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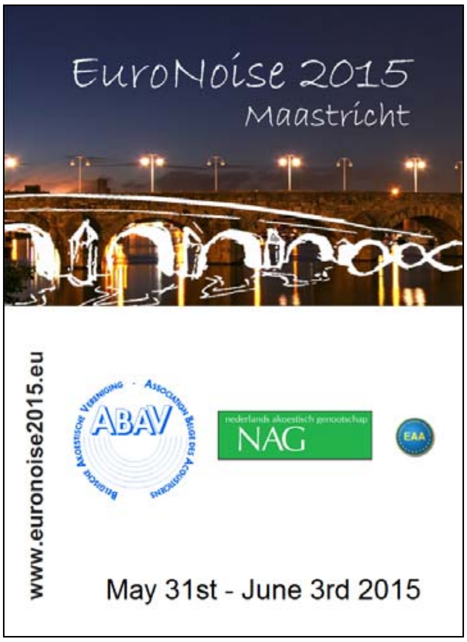

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Soundscape Analysis and Wildlife Presence in the Vicinity of a Wind Turbine

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Summary
The present work uses sound recordings to evaluate wildlife presence in the vicinity of a wind turbine. The setting is a rural nature park in Chevetogne, Belgium, where a single 800 kW wind turbine has been in operation since 2007. Two weeks of continuous sound data at 12000 Hz sampling frequency were collected at three positions around the turbine. Bird vocalizations from relatively common species are present throughout the audio records. Color-composite spectrograms, assembled from acoustic indicators that target wildlife detection, allow a direct visualization of 24 hours of sound data at once. Passerines are well detected by the acoustic complexity index and a modified spectral entropy; the latter also captures the voices of birds with more monotonous songs. A third dimension, derived from the sound pressure level, gives a sense of the weight of human activities on the soundscape, namely through road traffic. The final spectrograms display the musical composition of the day, showing birds singing on and off, captured with different color nuances. Wind turbine noise is present in the recordings although by design it does not appear on the wildlife spectrograms. No evidence was found of negative interactions between the turbine and the birds. However, generalization of this result is limited by the restricted timeframe of observations.

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1. Introduction

Birds are excellent bio-indicators [1], i.e. trends in avian populations are indicative of the global state of ecosystems. The rise of wind turbine developments also brought a renewed spotlight on bird conservation because of the inherent impacts on birds through collisions and the displacement of habitats and migration paths [2]. There is now a need for monitoring at continental scales, both on land and water. This is a titanic task and technology is therefore stepping in to supplement human observers. Radars, satellite tracking, rings fitted with cellular transmitters and acoustic monitoring are all at early stages of deployment. Acoustic monitoring applies well to birds because they are vocal creatures. Even in difficult visual environments such as forest or in cloudy weather, they can still be heard. Their vocalizations also bear markers of species and individuals [3]. Thus acoustic monitoring has the potential to provide a wealth of information to bird conservationists. The timing for this technology is right as the field of human voice and music recognition has known important developments in the past decades that can transfer to bird vocalizations. Encouraged by this, several research teams started to record sound extensively in the field (in Greece [4]; in Australia [5]; in Puerto Rico and Costa Rica [6]). Yet to the day, exploitation of the terabytes of recorded data remains a challenge. Recent advances in extraction of songs from long audio records and classification of large song databases were proposed by Potamitis [7] and Stowell and Plumbley [8]. However, the technology is still not at the stage where it can be autonomously deployed for the sound archives cited above. Meanwhile, Towsey et al. [5] offered to synthetize color-composite spectrograms highlighting animal sounds to at least have means to visualize and review large blocks of acoustic data at once. This is the approach pursued in the present paper. The visualization of soundscapes on a long timeframe (here, a 24-hour day) is in itself a significant descriptive tool. Degraded soundscapes are indicators of degraded environments, as acoustical niches reflect ecological niches [9].

Noise measurements that were planned in Chevetogne, Belgium, in July 2014 provided us with an opportunity to observe the birds living in close proximity to a wind turbine. We therefore proceeded with the analysis of the audio recordings. It must be noted though that this data was collected with parameters consistent with turbine noise and not ideal for bird vocalizations.

