

AUTONOMOUS WILDLIFE SOUNDSCAPE RECORDING STATION USING RASPBERRY PI

Juliette Florentin, Olivier Verlinden

Theoretical Mechanics Dynamics and Vibration, Université de Mons, Place du Parc 20, Mons, Belgium
email: juliette.florentin@umons.ac.be

As acoustic signal processing capabilities progress, it becomes possible to monitor wildlife by recording and analyzing outdoor soundscapes. This is especially true for birds and other vocal animals. The present paper tackles the hardware side and thus describes the components of an autonomous recording station, intended for winter and spring operation in Belgium (forest environment, negative temperatures, rain, snow, wind). The central element of the station is a Raspberry Pi computer, to which the following accessories connect: an external sound card and omnidirectional microphone, a 3G SIM card dongle (to operate the station remotely), a 64 GB memory stick, a Sleepy Pi module (Raspberry Pi power switch) and two 12 V lead acid batteries. The microphone head is protected from humidity and wind and its body is kept warm inside the sealed electronics box. The Raspberry Pi processes the audio stream as it is recorded using GNU Octave. The data is resampled and assessed to save disk space. The Acoustic Complexity Indicator (ACI) supplies a) a daily summary images that show the wildlife acoustic activity on site and b) a selection of interesting sound segments that are saved to disk. The primary challenges are the robustness and the autonomy of the station. For the first item, the Sleepy Pi in combination with proper scripting ensures rebooting of the station in case of failures. For the second item, battery voltage is tracked and power usage rationalized. The recording station was deployed in 2016 in Wallonia to study the local grey-headed woodpecker (*Picus canus*) population. It processed over 400 hours of sound and saved 100 hours. 18% of the recorded segments contained woodpecker drums. We collected 2232 woodpecker drums and were able to observe vocal interactions between *P. canus* and *Dryocopus martius* (black woodpecker).

Keywords: wildlife monitoring, recording station, Raspberry Pi, ecoacoustics, bioacoustics

1. Introduction

Ecoacoustics researchers invest significant time into recording outdoor soundscapes and then searching the recordings for wildlife sounds. Several groups developed their own prototypes of recording stations [1,2,3,4]. In recent years, the use of wildlife recordings as a viable monitoring tool has surged and commercial solutions have sparked to life. The private companies Wildlife Acoustics¹ and Frontier Labs² now sell popular portable recording modules. Despite flexible programming options, these commercial stations are typically used following a standard schedule. They record only a few minutes every hour. This is meant to help with sparing the batteries and controlling the volume of data that will later need to be reviewed. In fact, this sampling of the soundscape is inspired by the actual experience of ornithologists. Most bird counts are performed by listening in for a *total* of three to five minutes at given locations [5]. Ornithologists have long worked around the reduced species detectability that comes with it.

¹ Wildlife Acoustics Inc, Maynard, MA, USA.

² Frontier Labs, Brisbane, Australia.

The commercial stations store soundscapes as recorded. The sampling rate of the recordings depends on the target species; bats in particular require a special design because of their use of the ultrasound range. All further processing, such as the identification of species, is done in the lab after retrieval of the field data.

The present paper documents our experience with building a custom recording station tailored to our needs, which are to detect woodpecker sounds. This continues a study on the identification of European woodpecker species from their drums [6]. The core piece of hardware in our design is a Raspberry Pi computer³. This device is compact, consumes little energy, easily connects to other electronics using USB ports and comes with a Linux OS (Raspbian). Thus, building a station once seemed as simple as connecting a microphone to the Raspberry Pi and powering the set-up. Complications are detailed in the rest of the paper, along with the results from a measurement campaign in 2016.

