

Early Detection of the Wood-boring Insect *Semanotus Bifasciatus* Using Acoustic Detection Technology

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Research

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Abstract

BACKGROUND: *Semanotus bifasciatus* Motschulsky (Coleoptera: Cerambycidae) is one of the most destructive wood-boring pests of *Platyclus* trees in East Asia, threatening the protection of ancient cypress species and urban ecological safety. Acoustic detection technology has the advantages of high sensitivity, single wood diagnosis and anti-interference, which can be useful for early identification of cryptic wood boring damage. However, there has been limited research on detection time window and acoustics features that suitable for early detection of forest wood borers.

METHODS: In this study, we carried out a manipulated insect infestation experiment by inoculating *S. bifasciatus* into fresh logs, and the feeding sound signals of *S. bifasciatus* larvae were recorded in timeseries. Then, nine feature variables were selected to characterize the sounds of larval feeding activity. The best time window for acoustic detection during a single day and the whole larval growth stage was determined. And the optimal models for predicting larval instar and population were established using the stepwise regression (SR) and partial least squares regression (PLSR) approach.

RESULTS: (1) The single pulse duration of *S. bifasciatus* was less than 15 ms, and the peak frequency was approximately 8 kHz; (2) Within a 24-hour day, the feeding sound signals were strongest during 13:00 and 20:00; (3) The feeding activity of larvae was greatest during the 1st to the 3rd instar, declined from the 4th instar, and was lowest at the 5th instar; (4) Weak correlations were found between larval instar and feature variables, r ranging from 0.3 to 0.6. By contrast, the larval population has a strong linear correlation with all variables ($r > 0.7$). Except for Average pulse duration and Peak frequency, there indicated high or severe multicollinearity among other variables (the variance inflation factor, VIF > 10); (5) The SR model was optimal for predicting larval instar; its prediction accuracy was $R^2 = 0.71$, RMSEp = 0.42, and RPD = 3.38. Average entropy, Peak frequency, and Average pulse duration had the largest influence on the model. (6) The optimal model for predicting population was the PLSR model, and its prediction accuracy was $R^2 = 0.97$, RMSEp = 61.96, and RPD = 28.87. Except for Peak Freq, the other eight variables had a great impact on the model.

CONCLUSION: This study highlighted the suitable detection time window and acoustic feature variables for early identification of *S. bifasciatus* larvae, and optimal models for predicting its larval instar and population were provided. This work will promote further improvements in the efficiency and accuracy of acoustic detection technology for practical applications, providing a reference for evaluating the early damage of wood-boring pest.

1. Introduction

Hidden insect infestations such as those of wood-boring beetle larvae inside trees, logs and wood packing material have always presented a challenge for pest managers, regulators and researchers. Substantial progress has been made over the last few decades towards developing new and improved methods for detecting and monitoring such pests in order to prevent their spreading and to help eradicate them or at least contain outbreaks (Walker 1996; Smith et al. 2009; Mankin et al. 2011;).

Semanotus bifasciatus Motschulsky (Coleoptera: Cerambycidae) is one of the most destructive wood-boring beetles of *Platyclus* trees in East Asia. It was listed as a forest plant quarantine species in 1996 and has

been distributed in 15 provinces in China, greatly impacted the construction of urban ecological environment and the protection of ancient cypress species (Li et al., 2003; Gao et al., 2007).

At present, detection methods for *S. bifasciatus* mainly include field investigation, bait wood trap and insect pheromone trap (Gao et al., 2007; Zhao, 2009). However, field observation is both labor-intensive and time-consuming. Besides, the approach of bait wood and pheromone trap monitoring cannot accurately diagnose the damage degree of specific trees, locate active larvae in trunks, and thereby fail to achieve the goal of early prevention and control.

In recent years, acoustic detection of wood-boring pests is playing an increasingly important role in forestry pest management, port wood quarantine, as well as the protection of ancient and famous trees (Mankin et al., 2011; Pan et al., 2013). In comparison with other methods, it has the advantages of early identification, single wood diagnosis, anti-interference, and high accuracy. Especially for nondestructive, continuous monitoring of cryptic pests in plants which commonly cause strong-lag damage and destructive effects (Mankin et al., 2011; Wei et al., 2010; Wang et al., 2018).

Acoustic detection technology was first applied to the detection of fruit pests and stored grain pests (Brain, 1924; Adams et al., 1953). Many studies have been reported using acoustic detection technology on pest species identification, population estimation, and the pattern of insect activity (Mankin et al., 2011; Mankin et al., 2021). Lewis et al. (2011) and Hurng et al. (2012) used acoustic emission technology to study the seasonal/ daily activity patterns and the life history of *Incisitermes minor* and *Callosobruchus maculatus*, respectively. Eliopoulos et al. (2015, 2016) successfully predicted the population densities of several stored grain beetles in small containers by using an automatic monitoring system (a piezoelectric sensor and a portable acoustic emission amplifier connected to a computer). Banga et al. (2020) assessed bruchids (*Callosobruchus chinensis* and *C. maculatus*) density through acoustic detection and artificial neural network (ANN) in bulk stored chickpea and green gram. Despite these successful attempts, there is still limited research on using acoustic technology to detect wood-boring pests (e.g. *S. bifasciatus*).

So far, with the improvement and development of the detection system (including sensors and data storage), good opportunities for early detection of forest wood borer have been provided (Mankin et al., 2021). The basic principles of acoustic detection of wood-boring pests can be divided into the following steps (Fig. 1): (1) signals collection (conversion of collected insect-activity vibrations into electrical signals); (2) signals filtering (removal of environmental and irrelevant noise); (3) features extraction (transforming signals into feature variables of time and frequency domains); and (4) model classification and prediction (determination of insect species; estimation of insect population, age, etc.) (Wei et al., 2010; Chen et al., 2015).

Commonly, insect-produced signals are detectable both by the microphone as sounds and by contact sensors as vibrations, in which case they may be designated simply as “acoustic signals” or “sounds” (Webb et al., 1988a). The detectable sounds of wood-boring pests are vibrations, produced during feeding, crawling and other activities. As far as *S. bifasciatus* is concerned, there are following challenges for its early detection.

On one hand, acoustic attenuation occurs in the transmission of signals in the wood, and the weak signals can be masked by high-amplitude traffic and other background noise (Mankin et al., 2008b; Mankin et al., 2011). To improve signal-noise ratio (SNR), acoustic detection should be performed at the time when the

sounds are strongest. On the other hand, as larval activities of *S. bifasciatus* are comprehensively regulated by the development rhythm (life history) and the growth surroundings (diurnal replacement, temperature change, etc.), the rate and intensity of sounds produced may differ at different times in a day and different larval growth stages. Also, the larval feeding behavior may have a lag of few days since the initial infestation. Consequently, knowledge on the activity patterns of *S. bifasciatus* larvae is significantly important to determine the detection time window.

Besides, as the damage symptoms of *S. bifasciatus* are almost invisible to human eyes, this cryptic attack behavior hinders forestry managers to identify the early-attacked trees and diagnose the damage degree. By the time the attacked trees exhibited distinguishing symptoms (e. g. crown discoloration, defoliation, dieback), they can no longer be saved due to severe phloem destruction (Gao et al., 2007). In that case, the accurate evaluation of damage degree (i.e. insect population density) might provide essential guidance for timely and quantitative chemical control. Consequently, the accurate prediction of *S. bifasciatus* larval instars and population is a crucial step in its acoustic detection approach.

Therefore, to achieve the early acoustic detection of *S. bifasciatus*, we performed a manipulated infestation experiment by artificially inoculating *S. bifasciatus* adults into fresh *P. orientalis* wood, then the feeding sounds of its larvae were systematically recorded with an optimized AED-2010L instrument over time (24 hours a day at different larval growth stages). The main objectives of this work are to (1) characterize the feeding sounds of *S. bifasciatus* larvae with time-domain and frequency-domain features; (2) reveal the feeding activity patterns of *S. bifasciatus* larvae during a single day and the whole growth stages; (3) determine the best detection time window based on the abovementioned activity patterns; (4) analyze the correlations of feature variables with larval instar and insect population, and examine the multicollinearity among all feature variables; (5) establish the regression models for predicting larval instar and insect population and evaluate the model performance. The results of this study could further improve the efficiency and accuracy of acoustic detection technology for practical applications, providing a guidance for assessing the damage degree of forest wood-boring pests.

