Figure 14.3 A bat acoustic monitoring station; a bat detector is kept in the box (Photo: Sara Bumrungsri)

Figure 14.4. A heterodyne bat detector (left) and a time expansion bat detector (right) (Photo: Sara Bumrungsri)

Chapter 13

AUTO-MONITORING WILDLIFE RECOVERY

George A. Gale[1] and Sara Bumrungsri [2]

ABSTRACT

Wildlife monitoring during forest restoration addresses such questions as: What species re-colonize or disappear from restored areas? How many individuals are present? What are the population trajectories? In this review, we focus on issues related to automating surveys of forest birds and mammals, particularly bats. For both birds and mammals, the need to automate data collection and analysis is clear, but several constraints must be overcome, before such automation becomes practical, compared with labour-intensive, conventional methods. Currently, wildlife species can be recognized and their abundance estimated by using audio recording and photography. However, species recognition software, using audio data, generally performs poorly, compared with humans, particularly under field conditions, where such systems fail to distinguish multiple overlapping calls and separate them from interfering background noises. Similarly, for images, highly variable lighting and lack of clarity of camera-trap images often confuse auto-recognition software. Nevertheless, automated systems continue to improve, and it is likely that they will achieve parity with humans in the foreseeable future. In the near-term, they will have the ability to save considerable amounts of time, by searching through large numbers of files, to narrow searches for particular species and transmitting such files wirelessly over networks. Furthermore, outside of cellular network coverage, drones can be used to collect image or audio data from wireless devices in the field. Thus, while these techniques are currently far from being highly accurate, inexpensive and practical for broad-scale surveys, it is not difficult to imagine a future when assessments of the wildlife recovery that is expected to occur with forest restoration will become increasingly more automated.

***Key words*:** wildlife surveys, automated analyses, bat detectors, species recognition

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OBJECTIVES OF MONITORING

Wildlife monitoring has a long history, dating back to the 1890's (PETERSEN 1896). Wildlife monitoring typically starts with the basic question "how many individual animals are there in a population?" And if we are able to answer this question through time, then it is possible to address questions like "what is the trajectory of the population (declining, increasing, or stable)?" In the context of forest restoration, we need to determine: Which species have recolonized the restoration sites? And what are their relative abundances? Hence, we can answer questions regarding the relative representation of different feeding guilds, particularly frugivores that are likely to disperse seeds into regenerating sites, and perhaps threatened species.

Such questions are particularly pertinent, because community structure changes markedly, as vegetation regenerates from relatively open, perhaps mostly weedy plants, to closed canopy forest. More recently, occupancy, which uses presence/ absence data, to assess the proportion of sample sites occupied by a target species, can also be used to monitor wildlife. Such methods may be particularly useful for broad scale, long-term assessments (VAN STRIEN et al., 2013). While the basic techniques of wildlife monitoring are relatively straightforward, several issues complicate the process such as: observer bias (BETTS et al., 2007), imperfect detectability (MACKENZIE et al., 2002) and particularly, the prohibitive costs of sampling over large spatial and temporal scales, at sufficiently fine resolutions (APPLEGATE et al., 2011). Another complication is that species identification in the field and even from camera-trap photographs often requires extensive training and/or experience. Automation of survey processes would reduce some of these complications.

Which wildlife species to monitor?

Although monitoring a small set of species, as indicators of forest recovery, has some drawbacks (CARIGNAN & VILLARD, 2002), birds have been used widely because they provide critical ecosystem services (particularly seed dispersal), respond rapidly to change, are relatively easy to detect and may reflect changes at lower trophic levels (e.g., insects, plants) (SEKERCIOĞLU et al., 2004). Mammals can also be useful indicators of ecosystem health, hunting pressure (KIFFNER et al., 2014) and seed dispersal potential, particularly bats (SRITONGCHUAY et al., 2014). However, mammals are far more difficult to survey than birds—as most do not vocalize frequently (except bats and some primates). They often occur naturally at low densities and they are frequently nocturnal. In this review, we focus on forest birds and mammals, including bats. For both birds and mammals, the need to automate data collection and analysis is clear, but several constraints must be overcome, before such automation becomes practical, compared with labor-intensive, conventional methods.

