Analyzing the Beehive's Sound to Monitor the Presence of the Queen Bee

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***Abstract*—In this paper, a method for beehive monitoring is proposed that is focused on the spectral analysis of the bees' sound. Towards that direction, a system was implemented that allowed for constant acoustic monitoring and the creation of a database of audio recordings. Also, an experiment was performed to simulate two different states of the beehive's colony. One healthy state with the queen bee present and normal bee activity and one state where the queen bee is removed. The two different states are being analyzed in terms of their spectral content to establish their characteristic frequencies. Also, a set of features are extracted, the Mel Frequency Cepstral Coefficients (MFCC), and their distribution on each mel band is examined for a set of data taken from multiple days on two different beehives. By comparing these distributions, it was possible to make a clear distinction between these two states for both hives and to detect the state of the beehive based on half-hour measurements.**

Keywords—Beehive monitoring, queen bee presence, audio processing, spectral analysis, feature extraction, MFCC

I. Introduction

The bee is considered one of the most important insects for humans and the ecosystem, mainly because they play a key role in plant pollination and due to their honey and its byproducts. They are essential for the preservation and prosperity of the ecosystem as well as for agriculture. In the recent years, an increase in bee mortality has been documented that is linked to the Colony Collapse Syndrome (CCD), associated with a sudden disappearance of the honeybees from their hive [1]. There are multiple factors causing this syndrome with some of the most common being pests and diseases, beekeeping practices and breeding, climatic change, agricultural and the use of pesticides [2]. This decline in bee numbers has serious ecological and economic consequences that can affect the stability of the ecosystem, the maintenance of wild plant diversity, crop production, food security and human welfare [3]. For that matter, the need for intensive monitoring arises to protect the bee population and prevent these negative effects.

A vast variety of methods can be found in literature for monitoring the colony of a beehive. Some approaches include monitoring the weight, the temperature, the humidity and gas concentrations inside the beehive, the sound and vibrations that are produced, as well as the traffic of specific types of bees [4]. The purpose of the monitoring process is to determine eventually if the bee colony is in a healthy state or not. A basic approach to determine the health of a hive is to inspect if the queen bee is present. The absence of the queen bee can be caused by multiple factors and has significant negative effects for the hive. So, an effort has been made by researchers to distinguish and detect these two states.

A common practice with interesting results is the acoustic monitoring of the beehive and the analysis of the bees' sound in the hive. Bees have been observed to produce a variety of different sounds for their communication [5]. Early studies of the phenomenon indicated that the overall sound of a hive is the combination of the sound of each individual bee resulting in a low frequency hamming effect [6]. Most of the spectral content is found in the frequency range of 100 – 1000 Hz, with the most dominant frequencies being documented around 300, 410 and 500 Hz [7].

For the raw acoustic data, a feature extraction process is often followed that is used to generate a set of values either in the time or the frequency domain that contain information about the audio signals. A commonly applied technique in many speech-recognition and music information retrieval applications is the Mel-Frequency transformation and the extraction of the Mel Frequency Cepstral Coefficients (MFCC) [8]. This process involves transforming the raw audio signal in such a way that it mimics the psychoacoustic effect and the perception of loudness of the human ear. This can be applied in beehive monitoring applications since in many cases the different bee sounds are easily detectable by an experienced human ear. From these extracted features, different machine learning or deep learning models can be trained on the audio data, in order to perform the classification process. Some of the most commonly applied approaches include the Support Vector Machines (SVM), the Logistic Regression, random forests, and k-nearest neighbors, [9], as well as Convolutional Neural Networks implementations [10], and the Hidden Markov Models (HMM) [11].

In this work, the focus was given, initially, on performing a spectral analysis of a set of acoustic measurement data, in an effort to document the spectral signature between two discrete states of beehive, a healthy state with the queen bee present and one with the queen absent. Apart from that, the MFCC features were extracted and were evaluated on their ability to distinguish between these two states by examining the distribution of their values. The results of this study can be utilized and provide a background in order to implement a classification algorithm, either machine learning or conventional, to reliably distinguish between these states.