2. Materials And Methods

2.1 Logs for manual infestation(Manipulated infestation experiment)

The infested logs needed for this study were manually inoculated. In 2018, the *P. orientalis* bait woods used to trap *S. bifasciatus* at the Beijing Summer Palace were collected and placed indoors. At the adult emergence peak in March 2019, active adults were collected, distinguished into males and females, and then put into plastic tubes separately. Twelve non-infested logs of *P. orientalis* (length 50 cm, diameter 12 cm) were prepared and placed in net cages. Among these logs, one log without inoculation was treated as blank controls to record background sounds, and the other 11 logs were chosen for insect infestation. Five pairs of female and male adults of similar size were selected and placed in each net cage. Afterward, adults mated then oviposited on logs. By the time larvae started feeding, small wood chips were visible on the wood surface, and the feeding sounds of the larvae could be recorded in time series. In preparing each log for recording, a 1.6-mm-diameter, 76-mm-long signal waveguide screw was inserted midway down the length of the log.

2.2 Acoustic detection instrument

The AED-2010L (Acoustical Emission Consulting, Inc Fair Okas, CA) was an extremely sensitive instrument that can effectively detect wood-boring pests activity in the wood through a waveguide (e.g. bolt) both qualitatively and quantitatively. The instrument included a waveguide screw with a magnetic attachment (Model DMH-30, Acoustical Emission Consulting, Inc) to a sensor-preamplifier module (Model SP-1L, Acoustical Emission Consulting, Inc) connected to an amplifier (AED-2010L), leading to a digital audio recorder (model HD-P2, Tascam, Montebello, CA, USA) which stored signals at 44.1kHz digitization. However, the available AED-2010L produced a large noise that interfered with the target sound, thereby affecting features extraction of sounds. To eliminate the noise and improve sounds quality, the acoustic detection instrument used in this research was improved in the laboratory at Beihang University. The Model SP-1L probe and Model DMH-30 (attached with a 1.6-mm-diameter, 76-mm-long waveguide screw) were retained. A driving circuit board, an amplifier, and a NI9215 acquisition card were used to replace the AED-2010L (noise source). The acquisition card was connected to the computer, the sampling rate was set to be 44.1 kHz, and the bit depth was set to be 32 bits (Fig. 2).

2.3 Sounds recording

S. bifasciatus larvae sounds were recorded outdoors to simulate the field environment. In early April 2019, the sounds were recorded once every 7 days. During each recording, the non-infested log was recorded first for 3 min (the sounds denoted as 'no larvae'), then another infested log was recorded continuously for 24 h. After recording, the infested log was stripped to confirm the number of larvae, and the larvae were stored in a -4 °C freezer for assessment of larval instar later. The recording was stopped in late May when no feeding signals could be further detected.

2.4 Signals processing and features extraction

The methodology of this part consists of four main steps. First, the signals recorded in .tdms format were converted to .wav (wave audio files) format by using NI DIAdem software (National Instruments, USA). Secondly, the audio files recorded on the same day were divided into 24 audio files, one per hour with Adobe Audition CC 2018 software (Adobe, San Jose, CA). Then, twelve 30-s segments containing feeding sound signals were selected discontinuously every hour with Adobe Audition CC 2018 software. Finally, a set of feature variables were extracted from these segments by using Raven Pro 1.6 (Cornell Lab of Ornithology, Ithaca, New York).

Raven Pro is a software program for the acquisition, visualization, measurement, and analysis of sounds (Charif et al., 2010). In terms of target detection, Raven has two detectors: an amplitude and a band limited energy. The amplitude detector is based on the oscillogram while the band limited energy detector works on the spectrogram. In this study, nine feature variables were measured from the oscillogram and spectrogram (Table 1): RMS Amplitude (RMS Amp), Pulse number (Pulse Num), Average pulse duration (Avg Pul), Aggregate Entropy (Agg Ent), Average Entropy (Avg Ent), Energy, Average power density (Avg PD), Peak power density (Peak PD), and Peak Frequency (Peak Freq).

Table 1
The type and description of nine feature variables

Variable type	Variable	Description
Time-domain characteristics	RMS amplitude (RMS Amp)	The root-mean-square amplitude of the selected part of the signal
	Pulse number (Pulse Num)	The number of target signals within the selection
	Average pulse duration (Avg Pul)	The average duration of a single signal within the selection
Frequency-domain characteristics	Aggregate entropy (Agg Ent)	The overall disorder within the selection
	Average entropy (Avg Ent)	The amount of disorder for a typical spectrum within the selection
	Energy	The total energy within the selection
	Average power density (Avg PD)	The value of the power spectrum (the power spectral density of a single column of spectrogram values) averaged over the frequency extent of the selection
	Peak power density (Peak PD)	The maximum power in the selection
	Peak frequency (Peak Freq)	The frequency at which peak power occurs within the selection

2.5 Acoustic analysis of the feeding activity patterns

2.5.1 The daily pattern in feeding activity

The feeding sounds from three days were selected, and each day was divided into three different periods: (1) the first period from 5:00 to 12:00, marked as the morning, (2) the second period from 13:00 to 20:00, marked as noon, and (3) the third period from 21:00 to 4:00, marked as night. To assess the differences in each feature variable among the three periods, the value of each variable was normalized and then compared with Duncan's new multiple range test.

2.5.2 The feeding activity pattern during the entire larval growth stage

To study the patterns of feeding activities in different growth stages, it was necessary to determine the instar of larvae in the wood. Among the larvae collected on the same date, ten larvae were randomly chosen to

measure their prothoracic plate widths. And based on the division standard of *S. bifasciatus* larval instars (Jiang et al., 2021), all larvae were divided into five instars. The audio files were tagged with corresponding instars.

The audio files recorded on April 11, April 18, April 25, May 2, and May 16 were selected. These files correspond to the five growth stages of larvae respectively. And the numbers of larvae in the logs on the selected dates were 164, 168, 117, 63, and 61, respectively. Based on the results of the daily pattern in feeding activity, the period with the strongest feeding sounds of each date was selected for analysis. The value of each feature variable was normalized and Duncan's new multiple range tests were used to assess differences in variables among different larval growth stages.

2.6 Model development

2.6.1 Correlation analysis and multicollinearity examination

Correlation and collinearity among the feature variables, larval instar and population were examined by the Pearson t-test and variance inflation factor (VIF). A Pearson analysis was applied for examining the linear relationship between variables, larval instar, and population. A Pearson correlation coefficient (r) of 0-0.1 indicates a negligible correlation, 0.1-0.39 represents a weak correlation, 0.4-0.69 indicates a moderate correlation, 0.7-0.89 indicates a strong correlation and 0.9-1 indicates a very strong correlation (Schober et al., 2018).

The variance inflation factor (VIF) was applied to quantitatively evaluate multicollinearity. The rule for justifying collinearity among variables is as follows: if $0 < VIF < 10$, the feature variables have shown no multicollinearity. If $10 \leq VIF < 100$, there is high multicollinearity among the variables. If $VIF \geq 100$, there is severe multicollinearity.

2.6.2 Model development and validation

In this study, the stepwise regression (SR) and partial least squares regression (PLSR) methods were used to develop the larval instar and population predicting models. The data used to analyze the feeding activity pattern during the entire larval growth stage were split into a training set and a validation set following the ratio of 3:1. Variable importance can be obtained from regression coefficients in the SR model (Iman et al., 1981). And in the PLSR model, variable importance is ranked by the VIP (variable importance in the projection) scores (Wold et al., 1993). VIP scores summarized the influence of individual variables on the PLSR model.

Three statistical parameters such as coefficient of determination (R^2), root mean squared error of prediction (RMSEp), and relative percent deviation (RPD) were used to evaluate the performance of all models. Higher R^2 and RPD values, and a lower RMSEp value indicated the good stability and prediction accuracy of the model.

2.7 Statistical analysis

Data normalization, statistical analysis of differences, and correlation analyses were performed using IBM SPSS Statistics version 24 (IBM, USA). The R programming language was used to conduct Pearson correlation analysis, calculate the variance expansion factor and perform the SR regression and PLSR regression (R

studio 3.5.1, “car” and “pls” packages). Figures were generated using GraphPad Prism version 7 (GraphPad Software, USA) and R programming language.

