A STUDY TO CLASSIFY WILD BEES' SIGNAL USING TIME SERIES ANALYSIS

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Abstract

Bees (Anthophila) are among the most effective pollinators in nature being responsible for approximately one-third of the total crop pollination for human dietary supply. The interaction between plants and bees plays here an essential role and may also include vibro-acoustic signals as an important medium of information transmission. Plants have been shown to respond to airborne acoustic signals of flying pollinators by increasing the sugar concentration in the nectar. Yet very little is known about the pollinators' vibro-acoustic signatures and plant-relevant effective traits of the signal. Here we present an analysis framework of acoustic signals for three different bee species, namely *Rhodanthidium sticticum*, *Amegilla quadrifasciata*, and *Apis mellifera*, recorded in the rural areas (Chera, Chulilla, and Macastre) of the Province of Valencia, Spain, visiting *Antirrhinum* (snapdragon) plants. First, from audio-visual recordings, audio signals for different bee behaviours during visits were identified. We showed that periodogram and recurrence-based spectrograms could be used to classify real-life bio-acoustic data recorded outdoors. This approach can also be used to predict future data sets for which a traditional approach like spectral analysis is unsuitable, especially for noisy, more nonlinear, and complex data.

Keywords: Bio-acoustics, pollinator, recurrence plots, recurrence spectrogram

1. Introduction

In the twenty-first century, the ever-present global food crisis constitutes one of the world's major global challenges [1]. Among complex issues like climate change and geopolitics, decreasing pollinator populations and lack of pollination is one of the main driving factors of this crisis [2, 3]. Bees are among the most efficient pollinators and responsible for about one-third of the human dietary supply [4]. Apart from the quantity, also the quality of yield depends on the type of pollination, as in the case of strawberry plants which have been shown to produce better fruit quality when pollinated by bees as opposed to wind or self pollination [5].

Nectar and pollen are major factors for bees to visit plants [4]. Up to now, plant-pollinator communications have been studied primarily by assessing the production and perception of visual and olfactory cues [6]. However, the evening primrose (*Oenothera drummondii*) responds to vibro-acoustic signals of flying pollinators (*Apis mellifera*) by producing nectar with higher sugar concentration [7]. Still, very little has been investigated about the vibro-acoustic information exchange between plants and pollinators. Different plant tissues have been shown to respond to vibro-acoustic signals such as roots, leaves, or flowers [7, 8, 9, 10, 11], which show a growing interest in understanding the sound sensing of sessile organisms including plants. Nonetheless, not much has been reported on the behaviour of the pollinators and the emission of the acoustic signal when they approach a plant. Furthermore, is this vibro-acoustic information directed and two-way, i.e. does it represent a communication signal or is it indirect, unidirectional and therefore a cue? [12, 13]. Nonetheless, since the vibro-acoustic signal is produced by the contraction of wing muscles during the flight, are the signal features changing depending on different behaviours? To address the above questions, we need to gain a deeper understanding of the potential information encoded within the vibro-acoustic signals of pollinators (in short 'signal' in the following). Recently, Nerse et al. [11] have studied the efficiency of vibration transmission in *Antirrhinum majus* using finite element simulation of the stamen model. Volponi et al. [14] investigated the insect signals through recordings in the field and showed that their variation largely dependent on species rather than intra-specific differences due to sex, or activity related to the context, e.g. pollination or escape from predators. As highlighted in the above study, recording bio-acoustic signals in their natural state is important, yet it is difficult to reproduce them with a live organism in a laboratory setting or even synthesise them. This makes the study challenging due to uncertainty in the signal type, which is dependent on many environmental, seasonal, behavioural and circumstantial factors.

In this study, we have presented a framework for classifying pollinator signals during floral visitation in the wild. The signals from three selected species were recorded in the rural area of the Province of Valencia, Spain. With the help of a convolutional neural network and both linear and non-linear time series analysis, we could successfully classify the bee signals based on their behaviour during floral visitation.

