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Buzz-Based Recognition of the Honeybee Colony Circadian Rhythm

Tymoteusz Cejrowski[a], Julian Szymański[a], Doina Logofătu[b]

[a]*Faculty of Electronics, Telecommunications and Informatics*
Department of Computer Architecture
Gdańsk University of Technology, Poland
[b]*Department of Computer Science and Engineering,*
Frankfurt University of Applied Sciences

Abstract

Honeybees are one of the highly valued pollinators. Their work as individuals is appreciated for crops pollination and honey production. It is believed that work of an entire bee colony is intense and almost continuous. The goal of the work presented in this paper is identification of bees circadian rhythm with a use of sound-based analysis. In our research as a source of information on bee colony we use their buzz that have been analysed using algorithms. For the purpose of bees day/night definition, a dedicated electronic system has been developed. The data analysis involves demonstration of the circadian rhythm based on the RMS signal level. Method for defining the start and end of the presumed bees' night was also presented. Mel Frequency Cepstral Coefficients (MFCCs) features and SVM classifier were used. The performed experiment shown the existence of repetitive cycles, which may indicate the presence of bee night. An attempt was made to estimate the time range of this phenomenon.

Keywords: signal processing, hive monitoring, agriculture IoT, bee acoustic signal classification, SVM, MFCC

1. Introduction

Almost all animals need sleep, thereby they regenerate themselves or strengthen their immune system [1, 2, 3]. One might wonder if this also applies to insects. Honey bees, which are one of the main pollinators [4], have become a symbol of diligence and hard work over the years. Such belief might lead to the conclusion that bees never sleep. This phenomenon has been researched and it was proved that sleep is also honey bees' province [5]. Behavioural changes suggest that individuals are able to fall asleep. Bee's sleep has been examined, but concept proposed by Jürgen Tautz raises new questions arguing that within the hive bee population can be treated as one super-organism [6]. Comparing a bee colony to mammals, author states that bees maintain a constant temperature (around 35 °C). They also provide their offspring with a safe and stable environment. The analogy to mammals leads to the question whether bees also sleep in terms of the entire population or only in terms of particular organisms. Are there periods when the bees' work stops and their diligence decreases? Possible answer to this question could provide valuable information for beekeepers and researchers. For example, minimal bees activity can indicate the most optimal time for moving the hive to a new location. Mobile apiaries are common way for optimization of honey farming – beekeepers increase their yields by minimizing the effort that a bee is forced to make in order to reach the plants. The bee night time range definition could possibly help beekeepers to avoid colony losses caused by stress during hive transportation [7]. After all, proving the bees day/night existence can be yet another vote for Tautz hypothesis correctness.

To our best knowledge, there are not many research and electronic systems for sound-based bees' night identification. This

Email addresses: tymoteusz.cejrowski@pg.edu.pl (Tymoteusz Cejrowski), julian.szymanski@eti.pg.gda.pl (Julian Szymański), logofatu@fb2.fra-uas.de (Doina Logofătu)

paper attempts to fill the missing gap and combine research from biology, electronics and data analysis for bees' sleep detection. We present an approach to define bee day/night time range based on the audio analysis. Like Tautz, we treat bee colony as a single super-organism that produces sound in the form of common buzz. In order to carry out the research, a bee monitoring system was developed, described in Section 3. Our research on algorithms and findings from the audio analysis has been shown in Section 4. Our conclusions presented in Section 5 specify periodic time ranges of bee colony behaviour which can be considered as bees' night.

2. Related Work

Automatic sleep analysis has a long history. It is natural, that first research was done for human sleep monitoring, eg. in 1993 authors [8] propose the neural network for EEG signal classification. Extended review of the methods used for sleep classification task has been given in [9]. Research in that field is still developing, eg. in [10] the approach of human sleep patterns based on SVM ensembles is demonstrated. Authors claim that they achieved sleep stage classification accuracy over 90% with use of only one EEG signal channel.

It is difficult to gather bees EEG data like in human specific studies. Instead we try to present bee sleep work conducted with use of diverse methods. We focus on studies of bees sleep-like behaviour and give general description of the works done in that domain. Studies performed by biologists and insights into electronic systems for bee hive monitoring will be presented.