CURRENT STATE OF THE ART

Birds: species identification

For birds, one of the main constraints is reliable species identification. In tropical forested habitats, 90-95% of bird detections are by ear (GALE et al., 2009), requiring extensive experience. Even in more open habitats, a significant percentage of bird identifications are by sound rather than sight. However, the complexity of bird song, 'background' noises (present in most habitats) and multiple overlapping songs that occur in many bird communities make automated species identification a challenging task. Interestingly, automation of bat species recognition is far more advanced (SCOTT, 2012) (see below). For the purposes of thinking about automated sound analysis, there are at least five broad categories of discrete sound unit shapes that compose bird sounds: i) segments with constant frequency, ii) frequency-modulated whistles, iii) broadband pulses, iv) broadband with varying frequency components and v) segments with strong harmonics (BRANDES, 2008). If we think of those discrete bits of sound as syllables, then this complexity can range from simple repeated sequences of syllables to complex sequences of syllables with patterns that rarely repeat. We can add to this complexity field situations that make detection and classification more difficult such as when encountering duets, choruses of overlapping songs, intentional call masking or mimicry. Finally, difficulty in creating automated classifiers can arise from species that have regional dialects, very large song repertoires and even improvisational songs (BRANDES, 2008).

Overall, there are several problems with identifying all species present in noisy recordings, containing multiple, simultaneously-vocalizing birds (CHU & BLUMSTEIN 2011). A related problem is detection of one or a few target species (BARDELI et al., 2009), amidst other sources of noise, including other birds, and the detection of birds that make a particular type of call (e.g., tonal sounds) (JANCOVIC & KOKUER, 2011).

Automated analysis of bird sounds

The analysis process has two primary parts: i) call-feature extraction and ii) call classification. The choice of which features to measure depends mostly on the structure of the target calls, whereas the choice of the classifier depends on the way in which the feature measurements distinguish the various types of target calls (BRANDES, 2008). For example, features may include call duration, highest frequency, lowest frequency, loudest frequency, average bandwidth, maximum bandwidth and average frequency slope.

An entirely different approach is to use stochastic sequence modelling techniques to classify sounds, based on short-time measurements of sound features and how these features change in time. This is accomplished with hidden Markov models (HMM), a technique widely used for human speech recognition (TRIFA et al., 2008). However, perhaps the most common problem for automated identification of bird sound recorded in natural settings is background noise. It not only limits bird song detection, but also cause misclassifications (BAKER & LOGUE, 2003). The most common method for dealing with noise is to limit the sound analysis to the frequency bands where the target sounds are found by using band-pass filters. Unfortunately, these methods can also eliminate many of the target sounds if they overlap the high noise part of the spectrum (BRANDES, 2008).

Relatively recently, a multi-instance multilabel (MIML) framework for supervised classification has been used (ZHOU & ZHANG, 2007). The main idea of MIML is that objects to be classified are represented as a collection of parts (referred to as a "bag-of- instances") and are associated with multiple class labels (BRIGGS et al., 2012). In this application, the objects to be classified are recordings, the parts are segments of the spectrogram, corresponding to syllables of bird sound, described by a feature vector of acoustic properties and the labels are the species present (BRIGGS et al., 2012). All supervised-classification algorithms require some labeled training data to build a predictive model. A major advantage of MIML is that the only training data required is a list of the possible species present, rather than a detailed annotation of each segment, or training recordings, containing only a single species (which is required in most prior work) (SELIN et al., 2007). For recordings containing multiple, simultaneously-vocalizing bird species, it is less labor intensive to construct the former type of labels (BRIGGS et al., 2012).

