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3 authors:


Cassandra Uthoff
Helmholtz-Zentrum für Umweltforschung


Masun Nabhan Homsi
Simon Bolívar University


Martin Von Bergen
Helmholtz-Zentrum für Umweltforschung

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Review

Acoustic and vibration monitoring of honeybee colonies for beekeeping-relevant aspects of presence of queen bee and swarming

Cassandra Uthoff[a,1,*], Masun Nabhan Homsi[a,1], Martin von Bergen[a,b,c]

[a] Department of Molecular Systems Biology, Helmholtz Centre for Environmental Research (UFZ), Leipzig, Germany
[b] Institute of Biochemistry, Leipzig University, Leipzig, Germany
[c] German Centre for Integrative Biodiversity Research (iDiv) Halle-Jena-Leipzig, Puschstraße, 4, 04103 Leipzig, Germany

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ABSTRACT

Honeybees are social insects that use a range of signals and cues to communicate with one another. While many of these communications have been identified and studied, the use of acoustic and vibration recordings to automatically monitor colony behaviour and health is yet an upcoming field of research. Two indicators that are important for beekeepers to assess colony state are queen presence and swarming preparation, as their absence and presence, respectively, can lead to colony collapse and honey harvest loss. Microphones and accelerometers have been used to record hives that are showing those indicators and resulting data was used to analyse and classify different colony states. Although some studies have been quite successful in using data resulting from such recordings to detect queen presence and swarming, there are also many challenges and limitations; small sample sizes, the need for a standardised feature engineering approach and more robust models in terms of generalisability being just some of them. This review aims to give an overview of studies using acoustic and vibration recordings to determine queen presence and indicators of swarming, by presenting common methods and analyses and discussing challenges, as well as their limitations and future areas of improvement, to increase their use in precision beekeeping.

1. Introduction

Honeybees colonies form a complex system and are known to have a large range of signals and cues for communication amongst single individuals and between single individuals and the whole hive (Anderson and Ratnieks, 1999). Whereas cues are unintentionally left by the bees, signals are an active way of information transfer (Bradbury and Vehrencamp, 1998). Such signals include the widely known waggle dance in which foragers communicate the direction and distance of a profitable food source (Frisch, 1946), the tremble dance which aims to recruits more nectar-storing workers (Seeley, 1992) and many others. As colonies are self-organised in a bottom-up matter, local and global communication is crucial to ensure high efficiency of all relevant tasks.

Signals can be of different nature in honeybee colonies. Olfactory signals, such as the queen pheromone which indicates queen presence to other hive members, are usually slowly released and are often present prolonged amounts of time before they are either renewed or disappear (Free, 1987). Physical signals such as the stop signal involve bodily contact between individuals (Lau and Nieh, 2010) and are unsuitable for spreading wide-range messages. Vibroacoustic signals, on the other hand, are more commonly used for direct and 'urgent' signals about the present state of individuals or the colony and are often used in conjunction with physical contact (Eskov, 2013). They can be caused by honeybees contracting their thoracic wing muscles and pressing their vibrating bodies against the wax or wooden parts of the hive or another bee (Kirchner, 1993; Pastor and Seeley, 2005). This can cause substrate-borne vibrations and result in acoustic signals. An example is the commonly used 'whooping' signal, previously known as 'begging' or 'stop' signal. It has a fundamental frequency of about 355 Hz, lasts for 60 ms (Ramsey et al., 2017) and is transmitted on the comb as vibrations caused by the contraction of the flight muscles (Michelsen, Kirchner, & Lindauer, 1986). Moreover, bees can also generate airborne sounds with their wings which are commonly used as signals during the waggle dance (Michelsen et al., 1987) and round dance (Kirchner et al., 1988). There is no information in the literature about the resonant frequencies of the respective hive surfaces, however, bees show great sensitivity to

* Corresponding author.
E-mail address: cassandra.uthoff@ufz.de (C. Uthoff).
[1] equally shared authorship.

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frequencies of 280 to 350 Hz (Michelsen et al., 1987; Tsujiuchi et al., 2007), suggesting that this is the resonant frequency of the antennal flagellum and thus a main frequency used in the conduction of the above-mentioned signals.

While signals are used by the bees to transfer information between each other, they can also be used for obtaining information about the state of the respective hives and the behaviours of its inhabitants for science and beekeeping. Acoustic and vibration signals have been a main topic in research as airborne sounds and vibrational emissions can be recorded with microphones and accelerometers, respectively. While some studies have also measured other parameters such as humidity and temperature (Meitalovs et al., 2009; Stalidzans and Berzonis, 2013; Zacepins et al., 2016), acoustic and vibration signals are arguably more indicative of honeybee behaviour and the overall health of a colony as they are an intentional way of communication (Free, 1987). Currently, Machine Learning (ML) techniques are being broadly employed to automatically extract valuable patterns and related characteristics from these signals. (Qandour et al., 2014) were able to use electret microphone recordings from one infected and five healthy hives along with ML algorithms to differentiate between healthy and varroa-infected hives. Although these results have not yet been replicated and will need to be repeated with a much larger sample size to validate their findings, they show that characterising individual acoustic signals and the sound profile of a whole colony can potentially not only be crucial in our understanding of honeybee communication but can lead to great advances in precision beekeeping.

There are two aspects in the lifecycle of a honeybee colony which are partially overlapping; the presence of the queen bee and swarming, and both are associated with acoustic and vibration signals (Kirchner, 1993; Ramsey et al., 2020). The queen bee plays a crucial role in colony reproduction and survival (see 3.1). She is the only individual to produce female offspring (Beetsma, 1979) and to encourage colony reproduction, she leaves the hive with about half of the present workers to give way for a new queen to be reared (Seeley, 2010). Thus, queen presence is of great interest to the beekeeper and so is the colony's preparation for swarming (see 4.2). This review article focuses on the acoustic and vibration signals used in queen presence classification and swarming prediction and aims to give an up-to-date overview of the sound analysis methodologies, their findings, problems and current knowledge gaps in the field.

2. Bee Acoustic and Vibration Signal Processing and Machine Learning

Automatic beehive monitoring systems are an emerging tool for beekeepers to determine certain problems, including but not limited to queenless states and swarming preparation in colonies. Recently, several methods of bee acoustic and vibration signal collection (Table 1) and analysis of resulting data (Table 2) have been shown to be effective (for abbreviations of methodologies and analyses, see Table 3). Traditional methods of acoustic and vibration signal classification include pre-processing, dimensionality reduction, feature extraction and selection steps. Finally, an optimal set of features are introduced to ML for classification and evaluation (Kubat, 2021)(Fig. 1).

Table 1
Summary of the methods used to record acoustic signals within the beehives. Apart from the sensor type, studies also greatly differed in the sensor placement, total duration of the recorded data and the sampling frequency used. Studies are listed in the order that they appear in in 3.3/4 ad 4.4.

