APPLYING APPROACHES FROM AUTOMATED PROCESSING OF HUMAN SPEECH TO MONITORING AND PREDICTING IMPORTANT EVENTS IN HONEYBEE HIVES USING ACOUSTIC SIGNALS

Stenford Ruvinga*, Gordon Hunter*, Heather Sanders[&], Michael Kodwo Adjaloo[$]

* School of Computer Science and Mathematics, Kingston University, KT1 2EE, UK
[&] Agsenze Ltd.. U.K.
[$] Kwame Nkruma University of Science and Technology, Kumasi, Ghana

1 INTRODUCTION

Honeybees are major pollinators and of vital importance to both agriculture and the wider environment. Recently, honeybee populations have been in serious decline due to factors including pesticides, pollution, parasites, and disease. Furthermore, traditional bee monitoring methods are invasive and can be stressful and potentially even harmful to the bees, due to risks of beekeepers spreading diseases or parasites from one hive to another.

The death or other loss of a healthy queen bee is very hazardous for the survival of a colony, and prompt intervention is needed. The occurrence of a swarm, which normally occurs shortly before a new queen hatches, results in a large number of worker bees leaving the hive along with the old queen. Swarms are not popular with beekeepers, since they will tend to lose a substantial number of bees when swarms occur. Hence, successfully predicting that a swarm is going to occur soon is of great interest to beekeepers.

The auditory system of honeybees is very different from that of most mammals, including humans. Due to these differences, there should be no *a priori* reason to expect that approaches optimized for the processing of human speech should necessarily be successful for analyzing bee sounds. However, in this study, we show that features such as MFCCs commonly used in human speech processing can also form the basis of systems successfully used to analyze and classify signals relating to important events in the life of a honeybee colony, such as swarming or the queen dying. Monitoring devices using such approaches would allow reduction of the need and burden for regular, frequent physical colony inspections, a practice that disrupts the social life of the colony.

In this paper, we also describe an investigation comparing the acoustics of the activity of domestic honeybees from Europe, East Africa, South Africa and West Africa.

2 THE “AUDITORY” SYSTEM OF HONEYBEES

The auditory system of honeybees is very different from that of most mammals, including humans. Honeybees have two primary types of ways of sensing acoustic vibrations - "Johnston’s organ" in their antennae and the subgenual organs in their legs. The former detects airborne vibrations which we would interpret as sound, whilst the latter primarily detect mechanical vibrations, mainly transmitted through solid objects (see Figures 1 and 2). Both of these organs allow sound signals to be converted to nerve impulses which then get transported to the bee's brain [1]. Bees can respond to vibrational signals in the frequency range 10 to 500Hz, much more limited than the range of normal human hearing, but which covers the fundamental frequencies of most sound signals noted by beekeepers as relating to salient events in the lifecycle of a honeybee colony [2].

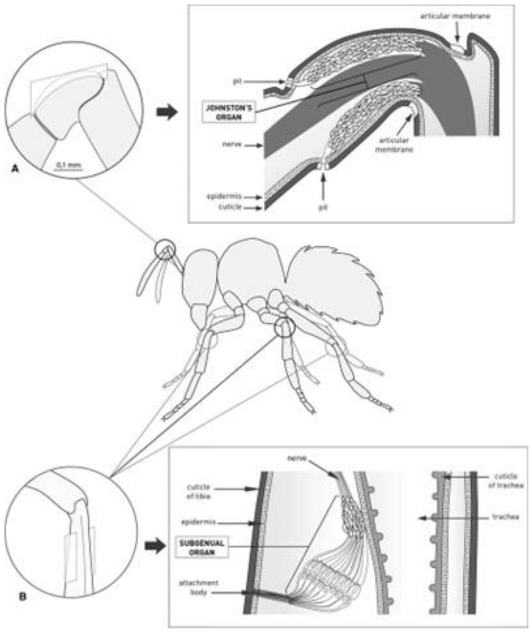

Figure 1 : The "auditory" system of honeybees, showing the locations of Johnston's organ and the subgenial organs (from [3]).

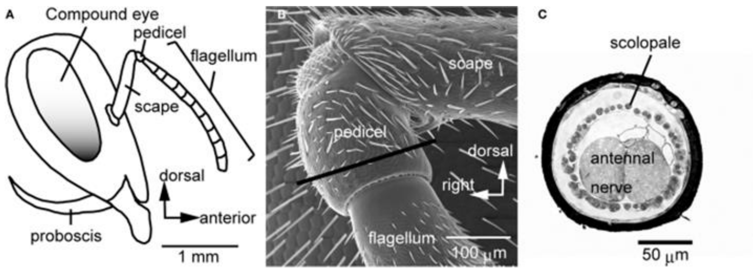

Figure 2 : More detail on Johnston's organ, showing its location on the antenna and its structure (from [4]).

