# SIGNAL PROCESSING THE ACOUSTICS OF HONEYBEES (APIS MELLIFERA) TO IDENTIFY THE "QUEENLESS" STATE IN HIVES

Donald Howard School of Mechanical and Automotive Engineering, Kingston University, U.K.
Olga Duran School of Mechanical and Automotive Engineering, Kingston University, U.K.
Gordon Hunter School of Mathematics, Kingston University, U.K.
Krysztof Stebel Institute of Automatic Control, Silesian University of Technology, Gliwice, Poland

**Abstract** : The honeybee, *Apis Mellifera*, is of vital importance to the agricultural sector across the World, primarily due to it exceptional abilities to pollinate crops. In 2006, honeybee colony numbers in developed countries experienced a dramatic decline, due to a diverse range of factors collectively known as Colony Collapse Disorder. At about the same time, revenue from using bees for pollination purposes surpassed revenue from honey production for the first time. Hive inspection is time consuming, disruptive and stressful to the colony, and can be the cause of accidental queen death. Furthermore, a colony without a queen will die unless a substitute queen is successfully introduced. A non-invasive method of hive monitoring is a therefore desirable objective. In this paper, we propose and investigate some acoustic-based methods, based on spectrographic analysis and inspired by established techniques commonly used in the analysis of human speech, to distinguish the "queenright" (i.e. with a live queen present) and "queenless" states. Namely, we compare the spectrograms, FFT and S-transform of the audio recordings. In order to assess the different methods, the results of the frequency analysis are classified using a Kohonen Self-Organising Map (SOM) artificial neural network, which is a useful tool for clustering and visualisation of high dimensional data into a lower dimension space. We evaluate our approach using acoustic data recorded from real beehives, under controlled conditions, over the course of a week, kindly provided by Arnia Ltd, a company specialising in beehive monitoring equipment.

## 1 INTRODUCTION

The honey bee (*Apis Mellifera*) is of crucial value to the agricultural industry across the world. In addition to commercial production of honey for human consumption, bees play an essential part in the cultivation of many grain and fruit crops due to their role in pollinating the plants. It is roughly estimated that one third of all crops grown for human consumption are pollinated by honeybees, although the numbers differ regionally and according to crop. In the US, for example, 100% of Almond pollination, and 90% of Apple and Blueberry pollination, is done by honeybees [1]. This is worth billions of pounds/dollars worldwide, and experts have speculated that agriculture would not be sustainable should bees become extinct. This has become a genuine concern over recent years, due to the serious decline in honey bee numbers in many countries, which has been at least in part attributed to infestation of hives by the Varroa mite (*Varroa Destructor*) and the recently much publicised use of pesticides such as neonicotinoids [2]. Some expert beekeepers claim that they can assess the state of well-being of the bees in a hive, including determining factors such as whether the hive contains a queen, by the sounds produced by the bees in it. There has been a large amount of research dedicated to bees' dance language [3], the social behaviour of bees and identification of the neural component of swarm intelligence [4]. However, little research has been conducted in the field of acoustics, signal processing and use of artificial intelligence to assess the state of well-being of the bees in a hive and hence identify problems early. The first scientific study to address the actual acoustic monitoring of bees would appear to be by Ferrari et al in 2008 [5]. The principal method used in their work was the use of Power Spectral Density (PSD) and spectrograms, although the temperature was monitored as well. The results of the investigation revealed significant acoustic characteristics in the immanent lead up to a swarming event. Bencsik et al [6] used Spectrograms to study the acoustic data, making use of Principal Components Analysis (PCA) and Eigenspectra to identify the sounds. One interesting and unusual aspect of their work was the use of accelerometers in place of microphones to gather their acoustic/vibration data. This paper proposes to investigate the use of acoustic data by employing Fourier-based signal processing and statistical pattern recognition and classification techniques to study sounds recorded in hives of known status. The techniques used are analogous to methods of proven value in the analysis of human speech and in the classification of other types of sounds. The remaining of the paper is organised as follows. Section 2 summarises the different communication aspects of bees. Section 3 describes the S transform and Self-Organising Map techniques that are used in this work. Section 4 describes the experiments conducted. Conclusions are drawn in Section 5.