One of the first studies focused on bee sleep has been presented in [5]. Research in this paper was based on observation of bee colony where author specified postures and specific behaviours reflecting forager bee's sleep. The bee is most susceptible to sleep when remains stationary in one and the same location for several hours. Motility should be greatly reduced in comparison to daytime with the motionless antennae. There is also progressive decrease in muscle tone during honeybee's rest at night. Finally, the bee's sleep is accompanied by a maintained reduction in thoracic temperature.

The extended analysis of sleep patters and circadian rhythms have been reported in [11]. Authors identify bee's sleep by observing following phenomena: a period of quiescence, an increased response threshold, and changes in homeostatic regulation mechanism. They describe circadian rhythms of individual bees depending on their colony function and regulated by contact with the brood. For example, nurse bees express no circadian rhythms and foragers rely on the circadian clock to forecast day and night fluctuations.

The dynamics of sleep-like behaviour of honey bees have been performed using video analysis. Authors [12] have developed a system that allows for continuous recording of position and movements of the bee's antennas, head inclination and ventilators movements that are one of the indicators of this insect's sleep. With continuous monitoring they successfully verify the conclusions drawn by Kaiser in [5]. Furthermore an attempt to determine the deepest bee "sleep" was presented. It was concluded that for honeybee case such phenomena occurs during the seventh hour of the total rest phase.

The research from [13] analyses influence of sleep disorder on bees and the effect of a 12-h total sleep deprivation by forced activity has been studied in [14]. Sleep-deprived insects behaviour was compared with the one of a controlled group being under exposure of periodic alternation between light and darkness with 12:12 hours ratio. The research indicated a significant difference with respect to the antenna mobility. Bees locomotor activity has been used for sleep pattern analysis in [15]. Authors also analyse the level of juvenile hormone (involved in the coordination of physiological and behavioral processes) to perform age-related division of labor honey bees.

In [16] patterns of bees sleep behavior have been visualized and interpreted using maps. Authors present graphically the occurrence of sleep across individuals. Their research indicates that the older worker bees generally slept outside cells, closer to the perimeter of the nest, in colder regions, and away from uncapped brood. Younger worker bees generally slept inside cells and closer to the center of the nest, spending more time asleep than awake when surrounded by uncapped brood.

All the above studies concern bee individuals and do not address the problem of the ”sleep” definition with respect to the entire colony. Authors focus on visual observations or temperature measurements which may not be feasible when analyzing more individuals at once. Electronic systems along with more sophisticated data analysis techniques are vital for better understanding the bee colony night.

There are many academic electronic devices performing basic bees monitoring [17, 18, 19]. All those systems are aimed towards aggregation of hive specific values such as: temperature, humidity or atmospheric pressure. More developed systems are extended by carbon dioxide, weight, air-flow sensors [20] or microphones. The research described in [21, 22] presents the Wireless Sensor Network (WSN) for apiary monitoring with a focus on power efficiency. Pre-processing and data analysis is often performed within device’s own computational power. In order to fully utilize the potential of collected data, it is necessary to analyze it using more sophisticated devices and sensors. Electronic bee-colony monitoring based on sound analysis is becoming increasingly popular, eg: [23] presents different machine learning methods for the detection of bee-specific sounds. Various electronic bee-hive monitoring systems with a focus on critical bee phenomena, such as swarming or disease detection, are presented in [24, 25]. The audio signal has been also used for automatic recognition of health status in [26]. Work presented in [27] focuses on sound analysis and relationship between spectral density and upcoming swarming. It was shown that before swarming process bees emit noise that affects the frequency bandwidth. Many other authors used audio analysis as a source of knowledge about the specific bee colony states [28, 29]. Analysis of temperature together with audio data has been also used in bees thermal comfort system monitoring [30].

3. System Design

In order to study bees behaviour during the night a dedicated monitoring system was developed. Monitoring device was designed for sensing beehive’s temperature, humidity and record sounds. Collected data was sent and stored on a remote server. The data analysis was designed as an offline process. A set of dedicated algorithms, presented in the following sections, has been used to define bees’ night presence and its time ranges.

Figure 1: Sensors installed in the hive frame.

