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Detection of the Bee Queen Presence using Sound Analysis

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Abstract. This work describes the system and methods of data analysis we use for beehive monitoring. We present overview of the hardware infrastructures used in hive monitoring systems and we describe algorithms used for analysis of this kind of data. Based on acquisited signals we construct the application that is capable to detect an absence of honey bee queen. We describe our method of signal analysis and present results that allow us to drown conclusions on honey bee behaviour.

Keywords: Honey Bees · Hive monitoring · Signal analysis

1 Introduction

Honeybee (Apis mellifera) is probably one of the most important insects in the agriculture. This extremely valuable insects are treated as the key factor in plants pollination [1, 2]. It is crucial that the number of bees increases. Their work is considered as the guiding light for the hard-workers and is appreciated for ages. People and especially beekeepers should provide special care for this insects. Unfortunately today's beekeeping is facing many issues which cause the number of insects to decrease [3]. Disease or uncontrolled swarming can be the cause of bee distinction. Also insufficient care of the beekeeper is very often the main factor of collapsing the whole bee's families.

One of the important tasks for beekeeper is to check whether the queen bee is healthy and capable to lay eggs. This is done by opening the hive and inspecting the hive frames. If there is no eggs or larvae, the queen bee might be dead, ill or just not present in the hive. In such situations life of the whole swarm could be in danger and an immediate action is required. Whenever there is no reproduction because of the death or disability of the queen bee there is also no more younger bees that could replace the older ones [4]. Usually the bee worker lives only up to 40 days and after that her work should be overtaken by another bee [5]. The lack of healthy queen bee is extremely unfavorable and should be detected as soon as it is possible. But on the other side, daily hive inspections and checking whenever queen bee is present can be harmful for the whole bee family. Frequent disturbances can be a stressful factor and introduce the anxiety to the swarm. To avoid such situations it is necessary to use a non-invasive method that is able to detect lack of the queen bee.

In this paper we present the remote, non-invasive system that monitors and analyzes the honey bees behavior according to different conditions. For our study we create the situation where the queen bee is not present inside the hive. We monitor that situation with the set of the sensors and based on it we create the classifier that indicates whether the bee family becomes aware of the missing queen. The system presented in this paper can possibly detect different illnesses of bee colony such as presence of Varroa Destructor or predict bee swarming but that analysis is a plan for the future work.

2 Related works

In recent years the interest in bees and their habits is increasing rapidly. Such situation cause growth the number of systems which are capable of collecting data from the hives.

For example, the commercial Arnia[3] system is designed for collecting weight, temperature and humidity measurements. The device is also equipped with microphone to obtain sound samples from inside the beehive. All data is transferred remotely to the server and then presented to the user. There are many similar projects with the same core objectives. For example, projects presented in [6] and [7] differ only in the set of sensors. Some of them like the BuzzBox[4] additionally provides open access to recorded data.

There are also number of scientific projects which are focused on detecting particular situations inside the beehive. For example, problem of bee swarming (when the insects leave the hive because of newborn queen) has been studied in [8]. The proposed solution uses cyclic temperature measurements and pattern recognition techniques which are based for a predictive algorithm. System is able to detect the preswarming moment by evaluating the increase in temperature inside the hive. Authors found five patterns that may occur during the year. Anomalies, which are accompanied by elevated temperatures within the hive, and hence the inability to classify data from a particular moment may be a sign of the incoming swarming.

Ferrari's work about the bee swarming prediction [9] describes wireless network of sensors that collect sounds, temperature and humidity values from the hive during the swarming periods. Based on empirical graphs observations some patterns were specified and determined.

There are also some projects focused on bee's diseases detection. Project which was developed at Edith Cowan University in Australia [10] aims to completely eliminate external parasitic mite Varroa Destructor from the Australian continent. Device collects sound samples and converts them to feature vector, at the end the data is classified using SVM or LDA algorithms. Mite detection

[3] Arnia system: www.arnia.co.uk, access 10 Sep 2017
[4] BuzzBox: www.osbeehives.com, access 10 Sep 2017

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such as Varroa Destructor can also be solved using image analysis processing. In Larissa Chazette's work [11] camera-equipped system has been developed which recognizes Varroa Destructor infected bees by using Convolutional Neural Networks (CNN). In Schurischuster's work [12] a Raspberry Pi 3 based device is able to collects high resolution and well-exposed pictures of bees entering the hive. The combination of [11] and [12] systems could lead to even better results.

3 System design

Our system is composed from three parts: server, client and embedded module. The wireless network of embedded devices was made according to master-slave architecture. The *endpoints* which are mounted directly inside the hive are responsible for collecting measurements and passing them to *accesspoint*. The *accesspoint* uploads raw data to the server where is processed.