# 2 THE COMMUNICATION SIGNALS OF BEES

Bees communicate by at least two distinct mechanisms; chemolfactory communication is effected by the use of pheromones, and oscillatory communication by the use of vibration signals. Moreover, there are two types of vibrations signal honeybees use, which are distinguished in this paper as *seismic* and *acoustic*. Table 1 summarises the different phenomena in bee communication using vibrations and the corresponding frequency ranges and typical durations [7, 8].

Table 1 : The communication signals of bees

| SIGNAL | TYPE | FREQUENCY | DURATION |
|---|---|---|---|
| **Queen Piping** - produced by rapid contractions of the thoratic muscles, and transmitted directly to the substratum. The wings do not vibrate? (or vibrate closed in a scissors motion (Rex Boys)). | seismic? | 400Hz? 340Hz | 1.250s |
| **Queen Quacking** - response by unhatched queens to hatched virgin queen. | seismic? | slightly lower than 400Hz or 450Hz | <200ms |
| **Freezing response** - a response by worker bees to queen piping, and possibly other signals. | seismic | | |
| **Worker Piping** - wings together (in swarms) / reminiscent of a racing car / frequency modulation / rise in fundamental freq from 100-200Hz to 200-250Hz. running / 30-60 pipes/bee/min presses thorax against substrate (often another bee), pulls wings together tightly over abdomen, arches abdomen, activates wing muscles (thoracic muscles) to produce seismic vibration. | seismic? | 100-200Hz<br>200-2000Hz (including harmonics) | 0.2-2s<br>or<br>0.82±0.43s |
| **Worker Piping** - wings apart (in hives) / reminiscent of a bleating sheep / no modulation<br>walking / 1-15 pipes/bee/min | seismic | 300-400Hz | 0.2-2s |
| **Waggle Dance** / Dance language - Dorsoventral vibrations of the wings + tail wagging occurring in short pulses at ≈ 15Hz.<br>tail wagging is infrasonic + perhaps tactile. | acoustic/ dance | 200-300Hz<br>13-15Hz (infrasonic tail wagging) | |
| **Round Dance** - like the waggle dance, but for food that is close to the hive | acoustic/ dance | | |
| **Tremble Dance** - used to recruit more bees for the task of unloading foragers, and to reduce the recruitment of more forager bees, acting as a negative feedback which counterbalances the positive feedback of the dance language. (Kirchner, 1993) | acoustic/ dance | | |
| **Stop Signal / Begging signal** | seismic | 300-400Hz (350Hz mean) | 0.05-0.2s |
| **Buzz Running** - performed whilst running, during build up to swarm exodus (from hive & swarm ball?). | acoustic<br>seismic<br>tactile | 190-220Hz | |
| **Vibration Signal / Shaking signal** - one bee grasps another and shakes this bee's body. A worker rapidly vibrates her body dorsoventrally (up and down - from back to belly) for 1-2s, usually while grasping a recipient with her legs. (Schneider and Lewis, 2003) | seismic/ tactile | 16-18Hz | 1-2s |

It has been suggested that a so-called "warble" in the range 225-285Hz [9] is the sound of main interest when trying to assess the health of the hive. It seems that 2 or 3 weeks leading up to a swarming event, the sound in that range would increase in volume. Swarming, like queenlessness, is something that beekeepers generally want to prevent, because the remaining colony is depleted of both honey and bees. The warble was noted to decrease in amplitude when the queen was inactive, and a lower frequency "moaning" would occur if the hive had no live queen [9]. Other than this, the "queenright" (i.e. when a live queen is present) sound is described as harmonious whereas the queenless (when no live queen is present) sound is described as discordant.