3 METHODS DEVELOPED AND OPTIMISED FOR THE PROCESSING OF HUMAN SPEECH

As has long been established, sound signals are processed by the human auditory system through mechanical vibrations of the eardrum being transmitted by the bones of the middle ear to the basilar membrane in the cochlea [5]. The basilar membrane then performs a mechanical form of frequency analysis of the vibrations, and the various frequency components are converted by nerve cells (sometimes known as "hair cells") into electro-biochemical pulse which are then transmitted to the auditory cortex of the brain.

Due to the way in which different sound frequencies are perceived by human hearing, automatic speech processing systems often use a frequency representation based on the Mel scale, since this is a model of human sound perception. In a Mel Filter bank, the spectrum from an FFT is warped along its frequency axis f (in Hz) into the Mel-scale, created to model human perception of sound, using triangular overlapping windows [6] using the formula:

$$f_{mel} = 1127\, ln(1 + \frac{f}{700}),$$

where f denotes the physical frequency in Hz, and f_{mel} denotes the perceived frequency [6].

A common frequency domain representation of sound signals – particularly in the analysis of human speech - used as an alternative to the FFT is a set of Mel Frequency Cepstral Coefficients (MFCCs), due to the Mel frequency scale being a good non-linear model of the frequency response of the human auditory system. Given a discrete set of N FFT coefficients $\{X[1], X[2], \ldots, X[N]\}$, these are then passed through a Mel filter bank :

$$Y[m] = \sum_{k=1}^{N} \mathrm{W}_m[k]|X[k]|^2 ,$$

for $0 \le k \le N$, $0 \le m \le M$, where k is the FFT bin number, m is the Mel-filter bank number, and the $\mathrm{W}_m[k]$ are weighting functions. The logarithm of each of these Mel frequency components is then taken to reduce the dynamic range [6], and finally a Discrete Cosine Transform (DCT) is applied, resulting in the MFCCs:

$$c(n) = \sum_{m=0}^{M-1} \log_{10}(Y(m))\cos\left(\frac{\pi\, n(m-0.5)}{M}\right)$$

for $0 \le n \le \mathrm{C}-1$ and $0 \le m \le M-1$. This gives a set of M MFCCs for a set of N sound samples centred on some particular time t. The MFCC values can be plotted as "intensity" values (or darkness of shading, or false colour) on a frequency against time grid to give a Mel spectrogram, showing how the frequency content of the sound signal changes over time.

4 STUDIES ON DETECTING "QUEENLESSNESS" AND PREDICTING SWARMS OF EUROPEAN HONEYBEES

As mentioned in section 1 above, the death or other loss of a healthy queen bee or the bees swarming are major events in the life of a honeybee colony of great concern to beekeepers, and prompt detection of the former and reliable and timely prediction of the latter would be of major benefit. Although many of the results of our investigations on these have already been published elsewhere, [7, 8] we will summarize them here for completeness.

4.1 Detecting Queenlessness in Beehives

Acoustic data recorded from four beehives, two of which had their queens intact throughout the 7 days of the experiment, but the queen bees were removed from the other two hives around noon on the third day, were provided by Arnia Ltd. The sound signals were sampled at 44 kHz. In addition to visual inspection of signal waveforms, spectra, and spectrograms, we employed various machine learning techniques to investigate differences between the signals from the "Queen Less" (QL) and "Queen Present" (QP) hives, and whether these could be used to reliably identify a hive as QL or QR solely from analysis of the sound signals produced by its bees [7]. Our results showed that whilst Logistic Regression and both Multi-Layer Perceptron (MLP) and Long Short-Term Memory (LSTM) neural network classifiers could give satisfactory success rates for identifying sound samples as coming from QL or QP hives, the best classification performance for this task was obtained using a Convolutional Neural Network (CNN) applied to MFCC spectrograms of the sound samples.

Classification Method	Logistic Regression	Multi-Layer Perceptron NN	LSTM Neural Network	Convolutional Neural Network
Mean Accuracy in Application	84 %	88 %	91 %	99 %

Table 1 : Classification Performance Accuracy (Correctly classified examples as fraction of all examples considered) for each classifier tested on the QP/QL sound data from hives of European honeybees. (Data from [7].)