The accuracy of such methods is still relatively low, compared with conventional techniques with human observers. For example, researchers using MIML had 20% false positives and 35% false negatives in 20 trials containing one to four species per trial, with a total of 13 possible species, (BRIGGS et al., 2012). Other methods, using complex descriptive statistics successfully recognized 317 out of 384 (82.5%) calls correctly for one species and 177 songs were correctly discovered out of 230 (77.0%) of a second species (POTAMITIS et al., 2014). Although specific accuracy relative to standard human observers appears to be lower for these automated techniques, overall, automatic species recognition can considerably reduce the search time for a human observer, when searching through thousands of audio files containing many different species (POTAMITIS et al., 2014).

Individual recognition

TERRY & MCGREGOR (2002) successfully used and compared three basic types of neural networks to identify individual Corncrakes (*Crex crex*). Since Corncrakes have calls that consist of broad-band pulses, with distinct timing, they found that the pulse-to-pulse timing is the most important feature to measure. Others, working with the same species, also found that they could assess the probability as to whether two calls belonged to the same individual or not, but definitive identification was not possible, if the number of individuals was not known beforehand. This was also shown in other species (EHNES & FOOTE, 2015). Furthermore, individual recognition can be used to estimate population sizes, using a mark-recapture framework (STEVENSON et al., 2015).

Occupancy and abundance estimation

Recent studies have demonstrated that species abundances of both birds (DAWSON & EFFORD, 2009) and frogs (STEVENSON et al., 2015) can be obtained using acoustic detection.

Hardware for automated bird recording

The basic components of hardware for use in automated recording of bird sound are a microphone, audio recorder, power supply, a mechanism for initiating and ending recordings and a weather-proof housing for the equipment. The first and simplest approach is to design a scheduling timer through a hardware interface to control a stand-alone commercial recorder. A second approach is to write software for a programmable recording device, such as a personal digital assistant (PDA) or a smart phone (BRANDES, 2005). The third and most complex approach is to develop recorders with single board computers (FITZPATRICK et al., 2005). Furthermore, in theory, recorders could be deployed into the field by UAVs as some are sufficiently lightweight (<100 g) (FURNAS & CALLAS, 2015).

BRANDES (2008) recommended that with automated recorders, omni-directional microphones could be used instead of directional microphones, because it is not possible to know *a priori* from where sounds will originate. Single-element, omni-directional microphones can be effective, but using a small array of microphones to create a more sensitive beam-pattern can increase effectiveness e.g. the linear 16-element microphone array (<15 cm in length), designed by the Bioacoustics Research Program at the Cornell Lab of Ornithology for use with their ARUs (autonomous recording units). They are most sensitive to sound around the axis of the microphone array and least sensitive in the direction pointing from each end. By placing this microphone array in the canopy hanging downward, it is sensitive to sound originating from any direction within the canopy. A second approach to improving omni-directional microphone gain is to use a specially designed waveguide to collect and amplify the sound before it reaches the microphone element. For further details see BRANDES (2008).

Software for automated bird recording

The review by BRANDES (2008) made several suggestions regarding organizations that provide software for acoustic sampling. A few commercially available software packages are used to analyze and develop automatic detection of bird sounds. The Extensible Bioacoustics Tool (XBAT) developed and distributed by the Bioacoustics Research Program at the Cornell Lab of Ornithology, has been particularly useful in developing avian sound-recognition algorithms (FIGUEROA & ROBBINS, 2008). It runs as a toolbox within the MATLABH mathematical programming environment. Other relevant software available includes Song Scope, sold by Wildlife Acoustics and SyrinxPC, provided by the University of Washington.

