ	3	5	512	1.4	1	98.8
VQ	3	10	512	0.7	2	98.6
VQ	3	10	1024	0.7	1.7	98.8
VQ	3	20	512	1.4	0.7	98.9
VQ	5	20	512	0.7	1.7	98.8

maintained the same detection ratios as the larger learning set, as seen in Table 2.

The algorithm showed different results mainly with respect to frame length. The parameters that resulted best detection are shown in Table 3.

The algorithm sensitivity to various parameters offers a tradeoff between type-2-errors and type-1-errors, as shown in Fig. 5, based on optimal detection rates from Table 3. Preferred behavior of the algorithm can be determined based on the actual cost of falsely detecting RPW activity (in this case, the cost of quarantine, or the in more extreme cases the cost of the offshoot) and the cost of not detecting an infected offshoot (the potential damage caused by an infected offshoot). It is tempting to conclude that because type-2-errors are much more expensive, we should without any doubt choose the algorithm parameters that assure the lowest possible type-2-errors, but, considering the posterior probability of the RPW in offshoots, this conclusion might be misleading. Further conclusions can be drawn from supplementary study of the subject, which is outside the scope of this paper.

4. Discussion

The approach of speech recognition-based algorithm for automatic acoustic detection of RPW larvae was proved feasible. Based on this algorithm, a simple front-end application can be utilized by untrained personnel. Although the algorithm was implemented on Matlab, it can easily be ported into any language that has mathematical and signal processing libraries.

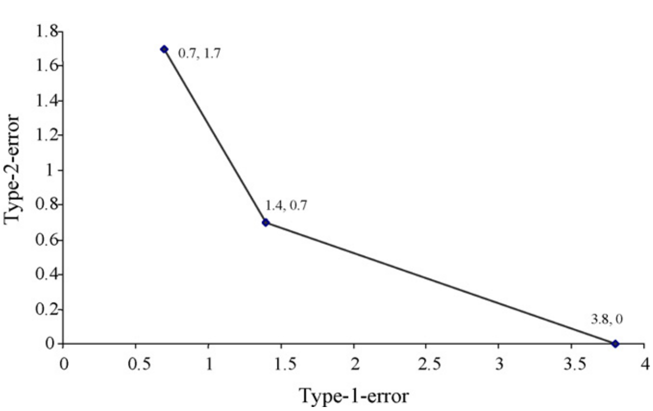

Fig. 5 – DET curve of highest detection rates.

The highest detection ratio, when using the algorithm with a variety of parameters, was 98.9% with type-2-error of 1.4%. The median detection ratio for frame length of 2048 samples was as high as 98.1% and type-2-error, which is non-detection of an active RPW larva, was less than 3%. This indicates a stable detection ratio in the vicinity of at least 98%. The parameter that most influenced the detection ratio, by far relative to other parameters, was the frame length. Detection ratio was invariant to algorithm (VQ or GMM) and to number of clusters. The lowest type-2-error was zero in a few sets of parameters (detection ratio 98.1%), but the type-1-error in that case was 3.8%. This type-1-error might be acceptable in case of severe quarantine pest such as the RPW.

In an attempt to analyze the error, sound files that were mislabeled by the algorithm were closely examined; we observed that the algorithm repeatedly failed to correctly label a group of files for any set of parameters. The mislabeled files from type-2-error (false negatives) featured low intensity and sparse RPW larvae sound. However, other files that exhibited sparse RPW larvae sound distribution and low intensity were labeled correctly. We observed that mislabeled files of type-1-error (false positives) featured intense plant activity. However this problem can be overcome, as acoustic activity of offshoots tends to decrease over time (within a period of 2–3 min), whiles the acoustic activity of RPW larvae continues at the same pace for several minutes.

The general performance of the algorithm is comparable with current state-of-the-art reported detection rates of speaker recognition systems (Petrovska-Delacretaz et al., 2007). Nevertheless, since our detection model is relatively simple (3–5 clusters), there is potential for improvement. Further development may include: (1) taking into consideration high-level features such as periodic patterns of pest activity, as proposed by Mankin et al. (2000). Contemporary speaker recognition systems utilize high-level features such as periodic patterns and word length to increase accuracy (Campbell, 1997). (2) Examining enhancements to the clustering algorithms such as adapted GMM's (Reynolds et al., 2000), or using temporal information utilizing HMM (Rabiner and Juang, 1993). (3) Adding robustness against clutter/world noise. (4) As international marketing of palm offshoots prohibits the presence of any borer, it is necessary to broaden the identification capabilities to include other significant palm pests such as the rhinoceros, sap beetles, etc. (5) Optimize the algorithm to perform on slow processors, e.g., handheld computers.

It should be emphasized, though, that our study was conducted under optimal conditions: the recording was taken inside a sound-proof recording box in a noiseless recording environment. This high detection rate is not guaranteed in real-life situations with ambient clutter noises. However, a sound-isolated box is affordable and simple enough to construct.

The weak point of any acoustic-based tool is its dependence on acoustic activity which might be absent if the pest is not active when sound is acquired. The problem of palms that are infected with eggs or pupae can be overcome using a proper quarantine for a period that depends of the RPW life cycle. Concerning the RPW larvae, we still lack the data on its diurnal activity patterns, such as eating and resting cycles. Even active cycles such as eating might be composed of short bursts rather than monotonous sound-producing activity. Further study must be made to determine what the minimal duration required to acquire data is and determine whether the offshoot is infested. This can be resolved by several means, such as: (1) conducting the detection in synchronization with the diurnal activity cycle of the RPW larvae. (2) Activating the RPW larvae at desired epoch. These however are the subjects for future entomological studies.

5. Conclusion

This study indicated that it is feasible to use commercial recording equipment to detect RPW in trading and transportation of palm offshoots. The detection ratio was as high as 98.9%, with average detection ratio of 98%. Human analysis proved unreliable. We observed significant variation among the four experienced listeners. These findings emphasize the importance of a repetitive, automatic acoustic tool. Devices based on the proposed algorithms can be used to monitor transactions of offshoots at trading posts. Although the study was conducted under laboratory conditions, we maintain that these difficulties that might be present in the field can be overcome after study and implementation of the RPW larvae diurnal cycle into the detection protocol, thus maximizing the probability of detecting the RPW larvae.

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