Author	Number of hives recorded	Sensor type	Sensor location	Time period of recordings (not always continuously)	Number of Recordings	Sampling frequency (kHz)
Queen presence						
Michelsen et al. (1986)	3	Microphone and Laser Vibrometer	Middle of brood frame (comb)	–	6	–
(Howard et al., 2013)	4	Microphones	–	6 days	480	44.1
(Ruvinga et al., 2021)	4	Microphones	–	6 days	480	44.1
(Robles-Guerrero et al., 2017)	2	Omnidirectional Electret Microphones	Middle of brood frame (comb)	45 days	186	4
(Robles-Guerrero et al., 2019)	5	Omnidirectional Electret Microphones	Middle of brood frame (comb)	2 months	720	4
Cejrowski et al. (2018)	1	Electret microphones with band-pass filters for 20 – 2000 Hz range	Middle of brood frame (comb)	6 months (1 s recording every 15 min)	347 (for testing dataset only)	–
Nolasco et al. (2019)	2	Micro-Electro-Mechanical System (MEMS) Microphones	–	96 h	576	32
Peng et al. (2020) Peng (*unpublished*)	–	–	–	4000 s	2000	16
Swarming						
(Zlatkova et al., 2020)	6	Omnidirectional microphones	Middle of brood frame (comb)	3 h per day for 1 month	–	22.05
(Hord and Shook, 2013)	4	Sterling Audio ST31 Microphones	Entrance to hive (wood)	13 h	8	–
(Ferrari et al., 2008)	3	Microphones	On top of brood frame (wood)	270 h	3	2
(Eskov and Toboev, 2011)	12	Type 4182 Electrostatic Probe Microphone	–	3 h per day in spring and summer	–	44.1
(Cecchi et al., 2019)	2	MEMS Microphones	–	2 swarming events	–	32
(Bencsik et al., 2011)	2	Accelerometers	Inside of hive wall (wood)	8 months / 13 months	20 / 2	8
(Ramsey et al., 2020)	25	Accelerometers and Microphones	Middle of brood frame (comb) – perpendicular to plane of the comb	2 consecutive seasons (only data from between 12 pm and 6am was used)	–	22

Table 2
Summary of the data analyses methods used in the discussed studies. Although the overall approach to data analysis is similar and involves steps in denoising, dimensionality reduction and some form of machine learning, studies differ in the details of analyses used. This leads to different results which are difficult to compare to each other due to a lack of commonality between the methodologies. Studies are listed in the order that they appear in in 3.3/4 and 4.4.

Author	Denoising Method	Dimensionality reduction algorithm (s) Feature Extraction	Feature Selection	ML/ Statistical algorithm(s)	Algorithm Type	Evaluation metric	Best Result (%)
Queen presence							
Michelsen et al. (1986)	–	• Temporal Structure Amplitude Spectra	–	Temporal Structure Amplitude Spectra	Detection through visual inspection	–	–
(Howard et al., 2013)	–	• S-transform PSD FFT	–	SOM U-matrix	Clustering	SOM Quantization Error	~40 for QR and ~ 35 for QL
(Ruvinga et al., 2021)	–	• MFCCs Log Energy	–	LSTM	Classification	Accuracy	92
(Robles-Guerrero et al., 2017)	–	• MFCC	Random Forest	Logistic Regression	Classification	ROC	100
(Robles-Guerrero et al., 2019)	–	• MFCC	Penalized Lasso	Logistic Regression	Classification	AUC	~100
Cejrowski et al. (2018)	–	• LPC *t*-SNE	–	SVM	Classification	Error	2.17 old queen 9.28 new queen
Nolasco et al. (2019)	–	• MFCCs HHT Algorithm	– -	SVM	Classification	AUC	~ 94 for the hive-independent scheme
		• MFCCs		CNN			~100 for the random split scheme
Peng et al. (2020) Peng (*unpublished*)	FIR Wiener filter	• Improved MFCCs	– -	MLP	Classification	Accuracy AUC	97.33 98
Swarming							
(Zlatkova et al., 2020)	–	PSD (time–amplitude)	–	PSD	Detection through visual inspection	–	–
(Hord and Shook, 2013)	–	Spectrograms	–	Frequency Analysis	Detection through visual inspection	–	–
(Ferrari et al., 2008)	Butterworth Filter	Time- and Frequency Domain Spectrograms PSD	–	Spectrograms PSD	Detection through visual inspection	–	–
(Eskov and Toboev, 2011)	–	SRARF	–	Generalised Mean Function (GMF)	Detection through visual inspection	–	–
(Cecchi et al., 2019)	–	Spectrogram MFCCs HHT WT DWT	–	Spectrogram MFCCs HHT WT DWT	Detection through visual inspection	–	–
(Bencsik et al., 2011)	Averaged Short Frequency Spectra	Instantaneous Spectra Eigenspectra from PCA	–	PCA components Cross-Correlation Function	Detection through visual inspection	PrincipalComponent (PC) Score	–
(Ramsey et al., 2020)	–	PCA/DFA FFT	–	Instantaneous Spectra Spectral Evolutions	Prediction through visual inspection	Accuracy	90 (for both)
						Error	6.3 (Instantaneous Spectra)
						Error	1.91 (Spectral Evolution)

Acquired signals can be easily contaminated by undesired noise that can hinder or affect analysis of the data. This noise may arise from natural environmental noises (rain, wind, etc.) and/or the measurement instruments. Noise reduction is thus an important pre-processing step and can be carried out in two different ways. Firstly, it can be done by employing sensors or microphones which are equipped with electronic filters to cut out frequencies below a certain point. However, filtering out low frequencies can also cause a loss of potentially important signals which occur at the same frequencies as the noise (see 4.4 for an example). Thus, one needs to be selective as to which frequencies to filter and whether other methods of noise reduction may be more suitable. For example, advanced digital filtering methods in the time domain can be used which are adaptively applied to the signal (e.g. Wiener filter) and allow modification of the local signal variance. Peng et al. (2020) and Peng, (unpublished) argued that Finite Impulse Response filter (FIR) along with Wiener filter is a suitable algorithm to obtain cleaned signals which are close to the original ones generated by bees.

Dimensionality reduction is the second main part of data analysis and is all about transforming data into a low-dimensional space in which data preserves its structure and relevant information, while reducing the amount of information necessary to represent. It includes two steps: feature extraction and feature selection (Kubat, 2021).

Feature extraction determines the most important data components that are useful for subsequent processing and analysis. Numerous algorithms can be used for feature extraction and analysis of bees' acoustic

Table 3
List of all abbreviations regarding methodologies and analyses used in the review article. Presented in alphabetical order.

Abbreviation	Definition
AUC	Area under the Curve
AutoML	Automated Machine Learning
CNN	Convolution Neural Network
DFA	Supervised Discriminant Function Analysis
DL	Deep Learning
DWT	Discrete Wavelet Transform
ECG	Electrocardiogram
EMD	Empirical Mode Decomposition
FFT	Fast Fourier Transforms
FIR	Finite Impulse Response Filter
FP	False Positive
GMF	Generalised Mean Function
HHT	Hilbert-Huang Transform
HSA	Hilbert Spectral Analysis
IMF	Intrinsic Mode Functions
Lasso	Shrinkage and Selection Operator
LPC	Linear Prediction Coefficients
LR	Logistic Regression
LSTM	Long Short-Term Memory Network
MEMS	Micro-Electro-Mechanical systems
MFCC	Mel Frequency Cepstral Coefficients
ML	Machine Learning
MLP	Multilayer Layer Perceptron
NS	Non-swarming
PCA	Principal Component Analysis
PSD	Power Spectral Density
PTS	Preparation to Swarm
RF	Random Forest
ROC	Receiver Operating Characteristic
SNR	Signal to Noise Ratio
SOM	Self-Organising Maps
SRARF	Sequences of Ranked Amplitudes of Relative Fluctuations
SVD	Singular Vector Decomposition
SVM	Support Vector Machines
TN	True Negative
TNR	True Negative Rate
TP	True Positive
TPR	True Positive Rate
t-SNE	*t*-Distributed Stochastic Neighbour Embedding
WT	Wavelet Transform

and vibration signals (Table 2). Some features are identified through human visual inspection, pattern-recognition, and research hypotheses. Others are identified by use of digital signal processing algorithms such as Fast Fourier Transforms (FFT), Discrete Wavelet Transform (DWT), Mel Frequency Cepstral Coefficients (MFCC), Hilbert-Huang transform (HHT), Linear Prediction Coefficients (LPC), Power Spectral Density (PSD), Principal Component Analysis (PCA), and *t*-Distributed Stochastic Neighbour Embedding (*t*-SNE). Out of these, MFCC, HHT, PCA and *t*-SNE are the most common ones; MFCC (Tiwari, 2010) extracts coefficients from the signal during multiple subsequent steps usually involving framing, windowing, FFT, power spectral distribution calculations, taking logarithms of filter bank energy and discrete cosine transformation (Fernandes et al., 2018; Robles-Guerrero et al., 2019; Ruvinga et al., 2021). Nolasco et al. (2019) and (Cecchi et al., 2019) employed HHT due to the fact that honeybee sounds are nonstationary signals composed of a superimposition of tones at various frequencies. HHT consists of two fundamental parts which are the Empirical Mode Decomposition (EMD) and Hilbert spectral analysis (HSA) method. The data signals are first decomposed into a finite and small number of features, which is a collection of intrinsic mode functions (IMF). The HSA is then applied to each IMF and used for the estimation of embedded structures.