2. Site and Recording Equipment

The Chevetogne domain is a publicly-owned 600 ha nature park located in a rural province of Belgium. In 2007, a single wind turbine (ENERCON E48, 800 W, 75 meter high nacelle, 25 meter blades) was installed close to the entrance gate of the Chevetogne nature park. Prior to construction, a landscape impact study was conducted but no wildlife impact study. The turbine is surrounded by fields and prairies for grazing horses. The first patches of mixed forest start 200 meters away. The park is bordered by a road connecting nearby villages. The village of Chevetogne also hosts a large abbey with two churches whose bells are heard from the park.

The sound level meters went in on July 2nd, 2014, under a warm and sunny weather. On July 2nd, the sun went down at 21:59 local time and dusk came at 22:44. On July 3rd, dawn was at 04:49 and the sun rose at 05:35. Three microphones were installed: S1 in a prairie, not far from the edge of the woods, at 200 meters from the turbine; S2 in a field at 100 meters from the turbine; finally, S3 inside the woods at 200 meters from the turbine, in a dip further away from the road. S1 and S2 were NORSONIC 140 sound level meters equipped with NORSONIC 1209 microphones (±1.5dB in 20 Hz – 12 kHz interval). They operated for two weeks. S3 was a SVANTEK 977 sound level meter with an ACO 7052E microphone (±2dB in 3 Hz – 20 kHz interval) which recorded for about thirty hours. All recorded continuous wav files at 12000 Hz sampling rate. In this low quality mode, the NORSONIC systems activate a built-in anti-aliasing filter (4000 Hz low-pass).

3. Processing Methodology

Composite spectrograms are assembled by merging three separate spectrograms, with color scales from black to red, black to green and black to blue [5]. The individual spectrograms each depict a different acoustic indicator. The indicators are calculated from an initial acoustic intensity spectrogram, which is obtained through the discrete Fourier transform (DFT) of successive frames of 1024 bins (85 ms) with a frame overlap of 50%. A Hamming window is applied before DFT calculations. The first indicator, the Acoustic Complexity Index (ACI, red scale), is defined by Farina et al. [10]:

$$\mathrm{ACI} = \frac{\sum_{k=1}^{n} |I_k - I_{k+1}|}{\sum_{k=1}^{n} I_k} \tag{1}$$

In Eq. 1, I_k is the acoustic intensity of a frame (frequency-dependent) and n the number of frames in the time interval under consideration (typically 30 seconds). Thus, the ACI is frequency-dependent and is computed every 30 seconds of the audio record. This form is suitable for a spectrogram representation. High ACI values reflect a strong vocal activity of birds. This success comes from the accurate description of bird songs as rapidly varying signal. Monotonous sounds such as an engine running at constant rpm would have low ACI values.

Sueur et al. [11] proposed spectral entropy as a wildlife indicator (green scale). With the p values of the intensity spectrum $I(f)$ normalized so that they sum up to 1, the spectral entropy formulation is:

$$H_s = -\sum_{f=1}^{p} \frac{I(f) * \log_2(I(f))}{\log_2(p)} \tag{2}$$

This is calculated for every time frame. The entropy of a flat function is 1, whereas a lonely peak concentrating the energy yields zero. The idea is that if the intensity remains high at all frequencies, it indicates intense wildlife, as all frequency niches are occupied. This not the case in Chevetogne. On the contrary, isolated individuals produce isolated signal peaks. Hence, in accordance with Towsey et al. [5], we resort to replacing H_s by $1 - H_s$, ensuring higher values where bird songs are found. A second issue with H_s is that for spectrograms, we need a quantity that depends on both frequency and time, and the calculated H_s is independent of frequency. To circumvent this issue, H_s at frequency f is calculated as the entropy of a subpart of the spectrum, namely the 200 Hz wide interval around f. Finally, we average the results over intervals of 30 seconds.

