FINAL REPORT

Automated Acoustic Identification of Bats

SERDP Project RC-1394

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14. ABSTRACT
This project developed a monitoring system to automatically and continuously monitor bats and birds for weeks to months by recording the vocalizations they produce. This project combined more than 10,000 sequences of species-known bat echolocation call recordings from 37 species in 30 states. High-resolution, full-spectrum data enabled an intelligent routine to automatically track call trends through noise and echoes and to extract and quantify subtle signal parameters, and enable the assessment of signal properties for quality control. The compiled known data supported the creation of an expert system to classify similarly parameterized unknown data. The expert classification of calls, and sequences of calls, uses an ensemble consensus of redundant hierarchical decision algorithms that reports a single species decision only when a result meets or exceeds an acceptance threshold at each decision step and satisfies redundant checks and signal assessments. Because of the greater number of bird species, their complexity, and variety of calls and songs, this project adopted an alternate approach to recognize target signals for bird signal recognition.

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Acronyms and Abbreviations

Eastern bats

Cora	Rafinesque's big-eared bat, *Corynorhinus rafinesquii*
Labo	eastern red bat, *Lasiurus borealis*
Lain	northern yellow bat, *L. intermedius*
Lase	Seminole bat, *L. seminolus*
Myau	southeastern myotis, *Myotis austroriparius*
Mygr	gray bat, *M. grisescens*
Myle	eastern small-footed myotis, *M. leibii*
Myse	northern long-eared myotis, *M. septentrionalis*
Myso	Indiana bat, *M. sodalis*
Nyhu	evening bat, *Nycticeius humeralis*
Pesu	tri-colored bat, *Perimyotis subflavus*

Eastern and western bats

Epfu	big brown bat, *Eptesicus fuscus*
Laci	hoary bat, *L. cinereus*
Lano	silver-haired bat, *Lasionycteris noctivagans*
Mylu	little brown bat, *M. lucifugus*
Tabr	free-tailed bat, *Tadarida brasiliensis*

Western bats

Anpa	pallid bat, *Antrozous pallidus*
Coto	Townsend's big-eared bat, *Corynorhinus townsendii*
Chme	Mexican long-tongued bat, *Choeronycteris mexicana*
Euma	spotted bat, *Euderma maculatum*
Eupe	mastiff bat, *Eumops perotis*
Idph	Allen's lappet-eared bat, *Idionycteris phyllotis*
Labl	western red bat, *L. blossevillii*
Laxa	western yellow bat, *L. xanthinus*
Leye	lesser long-nosed bat, *Leptonycteris yerbabuenae*
Maca	California leaf-nosed bat, *Macrotus californicus*
Myca	California myotis, *M. californicus*
Myci	western small-footed myotis, *M. ciliolabrum*
Myev	western long-eared bat, *M. evotis*
Myoc	Arizona myotis, *M. occultus*
Myth	fringed myotis, *M. thysanodes*
Myve	cave myotis, *M. velifer*
Myvo	hairy-winged myotis, *M. volans*
Myyu	Yuma myotis, *M. yumanensis*
Nyfe	pocketed free-tailed bat, *Nyctinomops femorosaccus*
Nyma	big free-tailed bat, *N. macrotis*
Pahe	canyon bat, *Parastrellus hesperus*

Other acronyms and abbreviations

ANN	artificial neural network
BAT	Binary Acoustic Technology
DFA	discriminant function analysis
DP	discriminant probability
FFT	Fast Fourier Transform
kbps	kilobits per second
kHz	kiloHertz
PI	Principal Investigator
spp	species
TES	threatened or endangered species

Keywords

Bat, echolocation, wildlife monitoring, presence, ultrasound, ultrasonic, bat detectors, acoustic discrimination

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Abstract

Objectives: The Endangered Species Act and other environmental regulations, such as the Sikes Act, require DoD installations to have Integrated Natural Resource Management Plans, and responsible biodiversity stewardship. This project sought to facilitate compliance with these regulatory imperatives by further developing software and hardware to automatically survey and monitor bats, with a demonstration application of this approach for birds. Particularly for rare species, monitoring accrues high costs because of the specialized skills, time, and spatial coverage required to perform this work. This project aimed to develop a system to automatically monitor bats for weeks or months by recording and analyzing the vocalizations they produce to assess species presence/absence, population levels, temporal movements, and acoustically gleaned demographic information.

Technical Approach: Although relatively easy to record with ultrasonic-sensitive recording equipment, confident matching of bat sounds to species requires a comprehensive collection of species-known recordings from a variety of conditions to sufficiently cover each species' call repertoire. This project combined more than 10,000 echolocation call sequences of species-known bats from 37 species in 30 states recorded as high-resolution, full-spectrum data. This format enabled analysis with an intelligent routine to automatically track call trends through noise and echoes to extract and quantify subtle signal parameters, and enable the assessment of signal properties for quality control. The compiled known data supported the creation of an expert system to classify similarly parameterized unknown data. This expert classification of calls and sequences of calls uses an ensemble consensus of redundant hierarchical decision algorithms that reports a single species decision only when a result meets or exceeds an acceptance threshold at each decision step and satisfies redundant checks and signal assessments. Because of the greater number of bird species, and the complexity and variety of their calls and songs, this project adopted an alternate approach to recognize target signals for bird signal search and recognition.

Results: Bat species classification using the expert system outperformed tests using other standard machine intelligence systems e.g., Artificial Neural Networks. Because of signal noise and that many bat species have overlapping call characteristics across some or all parts of their call repertoires, the classifiers cannot discriminate every recording to species, but did achieve correct identification rates of 90–100% from calls and sequences outputted from the classifiers as acceptable following signal assessment and redundant checks. Prototype field recording units enabled testing and assessment of recording under a variety of field conditions, and provided recorded sequences that directed improvements of the automated signal processing routines to reduce misclassifications and provide quality control. Bat classifier systems already developed include Northeastern, Midwestern, Ozark, Pacific Northwest, Great Basin, and Montane North regions of the United States. Some additional fieldwork remains to enable Southeast and Southwest classifiers. The bird signal search algorithm demonstrated robustness in its ability to rapidly find search targets even with low amplitude signals that occur among noise.

Benefits: The software analysis and hardware approaches developed and demonstrated by this project will enable both short and long-term non-invasive survey and monitoring of bat activity, bat species occurrence, and occurrence of targeted bird species at reduced cost and increased temporal and spatial coverage. This project will also make contributions of recording data to augment the collection of the Cornell Laboratory of Ornithology's Macaulay Library.

Objective

The Endangered Species Act and other environmental regulations such as the Sikes Act require the Department of Defense to manage threatened and endangered species (TES) on lands under its jurisdiction. Additionally Department of Defense natural resource managers require species presence and occurrence information to follow installation-specific Integrated Natural Resource Management Plans and remain in compliance with other environmental initiatives such as the Migratory Bird Treaty Act. The inventory and monitoring of bat and bird species necessary for this management accrues high costs because of the specialized skills required to perform the work. Rare and uncommon species require greater survey effort than more common species to acquire indisputable data, particularly over the many large landscapes of U.S. military installations. In addition, many installations have large tracts of land with limited access to personnel that curtails the opportunity to use standard monitoring protocols. Automated acoustic monitoring and identification of bats and birds can reduce costs and operate in personnel-restricted areas. Unlike intermittent personnel-based surveys, automated systems provide consistent data from survey to survey, allow a more thorough assessment of species presence-absence and abundances because sampling can continue in the absence of human observers, and reveal long-term trends of species, thus enabling the evaluation of military activities on TES. The methodologies and technologies developed and enhanced by this project will provide an efficient and cost-effective solution to meeting monitoring requirements for the management of endangered species, and will also be applicable to a wide range of other taxa found throughout U.S. military installations. Reliable, indisputable, and third party verifiable, biological survey data in the form of recordings can also avoid legal challenges and disputes that could otherwise delay projects.

This project advanced bioacoustic tools and techniques to automatically record, detect, and identify bats (and birds) to assess species presence and monitor spatial and temporal population dynamics. This technology can be deployed to automatically and continuously monitor bats and other acoustic signals (e.g., birds) for weeks or months at a time to assess presence/absence, population levels, temporal movements, and acoustically-gleaned demographic information.

Developing this technology entailed achieving these objectives:

- Expand an extensive and representative reference collection of species-known, high-resolution, information-rich full-spectrum recordings of bats flying under natural conditions, i.e., the type of vocalizations that passive recording stations would collect from free-flying bats.

- Develop an intelligent routine to automatically recognize calls, accept or reject them according to signal quality, and track the trend of echolocation calls through noise, echoes, and other distorting effects and automatically extract subtle signal characteristics essential to confidently discriminate acoustically similar species.

- Develop an automated system to batch process data from automated recording equipment to classify to species and extract other information such as temporal occurrence and activity.

- Develop prototype field recording hardware to acquire long-term series of recordings under field conditions for testing and development of batch processing procedures and software tools, and to collaborate with recording hardware makers to develop compatible recording systems.

- Refine processing and classification methods from proof of concept testing and field trials.

- Apply the methods and technologies developed and implemented for bats on a proof of concept demonstration application on bird vocalizations.

Background

The inventory and monitoring of bat and bird species necessary for natural resource management can accrue high costs because of the specialized personnel, time, and spatial coverage required to perform the work. Even when funds are available, the supply of individuals with the skills to acoustically identify bats and birds falls short of the demand (Hobson et al. 2002). Rare and uncommon species typically require greater survey effort (and cost) than more common species to acquire indisputable data (Green and Young 1993; Queheillalt et al. 2002), particularly over the many large landscapes under DoD jurisdiction. In addition, many military installations have large tracts of land with limited access to personnel that severely curtails the opportunity to survey bats and birds using standard protocols. Fortunately, both bats and birds leak considerable information to the environment in the form of acoustic signals that can be exploited for non-contact monitoring with automated recording equipment. For bats though, even the most experienced researchers cannot reliably discriminate many sensitive species with the currently used acoustic technology. This often necessitates the capture of bats for indisputable species confirmation, again requiring expert personnel at high cost.

Compared to traditional intermittent surveys, continuous automated monitoring can also improve the evaluation of long-term trends of species to improve the evaluation of military activities on TES. This ability will promote military activities while more thoroughly protecting TES. By deploying multiple units, automated monitoring can also facilitate simultaneous coverage over large landscapes, a feat that otherwise requires multiple personnel at high cost. In addition to identifying targeted species or multiple species for presence or absence, simultaneous multiple signal acquisition can also provide information regarding population levels and trends. Contemporaneous monitoring is particularly relevant for bats and birds that can readily move between monitoring sites and potentially be counted twice by asynchronous intermittent monitoring protocols.

Acoustic monitoring of echolocating bats

All North American bats emit regular pulses of vocalizations during flight to generate echoes they use for navigation, detecting, and pursuing prey. Biological sonar, or echolocation, provides important acoustic information that can be detected and used to indicate the presence of bats, and in many cases to identify species (Szewczak and Arnett 2007). Except for a few bat species in western North America that emit audible (to humans) echolocation calls, most bats vocalize at ultrasonic frequencies (well above the range of human hearing, > 20 kHz). Specialized bat detectors can capture and convert the ultrasonic calls of bats into audible sounds or to data that can be saved in digital form. Unfortunately, the rapid aerial attenuation of high frequency sounds (Griffin 1971) can bias detection rates toward species that produce low frequency sound. Although bats can generate sound intensities as high as 133 dB, among the loudest source levels recorded for any animal (Holderied et al. 2005), aerial attenuation of ultrasound renders many species undetectable at ranges beyond about 30 m. Because different bat species vary in their loudness, or intensity, those that vocalize at low intensities will be less detectable and thus introduce a bias toward those species that produce high intensity echolocation calls (Griffin 1958, Faure et al. 1993, Fullard and Dawson 1997). Low intensity echolocators (e.g., *Corynorhinus* spp.), or so-called “whispering bats,” have a smaller effective volume of detection, and thus may be missed during acoustic surveys unless they fly close to an ultrasonic detector (within 3–5 m for some species).

Acoustic detection of bats passing microphones provides a practical and effective means to monitor for bat presence, activity, and relative abundance (Figure 1). Fenton (1970) defined a "bat pass" as a sequence of two or more echolocation calls, with each sequence, or pass, separated by one second or more (also see Thomas and West 1989, Hayes 1997). Bat passes can only provide a relative index of abundance because we cannot typically determine the number of individual bats detected so in practice most acoustic surveys will only record events of detection, i.e., bat passes, of bats that enter the volume of airspace within detection range. These events can only provide an index of activity or abundance for example, one hundred different bats of the same species passing near an ultrasonic detector are generally indistinguishable from a single bat that returns to pass a detector one hundred times (Hayes 2000).

Because of this limitation, recorded levels of activity at any one site do not necessarily directly correlate with abundance because: 1) of differential detectability of bat species, 2) all bat species may not call at the same rate (e.g., *Myotis* versus *Lasiurus*), 3) all individuals within a given species may not call at the same rates (e.g., migrating vs. feeding), 4) some species may remain out of detection range of a detector despite their presence, 5) variable foraging behavior of some species (e.g., a detector deployed in the open is likely to miss bats that forage along the edge of vegetation), 6) weather and environmental factors, and 7) temporal variations in activity (Szewczak and Arnett 2007). The latter factor can vary on a scale of days as bats follow local insect activity or while in residence or during migration.

As bats exhibit dynamic movements across the landscape where they typically forage in several different locations each night (Lacki et al. 2007), activity as measured by bat passes can vary significantly at any one location so that a single night of data will not statistically represent the overall trend of bat activity at that location. Hayes (1997) showed that any one night of bat

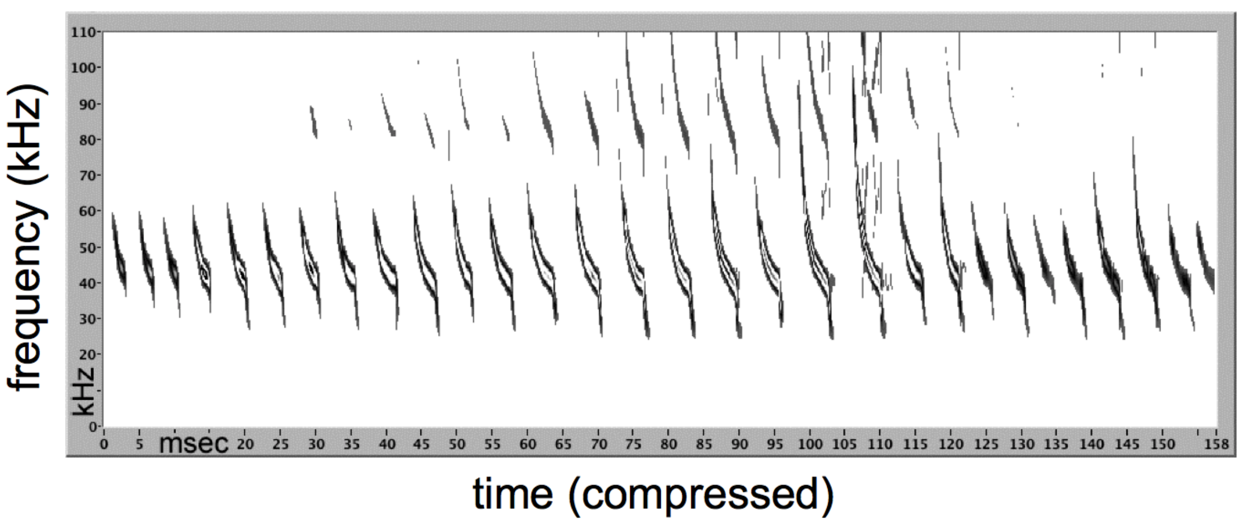


Figure 1. Sonogram of echolocation calls recorded from a bat flying past a detector. The actual time between calls has been compressed to better display the sequence of calls. Note that more call details are revealed in the center of the sequence as the bat made the closest approach to the microphone.

detection likely misrepresents the mean activity at a site, and that (at least for the sites he studied in western OR) as many as seven or eight days of monitoring were needed to approach a 90% confidence level of mean representation of activity (also see Gannon et al. 2003). Although mean bat activity can be assessed on the order of one week of monitoring, confident assessment of species presence in a given season requires even longer survey efforts, typically on the order of weeks (Moreno and Halffter 2000). Longer-term temporal variations occur from seasonal movements of bats, such as migration, (Johnson et al. 2004, Arnett et al. 2008).

Acoustic identification systems have only recently been applied to biological signals with the majority of work focusing on identifying individuals and species assemblages in bats (e.g., Parsons and Jones 2000, Szewczak 2004, Szewczak and Arnett 2007, Redgewell et al 2009), cetaceans (e.g., Deecke et al. 1999, Oswald et al. 2003), pinnipeds (e.g., Campbell et al. 2002), and prairie dogs (e.g., Placer and Slobodchikoff 2000). Techniques used to identify species and individuals include subjective classification by experienced listeners, multivariate statistics, synergetic pattern recognition, fuzzy logic, and machine learning techniques such as artificial neural networks (ANNs).

Acoustic identification of echolocating bats

Discriminating bat species based on their vocalizations presumes that discernible differences exist. O'Farrell et al. (1999) asserted that species-specific characteristics exist, although revealing those differences may require the application of new technology. Barclay (1999) countered that bat species have no particular selective pressure to emit calls differently than any other species and we should therefore not expect to find species-specific calls. Echolocating bats use their calls to serve a utility function to acquire information and we can expect selection has worked to optimize that process (Szewczak 2004). As a result, acoustic identification of bat species poses a greater challenge than that of birds whose calls have undergone selection to be different from those of other bird species. Natural selection has operated to optimize prey detection for echolocating bats and for some syntopic species (e.g., *Myotis* spp. or *Eptesicus* and *Lasionycteris*) the similarity of their echolocation call structure indicates little selective pressure to emit calls differently from one another. As an additional complication, bats exhibit considerable plasticity in their vocalizations (Figure 2) and can produce call variants that overlap in many parameters with those emitted by other species (Thomas et al. 1987, Obrist 1995, Barclay 1999). To achieve robust performance, any classification system must be capable of recognizing a given bat species when presented with calls from any part of its repertoire.

With such subtle differences between species, and the range of call variation within a species, the analysis of bat calls must embrace a comprehensive set of call characteristics. Numerous morphological characteristics have been used to describe and measure bat call structure and sequences (e.g., Betts 1998; Fenton and Bell 1981; Obrist 1988; Oliveira 1998; Parsons and Jones 2000; Szewczak 2000b). Quantitative approaches applied to call analysis have ranged from simple descriptive comparison (MacDonald et al. 1994; O'Farrell et al. 1999) to discriminant function analysis (DFA) (Krusic and Neefus 1996; Lance et al. 1996; Parsons and Jones 2000) and the more sophisticated approach of ANNs that we also implemented (Parsons 2000; Parsons and Jones 2000; Parsons 2004). The latter quantitative approaches have demonstrated the usefulness of incorporating characteristics beyond those that can be derived just from the basic time-frequency information; for example, the frequency of maximum power, which can only be derived from full-spectrum data.

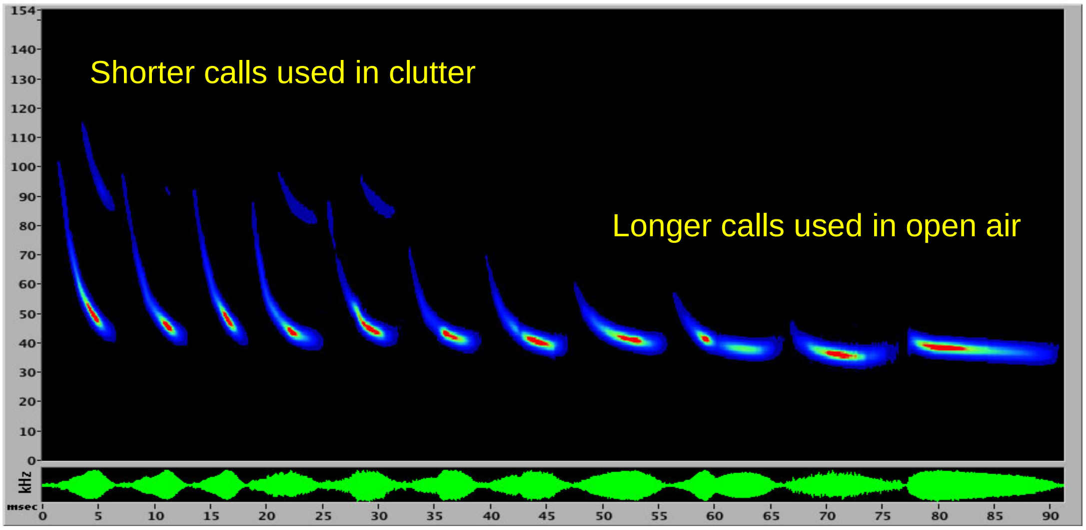


Figure 2. Compilation of different eastern red bat calls recorded from different bats in different locations arranged to show this species' repertoire from short to long call variants. Acoustic identification of bat species must be capable of recognizing species across such variation. Some parts of each species' repertoire may overlap with parts of another species' repertoire.

Materials and Methods

This project entailed both fieldwork and laboratory components. Fieldwork, both under the auspices of this project and in collaboration with other researchers across the continental United States, augmented a library of bat species-known reference recordings on which to base comparative identification of unknown signals using quantitative classifiers. We performed additional fieldwork to test and direct development of acoustic monitoring hardware and software, and to test and validate the acoustic monitoring methodology developed by this project. The laboratory research and development components addressed long duration recording solutions and software for processing, identifying, and efficiently searching long duration recording data for target signals.

Bat Fieldwork and Reference Recordings

Effective acoustic species recognition depends upon prior ascertainment of reliable species-discriminating data. We acquired recordings of bats (and a trial set of birds) from the field independently and in cooperation with ongoing monitoring projects. We only contributed to the reference library those recordings that had unambiguous species confirmation. We accepted only search phase calls from free foraging bats as these provide the most consistent and species-discriminating call variety (Betts 1998, Parsons and Szewczak 2009). Acquiring species-known bat reference recordings imposes the challenge of simultaneously satisfying the following conditions: *1)* having a previously-identified individual (Figure 3), *2)* fly in conditions that engender it to vocalize as it would under natural conditions and, *3)* fly sufficiently close to recording equipment to acquire a high quality signal while *4)* maintaining certainty that the acquired signal was from the previously-identified individual, i.e., avoiding confusion from unseen interloping bats that may enter the detection range of the microphone.

Figure 3. Acquiring reference recordings typically began with capturing bats. Here, graduate students erect a triple high mist net in the Ouachita Mountains of Arkansas in preparation of a night of recording (left) and remove a bat from the net (right).

We used a variety of methods to fill out bat species' call repertoires:

1) Calls recorded from bats flying near known roosts.
2) Calls recorded from captured bats released by hand (Figure 4).
3) Calls recorded from captured bats flying on a tethered zipline (Figure 5) (Szewczak 2000a).
4) Calls recorded from light-tagged free flying bats (Figures 6 & 7) (Hovorka et al. 1996).
5) Calls recorded from free flying bats from which a visual identification can be made with the aid of a spotlight or night vision equipment.

Figure 4. Hand release of a hoary bat in anticipation of acquiring a reference recording. Hand-released bats do not often fly in the desired direction of the microphone. Here, the bat flies contrary to the expected direction.

Figure 5. Clockwise from above, (a) Canyon bat (*Parastrellus hesperus*) flying with an elastic tether attached to a zip-line. (b) Zipline configuration. (c) Recording a bat flying along a zipline. Zipline flights allow bats to attain a modicum of normal flight in a controlled corridor from which to acquire reference recordings from species-confirmed bats. The elastic tether gently keeps the bat on track without abruptly shocking it at the end of the line.

