Chapter 1

Global estimation of animal diversity using automatic acoustic sensors

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1. Introduction

The estimation of biodiversity can be considered as one of the main challenges in modern biology. When dealing with ecology, evolutionary biology and conservation biology, there is an inescapable need to describe the composition and dynamics of biological diversity (Magurran, 2004). In ecology, the concept of biological diversity is mainly species-oriented, even if other evolutionary units or traits can also be used. In this context, biodiversity potentially refers to all species encountered in a given area at a specified time, including every potential species from underground bacteria to giant trees. Therefore, biodiversity assessment can turn out to be a time-consuming and complex task, as it relies on species inventory that may involve very different taxonomic groups.

Exhaustive approaches such as the all taxa biodiversity inventory (ATBI) programs aim at inventorying the whole biodiversity mainly in tropical habitats (Gewin, 2002), but these programs are highly sensitive to the logistic and time-constraints of most inventory studies. An alternative to these approaches is to focus on one or a few taxa and consider them as biodiversity indicators (Pearson, 1994), but the choice of representative taxa is not trivial (Lawton et al., 1998). In addition, it is well known that patterns of species diversity for different taxa are sensitive to the observation scale. More precisely, there is a general congruence for species diversity between different taxa at a large area scale (more than 1km^2) but not at a fine scale (less than 1km^2, Weaver, 1995). This renders difficult the definition of an indicator taxon or even of several indicator taxa supposedly representative of the diversity in other forms of organisms (Ricketts et al., 1999). Irrespective of the taxonomic breadth of any biodiversity assessment, the estimation of species biodiversity relies on inventories and species examination by one or several taxonomic experts that can be supported with genetic barcoding techniques (see chapter II, 3). Sampling in the field and identification in museum collections can require a considerable effort when the objective is to sample a large region for a long time period. To improve the rate of specimen collection, non-specialist taxonomic workers – or para-taxonomists – can separate morpho-species instead of identifying valid species. This solution is advocated by the rapid biodiversity assessment (RBA) programs that have been especially developed for the rapid exploration of biodiversity in tropical habitats (Oliver and Beattie, 1993; 1996; Oliver et al., 2000).

Biodiversity assessment is often restricted to species richness, i.e. to the counting of the total number of species. However, a collection of species cannot be described solely by the number of items it includes. The abundance of each species has to be assessed to provide an estimation of species evenness. Evolutionary, ecological and life history characters of the species also describe facets of biodiversity (Brooks and McLennan, 1991; Vane-Wright et al., 1991; Grandcolas, 1998; Pavoine et al., 2009; Petchey et al., 2009). Species turnover along time and/or spatial scales is also required to take into account biodiversity dynamics. All of these requirements led to a plethora of biodiversity indices that have been developed for decades (Magurran, 2004; Buckland et al., 2005; Pavoine and Bonsall, 2010).

In practice, a measure of biodiversity can be achieved with direct or indirect sampling. In the latter case, the use of a sensor should be ideally considered by employing a simple tool that returns an index of biodiversity. A human observer or a network of human observers might be considered as a “biodiversity sensor”, but may be biased by the experience of the observers and cannot be “deployed” in rough terrains for long periods of time. Another possibility is to work with local image, video capture instruments or with global satellite imagery. Satellite-based earth observations, or remote sensing, can produce environmental parameters from biophysical characteristics that can be indirectly used to assess species ranges and species richness patterns (Kerr et al., 2003, Turner et al., 2003; Wang et al., 2010; see also IV, 2). These methods are undoubtedly very attractive, but they rely on extremely expensive equipment and are difficult to adapt to small spatial scales. Like other methods, remote sensing often requires a time-consuming validation step. For instance, vegetation mapping with satellite images is based on a colorimetric calibration of pixels with a large set of direct vegetation samples.

The use of a given sensor should be made according to a sampling strategy designed and evaluated carefully with respect to the type of data to be collected. It is particularly important to identify the precision of the measurement system (data quality) and the level of accuracy that has to be reached along both time and space scales (data quantity). In most sampling strategies, there is a basic trade-off between precision and accuracy. In this context, we are currently developing an acoustic sensor that would produce a biodiversity index by analysing the sound produced by local animal communities. This approach could provide a portable, cheap, reasonably accurate and non-invasive animal diversity sensor that could be used at different space and time scales.