We derive our third indicator from the sound pressure level (SPL, blue scale). The SPL can be frustrating in the presence of a strong anthropophony as it has very high levels at low frequencies and not much contrast in the higher frequencies, where most of the bird songs are expected. In the Chevetogne records, most of the energy is found below 300 Hz and is either anthropogenic in nature (booming engines) or instrument noise. Road traffic further masks bird sounds up to 2000 Hz. We thus propose to a) A-filter the pressure data and b) subtract from the SPL a base SPL compiled from the most quiet moments around the same time of day. These operations flatten the intensity spectrum and bring the higher frequencies to more significant levels. In the formula below, n is the number of frames in the time interval under consideration (30 seconds). The reference intensity is irrelevant when subtracting a base SPL. We anticipate the modified SPL to provide a discrimination between stronger and quieter songs, i.e. possibly between birds at different distances from the microphone. With the ACI, modified spectral entropy and modified SPL, the three dimensions of sound are addressed: the time variation, the spectral content and the volume.

$$\mathrm{SPL} = 10 * \log_{10}\left(\frac{1}{n}\sum_{k=1}^{n}\frac{I_k}{I_{ref}}\right) \tag{3}$$

4. Results

Fig. 1 shows a color-composite image over 24 hours (from 22:00 on July 2nd to 22:00 the next day) and Fig. 2 a close-up on the two hours enclosing dawn and sunrise. All three sound meter levels recorded audio in this timeframe, but our present focus is on S1. Diurnal bird songs, visible through the ACI and H_s, start before dawn, last through the day and stop at sunset. The 24-hour spectrogram is further compressed by averaging the results over 300 second intervals (5 minutes). Throughout most of the day, the soundscape below 2000 Hz is dominated by the anthropophony. The ballet of commuters on the nearby road is visible around 8:00 and in the evening. The higher frequency components (above 500 Hz) of the pass-by noise from cars are well highlighted by the SPL-based indicator. Agricultural machines operating as early as 6:00 have a similar signature, whereas planes and the wind turbine remain invisible. Just before 16:00, a troop of boy scouts walked by the microphone, singing and shouting. Both the ACI and the entropy appear to capture human voices. They also both pick up a metallic chain rattle heard sporadically from mid-morning to evening (main peaks roughly at 1800 Hz, 2400 Hz, 3100 Hz and 4000 Hz). On a windless day, this noise is possibly connected to the presence of horses in the prairie by the microphone. The broadband red lines seen after midnight are brief shock noises captured by the ACI. A sound akin to an animal repeatedly hitting the plastic box containing the recording equipment is heard on the audio. First mass at the monastery is scheduled at 6:00 according to the monks' website and the bells are indeed heard ringing at 5:30, 5:45 and 5:55. The spectral entropy has high values at multiple frequencies corresponding to the harmonics of the bell sounds. Absent from the images are insects flying by the microphone and mammals (horses, cows, sheep, wild boar), with the exception of a barking dog in the early hours. In general, the images are apt at showing birds singing for longer periods by the microphone. Isolated calls are more difficult to pick up. For example, the recordings contain calls from a common buzzard (*Buteo buteo*) and various tits (*Parus major*, *Cyanistes caeruleus*) which are only briefly vocal at this location and escape detection. The closer dawn view (Fig. 2) helps with distinguishing nuances between the different bird species. A blackbird (*Turdus merula*, Bb.) starts the dawn chorus, soon followed by a blackcap (*Sylvia atricapilla*) and a chaffinch (*Fringilla coelebs*). A skylark (*Alauda arvensis*) leaves a distinctive trace reaching into the higher frequencies. At 5:55, in a moment of relative silence, a chiffchaff (*Phylloscopus collybita*) is visible. The call of a northern lapwing (*Vanellus vanellus*) is seen at 4:20. All are captured by the ACI and the spectral entropy which combine to form yellow and orange tones. At lower frequencies, the spectral entropy spots a domestic cock (*Gallus gallus domesticus*), then a turtle dove (*Streptopela turtur*).