List of Web Addresses relevant to acoustic sampling (from BRANDES, 2008):

1. Borror Laboratory of Bioacoustics https://blb.osu.edu/
2. Cornell University's Bioacoustics Research Program http://www.birds.cornell.edu/brp/
3. Hidden Markov Model Toolkit http://htk.eng.cam.ac.uk/
4. Macaulay Library of Natural Sound http://macaulaylibrary.org/
5. Oldbird, Inc. http://www.oldbird.org
6. River Forks Research Corp. http://www.riverforks.com/
7. Wildlife Acoustics, Inc. http://www.wildlifeacoustics.com/

CURRENT STATE OF THE ART

Bats: species recognition and automated species classification

The main constraint when studying bat communities is the difficulty of obtaining visual observations. Furthermore, bat calls are mostly inaudible. Thus, before acoustic sampling became possible, the most reliable species records were obtained by capturing bats in mist nets or harp traps. For thinking about automated species recognition, bats can be divided into two groups: fruit/nectar- eating bats and insect-eating bats. Old World, fruit/nectar bats can be identified to genera by their external morphology, especially their face, so camera trapping is needed. On the other hand, species of insectivorous bats, which produce echolocation calls, can be identified using echolocation call analysis.

Automated recognition and monitoring of insectivorous bat species is plausible because they emit echolocation calls for navigation and communication. These calls are characteristic and often species-specific. Compared with birdsong, bat echolocation calls are simpler and easier to identify using automated systems. Typically, bat calls can be classified into two types: i) quasi-constant frequency and ii) broadband frequency-modulated. Harmonics are usually present in bat calls and the harmonics with maximum energy (seen from spectrograms) are used for species identification. Similar to birds, automated monitoring requires recording and analyzing the echolocation calls. A bat detector, which converts inaudible (>20 kHz) calls to the audible range (<20 kHz), is used to record bat calls. During the last two decades, acoustic bat surveys, using bat detectors (Fig. 14.1 & Fig 14.2), have been widely used to study distributions, activity levels and habitat use and to monitor population trends of bat species of concern, both at local and regional scales (WALSH et al., 2004). Bat detectors can also be used with canopy-foraging species and bats which fly higher above the ground, provided their calls are loud enough. However, bat detectors have their drawbacks. They cannot determine the number of bats from the number of calls produced. Thus, a relative bat activity index is used, instead of the number of bats present. Researchers use the number of 'bat passes' to index relative abundance. In addition, acoustic sampling is much less effective for bats that produce faint calls (e.g. small gleaning species). Thirdly, some nocturnal insects (e.g. cicadas), which produce high frequency noises (up to 50 kHz), may partly interfere with bat acoustic sampling.

Hardware for detecting bats

There are four types of bat detectors: heterodyne (Fig. 14.2), frequency-division, time-expansion (Fig. 14.2) and full-spectrum.

Heterodyne bat detectors (like radio-receivers) tune to a particular frequency (of bats). If flying bats produce such a frequency, the apparatus detects it. It is the most sensitive of the detectors and can register very weak signals, but is limited to a narrow frequency range. Thus, heterodyne detectors are useful for monitoring single species, but it is usually not possible to save frequency information.

Frequency-division detectors use a broadband technique (i.e. the entire ultrasonic range is transformed at all times). The transformed frequency is usually one tenth of the original frequency. Thus, calls of 70 kHz in 5 ms generate an audible output at 7 kHz in 5 ms. They are less sensitive than heterodyne detectors, as they have a minimum threshold level. Signals below the threshold are not transformed. However, frequency division bat detectors provide more information about recorded calls and they can be used for sound analysis. The fundamental frequency is retained and pulse duration and other temporal parameters can be measured. Output is in real time and can consequently be used to continuously monitor bat activity, although some physical information of the calls is lost.

Time expansion detectors also use a broadband technique. They sample and digitize a signal and play it back over an expanded time. The time expansion factor can vary from 10-32, but 10 is commonly used. Since it plays back at slower speeds, the output frequency is lower and the pulse is longer. In using, for example, a 10x time expansion bat detector, a call of 70 kHz and 5 ms will play back at 7 kHz and 50 ms. All the physical properties of signals including the harmonics are virtually preserved and output is excellent for sound analysis. Once expanded, calls can be recorded via a recorder or directly recorded by a computer. This type of bat detector is suitable for studies of social behavior, as well as species identification. However, this system cannot record during playback. Thus, it cannot continuously monitor bat activity. With a 10x expansion, the system samples only 7-9% of the available time.

