

Paper SAS4509-2020

Noninvasive Beehive Monitoring through Acoustic Data Using SAS® Event Stream Processing and SAS® Viya® Yuwei Liao, Anya McGuirk, Byron Biggs, Arin Chaudhuri, Allen Langlois, and Vince Deters, SAS Institute Inc.

ABSTRACT

Honey bees are critical pollinators; their demise would probably be disastrous for human beings. Thus, maintaining healthy bee colonies is vitally important. Beekeepers usually monitor the status of beehives by performing manual examinations in order to check whether the queen bee is missing or to look for any other potential problems. But not only are manual hive inspections time-consuming, they are also disruptive to the colony. Research in computational bioacoustics has discovered connections between the sounds in the hive and different behaviors of bees. Yet, to date, no automatic acoustic monitoring system has been completely successful. Acoustic data from beehives are messy. With many thousands of bees performing an array of time-varying tasks, and with external sounds from birds, crickets, cars, trains, and other sources, it is difficult to make the link between sound recorded in a beehive and hive health. This paper shares our progress in developing a bioacoustic monitoring system. Along the way, we illustrate the usefulness of the digital signal processing tools and machine learning algorithms available in SAS® Event Stream Processing software and SAS® Viya® to noninvasively monitor the real-time condition of a beehive. The technical aspects of the acoustic monitoring system described here are part of a larger effort at SAS to monitor the four beehives at the Cary, North Carolina, campus headquarters with many different sensors.

INTRODUCTION

According to the United States Department of Agriculture, one out of every four bites of food depends on bee pollination, and the US Geological Survey states that 75% of the fruits, nuts, and vegetables produced in the US are pollinated by bees. Although these statistics include bees of all sorts, honey bees (*Apis mellifera*) play a significant role especially in the pollination of almonds, lemons, apples, okra, papayas, and watermelons. Thus, maintaining healthy honey bee colonies is of vital importance.

Maintaining healthy colonies seems to be getting harder and harder. Losses of bee colonies are at record levels. In the winter of 2018–2019, 37.7% of US beehives were lost, and annual losses exceeded 40% (Bee Informed Partnership 2019). Most of these losses have been attributed to nutrition problems, unplanned queen events, and perhaps most important, the presence of a mite, *Varroa destructor*, that has led to a plethora of bee viruses and weakened bees that are unable to handle external toxins (Cauble 2019). It is likely that many of these winter deaths could be reduced by a better and more timely understanding of what is happening in the colonies, and this understanding would naturally lead to more effective and efficient hive management.

Beekeepers usually monitor the status of their colonies by manual examination, in order to check whether the queen bee is failing or missing and to look for other potential health problems. But manual hive inspections are time-consuming, and worse yet, they disrupt the

life of the colony. Because inspections are so disruptive, beekeepers typically examine their hives only every two weeks on average during warm weather and much less often (or never) during the winter. A lot can happen in a hive during a two-week period. Any noninvasive tool that can help beekeepers learn about possible problems in the hive, *when* they happen, will lead to timelier, and hopefully less frequent inspections and reduce stress for both the bees and the beekeeper.

As sensor technology has advanced and sensors have become more affordable in recent years, some early-adopter beekeepers have started to use them to better understand what is happening in their hives. A handful of companies have emerged to provide sensors, along with mostly rudimentary analysis of the data the sensors collect. In other cases, beekeepers themselves are improvising to create their own sensors and monitor their hives. Existing systems use sensors to measure hive weight, internal temperature and humidity, and sometimes even the production of gases such as carbon dioxide. These systems are relatively easy to implement, in the sense that the amount of data required in order to understand what is happening in the hive is not overwhelming. More advanced monitoring systems use video cameras and sound recorders to collect image and acoustic data to monitor activity. These systems collect much more data more frequently and require high-performance computing for processing. However, they have the potential to tell us more important information about what is occurring in the hive.

Acoustic studies of honey bees are not new, and they have gained popularity in recent years. A British beekeeper and broadcasting sound engineer, Edward Woods, published his findings from studying the sound of bees in the journal *Nature* in the late 1950s (Woods 1959). He claimed that you could determine whether a colony was about to swarm (that is, reproduce—half the hive leaves with the old queen) or the queen was failing by listening for a **“warble,” or an increase in magnitude at 255 +/- 35 Hz**. Similarly, he noted that you could determine whether the colony was healthy by banging on the hive and listening for a **“hiss” at 3000+ Hz**. Based on his research, Woods patented a device to detect swarms, which was known as the Apidictor. The device was quite large and rather impractical, though it was amazingly complex for its time. But now, with high-performance computing available on very small devices and modern algorithms for digital filters and time-frequency analysis, it is no wonder that research in this area is blossoming. A smart phone app, Apivox Smart Monitor, which was developed in 2013 by Serjio Glebbskij, does essentially what Woods’s Apidictor did (Basic 2016). Although the Apivox was not designed to continuously monitor a hive, it can be a useful tool to assess hive health without the need to open the hive. In 2019, the beta version of another acoustic app, Bee Health Guru, was released to occasionally monitor the health of the hive. This app uses artificial intelligence to analyze a cell phone recording 30 seconds to 1 minute long taken just inside the hive entrance to determine whether the hive has a queen, has *Varroa* mites or small hive beetles, and so on (Bromenshenk et al. 2019). As of the writing of this paper, Bee Health Guru developers are still working on training their models by using the short snippets of data uploaded by beta users across the world and the users’ reports on the health of the hives they have just analyzed, so they can better predict the state of the colony. Many observers are skeptical about whether these objectives can be achieved, but the goal is admirable. Arnia, a hive monitoring company based in England, has also rekindled some of **Woods’s** findings and added acoustic analysis to its beehive sensor offerings (Beng and Evans 2013). Arnia uses acoustic information to look for Woods’s **“warble” and** to monitor flight and fanning activity to assess overall colony strength. Based on its website (Arnia.co.UK), it is clear that the company is still fine-tuning what it can learn from bee acoustics. The growing academic

literature on bee acoustics is part of the same hunt to find out what we can learn by listening to bees.

Where does SAS fit into this picture? SAS has the culture of innovation, the passion, the curiosity, the powerful analytics, the expertise in working with big data—and even the bees! SAS has four beehives at its main campus, in Cary, North Carolina. Together this all amounts to **the “perfect swarm”!** With this realization, the SAS Internet of Things (IoT) Division recently spearheaded an effort to equip the four SAS beehives with sensors to see what SAS analytics can do to help beekeepers in their quest to be more successful in raising healthy bees. In pursuing this effort, we can demonstrate both the power of our IoT analytical capabilities and what kind of company we are.

The purpose of this paper is to share our progress in developing a bioacoustic monitoring system as part of our more extensive real-time hive monitoring effort. Along the way, we illustrate the usefulness of the digital signal processing tools and machine learning algorithms available in SAS Event Stream Processing software and SAS Viya to noninvasively monitor the real-time conditions of a beehive.

OVERVIEW OF BEEHIVE ACOUSTICS

Unlike many other insects, honey bees do not appear to have the ability to make complex sounds. When they make sounds, they are making them with their wings, thoracic muscles, or breathing spiracles (Borst 2019). There are many academic articles that detail the sounds emitted by individual bees.

QUEEN BEE PIPING

The most famous and widely studied bee sound is the piping sound made by the new queens of a colony that has just swarmed. Usually during a primary swarm, the old queen departs with approximately half the worker bees. When the primary swarm has left, the workers raise multiple new queens. The piping sound is composed of two different signals: a tooting signal produced by a queen who has just emerged from her cell, and a quacking signal made by any other queen, typically still confined in her cell, in response to the toot. Upon hearing a quack, the free queen decides either to leave the hive with another swarm of worker bees or to go and kill the competitor. Although much is now known about the behaviors that accompany this piping, the descriptions of the signals have been qualitative and rather diverse (Michelsen et al. 1986).

Because the queen is the reproductive system of a colony—and there is typically only one queen per colony—it is important to know her status, which is critical to the **colony’s** survival. If beekeepers could detect a queen piping in real time, they would know that the bees have swarmed and the colony is attempting to establish a new queen—and might even swarm again.

Interestingly, the Bee Informed Partnership survey (2019), which calculates the staggering US colony loss rates, found that surveyed beekeepers blame 25%–40% of their colony losses on queen failure. If acoustic analysis could alert the beekeepers that something has happened to the queen in a colony right when it happens, the rate of colony loss would be likely to decline significantly.

WORKER PIPING

Researchers have discovered that worker bees also pipe. **Interestingly, “worker piping” has** been reported at many different fundamental frequencies, and the behaviors that

accompany the reported piping vary quite widely. For example, worker piping has been documented when the hive is queenless, when the hive is being invaded by an enemy pest, when workers return from foraging and dance, when the swarm is about to leave the hive, and when workers collide with each other in a crowded hive. Clearly, as pointed out by Hrnčir, Tautz, and Barth (2005), the term “**worker piping**,” as used in the literature, does not describe a distinct signal. As more audio samples are obtained from hives, it will be interesting to find out whether the worker piping signals that have been documented in the literature can be broken down into distinct signals on the basis of signal length and frequency. Tools are now readily available to estimate the length and frequencies of these signals more precisely.