2. Methods

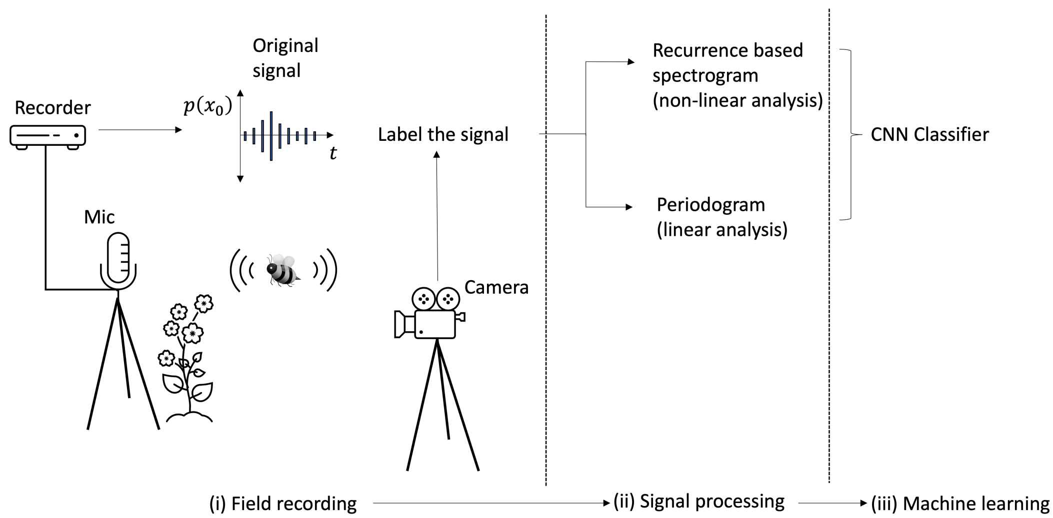


Figure 1: Schematic of the framework. CNN: convolution neural network.

The framework for this study can be divided into three parts: (i) field recording, (ii) signal processing, and (iii) implicit feature detection for classification using machine learning, as shown in schematic Fig. 1. The fieldwork was carried out in three different rural areas (Chera, Chulilla, and Macastre) in the Province of Valencia, Spain in 2023. We have selected three bee species for this study: *Rhodanthidium sticticum*, *Amegilla quadrifasciata*, and *Apis mellifera*. Out of three, *R. sticticum* and *Am. quadrifasciata* are solitary bees and they build nests in empty snail shells and soil, respectively. *Ap. mellifera*, also known as the European honey bee, is eusocial and one of the most efficient pollinators around the world. Pollinator acoustic signals were recorded using a Sennheiser MKE40-EW cardioid microphone and a Tascam DR-60DMkII audio recorder. Videos were recorded simultaneously using a Canon EOS R6 MKII digital camera. Audio and video were synchronized manually by labelling sound triggers. The audio recording was performed at a 48 kHz sampling rate and saved in WAV audio format. Cardioid-type microphones have a wider directional sensitivity ($\pm 120^\circ$ cone in this case) and are suitable for recording sound in the field when the location of the pollinator is close to the flower but not specified. The microphone was mounted on a rigid pole placed near the focus flowering plant, or under the camera with a clamp to actively reach to the pollinator.

The recording was continuous; however, due to environmental noise (wind, birds) and anthropogenic noises (lawnmowers, cars) we cleaned the data and only identified segments of signals which are clearly audible. We labelled these segments of audio signals based on five identified behaviours of the pollinators from the video, namely, hovering, landing, entering, leaving and passing by.

The labelled data was analysed using the periodogram and recurrence-based spectrogram presented in [15], which corresponds to standard frequency domain analysis techniques and modified spectrogram technique making use of non-linear time series analysis, respectively. It has been shown that recurrence-based spectrogram based on the recurrence-based power spectrum [16] is better suited to identify stable and unstable periodic orbits compared to classical periodogram techniques especially if noise is present and if the signal is nonlinear [17, 18, 15]. However, it is difficult to find the signal-to-noise ratio without a reference signal. As the bee signal recordings were outdoors and the data is inherently noisy, the non-linear recurrence-based method could be commendable as a general more broadly applicable solution.