2. Sensing diversity through bioacoustics

Some animal species, including taxa often used in biodiversity studies, produce active sounds during their social interactions or in other contexts. For example, some fish and reptiles, most amphibians, birds, mammals, insects and other arthropods use sound for communication, navigation or predation acts. These acoustic signals generally produce a species-specific signature and several techniques in bioacoustics were developed to exploit these signals as an indication of species occurrence and as a tool for biodiversity studies (Obrist et al., 2010). The most elementary application is sensing by observers. This is usually achieved when following animal populations through aural listening and identification (e.g., Cano-Santana et al., 2008, for crickets). When based on a massive network of listeners, such a census method can generate large datasets of strong interest to ecologists (e.g. Devictor et al., 2008, for birds). Nonetheless, volunteer-based call surveys tend to be replaced by the automated digital recording system (ADRS), which is an electronic equipment that allows automatic data collection and generates a large amount of high-quality information about species biodiversity (e.g. Acevedo and Villanueva-Rivera, 2006, for amphibians).

The problems alluded above for species identification with museum specimens is also true for species identification with sound. Acoustic identification is based on the experience of the observers, which can be biased due to sensory or training differences. As any other identification, it also relies on a taxonomic database providing information on the correspondence between every species and its acoustic signature. Automatic identification of the different songs embedded in the recording is rather complex and still suffers errors (e.g. Skowronski and Harris, 2006, for bats). These approaches are also difficult to deploy in complex acoustic environments like tropical forest soundscapes, where tens of signals mix up and many species still remain unknown (Riede, 1993). Reliable results can be obtained only when focusing on a single species with a rather simple and loud call as demonstrated with the neotropical bird *Lipaugus vociferans* (see I, 4) and the Blue Whale *Balaenoptera musculus* in a marine context (see I, 3).

Keeping in mind these constraints, we applied the concept of RBA to sounds produced by animals and even pushed the concept one step further. We recently suggested tackling the problem of diversity assessment at the community level by using bioacoustic methods (Sueur et al., 2008a). In the case of bioacoustics, the unit to work with is the acoustic community, which is defined as the sum of all sounds produced by animals at given location and time. The signals produced by different species can overlap, interfere and consequently reduce signal transmission between the emitter and the receiver of a focal species. Sound produced by other species is indeed considered as noise for the focal species and acts as a severe constraint on the evolution of conspecific signals (Brumm and Slabbekoorn, 2005). Consequently, species sharing the same acoustic space are supposed to show an over-dispersion of the frequency and time-amplitude parameters of their songs reducing the risk of interference. This has been reported in several acoustic communities (e.g., Lüddecke et al., 2000, for amphibians; Sueur, 2002, for cicadas; Luther, 2009, for birds). A measure of sound complexity could then work as a proxy of community richness and composition. The acoustic indices we are developing are mainly based on this concept of acoustic partitioning. We hereafter review the recording equipment and analysis we used to try and build an animal diversity acoustic sensor.

3. Listening and measuring acoustic diversity

A biodiversity sensor provides a measure of a single or a set of variables characterising biodiversity. Even if a sensor is composed of several probes and data analysers, it is often viewed as a all-in-one equipment that senses and analyses the environment concomitantly. Our method currently relies on two different equipments that are not used at the same time. However, we here consider that these sub-units constitute together a single sensor (figure 1). The first sub-unit is a digital sound-recorder that can be settled outdoor. The second sub-unit is a computer installed with software specifically developed to analyse sound diversity. Further statistical analyses on the acoustic indices, i.e. the biodiversity variables measured by the sensor, are not considered as part of the sensor but as part of data analysis processes. We hereafter detail the sampling protocols based on a single recorder or an array of recorders, the properties of the autonomous recorder currently in use and, eventually, the algorithm developed to compute the diversity indices from sound files.

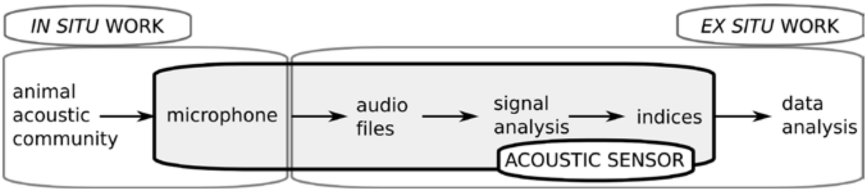

Figure 1: Diagram showing the successive steps of the global estimation of animal diversity. Here, the biodiversity sensor is considered as the combination of different processes: recording, audio file conservation, signal analysis, and indices computation. These processes – *in situ* recording step with autonomous equipment and *ex situ* calculation of indices from stored acoustic data – are currently separated from each other. However, a portable all-in-one system might be developed in the future.