OTHER BEE SOUNDS

Although it will be interesting to learn more about queen and worker piping, individual bee sounds are not the only acoustic information that will contribute to understanding what is happening in the hive. Experienced beekeepers have often said that they can tell whether a colony **is queenless by the general “hum” of the hive**.

A lot goes on in the hive that can affect the overall hum. The queen might or might not be present and, if present, might be laying eggs or not. Nurse bees might be feeding the young (and the queen); other worker bees might be regulating the temperature of the hive; and workers might be drawing honeycomb, gathering and storing food (or eating it), taking off to forage for food and water, dehydrating nectar, and so on. Although a lot is going on at the same time, with sounds probably at many different frequencies, there does seem to be an organized hum that can shed light on the state of the colony. This is best described by Eskov, as quoted by Borst (2019): “The acoustic noise produced by a bee colony is a largely random process . . . (but) its time-frequency structure has a certain degree of orderliness depending on the physiological state of the bees and the ecological situation.”

Certainly, the volume of the sound that the colony emits at different frequencies is likely to provide insight into the different tasks being carried out. Our goal in this part of the project was to see what we could learn from the sounds of the hive. The early work of Woods (Woods 1959; Boys 1999) gave us a logical framework to start from. Before discussing our bee research, it would be useful to give some background on acoustic analysis in general.

TIME-FREQUENCY ANALYSIS OF ACOUSTICS

Sound is produced when something vibrates. The vibrating body causes the medium (water, air, and so on) around it to vibrate. In fluids such as water and air, sound waves propagate as disturbances in the ambient pressure level. Digital sound signals, as represented in the time domain, measure the amplitude of the disturbances at the point in time at which it occurs. This representation of sound, known as a time waveform, is common and relatively easy to understand. However, acoustic signals are more fit for frequency-domain analysis (also called spectral analysis) because the human ear interprets sound by its frequencies. What the human ear senses as “**higher-pitched**” or “**lower-pitched**” sound results from pressure vibrations having a higher or lower number of cycles per second (that is, the frequency). The frequency-domain representation of sound uses “**trigonometric sums**” (sums of harmonically related sines and cosines or periodic complex exponentials) to describe the periodic phenomena within the signal (Oppenheim, Nawab, and Willsky 1997).

One key feature of acoustic signals is nonstationarity, which means that **the signals’ spectral characteristics change over time**. Time-frequency analysis is a commonly used technique in digital signal processing, which analyzes a signal in both the time and frequency domains

simultaneously. Time-frequency analysis estimates the spectral density of a signal over time to see how periodicities of the signal (reflected in the frequency components) change with time.

Figure 1 shows an example of the time-frequency heatmap of a short speech segment in which a **woman's** voice says, "I love bees. Bees are very interesting." **In the frequency** domain, voiced speech and music usually consist of strong magnitudes at the fundamental frequency and its multiples, which are called harmonics. The fundamental frequency is the lowest frequency of any vibrating object and is the frequency at which you hear the sound. Harmonics are the frequency components at the positive-integer multiples of the fundamental frequency. The importance of harmonics is that they help create the sound's unique timbre, which for example makes it possible to distinguish among the sounds of different musical instruments.

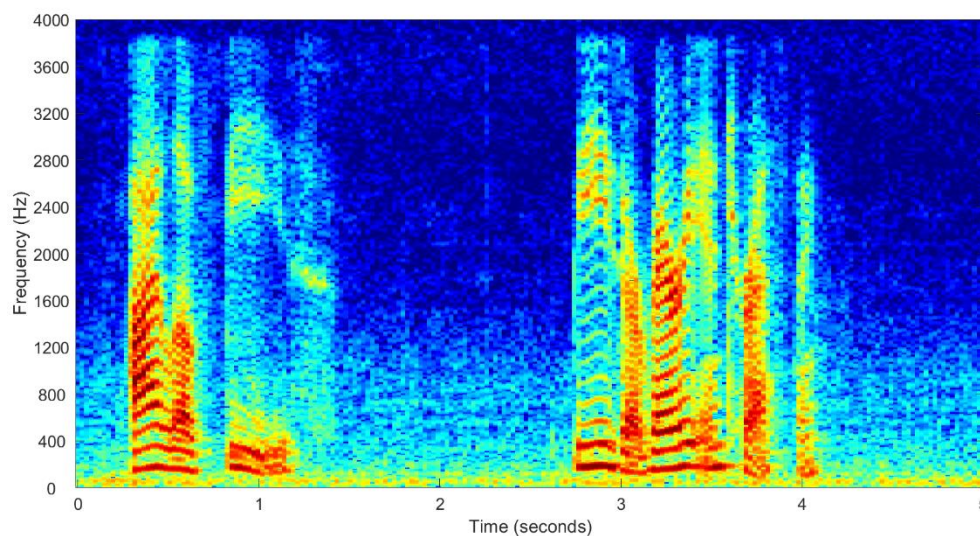


Figure 1. Time-Frequency Heatmap of a Short Speech Segment

There are two main types of spectral estimation methods: nonparametric and parametric. The most commonly used nonparametric technique is the short-time Fourier transform (STFT), which generates the spectrogram of a signal. Popular parametric estimation techniques include Yule-Walker autoregressive model estimation, Burg autoregressive model estimation, and maximum likelihood estimators.

In recent years, the SAS IoT Division has been adding digital signal processing capabilities to SAS products to extend their sensor data analysis capabilities. STFT is now available in both SAS Event Stream Processing and SAS Viya. Yule-Walker autoregressive model estimation is also available in SAS Viya. We illustrate how to apply these techniques to acoustic data recorded at the SAS beehives in the following sections.

DATA COLLECTION

Because of the potential benefits of understanding immediately any change in the status of the queen, we decided to conduct an experiment to understand the dynamics of the colony when a queen is gone. As a first step in our research, we continuously recorded the sounds in a newly made colony (a split) that was purposely made queenless. The new hive had eggs from one to three days old, so the worker bees could make their own queen as soon as they realized they were queenless. The idea was to see just what happens when a colony

becomes queenless; whether we can tell when the bees realize they are queenless; and if so, how long this realization takes.

To conduct the experiment, we used an inexpensive (\$10) single-head lavalier lapel microphone, dropped it into the hive, and recorded continuously by using an EVISTR 16GB digital voice recorder (\$35) for 21 hours (until the battery died). The recording, which was sampled at 48 kHz, had relatively low volume, so we had to amplify it by a factor of 20 during data preprocessing. A brief listen to some of the recordings revealed a lot going on inside and outside the beehive! Not only did we hear individual bees wandering close to the mic and buzzing frantically, but we could also hear airplanes flying over, trains blowing their whistles, sirens wailing, crows cawing, crickets chirping, bullfrogs croaking, and so on.

ACOUSTIC DATA ANALYSIS AND RESULTS

We soon realized that our initial plan—converting the sound waveform to the frequency domain by using a short-time Fourier transform (STFT) to monitor the frequency segments described by Woods—would clearly be futile. Any time-based spectrograms that were obtained would be highly contaminated by outside noise and frantic bees near the mic. If we were to learn anything about the bees from the recordings, we had to remove the random loud noises that told us nothing about the health of the hive from the general hum. A simple digital filter can remove those sounds at frequencies much higher than those we were interested in (fundamental frequencies of interest in the hive tend to be lower than 1000 Hz), but many of the stray noises occur at the frequencies of interest that Woods described.

Others who have conducted acoustic research on bees have faced similar issues. Two published papers reported attempts to solve the problem of segregating bee noise from other noise sources by using machine learning approaches with data that were meticulously labeled by type of sound (Kulyukin, Mukherjee, and Amlathe 2018; Nolasco and Benetos 2018). Unfortunately, they met with limited success. Further, some of the noises that we need to eliminate are bee noises—but very loud bee noises too close to the mic that obscure the general hum of the hive. **If we don't remove these sounds**, our spectrograms will still be contaminated. Thus, these other studies do not provide a realistic solution to our problem. Our own solution to this problem is to use robust principal component analysis (RPCA), currently available in SAS Viya.

ROBUST PRINCIPAL COMPONENT ANALYSIS

Robust principal component analysis (RPCA) is a matrix decomposition method that decomposes an input matrix M into a low-rank matrix L_0 and a sparse matrix S_0 , where $M = L_0 + S_0$. This method is a modification of the widely used statistical procedure of principal component analysis (PCA). What makes RPCA robust is that the principal components are computed from the low-rank matrix and are not affected by outliers that appear in the sparse matrix.

RPCA is used quite extensively in surveillance video to remove the static (typically uninteresting) background from the moving foreground, which appears in the sparse matrix. As we demonstrate later, RPCA applied to the STFT spectrograms is quite successful in separating the background and foreground sound. Thus, it is an essential element in our noninvasive monitoring of the beehive.

