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Buzz-based honeybee colony fingerprint

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ABSTRACT

Non-intrusive remote monitoring has its applications in a variety of areas. For industrial surveillance case, devices are capable of detecting anomalies that may threaten machine operation. Similarly, agricultural monitoring devices are used to supervise livestock or provide higher yields. Modern IoT devices are often coupled with Machine Learning models, which provide valuable insights into device operation. However, the data preparation step for ML models has to be addressed differently for industrial and agriculture cases. Animals are characterized by their circadian rhythms and seasonal dependence, which can bias the accuracy of classifiers. In the presented work, a Design-of-Experiment (DoA) approach for extracting valuable bee colony audio data is described. With the presented methods, it is possible to precisely define the most distinctive bee hours where unique colony sounds are emitted. The first step of the data filtering process is based on identifying the ambient temperatures that are conducive to its operation. The second step provides the unique hours specification based on the hives' characteristics comparison where dissimilar time periods are being marked. For this comparison, the most noticeable difference between the colonies is calculated with MSE integral and thus the trend's joint component is removed. A new concept of a bees' fingerprint was introduced for the identification of the particular bee colony.

1. Introduction

The field of remote surveillance and monitoring is developing rapidly. Increasingly cheaper and more efficient solutions for data collection are being delivered to the industry (Perera et al., 2014; Samie et al., 2016). Modern methods such as Neural Networks detect threatening situations and damage in advance based on data received from embedded devices (Yamato et al., 2017; De Benedetti et al., 2018; Ullah et al., 2017). Models are trained or inferred on large amounts of data, whereby high accuracy is achieved. The *Sound Event Detection* (SED) systems are supposed to inform supervisors about hazardous situations that threaten livestock or humans themselves (Cejrowski et al., 2018; Nóbrega et al., 2018). Such systems are often coupled with models that are mostly based on deep machine learning methods (Dang et al., 2017).

A similar trend can be observed for the Agriculture *Internet of Things* (IoT) where the number of Machine Learning models is increasing (Ruan et al., 2019; Mekala and Viswanathan, 2017). However, the question emerges whether the training process for both Industrial and Agriculture Deep Learning models should be performed in the same manner? Specifically, should one use the entire training dataset for training deep neural network both for ventilator audio and honeybee sounds? We argue not because industrial devices are supposed to work reliably 24/7 thus the collected data are mostly homogeneous. The data filtering step for Industry ML models is based on rejecting severely corrupted or missing data. After model training, any deviation could be reported as an anomaly and indicate device failure. Contrary to Industry, animals can manifest their own circadian rhythm and have a non-linear working characteristic that might be impacted by various external factors such as weather conditions or seasonality (Cejrowski et al., 2020). Measurements collected at regular time intervals may therefore comprise data that are not relevant for a given task. Classifiers trained on a biased data set will not reach their maximum accuracy.

Colony swarming, pest attack or disease could be identified as an undesirable bee hive situation. The bee swarming process involves the old queen bee escape assisted by high numbers of workers. A young queen remains in the hive to lead the rest of the colony. In such cases, the beekeeper is exposed to losses due to the missing half of the bees. A pest attack is most often related to wasps or rodents. Swarming and intrusion are associated with significant audio changes. Bees are excited or nervous which is directly reflected in the spectrum. On the contrary, for the disease case, the bee sound gradually weakens as the strength of the colony declines. To build an accurate and sensitive model for all

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scenarios, it is necessary to identify audio data that are specific for a particular bee colony and detect anomalies under specific operating conditions. At that point, the model ought to be sufficiently sensitive to capture all anomalies. Otherwise, when the model would be trained on all available data it could interpret the weakening colony strength as the nighttime sound of the bee colony. The dataset of the most distinctive colony sounds could be identified as a bee colony fingerprint and serve as a precise descriptor.

Authors in Cejrowski et al. (2020) stated that the time interval starting from 11 p.m. and ending with 4.00 a.m. could be considered as a bee night where colony activity decreases. It is assumed that irrelevant information for the task of anomaly detection occurs during the bee night. The bees do not leave the hive and the tones are similar. Moreover, the authors in Eban-Rothschild and Bloch (2012) specified that foragers rely on the circadian rhythm to forecast day and night fluctuations, thus no waggle-dance related sounds are emitted. It is indispensable to delineate the hours and weather conditions within the bee day to identify recordings valuable for bee colony characterization. During the day, the forager bees fly out of the hive, the temperature rises and bee activity increases. Opposed to the night hours the unique colony time range would identify the most distinctive hours within the apiary.

The presented work introduces a new methodology for identifying audio data which is essential for the bee colony characterization task. We present methods for the filtering process which could be vital for bee colony anomaly detection models. The extracted dataset contains information from the bee colony work which is probably the most informative part of the colony state. A two-step filtering process rejects recordings that are common within the dataset and extracts recordings that are unique to a particular bee colony. The process incorporates ambient temperature and compares feature characteristics in a hive-to-hive manner. From the extracted data, a feature vector called a bee fingerprint is created. A side product of the two-step filtering process is an hourly time range representing data unique for each hive. With the conducted experiments, the range of the bee day was thus made more precise.