Full-spectrum detectors record all frequencies. They sample at very high rates to capture all signal information and output it in real-time, so we get not only the details of call structure (as with time expansion systems), but also the real-time continuous monitoring (as with frequency division systems). They enable a very detailed analysis of the sound and a clearer sonogram, compared with frequency-division systems. Full-spectrum detectors are often used for passive monitoring, where a researcher does not need to be present to save recorded calls.

Although frequency-division detectors produce files that are approximately one tenth the size of those produced by time expansion detectors, their recorded calls are much less informative; hence species identification is more difficult, especially where calls are less well-documented or with relatively higher species richness. In some models, time expansion bat detectors provide a noise triggering option (allowing the device to start recording as soon as sound is detected), to save recording space. In most models, an on-off timer is provided, to save battery power, allowing batteries to last up to a month. The most fragile part of these bat detectors is the microphone, which is sensitive to humidity. Generally, most models of frequency division, time expansion and full-spectrum bat detectors use directional microphones. However, some models offer omni-directional microphones, which are less sensitive. Prices vary considerably; although heterodyne detectors are relatively inexpensive (under US$ 100 as of the year 2016), other types are generally higher in price, sometimes more than US$ 1,000.

Manual and automated analysis of bat sounds

Only recently has automated analysis of bat calls been available. However, manual call analysis is still needed for many areas of the world because call databases for automated call identification software are available only for bats in Europe and North and South America. Commonly-used manual call-analysis software include Batsound and Avisoft. Recorded calls are filtered, to delete background noise, and then six parameters, from the call harmonics with the most energy, are measured: call duration (ms), frequency at maximum energy, frequency at half of the call's duration, frequency at beginning of call and inter-pulse interval (PREATONI et al., 2005). Manual call measurement is time-consuming. Fortunately, up to 19 characteristics of an echolocation call can be automatically measured, with the free software available in the program R (SILVA, 2014). This identifies calls using discriminant function analyses (DFA) to compare recorded calls with those of known species (reference calls). Another call-identification technique uses artificial neural networks (ANNs). Neural networks are "taught" to recognise call characteristics of known species and when calls of unknown species are submitted, ANNs can classify them. This approach has been successfully used for dolphins and bats. PARSONS & JONES (2000) achieved an 87% success rate when identifying 12 bat species in Britain (with success rates for each species ranging from 75% to 100%). They also performed DFA, but the percentage of correct identification was lower; 79% overall. Similarly, RUSSO & JONES (2002) achieved an 82% overall success rate, using DFA to identify 20 bat species in Italy. PREATONI et al. (2005) compared DFA with ANNs to distinguish between bat species in the family Vespertilionidae. DFA had a higher correct identification rate, but both were 100% correct when identifying species of the Rhinolophidae. The efficacy of both DFA and ANNs depend on the quality and breadth of training data since they both “force” unknown calls into the groups predefined by such data (JONES et al., 2000).

For automated call analysis, several automated classifier software packages are now available. These include SonoBat, Kaleidoscope Pro, Bat Call Identification (BCID), EchoClass and SonoChrio. These packages are helpful where call databases are available, such as North America and Europe. Some of them only work with call files of particular formats (e.g. zero-crossing, wave files), produced from bat detectors. However, these call files can be converted to different formats. The cost of these programs is ca. US$ 1,500. Currently, automated call classifiers have several limitations. Typically, they do not include all call characteristics in their analyses, such as amplitude-time data. Consequently, they only work well with species that have distinct frequency characteristics. They are most useful where the call characteristics of every species in a community are well-understood. In addition, results from automated classifiers still need manual verification.

In summary, automated classifiers are still in their infancy and more research and development are needed to truly automate bat surveys (review by RUSSO & VOIGT, 2016).