GENERAL BEEHIVE HEALTH MONITORING

To separate the hum of the hive from the other irregular sounds both inside and outside the hive, we apply RPCA to the matrix of magnitudes obtained from the STFT output for a sound segment of fixed length (usually a few minutes). RPCA decomposes this matrix of magnitudes into a low-rank matrix and a sparse matrix. The resulting low-rank and sparse magnitude matrices, combined with phase information in the original STFT output, are converted back to the time domain by using an inverse fast Fourier transform (IFFT) to retrieve the background sound and foreground sound.

Our exploratory analysis using RPCA in SAS Viya can be summarized as follows:

1. Convert each 10-minute WAV file to a SAS data set (21 hours of data in total).
2. Apply STFT to each sound segment:
 - a. Use the CAS action `timeFrequency.stft`.
 - b. Action parameters: Rectangular window, window length = FFT length = 16384, window duration = 341.3 milliseconds
3. Perform RPCA on the matrix of magnitudes output by STFT.
 - a. Construct the STFT output magnitude matrix M :
 - i. Each column of M consists of the magnitude of the STFT output from one window of sound signal.
 - ii. Magnitude is calculated as $\sqrt{coeff_re^2 + coeff_im^2}$, where $coeff_re$ and $coeff_im$ are the imaginary and real parts of the STFT output.
 - b. Run RPCA with the parameter $\text{Lambda} = 0.009$.
 - i. Low-rank and sparse matrices are generated.
 - ii. Plot the low-rank and sparse magnitude matrices (in dB) as heatmaps.
4. Perform IFFT to obtain the different sounds associated with the low-rank and sparse matrices. The FFT length for the IFFT operation is the same as in step 2b.
 - a. Calculate the phase matrix to be associated with the low-rank and sparse matrices.
 - i. Assume that the phase **doesn't change** from the original STFT output during the decomposition.
 - ii. Calculate the phase as $\tan^{-1} \frac{coeff_im}{coeff_re}$, where $coeff_im$ and $coeff_re$ are the imaginary and real parts of the STFT output.
 - b. Calculate the following variables:
 - i. $Re_Sparse = \text{sparse magnitude} * \cos(\text{phase})$
 - ii. $Im_Sparse = \text{sparse magnitude} * \sin(\text{phase})$
 - c. Perform IFFT on each column constructed as $Re_Sparse + Im_Sparse * i$.
 - d. The foreground sound signal can be constructed as the concatenation of the real part of the IFFT output from each column.
 - e. Repeat for low-rank matrix to obtain background sound.

- Convert both the foreground and background signals from the SAS data set to *.wav files and listen.

We analyzed both 3- and 10-minute sound segments and got similar results. The results in Figure 2 are from using 10-minute sound segments. To illustrate the nature of our results, we show two 1-minute segments from two different 10-minute segments in Figure 2 and Figure 3. Each figure shows the original STFT magnitude and the RPCA-decomposed results in the low-rank and sparse matrices. Note that the color scales in all three heatmaps within a figure are identical and are displayed in decibels ($20\log_{10}(\text{Magnitude})$).

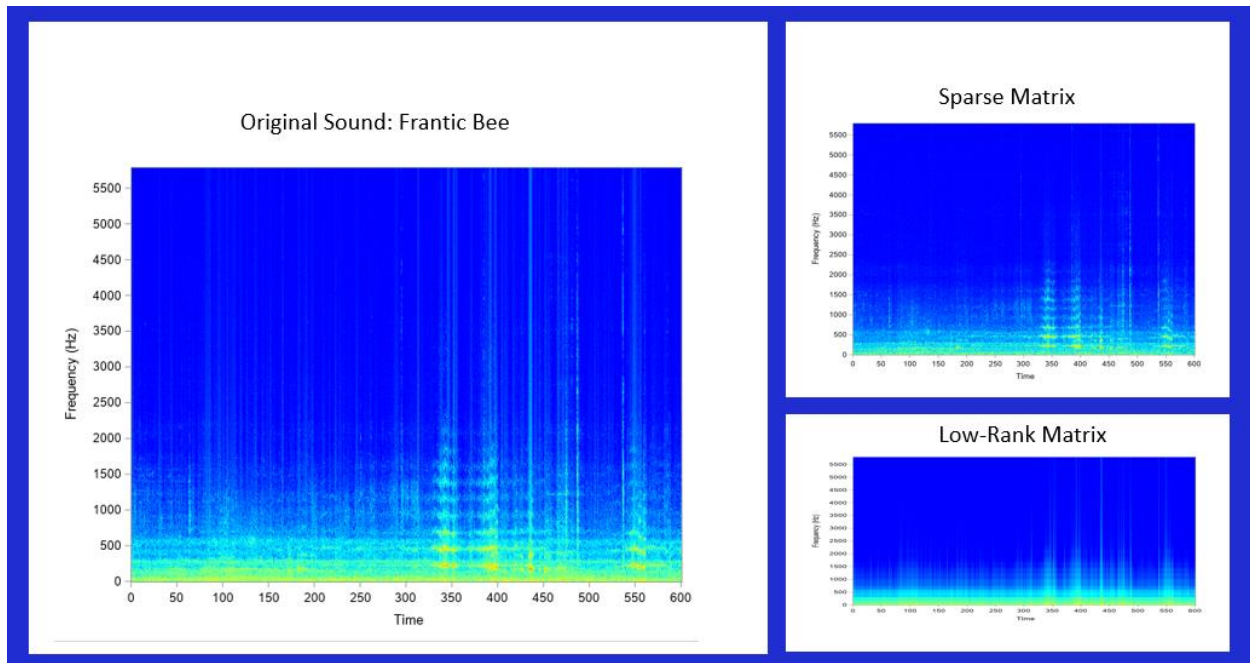


Figure 2. RPCA Results for Frantic Bee

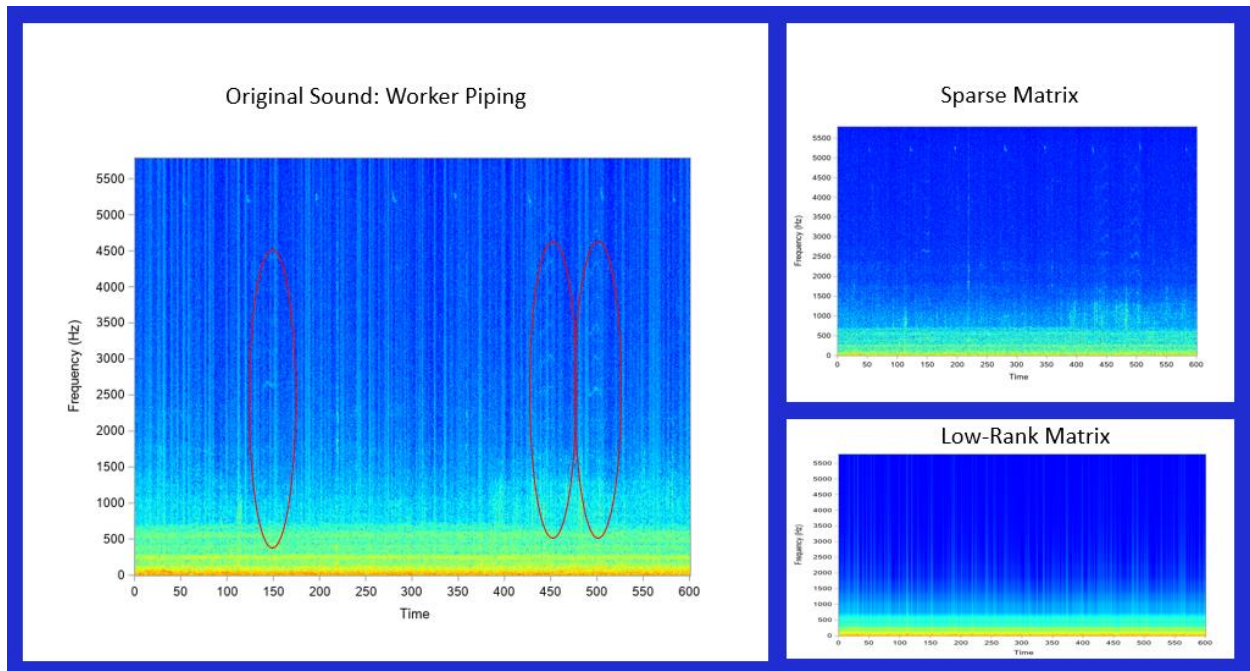


Figure 3. RPCA Results from Worker Piping

As you can see in Figure 2 and Figure 3, the low-rank matrix contains little evidence of the random noises that were obscuring the general hum of the hive. After studying the low-rank matrices from many different sound segments, we concluded that the low-rank matrix gives a reasonable approximation of this hum. As you would expect, the low-rank results describing the hum were relatively consistent over each 10-minute period. Consequently, we summarize the hum of the hive by calculating the median magnitude for each frequency bin over the 10-minute period.