3. Results

3.1 Larval feeding sound characteristics

Larvae of *S. bifasciatus* all produced sounds with trains of brief, high-amplitude pulses during feeding in the internal trunk (Fig. 3a). The feeding sound pulses observed in our study were similar in structure to those observed in previously published research: short (3-15 ms) pulses with a fast-rising front followed by a ‘tail’ with a time decay in amplitude (Mankin et al., 2008a, b; Alexander et al., 2019). Fig. 3b showed a very typical example of a feeding pulse generated by *S. bifasciatus* larvae. The power spectrum (Fig. 3c) of the above pulse showed that the frequency bandwidth of a feeding pulse was wide (0–20 kHz), with high energy between 7kHz and 9kHz, and the peak frequency approximately at 8 kHz.

3.2 The daily pattern in feeding activity

All variables except Agg Ent, Peak Freq, and Peak PD, exhibited significantly lower values ($P < 0.05$) in the morning than in the noon and night (Fig. 4). Although there were no significant differences between the sounds in the noon and night, higher values of RMS Amp, Pulse Num, Avg Pul, Energy, Avg PD, and Peak PD were observed in the noon, suggesting that the feeding activity of larvae was more active during this period.

These results indicated that the feeding activity was lowest in the morning, increased and peaked in the noon, and declined slightly in the night. Therefore, the best time to detect the larvae in a day was from 13:00 to 20:00, when the feeding sounds were the strongest.

3.3 The feeding activity pattern during the entire larval growth stage

As is shown in the sound oscillogram (Fig. 5a), during the growth stages from the 1st to the 3rd instar, the average number of feeding pulses was over 600/30 s. However, in the 4th instar stage, the average number of pulses dropped to 14/30 s. And feeding pulses could be barely detected in the 5th instar stage (mature larvae).

For the sound power spectrums (Fig. 5b), there was often a peak in relative energy at approximately 8kHz for all instars, and the peak energy of ‘no larvae’ sounds usually occurred at 2kHz around. The relative energy at a peak frequency of feeding sounds reached more than -50dB during the 1st to the 3rd instar and then weakened significantly in the 4th instar (< -65dB).

When comparing the feature variables of different instar stages, RMS Amp, Pulse Num, Avg Pul, Energy, Avg PD, and Peak PD in 2nd instar stages exhibited significantly higher values than in other instar stages ($P < 0.05$) (Fig. 5c). And values recorded from mature larvae did not differ from those recorded in non-infested wood (Fig. 5c).

These results helped to confirm that the feeding activity of *S. bifasciatus* larvae was greatest during the 1st to the 3rd instar, declined from the 4th instar, and was lowest at the 5th instar. Therefore, the optimal time for acoustic detection of *S. bifasciatus* was from the 1st to 3rd instar when the larval feeding activity was great.

3.4 Variable correlation analysis and multicollinearity test

Correlation coefficients of feature variables with larval instar and insect population are presented as a heat map in Fig. 6. A weak correlation was found between larval instar and feature variables, only r values of Avg Ent and Peak Freq were above 0.4, and others were below 0.4. By contrast, the larval population has strong linear correlations with all variables ($r > 0.7$), and the absolute r values of Pulse Num and Avg Ent were above 0.9.

VIF was used to assess for multicollinearity among all nine variables. As shown in Table 2, except for Avg Pul and Peak Freq displaying no multicollinearity ($VIF \leq 10$), the VIF values were over 10 for other variables, indicating high or severe multicollinearity among these variables. Collinearity of variables used for describing the feeding sounds would affect model performance and reduce prediction accuracy. To avoid this, SR regression and PLSR regression were used to eliminate the multicollinearity and establish prediction models.

Table 2
The variance inflation factor (VIF) values of nine feature variables

Variable	RMS Amp	Pulse Num	Avg Pul	Agg Ent	Avg Ent	Energy	Avg PD	Peak PD	Peak Freq
VIF	881.828	117.197	8.245	48.407	34.307	1901.023	2078.922	32.980	2.247

3.5 Model performance

Table 3 and Figure 7 showed the prediction accuracy and stability of models for prediction larval instar and population. In larval instar models, the predictive performance of the SR model was much better than that of the PLSR model. The values of R^2 and RPD in the SR model were higher, 0.71 and 3.38 respectively, and the value of RMSEp was 0.42. The importance of feature variables for estimating larval instar in the SR model, as shown in Table 3. Avg Ent, Peak Freq, and Avg Pul had the largest influence on the model.

In larval population models, the PLSR model showed higher prediction accuracy and greater stability, with higher R^2 and RPD values of 0.97 and 28.87, and a lower PMSEp value of 61.96. In the PLSR model, the VIP score of Peak Freq was the lowest, and the VIP values of the other eight variables were similar, indicating that except for Peak Freq, other variables had a great impact on the model.

Table 3
The performance of the SR and PLSR models for prediction larval instar and population

Dependent variable	Model	Selected variables (from the largest to the smallest importance)	Number of variables	R^2	RMSEp	RPD
Instar	SR	Avg Ent, Peak Freq, Avg Pul, Avg PD, Pulse Num, RMS Amp	6	0.71	0.42	3.38
	PLSR	Peak Freq, Energy, Avg PD, Avg Ent, Avg Pul, RMS Amp, Peak PD, Pulse Num, Agg Ent	9	0.67	0.49	2.13
Population	SR	Agg Ent, Pulse Num, Avg Ent, Avg PD, RMS Amp, Avg Pul, Peak Freq	7	0.87	238.12	4.73
	PLSR	Avg Ent, Pulse Num, Energy, Avg PD, RMS Amp, Avg Pul, Agg Ent, Peak PD, Peak Freq	9	0.97	61.96	28.87

4. Discussion

4.1 Optimization of the acoustic detection instrument

Some of the first sensors used for acoustic pest detection were microphones, which were useful sensors for airborne signals (Wei et al., 2010; Mankin et al., 2011; Chen et al., 2015). However, microphones were not suitable for detecting wood-boring pests, because they did not interface well with signals produced by insects in the soil, wood, or other solid substrates. Until the development of sound monitors (AED-2000L and AED-2010L) by the American Acoustic Emission Consulting (AEC) company and the application of the accelerometer, the acoustic detection objects expanded from stored grain pests to underground pests and wood borers. The Mankin research team used the AED to detect *Diaprepes abbreviatus* larvae (Mankin and Lapointe, 2003; Mankin et al., 2009b), *Rhynchophorus ferrugineus* (Olivier) larvae (Herrick and Mankin, 2012), and *R. cruentatus* (Fabricius) larvae (Dosunmu et al., 2014), and *Sitophilus oryzae* (L.) adults (Njoroge et al., 2017). Wei (2010) combined the AED-2000L with a sound analysis program to detect and analyze the sound signals of several wood-boring insects. Pan et al. (2014, 2015) used the AED-2010L to record and analyze the sounds of quarantine pests that were often intercepted at ports. Based on successful attempts with the AED-2010L for acoustic detection, we chose this instrument to record the sounds of wood-borers in this study.

After testing the available AED-2010L, the instrument could successfully detect the feeding sounds, but the noise of the amplifier (AED-2010L) was very loud (Fig. 8a), which affected features extraction. Based on the working principle of AED-2010L, the instrument was optimized: the driving circuit board, secondary amplifier, and NI9215 acquisition card were used to replace the amplifier (AED-2010L), but the Model SP-1L probe and Model DMH-30 were retained. Comparing the spectrograms of *S. bifasciatus* larvae feeding sounds recorded before and after instrument optimization (Fig. 8), it was found that four clear noise bands appeared in the spectrogram recorded by the original AED-2010L, but these noise bands disappeared in the spectrogram recorded by the optimized instrument, clearly revealing the feeding sound pulses.

4.2 Selection of target sound signals and feature variables

Generally, when pests produced a large number of high-energy sound signals with a broadband frequency, these sound signals were relatively easy to distinguish from low-frequency background noise and other behavior sounds (e.g. crawling, cleaning the tunnel) due to their high proportion and strong energy, and the accuracy of prediction results would be increased (Mankin, 2011). Many reports can confirm this. Wei (2010) studied the feeding sound and crawling sound of *S. bifasciatus* and *Apriona germari* (Hope) larvae, and found that the sound signal of the crawling was unstable, its frequency range was narrow, and the peak frequency was less than that of feeding sound signal. Bu et al. (2017) studied four types of acoustic behaviors of *Anoplophora glabripennis* and *Anoplophora chinensis* larvae, of which the feeding sound could be easily identified with short pulse duration (less than 30 ms), large amplitude (maximum relative amplitude of 0.8), and high frequency (peak frequency of about 7 kHz). Qi et al. (2016) demonstrated that the features of feeding sound of *Monochamus urussovi*, *A. glabripennis*, and *Eucryptorrhynchus brandti* larvae were the duration of pulse less than 10 ms and peak frequency range of 7–8.5 kHz, which were easy to distinguish from the calls of insects and birds that had long durations and a narrow frequency range. Therefore, the target signal detected in this study was the feeding signal. And it was found that the characteristics of feeding sounds produced by *S. bifasciatus* larvae were similar to those described above. The duration of the feeding sound pulse was less than 15 ms, and the frequency was distributed between 0 and 20 kHz. The energy was concentrated (7kHz-9kHz), and the peak frequency was about 8 kHz.