The paper is organized as follows: Section 3 describes the methodology for bee data filtering and defines the bee fingerprint feature. Especially two-step filtering is described in paragraph Sections 3.3 and 3.4. Section 4 address the exact definition of bee day time range based on the methodology presented in previous sections. Finally, the bee fingerprint application and future work are discussed in Section 5.

2. Related work

The problem of ML model training with a nonuniform trainset is most often described for industrial devices. The *Predictive Maintanace* (PdM) domain is the field where the most promising methodologies can be found.

Authors in Salmaso et al. (2019) highlight difficulties in existing approaches to *Machine Learning* (ML) model development. These include the assumption that greater the amount of data results in more accurate model. They argue that within bigger dataset it is impossible to detect its biases. Authors propose a dedicated *Design-of-Experiment* (DOE) approach based on the mean values of the measurements, the ANOVA methodology, and step-wise reduction of the model for HVAC-related PdM tasks.

The responsibility for classifying anomalies properly could be transferred to autoencoders and a residual error based approach (Oh and Yun, 2018). In such a case, an Autoencoder Neural Network is trained on the full dataset and the anomaly is detected based on exceeding a predefined threshold. Such threshold specifies the maximum distance, e.g., in Euclidean space between the anomaly hidden vector and the nearest cluster for the data defined as normal operation. However, such an approach fails when considering living organisms temporal dependencies. Softer night's sounds are incorporated into the training set so that the model is not sensitive to quieter sounds produced during the day. The autoencoder approach cannot be directly applied to bee anomaly detection task.

A related concept of essential feature extraction for the industry PdM is presented in Satta et al. (2017). Authors argue that concurrent mutual differences among the cohort of elements (ventilators, elevators, etc.) are more useful for Predictive Monitoring tasks than standard statistical analysis. Anomalies within a single element are easily detected when the analysis is incorporated with discrepancies among homogeneous appliances. A similar methodology defined as daytime filtering was proposed in Section 3.4.

Interest in numerical analysis of bee behavior is growing rapidly. Many researchers are building cost-effective and energy-efficient IoT devices for bee colony monitoring (Cejrowski et al., 2019; Cecchi et al., 2020; Qandour et al., 2014; Gil-Lebrero et al., 2017). Recently, machine learning approaches are widely used in a variety of bee-related tasks. Authors in Terenzi et al. (2020) summarize the systems for bee data analysis. The bee-related topics and recent methods for addressing beekeeper key problems are presented.

The work presented in Nolasco and Benetos (2018) addresses the problem of classifying recordings with and without bee sounds using Machine Learning methods. The authors test SVM models and Convolutional Neural Networks. However, the dataset is prepared only considering general rules for training a ML model. Predetermination of bee-specific data could improve the classification ability. Authors in Zgank (2021) propose *Deep Neural Networks* (DNN) for bee swarm detection. They use 3 s long audio recordings with MFCC features as a dataset and test the deterioration of network classification ability for audio compression methods. It was stated that MP3 encoding may decrease the model accuracy up to 12%. Work presented in Cejrowski et al. (2018), Nolasco et al. (2019) applied Machine Learning methods and statistical models for the queen bee detection problem. It was proven that using sound analysis techniques it is feasible to flag the queen-less colony.

The main motivation for the presented work was research presented in Sharif et al. (2020) and Cejrowski et al. (2020). Authors in Sharif et al. (2020) propose a new method for bees sound description which is the use of sound indices. They examined various description methods in the task of bee sound classification. The bees were exposed to trichloromethane gas and the capabilities of audio feature extraction methods such as *Acoustic Complexity Index*, *Acoustic Diversity Index*, *Acoustic Evenness* or *Bioacustic Index* were investigated. Sound indices features overcome low-level sound descriptions such as *Zero Crossing Rate* and *Spectral Centroid* for the classification task. The MFCC features performed comparably or worse for several cases. Having a group of sound description methods, it was decided to tackle the problem described in Cejrowski et al. (2020). The authors describe the issue of defining the bee night time range and point out the ability to safely transport hives as the main motivation. Here, an attempt is made to complement the study and identify the bee day as a convenient time for bee colony characterization. Following the authors' recommendations, it was decided to investigate sound indices features for the bee day definition problem.

3. Methodology

The process of extracting the bee fingerprint is based on two-step filtering. Temperatures conducive to bee colony activity are determined in the first place. Through the process, it is possible to extract the weather conditions that are favored by the bees within a given colony. The second step is an hourly filtration that incorporates the data from the temperature filtration. This step uses data from all hives within the dataset and identifies the hive-specific hours when the sound of a particular colony is most valuable. Finally, a set of filtered data is acquired, representing the most characteristic sounds of the hive within the context of the full dataset. An example of such a process could be the feature extraction within an apiary. The hourly averaged features of the dataset are identified as a bee colony fingerprint. Overall view on buzz-based honeybee colony fingerprint extraction process was show in Fig. 1.