3.1. Monitoring Device

The monitoring device was designed to extract bees most relevant physical quantities such as: temperature, humidity and sound. Measurements had to be performed in a way that did not negatively influence bees ecosystem that has been shown in Figure 1. In order to gather reliable information, the device should also work constantly for several days and nights. Considering the above-mentioned criteria, a dedicated measurement frame (shown in Figure 1) and a device with the functionality allowing beehive measurements were designed. The device was battery-powered and energy-efficient, with optimisation techniques (use of *Direct Memory Access* or dedicated low power modes) applied [22]. Ready-to-use solutions based on Raspberry Pi and commercial ones [31, 32], were excluded due to the lack of WiFi network access and external power supply at the place of device installation. Furthermore, access to sound data in commercial systems is often restricted, where only elementary parameters are reported. Such conditions are insufficient to carry out more extensive research. Given the restrictions we built our system from the scratch.

Our approach for bee family day/night definition as a data source employs sound emitted by whole family. To gather reliable data, it is necessary to design a hive-sensitive microphone. An analog microphone module has been developed in the form

Figure 2: Probe mounted in spatial center of the hive.

of a probe and mounted into measurement frame. Hive spatial center sensor installation allows the gathered sounds to reflect the actual state of the bee colony. Figure 2 shows probe installation point. The recorded sound for human perception resembles a common-buzz similar to the low-pitched tones of a hair trimmer. Sensor is sampled at 3 kHz with 12-bit resolution thus allowing frequency components detection up to 1.5 kHz.

Complete system is composed from three parts: server, client and embedded module. The wireless network of embedded devices was made according to master-slave architecture. Only one device within the network is equipped with a GSM module connecting to the Internet. Choosing master-slave architecture reduces overall system costs where GSM module is the most expensive component. Master uploads data from multiple slaves during a single connection. Server communication was implemented with use of TCP sockets and protocol buffers messages [33]. Choosing a Web Socket connection over HTTP and REST endpoints is presented as preferable for IoT devices in scope of energy efficiency [34]. Slave devices collect measurements and communicate with master via radio modules. To ensure the highest possible energy efficiency, each sensor and radio module is keyed, i.e. has its own power line transistor switching the power supply. Before entering a sleep mode, the processor switches off all sensors in order to eliminate leakages and minimize power consumption. In presented study only one master and one slave device was used to collect data and perform preliminary analysis of bee's night existence. In the future work complete network will be applied to more hives in order to validate drawn conclusions.

3.2. Data pre-analysis

In order to examine the feasibility of bees day and night classification problem preliminary work has to be done. We aim to assess whether our hypothesis about bees' night existence is reasonable. Our research involves study of the changes in the bee colony sound level from 9 days of operation. That period of time is considered to be reasonable for day and night preliminary observation. Finding signal level cycles may indicate the periodicity of particular bee sounds.

In order to carry out the test, monitoring device has been set up for this task. During the nine days of device operation data were collected within 15 minutes intervals resulting with 809 one-second length recordings. Next, the Root Mean Square (RMS) signal level related to the bees common buzz loudness, was extracted for every recording. The RMS feature for one-second audio signal X, sampled at 3000 Hz was calculated using Formula 1

$$X_{rms} = \frac{\sqrt{\frac{\sum_{i=1}^{N} x_i^2}{N}} * 3.3V}{4096} \qquad (1)$$

where, x_i is single, discrete microphone analog value collected by the microcontroller through Analog to Digital Converter (ADC), N defines how many analog samples were collected for one recording. In presented work, device collects one-second audio recordings with sampling frequency set to 3 kHz thus $N = 3000$. Value of 4096 is the maximum ADC resolution and $3.3V$ is the corresponding maximum voltage value.

Figure 3 presents the RMS level graph over time for all 809 recordings. One can see RMS growth in the early hours of the morning (green zones cover the time from sunset to sunrise) which may indicate the bees waking up. The loudness increases as the foragers prepare for the flight. The RMS characteristics for the mornings are not identical and may depend, for example, on the outside-the-hive weather conditions. It can be concluded