2. Materials and Methods

2.1 Hardware

2.1.1 General architecture

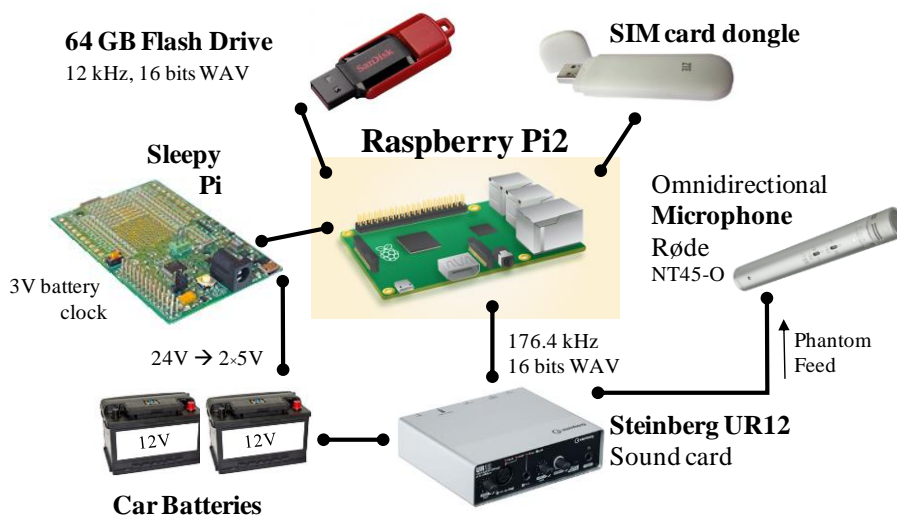


Figure 1: Recording Station Architecture.

Figure 1 shows the general architecture of the station. It uses a Raspberry Pi 2, which draws significantly less current than the Pi 3 (our readings: 4.6 W for the Pi 2, 8.1 W for the Pi 3, with 4 cores running). Its tasks were automated through one main shell script and a few GNU Octave scripts⁴. The main shell script organizes the station's work day and operates the auxiliaries (e.g. start or stop audio recording, move files around). Octave performs the signal processing (e.g. downsampling the signal, calculating indicators); these are the most computational intensive, energy-hungry tasks.

The Pi has no sound card, hence an external module was acquired. The main frequency of woodpecker drumming rolls (D.R.) generally lies below 1500 Hz [6] and the first harmonics of woodpecker calls below 3000 Hz, as observed in samples retrieved from Xeno-Canto⁵. Thus, all target signals should be well-captured with a sampling frequency of 12 kHz. Sound was recorded at a sampling frequency of 176.4 kHz in 2016 (limited by driver issues) and at 44.1 kHz in 2017 (OS upgrade). The encoding uses 32 bits. We set-up recording loops of 10 minutes, followed by immediate downsampling of the data to 12 kHz in Octave. The Pi has 4 processors and thus recording and processing the data can run in parallel. The primary aim of the resampling was to reduce the volume of stored data.

³ The Raspberry Pi Foundation, Cambridge, United Kingdom.

⁴ GNU Octave, version 3.8.2 (2014), <https://www.gnu.org/software/octave/>

⁵ <http://www.xeno-canto.org/>

However, the 64 GB USB drives we used to that end proved largely over-designed. We filled only a few percent of the capacity. The amount of data we needed to store was effectively reduced by calculating the Acoustic Complexity Index (ACI) and using it as a detector of relevant sound events (see Section 2.2). Resampling of the 176.4 kHz data remained critical as a means to downsize the calculation of the ACI, and consequently reduce power consumption.

We selected a single omnidirectional microphone (Røde NT45-O) to record as much as possible of the ambiance surrounding the station. The head of the microphone was tilted so that it would be ideally positioned to capture sounds at 7–15 meters of height, in a group of trees 3–5 meters apart. These considerations are superfluous in theory for omnidirectional microphones, but we anticipated a deterioration of performance at higher frequencies and because of the harsh conditions the microphone would be submitted to. The manufacturer indicates an almost perfect omnidirectionality up to 4000 Hz.

Using a SIM card dongle connecting to one of the USB ports and a program called *gammu*⁶, we had the station send us daily text messages (one in the morning, one in the evening). The texts contained information about how many sound files were recorded and whether the USB card was full. Indirectly, if the text arrived, we knew the station was still operating. This proved to be both essential and the root of a number of problems. First, the dongle is energy-hungry, to the extent that we had to power the sound card independently. Second, the cell phone network, particularly in rural areas, is unreliable. There is no explanation for some of the texts not being delivered to us. Third, there were interferences in the electronics box between the cell phone waves and the external sound card. The resulting noise tainted a large amount of our data. This situation improved by repositioning the dongle further away from the sound card. Finally, the 2016 station did not monitor its battery voltage; the texts therefore lacked a crucial piece of information to manage the battery cycles efficiently. Remote control of the Pi (retrieving log files, sending updated code) is also possible through the cell phone network.