3.1. Data acquisition

Collected audio recordings were 2 seconds long as the bee sound signal resembles a common buzz and exhibits the characteristics of a quasi-stationary signal. It was decided that collecting longer audio recordings would be not beneficial. Data were recorded with the use of RaspberryPi 3B+ boards and a digital microphone with a 44100 Hz sampling frequency. For this study, a custom board was used to provide the capability for adding more sensors. The extension board is separated into two sections: analog and digital. The ground masses of both are connected in one place exclusively so the potential interference could not propagate. For the analog section, there are four ADS1115 which are four-channel analog to digital converters with 16-bit resolution and I2S interface. Two channels for each converter have been routed with one micro-match connection allowing two voltage measurements in one wire. It is especially important for wind recording which requires double voltage measurements, one for temperature compensation and the second for the air flow. To adapt the logic levels of ADS1115 and Raspberry Pi B+, two voltage converters were used on the I2C bus lines consisting of a MOSFET-N transistor and two resistors. The digital part of the expansion board consists of the micro-match connections for the individual buses like I2S, SPI, 1-wire, I2C and UART. Two I2S bus connectors for stereo audio recording were designed.

Although having the possibility to collect a number of different quantities like in-hive temperature, humidity, gas level or wind measurements it was decided to use sound data as a primary feature. Other quantities should not be used as a main feature for the bee colony characterization task because of its low variability. The colony temperature, humidity or gas data could serve as an auxiliary source of data. The audio data provide the largest number of possibilities for bee swarm characterization due to the variety of methods dedicated to sound feature extraction task. Following Tautz's hypothesis that a bee population could be treated as one super-organism (Tautz, 2008), bee swarm audio would appear to be the way of communication for such an entity.

Collecting reliable audio data requires proper microphone placement. The incorrect measurement can lead to misleading conclusions, thereby extensive work has been done to properly position the monitoring devices. Dedicated bee hive frame was built where a sensor probe was installed providing reliable and high-quality recordings. The channel was fabricated within the frame where a microphone was placed. This allowed sounds to be collected directly from the hive interior. The custom frame was placed adjacent to the queen bee location or place where signs of her presence were observed in the form of recently laid eggs. Fig. 2 shows a frame with encapsulated honey indicating that bees accepted the modified hive frame.

Fig. 2. Hive frame with installed probe.

3.2. Feature extraction

Sound is a mechanical wave that is converted into an audio signal using a microphone. The raw audio signal, which is a time domain representation of the sound wave, can serve as a direct description for machine learning algorithms. However, employed models are often complex and used mostly for multi-class classification or auto-tagging tasks (Lee et al., 2017). Moreover, recent bee sound-based research mostly utilizes methodologies successfully applied in speech recognition systems like *Mel-frequency Cepstrum* or *Hilbert-Huang Transform* (Terenzi et al., 2020; Cejrowski et al., 2020; Ribeiro et al., 2021). Such an approach may seem reasonable, but one should notice that the bees audio might exhibit characteristics of a quasistationary signal resembling a uniform buzz. There are some significant differences between speech signals and bee colony audio. The characterization of an bees' audio implies an alternative strategy compared to standard speech recognition methods.

Recent studies show promising results on bees' sound description using so-called sound indices devoted to bioacoustic signals. The work presented in Sharif et al. (2020) tests several algorithms that generate indices, which are single values describing an audio classification task. The sound indices outperform MFCC method which is widely used as bees' sound feature. Based on conclusions drawn in Sharif et al. (2020), bioacustic sound indices were chosen as the sound's description. However, these methods incorporate a variety of algorithms for feature generation (Bradfer-Lawrence et al., 2019). For example, *Acoustic Evenness* detects absence of insect noise, *Acoustic Entropy* detects wind, faint bird calls or insect noise dominated with single frequency band, *Acoustic Complexity Index* serves as a bird activity detector. Most beneficial bioacustic features for the bees' fingerprint definition should be selected. Many researches (Aleixo et al., 2017; Corbet et al., 1993; Blažytė-Čereškienė et al., 2010) state that bees work intensity is strongly

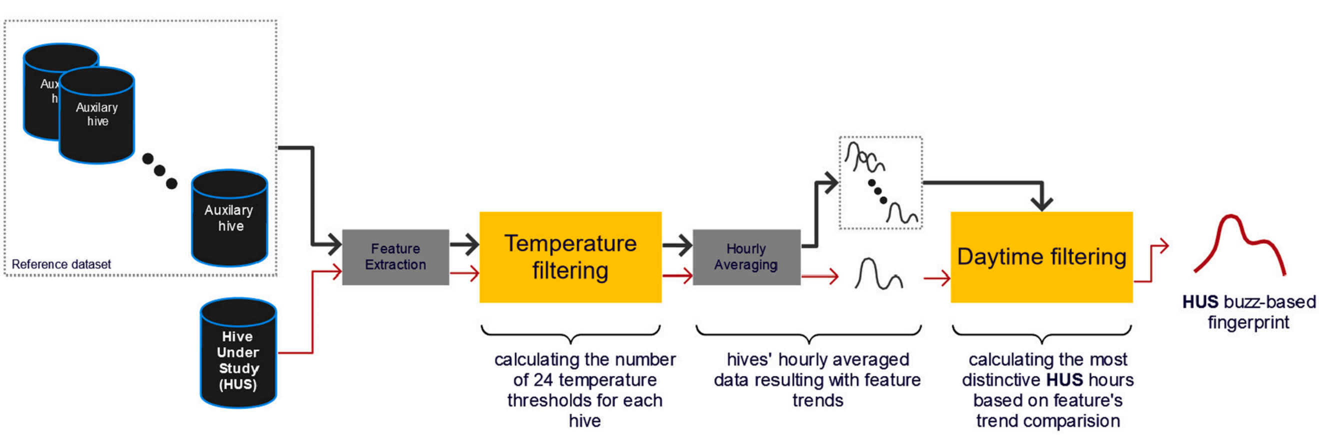


Fig. 1. Honeybee fingerprint workflow.

coupled with the ambient temperature. The easiest way to test the usefulness of a given bioacustic feature in an activity regression task is to examine its correlation with ambient temperature. The feature with the greatest correlation factor will be used as a method for bees' sound description.

