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ORIGINAL PAPER

Determining the sound signatures of insect pests in stored rice grain using an inexpensive acoustic system

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Abstract

Insect pests in storage are causes of major losses worldwide. Acoustic sensors can detect the presence of insects in grain through their sound signature, thus enabling early warning to farmers and traders. This research investigates the applicability of an affordable acoustic sensor, which uses micro-electromechanical systems (MEMS) microphone adapted to detect the sound produced by insect pests. Three major insect pests that commonly feed on paddy and milled rice (the lesser grain borer, *Rhyzopertha dominica*; the rice weevil, *Sitophilus oryzae*; and the red flour beetle, *Tribolium castaneum*), were collected in rice mills and grain storage warehouses in Laguna The Philippines, and reared at the International Rice Research Institute. Baseline sound recordings were replicated for each insect over three days using a completely randomized design (CRD). Recorded sounds were analysed to determine the sound profiles of each insect. Waveforms, root mean square (RMS) energy values, frequency domain, and spectrograms provided characteristics for the sound signal signature specific to each insect. Primary insect pests (*R. dominica* and *S. oryzae*) were differentiated from the secondary insect pest (*T. castaneum*) through signal analyses. Such data are useful to enable insect pest classification, which can be incorporated into more effective and timely postharvest pest management tools.

Keywords Sound signature · Acoustic · Rice storage · Insects

1 Introduction

Insects are economically important pests in stored grains because of the physical damage they can cause (Sontag, 2014; Alam et al., 2019; Megerssa et al., 2021). Such damage significantly reduces farmers' income and impact food security and grain nutritional safety (Gummert et al., 2009; Barkat et al., 2016; Liu et al., 2018). The activity of insect pests in stored grain enables the detection of their presence. Digital systems, such as acoustic sensors, can directly assess insect populations (Geng et al., 2017; Branding et al., 2023). The creeping sound of a single insect in grain is generally not easily detected, being a weak signal that can quickly be absorbed by grain mass (depending on the sound frequency; Geng et al., 2017; Hickling et al., 1997). Sound (and insect) detectability depends more on the interface between sensors and substrate (i.e., grain) than on the insect itself because insect signals tend to be broadband, which implies that signal can extend to a wide range of frequency (Phung et al., 2017; Čokl et al., 2006).

Insects have limited muscle power to produce sound; using acoustics is therefore challenging. However, insects

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are the only invertebrate group in which sound production is widespread via air and substrate vibration. Through evolution, some insects have been equipped with highly engineered acoustical devices that can produce loud acoustic and vibratory signals, known as calling songs, enabling them to signal their species identity, location, and their status as potential mates (Claridge, 2006; Miles et al., 2017; Prešern et al., 2018; Römer, 2020). Insect sounds are amplitude- or pulse-modulated; thus, information is encoded as temporal patterns of pulses and groups of pulses. These are discernible to the human observer in oscillograms (Claridge, 2006). This suggests that each insect sound may contain unique acoustic features as a signature (Pollack, 2017; Phung et al., 2017).

Previous literature considered acoustic system as a promising approach to detect insect presence in a grain mass. Various sensors have been tested to monitor the sounds and vibrations insects produce. These include piezoelectric sensors mounted on a probe (Eliopoulos & Potamitis, 2018; Fleurat-Lessard et al., 2006); the portable postharvest insect detection system (PDS) that detects infestations by comparing the recorded signals using electret microphones to the sound spectra of known pests (Mankin et al., 2020); bioacoustic detection technique combined with artificial neural network (ANN) in predicting bruchids density in stored green gram (Banga et al., 2020); and a noncontact, nondestructive microwave device for sensing adult insects in grain samples (Reimer et al., 2018). The success of acoustic detection technology for insects reflects the fact that many produce characteristic sounds that can easily be detected and recorded without much cost or effort (Faiβ & Stowell, 2023).

This study adapted the use of an affordable acoustic device from the Smart Apiculture Management Services (SAMS) project using a micro-electro-mechanical system (MEMS) microphone (Adafruit I2S MEMS SPH0645) to detect insect pests in stored rice grains (Fiedler et al., 2019). To properly distinguish the sound of the target insect species from background noise, baseline recordings of the insect sounds were performed using the acoustic device within a sound-proof chamber (Mankin et al., 2021).