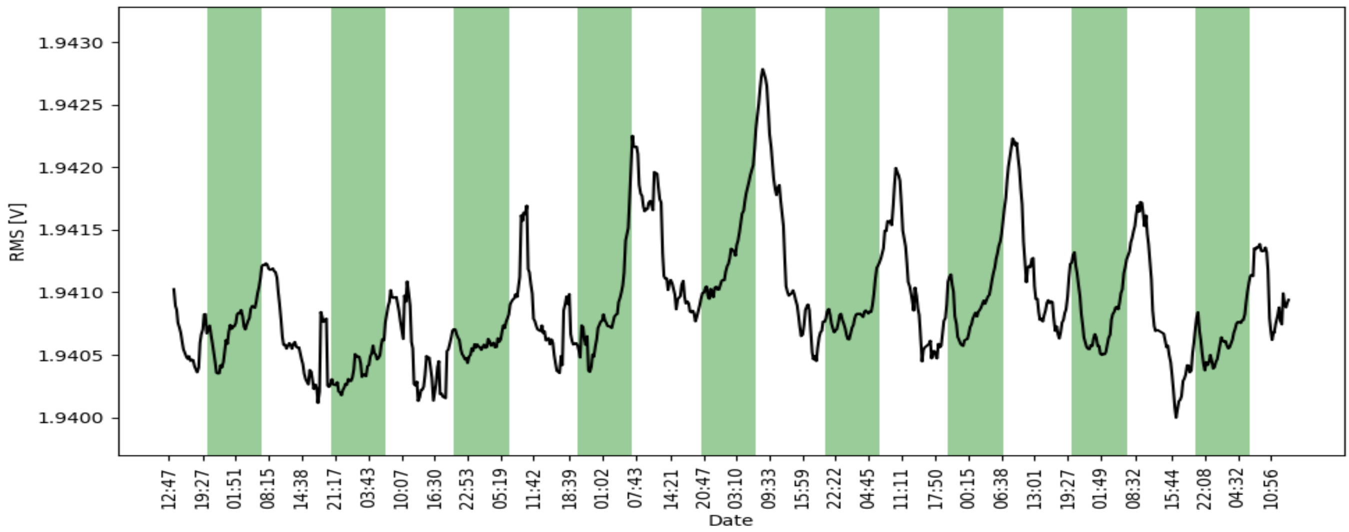

Figure 3: RMS signal level with green-marked sunless periods (from sunset to sunrise) for samples collected during 9 days of device operation (10-19.08.2019)

that in the sunless period the RMS level increases, but the dynamics of change as well as their beginning and end are not closely related to sunrise and sunset. Nevertheless, it is clear to spot repetitive cycles which might indicate bees night existence.

In order to formalise conclusions drawn about possible repetitive cycles the Autocorrelcation Function (ACF) was used, that is defined using Formula 2.

$$r_k = \frac{\sum_{t=k+1}^{T}(y_t - \bar{y})(y_{t-k} - \bar{y})}{\sum_{t=1}^{T}(y_t - \bar{y})^2} \tag{2}$$

where, k is a time-lag for which RMS autocorrelation coeficient will be calculated, r_k is the ACF coefficient, y_t is an RMS value at time t and $\bar{y}$ is an RMS average for the full dataset.

The ACF for discrete time-series refers to the similarity calculated with use of Pearson correlation coefficients, between the observations as a function of the time lag k. Autocorrelation analysis alows to find repeating patterns, which might indicate periodic bees behaviour. It describes how given RMS values depends on previous values within that time series. The ACF coefficient at given k ranges from $[-1, 1]$ and states if there is a correlation between the RMS values starting from k to T, where T is the time-series length in the range 0 to $T - k$. In presented work one-second audio recordings were collected every 15 minutes. Singular lag unit refers to 15 minutes period between successive measurements.

Figure 4 presents the RMS correlogram with statistical significance set to 95%. The significance level is reached for samples representing lags from 0 to 20 and 75 to 98. Values from 0 to 20 were excluded from analysis due to the need of long term dependencies identification (starting from 6 hours lag). The measurement interval has been set to 15 minutes, hence the first significant periodical dependence in bees' RMS sound levels appears after about 19 hours. The maximum correlation (0.6) is placed at lag of 90 which corresponds to 22 hours and 30 minutes. Calculated shift fits into a 24-hour cycle, which indicates the periodicity of RMS level emitted by the colony of bees during the day and night.

Statistical significance was exceeded for samples 75-98, which suggests that bees behave in similar way within period starting with 18 hours and 45 minutes and ending with 24 hours and 45 minutes. It can be concluded that the bees night is maximum 6 hours long. However, there is still lack of information about the night's beginning and end. Following paragraphs try to address that problem.