# 3 METHODOLOGY

## 3.1 S-transform

In the work described in this paper much use has been made of the Stockwell or S-transform (ST) [10], of which the main advantage is good resolution in both the time and frequency domains. Its main disadvantage is hunger for computer memory resources. This time-frequency transform decomposes signals into their spectrum in both frequency and time dimensions, with good resolution in both time and frequency. Its use permits the utilization of information contained in transients, with the advantages of being able to analyze the signals in real time. The ST was introduced as an alternative to the STFT for localization of time-frequency spectra. The ST gives time and frequency information, as does the STFT, but it uses a variable window length that provides information at different resolutions, such as is the case of the Wavelet Transform (WT). The ST can be derived from the WT by modifying the phase of the window function or mother wavelet. Given a time-dependent signal, x(t), the ST can be derived from the product of the signal and a phase correction function exp($-i2\pi f t$), where $i^2 = -1$.

The S-transform of $x(t)$ is defined as:

$$S(\tau,f)=\int_{-\infty}^{\infty} x(t)\, g(t) e^{-i2\pi f t} dt \qquad (1)$$

where $g(t)$ is the Gaussian modulation function, defined as:

$$g(t)=\frac{|f|}{k\sqrt{2\pi}} e^{-\frac{(\tau-t)^2 f^2}{2k^2}} \qquad (2)$$

The expression becomes:

$$S(\tau,f)=\int_{-\infty}^{\infty} x(t)\frac{|f|}{k\sqrt{2\pi}} e^{-\frac{(\tau-t)^2 f^2}{2k^2}} e^{-i2\pi f t} dt \qquad (3)$$

The discrete version of (3) is calculated, taking advantage of the efficiency of the fast Fourier transform. The discrete Fourier transform of the time series $h(kT) = x(t)$, where $(1/T)$ is the sampling frequency, is obtained as:

$$H\left[\frac{n}{NT}\right]=\frac{1}{N}\sum_{k=0}^{N-1} h(kT) e^{-i\left(\frac{2\pi nk}{N}\right)} \qquad (4)$$

where $n, k = 0,1,\ldots,(N-1)$, and $N$ is the number of samples.
The discrete S-transform is then obtained by setting $f \rightarrow n/NT$ and $\tau \rightarrow jT$:

$$S\left(jT,\frac{n}{NT}\right)=\sum_{m=0}^{N-1} H\left[\frac{m+n}{NT}\right] G(m,n) e^{\frac{i2\pi mj}{N}} \quad \text{for } j, m, n = 0, 1, \ldots, (N-1) \qquad (5)$$

where

$$G(m,n)=e^{-\frac{2\pi^2 m^2 \alpha^2}{n^2}} \qquad (6)$$

The discrete inverse of the S-transform can be obtained as:

$$x(t)=h[kT]=\frac{1}{N}\sum_{n=0}^{N-1}\left\{\sum_{j=0}^{N-1} S\left(jT,\frac{n}{NT}\right)\right\} e^{i2\pi nk} \qquad (7)$$

The output from ST analysis is a complex matrix whose rows and columns represent frequency and time, respectively. Each column represents the local spectrum at a particular time. Frequency-time contours with the same amplitude spectrum are also obtained. This information is used in our experiments to detect and characterize salient events in the bee sounds.

## 3.2 Self-Organising Maps (SOMs)

The self-organising map (SOM) [11] is a method to represent large amounts of high dimensional data in a space of much lower dimension and less complexity as a topological map. The SOM may be used for data visualisation, clustering, classification and many other applications. The SOM consists of a regular low-dimensionality (usually 2D) grid, each node of which is associated with a

weight vector $\{m_i\}$ (also called the prototype or codebook vector) with the same dimension as that of the data. The map nodes (or units) are connected to adjacent ones by a neighbourhood relation. Each map unit may then be considered as having two sets of coordinates: the weight vectors (in the input space) and the position within the map (in the output space). The SOM is trained iteratively by a two-layered neural network. The method used for SOM training resembles the k-means clustering algorithm [12]: at each training stage, data is presented to the network and the map unit whose weight is closest to each the input vector (the "best-matching unit", BMU) is updated and modified towards the input values. The distinction is that, for the SOM, not only the weight vector of the BMU is updated, but also those of its topological neighbours on the map. The units in the map become ordered in regions with similar weights, so that like patterns become clustered. One of the first applications of the SOM was to classify human speech sounds in the Finnish language [13].
With the SOM, high dimensionality data are visualised using low-dimensionality display. Further clustering has to be done if quantitative results are to be obtained, such as clustering based on distance matrices (U-matrix) [14]. The U-matrix is a tool to visualise the distances between each map unit and its neighbours. These distances are inversely proportional to the density of the map prototypes. High values in the distance matrix indicate where the cluster borders lie, while local minima in that matrix indicate cluster centres. Local minima in the distance matrix may be found and then used as cluster centres of the SOM. The rest of the map units are assigned to the cluster whose centre is closest to each of them.