The sound recordings stored as waveform audio format (WAV) files were analysed using the Audacity software (Audacity Team, 2024). Some computations were done under Python (e.g., NumPy, SciPy, and Librosa; McFee et al., 2015) to extract features of the WAV files and determine the characteristics of the insect sounds to establish the sound signature of each insect species.

The most common feature representation of an insect's sound is its waveform. The waveform depicts the pressure level of the sound generated by the insect over time, shown in a graph with pressure on the y-axis and time on the x-axis. A series of jagged lines along the x-axis would indicate variation in the pressure level created by the sound (Constantinescu & Brad, 2023).

Another important step in sound processing and characterization is the root mean square energy, which is a measure of the loudness of the sound signal. The root mean square energy (RMS) calculates the square root of the sum of the energy of the sound. RMS provides a stable representation of the energy of a signal (Constantinescu & Brad, 2023). While spectrum analysis is useful for sound parameterization for stored product insects (Phung et al., 2017), the power spectrum profile is more discriminating because it presents the relative amplitude or power of the frequencies generated by the insect sound (Geng et al., 2017).

2 Materials and methods

2.1 Location and purpose of the study

The study is part of a doctoral research project entitled "Enhanced monitoring of insect pests in stored rice based on their sound signature and evaluation of attractants for storage insects" conducted at IRRI, Philippines in collaboration with the Department of Agricultural Technology and Biosystems Engineering of the University of Kassel in Witzenhausen, Germany. This experiment aims to determine the sound characteristics of insect pests in rice storage that were detected using an acoustic device adapted from the SAMS project (Fiedler et al., 2019). The duration of recording the insects' sound at hourly interval for 10 min using the acoustic device was from April to June 2023 (Balingbing et al., 2024).

2.2 Collection and rearing of insect pests in rice storage

Mature insects of three different species (i.e., *R. dominica* or lesser grain borer, *S. oryzae* or rice weevil, and *T. castaneum* or red flour beetle) were collected in rice mill facilities in Laguna, Philippines (Fig. 1). Insects were reared at the postharvest laboratory in a storage system filled with mixed varieties of rice grain harvested from the Zeigler Experiment Station (ZES) of the International Rice Research Institute (IRRI).

2.3 Recording of insect sounds in an acoustic chamber

The recording of baseline insect sound within an acoustic shielding chamber (Fig. 2) followed a completely randomized design (CRD) experimental setup. The three insect pests considered served as treatment. Sound recordings replicated over three days were the observation.

Twenty adult insects were placed inside a sampling container (16 cm by 16 cm by 8 cm) filled with 500 g of rice grain (moisture content at about 13–14%, i.e., the standard of safely-dried grain for storage; Gummert et al., 2009). The acoustic

Fig. 1 Insect species that were subject to sound recording in the study: *Ryzopertha dominica* (left), *Sitophilus oryzae* (middle), and *Tribolium castaneum* (right). (Photos by: C. Balingbing, available at https://github.com/cbalingbing/Rice-Acoustic-Sensor/Sampleinsects)