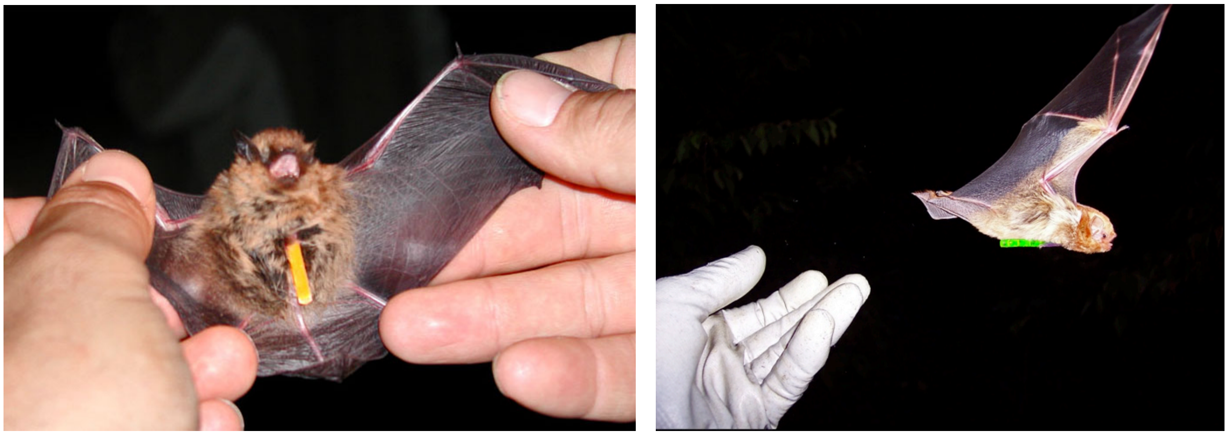


Figure 6. Bats with mini-cyalume light tags attached using a non-toxic school glue stick. Light tagging enables visual tracking of the bat after release and during free-flight after capture. Attaching the light tag to the ventral surface of the bat optimizes visibility of bats flying overhead, and enables the bat to readily remove the tag after flight.

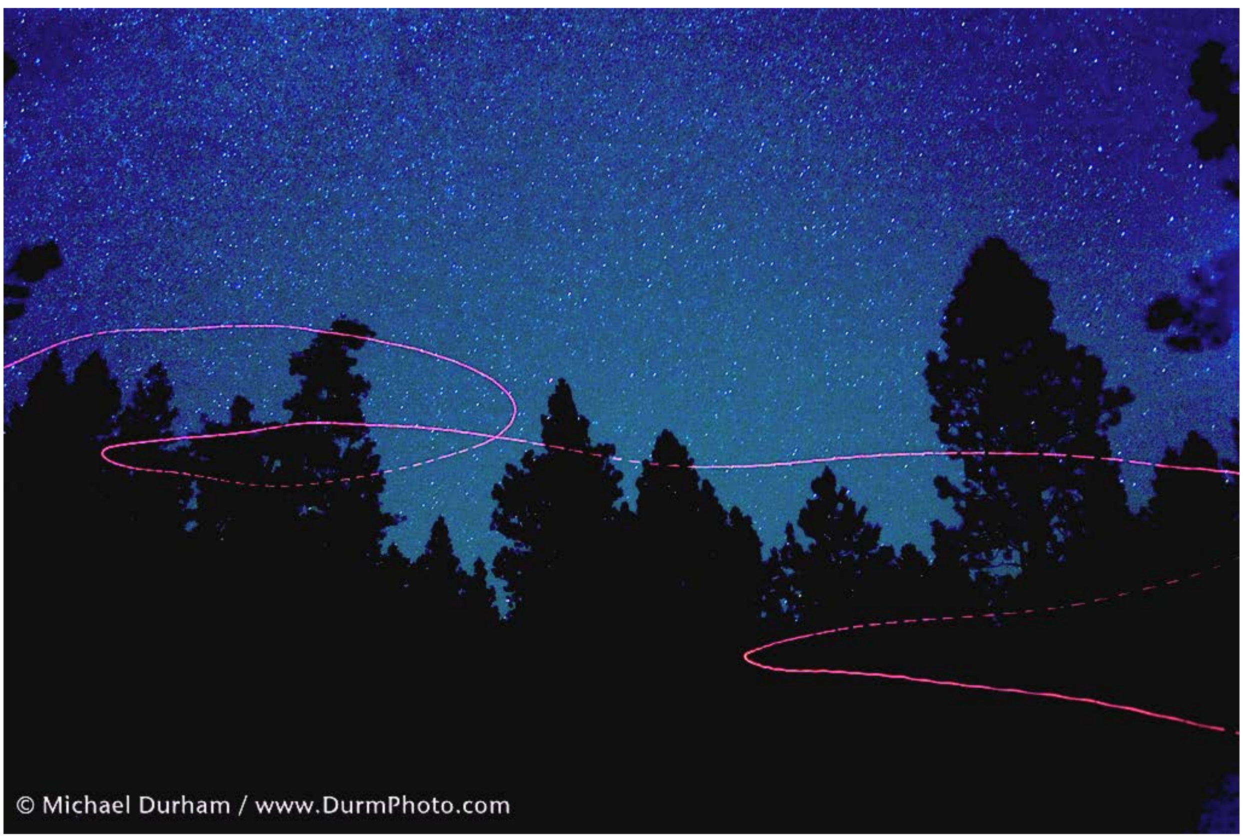


Figure 7. Time-lapse photograph of the light tag track from a silver-haired bat released in a montane meadow (Ochoco National Forest, OR). Note the interruptions of the track from the bat's wingbeat. Subsequent return flights of light tagged bats provide the most representative samples of free-flight bats.

We more readily acquired calls on the short end of each species' repertoire as bats generally use shorter calls when closer to the ground, or when accelerating as during a hand release (Parsons and Szewczak 2009). Unfortunately, although these readily acquired shorter duration calls helped to fill out the full repertoires of species' call types, they do not provide representative samples of longer duration free-flying search phase calls that are the type more typically recorded from unknown bats. We collected some longer duration call types by visual recognition, spot lighting, and light tagging. Some species have coloration or flight characteristics that render them distinguishable from sympatric species in ambient light at dusk when bats first emerge or when illuminated by spotlight.

Mini-cyalume light sticks attached to species-confirmed captured bat enabled us to track them after release, and maintain species recognition (Figures 6 & 7) (Hovorka et al. 1996). Occasionally, a light-tagged bat returned later in the night, was recognized and recorded providing ideal call specimens representative of free foraging bats. We attached different colored light tags to different species captured during a session to enable species differentiation after release. Light tagging provided the best method for acquiring standard reference calls because the recordings were acquired from bats foraging naturally. Unfortunately, the recovery rate of light tagged bats proved disappointingly low and required substantial effort and diligence. Light-tagged bats often flew off never to be seen again, or reappeared too far out of range to render suitable specimen calls.

Low light visual tracking, spot light, and light tagging may have produced some multiple recordings from the same individuals but we deemed these as acceptable (and beneficial to the project goal of robust species recognition) as they would provide further coverage of intraspecies and intra-individual variation, i.e., no one call typically represents an individual bat because of inherent variation and differences in recording conditions (Figure 8). With some individuals we deliberately included multiple recordings, but of different representative parts from their call repertoires, e.g., shorter duration calls recorded on a zipline and subsequent longer duration call sequences from a light tagged recording if acquired.

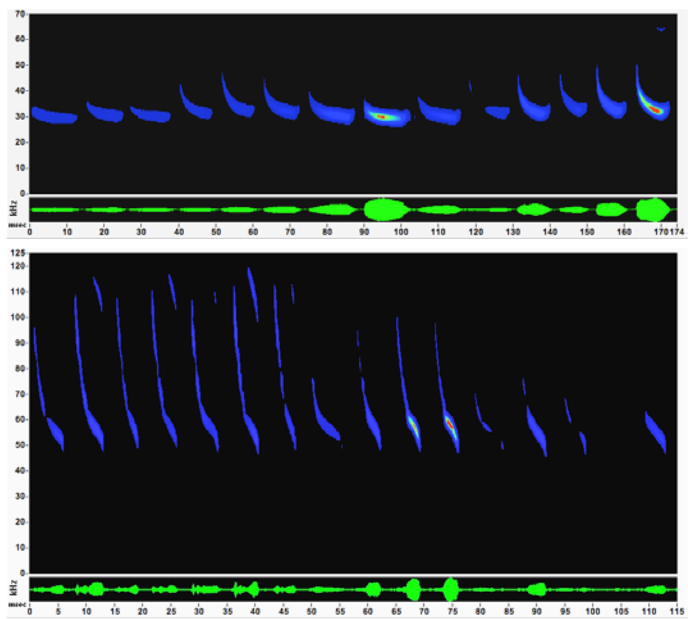


Figure 8. Call sequences from an individual western yellow bat (top) and an individual Yuma myotis (bottom). No one call represents the vocalization of the individual because of inherent variation and differences in signal level recorded as the bat changes its orientation and distance relative to the microphone.

We used Pettersson D240x, D500x, or D980 (Pettersson Elektronik AB, Uppsala, Sweden) and Binary Acoustic Technology FR125 (Tucson, AZ) ultrasonic detectors to acquire echolocation calls. We saved recorded sequences as digital files direct to digital memory, directly to laptops using SonoBat software (Arcata, CA), or with D240x and D980 detectors to digital recorders (iriver H320 and IFP series recorders, Seoul, Korea; Samson Zoom H2 recorders, Hauppauge, NY), at a sampling rate of 44.1 kHz (effective rate 441 kHz) with 16-bit precision. As the iriver units recorded only in mp3 format, we later converted files into wav format (44.1/16 bit, effective rate of 441 kHz for the x10 time expansion output of D240x and D980 detectors, although this over sampled the sampling frequencies of 307 and 350 kHz of these detectors, respectively). We recorded with the iriver units set to the highest mp3 quality setting of 320 kbps and found no functional difference in signal quality between files recorded directly as .wav or first as .mp3 format for the type of data extracted from these signals.

We used field recordings from locations across the North American United States (Figure 9) acquired by PI Szewczak dating back to 1991, confirmed recordings from colleagues, and recordings made as part of this project in collaboration with survey intitatives such as the US Forest Service Bat Grid Inventory and Monitoring Project. We aimed to optimize sample size and represent as many species as possible, with an emphasis on including sufficient recordings from TE species to fill out their call repertoires and variation. We designated recordings with a filename including species code (e.g., Mylu for *M. lucifugus*) recording location, date, and a designation of recording type; HR: hand release, ZL: zipline, LT: light tag, SL: spotlight, and FF: free-flight. We included field notes describing the recording location, habitat elements, and environmental conditions in the note field that SonoBat embeds in the metadata header of the wave files.

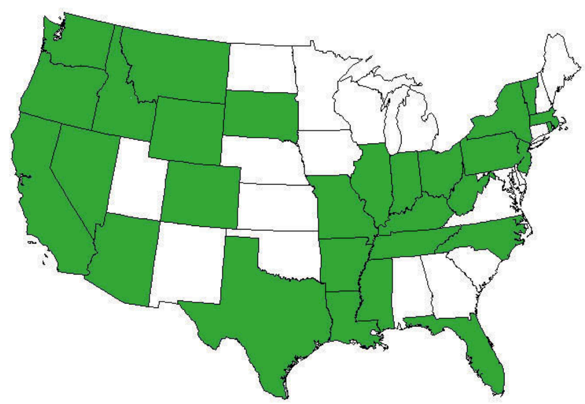


Figure 9. Geographic distribution of species-known bat recordings supporting the SonoBat classifiers discussed in this project (including Alaska, not shown on map).

Laboratory work

Long duration recording hardware

Recording hardware development for this project accelerated along a moving trajectory from changes in available audio recording technology and recording format licensing requirements. The project's ultimate goal of a high-capacity, high audio quality recorder with a programmable recording schedule to optimize data storage and analysis required a longer research and development cycle than originally anticipated for this project. To enable field testing and development of long duration recording methodology and application, we developed and deployed prototype recording units that also provided a testing platform to direct specifications of final production recording equipment to be produced by collaborating suppliers.

We based the initial audio data storage prototype units on DMC Xclef HD-500 digital mp3 player/recorders (Digital Mind, Corp., Carlsbad, CA) (Figure 10). The DMC mp3 units had 100 GB of storage, sufficient to store approximately 700 hours of data. We collected mono audio data at 320 kbps with a sampling frequency of 44.1 kHz. This audio format setting provided sufficient quality for species identification using comparative analysis and data extraction from sonograms displayed with SonoBat. While mp3 compression can distort signal quality, the 320 kbps “high quality” format provided ample signal integrity for species detection and analysis while extending recording time by a factor of three compared to 44.1 kHz wave format having no data compression, i.e., lossless. As “dumb” units, these DMC-based units could only record continuously once activated, as opposed to “smart” units with programmable scheduling and autotriggering to only record bat passes. With continuous recording, these dumb units recorded many unnecessary hours of non-bat content that was later discarded during post processing to parse out bat passes. This strategy ultimately limited their unattended duration of field deployment.

Figure 10. Initial mp3-based prototype long-duration field recording unit.

Although these dumb units did enable us to acquire long duration recordings to advance this project during its initial stage, we ultimately superseded this recording approach with a second generation prototype. Despite their rated 700-hour capacity, in practice the DMC-based units often stopped recording after fewer than 100 hours. Additionally, after we began with these units, the mp3 licensing regulations changed such that they required paying royalties for software and devices that *decoded* mp3 files rather than just those devices that created them. These developments, coupled with the availability of alternative recording options (and reduced cost of digital memory), convinced us to abandon the original mp3-based recording approach. Although we had a programmable digital recording option under development in cooperation with Binary Acoustic Technology (Tucson, AZ), already had format collaboration with Pettersson Elektronik AB, and had begun cooperation with Wildlife Acoustics (Cambridge, MA), those units had yet to become available. We continued field recording by replacing the DMC Xclef digital recorders with iriver H320 units (ReignCom, Seoul, South Korea) with Rockbox firmware (Rockbox Version 5, 2007) on each H320 to enhance recording functions, including programming a recording schedule (Figure 11). These recorders had internal 20-GB hard drives that we programmed to record in lossless 16-bit WavPack format at a sampling frequency of 44.1 kHz.

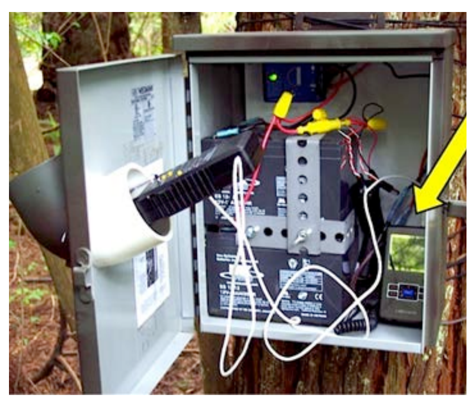


Figure 11. Second generation prototype long-duration field recording unit. Arrow points to programmable recorder.

Each recorder had an integral real time clock that conveniently labeled the recordings with a date and time stamp. Although these units had less hard drive capacity than the DMC units, they could record longer because they could be programmed to autotrigger and record only when the bat detector captured a signal.

The audio recording units were powered by two 12 volt, 12 Amp-hour batteries (24 Amp-hour total capacity) maintained with a 20-watt solar panel connected via a charge controller. We housed the power and recording equipment in a waterproof NEMA 3R enclosure (12” H X 10” W X 6” D, McMaster-Carr part number 7649K12). The prototype recording units successfully collected data in weather below freezing, above 100 degrees Fahrenheit, and also during inclement wind, rain, and snow conditions (Figure 12).

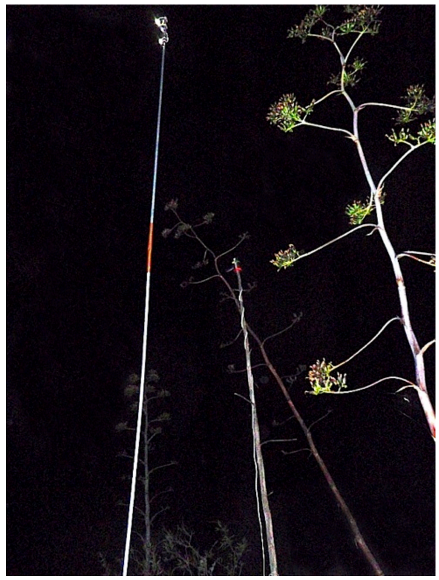


Figure 12. Field testing prototype automated recording units. Here shown with microphones on poles near agave blooms to acquire reference recordings of the federally listed lesser long-nosed bat (*Leptonycteris yerbabuenae*), Ft. Huachuca, AZ.

We provided collaborator Binary Acoustic Technology with our prototype recording unit and specifications of recording formats and scheduling logic to develop a recording unit that integrated the prototype concept and components into a final deployable unit. We also cooperated with Pettersson Elektronik AB and Wildlife Acoustics to provide feedback with their parallel field recording equipment development and they worked with us to ensure compatibility with our needs and analysis software. We directed these efforts toward a final end product that would meet the recording needs of this project and be a readily available and sustainable commercial device that would not require custom assembly or specialized work to place into service.

Bat software development

We built upon the user interface, processing, call detection (Figure 13), parameter extraction, and analysis software kernel of SonoBat acoustic software developed by PI Szewczak. We adapted processing routines originally coded to extract and display the subtle differences in the time-frequency and time-amplitude domains of bat echolocation calls to automate call trending analysis and parameter extraction. We also enabled the user interface to automate batch processing of recorded files. We coded and tested signal processing and analysis algorithms using MATLAB (Mathworks, Natick, MA) and LabVIEW (National Instruments, Austin, TX), and used SPSS Statistics software for discriminant function analysis (versions 13–19, IBM, Armonk, NY). All final algorithms were ported to LabVIEW for integration with the user interface. We implemented the final products of this project in LabVIEW to ensure and facilitate its sustainability and adaptability beyond the duration of this project, and because this coding platform readily enables compiling standalone executable software for both Windows and Macintosh operating systems.

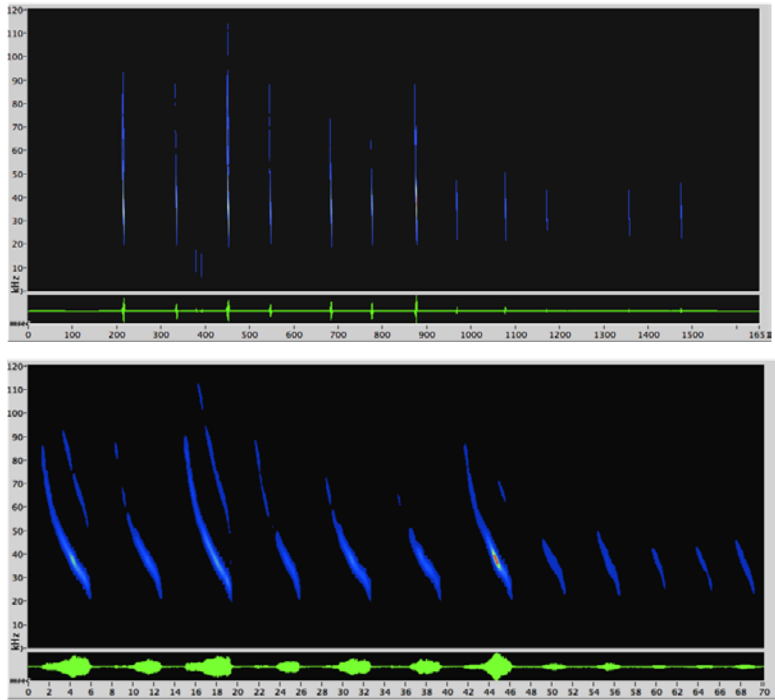


Figure 13. Fringed myotis sequence as recorded showing the actual spacing between calls (top). Same sequence after SonoBat detected the calls and compressed the time between calls (bottom). This facilitates call viewing of a sequence, but also call detection for ranking and parameter extraction.

We first refined automated batch processing and call quantitative parameter extraction routines as these enabled processing and analysis of the reference collections to generate the data needed for building classifiers to identify unknown bat calls to species. Using the existing logic in SonoBat to recognize calls from non-call content in recordings, we added a ranking system from best to worst of calls recognized in each sequence. The ranking routine assesses a combination of signal quality indicators such as amplitude, frequency bandwidth, tonal trend of the signal, signal to noise ratio, and saturation (i.e., clipping or overloaded signals). Call assessments for ranking that indicate clipping, excessive noise, or signal distortion may exclude a call from batch parameterization or classification. A preference selection enables the number of calls to consider per sequence during batch runs for parameter extraction (and for classification); we used a default value of 8 calls. During a batch processing run, calls undergo parameter extraction by order of ranking from the best ranked call onward until reaching the specified number of calls for the sequence, or running out of available calls. The parameter extraction steps assess additional signal quality indicators that can reject a call as unsuitable, and move on to the next call in the ranking.

Initial testing of early generation classifiers performed poorly on field-acquired data because of the highly variable quality of calls, signal level, unanticipated non-bat sounds, noise, and other signal distortions. In practice, classification could correctly identify to species most well recorded bats (like those used to build the classifiers), but many misclassifications and errors resulted from poorly rendered recordings and other non-bat acoustic phenomena. Basically, actual field recordings can cripple classifier performance even if that classifier has proven to perform well with test sets of good, species-known recordings. Determining when *not to output* a classifier decision on an unknown signal (or accept call parameter data from known calls) provides a vital quality control step in processing data. This prompted the addition of multiple signal condition and quality indicators to recognize the acoustic situations and signal characteristics that rendered unreliable results (Figures 14–19).

The complete information content of full-spectrum data facilitated signal assessment by enabling indicators sensitive to signal strength and multiple frequencies such as dynamic range and signal-to-noise ratio measurements. Additionally, because call harmonics typically have lower signal strength relative to the first harmonic (fundamental), the presence of harmonics can indicate that the recording captured the lower signal level elements of the call and thus indicate the presence of a fully-formed call rather than a fragment. Full-spectrum data also serves as a voucher of sorts for assessing ambient acoustic conditions during the time of a recording. It enables inspecting recordings to manually intrepret, confirm, or reject classification or parameterization results.

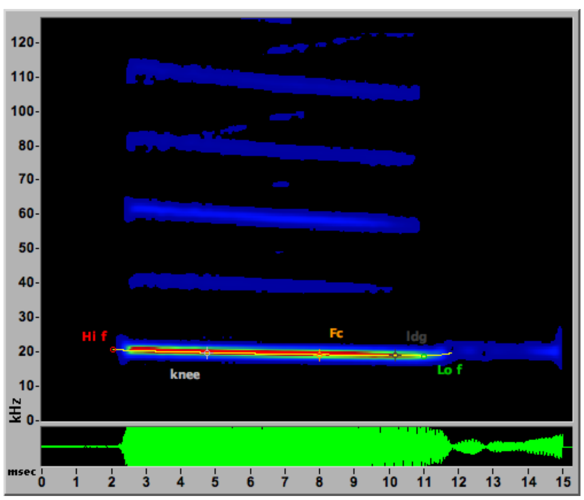


Figure 15. Example of an overloaded, or clipped, recording in which signal level exceeded the maximum sensitivity of the recording device. SonoBat signal assessment would reject such a signal as it would provide inaccurate time-amplitude information. The multiple harmonics arise from an artifact of the digital processing of the overloaded signal.

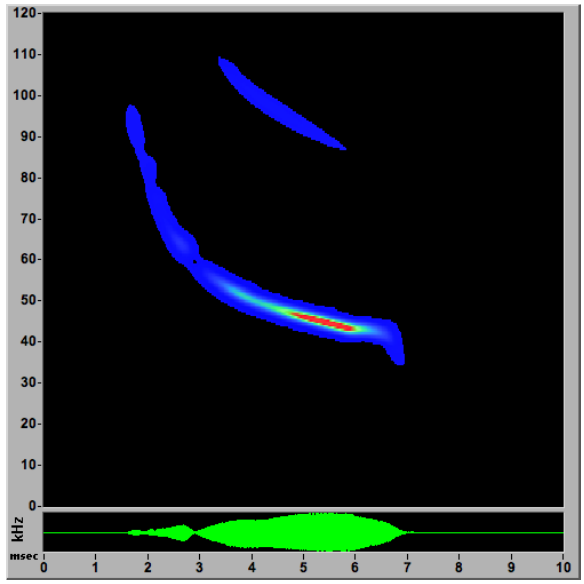


Figure 14. Example of a well recorded call having full rendering of call details for accurate trending and parameter extraction. For most species, the second harmonic has much lower amplitude than the first, and its presence indicates the recording captured low amplitude components of the call.