# 4 EXPERIMENTS & RESULTS

## 4.1 Data Used

The data consists of recordings of four separate hives, of similar size and bearing, made on four channels of an 8-track recording device. Two sub-species of honeybee, Italian (Apis mellifera ligustica - in hives ch1&2) and Slovenian (Apis mellifera carnica - in hives ch7&8) were studied. The control hives (ch2&8) were kept "queenright" (QR) throughout. The recordings started on 3 August 2012 ("day03"). The study hives (ch1&7) had their queens removed at about midday of the second day ("day04"), so became queenless (QL) at that point, see Table 2.

Table 2: Data description

| *Honeybee* | *Hive(ch)* | *day03* | *day04* | *day05* | *day06* | *day07* | *day08* | *day09* |
|---|---|---|---|---|---|---|---|---|
| Italian QR | 01 | QR | QR/QL | QL | QL | QL | QL | QL |
| Italian QL | 02 | QR | QR | QR | QR | QR | QR | QR |
| Slovenian QR | 07 | QR | QR/QL | QL | QL | QL | QL | QL |
| Slovenian QL | 08 | QR | QR | QR | QR | QR | QR | QR |

## 4.2 Spectral Analysis

The first step was to study the FFT and Spectrograms of the data. Figure 1 compares three different transforms of the queenright (QR) and queenless (QL) states. The dotted yellow lines highlight the "warble" band, as described by [9]. The "warble" feature [9] is clearly present in the queenless plots. The S-transform is chosen since, unlike the FFT, it is very effective to identify non-stationary or time-varying events that may occur when the queen is not present in the hive.

## 4.3 SOM Analysis

In this experiment, more quantitative methods were devised to locate the warble signal and determine experimentally the frequency range that provides distinguishable signals for QR and QL, respectively. The idea was to train a number of SOMs with both QR and QL data for a limited frequency range, effectively a frequency window, and then advance that window through the whole frequency range. The resulting maps should show areas of greatest separation between the neurons corresponding to QR and QL for the frequency range where the QL signal is more prominent, see Figure 1.