At present, researchers tended to choose several feature variables to describe the sounds and establish models, mainly including pulse number, average pulse duration, peak frequency, and peak power density. Hagstrum et al. (1990, 1991) established a linear relationship between the pulse number and the population of storage pests. Mankin et al. (2001, 2003) detected the sounds of *Diaprepes abbreviatus* (L.) by using acoustic detection technology and found that there was a significant regression relationship between the rate of sound pulses and population. Eliopoulos et al. (2015, 2016) chose a single feature of the pulse number to predicted the population of the most common beetles in wheat. Banga et al. (2020) input the formant parameters of sounds into an artificial neural network for modeling to evaluated and predicted the population of food legume bruchids in bulk stored chickpea and green gram.

However, this was a well-known classification problem: a single 'strong' feature does not exist; therefore, many 'weak' features must be used in parallel for acoustic detection and discrimination (Alexander et al., 2019). Sueur et al. (2014) studied acoustic indexes for biodiversity assessment and landscape surveys and also found that it was highly probable that a single index would never cover all biodiversity facets and be reliable in all contexts, and combinations of indexes could lead to more efficient results. Actually, the feeding vibration of wood borers was very weak, which was easily covered by electrical and background noise, and there was also the problem of acoustic attenuation (i.e., the gradual loss of magnitude as an acoustic signal pass through a substrate) (Robbins et al., 1991; Scheffrahn et al., 1993; Mankin et al., 2011). At present, there was no research to demonstrate that a single feature variable could fully describe the feeding sound of wood-boring insects in all situations. Therefore, nine feature variables were selected in this study, three variables of time-domain features (RMS Amp, Pulse Num, and Avg Pul) and six variables of frequency-domain features (Agg Ent, Avg Ent, Energy, Avg PD, Peak PD, and Peak Freq), to permit more detailed analysis of the differences in sounds produced by larvae at different times and stages. The established prediction model was more stable. By ranking the importance of variables in models, we found that Avg Ent, Peak Freq, and Avg Pul had a greater

impact on the results of prediction larval instar. By contrast, all variables except Peak Freq had a great influence on the results of the population prediction. These findings were consistent with the results of the correlation analysis. At the same time, it was also demonstrated that the sounds produced by *S. bifasciatus* larvae could be accurately described by these nine feature variables.

4.3 The best detection time window

The best detection time windows are defined as the time when the target sounds are the strongest and the rate of sound production is the fastest. Knowledge on optimal times for detection of the wood-boring pest would greatly improve inspection success. As detectable sounds are produced during larval activities in the wood, the activity patterns of pests may greatly affect our ability to detect wood borers in the early infested times. Therefore, the best detection time windows can be determined by knowledge on the activity patterns of pests. Exploring for patterns of seasonal and daily feeding and movement of *I. minor* in naturally infested logs, Lewis et al. (2011) determined that the optimal times of a day to detect termites was in the late afternoon and the best time of the year was in the summer. In this study, the optimal time to detect *S. bifasciatus* larvae in a day was from 13:00 to 20:00, when the feeding sounds were the strongest, consistent with the results of Lewis.

According to the biological characteristics of *S. bifasciatus*, larvae begin to attack the host trees in late March and pupate in late August, the whole larval development periods about 150 days (Gao et al., 2008). The feeding capacity of larvae increases with instars, peaked from April to early May (He et al., 2002). In this study, the feeding activity of *S. bifasciatus* larvae was greater during the 1st to the 3rd instar compared to the 4th and 5th instar, because the rate of sound signals produced by larvae was fastest and the feeding sounds were strongest during the period. The corresponding time was from April 11 to April 25, consistent with the overeating period mentioned above. In conclusion, the best detection time window was during the afternoon when larvae were in the 1st to the 3rd instar. During this time, sound detection should be more efficient and accurate.

4.4 Prediction of larval instar and population

When wood boring insects attack the host tree, some groups had obvious damage symptoms (e.g. defecation holes and frass, oviposition scars, entrance tubes, etc.) on the trunk surface, such as *Dendroctonus valens* and *Streltzoviella insularis*. Forestry managers can judge the degree of damage based on the number of damage symptoms and then apply appropriate control measures. However, other cryptic wood borers, such as *Eucryptorrhynchus brandti*, *Agilus planipennis*, and *S. bifasciatus*, can only be inspected when the emergence holes of adults are found and the host trees show signs of weak or dying. For this type of pest, acoustic detection technology can both identify pest presence and predict population so that tree damage degree will be evaluated in time.

In many cases, the infested logs used in the experiments are obtained by artificial inoculation. This approach enables the control of extraneous variables and ensures that there is only one type of pest in the wood and the growth of larvae is consistent (Mankin et al., 2008a; Herrick and Mankin, 2012; Bu et al., 2016; Qi et al., 2016; Hetzroni et al., 2016). And most experiments of sounds recording have been conducted indoors or in soundproof boxes. Therefore, to simulate a field detection environment, feeding sounds of *S. bifasciatus* were recorded from artificial infested logs in an outdoor environment without any sound insulation equipment. And we found that unlike the noise generated by shaking of the instrument due to strong winds, the sounds of bird

calls, human speech, and other insect calls usually had strong harmonic components which would be easily eliminated from the feeding sounds.

However, there are two or more species of pests in the same trees under natural conditions. For example, *Streltzoviella insularis* and *Agrilus planipennis* may damage ash trees at the same time, and *S. bifasciatus* and *Phloeosinus aubei* Perris may damage *P. orientalis* at the same time. Moreover, the growth of larvae in the host tree is not synchronous and the degree of differentiation can't be ignored. Therefore, based on analyzing the sound patterns of different pests and identifying the best detection time, it is necessary to study the characteristics of complex sounds, then increase sound sample size under natural conditions. This will enable us to determine whether there are significant differences in the feeding sounds produced by various insect species at different larval instars, thereby continuously optimizing the detection model. In addition, as the specific locations of the pests are not known during field detection and there is an issue with sound attenuation in wood, the effective detection range in which strong signals can be detected will be our next study.

Table 4
the abbreviation list of feature variables

Variable	Abbreviation
RMS amplitude	RMS Amp
Pulse number	Pulse Num
Average pulse duration	Avg Pul
Aggregate entropy	Agg Ent
Average entropy	Avg Ent
Energy	Energy
Average power density	Avg PD
Peak power density	Peak PD
Peak frequency	Peak Freq

Declarations

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Authors' contributions

Qi Jiang, Lili Ren and Youqing Luo conceived and designed the experiment; Qi Jiang and Yujie Liu performed the experiment; Qi Jiang analyzed the data, and wrote the paper; Lili Ren and Yujie Liu made valuable revisions and editing of the paper; Yu Sun contributed the acoustic detection instrument.

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Availability of data and materials

The datasets used in this study are available upon a reasonable request to the Authors.