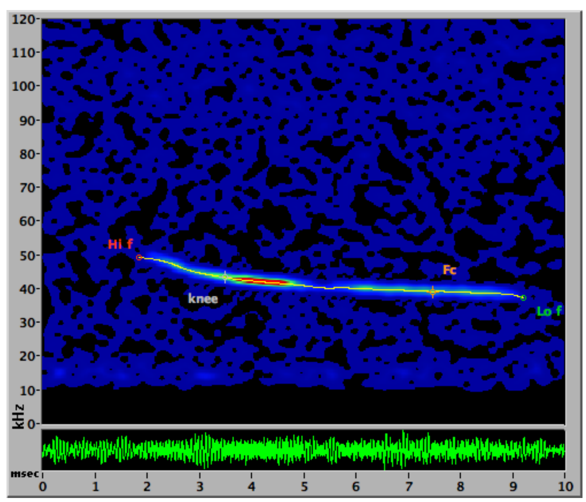


Figure 16. Example of a recorded call with low signal strength as indicated by a low signal to noise ratio. SonoBat signal assessment would reject such a signal as it indicates a probable out of range bat and likely an incomplete call that would render unreliable data.

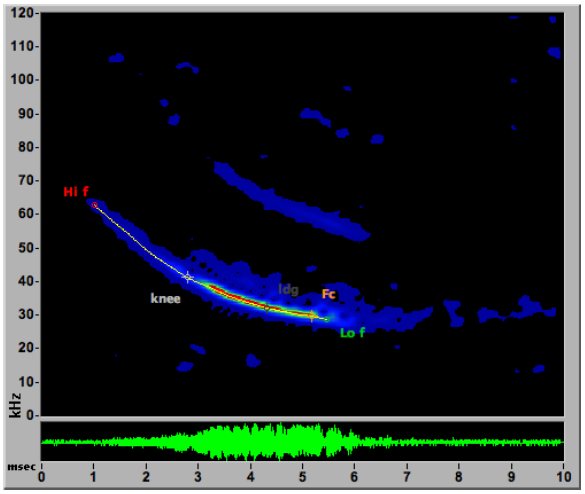


Figure 17. Example of a call with multiple echoes that interfere with resolving details of the end of the call. SonoBat signal assessment would reject such a signal for some types of calls that depend upon such ending details for reliable classification.

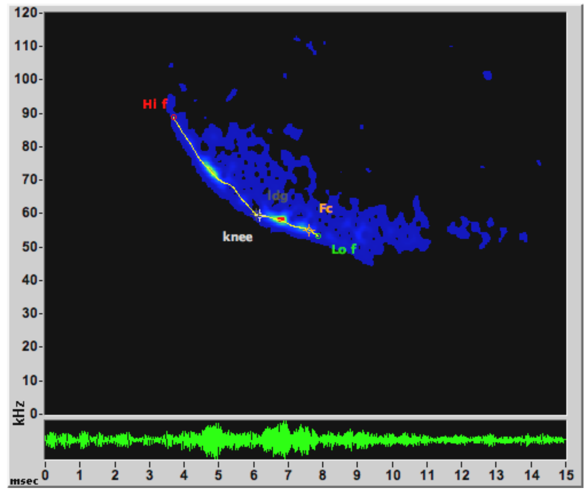


Figure 18. Example of a call having a high level of distortion. SonoBat signal assessment would reject such a signal as it prevents reliable tracking of the call frequency sweep and extraction of call parameters such that it would likely yield unreliable data.

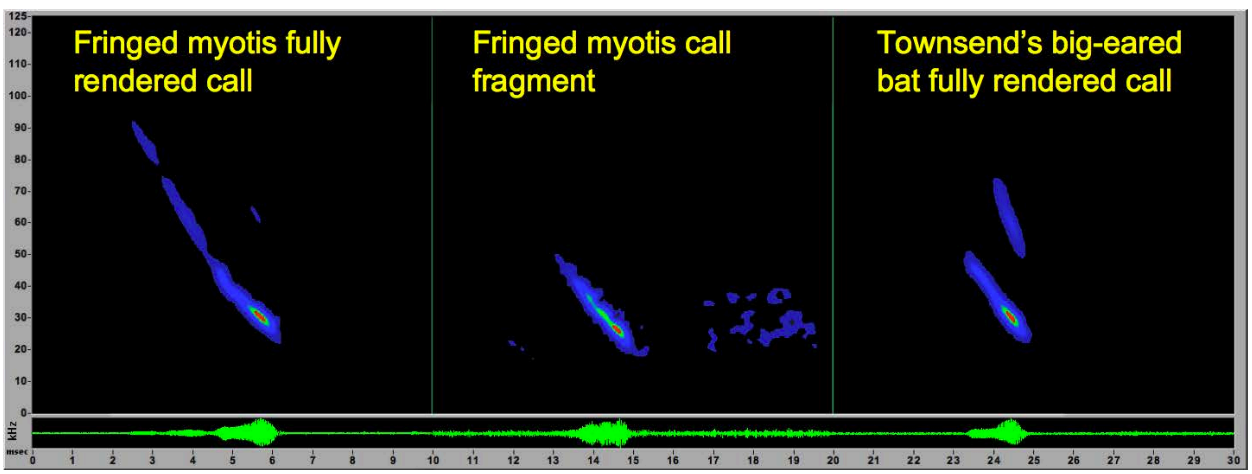


Figure 19. Example of how a low signal quality, or out of range recording of one species can mimic another species and lead to misclassification. Bats vary the amplitude through their calls. A recording from a close approach to a microphone will capture the full call as vocalized by the bat (left panel). However, only a call fragment from the higher amplitude portion of a call may be recorded if farther from the microphone (middle panel). The call fragments of some species can mimic the full-featured calls of other species, e.g., fringed myotis and Townsend's big-eared bat (right panel). Assessing signal quality indicators can provide essential quality control to prevent misclassification, particularly when working with highly variable field recordings.

Bat call trending analysis

Biologists have classified bats to species from their echolocation calls by both qualitative inspection (O'Farrell 1999) of sonogram displays and by using a variety of quantitative approaches (e.g., Krusic and Neefus 1995, Betts 1998, Parsons and Jones 2002; Preatoni et al. 2005, Redgwell et al. 2009). Qualitative inspection by an experienced expert can still rival or outperform quantitative attempts in some cases, but becomes impractical with large data sets, and from limitations of expert personnel costs and availability (Queheillalt et al. 2002). Qualitative inspection and call recognition can perform well in many situations because of the superior ability of our own human visual perception and pattern recognition. Machine image and pattern recognition (e.g., facial recognition) remains a computational challenge. Those with experience analyzing bat echolocation calls can readily see the pattern of a call and the trend of its content buried in a noisy sonogram, but distilling that process down to a reliable algorithm presents a nontrivial challenge.

Although human users can readily discern and recognize call content and trends in visual sonogram displays, qualitative species discrimination falters for species having very similar acoustic signatures, e.g., some call types for big brown bats vs. silver-haired bats or most calls from little brown bats vs. the federally listed Indiana bat. Quantitative analysis that simultaneously considers multiple parameters can outperform qualitative discrimination for such acoustically similar and cryptic species. Quantitative methods depend upon automatically extracting call descriptive parameters, and this in turn depends upon automatically recognizing call content from non-call content. Developing and implementing an intelligent machine call trending routine represented a keystone element to achieve this project's objectives. The development of species identification classifiers requires confident extraction of echolocation call quantitative parameters, and that depends upon a robust and reliable call trending routine. *Moreover, a robust and reliable call trending routine can minimize misclassification from field recordings that have highly variable quality and non-bat signal content.* Simply building a classifier from a library of manually selected species-known exemplar recordings can yield respectable classification performance in the lab, but stumbles when applied to field recordings if it cannot accurately extract the call parameter data from those recordings.

To reach this objective, we developed and implemented an intelligent call trending algorithm sensitive to multiple frequency content, signal amplitude, quality, and other signal characteristics. This trending algorithm seeks the organized tonal content of echolocation calls and follows that to discern the track of the signal, even through competing noise and echo signals. After this routine determines a call's start, end, and sweep of the time-frequency trend, then quantitative static and dynamic (i.e., functions quantifying shape) parameters can be calculated in both the time-frequency and time-amplitude domains.

A peak energy detector provides a simple approach to finding the trend of echolocation calls. A peak energy routine recognizes the strongest amplitude frequency content at each time interval in a recording and then accepts content from sequential intervals if they are maintained within some acceptable trend, i.e., do not jump so much in frequency that they indicate another signal. A commonly used system for detecting bats, the Anabat system (Titley Electronics, Ballina, NSW, Australia) developed by Chris Corben, determines call trends in this way by virtue of its operating principle, zero-crossing analysis. Zero-crossing rapidly extracts the basic time-frequency content of the dominant frequency by measuring the timing of period oscillations by detecting when the peak energy signal oscillates across the zero axis (Figure 20).

In practice this approach works well for strong, clear signals (Figure 21). However, field recording does not often yield data with perfectly strong and clear signals. Other signal sources contribute to the overall acoustic soundscape and interfere with discerning the bat calls from the background signals. In the worst of cases the situation can become the ultrasound equivalent of trying to record a voice interview next to a busy highway. In addition, the short wavelengths of ultrasound render it more susceptible to distorting effects from atmospheric thermal convection and wind (Parsons and Szewczak 2009). Even in acoustically quiet environments a simple peak energy tracking algorithm can fail to properly discern the trend of a call when echoes from ground clutter obscure the ending details of a call (Figure 22). With access to the multiple frequency content available in full-spectrum data, the more sophisticated intelligent call trending routine we developed can track call content even when portions of a call fall below the peak amplitude of other signals in the same time interval (Figures 22–24).

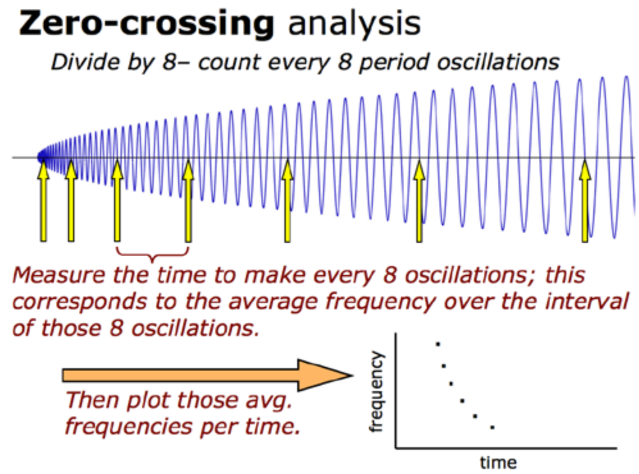


Figure 20. Zero-crossing analysis rapidly extracts a moving average of the dominant frequency content of a signal. With multiple frequency content, the strongest frequency component controls axis crossing and that frequency gets measured. Zero-crossing analysis cannot detect signal amplitude.

Background signals such as insect sounds can severely compromise peak energy call detection and trending. The SonoBat intelligent call trending routine can still render complete call trends in such situations (Figure 23). This can provide an augmented ability to detect and discriminate calls from mobile surveys, which have recently increased in use. Vehicle sounds, road noises, and the changing soundscape from moving can all exceed at least parts of the signal amplitude of bat calls. The ability to track the trend of a call independent of peak energy also enables complete rendering of species that oscillate peak energy between the fundamental and second harmonic, such as the federally listed lesser long-nosed bat (*Leptonycteris yerbabuenae*) (Figure 24).

The intelligent call trending routine we developed and used with this project also benefits from the amplitude domain and multiple frequency content to more accurately determine where calls end (Figure 25). This task can challenge simple peak energy call trending when echoes obscure the ends of calls. Finally, if needed for confirmation of results, full-spectrum data also provides an effective voucher for interpretation of the full acoustic soundscape at the time of the recording.

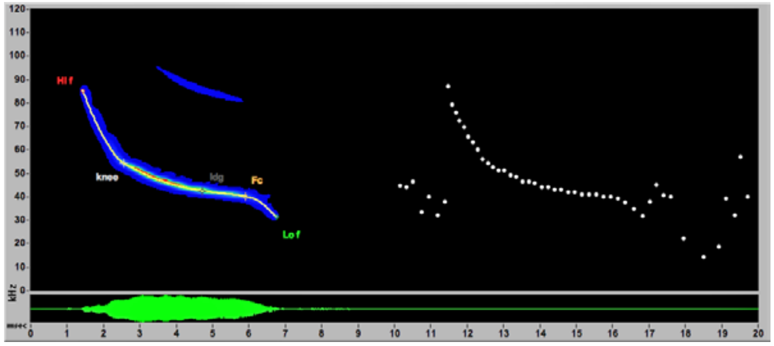


Figure 21. SonoBat intelligent call trending shown as yellow trace superimposed on full-spectrum sonogram (left) compared with divide by eight zero-crossing (Z-C) analysis of the same signal (right). With strong signals and no confounding additional signals or noise, full-spectrum time-frequency trending and zero-crossing produce similar results.

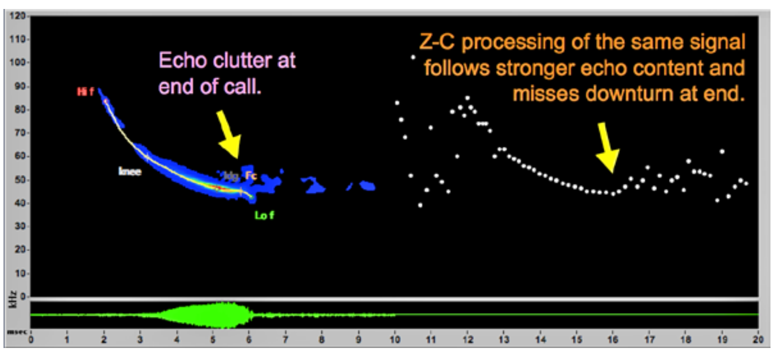


Figure 22. Example of echoes from higher amplitude earlier portions of a call obscuring the call ending details. This often occurs because most bats end their calls with diminishing amplitude. A peak energy call trending routine would follow the stronger echo content (right). In this example zero-crossing tracked upward with the echo leaving a call trend that would indicate a lasiurine-type call (e.g., red bat) rather than following the actual downward ending of the call trend that indicates a Myotis spp., e.g., Indiana bat (left).

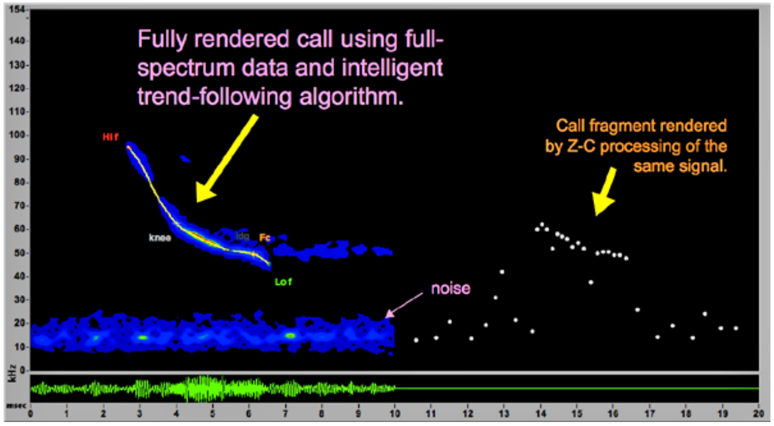


Figure 23. Example of an Indiana bat call recorded in the presence of insect noise. A peak energy call trending routine would only reveal the call fragment that exceeds the energy level of the background insect noise (right) and miss the lower energy call components. Intelligent call trending with full-spectrum data can reveal the full call (left). The full-spectrum data also provides documentation and interpretation of the full acoustic soundscape at the time of the recording.

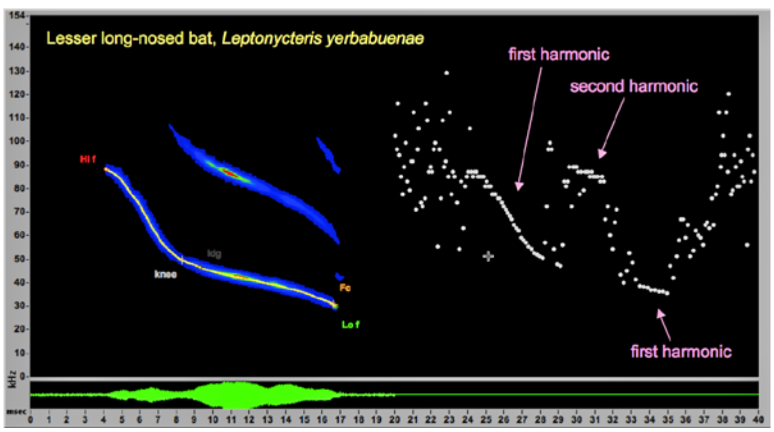


Figure 24. Example of a lesser long-nosed bat call with peak energy shifted to the second harmonic in the middle of the call. A peak energy call trending routine would jump between the harmonics leaving an interrupted call trend (right). Intelligent call trending with full-spectrum data can reveal the full uninterrupted call trend (left) that better supports automated analysis.

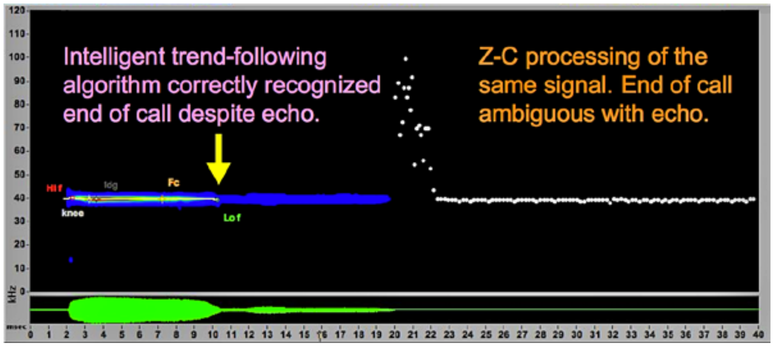


Figure 25. Low bandwidth call with a strong echo trailing the call. Intelligent call trending with full-spectrum data can correctly discern the endpoint of the call (left) that would be ambiguous with a simpler call trending routine (right).

Bat call quantitative parameter extraction

Once the call trending routine has determined the location of the call in the time-frequency domain, then that data and accompanying waveform was passed to the parameter extraction routines to evaluate quantitative static and dynamic (i.e., functions quantifying shape) parameters in both the time-frequency and time-amplitude domains. Traditional static call parameters include measures such as call duration, highest frequency, lowest frequency, characteristic frequency, steepest slope, and lowest slope. These traditional measures all assess only the time-frequency domain and provide single point measures that provide little quantification of the *shape* of call structure as a function of time. We derived a number of additional parameters with the aim toward more extensive and detailed shape-sensitive quantification of echolocation call structure in both the time-frequency and time-amplitude domains (Table 1).

Table 1. Quantitative descriptive echolocation call parameters determined and calculated in the parameter extraction routines, and used in building and implementing species classifiers.

Parameter	Description of parameter
PrecedingIntrvl	Time between the current call and the previous call (milliseconds).
CallsPerSec	Mean calls per second of the recording or section of recording displayed. The accuracy of the reported value depends both on the quality of the recording and the absence of other bats and other signals in the recording. Any other signal components that pass through the discrimination logic will be counted as calls and contribute to (and reduce the accuracy of) the calculation.
CallDuration	Duration of the call (milliseconds).
Fc	Characteristic frequency of the call. Determined by finding the point in the final 40% of the call having the lowest slope or exhibiting the end of the main trend of the body of the call (kHz).
HiFreq	Highest apparent frequency of the call.
LowFreq	Lowest apparent frequency of the call.
Bndwdth	Total frequency spread of the call. Calculated from the difference between the highest and lowest frequency.
FreqMaxPwr	The frequency of the maximum amplitude of the call.
PrcntMaxAmpDur	Percentage of the entire call duration at which the maximum amplitude occurs.

Table 1 (continued). Quantitative descriptive echolocation call parameters determined and calculated in the parameter extraction routines, and used in building and implementing species classifiers.

Parameter	Description of parameter
TimeFromMaxToFc	Time from the point at which the maximum amplitude occurs to the point in the call of the characteristic frequency.
FreqKnee	Frequency at which the initial slope of the call most abruptly transitions to the slope of the body of the call.
PrcntKneeDur	Percentage of the entire call duration at which the knee occurs, i.e., the point at which the initial slope of the call most abruptly transitions to the slope of the body of the call.
StartF	Frequency of the start of the call. Typically the same point as the highest frequency, but different if the call initially rises in frequency.
EndF	Frequency of the end of the call. Typically the same point as the lowest frequency, but different if the call ends with a rise in frequency.
DominantSlope	Slope of the longest sustained trend in slope of the call. Determined by finding the segment of the call having the minimum residue for a linear regression of a segment of the call of 20% the duration of the call (kHz/msec).
SlopeAtFc	Instantaneous slope at the point of the characteristic frequency.
StartSlope	Slope at the start of the call, calculated from the first 5% of the call duration.
EndSlope	Slope at the end of the call, calculated from the final 5% of the call duration.
SteepestSlope	Steepest slope of the call, calculated from a linear regression of a segment of 10% the duration of the call.
LowestSlope	Lowest slope of the call, calculated from a linear regression of a segment of 10% the duration of the call.
TotalSlope	Total slope of the call, calculated from the difference in frequency and time from the point of highest frequency to the point of the characteristic frequency.
HiFtoKnSlope	Slope of the call calculated from the difference in frequency and time from the point of highest frequency to the point of the knee.
KneeToFcSlope	Slope of the call calculated from the difference in frequency and time from the point of the knee to the point of the characteristic frequency.
CummNmlzdSlp	Average of the instantaneous slopes of the call.
HiFtoFcExpAmp	Amplitude parameter of an exponential fit of the call from the point of high frequency to the point if the characteristic frequency.
HiFtoFcDmp	Damping parameter of an exponential fit of the call from the point of high frequency to the point if the characteristic frequency.
KnToFcExpAmp	Amplitude parameter of an exponential fit of the call from the point of the knee to the point if the characteristic frequency.
KnToFcDmp	Damping parameter of an exponential fit of the call from the point of the knee to the point if the characteristic frequency.
HiFtoKnExpAmp	Amplitude parameter of an exponential fit of the call from the point of the high frequency to the point if the characteristic frequency.
HiFtoKnDmp	Damping parameter of an exponential fit of the call from the point of the high frequency to the point if the characteristic frequency.
FreqLedge	Frequency of the ledge, i.e., the most abrupt transition to the most extended flattest slope section of the body of the call preceding the characteristic frequency, also referred to as the "ledge" of the call.
LedgeDuration	Duration of the ledge, i.e., the most extended flattest slope section of the body of the call preceding the characteristic frequency.
FreqCtr	Frequency at the center of the duration of the call.
FBak32dB	Frequency of the call 32 dB below the point of maximum amplitude of the call, and preceding the point of maximum amplitude of the call.

Table 1 (continued). Quantitative descriptive echolocation call parameters determined and calculated in the parameter extraction routines, and used in building and implementing species classifiers.

Parameter	Description of parameter
FFwd32dB	Frequency of the call 32 dB below the point of maximum amplitude of the call, and after the point of maximum amplitude of the call.
FBak20dB	Frequency of the call 20 dB below the point of maximum amplitude of the call, and preceding the point of maximum amplitude of the call.
FFwd20dB	Frequency of the call 20 dB below the point of maximum amplitude of the call, and after the point of maximum amplitude of the call.
FBak15dB	Frequency of the call 15 dB below the point of maximum amplitude of the call, and preceding the point of maximum amplitude of the call.
FFwd15dB	Frequency of the call 15 dB below the point of maximum amplitude of the call, and after the point of maximum amplitude of the call.
FBak5dB	Frequency of the call 5 dB below the point of maximum amplitude of the call, and preceding the point of maximum amplitude of the call.
FFwd5dB	Frequency of the call 5 dB below the point of maximum amplitude of the call, and after the point of maximum amplitude of the call.
Bndw32dB	The total bandwidth covered from the point of the call 32 dB below and before the point of maximum amplitude and the point of the call 32 dB below and after the point of maximum amplitude of the call.
Bndw20dB	The total bandwidth covered from the point of the call 20 dB below and before the point of maximum amplitude and the point of the call 32 dB below and after the point of maximum amplitude of the call.
Bndw15dB	The total bandwidth covered from the point of the call 15 dB below and before the point of maximum amplitude and the point of the call 32 dB below and after the point of maximum amplitude of the call.
Bndw5dB	The total bandwidth covered from the point of the call 5 dB below and before the point of maximum amplitude and the point of the call 32 dB below and after the point of maximum amplitude of the call.
DurOf32dB	The duration of the call from the point of the call 32 dB below and before the point of maximum amplitude and the point of the call 32 dB below and after the point of maximum amplitude of the call.
DurOf20dB	The duration of the call from the point of the call 20 dB below and before the point of maximum amplitude and the point of the call 32 dB below and after the point of maximum amplitude of the call.
DurOf15dB	The duration of the call from the point of the call 15 dB below and before the point of maximum amplitude and the point of the call 32 dB below and after the point of maximum amplitude of the call.
DurOf5dB	The duration of the call from the point of the call 5 dB below and before the point of maximum amplitude and the point of the call 32 dB below and after the point of maximum amplitude of the call.
Amp1stQrtl	Total amplitude of the first quartile of the call (relative units).
Amp2ndQrtl	Total amplitude of the second quartile of the call (relative units).
Amp3rdQrtl	Total amplitude of the third quartile of the call (relative units).
Amp4thQrtl	Total amplitude of the fourth quartile of the call (relative units).
Amp1stMean	Mean of the first quartile amplitude (relative units).
Amp2ndMean	Mean of the second quartile amplitude (relative units).
Amp3rdMean	Mean of the third quartile amplitude (relative units).
Amp4thMean	Mean of the fourth quartile amplitude (relative units).
LnExpA_StartAmp	Amplitude parameter of an exponential fit of the time-amplitude trend of the call from the start of the call to the point of maximum amplitude.
LnExpB_StartAmp	Damping parameter of an exponential fit of the time-amplitude trend of the call from the start of the call to the point of maximum amplitude.