3.1. From a single manual recording spot to a network of autonomous recorders

The sampling protocol is mainly constrained by the recording equipment available. Our method was first tested with a comparison between two closely spaced dry lowland coastal forests in Tanzania. The recording of the animal communities inhabiting these forests was achieved with a digital recorder (Edirol© R09) equipped with an omnidirectional microphone (Sennheiser© K6/ME62). Recordings were done by a single person at three times of the day and successively in the two forests. This procedure limited the sampling to a few days and to only two sampling sites. Such digital recorders also provide internal microphones that can be used to reduce costs. In this case, several items can be purchased to cover a wider area and a longer period of time. However, the recorders still have to be triggered and stopped manually, a condition that makes field work rather challenging.

Unattended recorders were not available since the North American company Wildlife Acoustics© provided an autonomous digital field recorder (see details about this recording package in section 3.2). An autonomous system was absolutely necessary to design sampling protocols with synchronised units such as regular, cluster, multi-level, or stratified protocols. We first used three of these recorders to assess animal diversity within temperate woodlands by simultaneously recording a mature forest, a young forest and an edge forest (figure 2A, Depraetere et al., 2012). We then increased the number of recorders to estimate biodiversity endemism of three New-Caledonian sites. We planned a stratified sampling with four recorders set in each site. This ensured a repetition per site and allowed comparisons within and between study sites (figure 2B). Later, we tracked acoustic diversity of a typical tropical forest by deploying a network of 12 recorders regularly spaced on a 100 ×100m grid in French Guiana (see IV, 2). Each recorder was equipped with a microphone settled 1.5m high and a second microphone placed 20m high in the canopy (figure 2C). This 3D regular sampling covered 12ha of forest for more than 40 days. Eventually, we tried to transfer our method to freshwater habitats like forest ponds. This was achieved by adapting the autonomous recorder with a Reson© hydrophone and an Avisoft© pre-amplifier (figure 2D). This high-quality equipment is expensive (about 2700€ per unit) and sampling was therefore limited to three recording units. We therefore designed a rotating sampling by regularly moving the hydrophone position along transects.

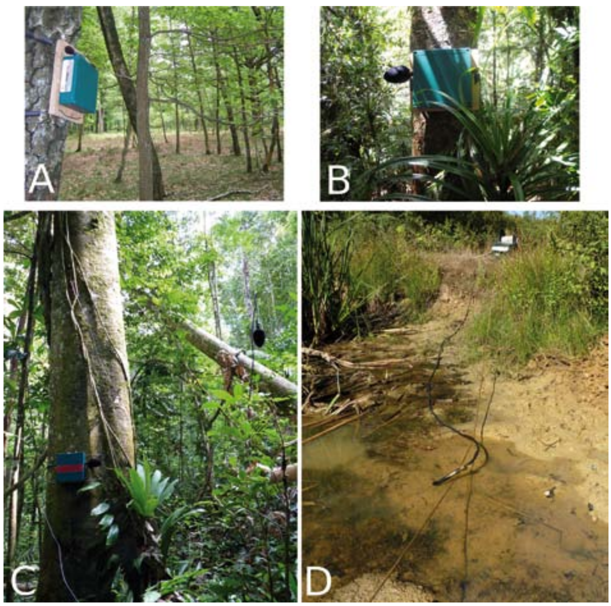

Figure 2: The autonomous Wildlife Acoustics© recorder installed for outdoor studies. A. First version of the recorder (SM1) settled in a temperate woodland to estimate local bird acoustic community (Rambouillet, France). B. Second version of the recorder (SM2) with a single microphone in action (Mandjelia, New-Caledonia). C. The same recorder with two microphones, one 2 m high and the other one ready to be set 20 m up in the canopy (Nouragues experimental station, French Guiana). D. Recorder connected to an hydrophone to record underwater sound of a pond (Rambouillet, France).

3.2. The Song Meter: an autonomous acoustic sensor

Wildlife Acoustics© developed two generations of autonomous digital recorders, namely the Song Meter SM1 and SM2 (figure 3). These stereo recorders, which weigh 1.6kg each and measure 20.3 × 20.3 × 6.4cm, possess a stereo recording system with omnidirectional microphones that have a flat frequency response between 0.02 and 20kHz. These microphones can be directly connected to the main box, where data are stored, or can be settled up to 50m away from it. Given that terrestrial animals produce sound with an intensity of *ca.* 80dB at 1m *re.* 2×10^{-5} µPa (Sueur, unpublished data) and given that the microphones have a sensitivity of -36 ± 4dB, we can estimate that in a closed habitat, such as a forest, the microphone detects sounds up to around 100m from the source. A SM2 platform would then cover an area of approximatively 3,1ha.