The temperature correlation study utilized 7 features from the bioacustic sound indices group with different parameters to select the most profitable configuration. Features included: *Spectral Entropy* (Acharya et al., 2015), *Acoustic Complexity Index* (Pieretti et al., 2011), *Bioacustic Index* (Boelman et al., 2007), *Acoustic Diversity Index* (Pijanowski et al., 2011), *Acoustic Evenness* (Villanueva-Rivera et al., 2011), *Normalized Difference Soundscape Index* (Kasten et al., 2012) and *Zero Crossing Rate* (Bachu et al., 2010). Table 1 presents the 5 highest Pearson's r coefficients calculated for different types of features.

The SE configuration's parameter *NFFT* stands for number of samples used for Spectrogram calculation which corresponds to window size, *Hop Length* is window offset for consecutive frames, *Decibel Scale* is a flag for transforming spectrogram amplitudes in decibel scale, *J-Samples* is a parameter specific for ACI calculation (Pieretti et al., 2011).

The highest Pearson correlation coefficient was obtained for *Spectral Entropy* feature defined with Eq. 1 and the "0" configuration. Comparatively, the SE-0 correlation factor was set against the second MFCC feature coefficient correlation value as it got the highest score within the full-size MFCC vector. The MFCC features of size $N = 13$ were calculated as an average of cepstrum calculated with 1024 hann window and 50% overlapping. The Pearson's r value for MFCC's second coefficient and ambient temperature was at the level of 0.422, which is close to the SE-2 score being the third best result. The Second and third highest correlation score was observed for the entropy with the configuration "1" and "2". The 4th and 5th highest value corresponds to *Acoustic Complexity Index* with configuration starting from "2" to "5". One can notice that similarly to the entropy, the *Acoustic Complexity Index* quantifies the spectrogram's volatility by calculating the derivative of the frequencies in the frequency bins. When the temperature is raising, the signal's variability is increasing, which results in more information encoded in the signal. Ambient temperature is an key factor that has to be considered for the bee fingerprint definition process. The *Spectral Entropy* feature with the "0" configuration was used for further analysis.

3.3. Temperature filtering

Given a complete set of audio recordings, the question emerges regarding the temperature ranges that yield the greatest amount of information characterizing a particular colony. To address the issue, a dedicated experiment of the feature's distribution with the average ambient temperature was carried out.

Firstly, the *Spectral Entropy* was extracted from the available sound recordings. Features were hourly averaged within each hive in order to eliminate the outliers effect. Furthermore, the hive's feature means between quantiles of $p = 0.05$ and $p = 0.95$ were used for the analysis. Resulting data were paired with the average ambient temperature for given hour yielded the final dataset with hourly resolution. Set of 24 averaged features for i-th hive was calculated with use of Eq. 1. Parameter h is the hour in 24-h day, N - the number of recordings in h-th hour, f - frequency bin for averaged spectrogram, p_{jf} - magnitude of f-th frequency bin for j- audio recording.

$$\mathrm{SEN}_{ih} = \frac{\sum_{j=1}^{N} \sum_{f} p_{jf} \log_2 p_{jf}}{N} \qquad \forall \qquad 0 \leqslant h \leqslant 23 \tag{1}$$

To specify the temperature ranges where bees produce their unique sounds, it is crucial to find the most common colony's sound. In this regard, for each day hour a *Spectral Entropy* feature's histogram was generated and paired with the average ambient temperature incorporated in a given bar. An example histogram for the *smrpiclient5* colony at 11:00 a.m. was shown in Fig. 3. For that plot, recordings with SE feature value of 0.114 are the most frequent in the dataset with an average ambient temperature of 6.62 °C. The rounded temperature of 7 °C was accepted as the temperature threshold for the given hour. One can notice that SE feature grows with the average temperature. Higher temperatures are favourable for bee work, especially for foraging (Blažytė-Čereškienė et al., 2010) thus the right side of the histogram might represent bees work. It can be concluded that work data might be valuable for colony characterization. However, it is necessary to specify a particular temperature that could be considered as the beginning of the work period. In the next step, the starting temperature of the colony unique recordings will be identified.

To identify the starting temperature at a given hour, the feature and its standard deviation within ambient temperature were plotted. Data for hive *smrpiclient5* and 11.00 a.m. is presented in Fig. 4 as an example. It can be observed that the lower the temperature, the smaller the feature's standard deviation. The amount of essential information characterizing the bee colony is decreasing with the ambient temperature. However, for the right side of the plot, the higher temperature yielded higher standard deviations thus having entropy increasing. The graphs were plotted and analyzed with 24 h configuration, each hive separately. Similar relationship between ambient temperature and feature standard deviation was observed within the bee day, defined as the time between 4 a.m. and 11 p.m. (Cejrowski et al., 2020).