Table 1 (continued). Quantitative descriptive echolocation call parameters determined and calculated in the parameter extraction routines, and used in building and implementing species classifiers.

Parameter	Description of parameter
AmpStartLn60ExpC	Time parameter of an exponential fit of the time-amplitude trend of the call from the start of the call to the point of maximum amplitude.
LnExpA_EndAmp	Amplitude parameter of an exponential fit of the time-amplitude trend of the call from the point of maximum amplitude to the end of the call.
LnExpB_StartAmp	Damping parameter of an exponential fit of the time-amplitude trend of the call from the start of the call to the point of maximum amplitude.
AmpEndLn60ExpC	Time parameter of an exponential fit of the time-amplitude trend of the call from the point of maximum amplitude to the end of the call.
AmpK@start	Slope of a logarithmic plot of the time-amplitude trend of the call from the start of the call to the point of maximum amplitude.
AmpK@end	Slope of a logarithmic plot of the time-amplitude trend of the call from the point of maximum amplitude to the end of the call.
AmpKurtosis	Kurtosis of the time-amplitude trend.
AmpSkew	Skew of the time-amplitude trend.
AmpVariance	Variance of the time-amplitude trend.
AmpMoment	Moment of the time-amplitude trend.
AmpGausR2	R-squared of a Gaussian fit of the time amplitude trend.

Bat species classifier development

Collaborating researcher Stuart Parsons (University of Auckland) experimented with the reference recordings to develop and test a variety of machine learning approaches for species signal recognition including discriminant function analysis, artificial neural networks, ensembles of neural networks, and support vector machines. However, in the initial proof of concept trials no one method could discriminate all species at or above the project goal of a 90% correct rate of identification (see Table 2 as an example for western bat species). In addition, the performance with the little brown bat caused particular concern as this species has calls very similar to the federally listed Indiana bat. Initial tests of discriminating little brown bats and Indiana bats yielded results of 66.5 and 49.1%, respectively.

Table 2. Initial results (%correct) of classifiers based on discriminant function analysis (DFA) and a prototype artificial neural network (ANN) compared with final project classifier (see results for more details).

western bat species	Initial DFA	Proto ANN	Final Classifier
Yuma myotis	86.5	91.3	*93.4*
California myotis	64.5	66.7	*98.2*
Western small-footed myotis	76.6	73.3	*98.5*
Hairy-winged myotis	65.5	91.7	*96.0*
Little brown bat	76.0	73.5	*95.3*
Canyon bat	91.9	98.3	*99.3*
Western long-eared myotis	94.9	89.7	*100.0*
Western red bat	71.0	88.5	*96.3*
Pallid bat	68.1	66.7	*89.3*
Big brown bat	51.2	74.5	*96.0*
Silver-haired bat	66.8	78.2	*93.9*
Fringed myotis	89.9	94.1	*100.0*
Free-tailed bat	69.2	100.0	*99.4*
Hoary bat	76.2	90.6	*99.0*
Townsend's big-eared bat	93.1	85.7	*99.5*
Spotted bat	98.8	100.0	*100.0*
Mastiff bat	90.3	100.0	*100.0*

Inspection of two primary parameters of the call data sets from the US northeastern and US northwestern species shows the overlap in many species' call repertoires (Figures 26 and 27). Inspection of plots like these with other parameters and corresponding quantitative analysis also revealed assemblages of call types across many species' repertoires, or groups of species that provided natural breakpoints or separations in data space that optimized classification performance. For example, for both northeastern (Figure 26) and northwestern (Figure 27) data sets, a cluster of higher frequency bats separate well from a cluster of lower frequency bats. That breakpoint provides a higher performing initial classification step than any other separation. Somewhat akin to constructing a dichotomous key, we iterated the highest performing classification choices at each step in a hierarchical classification scheme to build optimized classifiers. This directed hierarchical classification approach ultimately outperformed standard classification methods of discriminant function analysis and other machine learning approaches initially tested. Unlike a pure dichotomous hierarchical classification, some decision steps branch. We iterated to optimal decision performance at each step; in some cases this involved more than one different classification method that required agreement for acceptance, i.e., an ensemble classifier.

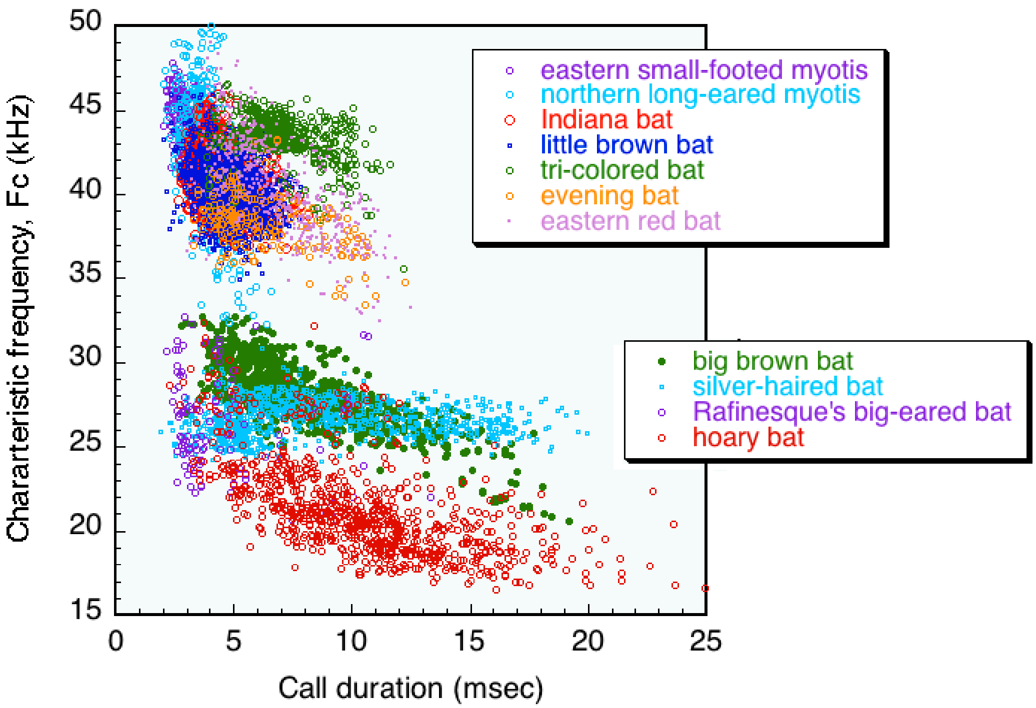


Figure 26. Characteristic frequency as a function of call duration for the northeastern species call data in the reference data set. Note the considerable overlap of call repertoires, but also regions of discriminating data space.

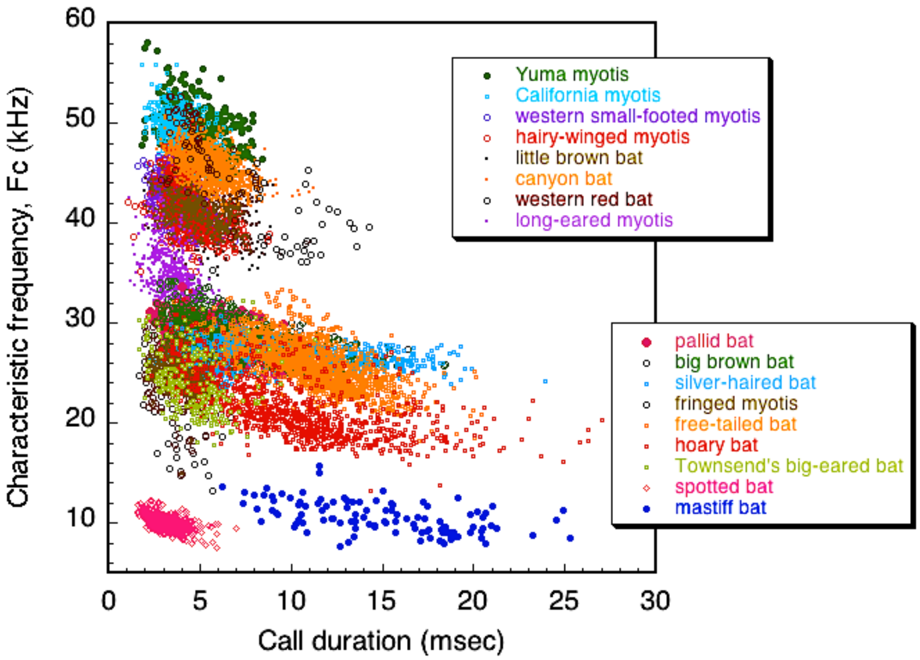


Figure 27. Characteristic frequency as a function of call duration for the northwestern species call data in the reference data set. Note the considerable overlap of call repertoires, but also regions of discriminating data space.

We tested iterations of classifier steps and full hierarchical classification using different groups from our reference data sets and field data to find optimal approaches and to uncover signal types on which the classifier would stumble. The stumbles directed further logic steps and redundant checks of results to recognize and avoid the misclassification situations and improve overall classification performance.

We implemented the hierarchical decision algorithms with an acceptance threshold setting to adjust tolerance. Most decision steps are implemented using discriminant function analysis that reports a discriminant probability (DP) for classification. Each decision step must meet or exceed the designated DP threshold to proceed to the next decision level. If any decision step does not meet or exceed the threshold, then SonoBat displays the species or hierarchical groups of that decision step that sum to the threshold at that step, e.g., with a default threshold of 0.90, 0.775 MycaMyyu, 0.225 MyciMyvoMylu. This indicates an ambiguous decision and replicates the way bat biologists have traditionally classified calls and sequences manually, i.e., bin them into similar groups such as 50 kHz *Myotis* vs. 40 kHz *Myotis* spp. in this example. The classifiers report a single species decision only if it successfully passes the DP threshold at each decision step in the hierarchical classification, *and* passes post-decision checks of known call characteristics. SonoBat then reports the DP of the final hierarchical decision.

Classifying an entire sequence (i.e., bat pass) typically provides more confident results than individual call classification as this method benefits from the combined information within the sequence. For a sequence classification, SonoBat first ranks the calls in a sequence based on coarse time-frequency and time-amplitude assessments and then classifies the individual calls in descending order of rank up to a designated number of calls to consider per file. If any of these calls result in a rejected classification, the sequence classification will move on to the next call in the ranked order until reaching the designated number of calls to consider per file or the end of the available ranked calls in the file. SonoBat reports two results for sequences, a decision by vote and a mean sequence decision. The vote requires a minimum of two calls per majority species (except for open air foraging bats that have low rates of call repetition such as *Lasionycteris noctivagans*, *Lasiurus cinereus*, or *Tadarida brasiliensis*) and requires the majority species to have equal to or better than twice the number of calls as the sum of the second and third most prevalent species (if classified). The mean sequence decision calculates mean parameter values of the most prevalent hierarchical classification group (e.g., MyvoMyluMyci or PaheLabl) of accepted calls with a minimum of two calls (except for low cycle open air foragers) and sends those mean values through the hierarchical classifier (Figure 28). Sequences that achieve an agreement by both decision approaches provide the most reliable classification results (see Results).

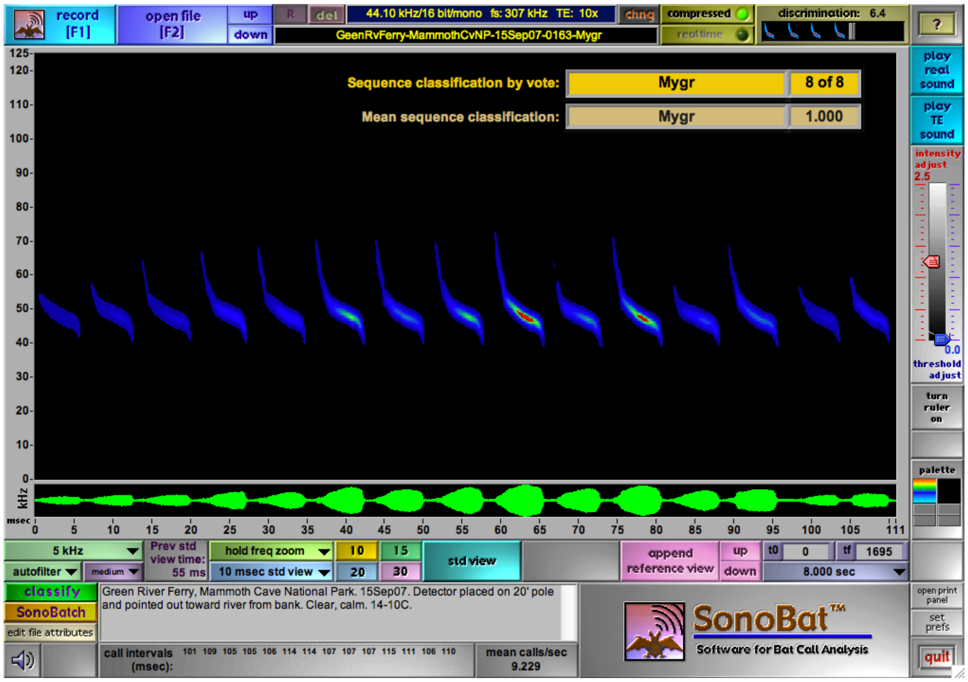


Figure 28. Sequence classification result of a recording from a federally listed gray bat (*M. grisescens*) in which the sequence decision by vote and the mean sequence decision reached a consensus.

Bird Software Development

With support from a parallel project for the California Department of Transportation (Caltrans CFS Number 2045DRI, XB05) we built upon the user interface and analysis software kernel of SonoBat acoustic software coded by PI Szewczak. We adapted search routines originally coded to interpret the subtle differences in the time-frequency and time-amplitude domains of bat echolocation calls to interpret lower frequency audible bird vocalizations. We also co-opted the user interface and automated batch processing functions of SonoBat and incorporated them into SonoBird to automatically process batches of recording files.

As with the development of the bat call classification, we worked with collaborating researcher Parsons to experiment with the reference bird recordings and test a variety of machine learning approaches for species signal recognition. Although these methods performed well on discriminating the limited data sets of proof of concept trials, these methods could not practically scale up to classify actual field data with extensive species and signal variations. Training machine learning systems to classify species requires a suitable library of representative reference signals encompassing everything likely to be encountered, and these methods also depend upon extracting quantitative descriptive parameters from those signals to feed into the training system. The quantitative parameters we considered included contextual characteristics such as time-frequency and time-amplitude measures and patterns, pulse interval, diagnostic signal patterns, harmonics, and amplitude modulations. Although these methods have demonstrated successful classification performance when applied to other acoustic signals such as bat echolocation calls (Redgwell et al. 2009), classifying bird songs presented a different and more complex problem. Machine learning methods for signal classification also depend upon quantitative descriptors for *every* type of signal likely to be encountered or else the uncharacterized signals will likely get classified as one of the characterized known signals in the absence of discriminating data for the unknown signal. With just two dozen or less sympatric bat species for a given geographic region such a data set can be achieved, but with hundreds of sympatric birds species, the variety of vocalizations they produce, and the considerable confounding noise at audible frequencies, assembling a sufficient data set for a machine learning approach to succeed exceeded the resources available for this project.

As an alternative approach to meet this project's goal of providing a system to recognize target signals from select species, we redirected our approach to developing a more flexible system that could efficiently and effectively search long duration recordings for similar signals to those provided as templates, or search terms. That is, instead of attempting to classify each and every signal encountered in a recording, this approach seeks only signals of a specified type. This provided a more computationally efficient and exacting approach. In practice more than one signal may be sought with each pass through recorded data, and ultimately this approach can form the basis of a multi-species classifier.

Searching for target signals in large files from long duration recordings generated conflicting demands of search accuracy and search speed. The more accurate the search, the more computational overhead required, thus slowing the search process. We addressed this conflict by implementing a two-step search procedure: a coarse resolution search to first seek candidate signals, and then a fine-scale, more discerning signal classification only applied to the candidate signals. By first parsing out candidate signals, this method applies the more processor-intensive but accurate signal discrimination algorithms to only a subset of the entire recording, thereby increasing processing throughput.

High-resolution, detailed interpretation of signal frequency and amplitude information content typically employs CPU-intensive Fast Fourier Transform (FFT) processing of recorded signals to generate sonograms (Figure 29). Searching through hundreds or thousands of hours of field recordings for the acoustic signatures of species of interest using high resolution sonogram-processed signals requires substantial dedicated computer time (or high-speed computers). As an alternative, we implemented an initial low resolution search that rapidly extracts just the basic time-frequency content of the signal with a less processor-intensive approach, and enhanced this search with frequency bandpass filtering to emphasize the frequency band of the signal of interest. Bandpass filtering removes extraneous signal content to improve signal detection. This provides particular advantage for revealing target signals in situations with a high ambient noise level, such as that typical of transportation corridors, where signals of interest, e.g., bird songs, can be masked by the ambient noise and lost (Figure 30).

This initial low resolution post-processing of full-spectrum recordings provides a methodology for rapidly scanning large data streams for candidate signals of interest. The candidate signals can then be subjected to secondary high-resolution processing for confident species identification and confirmation. We implemented this as an initial coarse search procedure with the facility to direct searches for any species (or signal) of interest to seek sections of the data stream, for example a custom template for southwest willow flycatcher (*Empidonax traillii extimus*) (Figure

31). We also implemented the coarse search to seek species-specific templates for multiple species or multiple song types of the same species as combinations to more efficiently search large data streams.

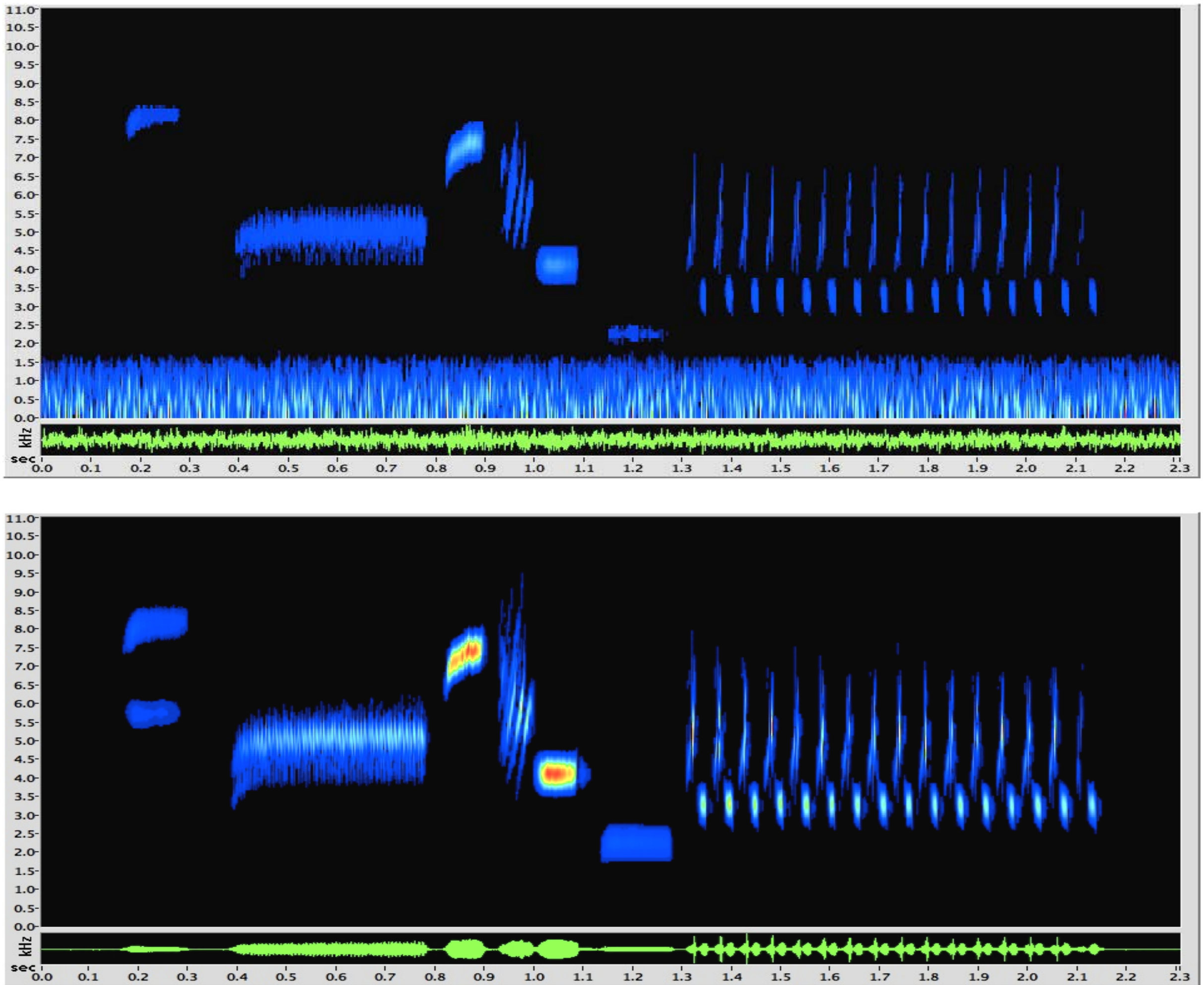


Figure 29. Example of a Bewick's wren (*Thryomanes bewickii*) song recorded in the presence of high amplitude low frequency noise, typical of that encountered near transportation corridors (top panel). This song was recorded using CD quality recording characteristics, i.e., 44.10 kHz sampling frequency and 16 bit resolution to fully capture the acoustic information with the full-spectrum sonogram processed using overlapping windows of frequency spectra analyzed from Fast Fourier Transforms. The lower panel provides the same example wren song after processing with a frequency bandpass filter to eliminate the low frequency noise. This is possible because the two signal components occupy different frequency regimes. The wren song becomes clearly rendered after filtering, even though the noise amplitude in the original signal exceeded that of the wren signal.