The recording sampling rate can be set from 4 to 48kHz with the standard SM2 and up to 384kHz with the ultrasonic SM2 option. The SM2 recorders are currently working with a lossless compression format (.wac) that can be written on four secure digital (SD) cards. The four SD slots provide 128Go storage space. Choosing an adequate sampling rate is not an easy task as it results from a trade-off between cost, data storage and the sound frequency used by animals. Increasing the sampling rate to high frequency requires a specific and expensive motherboard and, above all, generates very large sound files that are difficult to handle and to analyse. However, this is the only solution to record the acoustic activity of some insects and bats that emit ultrasound signals for communication or navigation. Up to now, we sampled the animal acoustic communities at a 44.1kHz sampling rate. A network of recorders generates thousands of files that need to be stored and analysed (see section 4.2). Using a higher sampling rate will certainly preclude the estimation of acoustic diversity by generating too high an amount of data.

Electrical power is provided by four alkaline or LR20 batteries ensuring a maximum of 240 hours of recordings. Energy can also come from an external 12V battery potentially connected to a solar panel. Eventually, the SM2 platform provides also an internal temperature sensor and a connection for an external sensor. The additional data are written on the SD cards together with sound files. The main advantage of the Song Meter is that it can be easily programmed to record on simple time-of-day schedules or to implement complex monitoring protocols, even scheduling recordings relative to local sunrise, sunset and twilight. For instance, a schedule can be programmed to record regularly all day and night long, but also to record more intensively around sunrise and sunset, when dawn and dusk choruses of birds, insects and amphibians occur.

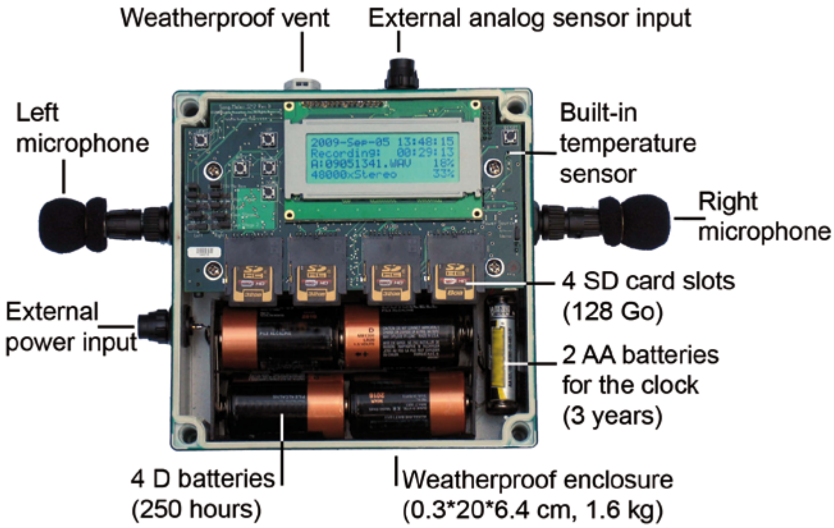

Figure 3: The second version of the recorder (SM2) opened to show the main characteristics. A cable can be used to set the microphones away from the main box. Detailed characteristics can be obtained at http://www.wildlifeacoustics.com. © Wildlife Acoustics.

3.3. Computing the acoustic indices

Biodiversity is traditionally decomposed into two levels, the average diversity within communities, or α diversity, and the diversity between communities, or β diversity. We therefore developed two acoustic indices aiming at estimating these two components of biodiversity (Sueur et al., 2008a). Both indices can be computed with the package *seewave* (Sueur et al., 2008b) of the free R environment (R Development Core Team, 2012). The first index, named H, is a Shannon-like index. The index H gives a measure of the entropy of the acoustic community by considering both temporal and frequency entropy. H is computed according to:

$$H = Ht \times Hf \text{ with } 0 \leq H \leq 1, \text{ and}$$

$$Ht = -\sum (A(t) \times \log(A(t)) / \log(n)), \text{ and}$$

$$Hf = -\sum (S(f) \times \log(S(f)) / \log(N)),$$

where n = length of the signal in number of digitized points, $A(t)$ = probability mass function of the amplitude envelope, $S(f)$ = probability mass function of the mean spectrum calculated using a short term Fourier transform (STFT) along the signal with a non-overlapping Hamming window of $N = 512$ points (figure 4).