To define the beginning of a unique colony temperature range, the previously estimated value of 6.62 °C was used. The temperature was rounded and used as the end of the range for which the average feature standard deviation will be calculated. For the data in Fig. 4 a mean value of standard deviations for bins within $[-3, 7]$ range was used. The beginning of the unique-colony temperature range was defined as the first temperature value (first bar) where the feature's standard deviation exceeds the calculated mean. For data presented in the Fig. 4 the value of 10 °C was considered as the unique colony temperature range beginning. Finally, 24 temperature values (one value for each hour) were retrieved and served as threshold values for the colony-unique data. Data where the ambient temperature was lower than the threshold within a given hour were rejected from the dataset.

In the Fig. 5 one can see the feature's mean value plotted on an hourly basis for the filtered data (blue) and the full data (red). Filtering process sharpens the graph and shifts it in the Y axis. The above analysis was conducted for each hive separately. The result contains a set of 24 element vectors with temperature threshold values.

3.4. Daytime filtering

Temperature values are defining the weather conditions favored by a single bee colony. As shown in Cejrowski et al. (2020), specific hours can be described as bee night. The bees' behavior within a given time range tended to be very similar, thus might serve as bee-night definition. Authors focused on the night-time range definition by searching for sound buzz similarities whereby not specifying hours for the bee day. That period was defined as a time range deduced from the night's complement data with the use of Eq. 2

$$BD = BN^C = B_{24} - BN \tag{2}$$

Table 1
Sound indices feature configurations.

Feature	Params NFFT	Hop Length	J-Samples	Pearson's r
Spectral Entropy "0"	4095	2048	n/a	0.436
Spectral Entropy "1"	2047	1024	n/a	0.425
Spectral Entropy "2"	1023	512	n/a	0.420
Acoustic Complexity Index "5"	1023	256	4	0.401
Acoustic Complexity Index "2"	1023	512	10	0.373

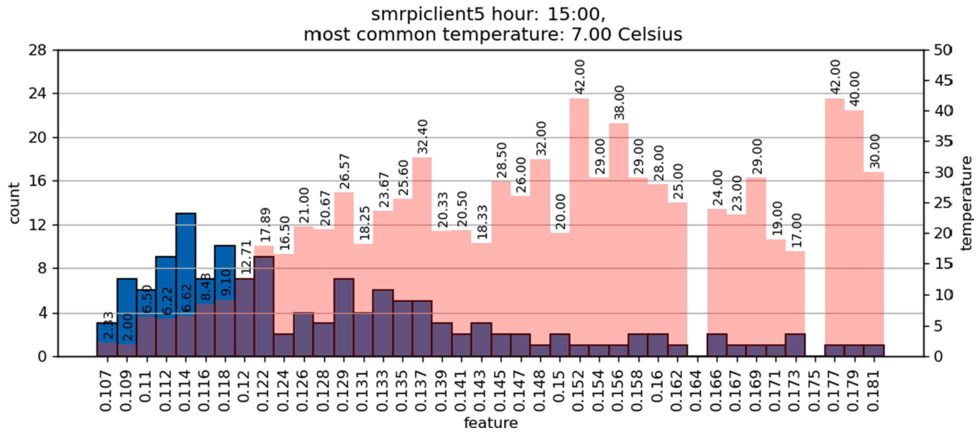


Fig. 3. Feature's histogram (blue bars) with average ambient temperature within given bar (red bars). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

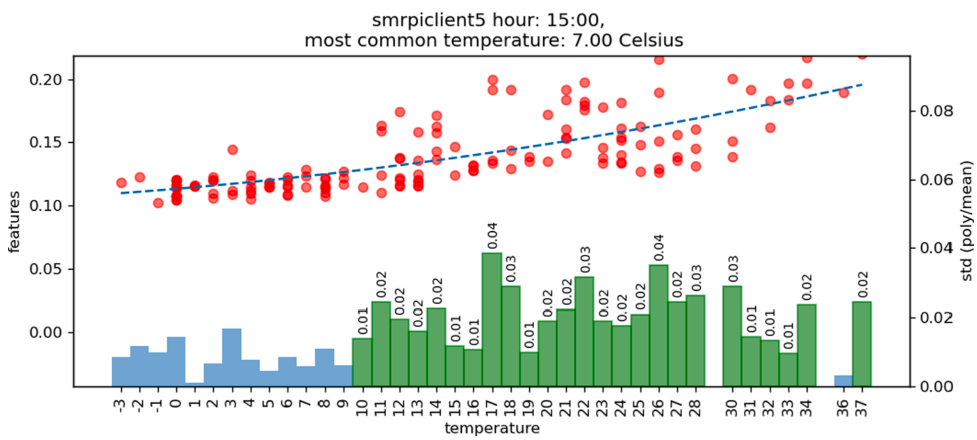


Fig. 4. Audio recordings feature collated with temperature (red dots) and feature's standard deviation (bars). Green bars indicate temperature values considered conducive to bee work. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

, where *BN* is a dataset containing sounds within bee-night time range, *BD* is data for bee-day time range and B_{24} stands for the complete dataset. The approach focuses less on the colony uniqueness and more on its similarities. For bee colony fingerprint definition, a more precise bee-day time range should be developed.