II. Experimental setup

For the experimental process, the agricultural facilities of the Aristotle University of Thessaloniki in Greece were chosen, where there are multiple beehives that are being studied. For this study's needs, two hives were selected for an experimental procedure that took place over a period of five months during the productive period of the bees. During the first months, the hives were left undisturbed until a certain point when the queen bee was removed by both hives and was returned after six days. The hives under inspection, were equipped with an acquisition system that allowed to constantly monitor them throughout this period. As a result, a database was created with audio recordings for two distinguishable states of the beehive, one healthy state with the queen bee present and one with no queen bee.

All of the measuring equipment are installed on a separate chamber (fig. 1) that is placed on top of the hive. It is separated from the bees' chamber by a thin wooden layer so that the bees have no access to it. The acquisition system for each hive consists of a set of two microphones (Behringer ECM8000) that are connected via wire to a computer with an external sound card (Focusrite Scarlet 8i6), recording at a sampling rate of 44.1 kHz and a 16-bit resolution. The system is also equipped with a set of temperature and humidity sensors (BME280) that are installed both inside and outside the hive. These sensors are connected to a Raspberry Pi that is used to handle the acquisition and send the data to the computer. As a result, the system can also monitor both the environmental and the internal conditions of the hive.

III. Method – Data Analysis

The proposed method is focused on analyzing the raw audio data on the frequency domain to establish the spectral signature of the bees' sound. Towards that goal, the data are first transformed from a time series into spectrograms, indicating the frequency components for each time segment of the recording. From that, the most dominant frequency components can be derived, as well as a set of representative features. These features and the distribution of their values are compared for the two states of the experiment so that a clear distinction can be established between them.

The different steps of the analysis are summarized in fig. 2. The first three steps of the procedure are part of the pre-processing of the raw audio data. First, the data are downsampled from the initial 44.11 kHz sampling rate down to 4096 Hz, resulting in a measurable frequency range up to 2048 Hz. Since most of the spectral content of the bees' sound is documented below 1 kHz, this new sampling rate is sufficient. As a result, a large portion of the external noise in frequencies outside that range is removed and, also, the complexity of the spectral calculations is reduced.

The signal is, then, pre-emphasized, which is a typical step of the MFCC extraction process that flattens the amplitudes of the spectrum by amplifying the higher frequency components. A value of 0.97 was chosen for the pre-emphasis coefficient, which is a typical value used in literature. After that, a Finite Impulse Response (FIR) band-pass filter is applied with a frequency range of 80 - 2000 Hz. This filter is used to attenuate the noise components generated by the supply circuit (60 Hz) and any residual higher frequencies.

The next step is calculating the spectrogram of the audio time series. This is done by performing the Short Time Fourier Transform (STFT), which is a process that involves framing and windowing the time series into small segments and calculating the Discrete Fourier Transform (DFT) on each segment. The result is the spectrogram, which is a two-dimensional array with amplitudes, with one axis corresponding to the N frequency bins that the N-point Fourier transform produced, and the other axis corresponding to the multiple frames of the overall signal. By examining the frequency content of the spectrogram, the most dominant frequencies of each time segment are derived.

The processing steps that follow are used for the feature extraction. The spectrogram is transformed through the Mel-Frequency Transform and is divided into N mel bands. This is accomplished by applying a series of triangular filters at certain frequencies. The resulting spectrum, called cepstrum, is customized in a way that it is more discriminative at lower frequencies and less discriminative at higher frequencies. By calculating the Discrete Cosine Transform (DCT), a set of coefficients are derived that correspond to the N different mel bands [12].

IV. Results

The processing steps were applied on a set of data taken from six different days for the two beehives that were monitored during the experimental procedure. Three days are taken from the period when the beehive is in the healthy state and three after the queen's removal, in order to compare the two states of the experiment.

First, the spectrograms are calculated along with the peak frequencies at each point in time. Some indicative spectrograms of hive A are shown in fig. 3, calculated over 30-minute measurements, where the top figures correspond to the healthy state of the beehive and the bottom to the queenless

Fig. 1. Picture of the acquisition system installed on a dedicated chamber on top of the beehive.