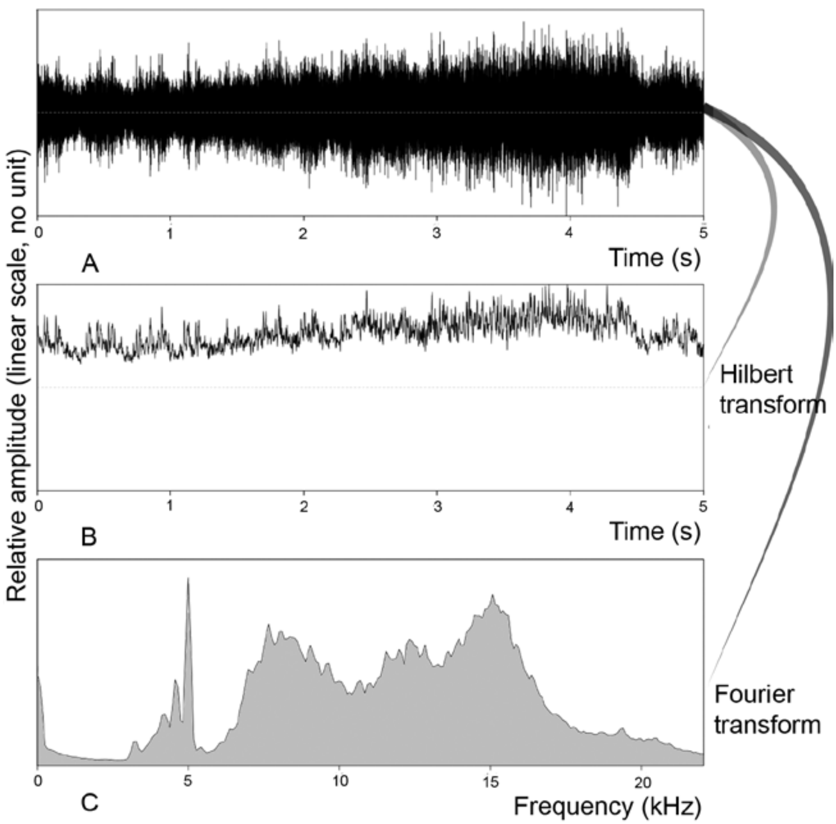

Figure 4: The main two transforms used on raw recordings. A. Waveform or oscillogram of a sound recording. B. Amplitude envelope, $A(t)$, obtained through the Hilbert transform. C. Mean spectrum, $S(f)$, obtained through a Fourier transform. Note the different x axes and that all y axes are in relative amplitude along a linear scale.

The H index increases logarithmically from 0 to 1 with species richness and evenness when considering species-specific calls (Sueur et al., 2008a). The index will be particularly high for a signal that has a flat amplitude envelope and a flat frequency spectrum. When only considering the spectral component of the index, a flat or multi-peak spectrum will give a higher Hf index than a single peak spectrum (figure 5 A, B). The H index was applied in Tanzania, and correctly revealed a higher acoustic diversity in the preserved part of the forest than in the disturbed part (Sueur et al., 2008a). However, Hf is not reliable when dealing with recordings made in the temperate woodland, where the acoustic activity is low and polluted with environmental noise. In this particular case, we developed another index, named Acoustic Richness *AR* which was computed according to:

$$AR = \text{rank}(Ht) \times \text{rank}(M) \times n^{-2}, \text{ with } 0 \leq AR \leq 1,$$

where rank is the value position along the ordered samples, *M* is the median of the amplitude envelope and *n* the number of recordings (Depraetere et al., 2012).

The second index, named *D*, is a simple acoustic dissimilarity measure. *D* is similarly composed of two sub-indices based on a difference between amplitude envelopes and frequency spectra respectively (figure 5 C). *D* is calculated like following:

$$D = Dt \times Df \text{ with } 0 \leq D \leq 1, \text{ and}$$
$$Dt = 0.5 \times \sum |A_1(t) - A_2(t)|, \text{ and}$$
$$Df = 0.5 \times \sum |S_1(f) - S_2(f)|,$$

where $A_1(t)$, $A_2(t)$ are probability mass functions of the amplitude envelope for the two recordings under comparison, and $S_1(f)$, $S_2(f)$ are probability mass functions of the mean spectrum for the two recordings to be compared. The *D* index increases linearly with the number of unshared species between the two recordings, or communities (Sueur et al., 2008a). Both indices may suffer a bias as some species naturally produce signals with high temporal and/or spectral entropy. This is particularly the case of cicadas whose noise-like sound can be mistakenly interpreted as a high local diversity. Such bias can be buffered with a large sampling including a high number of time and space repetitions. The indices can also produce false values when background noise overlaps with the sound produced by the animal community (see section 4.1). Both indices are currently tested in different temperate and tropical habitats in this respect.