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

1. Adams RE, Wolfe JE, Milner M et al (1953) Aural detection of grain infested internally with insects. *Science* 118:163–164
2. Alexander S, Alexander Y, Salloum HR et al (2019) Towards an automated acoustic detection algorithm for wood-boring beetle larvae (Coleoptera: Cerambycidae and Buprestidae). *Journal of Economic Entomology*. (3),3
3. Banga KS, Kotwaliwale N, Mohapatra D et al (2020) Assessment of bruchids density through bioacoustic detection and artificial neural network (ANN) in bulk stored chickpea and green gram. *J Stored Prod Res* 88:101667
4. Brain CK (1924) Preliminary note on the adaptation of certain radio principles to insect investigation work. *Ann Univ Stellenbosch Ser* 2:45–47
5. Bu YF, Qi XJ, Wen JB et al (2016) Acoustic characteristics analysis of seven species of tree trunk borers. *Journal of Nanjing Forestry University (Science Edition)* 40(02):179–184
6. Bu YF, Qi XJ, Wen JB et al (2017) Acoustic behaviors for two species of cerambycid larvae. *Journal of Zhejiang A&F University* 34(001):50–55
7. Charif RA, Waack AM, Strickman LM (2010) Raven Pro 1. 4 User's Manual. Cornell Laboratory of Ornithology, Ithaca, NY, p 379
8. Chen MX, Yang XT, Shi BC et al (2015) Research progress and prospect of technologies for automatic identifying and counting of pests. *J Econ Entomol* 37(1):000176–000183

9. Dosunmu OG, Herrick NJ, Haseeb M et al (2014) Acoustic detectability of *Rhynchophorus cruentatus* (Coleoptera: dryophthoridae). Florida Entomologist 97(2):431–438
10. Eliopoulos PA, Potamitis D, Kontodimas DC et al (2015) Detection of adult beetles inside the stored wheat mass based on their acoustic emissions. Journal of Economic Entomology
11. Eliopoulos PA, Potamitis D, Kontodimas DC (2016) Estimation of population density of stored grain pests via bioacoustic detection. Crop Protection 85:71–78
12. Gao SL, Xu ZC, Gong XC (2007) Progress in research on *Semanotus bifasciatus*. Forest Pest and Disease 26(3):19–23
13. Gao SL, Xu ZC, Gong XC et al (2008) Biological characters of *Semanotus bifasciatus*. Chinese Bulletin of Entomology 45(001):74–77
14. Hagstrum DW, Vick KW, Webb JC (1990) Acoustical monitoring of *Rhyzopertha dominica* (E) (Coleoptera: Bostrichidae) populations in stored wheat. Journal of Economic Entomology 83:625–628
15. Hagstrum DW, Vick KW, Flinn PW (1991) Automated Acoustical Monitoring of *Tribolium castaneum* (Coleoptera: Tenebrionidae) Populations in Stored Wheat. Journal of Economic Entomology. (5),1604–1608
16. He BL, Niu GP, Gu KS et al (2002) The study on *Semanotus bifasciatus*. Shandong Forestry Science and Technology. (3),10–13
17. Herrick NJ, Mankin RW (2012) Acoustical detection of early instar *Rhynchophorus ferrugineus* (Coleoptera: Curculionidae) in Canary Island date palm, *Phoenix canariensis* (Arecales: Arecaceae). Florida Entomologist. 95, 983-990
18. Hetzroni A, Soroker V, Cohen Y (2016) Toward practical acoustic red palm weevil detection. Computers and Electronics in Agriculture
19. Hurng HY, Chou JM (2012) Development of Automatic Bio-Monitoring System for the Life History of Insect. Appl Mech Mater 195–196:1078–1082
20. Iman RL, Campbell J, Helton J (1981) An approach to sensitivity analysis of computer models: part II—ranking of input variables, response surface validation, distribution effect and technique synopsis. Journal of Quality Technology 13(3):174–183
21. Jiang Q, Ren LL, Luo YQ (2021) Determination of larval instar number *Semanotus bifasciatus* (Coleoptera: Cerambycidae). Journal of Environmental Entomology 43(1):6
22. Lewis V, Leighton S, Tabuchi R et al (2011) Seasonal and Daily Patterns in Activity of the Western Drywood Termite, *Incisitermes minor* (Hagen). Insects. 2(4)
23. Li B, Yi SY, Sun XG (2003) Summarization of the studies on *Semanotus bifasciatus* (Motschulsky). Forest Pest and Disease 22(1):38–38
24. Mankin RW, Lapointe SL, Franqui RA (2001) Acoustic Surveying of Subterranean Insect Populations in Citrus Groves. J Econ Entomol 94(4):853–859
25. Mankin RW, Lapointe SL (2003) Listening to the larvae: Acoustic detection of *Diaprepes abbreviatus* (L.). Proceedings Florida State Horticultural Society. 116, 304-308
26. Mankin RW, Smith MT, Tropp JM et al (2008a) Detection of *Anoplophora glabripennis* (Coleoptera: Cerambycidae) Larvae in Different Host Trees and Tissues by Automated Analyses of Sound-Impulse

- Frequency and Temporal Patterns. *Journal of Economic Entomology*. (3),838–49
27. Mankin RW, Mizrach A, Hetzroni A et al (2008b) Temporal and spectral features of sounds of wood-boring beetle larvae: identifiable patterns of activity enable improved discrimination from background noise. *Florida Entomologist* 91(2):241–248
 28. Mankin RW, Samson PR, Chandler KJ (2009b) Acoustic detection of Melolonthine larvae in Australian sugarcane. *Journal of Economic Entomology* 102:1523–1535
 29. Mankin RW, Hagstrum DW, Smith MT et al (2011) Perspective and Promise: a Century of Insect Acoustic Detection and Monitoring. *American Entomologist*. (1),1
 30. Mankin RW, Hagstrum D, Guo M et al (2021) Automated Applications of Acoustics for Stored Product Insect Detection, Monitoring, and Management. *Insects* 12(259):259
 31. Njoroge AW, Mankin RW, Smith BW et al (2017) Effects of hermetic storage on adult *Sitophilus oryzae* L. (coleoptera: curculionidae) acoustic activity patterns and mortality. *Journal of Economic Entomology*, 110(6)
 32. Pan J, An YL, Liu X et al (2013) The application and prospect of sound monitoring in log quarantine. *Plant Quarantine* 27(005):17–20
 33. Pan J, Liu X, Shao PZ et al (2014) Acoustic characteristics and their comparison of *Gnathotrichus materiarius* and *Gnathotrichus sulcatus*. *Journal of Environmental Entomology* 36(03):395–401
 34. Pan J, Liu X, Shao PZ et al (2015) Preliminary study on the acoustic detection of larvae *Heterobostrychus aequalis*. *Journal of Environmental Entomology* 37(06):1237–1241
 35. Qi XJ, Bu YF, Xu ZC et al (2016) Using acoustic technology detect the different numbers of *Anoplophora glabripennis* larvae in poplar. *Journal of Environmental Entomology* 38(003):529–534
 36. Robbins WP, Mueller RK, Schaal T et al (1991) Characteristics of acoustic emission signals generated by termite activity in wood. In *Proceedings IEEE Ultrasonics Symposium*. 1047-1051
 37. Smith MT, Turgeon JJ, Groot P, Gasman B (2009) Asian longhorned beetle *Anoplophora glabripennis* (Motschulsky): lessons learned and opportunities to improve the process of eradication and management. *Am Entomol* 55(1):21–25
 38. Scheffrahn RH, Robbins WP, Busey P et al (1993) Evaluation of a novel, hand-held, acoustic emissions detector to monitor termites (Isoptera: Kalotermitidae, Rhinotermitidae) in wood. *Journal of Economic Entomology* 86:1720–1729
 39. Schober P, Boer C, Schwarte LA (2018) Correlation coefficients: appropriate use and interpretation. *Anesthesia & Analgesia* 126(5):1
 40. Sueur J, Fa RA, Gasc A et al (2014) Acoustic Indices for Biodiversity Assessment and Landscape Investigation. *Acta Acustica United with Acustica* 100(4):772–781
 41. Walker TJ (1996) Acoustic methods of monitoring and manipulating insect pests and their natural enemies.. In: In: Rosen D, Bennett FD, Capinera JL (eds) *Pest management in the subtropics: integrated pest management: a Florida perspective*. Intercept, Andover, pp 245–257
 42. Wang SK, Zhang JH, Zhou P et al (2018) Application of optics, acoustics and pheromone in insect monitoring. *Plant Quarantine*. (4)

- 43. Webb JC, Litzkow CA, Slaughter DC (1988a) A computerized acoustical larval detection system. *Applied Engineering in Agriculture* 4:268–274
- 44. Wei XQ, Wen JB, Zhao YJ et al (2010) Review on Monitoring Technology of the Insect Acoustic. *Scientia Silvae Sinicae*. (05),147–154
- 45. Wei XQ (2010) Primary Study on Sound Monitoring Technology of Wood Boring Insects. Beijing Forestry University
- 46. Wold S, Johansson A, Cochi M .,1993 PLS-partial least squares projections to latent structures. *ESCOM Science Publishers: Leiden*.523–550
- 47. Zhao YJ (2009) Study on acoustic detection technique for *Semanotus bifasciatus* (Motschulsky) larvae. Beijing Forestry University