The performance of the three acoustic indicators with respect to various types of sound events is double-checked by using 479 sound samples extracted from the full records, 266 of which are bird vocalizations. Fig. 3 shows the frequency-dependent ACI for all birdsong samples, sorted by species. Identified passerines have clear signatures (chiffchaff, skylark, blackbird, blackcap, tits and chaffinch). Some blackbird phrases are not convincingly detected. The first 7 blackbird samples are at dusk on July 2nd (no detection); the next 11 contain long and elaborate songs from around dawn (detection); the subsequent ones are chosen later in the day (low and variable detection). At times other than at dawn, the songs are cruder with only a few brief notes, and are more consistently picked up by the spectral entropy (Fig. 4). The difference in spectral extent between dawn songs and other songs is evident. Back to Fig. 3, three species do not show on the ACI image: the hooded crows (*Corvus corone corone*, song range 500 Hz – 3000 Hz), the domestic cock (700 Hz) and the turtle doves (500 Hz). The corresponding spaces on Fig. 3 are blank. Amongst the 15 samples containing hooded crow chants, the thirteenth one is the only one leading to a significant ACI value (single black line at File #238 in Fig. 3). The spectrogram from a syllable of this vocalization is shown on Fig. 5b. Other hooded crow samples rather resemble Fig. 5a. The critical difference between the two is that the signal in Fig. 5a is fairly constant over time, whereas Fig. 5b sees a modulation of the fundamental note. The ACI is designed to detect variation over successive 85 ms windows. It thus fails to see significant variation in Fig. 5a. This spectrogram also has its energy content in an almost continuous frequency interval. This is the contrary of an isolated peak and does not work well with the spectral entropy. On the upside, the spectral entropy is adequate to capture the vocalizations of the domestic cock and turtle doves. This conclusion stands after examination of samples from these two species. Schematically, their songs are single notes held for a certain duration; the constancy does not work with the ACI, but isolated notes lead to high H_s values.

5. Discussion

Color-composite spectrograms give a valuable overview of sound recordings. Both Fig. 1 and Fig. 2 work as representations of the acoustic niches in nature's orchestra (see Krause, 1993, as cited by [9]). When the details in Fig. 2 have been explored, we can re-read Fig. 1 and see the skylark (above 4000 Hz) and the blackbird (2000 Hz) singing mostly in the early morning and at dusk, the chaffinch (3000 Hz – 4000 Hz) going on through the day, sometimes doubled up by the blackcap. The song of the turtle dove