Other acoustic indices have been developed elsewhere to monitor habitat state or community activity. Qi et al. (2008) divided the soundscape of an ecosystem following three frequency bands: the anthrophony, between 0.2 and 1.5kHz, the biophony, which starts at 2kHz with a peak at 8kHz, and the geophony, which can cover the entire spectrum with dominant low frequency. By computing a ratio between biological and anthropogenic signals, they coined an ecological estimator of ecosystem health. This original procedure does not give an estimation of local diversity but assesses the level of biological sound activity relative to anthropogenic activities. Pierreti et al. (2010) and Farina et al. (2011) designed an acoustic complexity index (ACI). This index computes time and frequency variability of a sound extrapolated from a spectrogram. The ACI appears to be correlated with the number of vocalisations produced by a bird community. However, this index assesses neither species diversity nor community turnover. The ACI index proved to be poorly sensitive to invariant noise, such as continuous noise from cars or aircrafts, but can be impacted by unpredictable noise such as wind, running water or irregular human activity. All these acoustic indices, including *H*, *D*, and others in current development probably do not quantify the same facet of animal acoustic diversity.

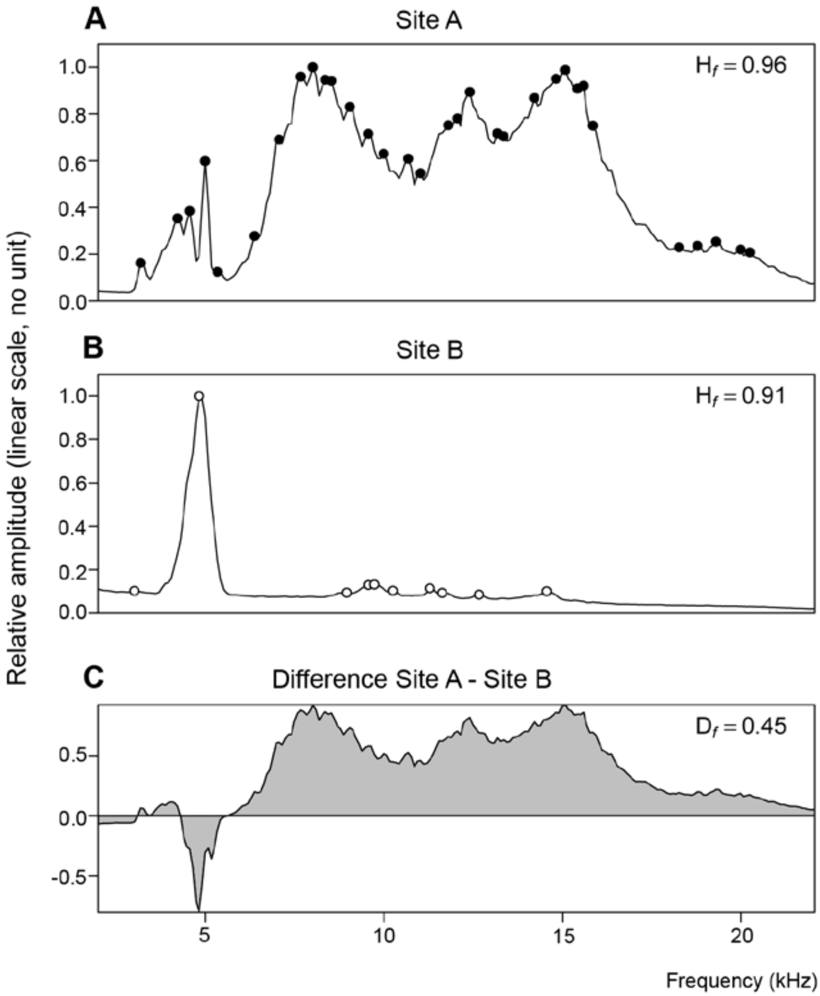

Figure 5: Illustration of a spectral analysis on recordings made in two sites in New-Caledonia (France). A. A recording showing a broadband frequency spectrum with a high H_f index and a high number of peaks. B. A recording with a single dominant frequency peak generating a lower H_f index and less frequency peaks. C. The difference between the two spectra used to compute the D_f index.