Figures

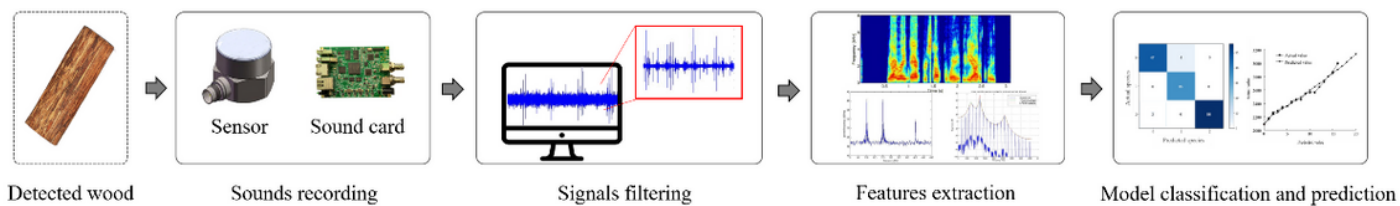


Figure 1

The basic principles of acoustic detection technology

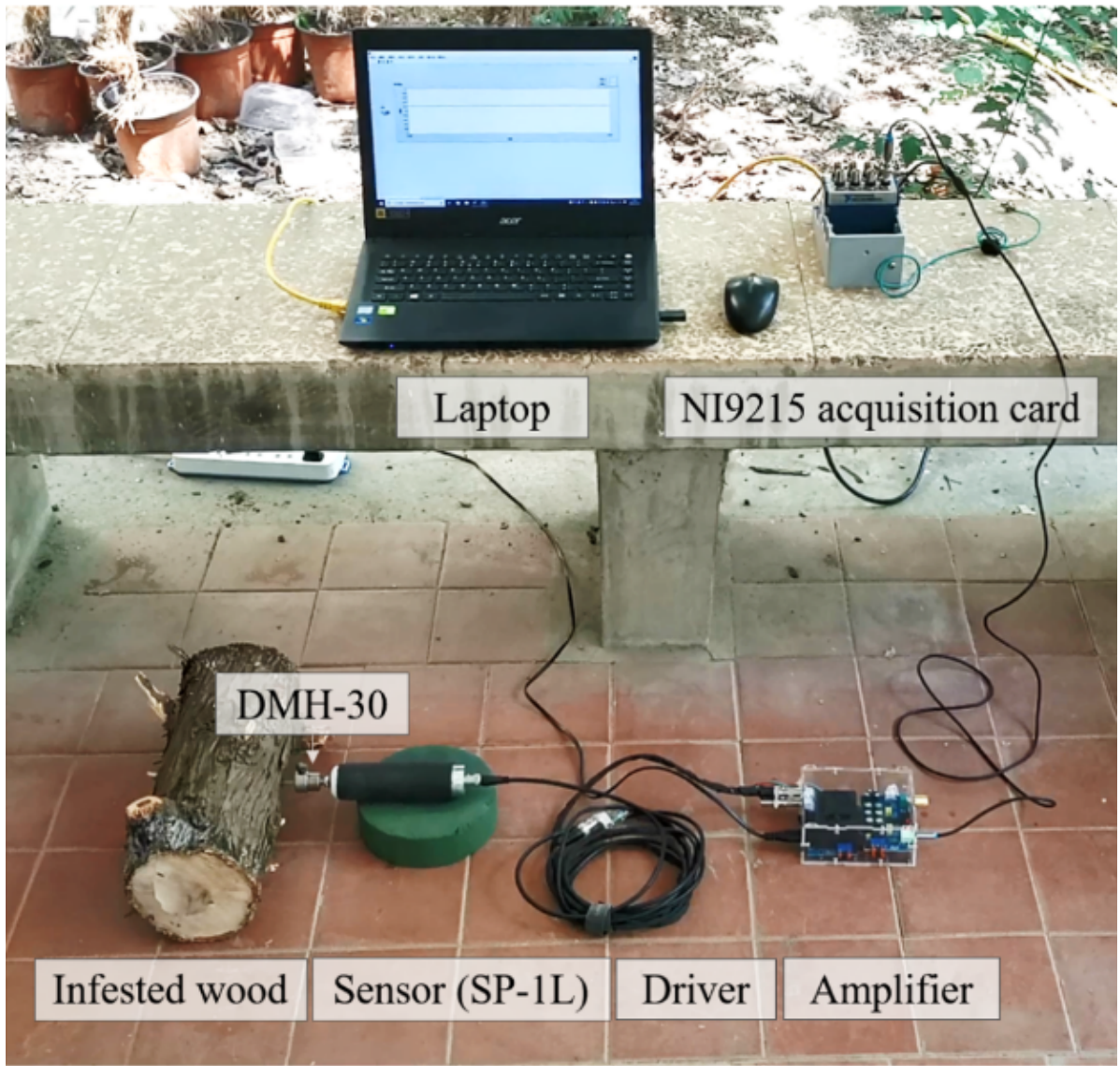


Figure 2

Sound recording with the improved acoustic detection instrument

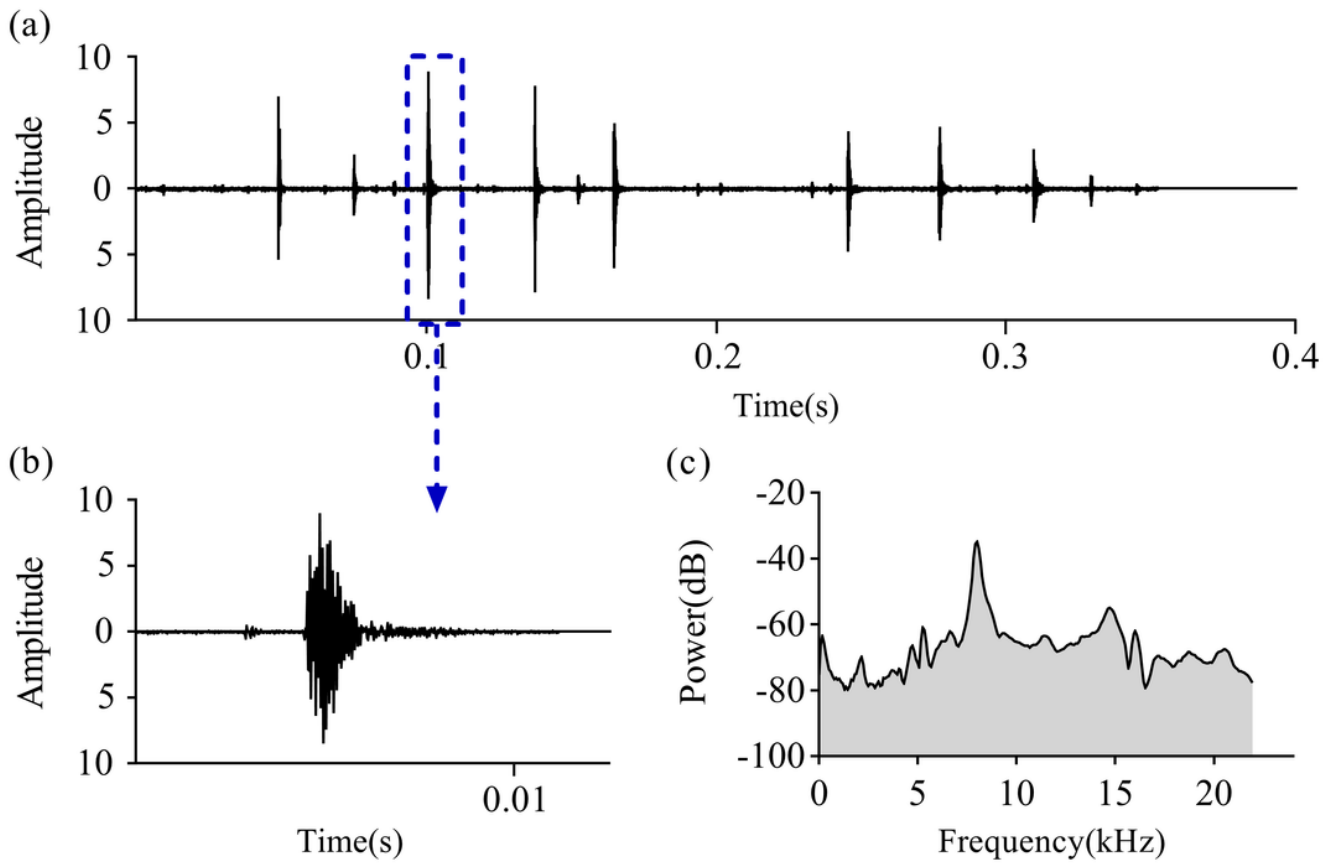


Figure 3

The feeding sound signatures of *S. bifasciatus* larvae. (a) The sounds oscillogram; (b) the oscillogram of a single sound pulse; (c) the power spectrum of a single sound pulse