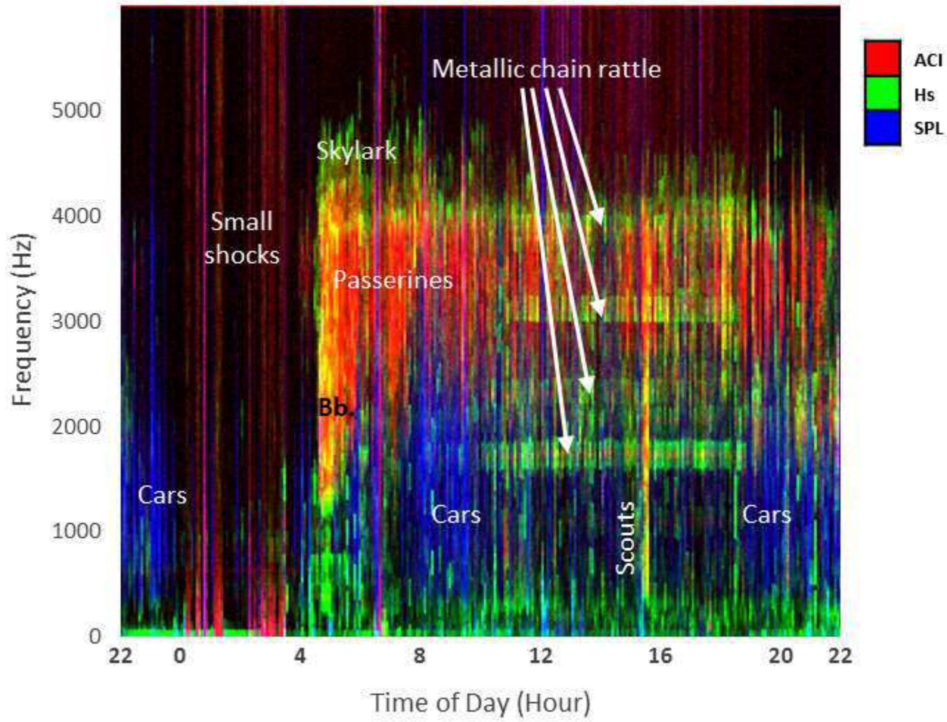

Figure 1. 24-Hour Color-Composite Spectrogram at Position S1

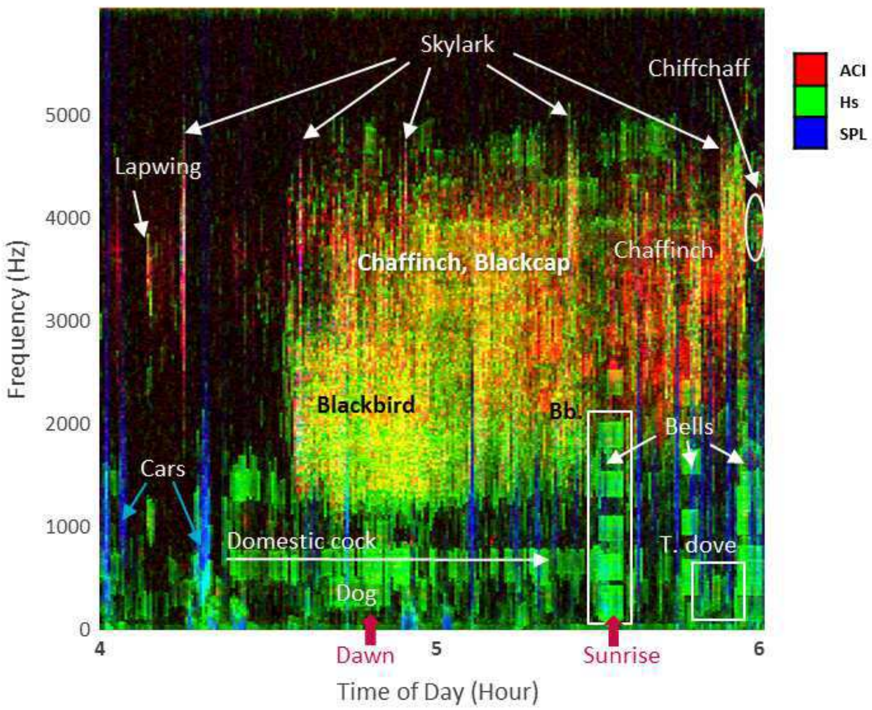

Figure 2. 2-Hour Color-Composite Spectrogram at Position S1

(500 Hz) intermeshes with anthropophony and thus remains hard to detect. The collection of such images day after day or month after month would show the evolution of the avian community in Chevetogne through the seasons. Towsey et al. [5] were able to compute images at the month and year scale. The interpretation of images without context or without going back to the audio seems out of reach at this