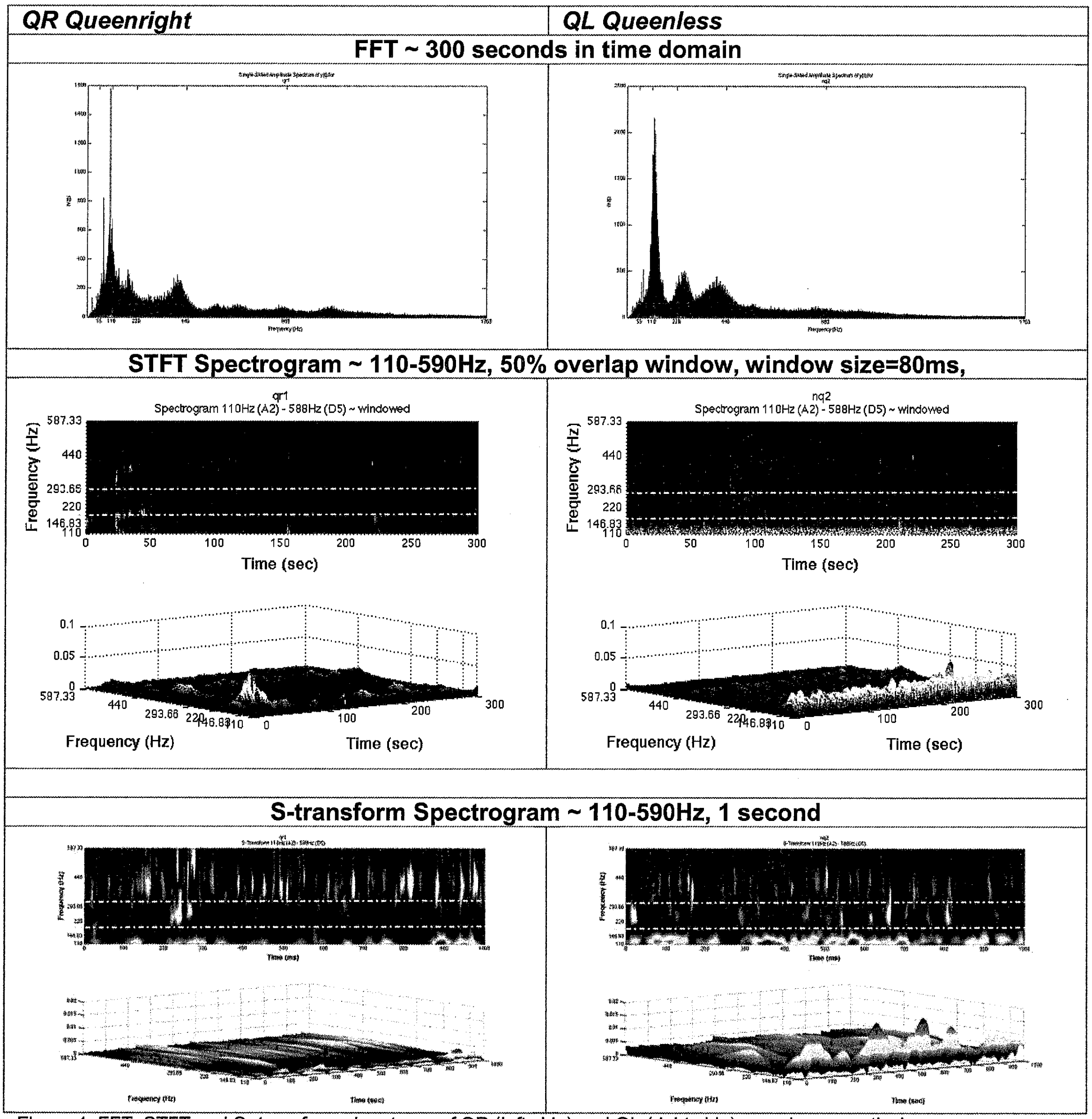


Figure 1: FFT, STFT and S- transform signatures of QR (left side) and QL (right side) sounds, respectively

For each hour of recording, a sample of one minute was taken to reduce the quantity of data. Then each such minute was S-transformed in frequency ranges corresponding to quartertones in the music scale, starting at 27.5Hz (A0) and going up to 880Hz (A5). The formula for incrementing the frequency by a quartertone is to multiply by the $24^{th}$ root of 2, since there are 24 quartertones in each octave. The resulting time-frequency matrices were reduced to a time vector by calculating the Power Spectral Density of each quartertone per sample. The data then consisted of 120 quartertone quantized time series for each hour of each day for each hive. The SOM was trained with various different combinations of QL & QR data, for various frequency ranges. An example is shown in Figure 2 where data from hive ch1 has been used (data from day03 will be queenright, and data from day05 queenless). The frequency range was limited from 220Hz to 440Hz (i.e. 1 octave). The features presented to the SOM were three quartertones. Figure 2 shows iteration $i=1$ which corresponds to the quartertones 220Hz, 226.45Hz & 233.08Hz.