To summarize the hum of the hive over the 21-hour period after the queenless split was made, we convert the median magnitude to decibels and show the resulting heatmap in Figure 4. This figure illustrates some interesting changes throughout the day (and night). The first finding is the obvious increased noise starting around 5:30 p.m. and settling down as sunset (8:20 p.m.) approaches and the worker bees come home for the night. Woods observed that workers fly at a frequency of 250 Hz, so it is likely that some of the increased activity (in the range of 200–270 Hz) is due to the workers returning. There is increased noise at much higher frequencies as well—maybe the word is spreading about the queenless state! The other obvious finding is the initial quieting at night and the resuming of activity as the sun rises (6:20 a.m.). From Figure 4 alone, it is difficult to know when the workers realize that they have no queen. There are some relatively subtle changes in volume in the hours after the split, but it is difficult to understand their cause and whether they have anything to do with the new queenless state of the colony. Perhaps when we have the equivalent data for many similar days of this colony with a functioning queen, we can see whether the hum observed here is different.

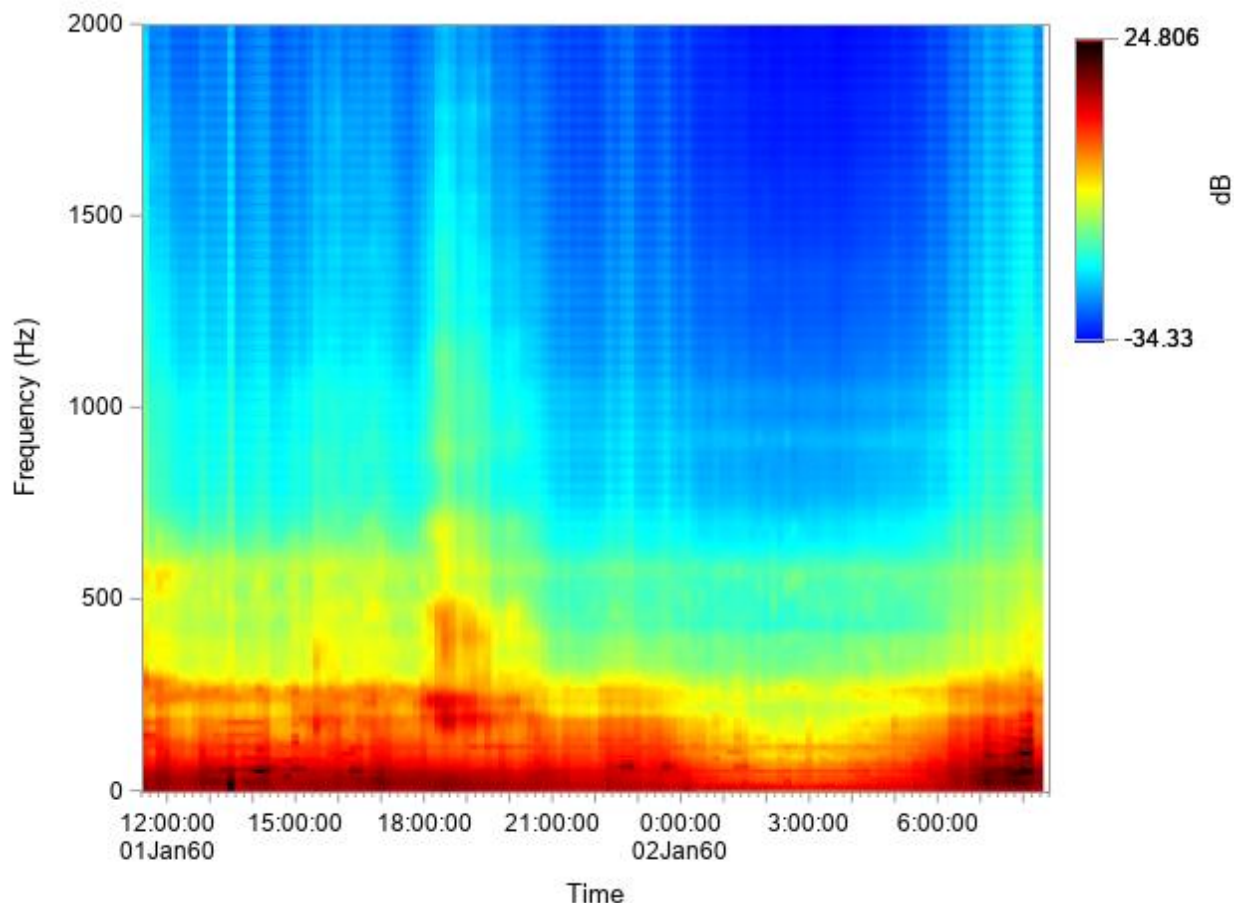


Figure 4. Low-Rank Matrix (Median over Each 10-Minute Segment) across the 21-Hour Recording Time

We discovered something quite interesting by looking through the sparse matrix heatmaps and then listening to the respective foreground sounds. Thirty minutes after the split occurred, we heard a (faint) worker piping that sounds just like a virgin queen toot—the frequency range and length of the worker piping that we hear (408–451 Hz, 1.5–1.6 sec.) are very close to the frequency range and length of the first syllable of a recording we obtained of a virgin queen tooting (408–470 Hz, 1.4–1.7 sec.; for more information, see the discussion of queen piping that follows). For the next five hours of the recording, we heard multiple pipings. How well we could hear the piping and how well we could identify the fundamental signal varied significantly throughout the recordings; some were very faint. Many of the piping sounds were found by first locating the distinct harmonics at higher frequencies, where there was much less noise from other sources. Figure 3 presents a good example of how distinct the harmonics were for the worker pipings that we observed despite the faint sound; the pipings in this one-minute segment are circled in red. The first piping was almost completely inaudible; the last piping was the most obvious, though it too was faint. Given that our mic was not placed centrally in the hive and that worker bees are much smaller than the queen, it is not surprising that the worker piping is not as loud as typical recordings of queen piping. However, the similarity of the sound characteristics to those of a virgin queen piping is unmistakable. We can only speculate, but it seems that the workers

might be calling to see whether a queen is anywhere around, just as the virgin queen does when she first emerges; a nonresponse probably indicates no queen.

Figure 5 displays the low-rank heatmap overlaid with a line graph that summarizes the number of instances of “easily” identifiable worker piping in each 10-minute period (right-hand-side axis).¹ You can see that most of the piping sounds—more than 70%—happen within the first 2.5 hours and that the worker piping stops altogether 6 hours after the split occurred. At this point, all hope of finding a queen must have been completely lost. There is some increased noise at 175–275 Hz after the piping slows to a halt, as well as some subtler increases at 500 Hz and higher frequencies. This could be due to the realization that the workers are now queenless, but we cannot definitively know from this experiment.

Two conclusions can be drawn from the results of this experiment. First, RPCA is a very useful tool in bee acoustic analysis, and the resulting low-rank matrix seems to summarize nicely the general hum of the hive. Based on this finding, we will implement a streaming bee acoustic monitoring system as outlined in Figure 6. Second, a system to automatically detect either a queen piping or workers piping (at the same frequency as a virgin queen) would be very useful to the beekeeper, who would know within a couple of hours that a significant queen event might have occurred. We propose such a system in the next section.

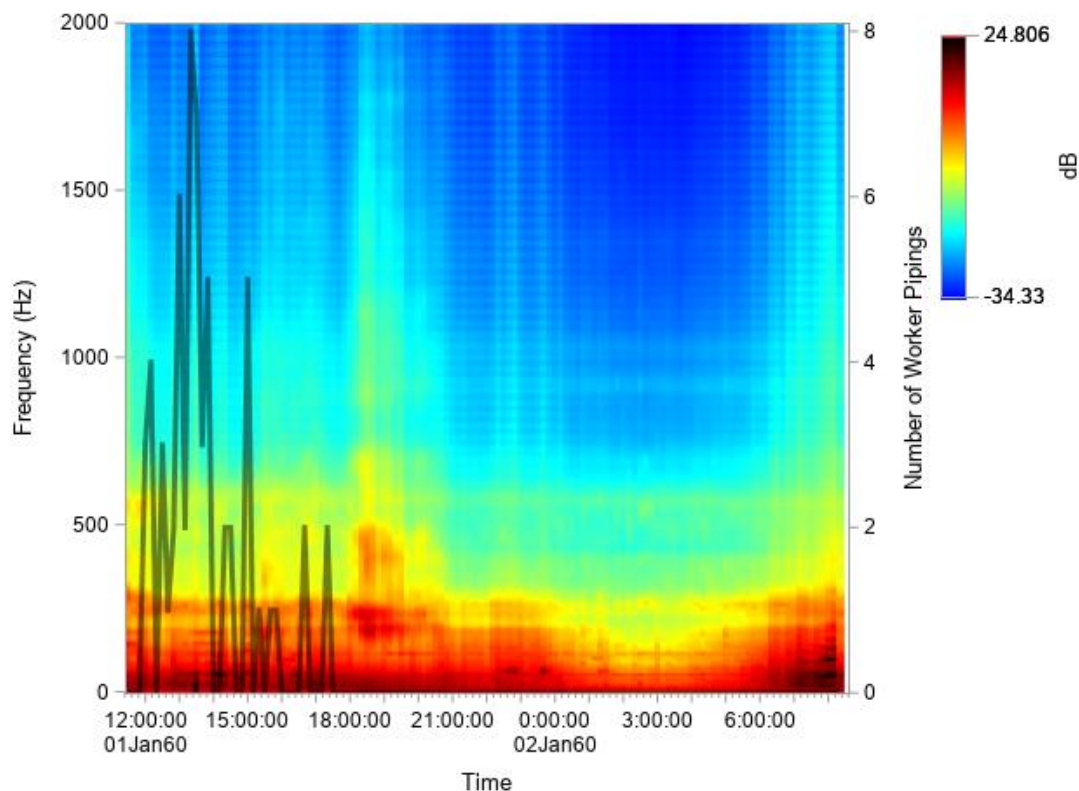


Figure 5. Low-Rank Heatmap with Number of Worker Pippings (Black Line) over Time

¹In some cases, the piping sound was so faint that we could not be sure whether it was worker piping; we counted only (relatively) obvious piping sounds.