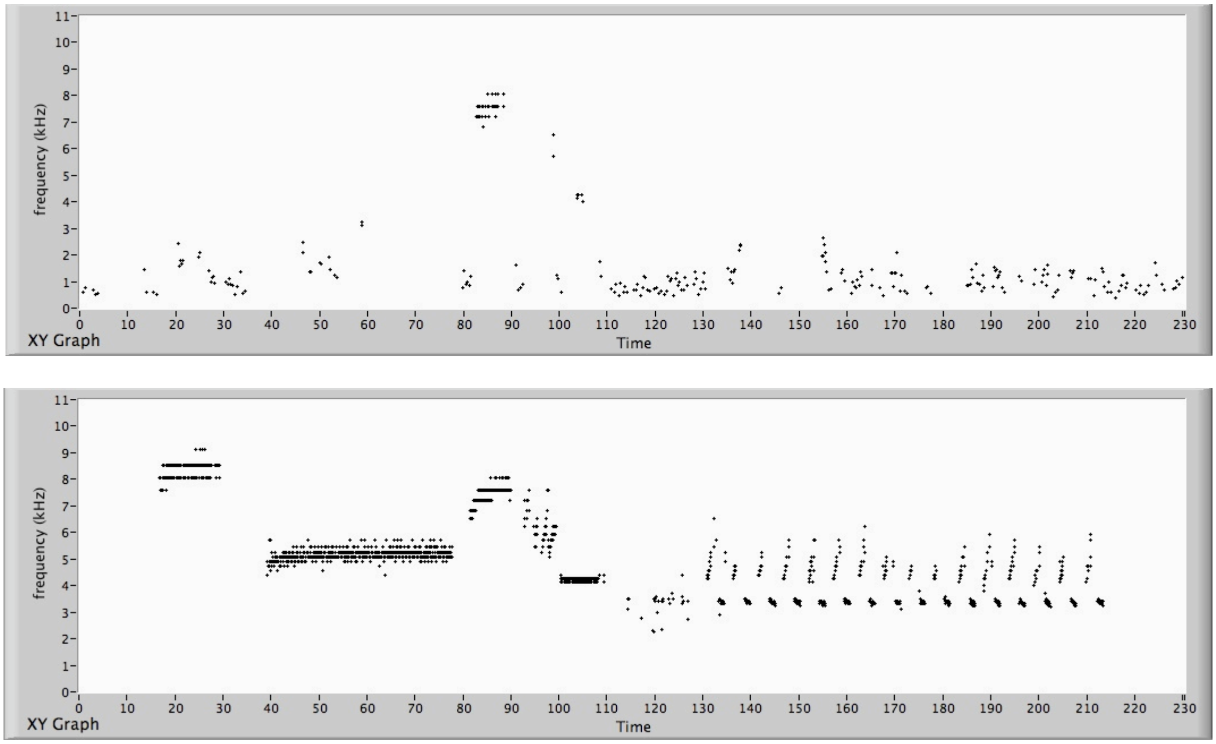


Figure 30. (Upper panel) the same example Bewick's wren song in the previous figure with rapid low resolution processing without initial bandpass frequency filtering. Much of the song was not revealed because the higher amplitude signal content of the lower frequency noise overwhelmed and masked the lower amplitude wren signal. (Lower panel) The same example wren song after first processing with a frequency bandpass filter to eliminate the low frequency noise, and then processed with rapid low resolution processing. Although this method yields a low-resolution rendering of the wren song, it reveals sufficient detail to enable recognition and selection of candidate signals for higher resolution full-spectrum processing as that shown in Figure 1. This enables rapid searching of candidate signals, but still depends on having a high-resolution recording with all frequency content intact.

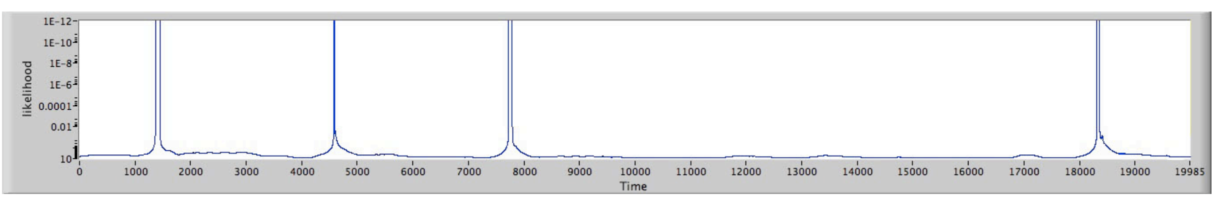


Figure 31. Likelihood of southwest willow flycatcher calls detected in a recording using low resolution processing and detection after frequency bandpass filtering. High points in the plot indicate sections of the recording to secondarily process with high-resolution FFT-based sonograms for final species identification and confirmation.

Results and Discussion

Northeastern United States bat classifier

Even among the known species of the library reference data, the rate of correct classification varies by species, situation, recording quality, and settings. The SonoBat classifiers allow users to control call discrimination settings and in general, more discriminating settings increase the rate of correct species classification (up to a point) but decrease the percentage of accepted files. The results reported here represent idealized classification performance based on good quality recordings (i.e., low noise, high signal-to-noise ratio, only one bat in sequence). Classification performance will vary depending upon recording quality. Although derived from a robust data set acquired from a variety of environments and conditions, the data used to construct the classifiers nevertheless encompasses a finite set of vocalizations from each species covered, and recording in nature will provide a virtually unlimited variety of vocal variants with an expectation that some will exceed that covered by any classifier. Each regional classifier only “knows” the data and call types used to build it, and many spurious signals may generate a parameter set that can fall into one of the known data spaces and be recognized as a species. In practice, automated batch processing should still receive oversight to confirm results, particularly for unexpected species and species with similar acoustic characteristics (refer to the documents in Appendices A and C for more detailed guidance).

SonoBat based the 11 species US Northeast classifier on an exemplar reference library set of 1,444 recordings[1] that yielded 8,116 parameterized calls using a maximum of 8 calls considered per sequence, a quality acceptance threshold of 0.80, and discriminant probability threshold settings for acceptance of **0.90**, **0.95**, and **0.98**. The classification algorithm based on these data yielded different performance results for **individual calls** for different DP thresholds (Table 3).

[1] The results reported here represent idealized classification performance based on high quality recordings made with Pettersson D240X and D500X detectors, and with Binary Acoustic Technology AR125 detectors. Actual performance will decline along with recording quality (see *Recommendations for quality recording* in this document).

Table 3. Northeastern bat species classification results for individual echolocation calls.

	0.90 DP		**0.95 DP**		**0.98 DP**	
	%correct	*%accp*[1]	**%correct**	*%accp*	**%correct**	*%accp*
All Spp	**97.3**	*53.8*	**98.0**	*47.7*	**98.7**	*41.3*
Myle	**97.7**	*37.7*	**99.2**	*28.2*	**100.0**	*18.5*
Myse	**99.4**	*42.2*	**99.6**	*34.0*	**99.4**	*22.8*
Myso[2]	**91.1**	*12.9*	**90.3**	*8.9*	**87.7**	*4.8*
Mylu[2]	**90.6**	*14.9*	**89.4**	*8.5*	**90.7**	*4.6*
Pesu	**98.7**	*93.0*	**99.2**	*90.7*	**99.4**	*87.3*
Nyhu	**91.6**	*96.9*	**94.4**	*40.8*	**94.8**	*35.4*
Labo	**96.9**	*54.1*	**97.3**	*41.6*	**98.8**	*30.1*
Epfu	**98.9**	*83.6*	**99.6**	*79.1*	**100.0**	*67.5*
Lano	**99.0**	*87.9*	**99.6**	*83.9*	**99.6**	*77.7*
Cora	**99.1**	*70.0*	**99.0**	*68.7*	**99.0**	*63.3*
Laci	**95.6**	*86.6*	**96.6**	*86.0*	**97.6**	*84.8*
Myso/Mylu[2,3]	**98.8**	*71.9*	**98.8**	*71.9*	**99.2**	*57.2*

[1] Values listed as %correct considered just those results that emerged from the classifier at or above a discriminant probability threshold of 0.90. The %accepted reports the proportion of the sample that met or exceeded the discriminant probability threshold, whether correct or incorrect.

[2] Refer to "SonoBat Discrimination of Myso *vs.* Mylu" for more information.

[3] Myso/Mylu indicates a result of MysoMylu, Myso, or Mylu, whether correct or incorrect for Myso (if Mylu) or Mylu (if Myso), i.e., the overall rate for correctly discriminating this species pair from other species.

To prevent outputting null species identification results, the SonoBat classifier uses this rubric: when a species decision for either of these species does not exceed the threshold discriminant probability setting (DP, SonoBat uses 0.90 as the default setting), and if the second potential species comes out as the opposite of this pair, and their combined discriminant probability score meets or exceeds the threshold setting, then SonoBat will output this result using the ambiguous designation "MysoMylu." This will indicate the call or sequence probably came from one of these two species, but presented call characteristics within overlapping data space that prevented disambiguation.

As species adjust their call characteristics across their repertoires from short to long calls, some similar species will discriminate better or worse for different duration calls. Generally, Myotis species discriminate better at the longer end of their repertoires in which they present more robust features. In contrast, Pesu, Nyhu, and Labo, which all have simple feature-thin calls, can present calls that discriminate better at the shorter end of their repertoires in which they present greater bandwidth (i.e., sweeping through a greater range of frequencies) and provide greater differences in shape and amplitude distribution. At the longer end of their repertoires Pesu, Nyhu, and Labo all present lower bandwidth more feature-thin flatter calls that do not discriminate as well. Refer to the special characteristics listed in the region-appropriate table of echolocation call characteristics for specific guidance (Appendix A), and use the results that follow for general guidance for classification performance for different duration calls to assess confidence in classification results.

Using the same 11 species US Northeastern exemplar reference library set of 1,444 recordings that yielded 8,161 parameterized calls using a maximum of 8 calls to consider per file, a quality acceptance threshold of 0.80 and a discriminant probability setting threshold of **0.90,** the classification algorithm based on these data results varied in performance on ***individual*** calls for different ranges of call duration (Table 4).

Proper interpretation of these classification results requires an appreciation that species discrimination by echolocation calls uses a probabilistic process. Although called a "discriminant probability," a DP = 1.00 does not indicate 100% confidence of the species classification result. Rather, it indicates that the quantitative parameters measured from the call or sequence under consideration fall completely at the centroid of the multi-dimensional data space of all the data known for that species. A species with similar call characteristics can occasionally (or often depending on the overlap) produce calls with data on the fringes of its parameter space that intrudes into the parameter space of another species, or even falls at the centroid of the other species' parameter space. But, a DP = 1.00 *probably* indicates the classified species, and that confidence increases for species having more unique parameter space. Although SonoBat may report a result indicating a greater likelihood of one similar species over the other, e.g., 0.85 Myso versus 0.15 Mylu, such a result only indicates the relative distances from the centroid of the known multivariate data space for each species. Because these species have their centroids buried in the multivariate data clouds of the other species (Figure 32), they never clearly separate, and either species could just have well vocalized a call producing those results, despite lying closer to the mean values of one over the other.

Table 4. Northeastern bat species classification results for individual calls by ranges of echolocation call duration using a discriminant probability threshold settings for acceptance of **0.90**[1]. (Empty cells indicate no calls in data set for that duration.)

	<4 msec %correct *%accp*[1]	4–5 msec %correct *%accp*	5–6 msec %correct *%accp*	6–8 msec %correct *%accp*	>8 msec %correct *%accp*
All Spp	**97.0** *29.8*	**96.0** *32.0*	**95.0** *50.4*	**97.7** *47.7*	**97.9** *82.0*
Myle	**98.6** *39.8*	**96.0** *27.6*	**75.0** *60.0*		
Myse	**100.0** *36.8*	**99.3** *50.6*	**94.7** *40.9*	**100.0** *70.0*	
Myso[2]	**33.3**[3] *0.7*	**92.3**[3] *5.6*	**96.9** *23.9*	**90.2** *54.1*	**100.0** *100.0*
Mylu[2]	**61.5**[3] *2.3*	**86.0**[3] *6.7*	**92.5** *21.3*	**94.4** *44.5*	**100.0** *41.3*
Pesu	**100.0** *55.6*	**93.3** *80.0*	**96.8** *92.9*	**99.7** *97.6*	**99.2** *88.7*
Nyhu	**100.0** *33.3*	**98.0** *87.7*	**90.0** *65.9*	**66.7** *17.8*	**90.0** *17.6*
Labo	**100.0** *25.0*	**97.3** *85.5*	**94.9** *68.5*	**98.7** *51.7*	**96.7** *35.3*
Epfu	**100.0** *41.2*	**100.0** *82.2*	**99.0** *88.8*	**99.5** *89.7*	**98.1** *80.5*
Lano	**97.6** *71.4*	**100.0** *87.6*	**100.0** *97.9*	**100.0** *92.4*	**98.1** *84.9*
Cora	**100.0** *61.9*	**94.7** *81.8*	**100.0** *85.7*	**100.0** *100.0*	**100.0** *83.3*
Laci	**100.0**[3] *20.8*	**86.4** *55.9*	**81.3** *78.0*	**93.4** *83.2*	**97.6** *92.4*
Mylu/Myso[2]	**97.8** *42.3*	**99.1** *72.9*	**99.2** *91.1*	**97.8** *83.1*	**100.0** *100.0*

[1] Values listed as %correct considered just those results that emerged from the classifier at or above a discriminant probability threshold of 0.90. The %accepted reports the proportion of the sample that met or exceeded the discriminant probability threshold, whether correct or incorrect.
[2] Refer to "SonoBat Discrimination of Myso *vs.* Mylu" for more information (Appendix A).
[3] Limited rate of acceptance for this duration; better to use longer calls to assess this species.

Combining the cumulative information of all calls in a sequence performs better than individual calls. SonoBat outputs sequence results from batch processing of recorded sequences. Using the same 11 species US Northeast classifier on an exemplar reference library set of 1,444 recordings using a maximum of 8 calls to consider per file, a quality acceptance threshold of 0.80, yielded different performance results for discriminant probability setting thresholds for acceptance of **0.90**, **0.95**, and **0.98** (Table 5).

Table 5. Northeastern bat species classification results for sequences of echolocation calls, i.e., bat passes.

		0.90 DP		0.95 DP		0.98 DP	
		%correct	*%accp*[1]	%correct	*%accp*	%correct	*%accp*
All Spp	by vote:	98.0	*82.0*	97.7	*80.6*	97.9	*78.1*
	mean sqnc:	96.9	*85.7*	97.7	*78.0*	98.3	*69.6*
	agreement:	**98.8**	***74.5***	**99.0**	***69.5***	**99.4**	***62.8***
Myle	by vote:	97.4	*57.4*	90.9	*61.5*	91.5	*66.2*
	mean sqnc:	95.0	*58.5*	96.4	*50.4*	100.0	*38.2*
	agreement:	**97.1**	***52.3***	**96.3**	***40.0***	**100.0**	***32.3***
Myse	by vote:	97.2	*56.1*	96.9	*51.2*	96.3	*42.3*
	mean sqnc:	94.0	*63.4*	96.4	*50.4*	100.0	*38.2*
	agreement:	**98.3**	***48.0***	**100.0**	***38.2***	**100.0**	***26.0***
Myso[2]	by vote:	95.2	*14.1*	100.0	*7.0*	100.0	*3.5*
	mean sqnc:	95.5	*14.8*	92.9	*9.2*	100.0	*4.2*
	agreement:	**100.0**	***12.7***	**100.0**	***5.6***	**100.0**	***3.5***
Mylu[2]	by vote:	100.0	*15.6*	100.0	*8.9*	100.0	*3.6*
	mean sqnc:	90.3	*12.5*	94.7	*8.0*	85.7	*2.7*
	agreement:	**100.0**	***10.3***	**100.0**	***6.7***	**100.0**	***2.2***
Pesu	by vote:	100.0	*86.0*	100.0	*86.0*	100.0	*86.0*
	mean sqnc:	99.0	*96.0*	98.9	*93.0*	98.9	*89.0*
	agreement:	**100.0**	***84.0***	**100.0**	***82.0***	**100.0**	***79.0***
Nyhu	by vote:	94.7	*41.9*	100.0	*41.9*	100.0	*41.9*
	mean sqnc:	87.1	*62.8*	85.7	*41.9*	93.8	*34.9*
	agreement:	**100.0**	***37.2***	**100.0**	***32.6***	**100.0**	***30.2***
Labo	by vote:	98.3	*62.8*	98.3	*61.7*	98.3	*61.7*
	mean sqnc:	96.7	*61.7*	100.0	*43.6*	100.0	*26.6*
	agreement:	**97.7**	***45.7***	**100.0**	***31.9***	**100.0**	***20.2***
Epfu	by vote:	99.1	*91.3*	99.1	*92.1*	99.1	*88.9*
	mean sqnc:	99.1	*87.3*	99.0	*79.4*	98.9	*69.0*
	agreement:	**100.0**	***83.3***	**100.0**	***77.0***	**100.0**	***64.3***
Lano	by vote:	94.6	*98.8*	94.0	*98.8*	93.5	*98.8*
	mean sqnc:	94.9	*93.8*	95.4	*91.3*	95.7	*83.8*
	agreement:	**96.8**	***93.8***	**96.7**	***91.3***	**97.1**	***83.8***
Cora	by vote:	100.0	*82.9*	100.0	*82.9*	100.0	*74.3*
	mean sqnc:	100.0	*100*	100.0	*100*	100.0	*97.1*
	agreement:	**100.0**	***82.9***	**100.0**	***82.9***	**100.0**	***74.3***
Laci	by vote:	100.0	*92.7*	100.0	*92.3*	100.0	*91.9*
	mean sqnc:	100.0	*88.7*	100.0	*87.9*	100.0	*85.4*
	agreement:	**100.0**	***87.9***	**100.0**	***87.0***	**100.0**	***85.0***

[1] Values listed as %correct considered just those results that emerged from the classifier at or above a discriminant probability threshold of 0.90. The %accepted reports the proportion of the sample that met or exceeded the discriminant probability threshold, whether correct or incorrect.
[2] Refer to "SonoBat Discrimination of Myso *vs.* Mylu" for more information (Appendix A).

Classification of Indiana Bats

The geographic range of the federally listed Indiana bat, *Myotis sodalis* (Myso) lies entirely within that of the morphologically and acoustically similar little brown bat, *M. lucifugus* (Mylu). The substantial overlap in their echolocation call characteristics renders only a small portion of their repertoires with a tendency toward discriminating characteristics. Sample bivariate plots display the considerable overlap and range of call characteristics from this species pair (Figure 32).

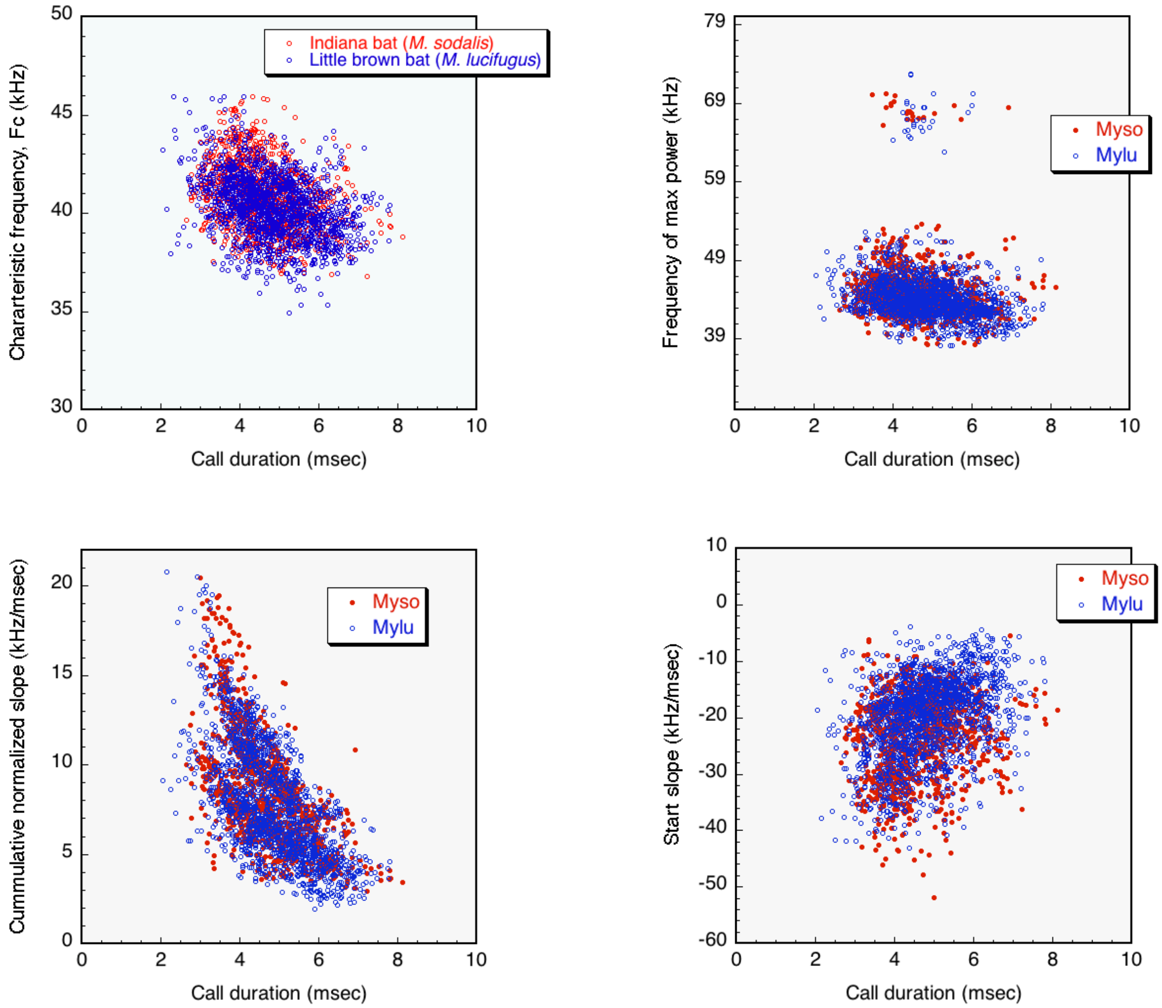


Figure 32. Sample bivariate plots of overlapping call parameters of Indiana bats and little brown bats showing the similarity in acoustic characteristics between these species.

Although the overlapping call characteristics of these two species present a challenge to discriminate, as with most species, longer duration calls provide more information content and consistent data that enhances discrimination performance (Table 4). Classification results parsed by call duration for 366 Indiana bat (Myso) and little brown bat (Mylu) sequences recorded in IN, IL, MO, KY, TN, PA, NJ, and VT that yielded 2,680 parameterized calls using a maximum of 8 calls to consider per file, and a quality acceptance threshold of 0.80 reveal classification confidence improved with longer duration calls (Table 6).

Table 6. Individual echolocation call classification results for Indiana bats (Myso) and little brown bats (Mylu) with discriminant probability threshold of **0.90**.

call duration (msec)		%correct	%accepted[1]
↓	Myso	0.0	0.0
	Mylu	100.0[2]	2.5
3.5	Myso/Mylu[3]	100.0	24.8
3.5	Myso	37.5	0.7
↓	Mylu	60.6	3.6
4.5	**Myso/Mylu**	**100.0**	**52.9**
4.5	Myso	93.5	11.7
↓	Mylu	78.0	5.8
5.5	**Myso/Mylu**	**100.0**	**92.2**
5.5	**Myso**	**96.0**	**36.9**
↓	**Mylu**	**89.7**	**32.1**
6.5	**Myso/Mylu**	**100.0**	**92.3**
6.5	**Myso**	**96.2**	**71.4**
↓	**Mylu**	**97.2**	**73.4**
	Myso/Mylu	**100.0**	**75.2**

[1] Values listed as %correct considered just those results that emerged from the classifier at or above a discriminant probability threshold of 0.90. The %accepted reports the proportion of the sample that met or exceeded the discriminant probability threshold, whether correct or incorrect.
[2] Although correct, just 3 calls of the 118 in the sample accepted.
[3] Myso/Mylu indicates a result of MysoMylu, Myso, or Mylu, whether correct or incorrect for Myso (if Mylu) or Mylu (if Myso), i.e., the overall rate for correctly discriminating this species pair from other species.

Calls less than 5.5 msec achieved high rates of correct classification. However, note the very low %accepted. Although correct, very few calls of the data set contributed to this result, and performance may reflect an artifact from the classifier being based on these data set rather than absolute performance. Accepting less than ~33% of the sample indicates a weak, non-robust discrimination that will likely produce unreliable results with actual field data, i.e., the inherent nature of the call characteristics do not separate well for confident discrimination.

For the acoustically difficult discrimination between Indiana and little brown bats, the results indicate diminishing confidence for calls less than 5.5 or 6 msec and increasing confidence for calls of longer duration. These results were from individual calls. The combined result of sequence classification based on longer calls would provide the most confident classification results.

Northwestern United States bat classifier

SonoBat based the 16 species US Northwest classifier on an exemplar reference library set of 1,854 recordings that yielded 11,026 parameterized calls using a maximum of 8 calls considered per sequence, a quality acceptance threshold of 0.80, and discriminant probability threshold settings for acceptance of **0.90**, **0.95**, and **0.98**. The classification algorithm based on these data yielded different performance results for **individual calls** for different DP thresholds (Table 7).

Table 7. Northwestern bat species classification results for individual echolocation calls.