PCA and *t*-SNE have been employed as dimension reduction methods as well as tools to interpret the dynamics of complex bees' acoustic and vibration data (Bencsik et al., 2011). PCA captures the maximum amount of variance in the observed data with the objective to identify a new set of features that represents a linear combination of the original ones. Lastly, the basis of *t*-SNE algorithms is to compare the density distribution of multivariate variables with the distribution of their projection on a two or three-dimensional plane. Kullback–Leibler divergence and gradient descent are utilized to calculate the difference between these two distributions and minimise it, respectively.

Shrinkage and selection operator (Lasso) and Random Forest (RF) algorithms are employed to remove redundant or irrelevant features extracted from bees' signals. The main idea of Lasso is to calculate model coefficients that assign every feature a level of relevance by optimizing the cost function. The higher the coefficient of a feature, the higher the value of the cost function. Lasso is mainly a regularisation method that helps to prevent model overfitting (Robles-Guerrero et al., 2019), while RF is based on a decision tree algorithm and selects features with high importance scores by calculating the Gini impurity. The Gini impurity refers to the probability of incorrect classification for each of the features when chosen randomly. This allows optimal node splitting at the root and each node of the decision trees.

Two approaches of ML have been utilised for queen presence classification: supervised learning and unsupervised learning. Supervised learning occurs when the algorithm is trained using data that is well labelled and can be separated in classification or regression. Support Vector Machines (SVMs) (Cejrowski et al., 2018; Nolasco et al., 2019), Logistic Regression (LR) (Robles-Guerrero et al., 2019), Multilayer Layer Perceptron (MLP) (Peng et al., 2020), Convolution Neural Networks (CNNs) (Nolasco et al., 2019) and Long Short-term Memory Network (LSTM) (Ruvinga et al., 2021) represent some examples of supervised learning methods in honeybee acoustic and vibration signal classification.

SVM classifies signals by finding the hyperplane that separates them in, for example, queenless and queenright classes by using what is called the kernel trick, while LR is used to model the probability of a certain queenless or queenright event. MLP is a feedforward neural network with three types of layers: input, hidden and output; and it is trained with the back propagation learning algorithm. CNNs and LSTM are deep learning (DL) neural networks that can learn effective data presentation through mapping inputs to outputs and have the advantage of handling many of these inputs and outputs automatically. CNNs learn appropriate filters that reduce the input signal dimensionality (Nolasco et al., 2019), while LSTMs are useful to extract patterns from the bee acoustic or vibration signal under different scenarios of stationarity and noise (Ruvinga et al., 2021).

On the other hand, unsupervised learning occurs when the algorithm discovers hidden patterns in data without the need for human intervention. Self-Organising Maps (SOMs) are a type of unsupervised artificial neural network employed to cluster high dimensional data by projecting it into a low-dimensional space. SOMs along with U-Matrix have been used as a prominent tool to explore areas of greatest separation between queenright and queenless recordings (Howard et al., 2013).

The performance of ML algorithms for either honeybees swarming detection or queen presence classification by sound signal processing is evaluated by using a set of metrics, comprising accuracy, error, Receiver Operating Characteristic curve (ROC), and Area under the Curve (AUC) (Cejrowski et al., 2018; Peng, unpublished; Robles-Guerrero et al., 2019). Accuracy refers to the percentage of correctly classified signals, while error indicates how often a classifier is wrong. ROC represents the ratio of recall and specificity. Recall is also known as True positive rate (TPR) and it can be defined as the ratio of true positives (TPs) and sum of TPs and false negatives (FN), whereas Specificity or True Negative rate (TNR) can be defined as the ratio of true negatives (TNs) and sum of TNs and false positives (FPs) (Witten et al. 2002).

The visual analysis of sound emitted by honeybees is one of the most used methods for swarming detection, including methods such as Power Spectral Density (PSD) (Ferrari et al., 2008), spectrograms in the frequency domain, sequences of ranked amplitudes of relative fluctuations (SRARF) (Eskov and Toboev, 2011), optimised instantaneous

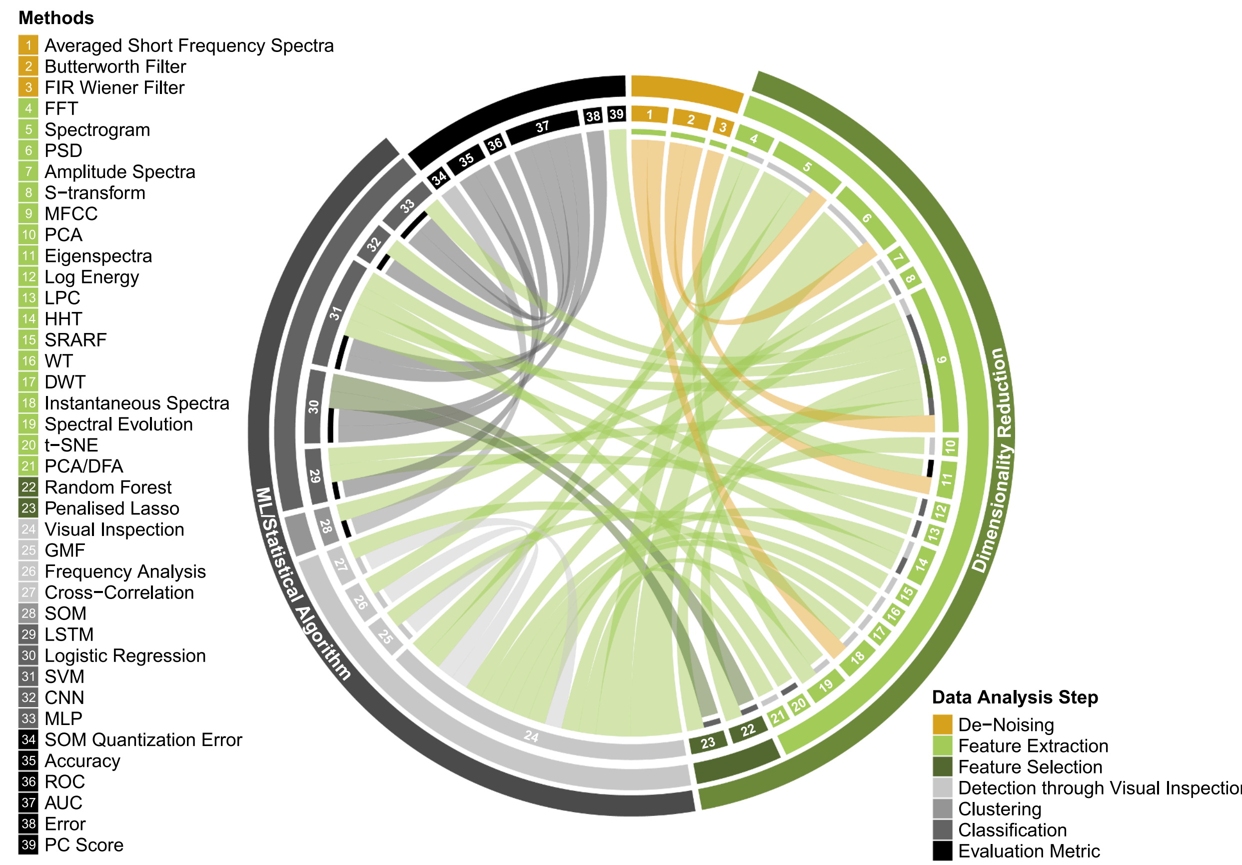

Fig. 1. Chord diagram representing the different ways of data analysis used for honeybee acoustic data in the here discussed studies. While there are only a few ways of de-noising, there is a large number and rate of combination of data dimensionality reduction methods and Machine Learning (ML) and Statistical Algorithm types used. Thus, no 'ideal' method of analyses of such data has yet been discovered, making it hard to compare the results of the studies directly. All abbreviations are explained in subsection 2. *(2 column width)*.