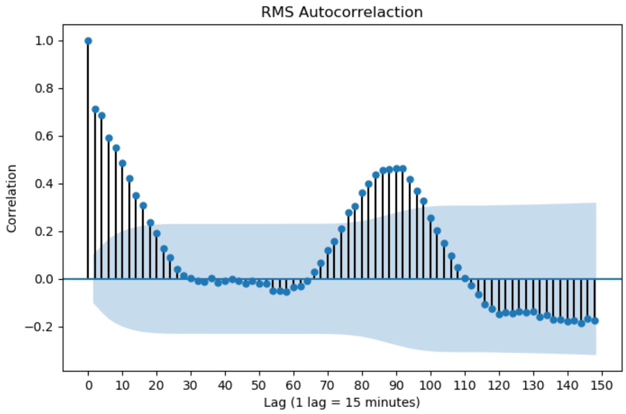

Figure 4: The 24-hour RMS level correlogram calculated for samples collected during 9 days of device operation (10-19.08.2019) with step of 2. Lag unit refers to 15 minutes interval between successive audio recordings.

4. Methodology

As it can be seen form preliminary analysis shown in previous section, to identify the bees' night and day time ranges with use of their sound analysis it is necessary to apply more advanced algorithms. Collected data reflects sounds produced by an entire bee family thus describing the whole colony state. Feature extraction technique followed by proper data preprocessing should be done to characterise the data. Mel frequency cepstral coefficients (MFCCs) [35] were used as features. Method is widely used in speech recognition [36], sound modeling [37] and bee-sound analysis studies [38, 39].

The resulting features describe the state of the colony at a given moment. Bees night time-range identification is based on marking out the most similar sounds in the sunless period. The machine learning based classifier was used for this purpose. Classifier training was performed with use of data from predefined time range, e.g. for first training process: 6 days with data from 9 p.m. to 11 p.m. labeled as bee night. After the training phase model accuracy was validated for the test data (consecutive days with same hours). The accuracy of the classification states about sounds similarity for given time range. Process was repeated for different expected bee night's start and end hours. The model with the highest accuracy is associated with the most similar sounds thus representing bees night time range.

4.1. Feature extraction and preprocessing

The one-second recording was sampled with a 3 kHz frequency with a use of dedicated microphone and analog to digital converter (A/D). In such manner, a harmonic component up to 1.5 kHz can be detected due to Nyquist–Shannon sampling theorem [40] which states that continuous-time signal can be sampled and perfectly reconstructed from its samples if the waveform is sampled over twice as fast as it's highest frequency component. If sampling rate follow Formula 3 then no information will be lost.

$$f_s > 2 f_{max} \tag{3}$$

Bee family sounds fluctuate around 200 Hz so there is no risk of losing vital information. However, recordings might be infected and contains problem-specific noise. For example, sound of a single bee that appears near the microphone might produce recordings that contain higher frequencies. These are not relevant to the day/night bee family classification so preprocessing should be done. Thus in our analysis, recordings whose most significant harmonic components are above 600 Hz or their signal RMS level deviate from the dataset average by at least 80%, have been removed.

Mel-frequency cepstral coefficients (MFCCs) as a method of sound parameterization is widely used in speech recognition and speaker identification. In the first step, signal is windowed and each window is converted to the frequency domain using Fast Fourier Transform (FFT) algorithm. Next, the power spectrum (periodogram) is computed with Formula 4

$$P = \frac{|FFF(x_i)|^2}{N} \tag{4}$$

where, x_i is the i^{th} frame of signal X and N is window length. The power components transformed to mel scale are filtered with triangular filter bank [41] that imitates human perception (Mel-scale filter). Calculation from the frequency domain to the Mel frequency is performed with the Equation 5. Mel spectrum is converted using Discrete Cosine Transformation (DCT) to obtain Mel Frequency Cepstrum Coefficients.

$$Mel(f) = 2595 \log_{10}(1 + \frac{f}{700}) \tag{5}$$

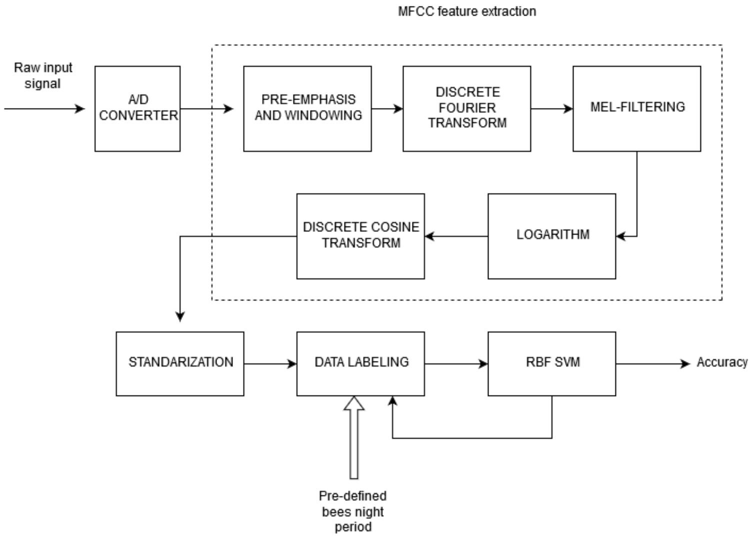

Figure 5: Classification flow of bees circadian rythm.