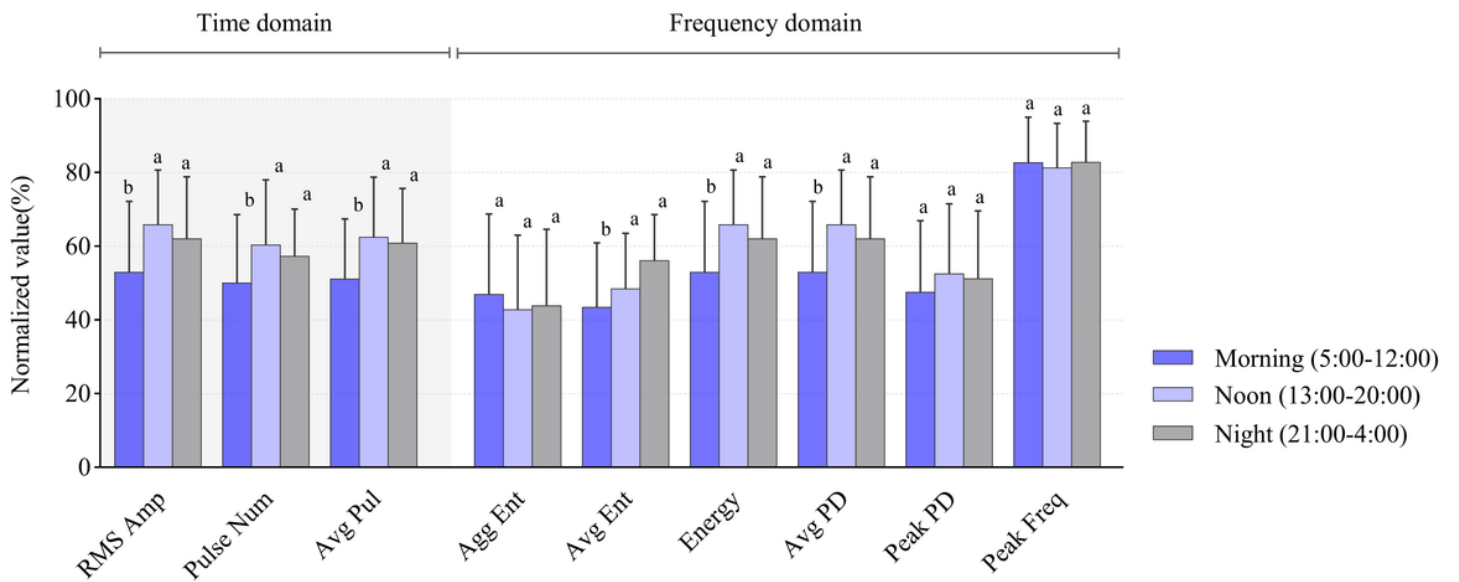


Figure 4

Comparison of feature variables of feeding sounds among three periods

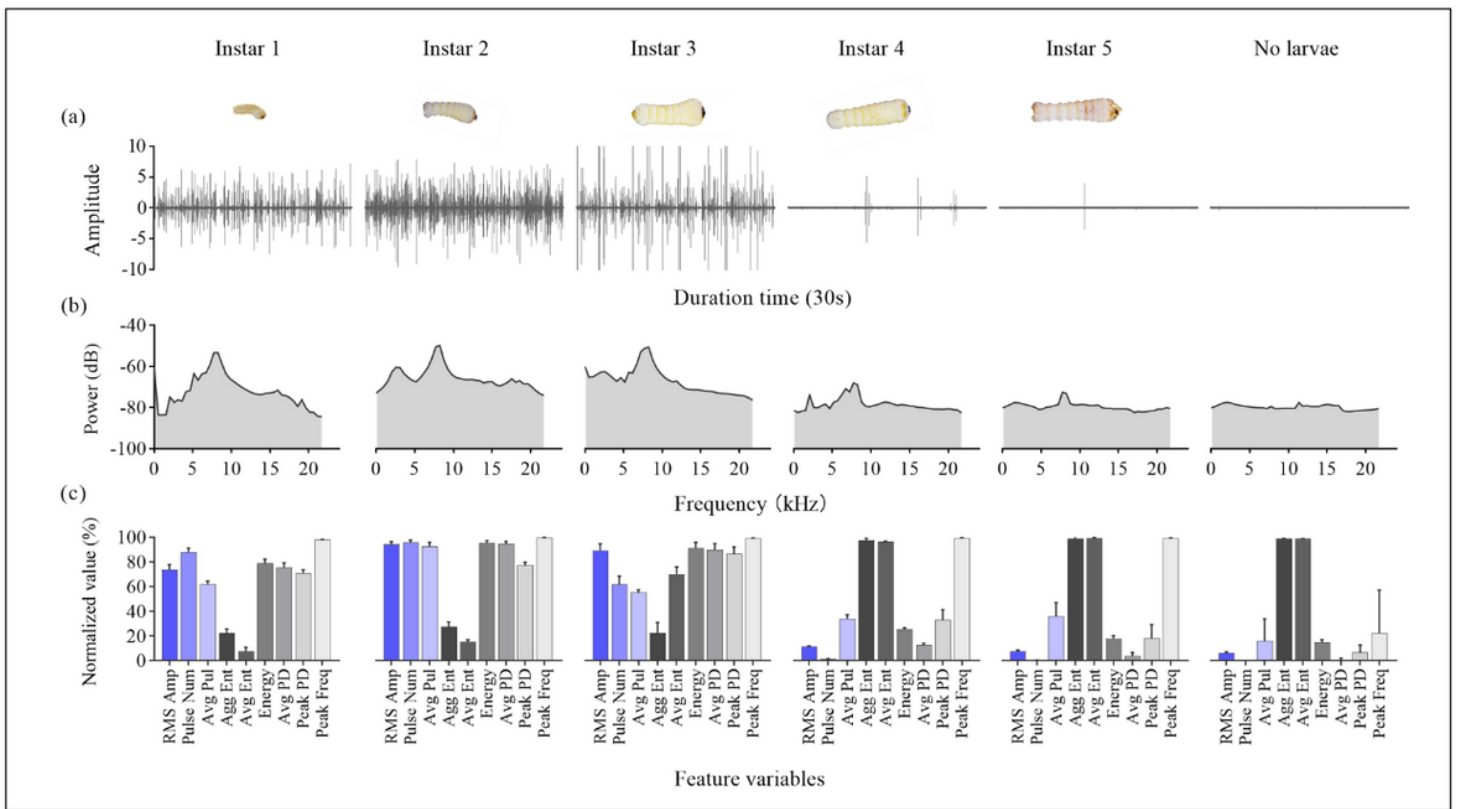


Figure 5

Acoustic characteristics of larvae feeding sounds throughout all growth stages, including (a) the sound oscillogram; (b) the power spectrum of sounds; (c) difference analysis of each feature variable.