discrimination spectra (Bencsik et al., 2011)and spectral evolution (Ramsey et al., 2020). These methods depict fluctuations in signal patterns related to power, frequency, noise and acceleration, respectively.

3. Acoustic and Vibration Monitoring of Queen Bee Presence

3.1. Importance of queen bee to colony survival

Honeybee queens are the only females that can mate and, thus, produce female offspring due to the haplodiploid reproduction in Hymenoptera (Barron et al., 2001). Female workers make up about 95 % of individuals within a colony, and are responsible for all major tasks within a hive, including foraging, food storage, nursing and cleaning (Seeley and Morse, 1976). Therefore, the lack of a queen results in no more female workers being born and their numbers will diminish rapidly. This can eventually lead to the collapse of the entire colony (Châline et al., 2004). Thus, the queen bee is crucial for colony survival, and upon her death, a new queen will be reared nearly immediately to prevent a decrease in the number of female workers (Butler, 1957). All fertilised eggs can develop into a queen bee if they are reared in queen cells and fed royal jelly continuously throughout their development (Laidlaw and Eckert, 1962) and workers will react quickly to build such cells around existing eggs to ensure a successful rearing of a new queen.

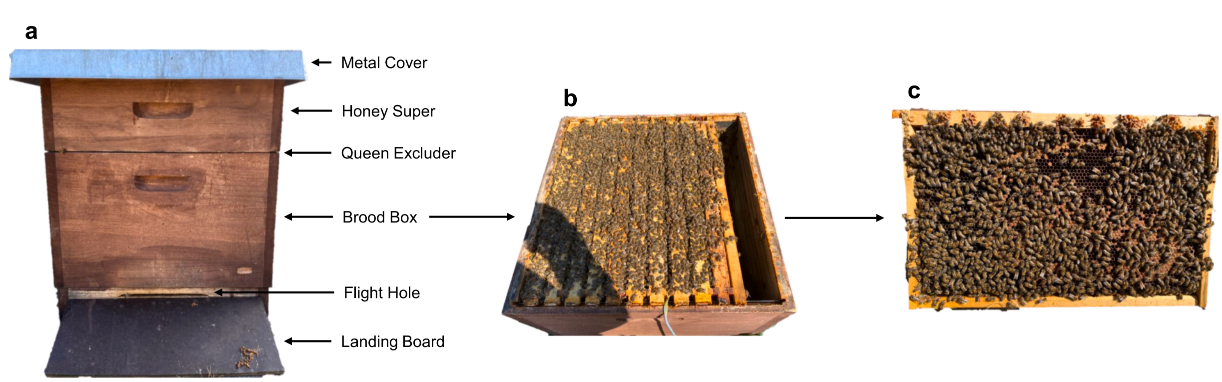

Fig. 2. Structure of a typical bee hive with a brood box and honey super(s). **(a)** Main parts of a hive, **(b)** top view of a US Dadant brood box, filled with ten brood frames and one division board on the far right, (c) single brood frame with workers and brood. Queen can be found on one of the brood frames. *(2 column width)*.

3.2. Current methods of checking for queen bee presence

To check whether a queen bee is present in a colony, the beekeeper has to manually inspect each hive. This involves opening the hive and removing the honey supers (if present) to get access to the brood box (Fig. 2a, b) where the queen can be found. Each frame then has to be taken out individually (Fig. 2c) and the queen has to be spotted by eye. In some cases, the queens may be marked with a coloured dot which makes them more conspicuous and thus easier to find. If they cannot find the queen, they can also examine the state of the brood. If eggs can be seen in the cells, the queen was still present within the last three days and has either been missed by the beekeeper or has died within the last three days. This causes the need for continuous checks in the subsequent days to either find the queen or to determine whether workers are building queen cells to rear a replacement queen. If neither is the case, the beekeeper may have to buy or rear a new virgin queen and manually introduce her to the colony. This is not only stressful and disturbing for the honeybee colonies but also very labour- and time-intensive, especially for commercial beekeepers who can have thousands of beehives each (Cilia, 2019). Thus, a new method to monitor colonies without manually opening the hives would decrease labour hours for beekeepers as well as unnecessary stress for the honeybees.

3.3. Acoustic and vibration signals indicative of queen presence/absence

The virgin queen is known for producing the substrate-borne ‘piping’ signal (Wenner, 1962), which is made up of two components: ‘tooting’ and ‘quacking’ (Michelsen, Kirchner, Andersen, et al., 1986). Huber (1792) was the first person to write about the ‘tooting’ sound and many studies have since investigated its use and underlying mechanisms (Grooters, 1987; Schneider et al., 2001; Simpson, 1964; Wenner, 1962; Woods, 1956). The signal is made by newly emerged queens as a sign of her presence and was thought to challenge other queens in the colony (Grooters, 1987). If more than one queen is being reared, individuals that are still in capped queen cells may respond to the tooting with a quacking sound. Upon making this sound, workers can decide to protect the responding queen and feed her through a small slit in the cap or may not react to it and let the emerged queen find and kill the other queen(s) (Simpson and Cherry, 1969). However, more recent research suggests that the piping signal serves as information to the workers about the number of capped and released queens. According to this information they can then coordinate the release of capped queens in order to decreased the rate of competition (Ramsey et al., 2020). Regardless of the signal function, it is still an indicator of virgin queen presence in preparation of a potential afterswarm and its characterisation and resulting recognition by statistical and ML algorithms may give an indication about hive status to the analysts. Both tooting and quacking are made up of a train of pulses but can be differentiated by their temporal structure. Michelsen, Kirchner, Andersen, et al., (1986) studied the acoustic structure of the signals by recording them simultaneously with a microphone and laser doppler vibrometer (LDV). The laser pointed at an area on the surface of the comb that was marked with highly reflective paint. Vibrations cause shifting of the reflective light frequencies and the resulting output voltage can be proportionally correlated to the vibration velocity. The velocities were then put through a bandpass filter and oscilloscope and saved on a PC desk drive before being visualised by the computer of a plotter to investigate the structural characteristics of queen signals. The resulting graphs showed that tooting has a long first syllable followed by subsequent short ones whereas quacking usually has a short first syllable followed by longer ones. The same pattern for tooting was found by (Wenner, 1964) who was the first to use spectral analyses on acoustic signals made by honeybees and suggested, that the signal has a first long pulse (or syllable) about one second in length followed by multiple shorter ones at a frequency of about 500 Hz. However, while Michelsen, Kirchner, Andersen, et al., (1986) suggest that the fundamental frequency is the main carrier of the signal as it has a higher amplitude than its harmonics when vibration velocity was recorded, other studies have regarded the second harmonic as the main carrier (Wenner, 1962). This difference may be the result of the realisation by Michelsen, Kirchner, Andersen, et al., (1986) that higher vibrations attenuate more rapidly over distance in substrates than lower ones, meaning that the differences between fundamental frequencies and its higher harmonics become more prominent with distance. Regardless of this discrepancy, the studies show that the two signals can be recorded and differentiated and can indicate the presence of a newly emerged queen and potentially other queens in capped cells to the experimenter.