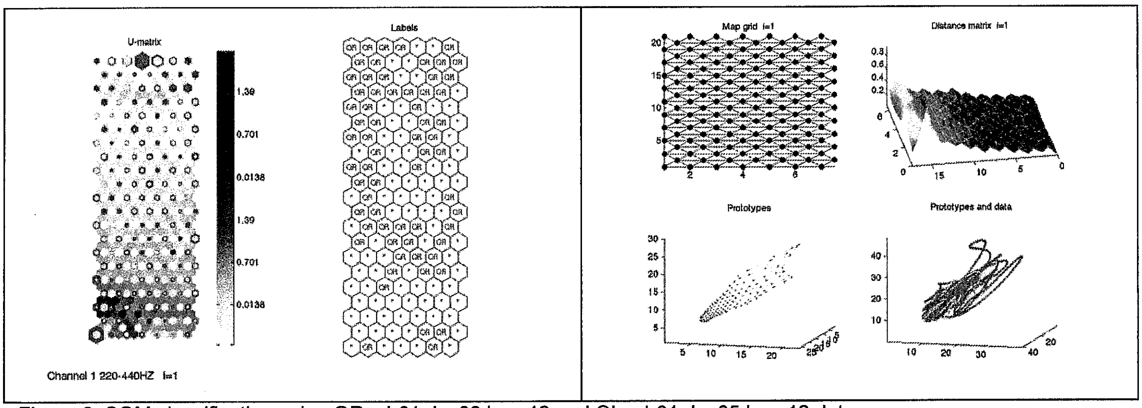

Figure 2: SOM classification using QR=ch01 day03 hour12 and QL=ch01 day05 hour12 data.

In Figure 2, the 'U-matrix' [14] to the left shows no distinct separation between the QR (green) and QL (red) hexagons, and these are almost evenly interspersed. In the 'Labels' there is no distinct separation either. To the right, the 'Map Grid' and subsequent 'Prototypes' map are shown. The 'Distance matrix' displays no signs of separation between the two states. In the 'Prototypes and Data' plot there is some small suggestion of queenlessness being identified by the red loops projecting into the top right hand corner. This might be due to the fact that the QL distinguishable signatures might transients and thus some of the features in the QL and QR might be identical. Thus, our experiment to determine what particular frequency range provided the most appropriate features for the SOM was inconclusive.

## 4.4 Hive Classification using a SOM

In this experiment, two separate SOMs were trained, the first with QL data (QL=ch01 day05 hour12-18) and the second with QR data (ch01 day03 hour12-18). The time range was limited to the afternoon period 12:00-18:00, where the bees displayed the highest levels of activity. Each SOM was then presented with a week's worth of data for each hive from those afternoon hours. Classification errors (i.e. Euclidean distance between each data sample and its best matching unit in the SOM) were computed and plotted in Figure 3. The blue line shows the error from using the QL SOM, so for a queenright hive we expect to see a large error, or the blue line being high. The red line ("danger") is the error from using the QR SOM, so for a queenright hive the error should be small, corresponding to the red line being low. In the event of queenlessness, the lines should swap positions. The difference between the two errors is far less pronounced than expected. The red and blue lines are too similar to each other, and also seem to rise and fall together. A comparison of these errors for hives ch1 and ch2 does indicate that ch1 shows a greater tendency towards what is expected from queenlessness, as seen in the higher red line in the circled regions of Figure 3, than does hive ch2. In the results for hive ch7 there are less convincing signs of queenlessness but, more disturbingly, Figure 3 shows a distinct sign of queenlessness in hive ch8, which should not be the case. However, it should be born in mind that the SOMs were trained with Italian bee data from hive ch1, whereas hive ch8 contains Slovenian bees, so what may be shown here is that the features of the QL state differ slightly for the different sub-species.

Further feature extraction techniques were also examined. Figure 4 shows the Power Spectral Density (PSD) signals extracted from the S-transform corresponding to QR and QL signals, respectively. It is only through the strong peaks that the red curve demonstrates the QL feature. During the training of the SOM, there are simply too many similarities between the QR and QL signals for the SOM to distinguish between them on the basis of the features currently presented to it. We are therefore investigating ways to filter the amplitude domain, possibly using some form of discretisation. The use of histogram analysis has also shown some promise (Figure 4). Finally, some sort of processing in the time domain is desirable to extract the duration and frequency of the "chirps" clearly present in this data. With a more extensive set of quality features extracted from the data, there is greater likelihood that the SOM will become a more successful classifier of hive status.