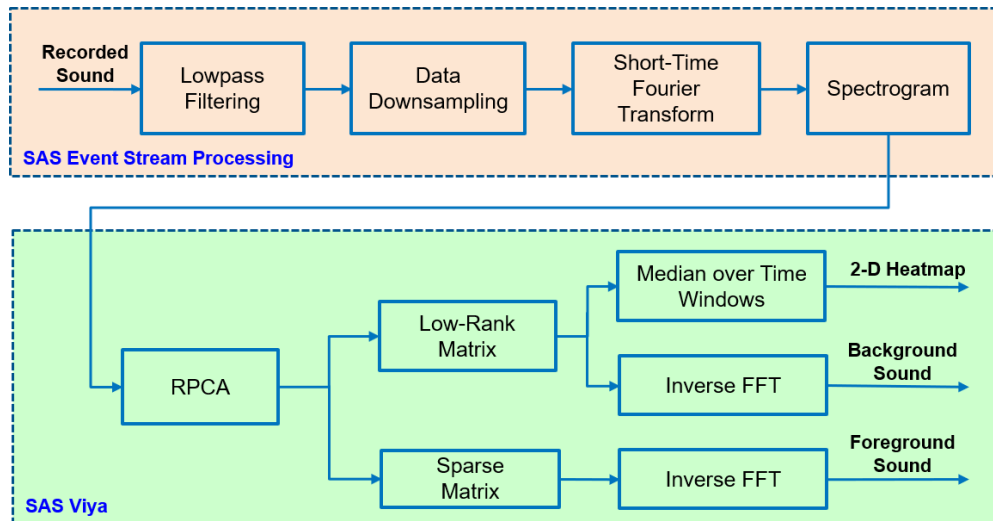


Figure 6. Flow Diagram of General Beehive State Monitoring

DETECTING QUEEN BEE AND WORKER PIPING

Because the spectral characteristics of worker and queen bee piping are similar, we begin by first designing a detection system to find the more obvious queen piping. After this system has been developed, we revisit the worker piping and show how the system also works on these pipings.

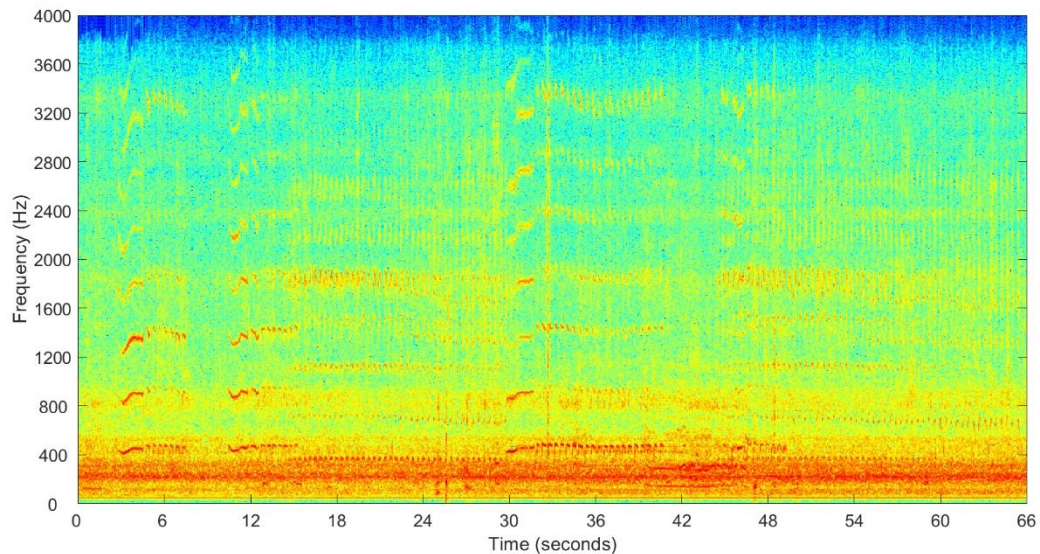
Queen piping (tooting and quacking) is usually much louder than any other sound that bees inside the colony produce (Von Frisch 1965). Both the tooting and quacking are composed of a sequence of pulses that can be distinguished by different fundamental frequencies and different temporal structures (Michelsen et al. 1986). The virgin queen toot starts with one or two pulses of typically 1 second or more in duration and has an initial rise in both amplitude and frequency (Michelsen et al. 1986; Kirchner 1993, 1997). The long pulses are followed by short pulses of about 0.25 seconds (Michelsen et al. 1986; Kirchner 1993, 1997). The quacking sound usually consists of a series of short pulses, each lasting about 0.1 second. There are intervals between pulses of tooting and quacking, and these intervals last about 0.1 second (Michelsen et al. 1986). The voiced speech of a typical human adult male has fundamental frequencies from 85 to 180 Hz, and that of a typical human adult female has fundamental frequencies from 165 to 255 Hz. So at fundamental frequencies of 300–500 Hz, the queen **bee's** piping sound is much higher-pitched than human speech.

As noted earlier, STFT is the most popular nonparametric spectral estimation method of time-frequency analysis of sound data. But FFT-based methods usually generate noisier spectrograms than parametric methods. Given the very noisy nature of our bee data, we explore the use of the (parametric) Yule-Walker autoregressive (AR) model spectral estimation method. The Yule-Walker method assumes that the sound signal can be modeled as the output of an autoregressive filter driven by a white noise sequence. The coefficients of the filter are solved by the Yule-Walker method. When **the filter's coefficients** have been obtained, the frequency response, which is equivalent to the frequency spectral of the sound signal, can be calculated. The only predetermined parameter that is required is the

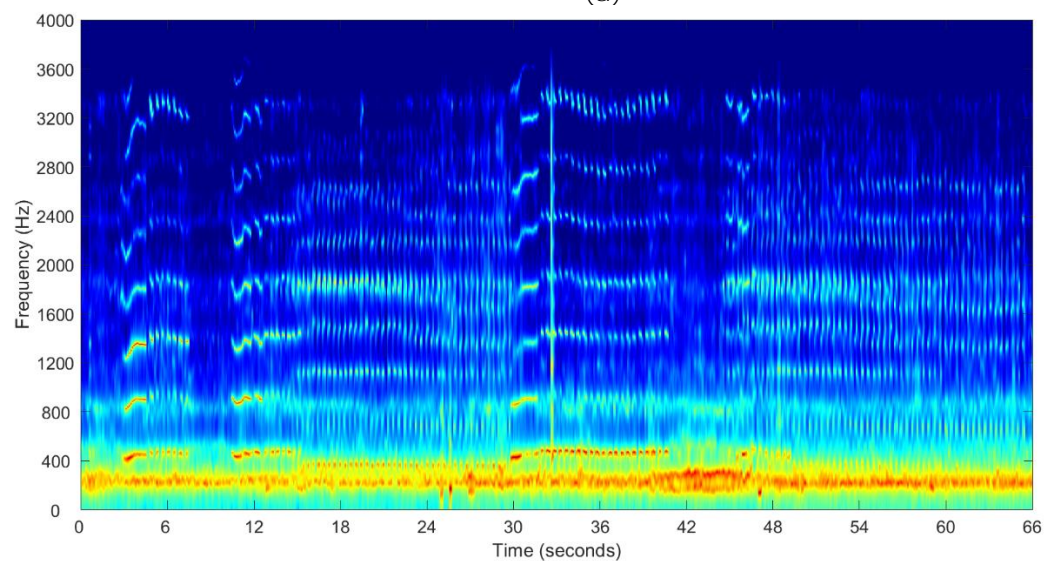
filter's order; here we have set the order to 50 on the basis of experimenting with some of the bee data. An order of 50 works well for all the sound recordings.

Figure 7 compares the time-frequency heatmaps of a queen bee piping that are generated by the nonparametric short-time Fourier transform (STFT) method and by the parametric Yule-Walker autoregressive model estimation method.² Notice how the Yule-Walker method produces a much less noisy spectral heatmap; this should help in detecting the fundamental frequency and harmonics. Thus, we will use this spectral estimation method for our detection system. Further, note that in both heatmaps, the queen piping sound is strong in magnitude at the fundamental frequencies (between 352 and 470 Hz) and harmonics. The fundamental frequencies **of the first queen bee's** tooting (408–470 Hz) are higher than the **second queen's** quacking (352–382 Hz). Finally, notice how the frequency range and variation in the **queen's** first toot syllables are similar to those of the observed worker piping.