As the recordings were in multiple files with different durations, the number of spectrograms for each file was decided based on the percentage of the duration of the file from total available duration in a specific label of data, e.g. if, for hovering, two files of equal duration were present, then each file contributed 50% of the total data set. Each periodogram was created for a time series of 0.2 s and 0.1 s window length with 95 % overlap. The first harmonic of the pollinator signal was found to be above 100 Hz. Hence, a 0.1 s length signal window was considered to be enough using a spectral resolution of 10 Hz. The recurrence-based spectrogram was also generated from the same 0.2 s duration of the signal. To randomise the signal window, we shifted 0.2 s signal window randomly for both periodogram and spectrogram. Furthermore, for recurrence-based spectrogram we have used biased recurrence rate estimation to avoid negative power [15]. The recurrence rate spectrograms were calculated with two approaches: (a) individual embedding for each segment of the signal under analysis ($\widehat{RR}^*_\tau$) and (b) fixed embedding for each species ($\widehat{RR}^*_{\tau,\mathrm{fe}}$). We have selected 30% recurrence rate criteria for the recurrence plots[15]. In total 1,000 snapshots of periodogram and recurrence-based spectrograms were created for each labelled set of data and were used to train a resnet50 convolutional neural network image classifier using MATLAB [19]. The image files should have a size of 224×224 pixels for resnet50. The network was modified for 13 classes in the output layer corresponding to five behaviours of three species. To avoid over-fitting, the data was augmented by translating horizontally to ± 24 pixels [15]. The neural network training was performed for ten epochs using stochastic gradient descent method with 0.9 momentum. During training, the initial learning rate was chosen to be 0.001, and the mini batch size was kept with 26 at twice the number of classes in the output layer. The training data was shuffled for every epoch and validation was conducted every 30 iterations.

3. Results

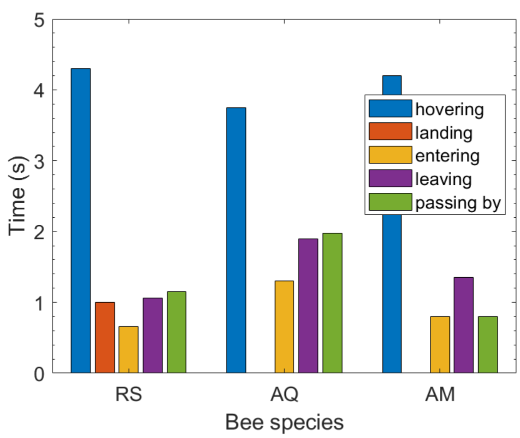
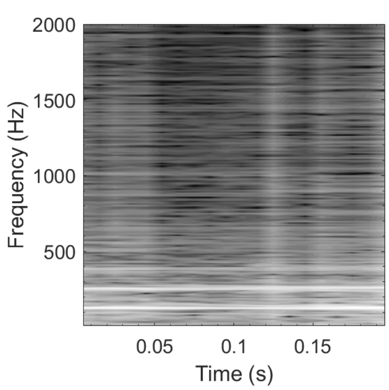
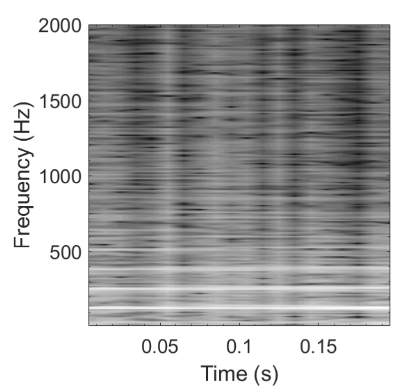


Figure 2: Duration of labelled time series data for the three species. RS: *Rhodanthidium sticticum*, AQ: *Amegilla quadrifasciata*, AM: *Apis mellifera*.