Analysis of bees behavior can only be performed by usage of sensors that provide case-essential data. Significant type of data can be specified basing on the related work. Bees like most of the insects produce sound during the flight. The bee worker emits sounds at 250 Hz on the air. But bees can be also considered as one super-organism where their sounds accumulates to one, common buzz. Seemingly irrelevant noise emanating from the center of the hive can be a source of valuable information. For example, when bees are preparing for swarming, they also change their extremely ordered behavior. Some of the insects start becoming restless, bring excitement to the hive and finally change nature of the common buzz. Without doubt sound is one of the most important factors in bee analysis. In presented work, sound samples are collected by specially designed microphone. The band-pass filters have been selected so that the microphone will be sensitive for bee's sounds (20 -2000 Hz).

Bees also need proper level of temperature and humidity inside the hive. Without suitable conditions the colony can leave their current place of occupation [8]. Invalid humidity level is causing multiple bee diseases so it is also significant value for monitoring. Temperature and humidity are the most sensitive factors among the bees and these two values are monitored using an integrated sensor HDC1008.

In our system the microphone, temperature and humidity sensors was inserted into a specially designed bee hive frame in order to not disturb the bees. The designed frame is shown in the Fig 1. Single data set contains one second sound sample and information about levels of temperature and humidity. Data is acquired every 15 minutes and then uploaded to the server.

4 Data processing

In our approach we divide the data into two sets: one derived from normal bees work and one from abnormal, where there is a lack of bee queen in the hive. Thanks to that it is possible to extract the pattern, which will allow us to differentiate particular behaviors. At the beginning of the analysis process

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Fig. 1. Bee hive frame used in experiment.

the data is downloaded from server. This step must ensure data consistency in which the sound, temperature and humidity values must be available at a given moment. Then, the features are extracted from the available data and classification potential is tested. At the end the model is worked out and final classification is performed.

4.1 Feature extraction - Linear Predictive Coding (LPC)

The process of the data analysis start from the transformation of the input data from the hive into a form that can be used as input for algorithms. Sound signal should be compressed into the finite element vector of the size significantly less than the original length of the sound sample vector. For this purpose Linear Predictive Coding was used.

LPC is a method used in a speech audio compression. This method assumes that signal is produced by a buzzer located at the end of the tube [13]. For the correct sound characterization it is important to determine the output signal parameters as the inverse of the impulse response of FIR filter that represents the vocal tract. In order to facilitate the use, the input is the Dirac delta function. Model can be represented as in (1)

$$H(z) = \frac{G}{1 - \sum_{k=1}^{m} a_k z^{-k}} \tag{1}$$

where G is the gain, m level of the model and a_k represents searched characteristic coefficients.

Using Z transform, and Levinson-Durbin algorithm a coefficient vector is obtained [14]. It is assumed that 10-14 LPC coefficients describe well the signal and further increasing this number results in an insignificant improvement in signal approximation. In this work the given sound sample with a dimension of 3000 was characterized using LPC algorithm by vector of size $N = 14$. The final

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data was extended by temperature and humidity values collected from the same moment of time as the sound sample.

4.2 Classification potential - t-SNE

Having some set of a data it is crucial to determine if the classification and model extraction is possible at all. This process is a supportive step and performed only in the case of recognizing new features. Could be carried out by viewing the 2D or 3D points which corresponds to input data. If there is possibility for data separation it means that examined feature can be used in hive modeling. To get 2D points from multidimensional input vector it is necessary to use technique for dimensionality reduction such as t-SNE.

Algorithm was introduced by Laurens van der Maaten in 2008 and is the variation of previously existing algorithm called SNE developed by Geoffrey Hinton and Sam Roweis in 2002. T-SNE converts multidimensional set of data $\chi = \{x_1, x_2, ..., x_n\}$ to 2D or 3D vectors $\Upsilon = \{y_1, y_2, ..., y_n\}$. The basis of this algorithm is to compare the density distribution of multivariate variables with the distribution of their projection on a two or three-dimensional plane [15]. The difference between these two distributions is calculated by Kullback–Leibler divergence and minimized by gradient descent.

In our work the t-SNE algorithm was used to evaluate the potential of the hive classification according to presence of the queen bee inside the hive. We treat LPC coefficients vectors, extended with humidity and temperature values, as the input for t-SNE algorithm. We perform dimension reduction on vectors of size $n = 16$ to obtain 2D or 3D map of points that corresponds to state of the colony at given moment. Then we can decide if future classification is reasonable. It is desired to observe clusters of data representing samples taken during the normal work and a separate set representing anomalies. If so, we can perform the last step which was the classification according to previously chosen feature.