We powered the station using two 12 V car batteries (60 Ah each) in series. Aide et al. [1] used similar equipment. The batteries were connected to the Pi through smartphone car chargers. We added a Sleepy Pi module⁷ to save battery life. The Sleepy Pi is an Arduino-based board that controls on- and off-times for the Pi. The Sleepy Pi keeps track of time through a real time clock powered by a 3 V lithium button cell. The Pi was turned on shortly before dawn and off at dusk (i.e., between 5:00 AM and 8:00 PM). Commercial stations have similar options to program a recording schedule. In its final configuration, our station had an autonomy of 10 days (2016) and 15 days (2017). For comparison, Wildlife Acoustics advertises an autonomy of up to six weeks; however their recorder does not operate continuously. The 2017 station benefits from a lower sampling rate and from powering the SIM card dongle only when needed. The latter is achieved by programming the Sleepy Pi 2 (2017 model) to supply a separate 5 V to the dongle at specific hours.

Car batteries (i.e. starting lead-acid) are not designed to sustain full loading and unloading cycles. The voltage should not drop below 11.9 V to avoid irreversible damage (or 9 V for deep cycle batteries). Below this threshold, the station must shut down. Battery voltage may be monitored using a feature of the Sleepy Pi 2. Alternatives for batteries are Ni-Cd (highly toxic and outlawed in the EU), alkaline (not rechargeable) and lithium-ion. The latter has two downsides: price and poor performance in cold weather. Depending on the context and budget available, a solar panel might be helpful.

The batteries were kept inside a plastic container and rested on wood planks to limit exposure to potential water infiltrations. Small holes were pierced under the handles for the ventilation of hydrogen emissions. All the electronics were kept dry and above freezing temperatures in a smaller, sealed plastic box (Fig. 5). To service the station in the field, we connected a laptop to the Pi using a simple network cable. We imposed the IP address of the Pi so that it fitted the IP address of the laptop, and accessed the Pi's console using terminal emulator PuTTY.

⁶ <https://wammu.eu/gammu/>

⁷ Spell Foundry, Wokingham, United Kingdom.

2.1.2 Microphone Protection against Belgian Weather

The microphone was mounted with its body inside the electronics box, so that the heat from the operating electronics kept it warm. The downside was that the microphone had a blind spot for direct acoustic waves because of the tree to which the box was attached. The microphone head was covered with a latex film cut from household gloves, then clamped into a cable gland to seal the set-up. We tested two varieties of latex in the lab, using an acoustic source. Figure 2a shows the results for the model we selected. We examined the ratio between the spectra measured in two conditions (with and without latex), keeping the source signal the same. It is acceptable that the latex increases the amplitude of the signal (ratio greater than 1) and that it does not decrease it excessively (ratio greater than 0.8, marked with a red line). We see that the signal is often enhanced by the latex, likely because of the modes of the latex membrane, or the modes of the cavity between the latex membrane and the microphone head. Up to 1500 Hz the ratio is stable and close to 1, which is sufficient for drumming. In any case, the parameters that characterize drumming are temporal, not dependent on amplitude. Finally, anticipating windy conditions, we designed a windscreen from surplus foam. Again, the impact on the microphone response was tested and found satisfactory (Fig. 2b). As final validation, we captured both the drums and the calls of woodpeckers with a high quality in our 2016 field trials. We did not encounter issues of wildlife eating up the foam or perching on the microphone.