	0.90 DP		**0.95 DP**		**0.98 DP**	
	%correct	*%accp*[1]	**%correct**	*%accp*	**%correct**	*%accp*
All Spp	**98.2**	*60.1*	**98.8**	*54.3*	**98.9**	*50.0*
Myyu	**93.4**	*45.0*	**95.7**	*35.4*	**97.1**	*31.1*
Myca	**98.2**	*41.4*	**99.4**	*32.5*	**98.6**	*25.7*
Myci	**98.5**	*51.0*	**99.0**	*42.7*	**99.3**	*34.0*
Myvo	**96.0**	*29.1*	**99.1**	*19.6*	**99.0**	*17.0*
Mylu	**95.3**	*30.3*	**97.1**	*22.6*	**99.3**	*19.1*
Pahe	**99.3**	*88.9*	**99.3**	*86.8*	**99.2**	*84.8*
Labl	**96.3**	*27.1*	**96.0**	*25.0*	**91.7**	*22.9*
Myev	**100.0**	*79.9*	**100.0**	*79.1*	**99.8**	*77.3*
Anpa	**89.3**	*7.1*	**91.1**	*5.8*	**92.2**	*5.0*
Epfu	**96.0**	*32.5*	**95.9**	*26.2*	**95.6**	*21.9*
Lano	**93.9**	*59.1*	**95.1**	*47.3*	**96.7**	*38.2*
Myth	**100.0**	*80.3*	**100.0**	*78.6*	**100.0**	*77.4*
Tabr	**99.4**	*68.9*	**99.6**	*62.9*	**99.5**	*57.6*
Laci	**99.0**	*70.7*	**99.3**	*68.2*	**99.4**	*65.4*
Coto	**99.5**	*69.5*	**99.5**	*67.5*	**99.0**	*64.0*
Euma	**100.0**	*96.0*	**100.0**	*96.0*	**99.8**	*95.4*
Eupe	**100.0**	*93.0*	**100.0**	*93.0*	**98.7**	*90.7*

[1] Values listed as %correct considered just those results that emerged from the classifier at or above a discriminant probability threshold of 0.90. The %accepted reports the proportion of the sample that met or exceeded the discriminant probability threshold, whether correct or incorrect.

Generally, species discriminate better at the longer end of their call repertoires in which they present more robust features. Using the same 16 species US Northwestern exemplar reference library set of 1,854 recordings that yielded 11,026 parameterized calls using a maximum of 8 calls considered per sequence, a quality acceptance threshold of 0.80, and discriminant probability threshold settings for acceptance of **0.90**, individual call discrimination performance varied with species for different ranges of call duration (Table 8).

Table 8. Northwestern bat species classification results for individual echolocation calls by ranges of call duration. (Empty cells indicate no calls in data set for that duration.)

	<4 msec **%correct** *%accp*[1]	**4–5 msec** **%correct** *%accp*	**5–6 msec** **%correct** *%accp*	**6–8 msec** **%correct** *%accp*	**>8 msec** **%correct** *%accp*
All Spp	**99.0** *55.5*	**97.8** *53.5*	**98.4** *58.1*	**97.8** *62.4*	**97.8** *75.9*
Myyu	**93.8**[2] *8.9*	**80.6** *46.3*	**98.3** *79.2*	**100.0** *84.1*	**100.0** *100.0*
Myca	**97.8** *42.9*	**98.5** *39.4*	**100.0** *37.5*	**100.0** *46.2*	
Myci	**98.6** *49.7*	**99.4** *53.7*	**96.4** *52.9*	**66.7** *28.6*	
Myvo	**93.9** *22.5*	**94.8** *31.1*	**100.0** *19.0*	**100.0** *58.9*	**100.0** *50.0*
Mylu	**90.0**[2] *10.3*	**85.7** *20.2*	**92.9** *27.7*	**100.0** *53.9*	**100.0** *41.2*
Pahe	**97.2** *90.2*	**100.0** *92.9*	**98.7** *91.9*	**100.0** *85.0*	**100.0** *63.4*
Labl	**0.0**[3] *0.0*	**0.0**[3] *0.0*	**0.0**[3] *0.0*	**100.0** *20.0*	**96.0** *66.7*
Myev	**100.0** *77.0*	**100.0** *88.9*	**100.0** *68.0*	**100.0** *100.0*	
Anpa	**100.0**[2] *7.4*	**100.0** *19.0*	**100.0** *16.3*	**83.6** *50.5*	**96.0** *64.9*
Epfu	**100.0**[2] *5.3*	**100.0**[2] *8.3*	**100.0** *20.6*	**96.4** *34.8*	**94.7** *54.0*
Lano	**100.0** *44.2*	**100.0** *24.3*	**97.4** *52.8*	**94.4** *63.2*	**91.9** *70.5*
Myth	**100.0** *81.2*	**100.0** *79.4*	**100.0** *80.0*	**100.0** *75.0*	
Tabr	**0.0**[3] *0.0*	**0.0**[3] *0.0*	**0.0**[3] *0.0*	**100.0** *23.6*	**99.4** *74.3*
Laci	**100.0**[2] *5.6*	**100.0**[2] *13.8*	**100.0** *46.5*	**99.1** *65.9*	**99.0** *85.2*
Coto	**100.0** *63.3*	**100.0** *65.0*	**98.1** *74.3*	**100.0** *89.7*	**100.0** *84.6*
Euma	**100.0** *95.9*	**100.0** *98.2*	**100.0** *90.9*	**100.0** *100.0*	

[1] Values listed as %correct considered just those results that emerged from the classifier at or above a discriminant probability threshold of 0.90. The %accepted reports the proportion of the sample that met or exceeded the discriminant probability threshold, whether correct or incorrect.

[2] Limited rate of acceptance for this duration; better to use longer calls to assess presence of this species.

[3] No calls of this duration met or exceeded threshold for acceptance; better to use longer calls to assess presence of this species.

Using the same 16 species US Northwest classifier on an exemplar reference library set of 1,854 recordings using a maximum of 8 calls to consider per file, and a quality acceptance threshold of 0.80 yielded different performance results for discriminant probability setting thresholds for acceptance of **0.90**, **0.95**, and **0.98** (Table 9).

Table 9. Northwestern bat species classification results for sequences of echolocation calls, i.e., bat passes.

		0.90 DP		**0.95 DP**		**0.98 DP**	
		%correct	*%accp*[1]	%correct	*%accp*	%correct	*%accp*
All Spp	by vote:	98.1	*72.2*	97.8	*75.1*	97.6	*77.3*
	mean sqnc:	99.0	*62.4*	99.3	*57.1*	99.6	*49.1*
	agreement:	**99.0**	***62.3***	**99.0**	***57.1***	**99.6**	***49.1***
Myyu	by vote:	93.5	*65.2*	95.2	*60.6*	95.6	*65.2*
	mean sqnc:	96.6	*42.4*	100.0	*37.9*	100.0	*43.9*
	agreement:	**96.6**	***42.4***	**100.0**	***37.9***	**100.0**	***30.3***
Myca	by vote:	97.8	*57.1*	100.0	*58.4*	97.9	*61.0*
	mean sqnc:	100.0	*49.4*	100.0	*39.0*	78.5	*66.2*
	agreement:	**100.0**	***49.4***	**100.0**	***39.0***	**100.0**	***26.0***
Myci	by vote:	97.9	*76.7*	99.0	*79.2*	99.0	*79.2*
	mean sqnc:	100.0	*60.8*	100.0	*52.5*	100.0	*66.7*
	agreement:	**100.0**	***60.0***	**100.0**	***51.7***	**100.0**	***25.8***
Myvo	by vote:	95.8	*52.3*	95.7	*51.1*	96.0	*54.5*
	mean sqnc:	96.3	*29.5*	100.0	*19.3*	93.1	*30.7*
	agreement:	**100.0**	***28.4***	**100.0**	***19.3***	**100.0**	***10.2***
Mylu	by vote:	98.0	*45.9*	96.2	*45.9*	96.6	*52.3*
	mean sqnc:	100.0	*34.9*	100.0	*25.7*	100.0	*35.8*
	agreement:	**100.0**	***32.1***	**100.0**	***25.7***	**100.0**	***18.3***
Pahe	by vote:	99.5	*97.8*	99.5	*98.4*	99.5	*98.4*
	mean sqnc:	100.0	*94.1*	100.0	*93.0*	99.5	*98.4*
	agreement:	**100.0**	***94.1***	**100.0**	***93.0***	**100.0**	***89.8***
Labl	by vote:	100.0	*55.6*	100.0	*22.2*	100.0	*22.2*
	mean sqnc:	100.0	*22.2*	100.0	*22.2*	100.0	*22.2*
	agreement:	**100.0**	***22.2***	**100.0**	***22.2***	**100.0**	***22.2***
Myev	by vote:	100.0	*93.8*	100.0	*85.0*	100.0	*85.0*
	mean sqnc:	100.0	*77.5*	100.0	*75.0*	100.0	*83.8*
	agreement:	**100.0**	***77.5***	**100.0**	***75.0***	**100.0**	***73.8***

[1] Values listed as %correct considered just those results that emerged from the classifier at or above a discriminant probability threshold of 0.90. The %accepted reports the proportion of the sample that met or exceeded the discriminant probability threshold, whether correct or incorrect.

Table 9 (continued). Northwestern bat species classification results for sequences of echolocation calls, i.e., bat passes.

		0.90 DP		0.95 DP		0.98 DP	
		%correct	*%accp*	%correct	*%accp*	%correct	*%accp*
Anpa	by vote:	96.0	*42.1*	95.7	*38.6*	89.3	*43.9*
	mean sqnc:	100.0	*24.6*	100.0	*19.3*	100.0	*31.6*
	agreement:	**100.0**	***24.6***	**100.0**	***19.3***	**100.0**	***17.5***
Epfu	by vote:	100.0	*47.6*	100.0	*53.2*	97.5	*61.9*
	mean sqnc:	100.0	*32.5*	100.0	*26.2*	100.0	*40.5*
	agreement:	**100.0**	***32.5***	**100.0**	***26.2***	**100.0**	***17.5***
Lano	by vote:	90.1	*86.4*	90.1	*87.1*	91.0	*89.8*
	mean sqnc:	94.9	*63.9*	96.1	*50.3*	91.9	*77.6*
	agreement:	**94.9**	***63.9***	**96.1**	***50.3***	**98.2**	***36.7***
Myth	by vote:	100.0	*93.2*	100.0	*89.8*	100.0	*89.8*
	mean sqnc:	100.0	*88.1*	100.0	*86.4*	100.0	*91.5*
	agreement:	**100.0**	***88.1***	**100.0**	***86.4***	**100.0**	***86.4***
Tabr	by vote:	98.3	*85.2*	98.2	*83.7*	98.2	*84.8*
	mean sqnc:	99.5	*71.6*	100.0	*65.9*	98.2	*84.5*
	agreement:	**99.5**	***71.2***	**100.0**	***65.9***	**100.0**	***53.8***
Laci	by vote:	97.3	*77.7*	98.6	*75.5*	98.6	*75.5*
	mean sqnc:	98.4	*67.6*	98.4	*65.1*	98.5	*71.9*
	agreement:	**98.4**	***67.6***	**98.4**	***65.1***	**98.8**	***61.5***
Coto	by vote:	97.4	*78.7*	97.2	*74.5*	97.2	*74.5*
	mean sqnc:	97.1	*70.2*	97.1	*70.2*	97.4	*80.9*
	agreement:	**97.1**	***70.2***	**97.1**	***70.2***	**97.0**	***68.1***
Euma	by vote:	100.0	*75.8*	100.0	*75.8*	100.0	*75.8*
	mean sqnc:	100.0	*75.8*	100.0	*75.8*	100.0	*75.8*
	agreement:	**100.0**	***75.8***	**100.0**	***75.8***	**100.0**	***75.8***

Midwestern United States bat classifier

The Midwestern classifier comprises a subset of the Northeastern classifier species set. Based on an exemplar reference library set of 1,274 recordings that yielded 7,577 parameterized calls using a maximum of 8 calls to consider per file and a quality acceptance threshold of 0.80, it includes all the same species as the Northeastern classifier with the exclusion of the eastern small-footed myotis, *M. leibii* (Myle), and Rafinesque's big-eared bat, *Corynorhinus rafinesquii* (Cora). One less myotis species operating in 40 kHz range (Myle) modestly increased the classifier performance for the three remaining 40 kHz range myotis species, the northern long-eared bat, *M. septentrionalis* (Myse), the Indiana bat, *M. sodalis* (Myso), and the little brown bat, *M. lucifugus* (Mylu). Applying the default classifier settings of a discriminant probability threshold of 0.90 for acceptance and a quality acceptance threshold of 0.80 correctly classified 96.9% and 98.2% of all bat calls and sequences, respectively, with acceptance rates of 58.0% and 62.2%, respectively (Tables 10 and 11).

Table 10. Midwest bat species classification results for individual echolocation calls using a discriminant probability threshold setting for acceptance of **0.90**[1].

	%correct	*%accp*[1]
All Spp	**96.9**	*58.0*
Myse	**99.1**	*55.2*
Myso[2]	**94.0**	*16.3*
Mylu[2]	**90.1**	*15.7*
Pesu	**99.1**	*89.8*
Nyhu	**95.2**	*72.8*
Labo	**95.9**	*67.7*
Epfu	**98.4**	*85.2*
Lano	**98.1**	*86.5*
Laci	**95.4**	*86.4*
Myso/Mylu[2,3]	**99.1**	*86.1*

[1] Values listed as %correct considered just those results that emerged from the classifier at or above a discriminant probability threshold of 0.90. The %accepted reports the proportion of the sample that met or exceeded the discriminant probability threshold, whether correct or incorrect.
[2] Refer to "SonoBat Discrimination of Myso *vs.* Mylu" for more information (Appendix A).
[3] Myso/Mylu indicates a result of MysoMylu, Myso, or Mylu, whether correct or incorrect for Myso (if Mylu) or Mylu (if Myso), i.e., the overall rate for correctly discriminating this species pair from other species.

Table 11. Midwest bat species classification results for sequences of echolocation calls, i.e., bat passes, using a discriminant probability threshold setting for acceptance of **0.90**[1].

		%correct	*%accp*[1]
All Spp	by vote:	**91.4**	*74.3*
	mean sqnc:	**97.7**	*67.0*
	agreement:	**98.2**	*62.2*
Myse	by vote:	**93.5**	*65.2*
	mean sqnc:	**96.6**	*42.4*
	agreement:	**96.6**	*42.4*
Myso[2]	by vote:	**97.8**	*57.1*
	mean sqnc:	**100.0**	*49.4*
	agreement:	**100.0**	*49.4*
Mylu[2]	by vote:	**97.9**	*76.7*
	mean sqnc:	**100.0**	*60.8*
	agreement:	**100.0**	*60.0*
Pesu	by vote:	**95.8**	*52.3*
	mean sqnc:	**96.3**	*29.5*
	agreement:	**100.0**	*28.4*
Nyhu	by vote:	**95.8**	*52.3*
	mean sqnc:	**96.3**	*29.5*
	agreement:	**100.0**	*28.4*
Labo	by vote:	**95.8**	*52.3*
	mean sqnc:	**96.3**	*29.5*
	agreement:	**100.0**	*28.4*
Epfu	by vote:	**95.8**	*52.3*
	mean sqnc:	**96.3**	*29.5*
	agreement:	**100.0**	*28.4*
Lano	by vote:	**95.8**	*52.3*
	mean sqnc:	**96.3**	*29.5*
	agreement:	**100.0**	*28.4*
Laci	by vote:	**95.8**	*52.3*
	mean sqnc:	**96.3**	*29.5*
	agreement:	**100.0**	*28.4*
Myso/Mylu[2,3]	by vote:	**95.8**	*52.3*
	mean sqnc:	**96.3**	*29.5*
	agreement:	**100.0**	*28.4*

[1] Values listed as %correct considered just those results that emerged from the classifier at or above a discriminant probability threshold of 0.90. The %accepted reports the proportion of the sample that met or exceeded the discriminant probability threshold, whether correct or incorrect.
[2] Refer to "SonoBat Discrimination of Myso *vs.* Mylu" for more information (Appendix A).
[3] Myso/Mylu indicates a result of MysoMylu, Myso, or Mylu, whether correct or incorrect for Myso (if Mylu) or Mylu (if Myso), i.e., the overall rate for correctly discriminating this species pair from other species.

Ozark to northern Georgia bat classifier

The Ozark-northern Georgia classifier adds the federally listed gray bat, *M. grisescens* (Mygr) and the free-tailed bat, *Tadarida brasiliensis* (Tabr). This classifier's exemplar reference library set of 1,810 recordings yielded 10,821 parameterized calls using a maximum of 8 calls to consider per file and a quality acceptance threshold of 0.80. Using default classifier settings of the discriminant probability threshold at 0.90 for acceptance and a quality acceptance threshold of 0.80 correctly classified 97.6% and 98.5% of gray bat calls and sequences, respectively with acceptance rates of 77.1% and 93.1% respectively (Tables 12 and 13).

Table 12. Ozark-northern GA bat species classification results for individual echolocation calls using a discriminant probability threshold setting for acceptance of **0.90**[1].

	%correct	*%accp*[1]
All Spp	**97.0**	*57.2*
Mygr	**97.6**	*77.1*
Myle	**98.0**	*31.4*
Myse	**98.2**	*49.5*
Myso[2]	**92.0**	*15.5*
Mylu[2]	**89.6**	*18.4*
Pesu	**99.4**	*89.8*
Nyhu	**96.2**	*72.4*
Labo	**95.5**	*61.6*
Epfu	**98.5**	*76.9*
Lano	**98.6**	*72.4*
Cora	**96.0**	*55.3*
Tabr	**97.9**	*71.2*
Laci	**96.9**	*79.4*
Myso/Mylu[2,3]	**99.8**	*55.8*

[1] Values listed as %correct considered just those results that emerged from the classifier at or above a discriminant probability threshold of 0.90. The %accepted reports the proportion of the sample that met or exceeded the discriminant probability threshold, whether correct or incorrect.
[2] Refer to "SonoBat Discrimination of Myso *vs.* Mylu" for more information (Appendix A).
[3] Myso/Mylu indicates a result of MysoMylu, Myso, or Mylu, whether correct or incorrect for Myso (if Mylu) or Mylu (if Myso), i.e., the overall rate for correctly discriminating this species pair from other species.

Table 13. Ozark-northern GA bat species classification results for sequences of echolocation calls, i.e., bat passes, using a discriminant probability threshold setting for acceptance of **0.90**[1].

		%correct	*%accp*[1]
All Spp	by vote:	97.7	*84.6*
	mean sqnc:	**97.6**	*72.0*
	agreement:	**98.5**	***64.9***
Mygr	by vote:	98.5	*93.1*
	mean sqnc:	97.1	*91.7*
	agreement:	**100.0**	***90.3***
Myle	by vote:	100.0	*53.8*
	mean sqnc:	95.2	*61.5*
	agreement:	**100.0**	***46.2***
Myse	by vote:	95.4	*66.9*
	mean sqnc:	94.6	*71.0*
	agreement:	**95.9**	***57.3***
Myso[2]	by vote:	92.6	*17.5*
	mean sqnc:	95.0	*13.3*
	agreement:	**100.0**	***10.5***
Mylu[2]	by vote:	98.4	*27.4*
	mean sqnc:	97.4	*16.1*
	agreement:	**97.0**	***13.9***
Pesu	by vote:	97.6	*81.2*
	mean sqnc:	98.9	*92.1*
	agreement:	**98.8**	***79.2***
Nyhu	by vote:	100.0	*68.1*
	mean sqnc:	90.9	*85.1*
	agreement:	**100.0**	***61.7***
Labo	by vote:	98.5	*71.0*
	mean sqnc:	98.6	*76.3*
	agreement:	**98.3**	***61.3***
Epfu	by vote:	97.4	*87.4*
	mean sqnc:	96.3	*82.7*
	agreement:	**97.1**	***78.7***
Lano	by vote:	91.0	*93.2*
	mean sqnc:	96.0	*88.9*
	agreement:	**96.0**	***88.3***
Cora	by vote:	100.0	*75.5*
	mean sqnc:	100.0	*91.8*
	agreement:	**100.0**	***73.5***
Tabr	by vote:	99.7	*88.3*
	mean sqnc:	99.7	*89.7*
	agreement:	**100.0**	***83.0***
Laci	by vote:	98.7	*89.1*
	mean sqnc:	98.6	*85.4*
	agreement:	**98.6**	***85.0***
MyluMyso[2,3]	by vote:	97.5	*75.5*
	mean sqnc:	97.6	*75.0*
	agreement:	**98.5**	***67.6***

Table 13 (continued). Ozark-northern GA bat species classification results for sequences of echolocation calls, i.e., bat passes, using a discriminant probability threshold settings for acceptance of **0.90**[1].

[1] Values listed as %correct considered just those results that emerged from the classifier at or above a discriminant probability threshold of 0.90. The %accepted reports the proportion of the sample that met or exceeded the discriminant probability threshold, whether correct or incorrect.
[2] Refer to "SonoBat Discrimination of Myso *vs.* Mylu" for more information (Appendix A).
[3] Myso/Mylu indicates a result of MysoMylu, Myso, or Mylu, whether correct or incorrect for Myso (if Mylu) or Mylu (if Myso), i.e., the overall rate for correctly discriminating this species pair from other species.

Bat analysis application

The user operation of SonoBat software provides a comprehensive tool for analyzing and comparing high-resolution full-spectrum sonograms of bat echolocation calls recorded from full-spectrum and time-expansion bat detectors. SonoBat has an intuitive and direct interface that enables users to process, display, and analyze calls and sequences, and progress to sophisticated analysis.

After opening a file to view a bat pass sequence, users may select individual calls to reprocess into high resolution sonograms for call by call comparison with reference calls or for parameter extraction (and data export to a spreadsheet), or have the individual call classified (Figure 33). Users may elect to classify an entire sequence (i.e., bat pass) as that typically provides more confident results than individual call classification as this method benefits from the combined information within the sequence (Figure 34). SonoBat will also batch process sequence classifications (Figure 35) and output a spreadsheet of the results (Figure 36). For overviews of SonoBat software, classification, and operation, refer to links in Appendices A and C.

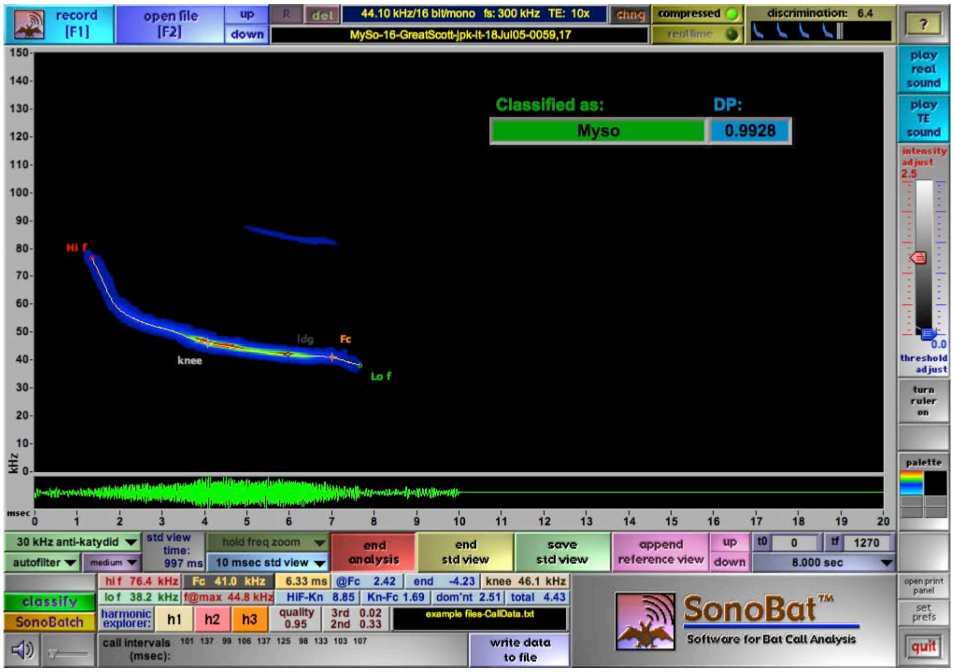


Figure 33. SonoBat high resolution display of an individual call analyzed and displaying the classification decision.