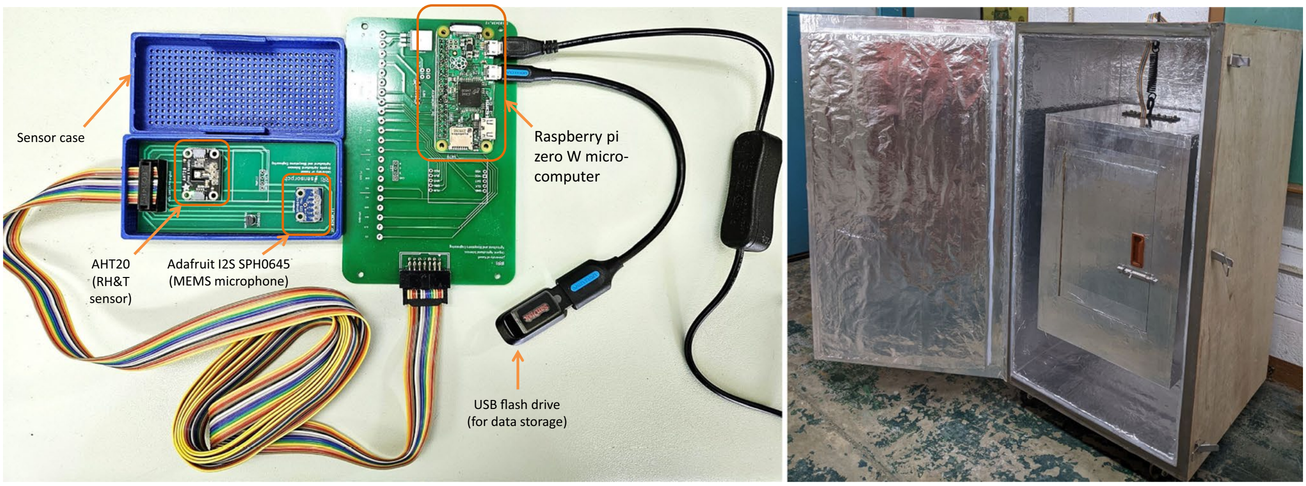

Fig. 2 The acoustic device consisted of a MEMS microphone and Raspberry Pi Zero W microcomputer (left); the acoustic shielding chamber for recording baseline sound using the acoustic device and sampling container (right)

device consisted of a microphone with a recording frequency range of 50 Hz to 15,000 Hz (Hz; Adafruit MEMS SPH0645) and a relative humidity and temperature sensor (AHT20; https://www.adafruit.com/) set up inside the sampling container. A single-board microcomputer Raspberry Pi Zero W (Raspberry Pi Ltd) was used to run the acoustic device. The acoustic device used in this study consists of a MEMS microphone as the main component, which makes use of a tiny, thin diaphragm (that vibrates in response to sound waves) and a series of microelectronic components that detect these vibrations and convert them into electrical signals (Kumar et al., 2024). The acoustic device was programmed with Python scripts (Version 3.12) executed by the microprocessor to capture sound iteratively every hour for 10 minutes. The recorded sound was saved as a waveform audio format (WAV) file.

2.4 Analysis of sound recordings

The recorded sound files from each insect species were pre-processed and analysed using band-pass filtering and WAV trimming to 3-minute signals to generate waveforms; to create power spectrum profiles and spectrograms; and to calculate RMS energy using matplotlib (Solomon, 2024), through fast Fourier transform (FFT), and short-time Fourier transform (STFT) functions in Python.

The original 10-minute recording was filtered at 2500 Hz low pass cut-off frequency and 93.75 Hz high pass cut-off frequency using a fourth-order Butterworth band-pass filter. The first four-minute and last three-minute signals files of the band-pass filtered WAV were then trimmed. The remaining 3 min were deemed sufficient to contain relevant information about the insect sound signal. Preprocessing of the WAV files was done using the SciPy (Arzaghi, 2020) function in Python.

The waveform of the time domain features of the WAV file was generated in Python using matplotlib. The RMS energy for each WAV file during the 24-hour recordings was calculated as shown in Eq. 1 (Constantinescu & Brad, 2023). Calculated RMS energy values were plotted over time to visualize the RMS energy profile of the insects' signal.

$$\text{RMS}_t = \sqrt{1/K\left(\sum_{K=t*K}^{(t+1)K-1} s(k)^2\right)} \quad (1)$$

Where: t is the frame; k is the index of individual sample within the frame; K is the total number of samples in the frame; and s is the amplitude of the signal. The sum of the energy for all the samples in frame t was computed, and the mean of the sum of the energy was determined.

Spectrograms were generated by calculating the short-time Fourier Transform (STFT) of the WAV files using the Librosa function (McFee et al., 2015) in Python.

3 Results

3.1 Waveform profile in time domain representation

The time-domain features of the recorded sound files at certain periods are represented by the waveforms shown in Fig. 3, which provide visual snapshots of the sound of each insect species. The jagged vertical lines depict the air pressure generated by the sound of the insect and some background noises, which are visible across time periods at varying amplitude levels. RMS energy plotted beneath