Defining the hourly ranges where a colony produces their characteristic sound is based on a comparison of temperature-filtered feature's plots across the hives in the dataset. Firstly, all temperature-filtered daily feature's plots were upsampled using Fourier method (Oppenheim, 1999) to provide better hour resolution. From each filtered feature graph, its mean value was subtracted to eliminate the bias. The *Mean Square Error* (MSE) was used as a metric for calculating the difference between the graphs. Points where two plots intersect were defined as the intervals' start/end where the MSE value is set to 0. For each *i*-th hive from set of apiary hives *H*, the maximum integral of MSE value across all intervals is calculated according to Eq. 3.

The *X* limits' set is defined with Eq. 4.

$$X = \left((a_k, b_k) \in A_{ij} \times B_{ij} \;\middle|\; k \in I_b\right), \tag{4}$$

where:

$$\begin{aligned} A_{ij} = &\ \{h \mid \mathrm{MSE}(\mathrm{SEN}_i(h), \mathrm{SEN}_j(h)) = 0\ \forall\ 0 \leqslant h \leqslant 23\} \cup \{0, 23\} \\ B_{ij} = &\ A_{ij} \backslash \{0\} \end{aligned} \tag{5}$$

and I_b is an index set of B_{ij}.

The area with the maximum integral value is the time range where the difference of two hive's characteristics is most noticeable, thus can be considered as colony unique hours. Fig. 6 presents the daytime filtering between two hives: *smrpiclient6* and *smrpiclient7*, where vertical blue lines are the intersection marks and yellow plot is representing the MSE result. The graph was splitted into *N* intervals indexed from the left and starting with 1. The maximum value was found for area No. 8. It can be concluded that hive *smrpiclient5* and *smrpiclient6* differ the most between 11:40 a.m. and 4:51 p.m. Results from all one-to-one hive com-

$$y_i = \max_{t \in X} \int_t \mathrm{MSE}\left(\mathrm{SEN}_i\left(h\right), \mathrm{SEN}_j\left(h\right)\right) dh = \max_{(a_k, b_k)} \sum_{h=a_k}^{b_k} \frac{1}{2}\left(\mathrm{SEN}_i[h] - \mathrm{SEN}_j[h]\right)^2 \Delta \qquad \forall_{j \in H} \tag{3}$$

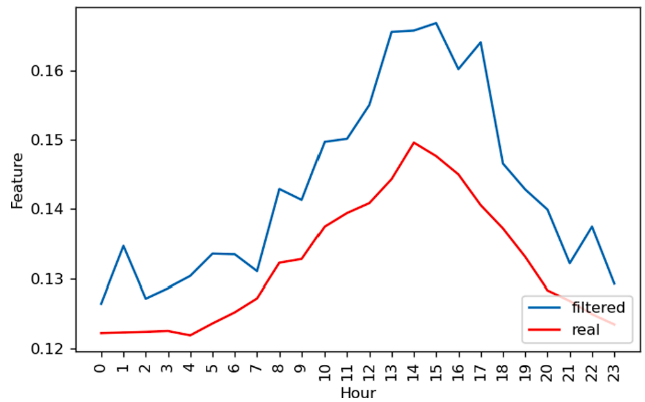


Fig. 5. Filtered and real daily ACI feature trend for *smrpiclient5* colony.

parisons were averaged and served as the final time range.

3.5. *Buzz fingerprint*

The hourly and temperature-wise filtered feature data for smrpiclient6 is presented in the Fig. 7. The calculated time range (11:29 a.m. to 04:51 p.m.) fits within the high insolation hours where favorable for bee work weather conditions were present. It can be concluded that bee colonies are best distinguished during this time. The filtered feature from 11:29 to 16:51 is called the colony's fingerprint and describes its unique characteristics in the context of the entire apiary.

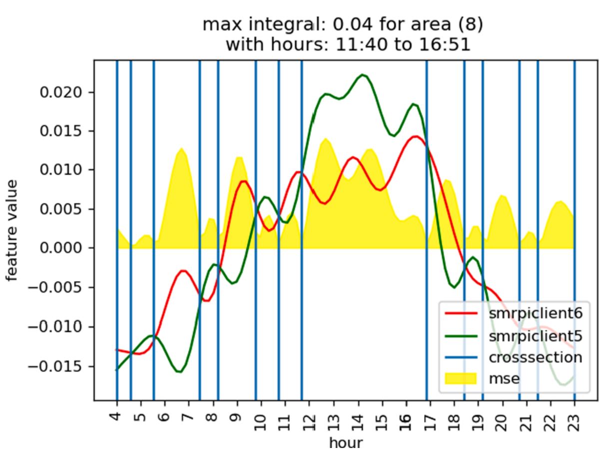


Fig. 6. Daily feature graph comparision for *smrpiclient5* hive (green) and *smrpiclient6* hive (red). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

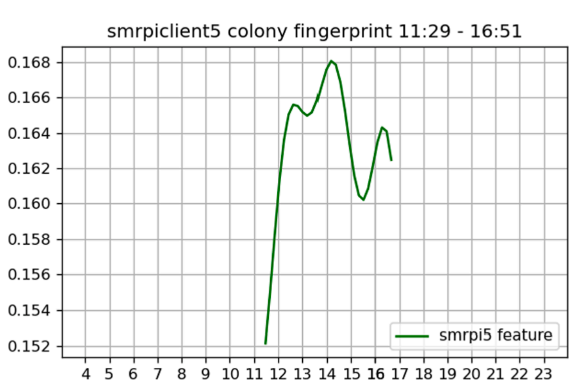


Fig. 7. Bee-fingerprint for *smrpiclient5*.