The first DCT coefficient represents the average power in the spectrum and the following coefficients approximates the broad shape and minor spectral details [42]. It can be summarized that the first 8–13 MFCC coefficients sufficient to represent the shape of the spectrum. In presented work, 13 coefficients were used and calculated as an average from 50% overlapped hanning windowed MFCCs. The number of 13 coefficients is widely used and considered to be sufficient for language modeling and speech recognition tasks [43, 44]. Window length was set to 50 ms resulting with 150 samples of original 3000 samples length, one second audio signal. Each audio is described using 13 element feature vector.

4.2. Night detection with Classification

The definition of bees day and night can be solved using classification approach. At the beginning the complete dataset of MFCCs values and corresponding timestamps was labeled with two classes ($day = 0$ and $night = 1$) according to the presumed bees night start and end. Data was divided into training and testing set, respectively 80% and 20%. After model training and testing, the accuracy was saved and whole process was repeated for the shifted bees night hour range. Set of models with the corresponding bee night classification accuracy was obtained. Model with the highest accuracy reflects situation where in given hour range (night start and end) bees behave similarly for each day in the test set. Such observation may serve for bee night definition.

In our research we employ the Support Vector Machine classifier (SVM) [45] as a tool which is well suited and successfully tested on multidimensional MFCCs classification tasks [46, 47, 48]. The classifier was used with Radial Basis Function (RBF) kernel [49] and parameters $\gamma = 0.5$, $C = 1$ as it has been used and tested in scope of queen bee presence detection [29]. The detailed algorithm flow was shown in the Figure 5.

4.3. Results

Monitored devices were constructed and mounted inside the two hives to carry out the experiment. For the first colony the Buckfast bee colony was selected, which, in the owner's opinion, was healthy and described as severe. The examined hive was placed in the North Poland and was considered as the main subject of research. Second hive was also the Buckfast breed but this time colony was described as calm and weaker (less bees within the colony). Fewer bees produce less distinct tones, therefore second hive has been classified as a validation one. Hive was placed 50 km from the first location.

Experiment took place in August 2019 which was a warm month with average temperature of 19.3 °C and relative humid-

Table 1: SVM accuracy with presumed bee night end time for main hive. Green cells indicate models with the highest accuracy

Start \ Length	1-hour	2-hour	3-hour	4-hour	5-hour	6-hour
8 p.m	80.52%	71.21%	67.24%	66.50%	65.38%	65.63%
9 p.m	72.08%	67.49%	66.62%	66.00%	67.99%	72.45%
10 p.m.	77.29%	72.70%	72.58%	73.94%	76.30%	78.66%
11 p.m.	79.90%	75.93%	76.17%	78.41%	**79.15%**	**78.78%**
12 a.m.	80.14%	76.79%	77.91%	**79.28%**	78.28%	77.29%
1 a.m.	80.39%	**79.40%**	**78.03%**	76.92%	75.80%	73.20%
2 a.m.	**81.14%**	77.66%	74.19%	72.82%	71.33%	68.23%
3 a.m.	78.41%	73.57%	70.22%	68.23%	66.50%	65.50%
4 a.m.	73.44%	71.09%	68.85%	66.37%	66.25%	63.52%
5 a.m.	76.17%	73.07%	70.34%	67.24%	67.49%	67.24%

ity 70%, favorable for bees' work. No extensive rainfall was observed during this time.

For the main hive data was collected over three time intervals with a total number of 22 days and nights. First set has 455 recordings collected from August 2 to August 9. The second one consists of 809 recordings from August 10 to August 19. The last one contains 352 sounds from August 23 to August 28, 2019. Possible bees' night time is assumed to be between sunset to sunrise which is from 8 p.m to 5 a.m. for August. All recordings were described using the 14 element MFCC vector and standardized. We assumed that bees night could possibly lasts from 1 to 6 hours, starting between 8 p.m and 5 a.m. thus full dataset was standardised and replicated to 60 identical ones. Audio samples from each subset were labeled differently based on presumed bee night length (with step of one hour) and time range within sunless period. For every subset the SVM classifier with RBF kernel was trained and validated. Results with SVM accuracy for different bees night setups are presented in Table 1.