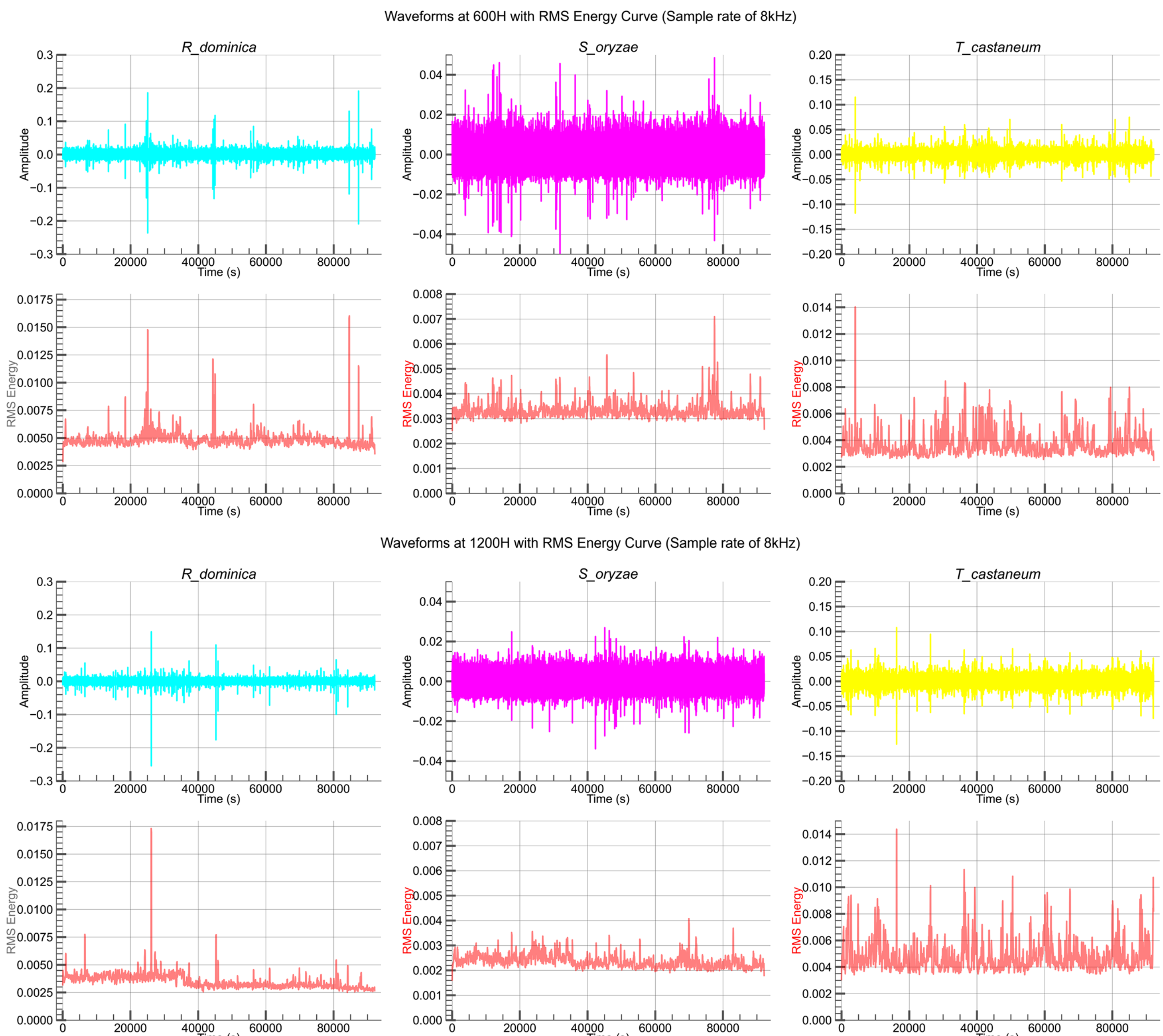

Fig. 3 Waveforms and root mean square (RMS) energy of the three insect species generated from two sound recording periods (i.e., Top: 600 H; and Bottom: 1200 H) generated using NumPy and SciPy functions in Python at 8000 Hz sample rate

each waveform is the corresponding energy level of the sound files for the two recording periods (i.e., 600 H and 1200 H). The sound signal captured from each insect species shows fluctuating average energy for the entire period.

3.2 Root mean square (RMS) energy of the insects' sound signals

The RMS energy values calculated from the sample waveforms show the average magnitude of the hourly signal for the 24-hour recording, which shows fluctuations for each insect species (Fig. 4).

3.3 Signal strength and frequency profile

The frequency domain representation for 600 H and 1200 H sound files (Fig. 5) indicates the highest frequencies with peak power (dB) contributing to the sounds generated by each of the three insects across the time periods.