However, these signals do not occur later throughout the queen bee’s life (apart from in preparation for swarming, see 4.3) and are thus not a good indicator of queen presence for the beekeeper in the long-term. Instead, (Woods, 1959) investigated the sound profile of a whole colony as an indicator of queen status. By using a standard wave analyser, they plotted curves showing frequency ranges for common behaviours such as fanning, flying and humming. After the queen was removed from the hive, new recordings were made which resulted in the definition of the ‘warble’ signal; a sound with a frequency of 225–285 Hz and a maximum amplitude of 3 dB. It was found to develop within the first five hours after queen bee removal, before it turns into a roaring sound at 180 Hz and roughly 20 dB accompanied by vicious behaviours by female workers. Thus, these frequencies and their corresponding amplitudes could be used to detect queen absence by acoustic and vibration monitoring without the need to open brood boxes to manually search for the queen bee. However, the results of this study should be interpreted with caution as the data comes from only a small sample size and the outcomes have not been replicated by a subsequent investigation. Moreover, next to the use of the standard wave-analyser the author used their own hearing ability to match sounds to musical tones. This is a highly subjective method of recording data and the similar results between the two methods suggest that there may have been observer bias. Hence, one cannot reliably generalise the results to other bee hives and behaviour of the individuals within.

Furthermore, (Eren et al., 1997) conducted a study to find queen-specific frequencies which could elicit a response from workers and queens if played back to them. They used an IBM compatible computer with a 16-bit sound card to record and playback sounds from individual colonies. Moreover, in order to imitate recorded sounds for playback the authors created a C++-based software which allows manipulation of frequencies, harmonics and amplitudes. They recorded the sounds of 150 queen bees as well as many worker bees and showed that although they share a large range of frequencies, queens show a peak frequency between 400 and 550 Hz and can also generate significantly higher frequencies than worker bees. Both queen bees and workers responded to the queen signal if played back to them, indicating that the signal is in fact a queen-specific sound that could be used for her detection. However, that was not done as part of the study but their results made way for future research to use the acoustic and vibration profile of the signals to develop a queen presence detector.

3.4. Acoustic and vibration monitoring to detect queen presence/absence

Although (Woods, 1959) developed the ‘Apidictor’ to monitor and define acoustic signals within a colony (Woods, 1957), this method still required the beekeeper to check on the Apidictor apparatus manually and interpret its interface. As a result, more recent studies have focused on finding patterns indicative of queen presence as well as developing algorithms to automatically detect these signals in long-term recorded data.

Howard et al., (2013) installed microphones into four honeybee hives, two of which had their queen manually removed by a beekeeper. All hives were recorded for six days after queen removal and one minute per recorded hour for each colony was used as training data. Audio data underwent an S-transform where the signal is decomposed into a complex matrix so each column shows the local spectrum to each corresponding time point (Stockwell, 2007). These matrices were decreased in their dimensionality using SOM. The SOM was then trained with a two-layered neural network which clusters data points based on their weights derived from the data dimensionality reduction. Thus, it can be expected that data points from the two treatments aggregate separately as they differ in their frequency profiles. The results showed that spectrograms derived from the S-transform showed more detailed differences between treatments than the ones made from an FFT, implying that they are more appropriate for visualising sound profiles of honeybee hives. However, the authors did not find that SOMs are suitable for classifying queenless and queenright colonies as there was no clear separation between them. This may be due to a too small number of features extracted from the signal or the use of an unsuitable algorithm for this type of analysis.

Indeed, (Ruvinga et al., 2021) reanalysed the same data but instead extracted 13 MFCCs and the log energy of each sample. The features were then fed into an LSTM. By comparing the features of each group with an ANOVA, they found significant differences between the treatment for all features. Moreover, the LSTM network was able to classify queenright and queenless colonies and showed an accuracy of 92 % when used on the test data. Therefore, choosing the right type of features together with an appropriate classification method is crucial to ensure high accuracy in identifying the different hive states.

Although many classification methods have been attempted, a lack of flexibility in the models is present in almost all studies which may decrease their accuracy when needed to classify hives that were not used to train the algorithms. For example, (Robles-Guerrero et al., 2017) and (2019) also used MFCCs but different types of classification analyses including Singular Vector Decomposition (SVD). The earlier study recorded two hives, one of which was large and healthy whereas the other was a smaller colony that had lost its queen. Recordings were made for 3 min every 15 min for 24 h and repeated on 45 days between April and May with omnidirectional electret microphones placed in the comb in the middle of the brood frame. From this data they computed MFCCs for each of their 12 chosen statistical descriptors (e.g. mean, variance, etc.). With the SVD they selected the most relevant features for classification, as crucial ones form separate clusters depending on queen status. Based on these clusters, they decided that mean was the most important feature and attempted categorisation of sound samples with only two out of 12 MFCCs calculated for the mean. This was done by training a logistic regression model with 70 % of the data and testing it with the remaining 30 %. They achieved an accuracy of 100 %. However, although the model provides perfect information, the same methodology was not tried on data from other hives that were not included in the training set, decreasing the generalisation potential of the analyses used.

In the latter study (Robles-Guerrero et al., 2019) five colonies were acoustically monitored using the same recording equipment as before. One of the colonies had lost its queen and the other four were queenright. Moreover, during a second experiment, two queens were removed manually from queenright colonies and further monitored to examine changes in the sound profile. Each hive was equipped with an electret omnidirectional microphone which recorded 30 s of data every 10 min; continuously throughout the day. This was done for 38 days before MFCCs were computed for 144 recordings from each hive. The most important features were then selected using Lasso regression, an SVD was done to investigate classification potential of the hive treatments before 70 % of the data was trained with a logistic regression. The AUC for the test data was over 95 % and as an additional step, the training and validation were repeated with data from two separate days in each set, which resulted in an even higher classification accuracy. Nonetheless, this study also lacks replicate examples on recordings from other honeybee hives or to the same colonies at a different time of the year. Thus, the model may have been subject to overfitting and would potentially have low accuracy if used on signals recorded from other hives.

This issue of overfitting has been discussed in a study done by Cejrowski et al. (2018). Electret microphones with an increased range of 20 – 2000 Hz (due to a specific band pass filter) were integrated into the comb of a frame which was then inserted into the brood box of one colony. It recorded one second of audio, the temperature and humidity measurements every 15 min. The hive started off with a healthy colony, from which the queen was removed after initial recordings, and the colony was left queenless for some time before a new queen was introduced to the hive. Resulting data was transformed into Linear Predictive Coding coefficients which were fed into a *t*-SNE algorithm to determine classification potential. The algorithm showed great differentiation between queen states so an SVM algorithm was employed to classify queenright from queenless recordings. Again, the method showed great accuracy in classifying queen status, but only when signals from the first, original queen were compared to the queenless condition. The accuracy, when done with the newly introduced queen, dropped to about 25 % only, and thus shows that different queens cause different sound profiles within colonies and that training classification algorithms to a small number of hives (in this case just one) significantly decreases the application potential of such models to apiaries with multiple hives. Hence, one may be able to develop a more robust model where the focus lies on overall changes within the signal rather than extracting a set of specific features from individual colonies to see how only these change in response to queen removal.