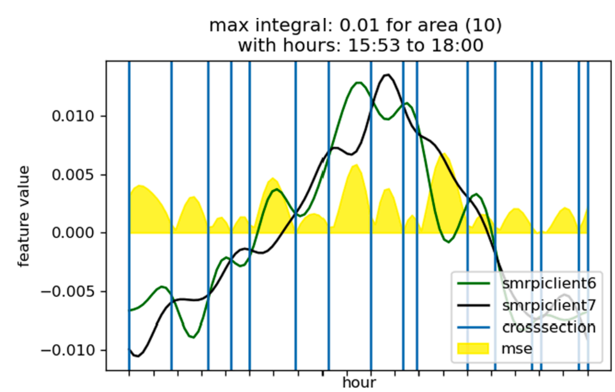
Table 2
Time range for bee unique-colony data.

	Hive		
Feature	smrpiclient5	smrpiclient6	smrpiclient7
Spectral Entropy "0"	11:29 a.m.–04:51 p.m.	11:40 a.m.–04:05 p.m.	11:29 a.m.–04:05 p.m.
Spectral Entropy "1"	11:29 a.m.–03:53 p.m.	09:56 p.m.–01:12 p.m.	08:24 a.m.–01:12 p.m.
Spectral Entropy "2"	11:17 a.m.–04:51 p.m.	08:13 p.m.–01:35 p.m.	08:47 p.m.–01:47 p.m.
Acoustic Complexity Index "5"	10:31 a.m.–03:07 p.m.	10:31 a.m.–02:56 p.m.	10:43 a.m.–04:05 p.m.
Acoustic Complexity Index "2"	10:54 a.m.–03:42 p.m.	11:40 a.m.–03:07 p.m.	11:04 a.m.–04:39 p.m.

4. Experiment

To test the reliability and versatility of proposed methodology, the workflow was repeated for three different bee colonies including all features from Table 1. The number of 35830 audio recordings collected from August 10, 2020 until January 19, 2021 served as a dataset. Data were obtained with 20 min intervals resulting to 3 recordings per hour. Data collection process was not continuous due to technical work and periodic power outages. Temperature and hourly filtration methods were applied for each hive. Calculated unique colony time ranges are shown in Table 2.

The unique colony start time for the *smrpiclient5* colony varies between 10:31 and 12:38 p.m. The end time is defined as 3:07 p.m. until 4:51 p.m. The average start time of the hive unique hour range for the SE feature is 11:25 a.m. while the end time is 4:32 p.m. Comparatively, the range for the ACI feature is 10:43 a.m. to 3:25 p.m. The difference is 42 and 67 min, respectively. Due to relatively small hourly range variability it might be concluded that *smrpiclient5* bee colony exhibits its unique



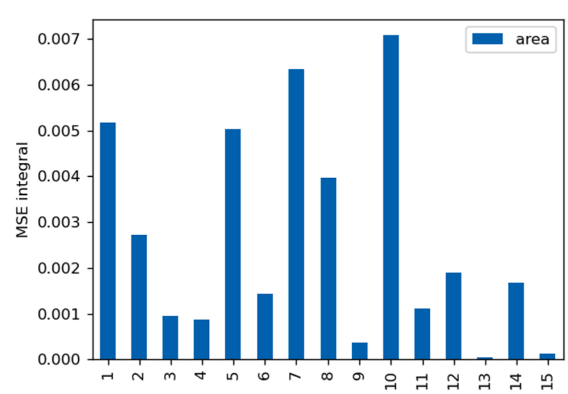


Fig. 8. MSE difference integral values for the feature trend characteristics comparison.

rhythm in a narrower range than the proposed 4:00 a.m. to 11:00 p.m. Cejrowski et al. (2020). As *Spectral Entropy 0* has the highest Person's r correlation factor, 11:29 a.m.–04:51 p.m. was considered an accurate time range for the unique colony data.

For the *smrpiclient6* the start hours are between 8:13 a.m. and 11:40 p.m. Specified time range corresponds to *smrpiclient5* characteristics but only for a lower limit. The variance is larger than for *smrpiclient5* because of the high similarity between colony *smrpiclient5* and *smrpiclient7* for SE-1 and SE-2 feature trends. The colony similarity implies the high number of short MSE's zero value periods. It is not possible to correctly classify these two colonies with entropies "1" and "2". The Fig. 8 presents the hourly filtering step for two similar colonies. The dynamics of the presented colonies are similar, whereby area 10 ranging from 3:53 p.m. to 6:00 p.m. was identified as the most divergent. However, with only 10% decrease in the MSE integral for area 7, the max integral for the 10th area could be identified as random. Presented situation reveals the vulnerability of described methodology. The unique hours identification requires features that could well distinguish between the colonies. Rejecting both entropies "1" and "2" sets the start hour to be 10:31 a.m.–11:40 a.m. with the average of 11:16 a.m. and end hour of 14:56 p.m.–4:39 p.m., averaging to 3:23 p.m.