3.4 Frequency characteristics across time via spectrogram representation

The spectrograms generated from the sound signals (Fig. 6) indicate the amplitude level of the frequency profile of signals across the considered time frame. The varying colour intensity (dark to light) shows the increasing amplitude of the sound frequencies generated by each insect species. Vertical streaks with lighter shade characterize the frequency range of the sound bursts from insects that might correspond to specific activity in the grain mass.

4 Discussion

The time domain profile (Fig. 3) of the sound signals captured from the three insects shows the acoustic characteristic of each insect in terms of signal amplitude. The lesser grain borer (*R. dominica*) produces a higher amplitude sound with perceptible and frequent signals at 06.00 h and 12.00 h. The rice weevil (*S. oryzae*) actively emits sound signals too, but at lower amplitudes than the lesser grain borer. Of the three insects, the red flour beetle (*T. castaneum*) produced frequent and successive trains of signals across time with fluctuating amplitudes.

The 24-hour RMS plot of Fig. 4 indicates pronounced fluctuations in the energy level of the lesser grain borer. The rice weevil shows moderate fluctuation, with the highest peak in the energy level at 04.00 h and 12.00 h. Figure 4 also shows the variability of the signal strength for each insect species throughout the day. The sound file of the lesser grain borer shows intense segments but with some "valleys", indicating low or quieter signal strength. The energy level of the red flour beetle is comparatively stable, with minimal variation in signal strength.

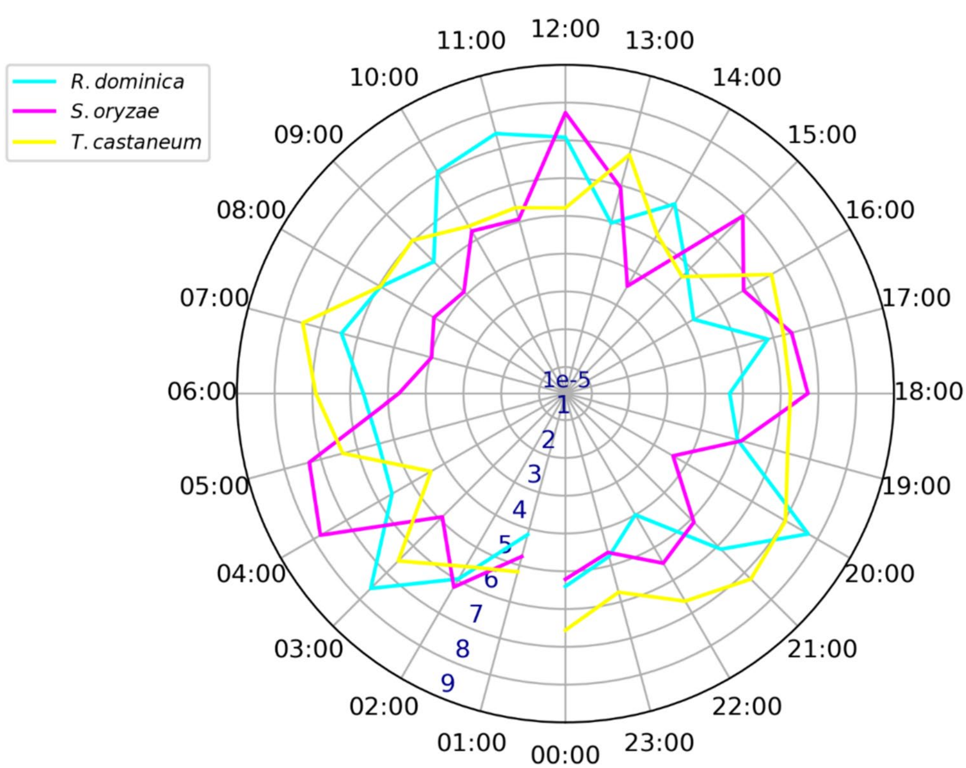

Fig. 4 Circular plot of root mean square (RMS) energy values of waveforms from 24-hour recordings calculated using the PyCircular and Matplotlib functions in Python

As shown by the RMS energy plot in Fig. 4, insect activities throughout the day vary and are uncertain for any species, as reported by Phung et al. (2017). Both the lesser grain borer and red flour beetle showed activity early in the morning (03.00 h), as indicated by the peak energy. The rice weevil became active an hour later (04.00 h), followed by inactivity until mid-day (12.00 h), then becoming active again, with higher RMS energy in the late afternoon (15.00–18.00 h). The red flour beetle had several activity peaks in the day indicated by higher RMS energy from early morning, mid-day, and late afternoon to evening (12.00 h, 15.00 h, and 19.00–22.00 h). The series of peak RMS energy of the bigger red flour beetle (~ 3.0–4.0 mm versus the lesser grain borer at ~ 3.0 mm and the rice weevil at ~ 2.0–3.0 mm; Fig. 1; USDA, 2016; Koehler et al., 2022) may be attributed to the signal generated when feeding on the powdered grain kernels.