One study that has attempted to use a more adaptable classification method was done by Nolasco et al. (2019). Data was taken from hives recorded as part of the NU-Hive project (Cecchi et al., 2018). They installed Micro-Electro-Mechanical System (MEMS) microphones and extracted MFCCs from the resulting data. Moreover, they also extracted an additional feature by using the Hilbert-Huang transform (HHT) as it does well in dealing with nonstationary signals. For classification, a CNN was designed and to improve the generalisation of the model, the signals were augmented to create three versions of each sample that had a pitch shift between 1 and −1 semitone. Moreover, apart from training one model with a random 95 % / 5 % training and testing split, they also conducted a hive-independent classification where data for the training set came from one hive whereas the data for the testing set came from a different colony. As expected, the model trained with signals from a range of hives had higher accuracy than the hive-independent model but, nevertheless, the best hive-independent CNN classified 80 % of samples correctly. This once again showed that MFCCs are useful features for queen presence detection but also that further research into more flexible algorithms and networks is crucial to successfully use these methods in real-life scenarios.

Lastly, in a more recent study Peng et al. (2020) additionally investigated the effects of signal to noise ratio (SNR) on the rate of successful classification. The authors tried to improve data analysis in a way that allows the model to deal with data recorded from hives in their normal environments where the SNR can be greatly disrupted by environmental sounds. To do so, they put recorded signals through a signal enhancement algorithm in order to maximise the SNR. Moreover, they extracted so-called improved MFCCs, which are signal-filtered after initial extraction, allowing consistent classification accuracy even when the noise proportion increases. Similarly to (Howard et al., 2013), a layered neural network was used to classify the signals, although in this case it was an artificial neuron network using three, and not two, layers. Results showed a significant decrease in accuracy of classification as the signal became noisier. Using signal enhancement greatly reduced noise and the optimised MLP classification model yielded an accuracy of 97.33 %. Hence, SNR seems to play a crucial role in the ability of algorithms and neural networks to correctly classify signals and methods to enhance the signals relative to the background noise should be considered in all sound analyses in order to maximise classification accuracy.

3.5. Knowledge gaps and further research

Queen presence detection by analysis of acoustic and vibration data has been attempted by a range of studies and has used a number of different approaches (Table 2). However, all studies follow a general method consisting of the use of sensors in beehives, the analysis of data and the use of an analytical model to detect queen presence (Fig. 3). There is, however, an overall issue of robustness and generalisation potential of the algorithms and neural networks that are used in the process, and many are prone to overfitting (Fig. 3) and can, hence, not be effectively used for other hives and apiaries. Thus, one main focus of future work should be the search for more suitable features apart from MFCCs and the use of data from a larger number of hives to determine a more general trend in the changes of the sound profiles caused by queen absence. Furthermore, decreasing the noisiness of signals is crucial to filter out only the relevant bee-related sounds from the overall signal. As there is not yet an ideal algorithm for the denoising of the data, this could be a focus of studies looking into bioacoustics of not only bees but also other animals. Moreover, algorithms should be tested on recordings from hives that were not included in the training dataset as done by Nolasco et al. (2019) to develop an optimised version that can accurately classify states of independent hives. Additionally, emphasis should also be put on real-time experiments. Currently all studies use data that had previously been recorded to train and test their respective classification methods but none have tried to use those models on real-time data (Fig. 3). In order to successfully detect queen absence, the model needs to be able to continuously analyse incoming data and update its classification outcome.

4. Acoustic and Vibration Monitoring to Predict Swarming

4.1. Relevance of swarming

Swarming is part of the reproduction of colonies in honeybees (Winston, 1980) and involves a series of complex social behaviours during the preparation, swarming and scouting phases (Camazine et al., 1999; Grozinger et al., 2014; Seeley and Tautz, 2001). During the so-called primary swarm, the old queen leaves with about half of the workers in the colony and a newly reared queen will take over as the primary reproductive female in the hive (Seeley, 2010). However, sometimes the primary swarm is followed by one or more afterswarms, in which newly reared queens leave with a part of the present workers to form a new colony someplace else (Winston, 1980). In preparation for swarming, the number of female workers within the nest increases up to a point where there is no longer sufficient space for all and thus a new queen will be reared and left with the remaining workers (Rangel and Seeley, 2012). Overall, swarming is an important way for honeybees to spread to new locations and increase in numbers due to dividing into two or more separate colonies.

4.2. Current methods of checking for swarming

Beekeepers usually want to prevent swarming, not only as it causes a reduction of honey production later in the season (Zacepins et al., 2021) but also because the swarmed colony only has a survival rate of about 50 % (Winston, 1991). Swarming usually occurs in spring and early summer so that the new colonies have the necessary time to build their nest and secure enough honey stores to survive the winter months (Ferrari et al., 2008). Hence, during this time a large amount of time is spent by the beekeeper to check each hive for signs of swarming preparation. One main indicator for the inspector is the presence of queen cells which are primarily found on the periphery of brood frames in larger cells than the ones for worker rearing (Buttstedt et al., 2018). However, the beekeeper should also check for the number of brood frame gaps (as seen in Fig. 2b) that are filled with workers to get an idea as to whether their numbers are increasing to a point where the hive will be too small and they will start preparing for swarming. This, just as checking for queen presence, is a time- and labour-intensive task which requires all brood frames to be taken out and if a queen cell is found, the beekeeper will usually destroy it to prevent swarming. Moreover, another way of preventing swarming is to clip the wings of the queen to prevent her from leaving the nest and thus causes already swarmed