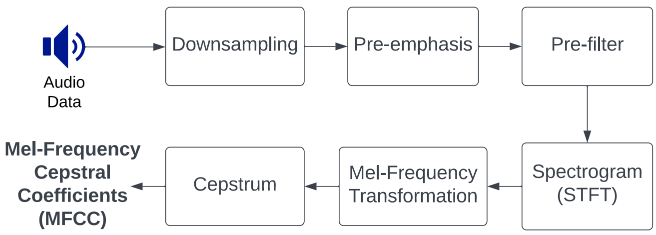

Fig. 2. The processing steps to extract the spectrograms and the MFCC features.

state. With a first look, there are significant differences between the two spectrograms, with the queenless state exhibiting new frequency components and significantly higher amplitudes overall. Also, it is possible to recognize some characteristic frequency components in both states, likethe ones at around 100 Hz, 250 Hz and 500 Hz, which in the healthy state are narrow with low amplitude. In the queenless state, these components are higher in amplitude and the peaks are more spread out. Also, new frequencies are introduced, like the ones around 400 Hz and 130 Hz, that in the healthy state are not visible.

For the MFCC feature extraction, a total of nine mel bands were selected in such a way that the measurable range is divided in bands of approximately 200 Hz, centered around the frequencies exhibited by the spectrograms. As a result, the spectrum is divided in nine bands ranging at the frequencies listed below:

- 80, 279, 478, 677, 876, 1080, 1326, 1629 and 2000 Hz

Each of the nine features corresponds to a specific band of the spectrum, so certain bands are expected to differentiate

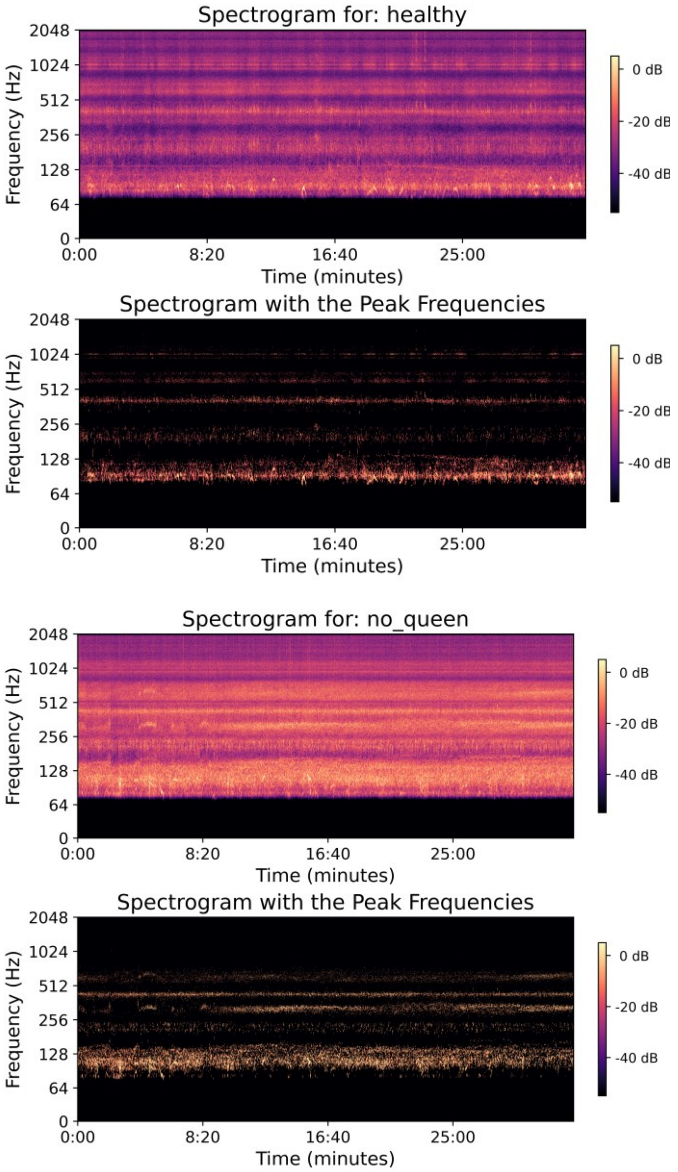

Fig. 3. Spectrograms for the two states of the beehives.