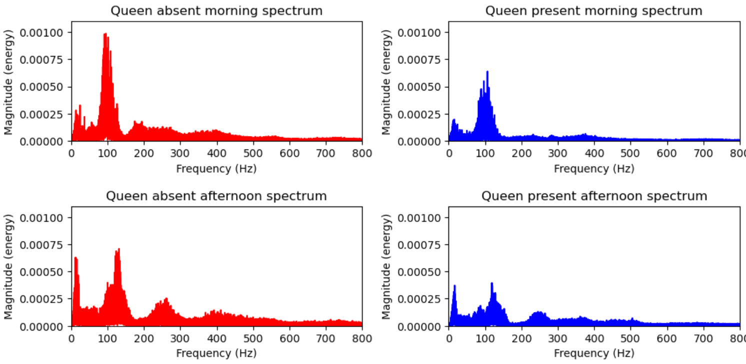

Figure 3 : Example spectra from European honeybee hives with Queen Present or Queen Absent, as indicated. The spectra were obtained from sound files in the very early morning or very early afternoon respectively. Note that there would probably be rather more bees in the hives during the very early morning, which may explain the difference in amplitudes for the morning and afternoon spectra. (From [7].)

4.2 Predicting Swarms from Beehives

In a similar manner to the Queenlessness study described above, we also investigated the possibility of prediction the occurrence of a swarm of bees from a hive several days, or even weeks, in advance of the event. Acoustic data recorded both from several hives which did eventually produce a swarm, and several which did not, on various occasions over several weeks, were provided by Arnia Ltd. A Convolutional Network (CNN) was trained for each of Short-Time Fourier Transform (STFT) and MFCC-based spectograms to classify whether bees from a hive would or would not eventually swarm.

Acoustic data recorded from non-swarming hives, and from hives 7, 14, 21 and 28 days before a swarm occurred was processed and the resulting spectrograms classified as “Going to swarm” or “Non-swarming” by our CNN models. All cases gave very encouraging results (see Table B below).

	Days Before Swarm	3	7	14	21	28
Mean Accuracy	STFT	98.5 %	99.5 %	99.0 %	97.9 %	90.9%
	MFCC	99.6 %	99.8%	98.6 %	95.1 %	89.6 %

Table 2 : Classification performance accuracy for “Going to swarm” or “Non-swarming” based on hive acoustic data (from [8]).

Although both FFT and MFCC spectrograms gave excellent prediction success rates of a hive swarming in the future – even as much as 28 days beforehand – the MFCC approach worked slightly better closer to the date of the swarm, but the FFT-based method was marginally superior at dates longer before the swarm occurred. The small dip in prediction performance very close to the swarm date may be due to less data being available for the “3 days before” situation. An interesting point to note is that our methods give very good prediction success rate (greater than 89%) even as long as 28 days before the eventual swarm, despite the eggs which subsequently develop into new queens only being laid approximately 16 days before a swarm tends to occur. This suggests that the worker bees decide that the circumstances are appropriate to rear new queens several days before the necessary eggs are laid by the old queen.

Example sound spectra from one hive which later swarmed and one which did not swarm are shown in Figure 4 below.

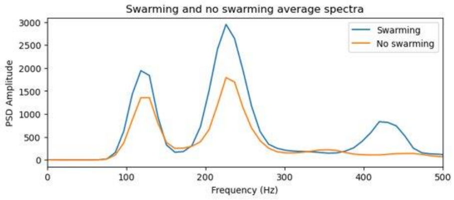

Figure 4 : Spectra from a European hive which (7 days) later produced a swarm and from a hive (with the Queen present) which did not go on to swarm, recorded under the same conditions. Although the first two spectral peaks are at very similar frequencies for both hives, marked differences can be observed between the third spectral peaks for the two hives.

5 ACOUSTICS OF EUROPEAN AND AFRICAN HONEYBEES.

African honeybees have, to date, apparently been more resilient to the problems affecting their European and North American cousins, although reliable data on the former has been rather limited. The African domesticated honeybees (Apis mellifera adansonii, Apis mellifera capiensis and Apis mellifera scutellata) are of different sub-species to the European (Apis mellifera carnica and Apis mellifera ligustica) honeybees and we believed that a comparison of the acoustic properties of their typical sounds could be useful in advance of performing further research. The data on European honeybees was the same as used in the studies described in section 4 of this paper and in [7, 8]. However, the data on African honeybees was provided by Agsenze Ltd from recordings made using a 1 kHz sampling rate of bees in Ghana (West Africa) and South Africa or 16 kHz (Kenya). The bees monitored in Ghana were Apis mellifera adansonii but those in Kenya and South Africa were Apis mellifera scutellata. Note that the Kenyan bees were monitored in flight by sensors located on tree trunks, rather than in-hive.

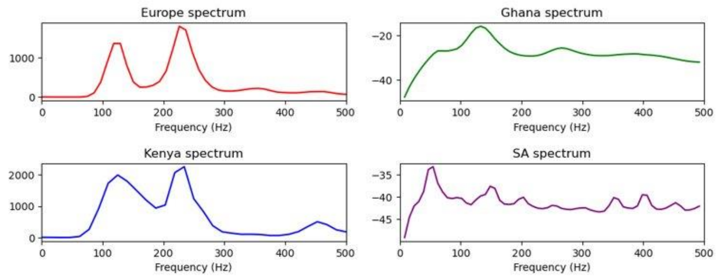

Figure 5 : Example spectra of European (Queen Present, non-swarming), West African (Ghana), South African and East African (Kenya) honeybees. The Kenyan bees were recorded in flight, all the others inside a hive.