The power spectrum curves (Fig. 5), where the x-axis represents frequency (in Hz), characterized the sound component that identifies the insect species. The lesser grain borer is characterized by peak frequencies at 355.54 Hz and 371.09 Hz at 600 H and 1200 H recordings, respectively. The highest peak shown in the plot at low frequency may be attributed to background noise, which is also observed for signals of the rice weevil and red flour beetle. The rice weevil showed varying peaks at 441.41 Hz and 437.50 Hz for 06.00 h and 12.00 h recordings, respectively. The red flour beetle had broader peaks at lower to middle frequency ranges, but the frequencies with the highest power were 175.78 Hz and 433.59 Hz at 06.00 h and 12.00 h recordings, respectively. These findings conform to the description by Claridge (2006) that insects, many of which are small, produce low-frequency sounds.

The time domain and spectral profiles for the rice weevil (*S. oryzae)* determined in this study were consistent with the findings of Kiobia et al. (2015), showing the variability of sound impulses.

The spectrograms in Fig. 6 illustrate another dimension of the signal characteristic for the three insect species.

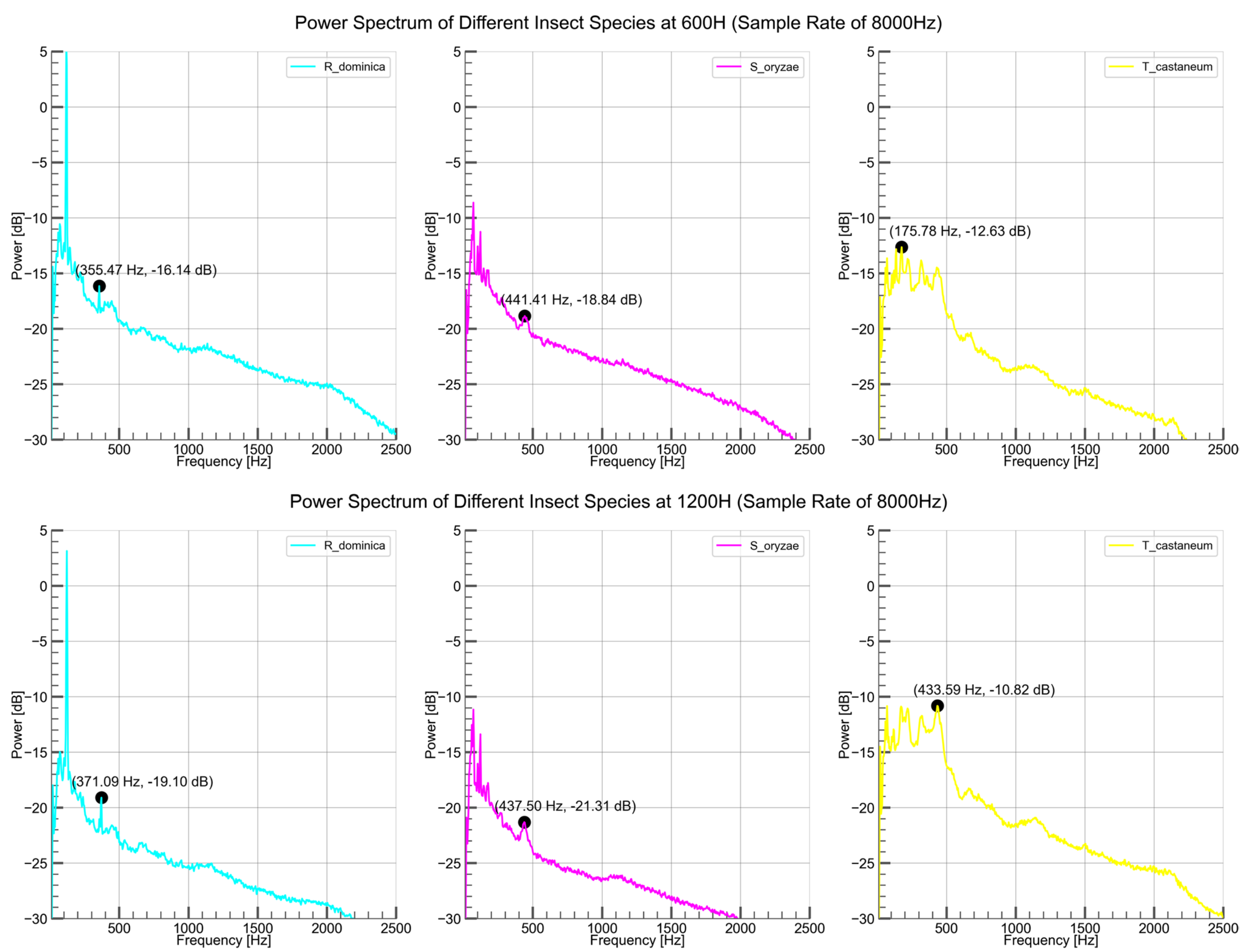

Fig. 5 Power spectrum profile of the insects' sound signals at 600 H (Top) and 1200 H (Bottom) with peak frequencies marked on the plot, generated using fast Fourier transform (FFT) and short-time Fourier transform (STFT) functions in Python