4.3 Learning - SVM

Information of the separation capacity is important for the next stage of the mathematical bees modeling. Input data in the form of n-dimensional vector is given as the input to the classifier. Presented system use SVM classifier developed by Vapnik [16] in 1963 with the modification [17] from 1992 introduced by Boser, Guyon and Vapnik himself.

The basic SVM classifier is capable of separating two sets that are linearly separated so that the hyperplane spreading the training data maximizes the value of the geometric margin. The output of SVM algorithm is the separating hyperplane which form is presented in (2)

$$y(\boldsymbol{x}) = \boldsymbol{w}^T \boldsymbol{x} + b = 0 \tag{2}$$

where $\boldsymbol{w} = [w_1, w_2, ..., w_N]^T$ is the N dimension weight vector and $\boldsymbol{x} = [x_1, x_2, x_N]^T$ is the input vector. As a matter of fact the input data rarely can

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be linearly divided into two separate sets. Separation of the data that can not be linearized is solved with the help of a so-called kernel trick [18]. It transforms nonlinearly input data so that they are likely to be linearly separable.

In presented work non-linear, Gaussian-kernel, SVM classifier was used to obtain a model of the hive in relation to the designated feature. We have used SVM method on two data sources: previously described $n = 16$ dimensional vectors and the output of t-SNE. Both approaches provide similar results. The SVM output is the hyperplane dividing learning set into two separate clusters, one indicating anomaly and second describing normal swarm behavior. Such model can be later evaluated on testing data and relevant conclusions regard to the behavior of bees can be learned.

5 Experimental results

Bee colony was monitored in the period from February 2017 to August 2017. Unfortunately, the bees did not swarm in that time also they were not infected by any of the diseases. To test our classification system, it was decided to force a critical situation for the bees. Absence of a bee's queen in the hive was chosen and it was caused manually by a beekeeper. The aim of the experiment is to develop a hive model in which will be possible to observe and specify the patterns characteristic for bees living without the queen.

The experiment was carried out using embedded system described in Section 3. Bee hive frame was inserted into the hive as third frame from the entrance. The mother exchange process together with periods of downloading of sound data is presented in Fig 2.

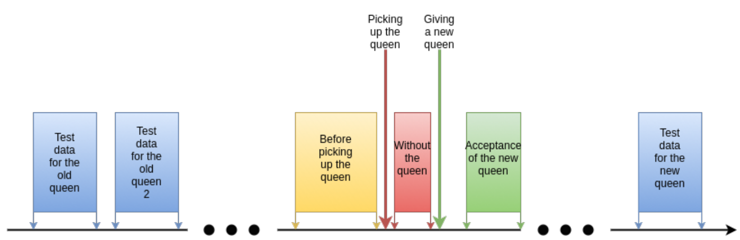

Fig. 2. Queen exchange workflow.

In the first step, two data sets previously designated as "Before picking up the queen" and "Without the queen" were used as input data. The audio samples were compressed into a feature vector, which was the LPC coefficients. These vectors were also extended with temperatures and humidity values. At the end data was normalized. Such prepared vector was provided for the input of the t-SNE dimension reduction algorithm to identify the classification potential. Result was shown in Fig 3.

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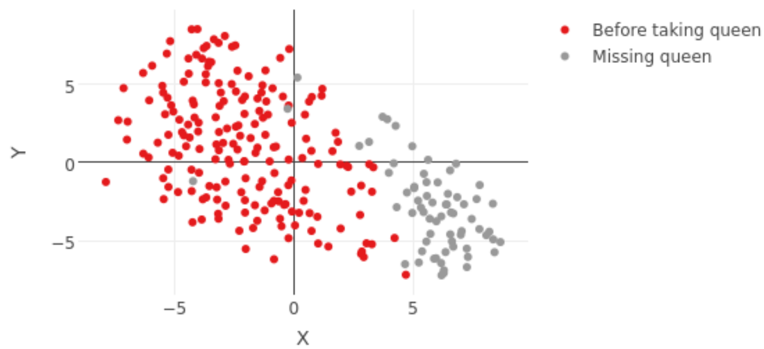

Fig. 3. Output of t-SNE algorithm with data "Before picking up the queen" and "Without the queen".

Based on output of t-SNE algorithm it is clear that bees with and without the queen act differently. Thus detection of this two cases can be performed using classification method. For that purpose Support Vector Machine algorithm with C-classification was used. Cost was set to $C = 100$ and kernel was defined as $K(\boldsymbol{x}_j, \boldsymbol{x}) = exp\Big(-\gamma\|\boldsymbol{x} - \boldsymbol{x}_j\|^2\Big)$ with $\gamma = 0.4$. Result as shown in Fig 4.