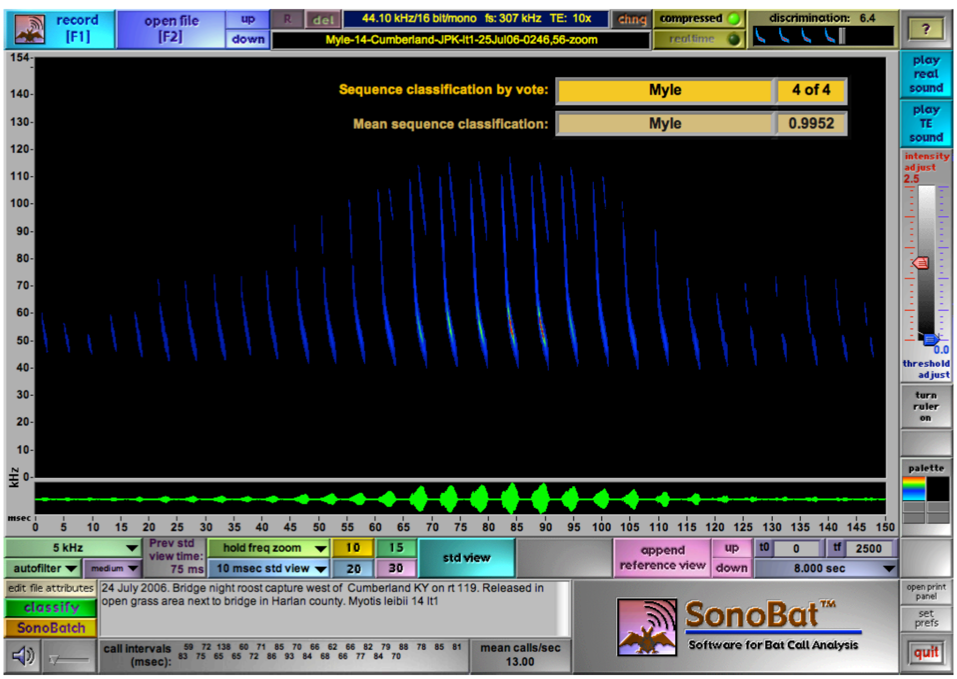


Figure 34. SonoBat display of a full call sequence after classification analysis and displaying the classification decision. Note the progression from call fragments to fully formed calls and back to fragments as the bat approached, passed, and then receded from the microphone.

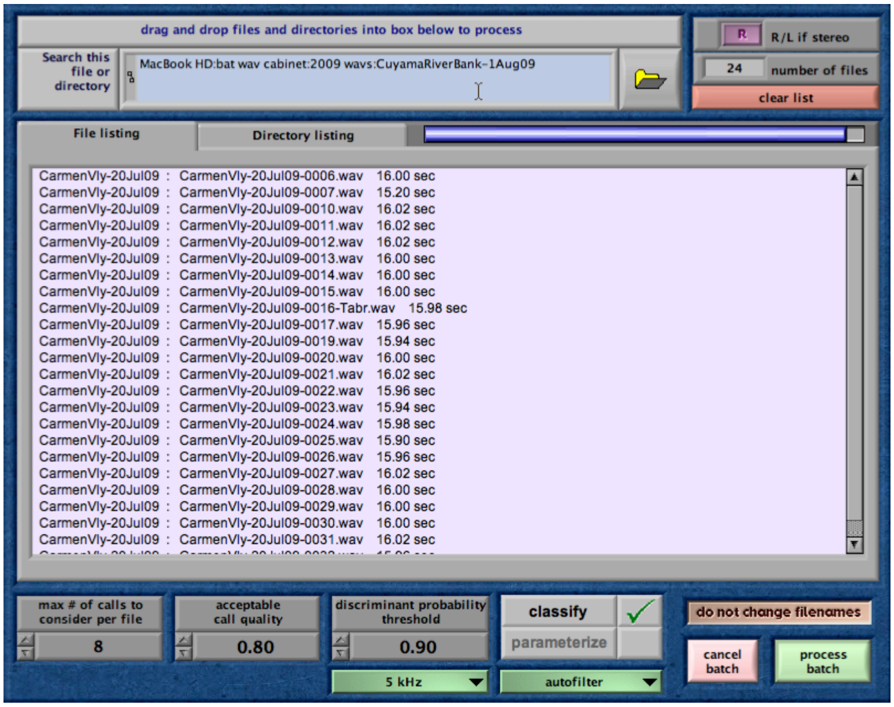


Figure 35. SonoBat batch process setup panel. Directories or directories of directories can be dropped to populate the batch job list.

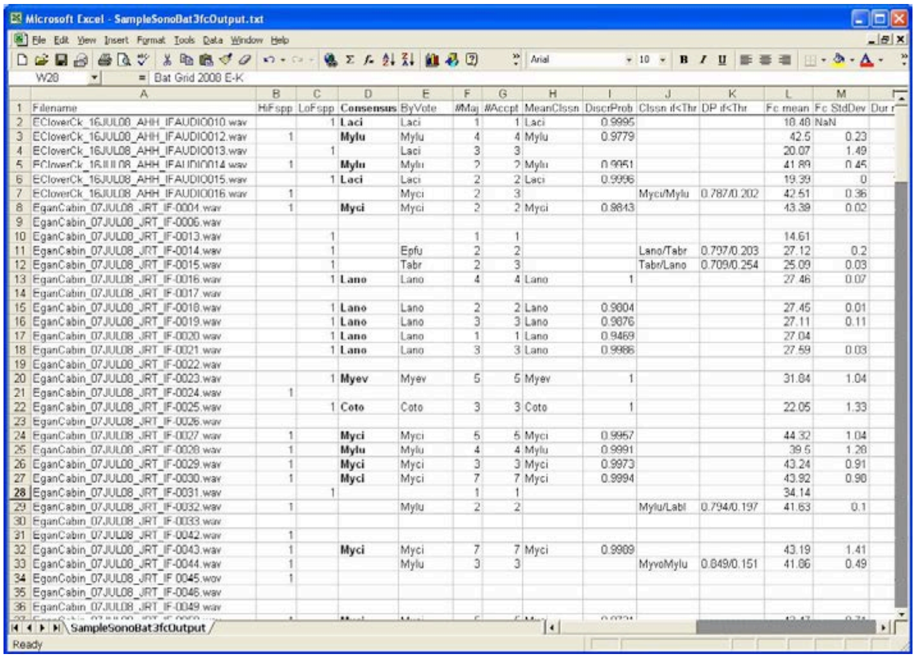


Figure 36. Spreadsheet output from a SonoBat batch process run of call sequence classification analysis. Columns B and C display the lowest level of bat recognition even if there was no species decision to enable tallying of bat passes. Additional columns to the right display individual call results and other data to support post processing analysis and vetting of results.

Recording hardware

The prototype recording units developed by this project supported the initial field studies for validation of long term acoustic monitoring methodology and directed the development of programmable recording units that were developed in collaboration with Binary Acoustic Technology (BAT). BAT will continue to provide them under the product designation FR125 (Figure 37). These programmable recording units store audio data on any USB memory device and, when implemented with a power connection or a self-powered (e.g., by photovoltaic panels) system, enable long duration recording for weeks or months, limited only by memory configuration. The FR125 also has capability to remotely relay data.

The Binary Acoustic Technology supports recording of ultrasound for bats using the matching AR125 ultrasonic microphone unit. The FR125 also supports audible frequency recording for birds and other signals, and accepts any standard line-in signal from a microphone.

We collaborated with Pettersson Elektronik to maintain compatibility with SonoBat software and requested features for the D500X automated detector (Figure 38). Pettersson Elektronik has produced bat detectors since 1983 and has established a reliable standard of acceptance for ultrasound recording. These units are weatherproof and can operate self-contained with built in microphones, power, and digital memory. They accept remote microphones to enable flexible deployment options.

The other domestic maker of recording equipment with whom we cooperated, Wildlife Acoustics, has begun supplying a similar programmable long duration recording hardware under the trade name Song Meter SM2 (Figure 39). These units provide an all-in-one recording solution with a built in controller panel and batteries (with capability for external power input for longer duration recording).

CrystalFontz USB controller for FR125.

Figure 37. Binary Acoustic Technology FR125-III field recorder. The FR125 has a line in audio jack for connecting to a microphone and has two high-speed USB 2.0 ports for connecting to external USB hard-drives, Compact Flash devices, or USB thumb-drives. This unit can also control and operate an AR125 ultrasonic receiver to record bat echolocation calls. When writing to solid state memory the FR125 consumes only 6.5 Watts of power. This unit separates the microphone from electronics for flexible deployment.

FR125-III Front and Rear Views

Figure 38. Pettersson D500X ultrasound recording unit intended for long-term, unattended recording of bat calls. The recorder is equipped with four slots for CF cards. The triggering system allows the device to start recording as a sound is detected. The recording length can be selected in steps from 0.3 up to 20 seconds. The recorder is normally operated in a low-power mode with no pre-trigger (i.e. the recording starts as the sound exceeds the chosen threshold level), but both pre-and post-trigger functions are available in the standard (not low-power) mode. This unit accepts an external microphone for flexible deployment.

Figure 39. Wildlife Acoustics Song Meter SM2 recorder. The SM2 can be programmed to record on simple time-of-day schedules or more complex monitoring protocols such as recording relative to local sunrise, sunset and twilight. This unit accepts an external microphone for flexible deployment.

Bat mobile transects

The SonoBat batch process output supports integration with gps track data from mobile transect surveys. The Myotisoft Transect software (Myotisoft, Morgantown, WV) combines the SonoBat batch processed automated species identification output with the transect's gps file (even from an iPhone, e.g., using MotionX-GPS) to generate tabulated location, time, and species data. Myotisoft Transect will also output a .kmz file for viewing the transect in Google Earth with SonoBat metadata popups for each classified bat along the transect (Figure 40).

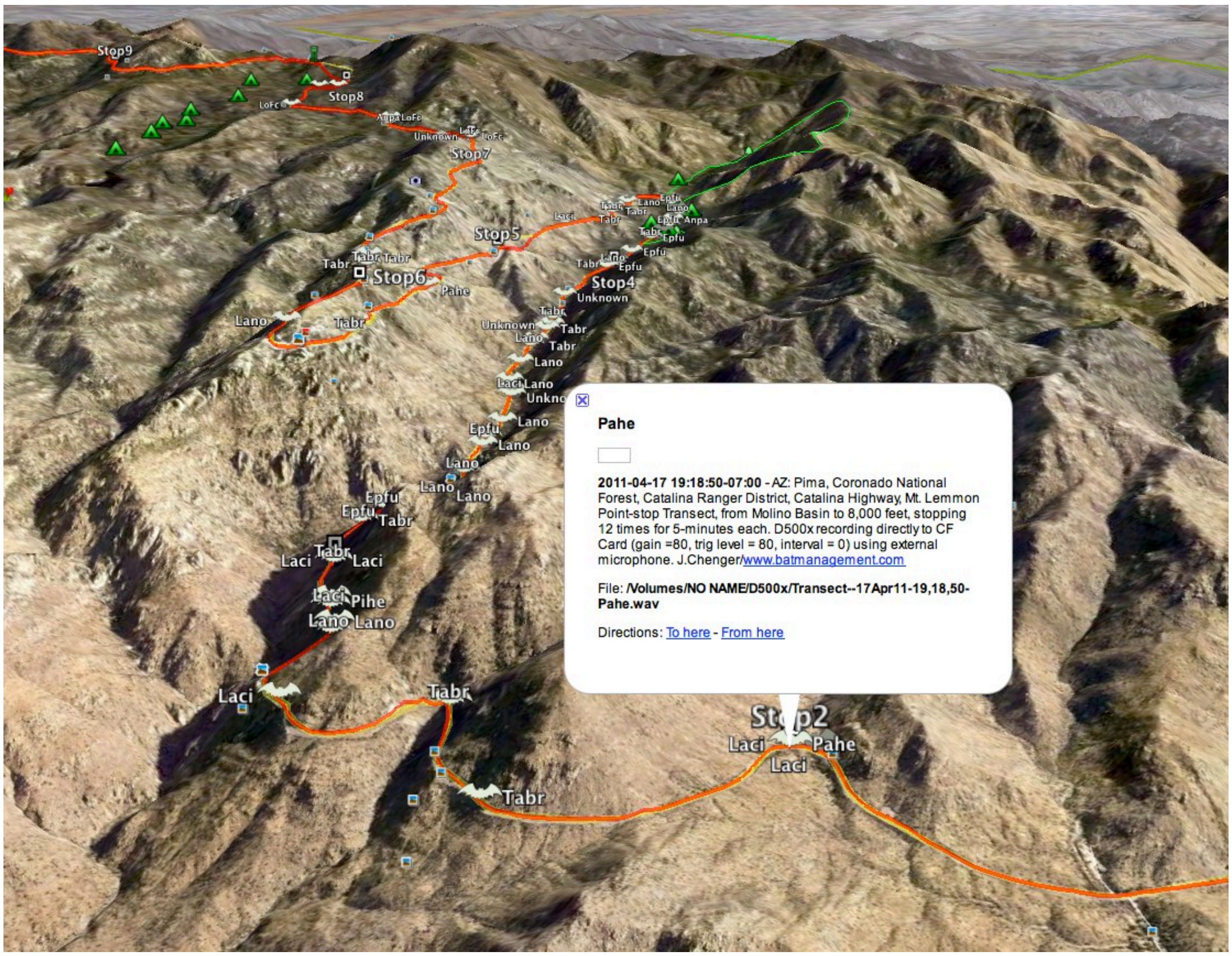


Figure 40. Screenshot of a mobile transect displayed in Google Earth showing the distribution of bats along the Catalina Highway, Coronado National Forest, AZ. Myotisoft Transect (Morgantown, WV) prepared this Google Earth .kmz file from a SonoBat batch processed automated species identification output file integrated with a gps track file of the transect.

Bird analysis software operation

SonoBird acoustic analysis software provides a tool to rapidly view, assess, and qualitatively or quantitatively analyze bird vocalizations. SonoBird presents visual displays of acoustic data as sonograms with color mapping of amplitude. An intuitive graphic interface provides full control of display characteristics such as frequency scale, time scale, and filtering. To facilitate recognition and identification of signals, SonoBird automatically reprocesses zoomed signal selections to optimize display resolution and then enables comparative side by side viewing of reference signals (Figure 41). A moving cursor tracks the position on the display when playing sounds for recognition and comparison by ear.

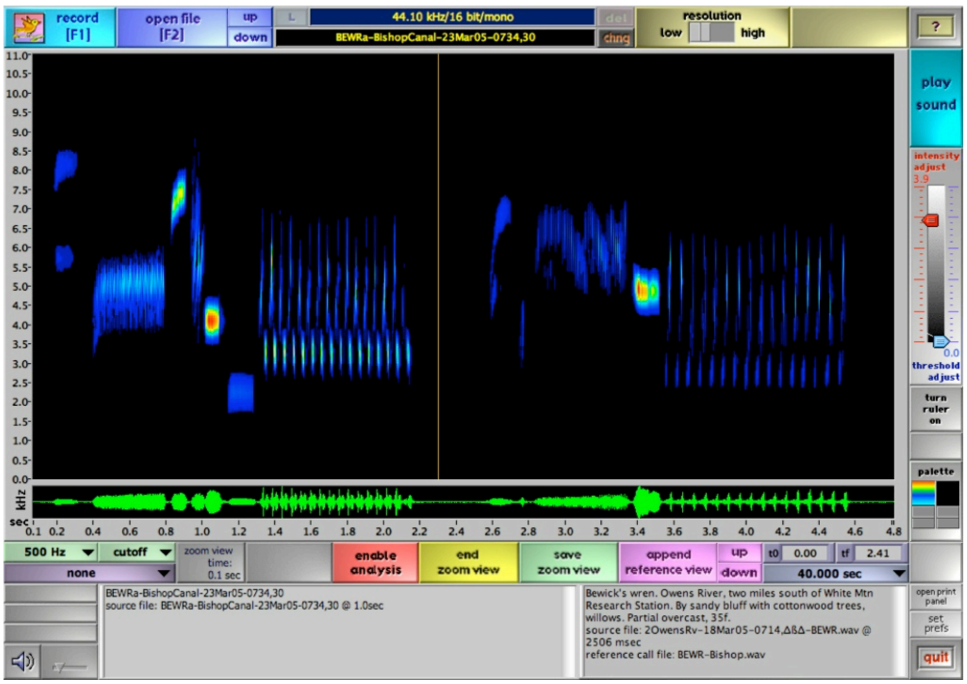


Figure 41. Zoomed song selection from a recorded file (left) displayed next to an appended reference file (right) invoked from a library of species-known recording samples. SonoBird automatically normalizes the amplitude and adjusts the time and frequency scales to enable an equal comparison.

The batch processing and signal searching capability of SonoBird provide automated processing of long duration recordings to seek and locate target signals of interest (Figure 42) from specified search terms and criteria (Figure 43). SonoBird extracts these and compiles them as separately saved hit file snippets or marked sections in the search file to then confirm by inspection, listening, or comparison with reference files. By default, SonoBird presents hit files sorted by correlation ranking with the search term. This sorts them for additional inspection by quality of match with the search term for inspection and facilitates presence/absence surveys by minimizing the potential data burden to inspect for confirmation. Alternately, hit files may be sorted by name, which because of the naming convention sorts them by chronological occurrence in the search file. This enables an evaluation of the time course of the vocalizations. SonoBird facilitates generating new search terms from any recording to seek any particular bird or signal of interest.

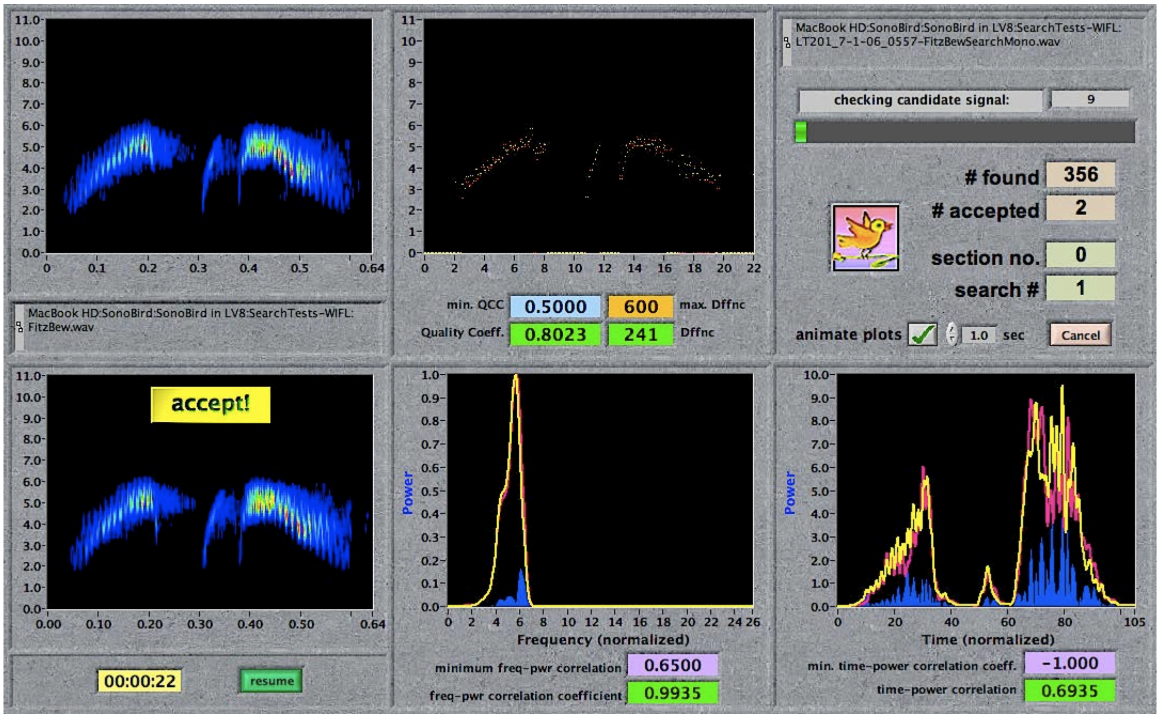


Figure 42. SonoBird search panel. SonoBird seeks signals similar to a known species search term (upper left sonogram) by first running a coarse search to select file segments having basic similarity, then performs a more discriminating comparison with the candidate signal (lower left sonogram) using user-defined criteria. SonoBird saves search criteria in the search term file to facilitate repeated searches.

In practice, depending upon search term and criteria, a moderately fast desktop computer can search one hour of recorded data in about one minute. The ability of the searches to correctly find specific signals varies according to signal characteristics, search sensitivity settings, competing and overlapping signals, and recording quality. Generally, search terms with more distinctive and consistent time-frequency characteristics perform better. Indistinctive signals such as single note owl calls that have substantial overlap with competing low frequency noise will generate many false hits. However prudent selection of time-power characteristics as primary search criteria can still reduce long term recordings down to a much smaller subset of target calls to manually inspect and accept or reject.

A one hour example recording from a Sierra meadow searched to find willow flycatchers and Lincoln’s sparrows found 76.1% of the signals recognized by a careful manual listening and visual inspection of sonograms through the recording (Tegeler-Amones et al. 2011). The search process missed signals having variation in pattern or when overwhelmed by competing signals. Additional new search terms could be used to find all types in such an example. Reducing the tolerance settings for acceptance can boost the acceptance of signals with competing noise, but generate more false hits to inspect. Presence/absence surveys require the recognition of only a single confident signal. If the target species is present and vocalizing, even with only a small percentage of signals recognized, the probability of signal recognition (detection) will be very high with long duration recording.

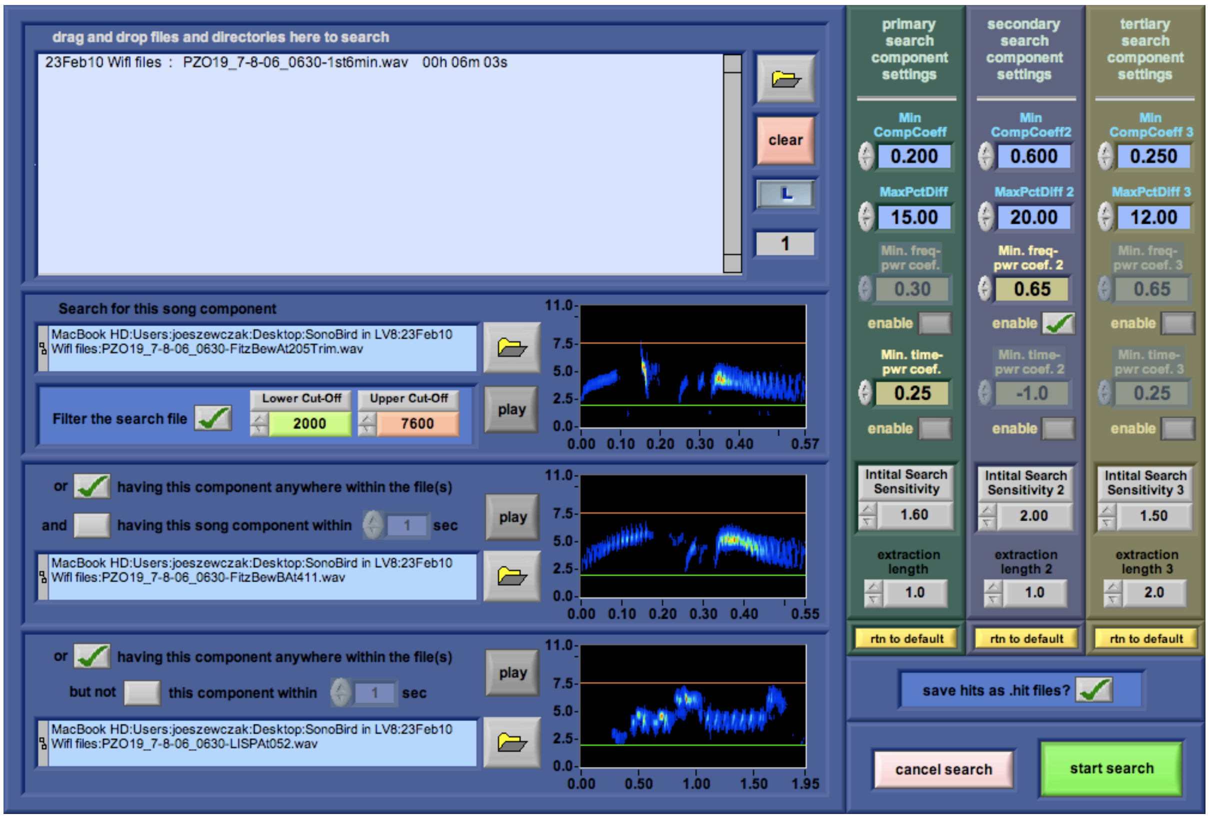


Figure 43. SonoBird search settings panel. Dropping individual files or directories of files onto the search file listing field (upper left) loads files for a batch run. Dropping search terms onto the path display fields (light blue) loads up to three search terms. The settings control search criteria to optimize for each signal type. SonoBird provides manual oversight of search progress to initially determine settings, and then saves the selected settings within the search term files for subsequent searches.