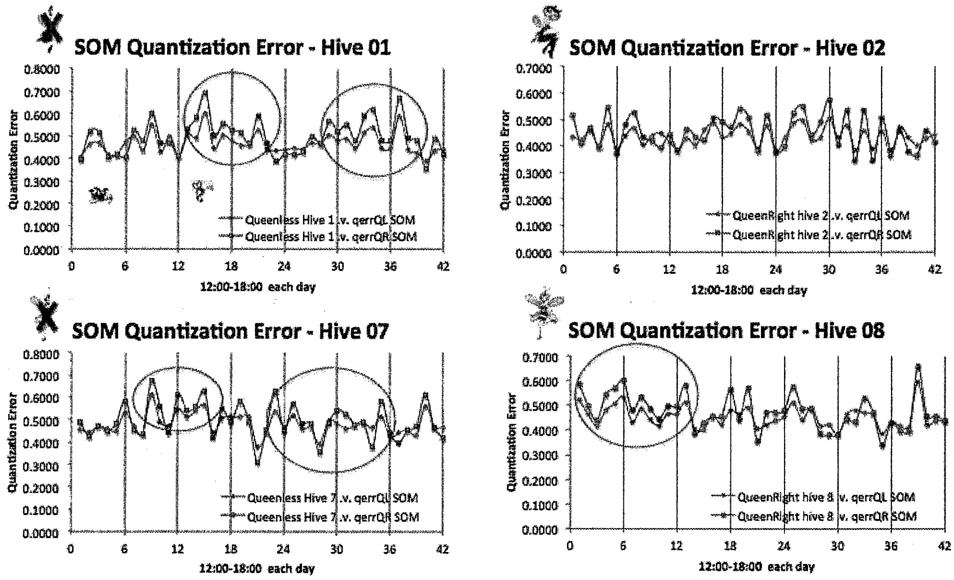


Figure 3: Classification results. High blue line, low red line => QR = good => hive inspection unnecessary.
Low blue line, high red line => QL = bad => hive inspection recommended.

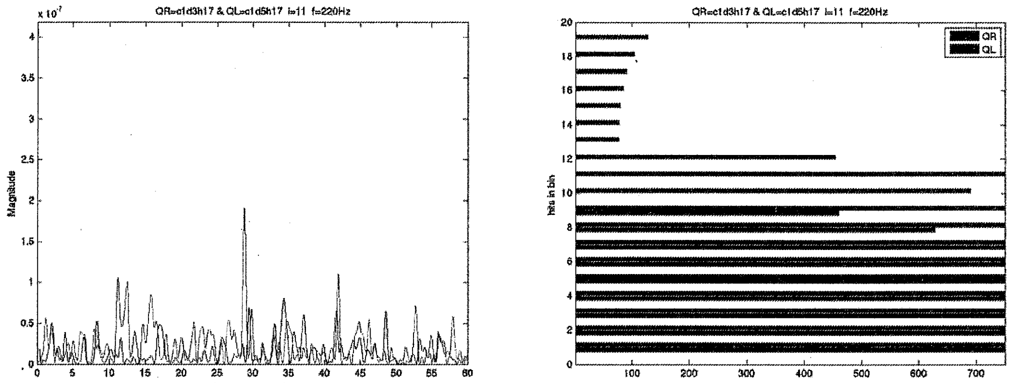


Figure 4 : PSD of hive ch1 on day 3 (blue QR) & day 5 (red QL). Queenlessness is suggested by high peaks in the red curve. The histogram on the right shows the different distributions of the peaks heights found in the red and blue curves respectively, with only the red curve showing higher amplitude peaks.