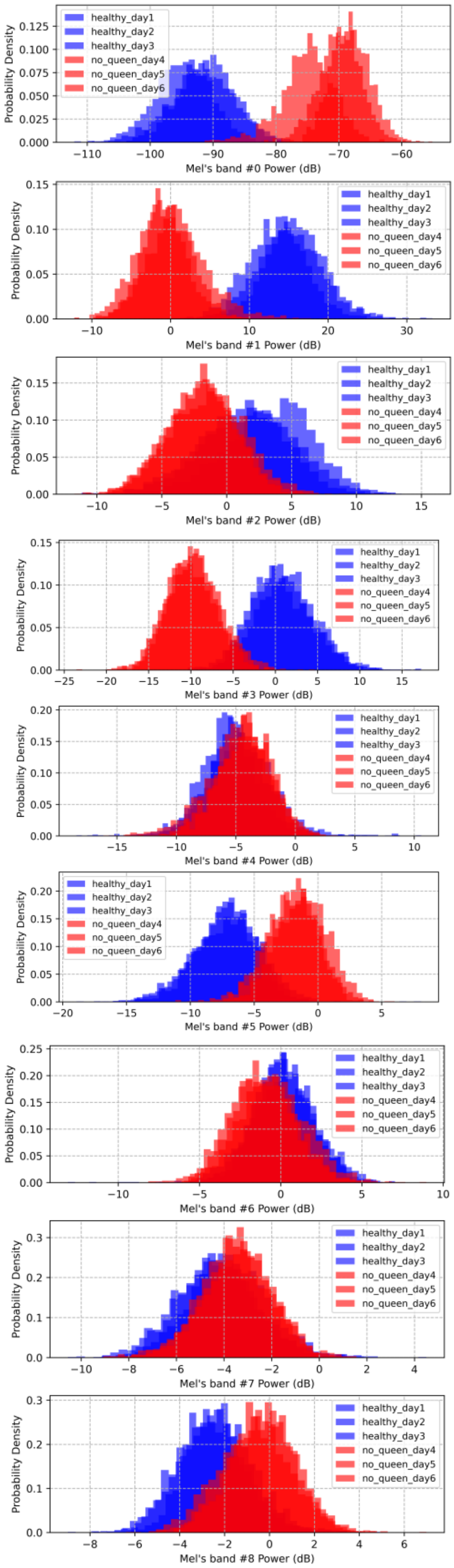

Fig. 4. Probability densities of the MFCC value distributions on the nine mel bands for six different days of measurements for hive A.

between the two states as well as the corresponding features. This is indicated in fig. 4, where the probability densities of the nine feature values (mel bands) are depicted, for six half-hour measurements taken from different days at roughly the

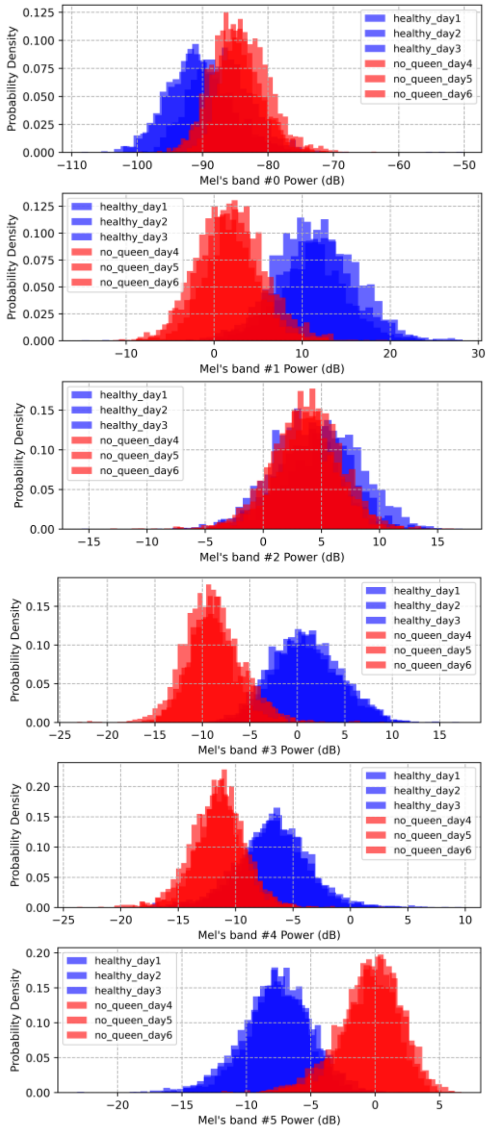

Fig. 5. Probability densities of the MFCC value distributions on the nine mel bands for six different days of measurements for hive A.