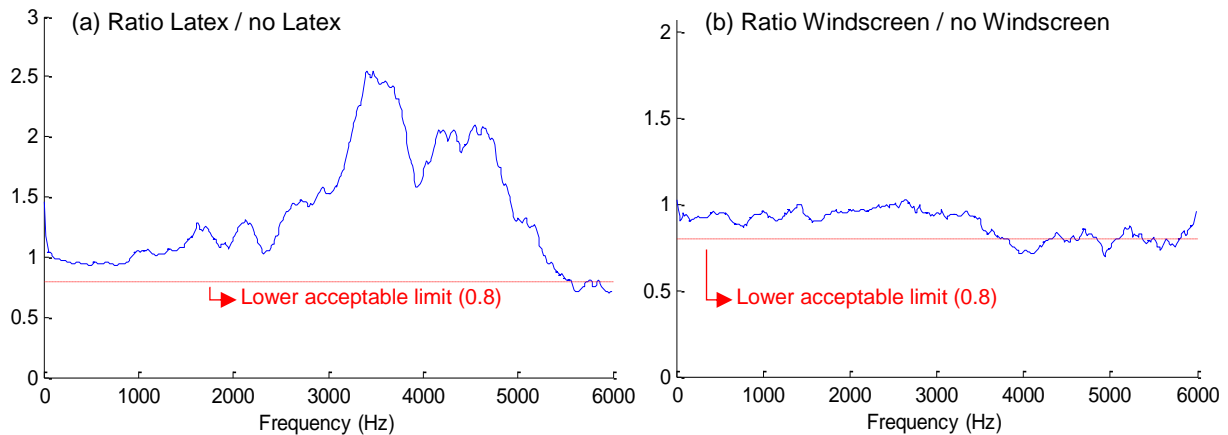


Figure 2: Lab Tests on Microphone Response.

2.2 On-the-Spot Processing

The Acoustic Complexity Index (ACI) of Farina et al. [7] is a simple indicator with an important capacity to detect passerine songs and for that matter all fast-varying sounds including impacts and shocks. Evidence that the ACI is able to detect drumming was obtained in [8]. Accordingly, the station calculates the ACI spectrum for each successive 30-second segment of audio. Segments for which the maximum ACI in the 300–1500 Hz range is greater than 1.2 are stored to disk and others are discarded. The ACI spectrum is saved in any case.

The 1.2 threshold was inferred from the Xeno-Canto / Tierstimmen drumming database used in [6], which contains 2665 drumming rolls for all nine European drumming species (see Table 1 for a list). Note that the ACI depends on the processing parameters, namely the frame duration. Our results stand for frames of 512 samples, i.e. 46 ms at 12 kHz. All drumming samples were found to have ACI values greater than 1.2 (the minimum is 1.24). The frequency at which the maximum ACI value occurred was always less than 1500 Hz. Preliminary results for woodpecker vocalizations also indicate ACI values greater than 1.2, at frequencies less than 3000 Hz.

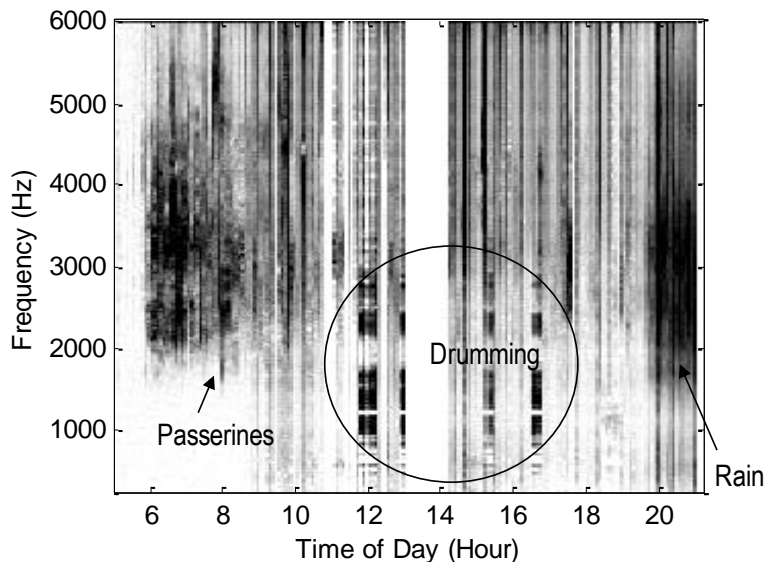


Figure 3: ACI Spectrogram for March 18th, 2016.



Figure 4 *Picus canus*, photographed by Didier Vieuxtemps.



Figure 5: The Electronics Box, with Sound Card Fixed to the Top and no SIM Dongle yet.



Figure 6: The Autonomous Recording Station, Deployed.

At power-up the station reviews the ACI spectra from the previous day and generates an ACI spectrogram image (Fig. 3). This gives a daily overview of recorded events. Blanks appear when the station was not operating properly or shut down. The shape of the dawn chorus of passerines is reminiscent of images in [8]. Other large black areas are caused by rain. The white horizontal lines above 3000 Hz are interferences with the cell waves. Finally, the black vertical patterns in the 500–2000 Hz frequency range are drumming. This is unmistakable; few sounds below 2000 Hz have the inherent variability that generates high ACI values. Alas, woodpecker calls are less discernible.