Bat species abundance/density

As bat detectors are not able to distinguish individual bats, an index of relative abundance, based on the number of recorded calls or ‘bat passes’ of each species, is used. A bat pass is defined as an echolocation call with at least two consecutive pulses. However, with the Anabat frequency-division bat-detector for example, researchers can use the number of files with calls of a particular species as an abundance index. Using this protocol, bat researchers could quantify habitat use/selection of particular bat species in restoration sites.

Internet sources for bat detectors and automated classifier software:

1. http://batdetecting.blogspot.com/
2. https://www.bats.org.uk/our-work/training-and-conferences/training-for-ecologists/using-bat-detectors
3. https://batmanagement.com/collections/software

TERRESTRIAL MAMMALS

Camera trapping

For assessing communities of medium- to large-bodied terrestrial mammals, camera trapping is the most reliable method (CHUTIPONG et al., 2014) (e.g., Figs. 14.3 & 14.4), although identification of species from photos is still problematic, because of the level of experience and expertise required (MEEK et al., 2013). Researchers have been estimating abundance of large mammals with camera traps for more than two decades (KARANTH & NICHOLS 1998), particularly large cats such as tiger (*Panthera tigris*) (KARANTH & NICHOLS, 1998). However, extensive manpower is needed to check and retrieve data from traps. Currently there are study plots where cameras have been networked to run continuously, but areas sampled are small (~10 ha) (KAYS et al. 2009). Some commercially available trail cameras have wireless support, such that photos and video can be sent through text messages and email within 90 seconds after an animal has passed triggering the trap, but they require a cell phone signal. To overcome this limitation and allow remote data collection from traps outside the ranges of cellular networks, drones are being developed as "data mules". For example, the Wadi Drone (http://wadi.io/) homes in on Wi-Fi signals emitted by camera traps and circles the traps until all images are uploaded to the drone, which then returns to base. The traps are powered by solar cells so no battery changes are needed. Presumably, a similar system could be used to retrieve audio files. Pattern recognition and other data management software have also been used with camera trap photos to identify species (FEGRAUS et al., 2011) or individuals within a species (HIBY et al., 2009). Drone-mounted cameras (including thermal/infrared imagery) have also been used to accurately detect some species of wildlife, although over relatively small areas (Christie et al. 2016).

THE NEXT STEPS

Currently, wildlife species can be recognized and their abundance estimated using automated processes, both for audio data and images. However, species-recognition software generally performs poorly compared with humans, particularly under field conditions, where multiple calls overlap and background noises interfere with and obscure audio data, and highly variable lighting and limited image clarity from camera traps confuse image-recognition systems. Nevertheless, automated systems continue to improve and it is likely that they will achieve parity with humans in the foreseeable future. In the near-term, they will have the ability to save considerable amounts of time by searching through large numbers of files to narrow searches for particular species for example, and such files can be transmitted wirelessly over networks. Furthermore, outside of cellular network coverage, drones can be used to collect image or audio data from solar powered, wireless devices in the field. Thus, while these techniques are far from being highly accurate, inexpensive and practical for broad-scale surveys, it is not difficult to imagine a future where assessments of the wildlife recovery that is expected to occur with forest restoration will become increasingly more automated.

FURTHER DISCUSSION

One of the important issues for automated wildlife monitoring is how to improve the accuracy of automated systems, such that they are on a par with or even less biased than human observers. One critical set of experiments/research areas towards this goal is field validation. Field validation essentially requires placing automated devices where target species and their abundances are precisely known. Although such sites are rare, particularly in the tropics, they do exist (e.g., Gale et al. 2009). We therefore suggest that a rich opportunity for collaboration is possible between researchers who are interested in automated monitoring and those running long-term wildlife-monitoring sites.

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Figure 14.3 - A Large Indian civet *Viverra zibetha* a common and regionally important seed disperser, photographed with a trail camera in Thung Yai Naresuan Wildlife Sanctuary (Thailand), April 3, 2011. Populations of species with unique, individual markings can be monitored during restoration using automatic camera traps (photo: Wanlop Chutipong).

Figure 14.4 – Thai researchers setting a camera trap (photo: Wanlop Chutipong)