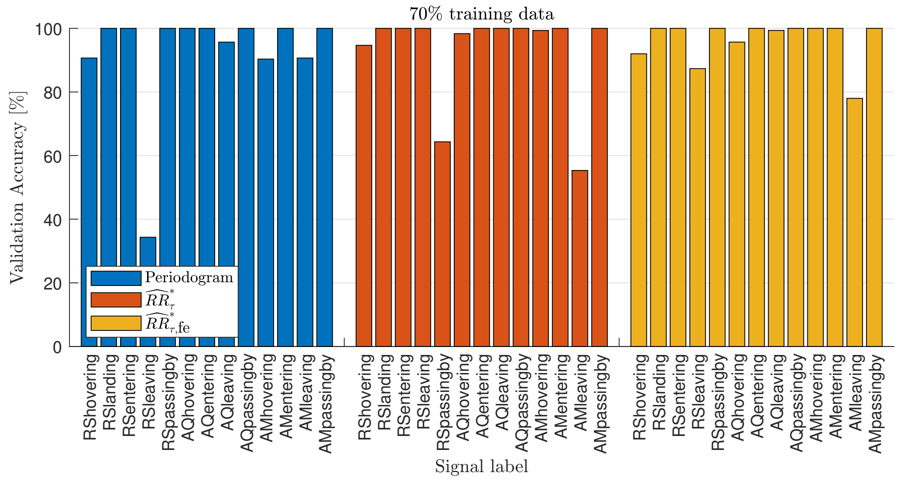
(a)



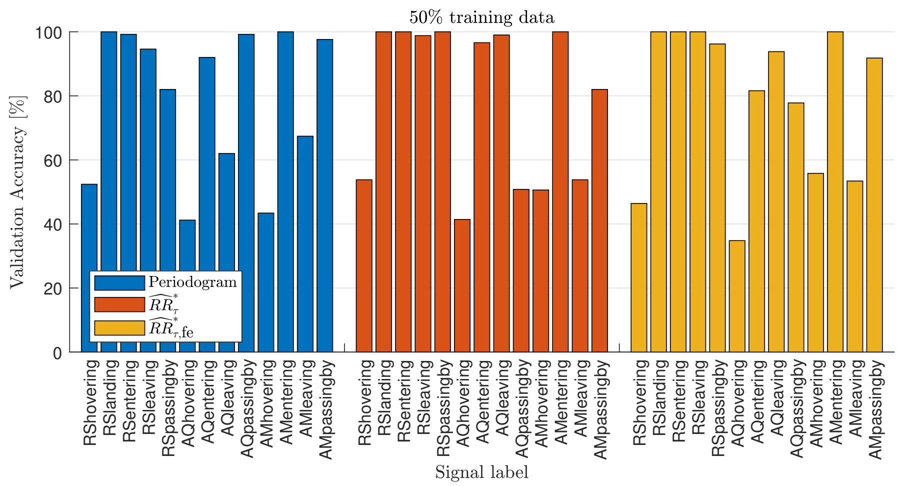
(b)

Figure 3: Example of periodogram in (a) and recurrence-based spectrogram in (b) for acoustic signal of *Rhodanthidium sticticum* during landing.

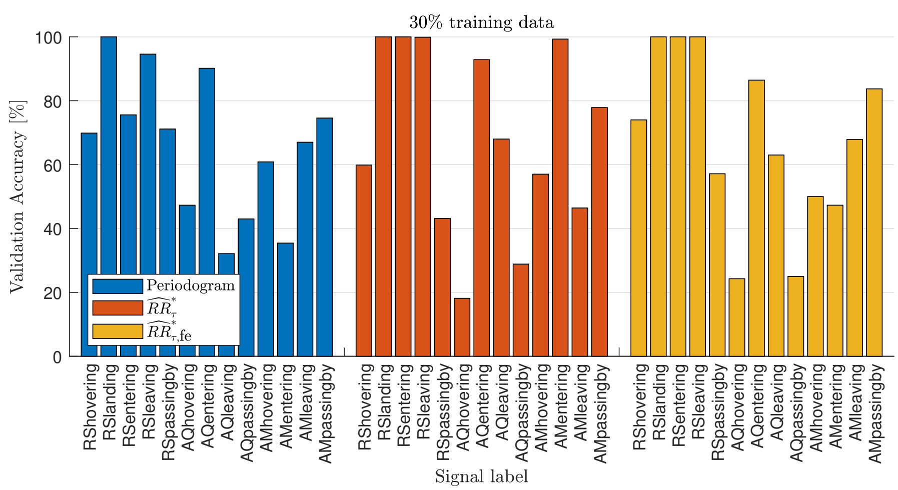
The audio recordings from the field were captured over multiple files on different days. *Ap. mellifera* had only six audio files, while *R. sticticum* and *Am. quadrifasciata* had ten and thirteen files, respectively. Fig. 2 presents a bar chart of the total duration of the available signals for each species segmented into five different behaviours.