2.3 Post-Processing of the Recordings

The recordings were processed using previously developed algorithms for drumming detection and species identification [6]. The detection algorithm takes advantage of the repetitive nature of the signals. Drumming is a succession of identical strokes. We then detect spectral frames repeated at a

certain pace. The same is done for calls, because woodpecker calls are typically repetitions of a base syllable. The mean time interval lies in the 40–90 ms range for drumming (interval between strokes) and 125–350 ms range for a number of woodpecker calls (interval between syllables). The drumming species can then be identified from the duration of drumming rolls, the drumming speed and drumming acceleration [6]. The recognition is done by a k-NN algorithm trained on the database of 2665 drumming rolls. Identification of calls at this stage is done manually.

3. Station Operation: Context and Field Notes

Belgium sits on the edge of the distribution area for *Picus canus* [9]. References mention 10-15 pairs in 1998 [10], three or four males today⁸. NGO AVES-Natagora is monitoring this fragile population, but ornithologists have not always been able to confirm presence after multiple visits to the target sites. We thus deployed a recording station at a location where a single individual had been spotted in 2015 (Fig. 4). The goals were to demonstrate the robustness of the station, to test the performance of species detection and identification programs, and to shed some light on the drumming and calling habits of *P. canus* that could facilitate its monitoring in the future.

The 2016 station was deployed to the field from February 25th to April 22nd (Fig. 6). The campaign ended when the batteries went out of commission after several full discharge cycles. All other equipment (Pi, microphone, sound card) came back to the lab in pristine shape. In the field, our equipment routinely experienced mishaps. The USB card would not mount properly at start-up. The sound card stopped working. For random reasons the scripts failed; then the audio data was not moved along and accumulated in the Pi's RAM, which eventually crashed the sound recording function (arecord). The blanks in the ACI images reflect this unpredictable station downtime. However we had a number of recovery procedures in place that checked for proper operation of the key components and if needed, rebooted the station.

The station acquired audio for 458 hours. We collected 11527 30-second WAV audio files, which amounts to 22% of the listening time. In total, including ACI data and images, we stored 8 GB. We coalesced the consecutive WAV files to end up with 1951. Ninety-eight of these lasted more than five minutes, the maximum being 1 h, 4 min, 30 s. These long files correspond to sustained periods of rain or wind. Numerous plane flyovers were also recorded.

4. Results

Eighteen percent (18%) of all saved WAV files contained drumming rolls. After April 6th, when the rain receded and bird activity picked up, the percentage climbed to 34%. This indicates that the pre-selection using the ACI is on point. The detection algorithm proves accurate for drumming (3% of false positives), but less so for calls (92.6% of false positives). We were able to extract 2232 drumming rolls from the data and 86 *P. canus* calls. An uncertainty remains on the reach of the station; faint drums are not picked up by the algorithm.

Table 1 gathers the results of the identification run. *Dendrocopos minor* and *P. canus* have similar drumming parameters (fast start, deceleration, overlapping duration range) [6]. The recognition is biased towards *D. minor* because there are 832 *D. minor* samples in the training database and only 104 *P. canus* samples. Here, the context informs us that the 1993 *D. minor* identifications are misattributions. The same conflict arises with *P. viridis*, a rare drummer in any event. In reality, we recorded 2016 *P. canus* drumming rolls (1993+108+5). Next, the algorithm identifies poor quality drumming rolls as *D. major*, because *D. major* has the shortest rolls. There is a residue of these occurrences over the timeline of the experiment. *D. major* is an abundant drummer and its presence near the station would likely result in a drumming spike. Finally, 86 identifications of *Dryocopus martius*, *D. leucotos* and *Picoides tridactylus* (all with long-duration drums) occur on April 14th; the likely scenario is that *D. martius* visited the site. Figure 7 shows further supporting evidence: on the ACI

⁸ Per AVES-Natagora.

spectrogram, the morning drums look different from the extremely regular afternoon drums (one bird repeatedly hitting the exact same tree spot); spectrograms from the recordings show *P. canus* drumming on top of *D. martius* shrieks and *D. martius* drumming while *P. canus* responds by calling. The ACI image shows that the encounter was over by 9:00 AM and that *P. canus* spent the rest of the day drumming to reaffirm its territory. The recordings also contain *D. martius* calls that cement the identification. Other sporadic *D. martius* calls were stumbled upon at earlier dates, hinting at possible overlapping territories for the two birds. Figure 8 shows all drumming samples of our collection on a t-SNE map [6]. This is a non-linear representation that locates similar samples close together. The different species are well separated thanks to an adequate parameterization of drumming.