Classification accuracy for all main hive models exceeds 65%. The highest accuracy level of 81.14% was observed for time between 2 a.m. and 3 a.m. When one-hour and two-hour long bees night is considered, the most similar colony behaviour was observed from 2 a.m. to 3 a.m. (or starting from 1 a.m for two-hour setup). For three-hour and four-hour bees night, the most similar colony behaviour starts at 12 a.m. and ends at 3 a.m. or 4 a.m. Bees night of five-hour and six-hours long starts at 11 p.m. and lasts up to 4 a.m. or 5 a.m.

The same procedure where models were trained and tested against different bees' nights was run on a validation hive. Data consists of 585 recordings, collected from 14 to 22 of August with similar external atmospheric conditions as for the main hive. For the sake of simplicity only the top results from different presumed bees' night duration was shown in Table 2. The SVM models accuracies exceed 70% for all cases. The 1-hour and 2 hour night starts at 2 a.m. and ends at 3 a.m. or 4 a.m respectively. The 3-hour night is placed between 1 a.m. and 4 a.m. The 4-hour night is 12 a.m. - 4 a.m. The 5-hour and 6-hour bees' night is considered to start with 11 p.m. and ends at 4 a.m. or 5 a.m.

Results from tests carried out on two different beehives reveal 83% convergence in terms of night existence. The only deviation is the 2-hour case, which was defined for the main hive as 1 a.m to 3 a.m. and 2 a.m. to 4 a.m for the validation hive. The accuracy of the classification models for these two hives are not identical for due to the varying size of the family and different Bee Queens across the colonies. In [29] it was shown that even in the same hive different Bee Queens make colony to produce different sounds. Nevertheless, the SVM models with the highest accuracy for 1, 3, 4, 5 and 6 hour cases arise in the same hourly ranges for main and validation hive. Furthermore, all the max-accuracy hourly models involve time between 2 a.m. and 3 a.m. This time-range could be considered as bee midnight. The 4 a.m. appears in 58% of models as the end-time (contrary

Table 2: SVM accuracy with presumed bee night end time for validation hive.

Start \ Length	1-hour	2-hour	3-hour	4-hour	5-hour	6-hour
11 p.m.	82.96%	81.48%	86.66%	88.88%	**91.11%**	**90.37%**
12 a.m.	77.77%	82.22%	85.92%	**90.37%**	87.40%	83.70%
1 a.m.	81.48%	85.92%	**89.62%**	88.14%	82.22%	77.77%
2 a.m.	**88.14%**	**89.62%**	88.14%	82.96%	80.74%	77.03%

to 16% for 5 a.m and 25% for 3 a.m.) thus could be defined as bees' night end. Determining the beginning of bees' night is problematic because of a almost uniform start-time distribution (33% for 11 p.m., 25% for 1 a.m. and 2 a.m., 17% for 12 a.m.). The ACF findings from 3.2 suggest a maximum bees' repetitive cycle duration of 6 hours long. Starting with 4 a.m as end-time the bees' night could possibly start with 11 p.m.

5. Conclusions and Future Work

This paper presents an attempt for summer bees' night definition based on the colony sound. Conclusions drawn from RMS level show the repetitive bees night-time behaviour. The ACF was used for that purpose. Methodology for bee night start/end definition proposes the use of Mel Frequency Cepstral Coefficients as sound features and SVM-based classification for bee night inference. Time range between 11 p.m. and 4 a.m. was concluded as the bees' deep night. Within that time bees reveal repetitive behaviour during which colony activity decreases the most. This is probably the most suitable time for hive relocation.

It should be noted that the results presented here are made on the data which acquisition was maid during summer period and is a ground-work for multi-hive setup. Also the conclusions drawn for winter might be different and should be analysed. Future studies aim to extend presented analysis with external/internal gas measurements and quantities from more sophisticated sensors. Temperature and humidity relevance in a bee day/night evaluation will be also examined. New sound parameterization algorithms will be tested and extended (such as Linear Predictive Coding or Autoencoder models).

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