4. Sensitivity to noise level, sensor size and autonomy

4.1. Everything but noise

Background noise is probably the primary issue in bioacoustics. Noise can significantly impairs acoustic observations and experiments by masking or distorting both time-amplitude and frequency parameters (Hartmann, 1998; Vaseghi, 2000). There are three main sources of noise to consider when recording outdoor: *i*) anthropogenic noise due to machinery, car, boat, plane, train traffic, or any other human activity, *ii*) biotic noise due to the activity of surrounding species, and *iii*) environmental noise due to rain, wind, river stream, waterfall, or sea wave (Brumm and Slabbekoorn, 2005; Laiolo, 2010). The estimation of animal diversity through acoustics is based on the recording of a whole community and as such does not face the classical problems encountered when trying to record a single species in the background noise generated by surrounding active species. However, anthropogenic and environmental noise can have negative effects on the results. In a few instances, anthropogenic noise can be removed by applying classical frequency filters (Stoddard, 1998). Recordings made close to an airport or a road with a regular traffic can be cleaned with a high-pass filter that will remove the low frequency band generated by plane or car engines. Such filters might exclude low pitch animal calling songs, but this can be accounted for when computing diversity indices. The main difficulty arises when recordings are polluted with unpredictable and/or broadband noise that can be interpreted erroneously as animal sounds. Removing such chaotic sound is a challenge to be solved in bioacoustics as well as in other acoustic disciplines (Rumsey and McCormick, 1992; Hartmann, 1998; Stoddard, 1998; Vaseghi, 2000). Usual frequency filters cannot be used as noise may overlap the frequency band used by the animal community. Other noise reduction algorithms use noise spectrum as a reference to be convoluted with the original signal. This solution might appear elegant but still suffers important limitations. First, the noise has to be constant in its frequency content, a condition rarely met in a natural acoustic environment. Second, it is necessary to identify accurately a time window where only noise occurs. This latter condition is very difficult to meet when faced with hundreds or thousands of recordings.

Fortunately, some upstream solutions can be considered to reduce the anthropogenic and environmental noise (Obrist et al., 2010). When using an outdoor acoustic sensor, the most important parameter to consider is the direction and the protection of the microphone. The microphone can be oriented in a horizontal or vertical position as soon as its directivity pattern is omnidirectional. A vertical upward position should be avoided when possible, as rain drops might directly strike the microphone membrane. A vertical upside-down orientation might be the best solution in avoiding rain and lateral wind effects. More generally, adapting the orientation of the microphone to the local main sources of noises is usually advocated. For instance, the noise of running water or passing-by cars can be reduced by orienting the microphone perpendicularly to the source, and windscreens should be used to attenuate wind noise. Another upstream solution is to exclude data potentially corrupted with environmental noise. This can be achieved in three ways. The first option consists in cutting off the recording session when weather conditions are too bad. It is not yet available but could certainly be implemented quickly, given the availability of climate sensors in sound meter devices. The second option is to apply a signal-to-noise algorithm that indicates the occurrence of an important background noise. A threshold could be used as a reference to keep or to remove the files from the dataset. This solution is under development in our group. The third and last option, which is currently in use, is to gather climatic parameters from a local station and identify the time periods when the weather was too bad to allow a correct estimation of the acoustic diversity. This identification can be achieved automatically with a threshold applied on the climatic parameters or by running a redundancy analysis (RDA, Rao, 1964) to the acoustic indices with the climatic parameters as factors (Depraetere et al., 2012).

4.2. Optimal size of recorders

As described above, the SM2 recorder weighs around 1.6kg and can be fitted with two microphones (figure 3). Hence, handling several of these units in a hard-to-reach environment requires a significant effort. A reduced size and weight would make field work easier and could also allow settling more units in the habitat. However, this has to be traded off against the size of the data that needs to be stored and analysed. A typical .wav file, which is the most popular uncompressed audio format, has a size of around 690kb/s (= 84ko/s) when sampled at a 44.01kHz rate. This means that one minute of recording is roughly equivalent to 5Mo for a single channel (mono) or around 10Mo for two channels (stereo). Sampling quickly generates $x \times 10^2$ hours of recording in $x \times 10^3$ files for a total $x \times 10^2$ Go data. As detailed above, the recorders have storage capacity of 128Go, which is enough for most applications sampled at 44.01kHz, but might appear limited for an over-month or over-year survey or for a long ultrasound monitoring. The next step of data transfer onto a hard disk for storage and conservation can take a significant time as writing speed is usually slow (around 6Mb/s = 0.7Mo/s). Eventually, the long-term storage of teraoctets of data can encounter some limits with a standard hard disk or server capacity.