5. Conclusion

This exercise of building a recording station and processing the data gave us a good perspective on the reliability of the hardware and on the applicability of woodpecker detection and identification algorithms. Despite the odd failures, our station proved resilient enough to always resume operation by itself. The greatest challenge is to control power consumption so that the battery replacement cycles are practical. The technology is definitely at a stage where we can use it for the surveillance of (drumming) European woodpecker species. Of course, it would take an array of stations (or a moveable station and significant field time) as well as mass processing capabilities to monitor a region rather than a single bird as we did here. But feasibility is not in question. The door is also open to address further questions in the fields of Bioacoustics and Animal Behavior. Do woodpeckers drum differently when they face competition from conspecifics or from species with similar drumming parameters? When and why do they use drumming over calling when they can do both? Autonomous recording stations and post-processing algorithms can support this type of research.

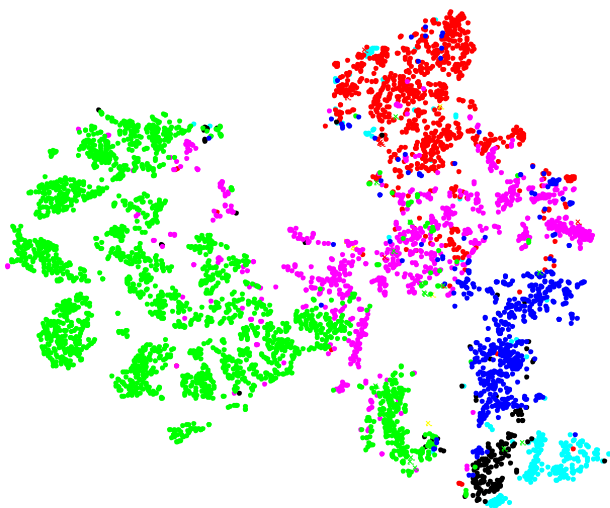


Figure 8: t-SNE Map of Drumming Rolls including Xeno-Canto, Tierstimmen and New Data.

Table 1: Identification of Woodpecker Drums by k-NN.

Species	Nb. of DRs	Comments
◆ <i>D. leucotos</i>	13	Unlikely in Belgium → confusion
◆ <i>D. major</i>	40	Poorly formed DRs?
◆ <i>D. martius</i>	44	Need confirmation
✕ <i>D. medius</i>	0	
◆ <i>D. minor</i>	1993	Confusion w/ <i>P. canus</i>
✕ <i>D. syriacus</i>	0	
◆ <i>P. canus</i>	108	
◆ <i>P. tridactylus</i>	29	Unlikely in Belgium → confusion
✕ <i>P. viridis</i>	5	Confusion w/ <i>P. canus</i>