²The queen bee piping example used here is downloaded from <https://holybeeexpress.com/2018/03/song-of-the-unborn-virgins/>. Permission for using the data has been granted by Debra Roberts, who recorded and owns the data.



(a)



(b)

Figure 7. Comparison of Time-Frequency Heatmaps for Queen Piping Sound. (a) Short-Time Fourier Transform (STFT), a Nonparametric Method. (b) Yule-Walker Autoregressive Model (AR) Estimation, a Parametric Method.

From Figure 7, it is clear that the magnitudes of the higher-frequency components are much lower than those of the lower-frequency components; this makes the high-frequency harmonics difficult to detect. To compensate for these differences in magnitude, we apply an adaptive magnitude adjustment scheme. We first compute the average magnitude of the spectrum across all time windows, as shown in Figure 8. Then the magnitude adjustment curve is obtained by the inverse of the average magnitude at each frequency, as shown in Figure 9. For each short-time window (that is, each column of the time-frequency

heatmap), the spectral magnitude is adjusted by the magnitude adjustment curve, making the high-frequency harmonics more prominent. Figure 10 shows an example of the frequency spectral curves before and after the magnitude adjustment at the window between 4.20 and 4.35 seconds. The resulting new magnitude-adjusted time-frequency heatmap is shown in Figure 11.

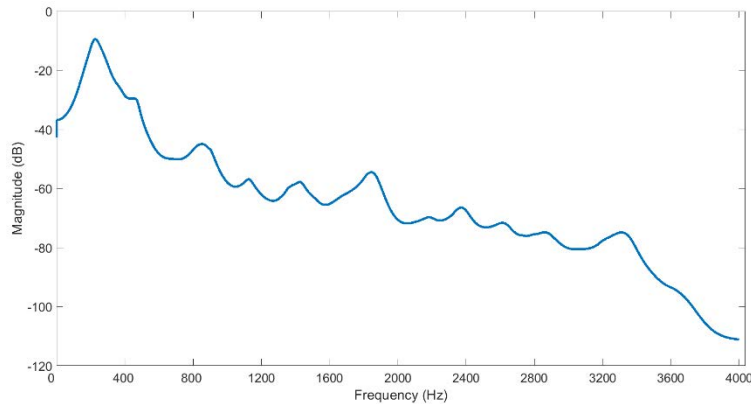


Figure 8. Average Spectral Magnitude across Windows (Queen Piping)

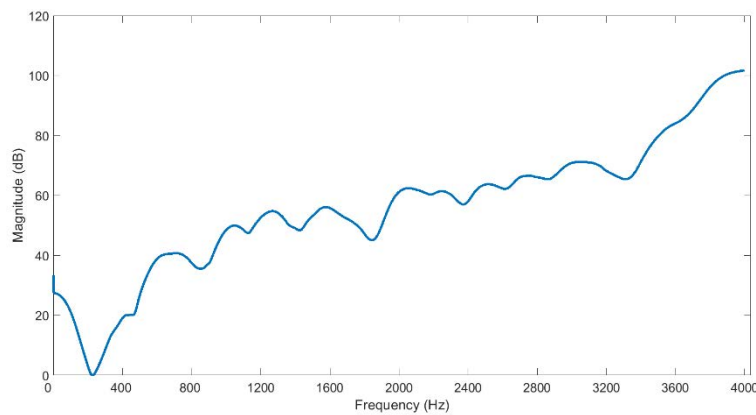


Figure 9. Magnitude Adjustment Curve Based on the Average Spectral Magnitude (Queen Piping)

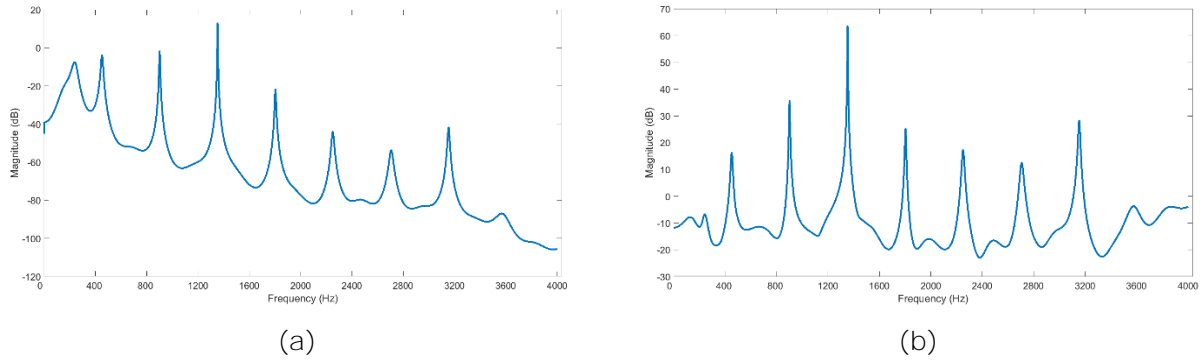


Figure 10. Comparison of Queen Piping Spectral Curves (Time Window 4.20–4.35 Seconds). (a) Before the Magnitude Adjustment. (b) After the Magnitude Adjustment.

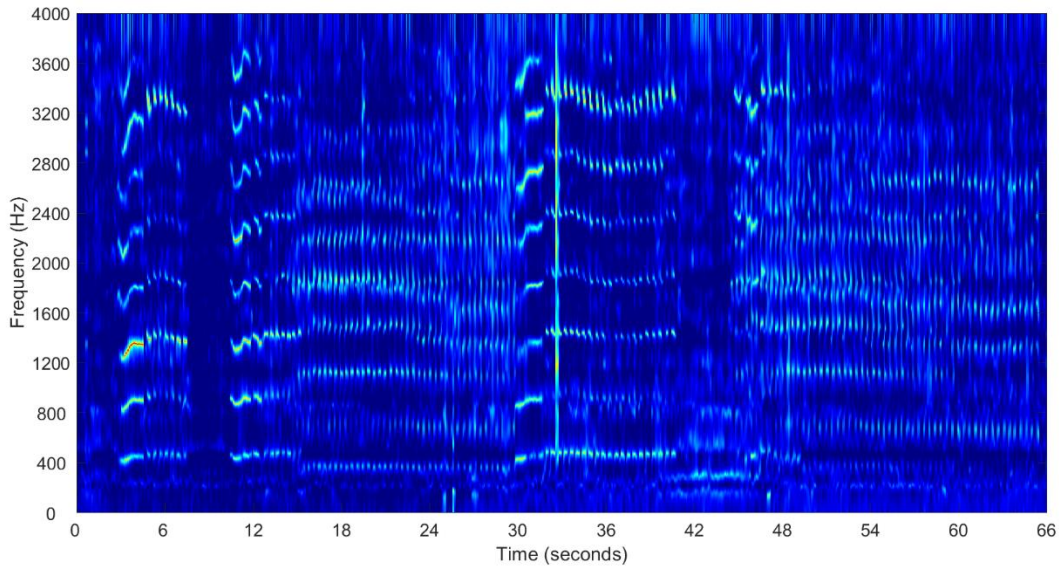


Figure 11. Time-Frequency Heatmap of Queen Piping after Adaptive Magnitude Adjustment

The last step in detecting the fundamental frequency and its harmonics is to use a peak-finder algorithm to find the peak frequency between 300 and 500 Hz and its integer multiples. Figure 12 shows an example of the detected tooting fundamental frequency and its harmonics from the adjusted frequency spectrum at the window between 11.25 and 11.40 seconds. The peak marked with a red cross is within 300–500 Hz and is identified as the fundamental frequency ($f_0 = 441$ Hz). We use linear fitting to find all the peaks, which occur at the integer multiples of the fundamental frequency, as shown in Figure 12(b). In

this example, seven harmonic frequencies are detected. The real test of our proposed piping detection method will be to see whether we can detect any of the fainter worker pipings.

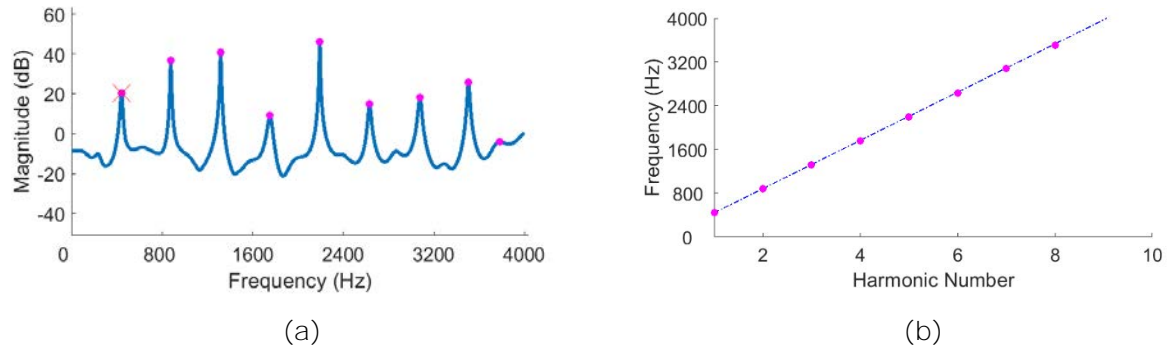


Figure 12. Example of Queen Piping Detection Results (Time Window 11.25–11.40 Seconds). (a) Peaks Detected from the Adjusted Frequency Spectrum. (b) Use of Linear Fitting to Find Harmonics.