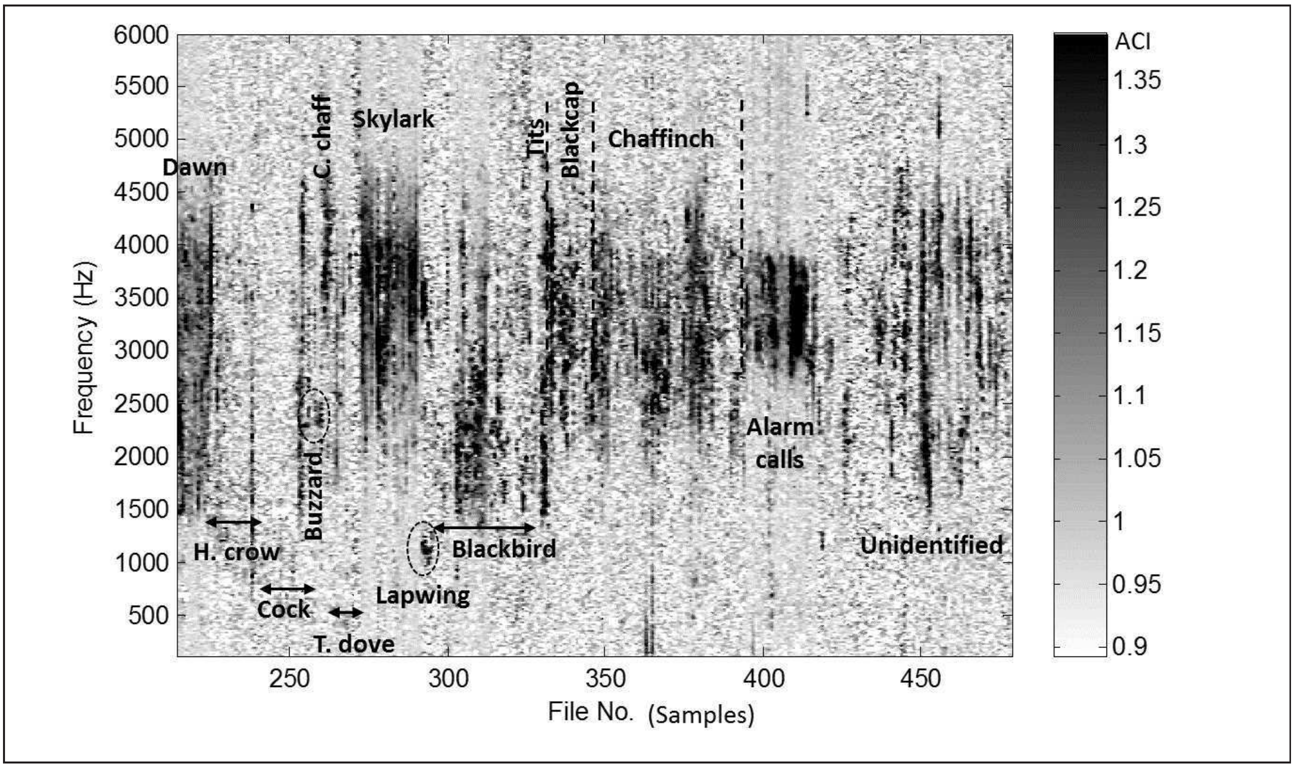

Figure 3. ACI Profiles for 266 Bird Sound Samples

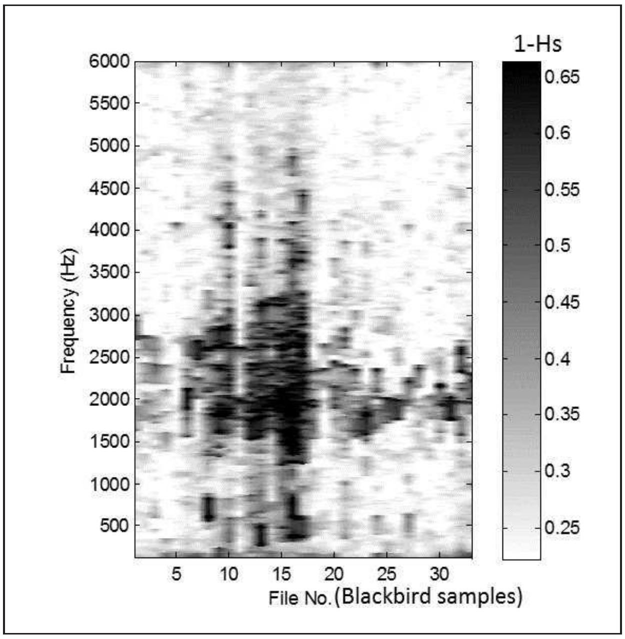

Figure 4. Spectral Entropy Profiles for 33 Blackbird Samples

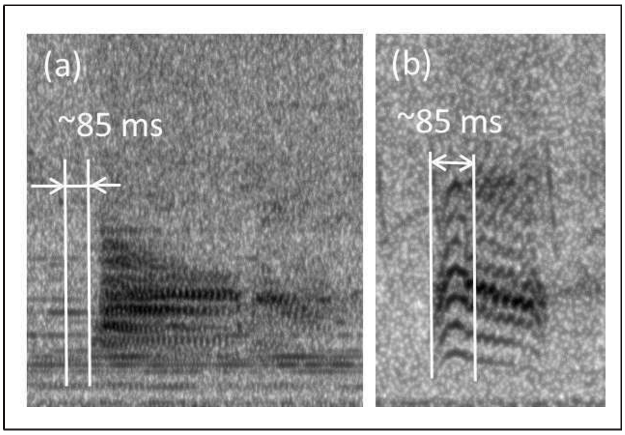

Figure 5. Hooded Crow — Pressure Amplitude Spectrograms with y-axis 0 to 6000 Hz

time. Some passerines have too similar a signature (e.g., see in Fig. 3 for the ACI of the chaffinch and the blackcap). In the case of the common buzzard, the pattern is elusive (brief call compared to the volume of passerine songs) and unspecific (confusion with blackbirds). Nevertheless, browsing through images looking for possible positives remains faster than listening to the full recordings.

Both the ACI and the spectral entropy are great passerine detectors; in addition, H_s is adequate to capture some of the more monotonous songs. Both are unconvincing in the case of the hooded crow. The intensity of anthropogenic noise (mainly cars) up to 2000 Hz remains too high to obtain an image scale in which the modified SPL indicator would highlight distinct birds. The skylark song is barely accented (some nuances of white). Overall, it is mainly the combination of red and green that successfully brings different nuances to the different species, as most visible on

Fig. 2. Still, the proposed indicators (ACI, H_s, SPL) do not claim to provide a full differentiation of all bird species. In general, the search for the acoustic parameters that would best characterize and differentiate all bird vocalizations is ongoing. Brandes [12] has a good overview; Stowell and Plumbley's [8] is a recent study that builds on the current consensus.

High-end bioacoustical setups record audio at a 44.1 kHz rate as it is not uncommon for bird songs to reach 15 kHz. Nevertheless, despite our 4000 Hz limitation, a respectable volume of information was gathered in Chevetogne. There is value for ecologists in exploiting the noise survey data that is routinely available by wind turbines. This being said, the output is not the same as an ornithological census. Here, twelve wild bird species were identified when sampling the recordings. For comparison, Chevetogne was visited on June 8$^{\text{th}}$, 2014, by a member of the association which surveys birds in the region (AVES). Members log in their sightings online at www.observations.be. On June 8$^{\text{th}}$ at 12:00 (noon), the visiting ornithologist reported the presence of twenty-four species. The northern lapwing, the skylark and the turtle dove are missing from his list. The three are common birds, active mainly in the early hours. Hence, acoustic monitoring is limited by a fixed location and the absence of eyes and context, but advantaged by its continuous surveillance.