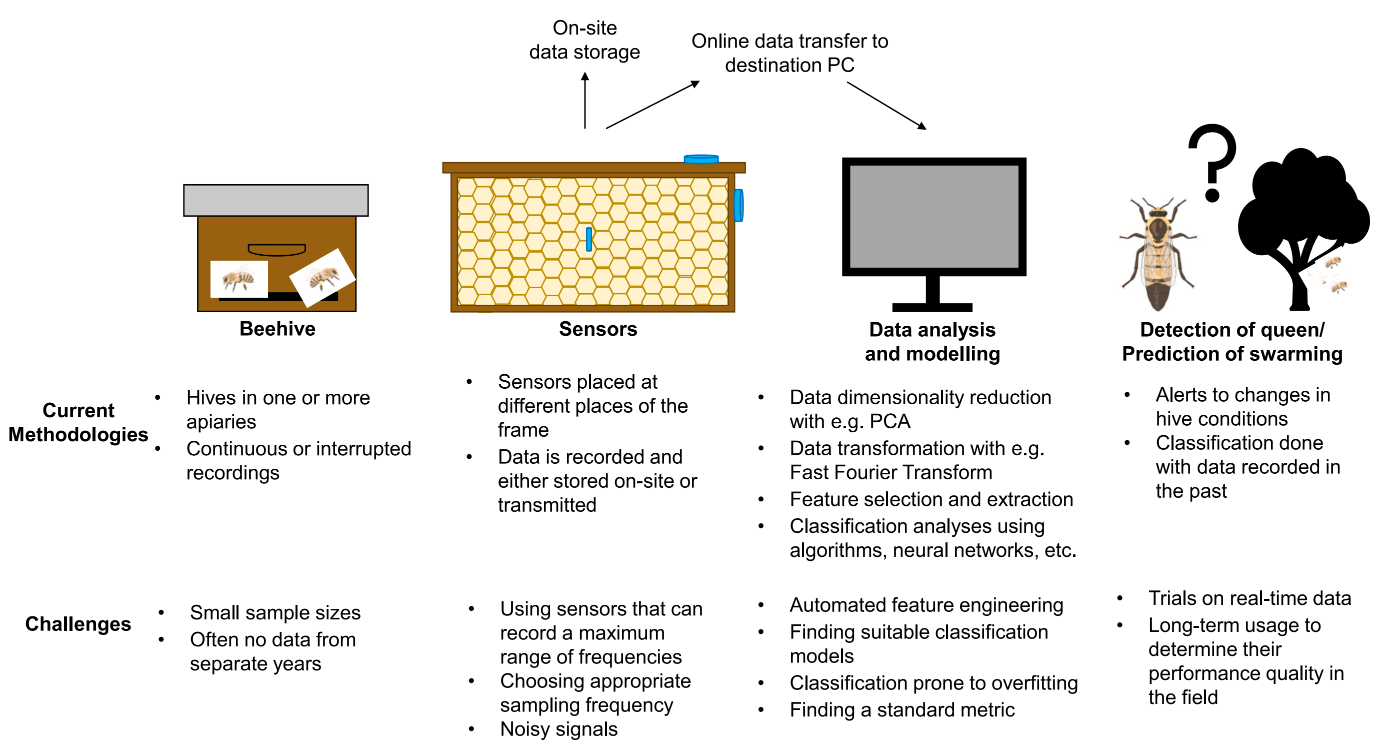

Fig. 3. Overview of current methodologies and challenges in studies investigating honey bee audio signals to determine queen status and predict swarming. *(2 column width)*.

workers to return to the colony (DeBerry et al., 2012). However, in some cases the colony may still swarm by rearing a virgin queen which will then swarm with half of the workers, leaving the original queen behind as the reproducing female (Ramsey et al., 2020). Thus, continuous checks are yet the most reliable way to prevent swarming but it is time consuming for the beekeeper and will cause reoccurring stressful situations for the colony (Zacepins et al., 2021). Hence, finding a way to remotely monitor beehives and detect signs that are indicative of preparation for swarming would be a major advance in precision beekeeping and can potentially be integrated into smart automated beehives like BEEWISE (2019).

4.3. Acoustic and vibration signals indicative of swarming

Swarming requires a lot of preparation and the signals used can be olfactory as well as acoustic or vibrational (Rangel and Seeley, 2008; Schlegel et al., 2012). (Winston, 1991) observed that just imminent to swarming the workers seem to get excited and are seen running forth and back while also trying to motivate surrounding workers. The preparation for an afterswarm is greatly related to the signals of queen rearing and presence discussed in 2.3. The newly emerged queen that will take over after the swarm has left will signal her presence by tooting, to which mature, but non-emerged queens will respond by quacking (Michelsen, Kirchner, Andersen, et al., 1986). If an afterswarm does occur, the workers will protect the queens in capped cells so that they can then emerge to take over the reproductive role in the colony (Simpson and Cherry, 1969). However, if the emerging queen does not leave the hive with some of the workers, the non-emerged queens will be left to compete with the present queen for survival. Thus, tooting and quacking can indicate to the analysts that an afterswarm may happen but cannot be used to predict primary swarms as the new queen only emerges after the swarm has already left. Until now, no direct signal has been found that precedes swarming and is hence the focus of studies using acoustic and vibration monitoring to detect and predict swarming events.

4.4. Acoustic and vibration monitoring experiments

In most acoustic and vibration monitoring studies that analysed swarming signals the focus lied on identifying patterns that arise during or in preparation to swarming. (Zlatkova et al., 2020), for example, produced normalised, average power spectral density plots from data from six separate colonies which were recorded between 3 pm and 6 pm for the duration of one month using microphones positioned in the middle of the brood frame. Samples from before and after swarming were compared on periodograms and it was shown that prior to swarming the colonies showed an increase in the power spectral density by about 200 Hz in comparison to afterwards. Furthermore, as previous observations have discovered, they recorded an increase in the general amplitude before swarming and a 50 % reduction following swarm departure. However, signals that showed patterns of disorder caused by, for example, human disturbance were excluded from analyses. It is important to also include such signals, as they can commonly occur in field conditions and can give the analyses more power and generalisability but also allows the determination of differences between patterns of stressful (due to human disturbance) and normal situations.

Hord and Shook, (2013) investigated the signals of two beehives for two days by placing a Sterling Audio ST31microphone in front of the hive entrance hole so that sounds from within the hive and from individual workers entering/leaving the nest could be recorded. The microphone recorded between 11 am and 2 pm on each of these days and spectrograms were made of each ten-minute interval. Data evaluation suggests that frequencies of about 250 Hz were most prominent during the swarming event and that the overall sound intensity increased. Thus, they found similar patterns as (Zlatkova et al., 2020) in terms of the sound intensity rising during swarming, but as results came from only two days of data, one cannot be sure that the arising patterns were due to swarming or some other aspects of behaviours happening during the monitored time. Thus, more long-term recordings in a larger number of hives would be useful in ensuring signal specificity for swarming events as well as differences between individual colonies.

Another study investigating the sound profiles that occur during swarming was conducted by (Ferrari et al., 2008). Three colonies were monitored for eleven days and nine swarming events occurred during this time span. Here, instead of integrating the microphones into the actual brood frame, they were placed on top of the wooden frames and covered by a net to prevent propolisation. As well as an increase in power, just as the other studies had found, the results also showed an increase of frequency during swarming from about 150 Hz to 500 Hz, as well as an increase in overall signal magnitude, the latter of which had been observed as well in previously mentioned studies. Interestingly, the previously mentioned studies did not record such changes in frequency which may be due to recording device sensitivity, the way the data was analysed but also due to the fact that recordings in this study were made over a slightly longer time and more swarming events were included in the dataset. Nevertheless, the study also focuses on patterns that occur imminent to or during swarming and are thus not useful in predicting and preventing the colony separation.

Eskov and Toboev, (2011), on the other hand, attempted to determine signals in the recordings that are indicative of preparation to swarming by manipulating amplitude values before using statistical analyses. Data was recorded with a type 4182 electrostatic probe microphone for three hours per day over the spring and summer time. Selected segments of recordings were numerically integrated in order to visually investigate temporal changes. These segments were later clustered and then distinguished by their SRARF. The correlations of SRARF approached a value of 1 as the swarming date came closer, and was closest to 1 one day before swarming occurred. Thus, a continuous record of this parameter revealed its trends and if the value is approaching 1, an inspection by the beekeeper may be needed to see whether they can find any indicators of swarming preparation. However, follow up studies to validate the parameter value as a predictive signal have not yet been conducted. Moreover, SRARFs should be used with care as they apply mostly to acoustic signals in small hives. Low frequencies attenuate less rapidly than high frequencies in most substrates. Such an effect could reduce the effectiveness of SRARF if it was not applied properly.

Cecchi et al., (2019) investigated the bees' sound emitted during swarming and non-swarming states, but more specifically they focused on which features are the most suitable ones to use in machine learning algorithms. They used spectrogram analysis, MFCCs, HHT, wavelet transform (WT) and DWT as potential methods of classification for swarming behaviour. MEMS microphones were used to monitor the bee hives and data was comprised of two swarming events recorded as part of the Nu-Hive project (Cecchi et al., 2018). Overall, HHT gave a better assessment of the original frequencies than the other methods. Regarding feature extraction, although the first few MFCCs showed great differentiation between swarming and non-swarming states, nearly all of the DWT showed distinction between the two states and was thus claimed to be the best way of extracting features for audio classification of swarming data. Moreover, DWT has a low computational cost which further increases its usability for long-term recordings. Thus, although the study focuses more on a differentiation between classes and the methodologies have not been explored in the context of swarming prediction, the DWT may be a useful feature to predict swarming in future studies.