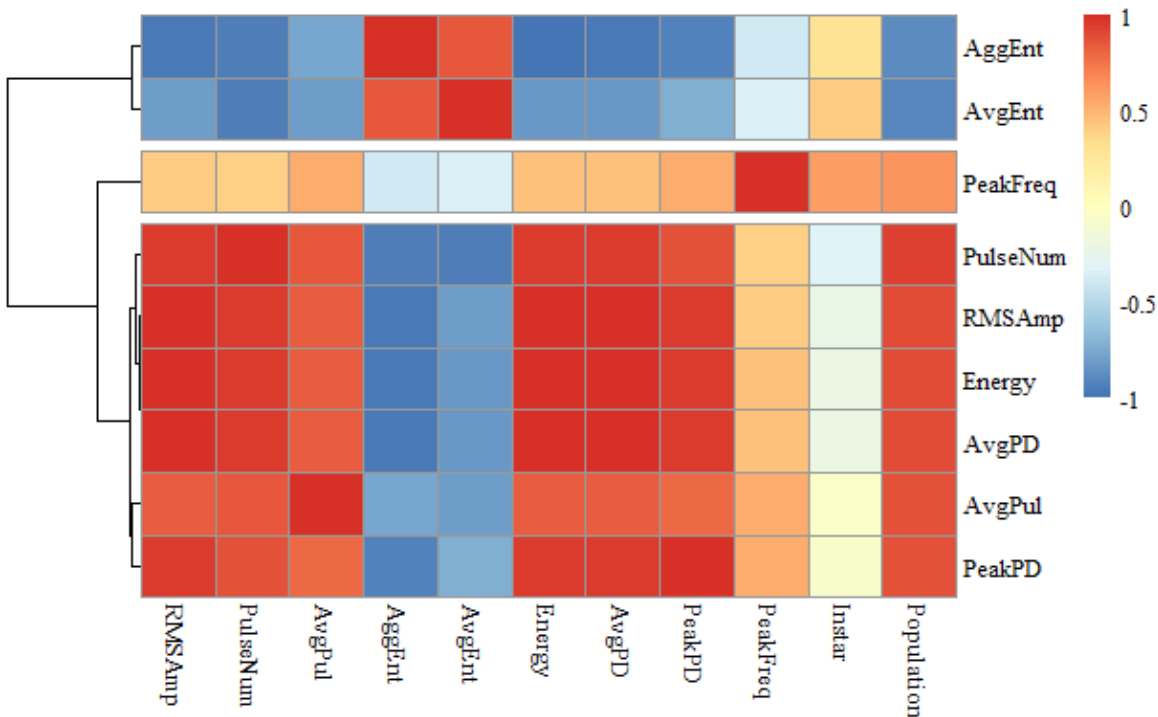


Figure 6

Correlations analysis of feature variables with larval instar and population

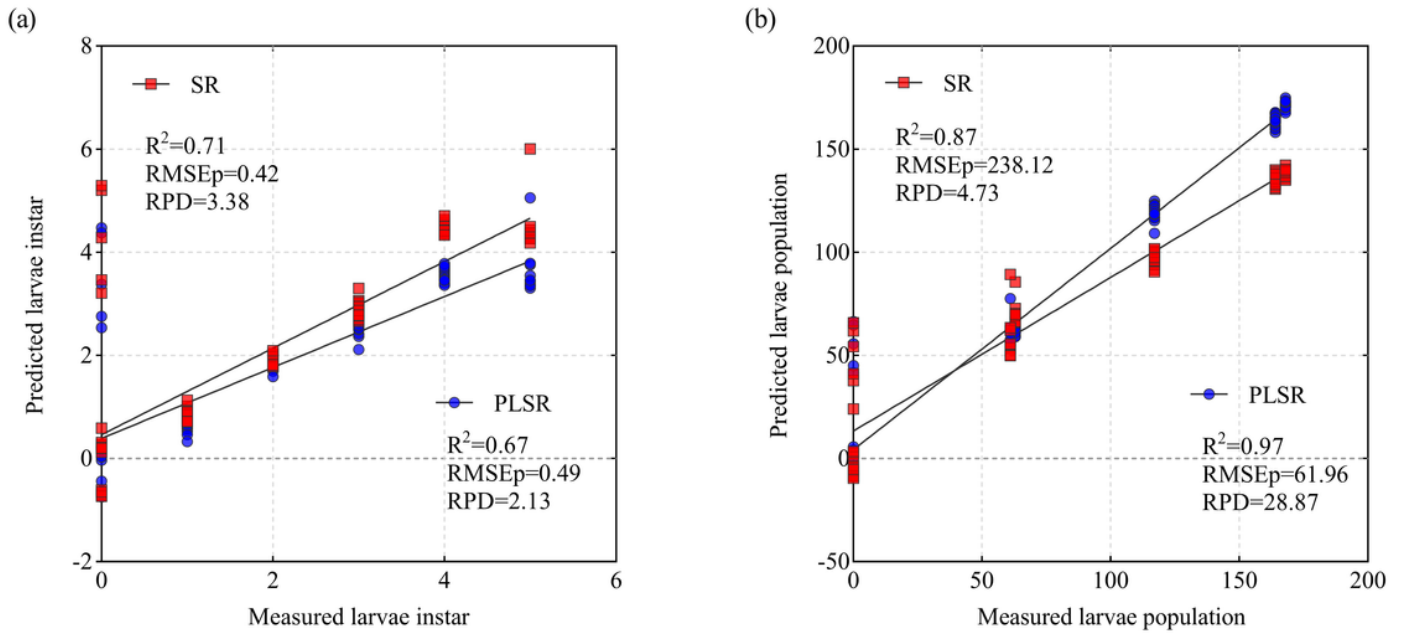


Figure 7

Measured versus predicted larval instar (a) and population (b) derived from SR models and PLSR models

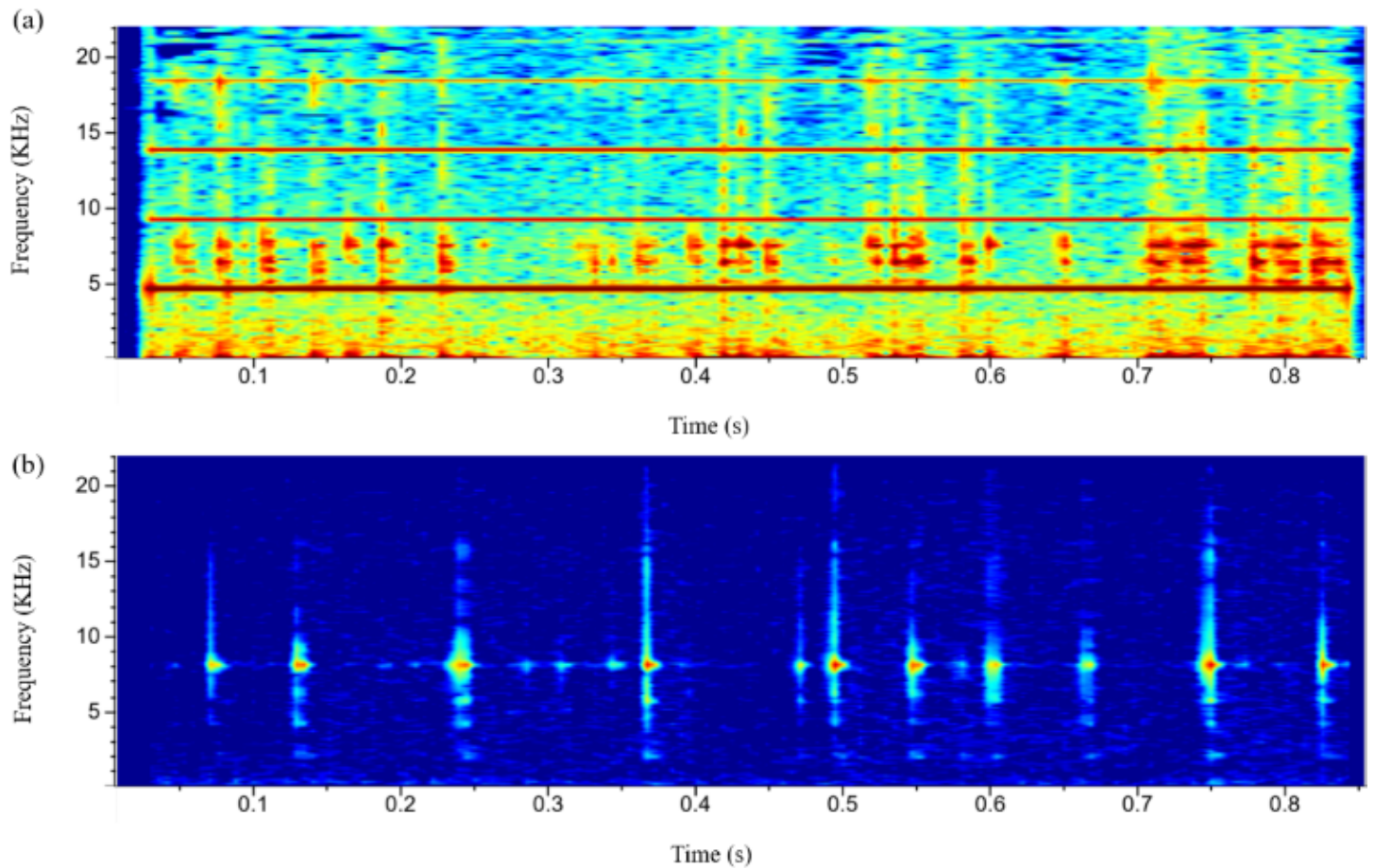


Figure 8

Spectrogram of the feeding sounds of *S. bifasciatus* larvae recorded before and after the optimization of the AED-2010L: (a) sounds recorded by the original AED-2010L; (b) sounds recorded by the optimized AED-2010L.