The *smrpiclient7* reveals similar start-end unique time range. It is necessary to discard feature SE-1 and SE-2 because of the high similarity for *smpirclient6* and *smrpiclient7* trends. The average start time of the bee fingerprint is 11:13 a.m. and the end time is 4:16 p.m. After rejecting the two features that produce similar hive characteristics, the start and end of the unique trend coincide for all tested hives.

The temperature-wise and hourly filtering was tested on colonies' audio fundamental frequency. As stated in Cejrowski et al. (2020) bees acts differently within daytime and night hours, which was proved with SVM model and MFCC values. However, the MFCCs features are nonintuitive and used as abstract values for sound recognition systems. Derivating MFCC mean values for bee night and day will not supply beekeepers with any new insights about the colonies. Using less abstract methods such as fundamental frequency can demonstrate the utility of the presented methods and give a new look to bees activity.

From the complete dataset, the fundamental frequencies were extracted. For unfiltered data, the average feature value was 262 Hz whereas after two-step filtration the value was 242 Hz. The filtration process discarded 31400 recordings resulting with 88% of total dataset. The 99.9 % of data from November 27 to December 13 were rejected. During that period unfavorable bee weather conditions (Blažytė-Čereškienė et al., 2010; Beyer et al., 2018; Güler and Dikmen, 2017) were most present with average temperature value of 2.8 °C and humidity 86.9%. It was observed that the bee activity was minimal during this time.

5. Conclusions and future work

This paper presents a workflow for extracting distinctive bee sound data from a uniformly sampled audio dataset. The proposed approach focuses on temperature and time as the two factors that have the greatest effect on bees' behavior. Temperature filtering step involves rejecting recordings collected during weather conditions that are not favorable to bees. An average temperature is calculated for the most frequent recordings at a specific hour. Based on the derived temperature value and the audio feature's standard deviation, a new temperature is calculated as the beginning of a weather distinctive range. These are temperatures where the audio feature entropy is the highest, thus bees make the most diverse sounds. In the second step, the hourly filtering process involves comparing each hive's feature daily trends built on the filtered dataset. The area where the hive's trend difference is most noticeable defines the time range where the bees make the most distinct sounds within the apiary context. The result of two-step filtering is a set of sound data that characterizes a particular hive most effectively. Data are deprived of a constant component existing among all hives so it is possible to clearly identify the bee hive within an apiary or subspecies.

The *Spectral Entropy* was used as the sound feature due to its highest correlation with ambient temperature. Nevertheless, the experiment was repeated for *Acoustic Complexity Index* feature and conclusions were found to be consistent. The ACI feature was originally used to classify birdsong and applied to lengthy recordings with a large value of *J*. The frequency variable audio recordings were found well characterized by the ACI feature. In the present study, the ACI index was successfully adapted for 2 s's long bee colony recordings in the hive characterization task. While exploring the sound indices group, the ACI index was considered the most reliable method for bees' sound description. The authors will explore sound indices methods further and encourage the research community for applying these methods to other bee sound-related problems.

A new method for colony description has been proposed. Bee fingerprint is a SE-0 feature vector of length *N*, where *N* is the length of the output of the daytime filtering step. It consists of hourly averaged features calculated from temperature-filtered data and cropped to a unique hourly range. Such an entity could be used to identify a swarm, assess its dynamics or health. Comparing bee fingerprints could provide information about the species similarity of bee swarms. It is believed that colonies of the same subspecies may be characterized by a similar fingerprint. More work is planned for exploring the bee fingerprint feature for the problem of bee colony comparison.

The time range of the bee day, which was previously defined as the bees night's complement, is now made more precise. Inference of exact bee day hours is based on the averaged ranges of bee fingerprints calculated from available hives. The hours between 11:00 a.m. and 4:00 p.m. for the fall and winter seasons were considered as a bee day. One could be aware that such time range was inferred based on three different hives which should be extended and validated on more bee colonies. However, due to the lack of similar experiments in the scientific community, the defined time range could be considered a suitable reference. Defined time range combined with the ambient temperature exceeding the level calculated with the temperature filtering step best characterizes bee activity. It is strongly recommended that the analysis of bee activity should be conducted on data which satisfy the temperature and hourly criteria.

The presented methodology can be successfully applied in other areas such as Predictive Maintenance or Fault Diagnosis. Hourly filtering might be helpful in identifying machine working hours and diagnosing unbalanced load distribution. Temperature filtering, or other external factor filtering, could provide information about the effect of an observed quantity on the performance of the monitored object. Whenever unique identification of an entity within a homogeneous set is needed, a discriminant filtering methodology could be helpful.

Future work addresses the use of the presented methods for developing neural network-based anomaly classifiers. The irrelevant data filtering process is an essential step for training the sensitive classifiers. Moreover, the Contrastive Autoencoder will be investigated for the anomaly detection task. An gas effect experminet is planned to verify the ability to detect adverse events.

CRediT authorship contribution statement

Tymoteusz Cejrowski: Methodology, Software, Investigation, Formal analysis, Data curation, Writing – original draft. **Julian Szymański:** Conceptualization, Supervision, Validation, Writing – original draft, Writing – review & editing, Visualization.

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.

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