Multiple turbine sounds are heard on the recordings (blade flow noise, mechanical whines, nacelle rotation). They are mostly monotonous and of low intensity. Many are also low frequency and therefore washed away by the A-weighting. The highest frequency components are observed around 1700 Hz (whines); they produce only limited local H_s spots and thus the turbine remains invisible in the images. In all cases, the frequency range remains in line with the typical anthropophony and consequently this noise would not hinder passerine songs. However, the variety of possible turbine operational modes and associated noises prohibits our data from being representative. Birds are heard singing as close as 100 meters away from the turbine (at microphone S2). This is territorial behavior, meaning that the birds do not find themselves only briefly in the vicinity of the turbine. This is consistent with previous knowledge that passerines are not significantly displaced by wind turbines [2]. Raptor observations are more remarkable. Wind turbines are known to displace nesting and foraging activities of raptors by distances on the order of 200 meters [2]. Here we have a common buzzard on tape and sighted in stationary flight by the blades on the day of equipment installation. There is no reliable collision data available for the site.

6. Conclusions

Color composite spectrograms built from three acoustic indicators successfully extract the wildlife information from ordinary intensity spectrograms that are plagued by anthropophony. With some investment in understanding the soundscape of a place, the vocal activity of a number of species, mainly passerines, can be tracked. The more discrete species remain elusive on overview pictures. Yet, the color-composite spectrograms provide a valuable assistance in browsing through long audio records of nature sounds. In any context, the ACI and the spectral entropy are great passerine detectors. Our modified spectral entropy also allowed or enhanced detection for a few species (blackbird, turtle dove and domestic cock). This was achieved using low quality audio records.

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