# 5 CONCLUSIONS

Our results have shown strong corroboration of Woods's "Warble" and Boys' "Moaning" signals [9] in the relatively low frequency ranges for queenless hives. These features can be described as bulges in the frequency spectrum, relative to normal activity, between 165Hz and 285Hz. However, the results from using an SOM to classify the data from different hives have been less successful. Further effort is required to improve the classification method and make it more reliable. Perhaps the optimal set of training data and features have not yet been found. Hives are complicated environments and there may be some undetected problem in one hive or another that is causing misinterpretation of the data. There is a clear difference between the two bee sub-species and, while this is informative, it is also difficult to establish a standard behaviour from this data. Another possibility is human error during the recording and/or processing of the signals. The data is very dense and very regular, with only subtle differences between cases. It is possible that the SOM is simply not sufficiently sensitive to the type of data features being presented to it. If this is the case, ways must be found to extract more appropriate features from the data in order to characterise the data. Many approaches to the automated analysis of human speech have made use of Mel Frequency Cepstral Coefficients (MFCCs) as features [15]. Current work using histogram analysis has also shown some potential. Furthermore, one very simple feature – a simple "chirp" – does appear to distinguish queenless from queenright hives. However, this is not a unique or distinct acoustic signal, and could easily be confused with a hive's intention to swarm.

In data from real hives, the queenless state is not fixed – it changes from hive to hive, day to day and even hour to hour. However, this aspect was not present in the data used in this study and might prove to be a further complication. There may be more direct ways to detect the queenless state – for example, using a chemical sensor to detect the presence or absence of appropriate pheromones. However, use of the acoustic signal still appears to have potential to warn the beekeeper that an inspection of a hive may be necessary, or if certain features are absent in the signal, then the costly and potentially harmful inspection can be forgone.

# 6 REFERENCES


[1] Barrionuevo, A., 2007. Honeybees Vanish, Leaving Keepers in Peril. *The New York Times*, 27 February.

[2] Morelle, R., 2013, Neonicotinoid pesticides 'damage brains of bees', [Online] http://www.bbc.co.uk/news/science-environment-21958547 , 27 March 2013

[3] Frisch, K.v., 1993. *The Dance Language and Orientation of Bees*. 2nd ed. Harvard University Press, Cambridge, Massachusetts, USA. First published in 1886.

[4] Seeley, T.D., 2010. *Honeybee Democracy*. Princeton: Princeton University Press.

[5] Ferrari, S., Silva, M., Guarino, M. & Berckmans, D., 2008. Monitoring of swarming sounds in bee hives for early detection of the swarming period. *Computers and Electronics in Agriculture*, 64, pp.72-77.

[6] Bencsik, M. et al., 2011. Identification of the honey bee swarming process by analysing the time course of hive vibrations. *Computers and Electronics in Agriculture*, 76, pp.44-50.

[7] Kirchner, W.H. & Dreller, C., 1993. Acoustical signals in the dance language of the giant honeybee, Apis dorsata. *Behavioral Ecology and Sociobiology*, 33, pp.67-72.

[8] Seeley, T.D., 1995. *The Wisdom of the Hive*, Harvard University Press, Cambridge, Massachusetts, USA.

[9] Boys, R., 1999. *Listen to the Bees*. [Online] Available at: http://www.beedata.com/data2/listen/listenbees.htm [Accessed June 2012].

[10] Stockwell, RG, L Mansinha, and RP Lowe, 1996. Localization of the complex spectrum: the S transform, *IEEE Transactions on Signal Processing* 44 (4), pp 998-1001.

[11] Kohonen, T., 1995, *Self-Organizing Maps*. Springer Series in Information Sciences, Berlin, Heidelberg. (Third Extended Edition, 2001)

[12] Hartigan, J.A. and Wong, M.A., 1979, Algorithm AS 136: A k-means clustering algorithm. *Applied Statistics*, 28(1):100–108

[13] Kohonen, T., 1988, The "Neural" Phonetic Typewriter, *IEEE Computer*, 21, pp 11-22

[14] Vesanto, J. and Sulkava, M., 2002, Distance matrix based clustering of the self-organizing map. In Jos R Dorronsoro, editor, *International Conference on Artificial Neural Networks (ICANN)*, Madrid, Spain, August 2002, Lecture Notes in Computer Science, volume 2415, pp 951-956, Springer

[15] Holmes, J. and Holmes, W., 2001, *Speech Synthesis & Recoginition* (2nd Edition), Taylor & Francis, London.