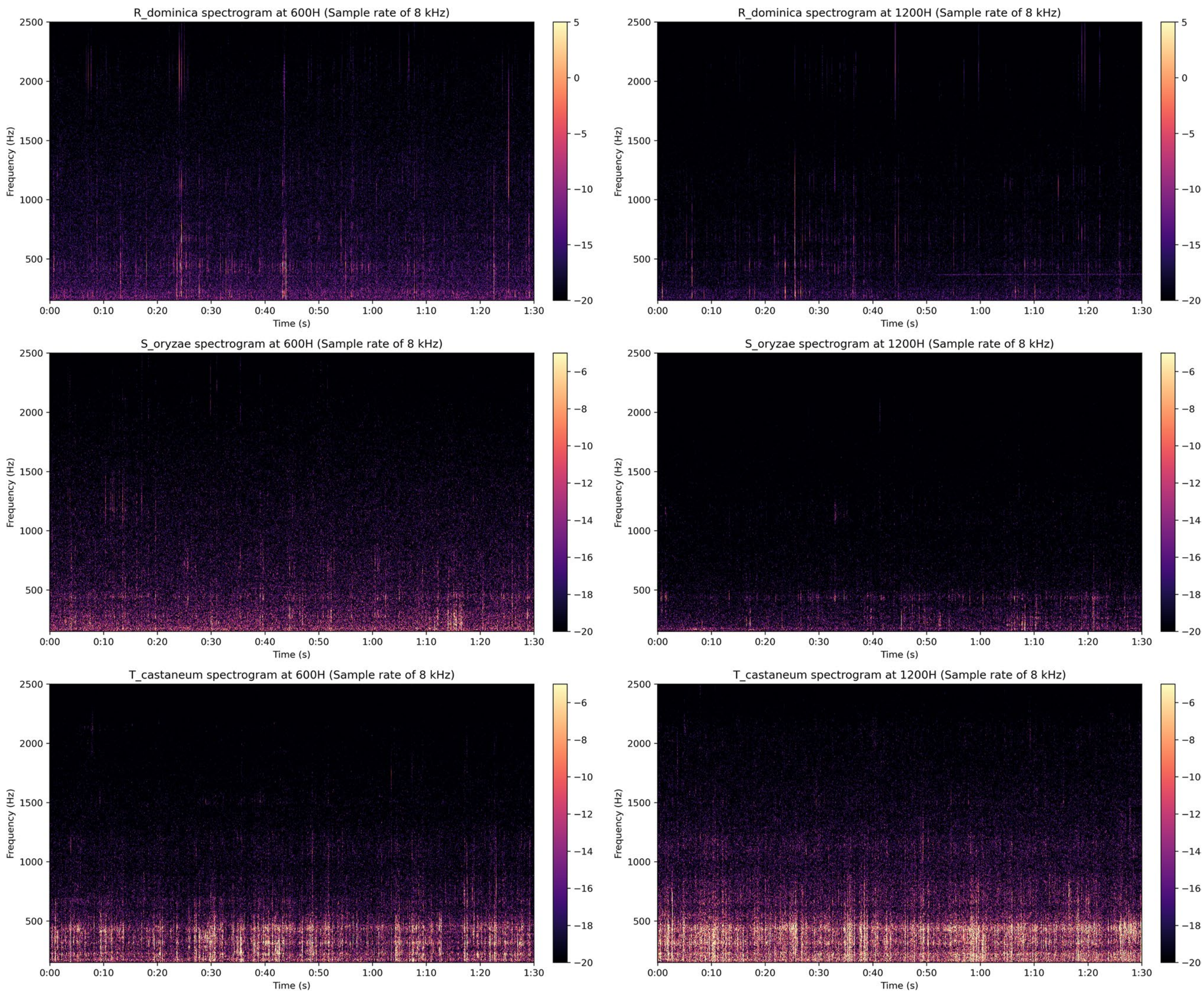

Fig. 6 Spectrogram of insects' signals from two recording periods (i.e., 600 H and 1200 H) and WAV files generated using the short-time Fourier transform (STFT) function in Python

Prominent peaks at certain frequencies characterize the lesser grain, and the amplitude of the most prominent peak is relatively high for the sound captured at 06.00 h and 12.00 h. The rice weevil is characterized by certain peak frequencies with relatively high amplitude and a few trains with high frequencies but low amplitude.

The red flour beetle has multiple peaks with low to moderate amplitudes at both time periods (06.00 h and 12.00 h), indicating a more complex composition or harmonics (frequency peaks). Using a PDS consisting of an electret microphone as the main component for capturing sounds, Mankin et al. (2020) also observed varying spectral profiles for *T. castaneum* and *S. oryzae* during moving and eating activities on flour and wheat grain substrates, respectively.

The spectrogram for the lesser grain borer in Fig. 6 exhibits a mix of low and high frequencies and intensities more pronounced across the frequency range from low to high. The peaks at specific frequencies in the waveform are associated with this insect pest. The prominently high intensity at low frequency for both recordings (06.00 h and 12.00 h) for the lesser grain borer may be attributed to the background noise or some error effects of the measurement device, as in Fig. 5. Unlike the lesser grain borer, the red flour beetle shows a distinct pattern of moderate frequencies and the intensity of the sound is relatively high. The rice weevil had a relatively lower intensity than the red flour beetle but higher than the lesser grain borer. The amplitude peaks for the red flour beetle vary between the 06.00 h and 12.00 h recordings, which characterize the different frequency components in the waveform of the signal captured from the insect.