Regarding the calculation of indices, the larger the file, the slower the analysis process. Even if automated with R scripts, the analysis of thousands sound files is time-consuming. This is due to three main factors: *i*) the number of files to be analysed, *ii*) the size of each file, and *iii*) the time taken by R to work with large files. There is no easy way yet to counteract these three caveats. The number of files will increase as samples will be larger. The size of each file cannot be reduced. Compressed formats in particular, such as .mp3, cannot be used for obvious reasons of signal quality. The platform R is very convenient as it is free and open-source. It makes it a perfect tool for sharing our research and transferring our techniques to other laboratories. However, it may be relevant to look for other software solutions (see section 5.2).

4.3. Energy

The SM2 recorder was developed to consume as less energy as possible, but current batteries ensure 240 hours of recording and therefore put a strong limit on the duration of sampling. A solution is to connect the recorder with a 12V battery fuelled with solar energy. However, if such autonomous energy system properly works in sunny areas, it is not adapted to cloudy or shaded areas like the understory of a tropical forest where a very low percentage of solar radiation reaches the ground.

5. What's next?

5.1. Sampling

Our method needs to be tested, validated and eventually applied in several acoustic conditions from different habitats. So far, we have tested it with both simulated and field acoustic communities (Sueur et al., 2008a; Depraetere et al., 2012). Tests on field communities concerned African tropical coast forest and temperate forest habitats. The latter test implied a modification of the indices to take into account the background noise and the low activity of the acoustic community. We are currently sampling several other places including mountain tropical forests in New Caledonia, neotropical evergreen forest in French Guiana, and evergreen monsoon forest in India. We are also transferring the technique to freshwater habitats by using hydrophones immerged in ponds.

One of the aims of our method is to provide a long-term and large-scale sampling. We are currently sampling species diversity with a network of 10-16 sensors working about 40 days long over approximately 16 ha of tropical forest in French Guiana and India. This time period is too short to track seasonal variations of species diversity. We would like to extend it to at least one year or even longer periods. Moreover, we plan to increase the number of sensors to monitor a larger area. Increasing the sampling time and network size will generate serious storage issues. A cut-off system that stops recordings when the meteorological conditions are not good enough could constitute a nice and cheap solution to overcome this difficulty. Another way could consist in sending directly the data from the recorder to a server through a satellite connection, as wireless connection to a base radio may be too slow for heavy sound files (see IV, 2 section 2.3). However such technological improvement mainly depends on the industry and may take some time to emerge.

5.2. Improving the indices

As explained earlier, background noise is a central issue, and our indices, especially the index *H*, are particularly sensitive to noise. It is therefore necessary to develop new indices that are noise-resistant. Current research is ongoing in our laboratory to develop a new measurement of the richness based on the frequency peaks of the Fourier spectrum (figure 5). The spectrum can be smoothed or residual peaks due to noise can be filtered out so as to improve the measure in case of rain or wind noise. Amplitude or frequency threshold will be also applied on the envelope and the frequency spectrum respectively, to try to increase the signal-to-noise ratio. Whatever the index in use is, we also need to exactly identify which biodiversity information is collected by using the acoustic community as a proxy of animal diversity. Does the *H* index only embed a richness-evenness value or does it include phylogenetic and/or functional diversity information? Eventually, as outlined above, the signal analysis can be slow due to R process. Software directly written in C language will be developed on the next years to significantly speed up the analysis process.

5.3 Sharing the method with other scientists and citizens

There is an important ethical requirement for making available the bioacoustic sensor and primary biodiversity data for later uses in terms of knowledge, engineering or conservation (e.g. Graham et al., 2004; Suarez and Tsutsui, 2004). The recording equipment we used so far can be purchased to the company Wildlife Acoustics©. The *H* and *D* index can be computed with the free R package *seewave*. The sensor and integrated bioacoustic system is therefore available to anyone. However, R does not have a user-friendly interface and we plan therefore to share the method soon through an interactive website. Any user will be able to upload recording files for analysis. The acoustic indices will be returned to the user together with an optional graphical representation of the sound analysed (e.g., waveform, envelope, spectrogram, spectrum). On a long-term scale, the recorder and the signal analysis would not be separated but associated in a small and light all-in-one system. This system could be a 'smartphone' including a free application that computes the indices. Smartphones were proved to work as nice sensors for mapping the noise level of European cities (Maisonneuve et al., 2010). A similar citizen-science experience could be undertaken to assess animal acoustic diversity inside or around cities.

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