The distributions of each peak for each locations varied considerably, with the South African data being particularly non-Normally distributed. The high standard deviations of peak frequencies in some of the datasets also made more detailed analysis somewhat impractical. The South African spectra also all showed a spurious peak around 50 Hz, which was believed to be an artefact due to "mains hum" from an electricity power supply.

Location	Europe	Kenya	South Africa	Ghana
Mean (SD) - First Spectral Peak (Hz)	129.2 (15.2)	128.6 (18.2)	156.4 (55.8)	125.4 (13.2)
Mean (SD) - Second Spectral Peak (Hz)	226.1 (31.2)	238.8 (23.8)	246.1 (83.5)	261.7 (35.6)
Mean (SD) - Third Spectral Peak (Hz)	398.4 (49.8)	466.1 (29.5)	348.6 (90.1)	377.9 (47.4)

Table 3 : Means (and Standard Deviations) in Hz of the first, second and third spectral peaks for European (non- swarming, Queen Present), East African (Kenya), South African and West African (Ghana) bees.

6 DISCUSSION, CONCLUSIONS AND FUTURE WORK

The results of our studies have shown that methods developed and optimized for use in the processing of human speech are also successful for the processing and analysis of honeybee sounds, notably in detecting when a colony lacks a queen bee and predicting that a colony is shortly going to swarm. Our results comparing the sounds of European and African honeybees showed these were quite similar, but high standard deviations in the peak frequencies (particularly in the South African data) made further in-depth analysis difficult. Better quality data would be necessary if, for example, one wanted to identify honeybees as being from one particular sub-species of Apis mellifera from their sounds alone.

We hope to extend this work to provide a prediction of when a colony is likely to swarm based on acoustic data, and also to investigate relations between hive sounds and the quantity of honey present in the hive. We also aim to study the acoustics of other pollinator insects, and possibly pests and predators, in the future.

7 ACKNOWLEDGMENTS

This research was partly funded by Innovate UK as part of the Bee Smart project, grant number 45568. The datasets were provided by Arnia Ltd. and Agsenze Ltd. Stenford Ruvinga is grateful to the Graduate School of Kingston University for awarding him a Postgraduate Research Studentship enabling him to work on this project. We would all like to thank Arnia Ltd and Agsenze Ltd for making their data available for us to use, Raymond Kwabena Shaker of Nature Development Ghana for facilitating the fieldwork and data collection in Ghana, and to beekeepers John Futcher, Colm Treacy and Stewart Westsmith for providing valuable insights into the life of honeybees.

8 REFERENCES

1. H. Ai, H. Nishino, T. Itoh 'Topographic organization of sensory afferents of Johnston's organ in the honeybee brain', Journal of Comparative Neurology, 502(6), pp 1030-1046, https://doi.org/10.1002/cne.21341 (2007)

2. R. Boys 'Listen to the Bees', available on-line https://beedata.com.mirror.hiveeyes.org/data2/listen/listenbees.htm (1999)

3. J.H. Hunt, F.-J. Richard 'Intracolony vibroacoustic communication in social insects', Insectes Sociaux, 60(4), http://dx.doi.org/10.1007/s00040-013-0311-9 , (2013)

4. Ai, H. 'Vibration-Processing Interneurons in the Honeybee Brain', Frontiers in Systems Neuroscience, 3(19), https://dx.doi.org/10.3389/neuro.06.019.2009 (2010)

5. J.N. Holmes, W.J. Holmes, 'Speech Synthesis and Recognition' (2nd edition), Taylor & Francis, London, pp 33-46, 160-164 (2001)

6. H. Shimodaira, S. Rennals, 'Speech Signal Analysis', Available online: https://www.inf.ed.ac.uk/teaching/courses/asr/2012-13/asr02-signal-4up.pdf (2013)

7. S. Ruvinga, G. Hunter, O. Duran, J-C Nebel, 'Identifying Queenlessness in Honeybee Hives from Audio Signals using Machine Learning', Electronics, 12(7), p. 1627 (2023) https://doi.org/10.3390/electronics12071627

8. S. Ruvinga, G. Hunter, J-C Nebel, O. Duran, 'Prediction of Honeybee Swarms Using Audio Signals and Convolutional Neural Networks', Proceedings of the International Workshop on Edge A.I. for Smart Agriculture (EAISA 2022), Biarritz, France, June 2022, doi:10.3233/AISE220032