WORKER PIPING DETECTION

Earlier we say that the worker piping detected after the creation of the queenless split was similar to that of the first syllable of a virgin queen toot. We also speculate that the worker pipes at this frequency to elicit a response from a queen. A nonresponse would indicate that the colony is queenless. If our intuition is correct, it would be extremely valuable to the beekeeper if we could automatically detect this type of worker piping. Detecting this piping automatically is not likely be easy—the piping was very hard to hear in most instances. Without more experimentation, it is difficult to determine how much of this problem is due to our recording setup and how much is due to the nature of the much smaller (than the queen) worker bee attempting to pipe. The detection task will be challenging, but if we could just detect a couple of the pipings, the beekeeper would know there is a potential issue and would benefit tremendously.

Given the similarity of the spectral characteristics of the worker and queen piping, we can apply the queen piping detection pipeline to find worker piping. In the 21 hours of acoustic data recorded in the SAS beehives, there were many worker pipings (see Figure 5). Figure 13 shows an example of the time-frequency heatmap produced using the Yule-Walker autoregressive model method. The most obvious of the three worker pipings in this 1-

minute segment (the 66th minute) happens at around 50 seconds, in the region circled in red.

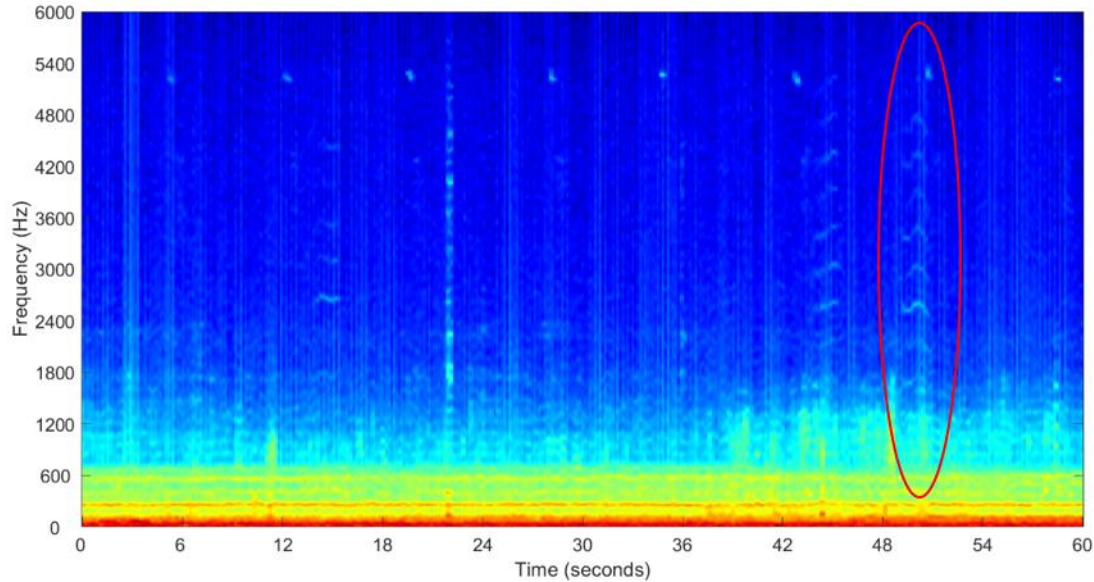


Figure 13. Time-Frequency Heatmap of Worker Piping Sound Using the Yule-Walker Autoregressive Model Estimation Method. (Data are from the 66th minute in the 21-hour recording of the SAS beehives.)

We compute the average magnitude of the spectrum across all windows to obtain the magnitude adjustment curve, as shown in Figure 14 and Figure 15.

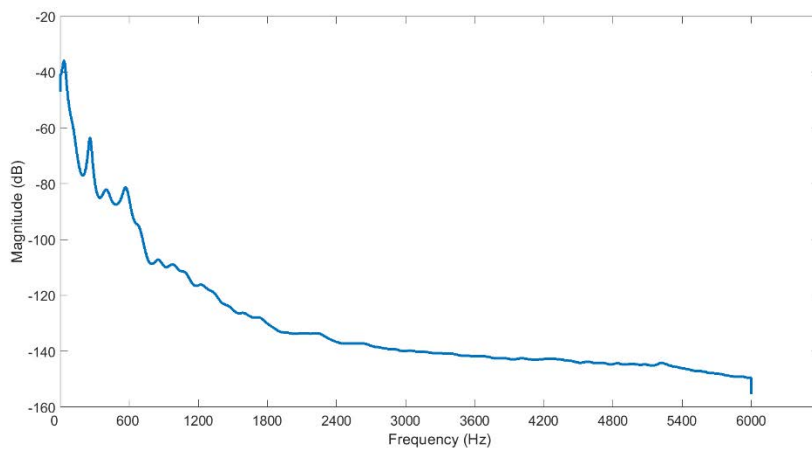


Figure 14. Average Spectral Magnitude across Windows (Worker Piping)

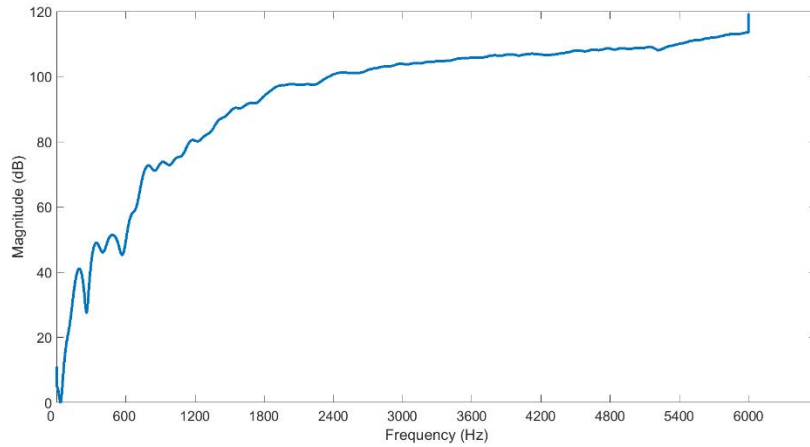


Figure 15. Magnitude-Adjusted Curve Based on the Average Spectral Magnitude (Worker Piping)

Figure 16 shows an example of the frequency spectral curves before and after the magnitude adjustment at the window between 49.50 and 49.80 seconds. The resulting new time-frequency heatmap is shown in Figure 17. The adaptive magnitude adjustment is more helpful in detecting worker piping than queen piping—it makes the high-frequency components stand out much more.

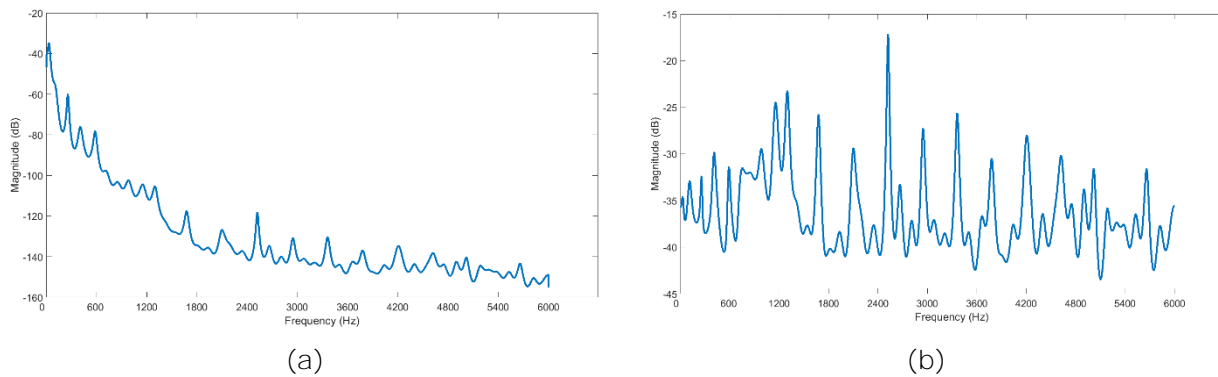


Figure 16. Comparison of Working Piping Spectral Curves (Time Window 49.50–49.80 Seconds). (a) Before the Magnitude Adjustment. (b) After the Magnitude Adjustment.