A study by Bencsik et al., (2011), on the other hand, recorded sounds from two hives from November to June and identified some patterns that happen before rather than during swarming. However, instead of using microphones they used accelerometers installed to the inner side of the hive wall to measure the vibrational emissions caused by the bees' motion. Instantaneous spectra were created, averaged for small segments and later stacked to show data from each day, allowing visualisation of the frequency peaks. Features were extracted and a PCA was conducted to analyse relationships between those features and bee behaviour. The effects of resulting PC scores were interpreted visually and showed that the first four scores contribute largely to explaining changes in the vibrational emissions. More specifically, they observed an exponential-like divergence about five to ten hours prior to the swarming event, followed by a peak amplitude and a polarisation turnaround of some of the scores. Furthermore, one of the scores had negative values throughout the recording but moved into the positive area just eleven days before the swarming event, implying its correlation to preparation to swarming. However, this was only done for the recordings of one single hive and can thus currently not be validated as an actual signal for swarming preparation.

A recent publication by Ramsey et al., (2020) is the first to our knowledge that was able to successfully find a signal indicative of swarming in their data and was able to trigger accurate pre-swarming alarms. They improved the methodologies of previous studies in terms of sample size and recording length and monitored a total of 25 hives over two seasons. Just as in Bencsik et al., (2011), accelerometers were used but were integrated perpendicularly into the middle of comb in one of the brood frames. Moreover, in seven of the colonies, microphones were additionally installed. For data analysis two different methods of manipulating the data were applied, one to create instantaneous spectra and one to generate spectral evolution series. Both were separated into training and testing sets where training data was made up from preparation to swarm (PTS) and non-swarming (NS) segments of the data. The datasets underwent a PCA followed by a supervised discriminant function analysis (DFA) to reduce data dimensionality and separate the data points on a two-dimensional grid. Parametric optimisation was done on different aspects of analysis to get the most suitable parameters of data for signal differentiation. Discriminant spectra showed that the highest variation between the two states occurred at a frequency of 20 Hz for the instantaneous spectra. If only data collected between midnight and 5 am was used, the model was able to predict swarming up to one month before its actual occurrence based on the visual spectra. The resulting alarm was triggered in over 90 % of the swarming occurrences and was never prompted for hives that did not swarm at all. Using spectral evolutions, the algorithm had a lower success rate of about 80 % and also only gave warnings roughly 10 days before the event. Thus, using instantaneous spectra was an overall more effective method of predicting swarming and indeed a pioneering model in accurate predictions for swarming behaviour in honeybees.

4.5. Challenges and future work

The aspect which makes swarming recognition debatably harder that determining queen presence is that it is about the prediction of an event rather than a classification. Determining that swarming is occurring just as the classification alarm is triggered is not helpful for most beekeepers, as their apiaries are often not on their residential properties and there is no direct action they can take when the bees are about to leave the hive. Although most studies found patterns in their data that are indicative of imminent swarming, only a few actually tried to classify swarming behaviour (Table 2) and only (Ramsey et al., 2020) was able to predict swarming several days before its occurrence. Interestingly, a frequency of 20 Hz seemed to be a key determinant of the prediction ability which none of the other studies in the field identified. This may be due to the fact that low-mass accelerometers with low sensitivity to 20 Hz and microphones with a frequency threshold of 50 Hz were used in other experiments that did not identify these to be important frequencies. Hence, further studies may aim to include low-frequency accelerometers as well as a mix of microphones and accelerometers in their setup (Fig. 3). For this, studies should be conducted to determine the best location in the hive (and on the frames) where the transducers should be installed. For using a combined approach with microphones and accelerometers, it should also be tested whether these signals are correlated to one another and thus provide us with redundant information. In those cases, only one of the two transducer types would need to installed without compromising the quality of the data recorded. Furthermore, studies should potentially use data from the night time, as the most significant differences were found by Ramsey et al., (2020) only during that time span. This is in line with (Woods, 1959) who found that the warble indicating queen absence could only be detected at night. Thus, the most indicative sounds of queen presence and swarming may arise during the night and should therefore be a focus of future work.Moreover, larger sample sizes should be used (Fig. 3) in order to increase generalisability of results and to prevent biases in data due to outliers. Data analysis methods are almost never tested on either different hives than the ones used in the study nor on data from the same hives in the following year (without them being part of the testing data for classification algorithms). Adapting methodologies and methods in such ways may enable more successful predictions of swarming events that can be used in different apiaries and potentially different hive types and honeybee subspecies. Last but not least, it would be interesting to see whether there is an acoustic or vibration communication signal which can stop the swarming preparation or the swarming process itself. If such signal existed, it could be used to play back to the hive after an alert of swarming preparation has been sent out as a result of a statistical or machine learning algorithm. This way no further intervention by the beekeeper would be required to prevent the swarming event.

5. Conclusions

Signals caused by airborne or substrate-borne sounds as well as vibrational emissions have been shown to be important methods of communication within honeybee hives and de-coding these messages can give us insight into the state and behaviour of colonies. Many studies have managed to use acoustical and vibration signals to classify queenless states by extracting features and feeding it into a statistical or machine learning algorithm (Fig. 1). However, only Nolasco et al. (2019) used their model in a hive-independent matter to test its accuracy for data that was not included in the training stages. More studies like this are necessary to develop flexible yet robust classification methods for queen presence. Regarding the prediction of swarming, only one study has been successful in accurately predicting swarming events in honeybee hives (Ramsey et al., 2020). While some have provided great foundation work by investigating the acoustic and vibration signals commonly found during and before swarming, others have been able to detect changes in the days leading up to the swarming event (Bencsik et al., 2011). Just as for the studies regarding queen presence, however, most studies lack a large sample size and replicability of their results with different hives or data from the same hive in the following year. Additionally, (Ramsey et al., 2020) found that one of the frequencies that is potentially important for predicting swarming is at about 20 Hz and cannot be recorded by most microphones. Thus, including low-frequency accelerometers into the setup may be a great way of maximising the data quality. Moreover, some studies have found correlations between temperature and swarming and, hence, future research may want to integrate such parameters in addition to acoustic and vibration data to get more detailed information about hive status.

All the surveyed studies present feature engineering approaches depending on the manual process of extracting relevant features from bee acoustic and vibration signals. This process is error-prone, tedious, and time consuming because features are being reinvented from the scratch for each new dataset (Fig. 1). Consequently, applying automated features engineering is a necessity for future beehive monitoring approaches. Automated features engineering has been applied widely in speech recognition and in diagnosing cardiac arrhythmias in electrocardiograms (ECG) recordings by employing DL (Warrick and Homsi, 2017) and/or Automated ML (AutoML) algorithms (Masood, unpublished).

The lack of a common dataset and a standard evaluation metric, either for the classification of queen presence or for the swarm detection and prediction, has prevented different methods and approaches from being compared to one another and to conclude which features and methodology are the best. In addition to that, datasets, code and trained models from most of the surveyed studies are not released publicly, making it difficult to verify and build on previous results. Therefore, the development of a platform to promote a harmonised and standard data collection for the research community, containing big annotated bee acoustic and vibration signals from different countries, hives and subspecies of honeybees along with different recording conditions and quality, will foster research in this area and help in benchmarking the results.

Both accuracy and ROC/AUC (present in eight of the here reviewed studies) can be misleading scoring metrices when data is heavily imbalanced. ROC/AUC is specifically good at ranking predictions, instead of using only the probability the predictive model is giving. On the other hand, the quality performance of the approaches proposed in seven of the here mentioned studies (see Table 2) depend on the interpretation of different visual plots, which can be highly subjective and may give rise to inconsistency in their conclusions.

Overall, future studies may benefit from going beyond manual feature extraction methods, traditional metrics, supervised learning algorithms and visual inspection of results to build more trustable beehive monitoring approaches that provide transparency and interpretation regarding their predictions and decisions.

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Declaration of Competing Interest

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.

Data availability

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