(a)



(b)



(c)

Figure 4: CNN validation accuracy for all 13 classes. RS: *Rhodanthidium sticticum*, AQ: *Amegilla quadrifasciata* , AM: *Apis mellifera*. $\widehat{RR}_\tau^*$: recurrence-based spectrogram with individual embedding. $\widehat{RR}_\tau^*$: recurrence based-spectrogram with fixed embedding.

It can be seen that the bees spent more time hovering than any other behaviour. Also, when the bee hovers, it is easier to record a higher quality signal than when it is moving around, like when leaving the flower or just passing by, due to a moving source (sound field) relative to the sensor location. Furthermore, each time series was a minimum of 0.3 s long for a random selection of the 0.2 s duration of signal as used for the spectrogram. We could not record any clear signal of at least 0.3 s for flower landing in case of *Am. quadrifasciata* and *Ap. mellifera*. The data are of unequal length which makes the training more challenging. Longer durations indicate the possibility of better randomisation of the training data, while smaller durations are not truly representative of the population.

All time series were analysed for the periodogram and the recurrence-based spectrogram technique. Fig. 3 shows sample images of the periodogram and recurrence-based spectrogram for acoustic signal recorded during the landing of *R. sticticum*. In the spectrograms, the frequency (y-axis) was limited to only 2 kHz for high enough resolution. The duration of each spectrogram is 0.2 s and corresponds to x-axis. Fig. 4 presents the validation accuracy of all 13 classes of the behaviour for all three species. The validation accuracy for 70%, 50% and 30% of training data are presented in (a), (b) and (c), respectively. As expected, the overall validation accuracy for all three methods of signal processing decreases with decreasing training data. For example, the accuracy of hovering for all three species decreased as the training data decreased from 70% to 30%. This could be due to the longer time series data for hovering, which resulted in better randomisation of input data for training. However, the classification of some of the behaviours suffers more compared to others relative to a specific method. Also, behaviours like passing by had very low intensity as the bees were away from the microphone, which affected our analysis. Furthermore, validation accuracy of *R. sticticum* is less sensitive to percentage of training data compared to other two species. As the data was recorded outdoors, the environmental noise, like birds chirping, might have affected our analysis. Nonetheless, with 70% training data, neural networks with all three methods show good validation accuracy to identify both species and behaviour. Hence, this framework can be used to classify the acoustic signals of pollinators based on their vibro-acoustic behaviour around the plant.

4. Conclusion

In this study, we presented a framework to investigate the pollinators' behaviour from the field recordings. We classified pollinator behaviour based on the vibro-acoustics around the plant. Our result shows that the behaviours can be successfully identified from the time series analysis of acoustics signal and use of machine learning, which is difficult to identify for a human using traditional methods such as spectrograms or periodograms [15]. Furthermore, the success of the neural network classifier suggests that the vibro-acoustic behaviours of the pollinators are different and it requires in-depth analysis to understand the information transfer mechanism and responses between plants and pollinators. Nonetheless, this study can be extended to build a database of the pollinator signals and behaviour around flowering plants, which will help us to understand the role of vibro-acoustic communication during pollination.

5. Acknowledgments

The authors acknowledge the support of the Human Frontier Science Program (HFSP) grant RGP0003/2022 (Good vibes: how do plants recognise and respond to pollinator vibroacoustic signals?).

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