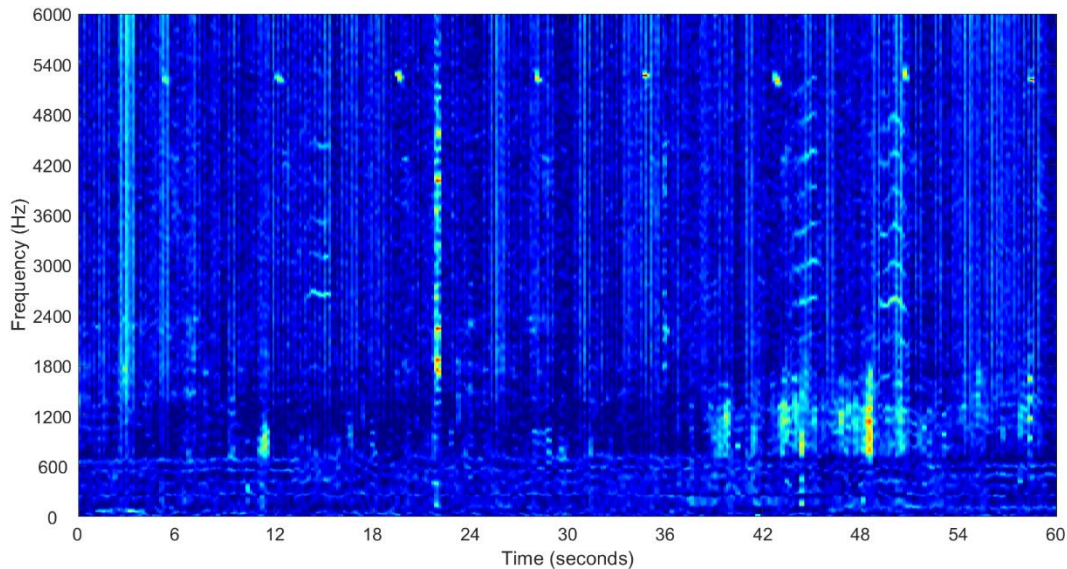


Figure 17. Time-Frequency Heatmap of Working Piping after Adaptive Magnitude Adjustment

Figure 18 shows an example of a detected worker piping fundamental frequency and its harmonics from the adjusted frequency spectrum at the window between 49.65 and 49.95 seconds. The peak marked with a red cross (x) is within 300–500 Hz and is identified as the fundamental frequency ($f_0 = 428$ Hz). We use linear fitting to find all the peaks, which occur at the integer multiples of the fundamental frequency, as shown in Figure 18(b). In this example, nine harmonic frequencies are detected, and it is clear that there is a worker piping. It was challenging to find the two less obvious pipings shown in Figure 17 (at approximately 12 and 45 seconds), because the fundamental frequency was not clearly detectable. Further research will be conducted to address this challenge. Meanwhile, as noted earlier, our algorithm needs to identify only a couple of pipings to alert the beekeeper that a queen event might be happening.

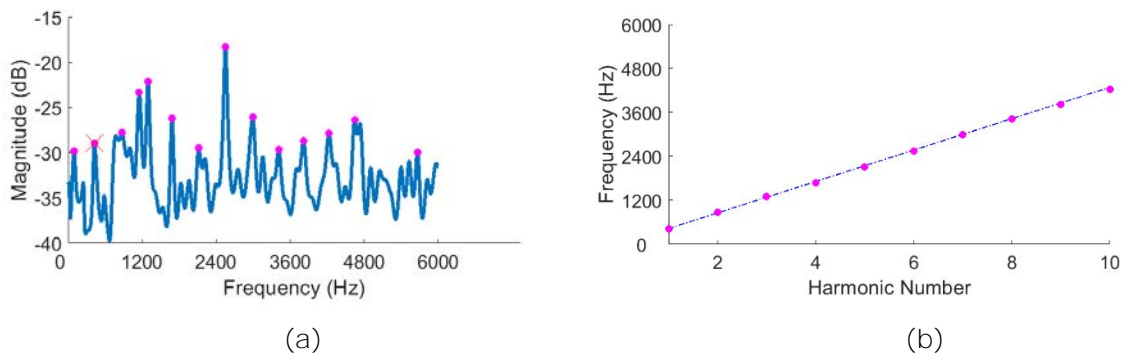


Figure 18. Example of Worker Piping Detection Results (Time Window 49.65–49.95 Seconds). (a) Peaks Detected from the Adjusted Frequency Spectrum. (b) Use of Linear Fitting to Find Harmonics.

Figure 19 illustrates our detection process flow in SAS Event Stream Processing and SAS Viya. The bee sounds are recorded at a sampling rate of 44.1 kHz. Since most of the useful frequency components are within the range of 0 to 6 kHz, an anti-aliasing lowpass filter is applied to the original sound data to remove the high-frequency spectrum, and the data samples are then subsampled to one-quarter of the original sampling rate. The heatmap of the **subsampling signals' time** frequency is produced by the Yule-Walker autoregressive model method. Adaptive magnitude adjustment is applied to each short window, and the peak detection algorithm will find the **piping sound's** fundamental frequencies and their harmonics, as discussed earlier.

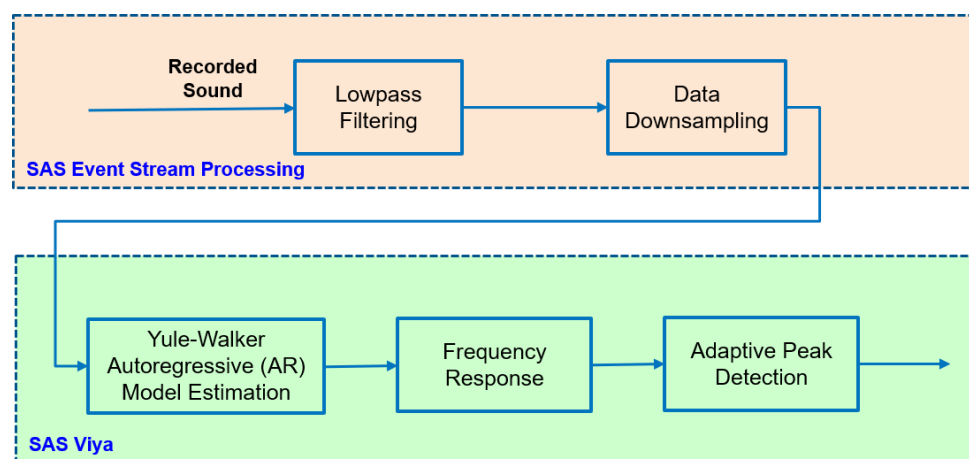


Figure 19. Flow Diagram of Bee Piping Detection

CONCLUSIONS AND FUTURE WORK

This paper shares our progress in developing a noninvasive beehive monitoring system that uses acoustic data. Our main objective is to see what we can learn about the health and happiness of bees by listening to the sounds in the hive. Experienced beekeepers have always claimed that they can open a hive and tell by the sound whether a queen is present, and academic research suggests that we can use hive sounds to determine when a swarm is imminent or a queen is missing, and possibly even understand other hive states.

Based on our initial experimental work, we demonstrate how robust principal component analysis (RPCA), available in SAS Viya, can be used to decompose the matrix of time-frequency results from short-time Fourier transform (STFT) for a given time segment. The resulting low-rank matrix from RPCA provides a relatively clean spectral estimate that characterizes the hum of the hive for that time segment. According to our analysis, the low-rank matrix estimates of the frequency magnitudes over a 10-minute period are relatively stable. Thus, we characterize the hum for each 10-minute segment as the median magnitude of each frequency. We plan to track this 10-minute spectral estimate and various features of it as a data stream in SAS Event Stream Processing. The proposed bee health acoustic monitoring system incorporates digital signal processing tools and machine learning algorithms available in SAS Event Stream Processing and SAS Viya.

We also demonstrate how to convert the results from RPCA (low-rank and sparse matrices) back into sound so that you can investigate these sounds in more detail when an interesting

event occurs in the hive. In our experiment, where we made a colony queenless, we were able to detect worker bees piping at the same frequency range at which a virgin queen pipes after a swarm. We speculated that the workers were calling out to assess whether a queen was present, just as the virgin queen does. Given the importance of the queen in the hive, it is critical for the beekeeper to know as early as possible whether there has been a queen event. We designed an automated pipeline to detect either queen piping following a swarm or worker piping that occurs when the colony is queenless—information that would greatly benefit the beekeeper. This paper outlines the details of this novel pipeline to detect both queen and worker piping by using SAS Event Stream Processing and SAS Viya.

Although the acoustic streaming system has not yet been put into action, we now have a system design and plan to begin implementing the system very soon. The technical aspects of the acoustic monitoring system that are described here are part of a larger effort at SAS to monitor the four beehives at the Cary, North Carolina, campus headquarters with many different sensors. Clearly, hive monitoring is still in its infancy, and there is plenty of room for additional discovery that can help save honey bees—and perhaps, ultimately, help humankind.

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ACKNOWLEDGMENTS

The authors would like to thank Gul Ege, Michael Leonard, Brad Klenz, Seunghyun Kong, Priya Sharma, Ravi Devarajan, Lingxiao Li, and the rest of the Bee Team for all their help and insights on this project.

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