the same hour. As depicted, there is a clear distinction between the distributions of the two states (blue for healthy and red for queenless), for the majority of the bands. Some bands are, also, exhibiting similar distributions, which is expected since not all parts of the spectrum differentiate between the two states, like the higher frequency bands (6,7 and 8). As a result, it is possible to distinguish between the two states based on the distributions that these features exhibit during a half-hour measurement. The results are, also, similar in the case of hive B. This time only the first six mel bands are considered (fig. 5) and a clear distinction can be made between the two states. In this case, however, that distinction is exhibited in different mel bands than hive A, which is attributed to the unique spectral signature of each hive. As a result, in both hive cases the two states are distinguishable based on the distributions of the features.

V. Conclusion

Summing up, a system for acoustic monitoring was implemented to constantly monitor two hives for a prolonged period of time to analyze two different states of the beehive, the healthy state with the queen bee present and one state with the queen absent. By examining the spectrograms of these states, the two states exhibited different spectral contents and the most dominant frequencies were established for each state. Also, by extracting the MFCC features and inspecting their distributions over different days of measurements, it was possible to distinguish between these states based on half-hour measurements.

For future development, one of the goals is to explore and evaluate more features from the audio signals and the data from the temperature and humidity sensors, as well as perform more tests and measurements on multiple beehives on different environments to evaluate the generality of the proposed method. Another goal is the development and evaluation of different machine learning approaches in order to automatically classify between these two states, with the lowest possible power consumption, implementation cost and complexity.

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References

[1] A. Terenzi, S. Cecchi, and S. Spinsante, “On the importance of the sound emitted by Honey Bee hives,” *Veterinary Sciences*, vol. 7, no. 4, p. 168, 2020.

[2] P. Hristov, R. Shumkova, N. Palova, and B. Neov, “Factors associated with honey bee colony losses: A Mini-Review,” *Veterinary Sciences*, vol. 7, no. 4, p. 166, 2020.

[3] S. G. Potts, J. C. Biesmeijer, C. Kremen, P. Neumann, O. Schweiger, and W. E. Kunin, “Global Pollinator declines: Trends, impacts and drivers,” *Trends in Ecology & Evolution*, vol. 25, no. 6, pp. 345–353, 2010.

[4] W. G. Meikle and N. Holst, “Application of continuous monitoring of Honeybee colonies,” *Apidologie*, vol. 46, no. 1, pp. 10–22, 2014.

[5] F. Barth, M. Hrncir, and J. Tautz, “Vibratory and airborne-sound signals in bee communication (hymenoptera),” *Insect Sounds and Communication*, pp. 421–436, 2005.

[6] A. Terenzi, S. Cecchi, S. Orcioni, and F. Piazza, “Features extraction applied to the analysis of the sounds emitted by honey bees in a Beehive,” *2019 11th International Symposium on Image and Signal Processing and Analysis (ISPA)*, 2019.

[7] D. G. Dietlein, “A method for remote monitoring of activity of Honeybee Colonies by sound analysis,” *Journal of Apicultural Research*, vol. 24, no. 3, pp. 176–183, 1985.

[8] V. Bisot, R. Serizel, S. Essid, and G. Richard, “Feature learning with matrix factorization applied to acoustic scene classification,” *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, vol. 25, no. 6, pp. 1216–1229, 2017.

[9] V. Kulyukin, S. Mukherjee, and P. Amlathe, “Toward audio beehive monitoring: Deep learning vs. Standard Machine Learning in classifying beehive audio samples,” *Applied Sciences*, vol. 8, no. 9, p. 1573, 2018.

[10] J. Kim, J. Oh, and T.-Y. Heo, “Acoustic scene classification and visualization of beehive sounds using machine learning algorithms and grad-cam,” *Mathematical Problems in Engineering*, vol. 2021, pp. 1–13, 2021.

[11] A. Zgank, “Acoustic monitoring and classification of bee swarm activity using MFCC feature extraction and HMM acoustic modeling,” *2018 ELEKTRO*, 2018.

[12] A. Terenzi, N. Ortolani, I. Nolasco, E. Benetos, and S. Cecchi, “Comparison of feature extraction methods for sound-based classification of Honey Bee Activity,” IEEE/ACM Transactions on Audio, Speech, and Language Processing, vol. 30, pp. 112–122, 2022.