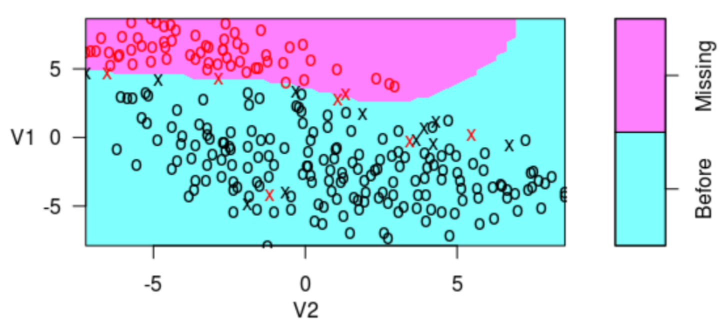

Fig. 4. SVM classification borders plot. Modeling the hive with absence queen bee as feature: queen inside the hive (Before) and Queen taken (Missing).

Such defined model was tested with test data presented in Fig 2. Table 1 presents classification on the test data.

Data named as "Test old queen" and "Test old queen 2" indicates normal work of the swarm. Such situations was classified correctly and model was very accurate. It is possible to determine the moment when the queen bee may suffer

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Table 1. Test data classification.

Name	Samples	With queen	Without queen	Error
Test old queen	92	90	2	2.17%
Test old queen 2	72	70	2	2.77%
Test new queen	130	98	32	75.38%

or even die for example from a pest attack. In such cases we should found samples which significantly differ from the others.

It was also expected that after some time the data and situation inside the hive should return to the situation before the mother's removal. The experiment showed that the colony did not return to the same state even 15 days after new queen bee insertion. To more precisely examine this situation it was decided to check classification potential between "Test data for the old queen bee" and "Test data for the new queen". Result as shown in Fig 5.

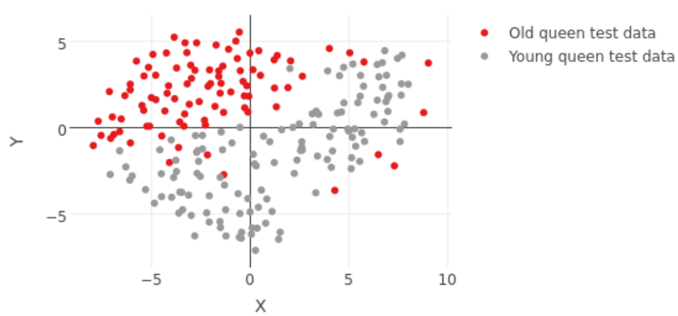

Fig. 5. Swarm classification with two different queen bees.

Output data is quite easy separable what indicates that different bee queens cause different behaviors across the swarm. For queen bee collapse detection the system should only analyze changes of the behavior patterns but expecting same behavior patters with fresh and old queen could be misleading. These observations was discussed with two independent beekeepers who confirmed that queen bee influences the behavior of the whole family. The new queen bee after introduction into the family makes the bees subordinate to her disposition and sound significantly changes. Model derived from "normal state" of two different bee queens has been tested on two extra test datasets.

Results presented in Table 2 show that it is necessary to calculate a new model for the newly introduced queen bee in order to detect next possible swarm collapse. New queen is significantly different from her predecessor, and thus the old model loses its usefulness.

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Table 2. Classification of two test datasets from two different queen.

Name	Samples	Old queen	New queen	Error
Test data old queen	72	68	4	5.55%
Test data new queen	183	17	166	9.28%

6 Conclusion and future work

The experiment and its results confirm the validity of the proposed model. It has been proved that there is a pattern that characterizes the normal work of the swarm and it can be correctly identified using the system presented in this paper. The anomalies such as the exchange of the mother are distinguishable and extracted by the presented system.

The developed classification system can also be significantly improved. It is necessary to collect much more data from different anomalies occurring inside the hive in order to develop a global model of bees behavior. Detection of swarming or diseases with usage of the described system can be real. For that purpose we plan to use more sophisticated classifiers [19] ant their parallel implementation [20] that should allow us to process larger set of the data in more effective way. We can also obtain some improvement on the level of the data representation. Here, we plan to add to Linear Predictive Coding analysis of particular feature context in the similar way done in [21].

Our system is only a starting point for further work that is currently being conducted. The life and behavior of animals in particular bees can be a source of valuable information. Researchers at Nanchang University in China [22] have found that bees work harder the day before the expected rain. This observation is the basis for extending the system for predicting temperature and humidity based on data coming from the hive.

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