According to Bradbury and Vehrencamp (1998) (cited in Cocroft & De Luca, 2006), insects favour lower-frequency sound for long-distance communication. For insects in grain storage, the frequency generated by the sound can be radiated through substrate vibrations (Claridge, 2006; Bennet-Clark, 1998). In this case, vibration sensors interface better with signals produced in solid substrates, such as grains (Mankin et al., 2011).

5 Conclusion

The small sized the insects of this study, were found to produce specific, low-frequency sounds radiated through the air. This study differentiated the sound profiles captured from three species (*R. dominica*, *S. oryzae*, and *T. castaneum*). Based on the frequent and successive signals of varying amplitude levels consistently shown in the RMS energy level curve, the red flour beetle (considered a secondary insect; Deshwal et al., 2020; Mankin et al., 2020) was differentiated from the other two. The generated spectrogram profiles also depicted specific frequency ranges and spikes with remarkable intensity for the lesser grain borer, which spans frequencies from low to high at specific time frames. On the other hand, the red flour beetle showed higher signal intensity at stable frequency ranges. The rice weevil showed the lowest signal intensity among the three insect species.

The signature characteristics of the three insect pests identified in this study are useful contributions for classification algorithms that are used for automated detection of insect presence in grain storage. The information generated from these analyses can usefully contribute to the engineering of higher prediction accuracy of machine learning algorithms. The inexpensive acoustic device and machine learning algorithm can be used as tools to help farmers, processors, and traders minimize losses in grain storage through timely and accurate detection and early implementation of control measures.

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Data availability The data described and used in this article are available and can be accessed at https://github.com/cbalingbing/Rice-Acoustic-Sensor/tree/main/Insect_wav_files_FOSE.

Declarations

Competing interests The authors declared that they have no conflict of interest.

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