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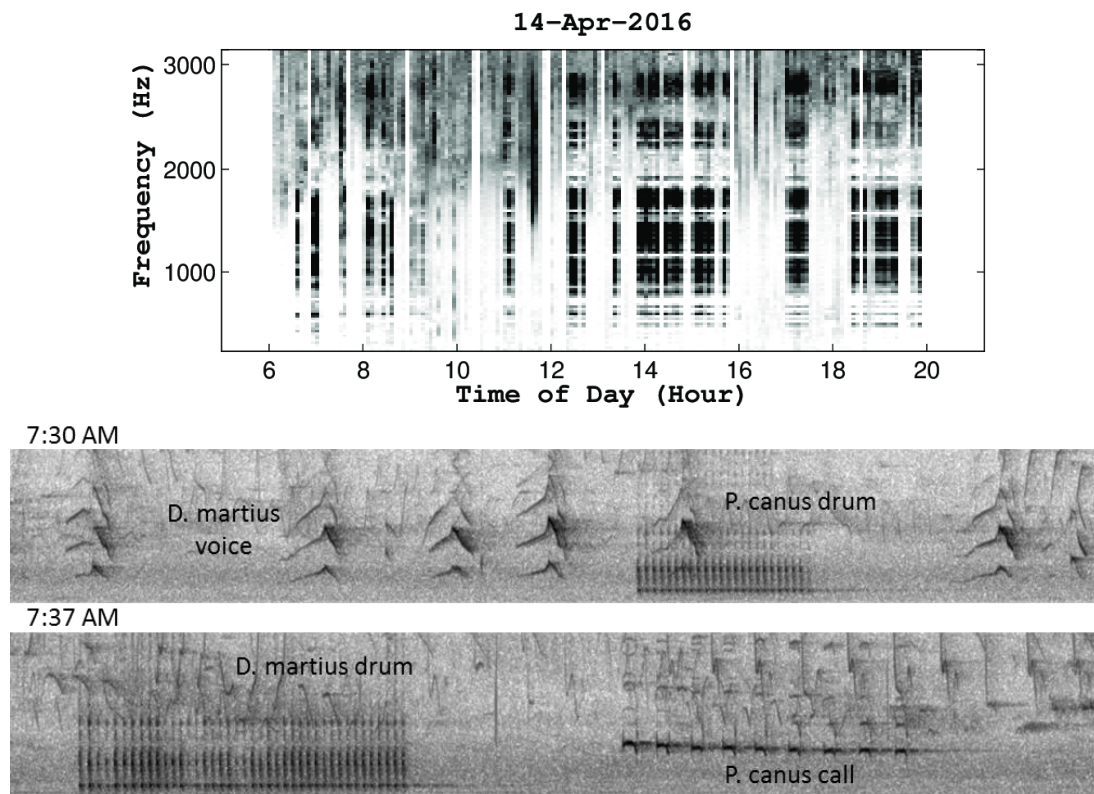


Figure 7: Events of April 14th, 2016.

REFERENCES

- 1 Aide, T. M., Corrada-Bravo, C., Campos-Cerqueira, M., Milan, C., Vega, G. and Alvarez, R. Real-time bioacoustics monitoring and automated species identification. *PeerJ*, **1**, e103, (2013).
- 2 Farina, A., James, P., Bobryk, C., Pieretti, N., Lattanzi, E. and McWilliam, J. Low cost (audio) recording (LCR) for advancing soundscape ecology towards the conservation of sonic complexity and biodiversity in natural and urban landscapes, *Urban Ecosystems*, **17** (4), 923–944, (2014).
- 3 Jahn, O., Mporas, I., Potamitis, I., Kotinas, I., Tsimpouris, C., Dimitrou, V., Kocsis, O., Riede, K. and Fakotakis N. The AmiBio Project – automating the acoustic monitoring of biodiversity. *24th International Bioacoustics Congress (IBAC)*, Pirenopolis, Brazil, 8–13 September, (2013) [Poster].
- 4 Wimmer, J., Towsey, M., Roe, P. and Williamson, I. Sampling environmental acoustic recordings to determine bird species richness. *Ecological Applications*, **23** (6), 1419–1428, (2013).
- 5 Voříšek, P., Klvaňová, A., Wotton, S. and Gregory, R. D. A best practice guide for wild bird monitoring schemes. First edition, CSO/RSPB (2008).
- 6 Florentin, J., Dutoit, T. and Verlinden, O. Identification of European woodpecker species in audio recordings from their drumming rolls. *Ecological Informatics*, **35**, 61–70, (2016).
- 7 Farina, A., Pieretti, N., Piccioli, L. The soundscape methodology for long-term bird monitoring: a Mediterranean Europe case-study. *Ecological Informatics*, **6**, 354-363, (2011).
- 8 Florentin, J., Fauville, B., Gérard, M., Moïny, F., Rasmont, P., Kouroussis, G., Verlinden, O. Soundscape analysis and wildlife presence in the vicinity of a wind turbine. *Proceedings of Euronoise 2015*, Maastricht, The Netherlands, (2015).
- 9 Schmitz L. Hybridation des Pics vert et cendré (*Picus viridis*, *P. canus*) en Belgique. *Aves*, **41** (1–2), 91–106, (2004).
- 10 Testaert D. Découverte de la présence du Pic cendré (*Picus canus*) dans le sud de la Province de Namur. *Aves*, **35** (1), 67–68, (1998).