The SonoBird search algorithm has demonstrated excellent robustness to find search targets even with low amplitude signals that occur among noise (Figure 44).

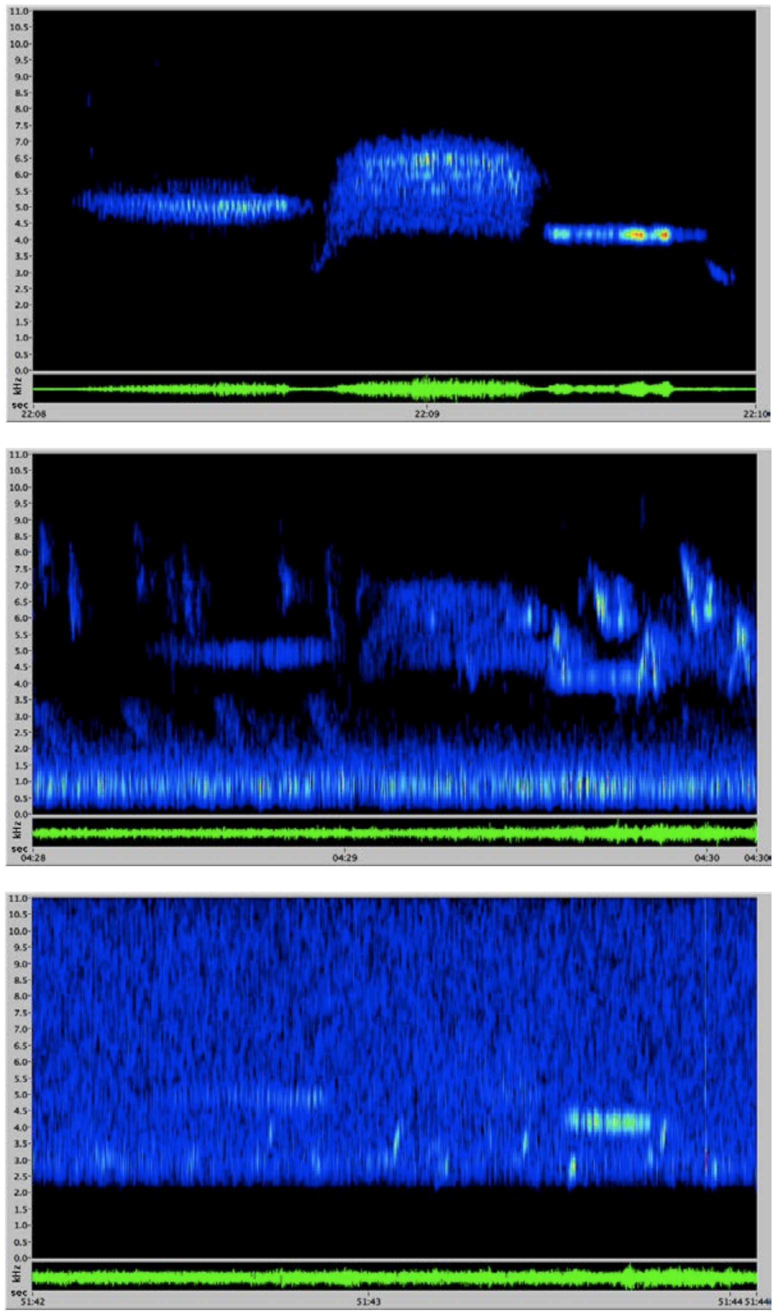


Figure 44. Examples of search results for federally listed golden-cheeked warbler (*Setophaga chrysoparia* formerly *Dendroica chrysoparia*) songs in a four hour recording made in central Texas. The search revealed 211 accepted hits (matching signals). The strong signal in the top panel displays an obvious and easily discernible match. However note that the search algorithm also found the matching golden-cheeked warbler calls amid noise from other birds (center panel) and at very low signal levels (bottom panel). Even with high pass filtering this last signal becomes barely discernible from background noise, yet the search algorithm still found it.

Conclusions and Implications for Future Research/Implementation

We compiled and analyzed a large and diverse collection of species-known high resolution full-spectrum reference recordings of bats from North America. This full-spectrum data format captured the full information content of the calls, optimizing the potential to reveal species discriminating characteristics and enabling analysis with sophisticated signal processing algorithms to recognize and extract quantitative parameters. We used a parameter extraction routine employing an intelligent and reliable call trending routine that minimized incorrect trends (and resulting misclassifications) such as can occur when echo clutter overwhelms the diminishing signal amplitude at the ending of many bat calls (e.g., Figures 22 and 23). This data extraction approach supported the development of a novel expert system classification approach that outperformed machine learning classification systems. Furthermore, we implemented multiple signal quality and decision confidence indicators to control and guide classification decisions to make the system perform optimally with unpredictably variable field-acquired recordings. We also demonstrated the extension of these approaches to avian vocalizations.

Even with the best data and analysis, the considerable plastic range in the calls from each species fills out a broad repertoire that unavoidably overlaps in characteristics with parts from the repertoire of one or more other species (e.g., Figures 26 and 27). This leaves the discrimination of some species a probabilistic rather than absolute process over much of their repertoire of call types. Definitive species recognition relies upon unique subsets of data space within each species' repertoire. However, some species such as the Indiana bat (*M. sodalis*) and the little brown bat (*M. lucifugus*) overlap completely in their repertoires and this prevents unambiguous discrimination (Figure 31). For such acoustically cryptic species, identification remains in the realm of calculating a statistical likelihood. However, initial field studies show promise for confident results (see Addendum, Appendix D). Continued expansion of the call reference collection to provide a greater sample pool and additional refinements in signal processing and classification should ultimately lead to increased throughput and higher confidence in results. These improvements should also lead to the need for less oversight and vetting of post-processed results. Eventually, field deployed detectors may perform analysis “in the box” and merely report results.

Continued expansion of reference collections of known bat species recordings will facilitate improving classifier species discrimination, particularly for acoustically ambiguous species, such as the Indiana bat and little brown bat. Finally, additional data sets of species-known recordings from the field distinct from those used to build the classifiers would provide demonstration and validation of the methodologies developed by this project.

Recording and classification implementation recommendations

Successful classification of the many bat species having overlapping acoustic characteristics depends upon discerning subtle nuances in their calls, and that depends upon clear, strong, and undistorted signals that rise above the background noise level. The reference data used to generate the SonoBat classifiers are based on recordings from electret condenser microphones and electrostatic condenser microphones (e.g., the types used in Pettersson, Binary Acoustic Technology, and Avisoft detectors) as these produce recordings having good contrast between the bat echolocation signals and background noise, both external and internal to the microphone (i.e., the microphone's noise floor). A sensitive microphone with a low noise floor will retain and enable discernment of lower amplitude call details from bats at greater distances from the microphone, and so provide a larger volume of airspace from which to acquire species-discriminating recordings that classify without error. SonoBat classification performance will decrease and the number of misclassifications will increase with degraded signals that cannot reveal low amplitude components of call structure. The comments that follow provide general guidance for interpreting call classification results, and recommendations for recording. Refer to the classification notes linked in Appendix A for more detailed region-specific guidance.

Both the orientation of a bat relative to a microphone (Surlykke and Kalko 2008) and its distance from a microphone will affect the strength of a recorded call. Because bats vary the amplitude through their calls, typically initiating a call at low amplitude, intensifying to a peak, then ending with diminishing amplitude, more weakly recorded calls become truncated to just their strongest portions (Figures 19 and 34). In some cases these fragments of fully formed calls can mimic other species, e.g., the body fragment of a little brown bat (*M. lucifugus*) may render as a simple curved call missing the final downward "toe" and so mimic the simple curve of a fully formed red bat (*Lasiurus borealis*). SonoBat performs a number of signal quality checks to reject weak and poorly formed calls, overloaded calls, and those with distorted signals or too much noise. However, any analysis remains limited to the available information and poor recordings with missing or obscured information content can produce spurious results. As a general recommendation, if a classification result seems unexpected, check it or reject it.

As the quality of call recordings strongly affects classification performance, achieving faithful and confident results begins with proper deployment of recording devices. Avoid recording with a detector's microphone placed directly on the ground. Simply elevating a microphone one or two meters above ground level can dramatically improve recording quality by reducing surface echoes, avoiding thermal layering, or near-ground air convection currents, all of which can distort ultrasound signals. In general, the longer duration calls that most species produce in open air flight, i.e., away from clutter, provide more information content and greater species-discrimination confidence. Bats flying in confined spaces or near roosts will generally provide shorter, less discriminating and perhaps ambiguous call variants. When bats must be identified in such situations, try to record them on approach to such a space or follow them out and away from a roost to acquire longer and more representative search phase calls.

To record search phase call sequences of bats along a flyway, place detectors *out* of the flyway as bats may investigate the novel object resulting in many recorded sequences of short "inspection calls." Where possible, place detectors to blend in with vegetative clutter (but clear from it) to listen out into a flyway. Avoid placing detectors near large echo-producing surfaces such as asphalt, building facades, bridge structural surfaces, or flat water. When you must record near such surfaces, attempt to position the detector to listen *away* from these surfaces rather than toward them. When possible, use a handheld detector to acoustically sample the potential detector placement site to reveal sources of ultrasonic noise before a recording session. Many things that seem quiet to our human ears can emit overwhelming ultrasonic noise, e.g., dried leaves or other vegetation rustling in a breeze, insects, loose cables and other windblown components, or metal structures cooling in the evening. *Detectors with microphones remote from the detector electronics provide the best options for placement and best results* (Figure 45).

Figure 45. Bat detector remote microphones enable placement up and away from ground clutter and other surfaces that can generate echoes that distort recordings. Elevating the microphone can also increase the vertical coverage, from the microphone to the ground, and from the microphone upward; rather than just from the ground upward.

Transition, continued development, and software maintenance

Initial development of SonoBat software and collection of reference recordings began in 1991 and full commercial distribution in 1998. Access and availability of SonoBat and SonoBird software will continue through commercial distribution of the software (www.sonobat.com). The income from commercial distribution will support ongoing maintenance, support, continued fieldwork and recording, and continued development and improvement of processing algorithms and classifiers. We have completed seventeen regional classifiers and have four in beta development that cover most of the United States (Tables 14 and 15). We have six more additional regional classifiers in development for which we have sufficient data to build and then test to determine performance and assess whether these classifiers will require additional data to complete (Tables 14 and 15). This project will also contribute samples of recording data to augment the collection of the Cornell Laboratory of Ornithology's Macaulay Library.

Table 14. Species matrix of eastern bat classifiers indicating build status (√ = complete). Proper selection of a regional classifier with the appropriate species known for an area will provide the best performance and minimize misclassifications[1]. Applying a classifier to a geographic region outside the range of a species may result in some misclassifications of the out of range species from the overlap of species' call characteristics over parts of their call repertoires and the probabilistic nature of classification (see text).

north east	**NY-PA-WV**	**north north east**	**KY-TN**	**Ozark –nGA**	**Missi-ssippi Basin**	**Great Lakes / MW**	**Great Lakes / nMW**	**Isle Royale / nnMI**	**IL-IN-OH lower MW**	**south east -AL**	**south east**
			Mygr	Mygr	Mygr				Mygr	Mygr	
Myle	Myle	Myle	Myle	Myle	Myle						
					Myau					Myau	Myau
Myse	Myse	Myse	Myse	Myse	Myse	Myse	Myse	Myse	Myse		
Myso	Myso		Myso	Myso	Myso	Myso			Myso		
Mylu	Mylu	Mylu	Mylu	Mylu	Mylu	Mylu	Mylu	Mylu	Mylu		
Pesu	Pesu	Pesu	Pesu	Pesu	Pesu	Pesu	Pesu	Pesu	Pesu	Pesu	Pesu
Nyhu			Nyhu	Nyhu	Nyhu	Nyhu	Nyhu		Nyhu	Nyhu	Nyhu
Labo	Labo	Labo	Labo	Labo	Labo	Labo	Labo	Labo	Labo	Labo	Labo
				Lase						Lase	Lase
Epfu	Epfu	Epfu	Epfu	Epfu	Epfu	Epfu	Epfu	Epfu	Epfu	Epfu	Epfu
Lano	Lano	Lano	Lano	Lano	Lano	Lano	Lano	Lano	Lano	Lano	Lano
										Lain	Lain
Cora	Cora	Cora	Cora	Cora	Cora					Cora	Cora
				Tabr						Tabr	Tabr
Laci	Laci	Laci	Laci	Laci	Laci	Laci	Laci	Laci	Laci	Laci	Laci
√	√	√	√	√	(√) beta	√	√	√	(√) beta	in prog-ress 2013	in prog-ress 2013

Key to species codes.

Myotis grisescens (Mygr)	*Lasiurus borealis* (Labo)
M. leibii (Myle)	*L. seminolus* (Lase)
M. austroriparius (Myau)	*L. intermedius* (Lain)
M. septentrionalis (Myse)	*Eptesicus fuscus* (Epfu)
M. sodalis (Myso)	*Lasionycteris noctivagans* (Lano)
M. lucifugus (Mylu)	*Corynorhinus rafinesquii / C. townsendii* (Cora / Coto)
Perimyotis subflavus (Pesu)	*Tadarida brasiliensis* (Tabr)
Nycticeius humeralis (Nyhu)	*L. cinereus* (Laci)

[1] Classifiers use a nominal nomenclature designating a core region of their coverage. Users should select the most appropriate classifier for their needs based on the known expected occurrence of species for their location. Because of the intraspecies and intra-individual variation in calls, interspecies overlap of call characteristics, and probabilistic nature of many classifications, in most cases acoustic data alone can not provide reliable evidence of bat species occurrence outside of known ranges.

Table 15. Species matrix of western bat classifiers indicating build status (√ = complete). Proper selection of a regional classifier with the appropriate species known for an area will provide the best performance and minimize misclassifications[1]. Applying a classifier to a geographic region outside the range of a species may result in some misclassifications of the out of range species from the overlap of species' call characteristics over parts of their call repertoires and the probabilistic nature of classification (see text). The US west and Great Basin classifiers cover most of the western states. The additional classifiers cover specific areas with different species assemblages.

	US west	**Great Basin OR east**	**OR west**	**WA east**	**WA west**	**WY east**	**WY west**	**NW montane**	**MT core**	**MT south**	**MT plains**
	Myyu	Myyu	Myyu	Myyu	Myyu	Myyu	Myyu	Myyu			
	Myca	Myca	Myca	Myca	Myca	Myca	Myca	Myca			
	Myci	Myci		Myci		Myci	Myci	Myci	Myci	Myci	Myci
	Myvo	Myvo	Myvo	Myvo	Myvo	Myvo	Myvo	Myvo	Myvo	Myvo	Myvo
	Mylu	Mylu	Mylu	Mylu	Mylu	Mylu	Mylu	Mylu	Mylu	Mylu	Mylu
											Myse
	Pahe	Pahe		Pahe							
	Labl	Labl	Labl			Labo		Labo			Labo
	Myev	Myev	Myev	Myev	Myev	Myev	Myev	Myev	Myev	Myev	Myev
	Anpa	Anpa	Anpa	Anpa		Anpa	Anpa			Anpa	
	Epfu	Epfu	Epfu	Epfu	Epfu	Epfu	Epfu	Epfu	Epfu	Epfu	Epfu
	Lano	Lano	Lano	Lano	Lano	Lano	Lano	Lano	Lano	Lano	Lano
	Myth	Myth	Myth	Myth	Myth	Myth	Myth	Myth	Myth	Myth	
	Tabr	Tabr	Tabr								
	Laci	Laci	Laci	Laci	Laci	Laci	Laci	Laci	Laci	Laci	Laci
	Coto	Coto	Coto	Coto	Coto	Coto	Coto	Coto	Coto	Coto	Coto
	Euma	Euma	Euma	Euma	Euma	Euma	Euma	Euma	Euma	Euma	Euma
	Eupe										
status	√	√	√	√	√	√	√	√	(√) beta	(√) beta	√

Key to species codes.

M. yumanensis (Myyu)	*L. xanthinus* (Laxa)
M. californicus (Myca)	*M. evotis* (Myev)
M. ciliolabrum (Myci)	*Antrozous pallidus* (Anpa)
M. volans (Myvo)	*Eptesicus fuscus* (Epfu)
M. lucifugus (Mylu)	*Lasionycteris noctivagans* (Lano)
M. occultus (Myoc)	*M. thysanodes* (Myth)
M. septentrionalis (Myse)	*Tadarida brasiliensis* (Tabr)
M. velifer (Myve)	*L. cinereus* (Laci)
M. auriculus (Myar)	*Corynorhinus townsendii* (Coto)
Parastrellus hesperus (Pahe)	*Euderma maculatum* (Euma)
Choeronycteris mexicana (Chme)	*Idionycteris phyllotis* (Idph)
Macrotus californicus (Maca)	*Nyctinomops femorosaccus* (Nyfe)
Leptonycteris yerbabuenae (Leye)	*N. macrotis* (Nyma)
Lasiurus blossevillii (Labl) / *L. borealis* (Labo)	*Eumops perotis* (Eupe)

Table 15 (continued). Species matrix of southwestern bat classifiers indicating build status (√ = complete).

	CA south	AZ north	AZ southwest	AZ southeast
	Myyu	Myyu	Myyu	Myyu
	Myca	Myca	Myca	Myca
	Myci	Myci		Myci
		Mylu		Myvo
			Myoc	Myoc
	Myve		Myve	Myve
				Myar
				Chme
	Maca		Maca	Maca
			Leye	Leye
	Pahe	Pahe	Pahe	Pahe
	Labl	Labl	Labl	Labl
	Laxa		Laxa	Laxa
	Myev	Myev		
	Anpa	Anpa	Anpa	Anpa
	Epfu	Epfu	Epfu	Epfu
	Lano	Lano		Lano
	Myth	Myth		Myth
	Tabr	Tabr	Tabr	Tabr
	Laci	Laci	Laci	Laci
	Coto	Coto	Coto	Coto
	Nyma	Nyma	Nyma	Nyma
				Idph
	Nyfe		Nyfe	Nyfe
	Euma	Euma	Euma	Euma
	Eupe	Eupe	Eupe	Eupe
status	In progress 2013	In progress 2013	In progress 2013	In progress 2013

[1] Classifiers use a nominal nomenclature designating a core region of their coverage. Users should select the most appropriate classifier for their needs based on the known expected occurrence of species for their location. Because of the intraspecies and intra-individual variation in calls, interspecies overlap of call characteristics, and probabilistic nature of many classifications, in most cases acoustic data alone can not provide reliable evidence of bat species occurrence outside of known ranges.

Literature Cited

Arnett, E.B., K. Brown, W.P. Erickson, J. Fiedler, T.H. Henry, G.D. Johnson, J. Kerns, R.R. Kolford, C.P. Nicholson, T. O'Connell, M. Piorkowski, and R. Tankersley, Jr. 2008. Patterns of fatality of bats at wind energy facilities in North America. Journal of Wildlife Management 72: 61–78.

Barclay, R.M.R. 1999. Bats are not birds—a cautionary note on using echolocation calls to identify bats: A comment. Journal of Mammalogy. 80 (1): 290-296.

Betts, B.J. 1998. Effects of interindividual variation in echolocation calls on identification of big brown and silver-haired bats. Journal of Wildlife Management. 62(3): 1003-1010.

Campbell, G.S., R.C. Gisiner, D.A. Helweg, and L.L. Milette 2002. Acoustic identification of female Steller sea lions (*Eumetopias jubatus*) Journal of the Acoustical Society of America 111(6): 2920-2928.

Deecke, V.B., J.K.B. Ford, and P. Spong. 1999. Quantifying complex patterns of bioacoustic variation: Use of a neural network to compare killer whale (*Orcinus orca*) dialects. Journal of the Acoustical Society of America, 105: 2499-2507.

Faure, P.A., J.H. Fullard, and J.W. Dawson. 1993. The gleaning attacks of the northern long-eared bat, *Myotis septentrionalis*, are relatively inaudible to moths. Journal of Experimental Biology 178: 173–189.

Fenton, M.B. and G.P. Bell. 1981. Recognition of species of insectivorous bats by their echolocation calls. Journal of Mammalogy 62: 233–243.

Fenton, M.B. 1970. A technique for monitoring bat activity with results obtained from different environments in southern Ontario. Canadian Journal of Zoology, 48: 847-851.

Fullard, J., and J. Dawson. 1997. The echolocation calls of the spotted bat *Euderma maculatum* are relatively inaudible to moths. Journal of Experimental Biology 200: 129–137.

Gannon, W.L., R.E. Sherwin, and S. Haymond. 2003. On the importance of articulating assumptions when conducting acoustic studies of habitat use by bats. Wildlife Society Bulletin 31: 45–61.

Green, R.H., and R.C. Young. 1993. Sampling to detect rare species. Ecological Applications 3: 351-356.

Griffin, D.R. 1958. Listening in the dark. Yale University Press, New Haven, Connecticut, USA.

Griffin, D.R. 1971. The importance of atmospheric attenuation for the echolocation of bats (Chiroptera). Animal Behaviour, 19:55-61.

Hayes, J.P. 1997. Temporal variation in activity of bats and the design of echolocation monitoring studies. Journal of Mammalogy 78: 514–524.

Hayes, J.P. 2000. Assumptions and practical considerations in the design and interpretation of echolocation-monitoring studies. Acta Chiropterologica 2: 225–236.

Hobson, K.A., R.S. Rempel, H. Greenwood, B. Turnbull, and S.L. Van Wilgenburg, 2002. Acoustic surveys of birds using electronic recordings: New potential from an omnidirectional microphone system. Wildlife Society Bulletin, 30 (3): 709-720.

Holderied, M.W., C. Korine, M.B. Fenton, S. Parsons, S. Robson, and G. Jones. 2005. Echolocation call intensity in the aerial hawking bat *Eptesicus bottae* (Vespertilionidae) studied using stereo videogrammetry. Journal of Experimental Biology 208:1321–1327.

Hovorka, M.D., C.S. Marks, and E. Muller 1996. An improved chemiluminescent tag for bats. Wildlife Society Bulletin, 24:709–712.

Johnson, G.D., M.K. Perlik, W.P. Erickson, and M.D. Strickland. 2004. Bat activity, composition, and collision mortality at a large wind plant in Minnesota. Wildlife Society Bulletin 32:1278–1288.

Krusic, R.A., and C.D. Neefus 1996. Habitat associations of bat species in the White Mountain National Forest, *in* Bats and forests symposium: 185–198. R.M.R. Barclay and R.M. Brigham, (Eds). Victoria, British Columbia: British Columbia Ministry of Forests.

Lacki, M.J., S. Amelon, and M.D. Baker. 2007. Foraging ecology of bats in forests. Pages 83–127, *in* Bats in forests: conservation and management. M.J. Lacki, J.P. Hayes, and A. Kurta, editors. Johns Hopkins University Press, Baltimore, Maryland, USA.

Lance, R.F., B. Bollich, C.L. Callahan, and P.L. Leberg 1996. Surveying forests-bat communities with Anabat detectors, *in* Bats and forests symposium: 175–184. R.M.R. Barclay and R.M. Brigham, (Eds). Victoria, British Columbia: British Columbia Ministry of Forests.

MacDonald, K., and E. Matsui, R. Stevens, and M.B. Fenton, M.B. 1994. Echolocation calls and field identification of the eastern pipistrelle (*Pipistrellus subflavus*: Chiroptera: Vespertilionidae), using ultrasonic bat detectors. Journal of Mammalogy, 75: 462–465.

Moreno, C.E., and G. Halffter. 2001. On the measure of sampling effort used in species accumulation curves. Journal of Applied Ecology 38:487– 490.

O'Farrell, M.J., B.W. Miller, and W.L. Gannon 1999. Qualitative identification of free-flying bats using the Anabat detector. Journal of Mammalogy 80:11-23.

Obrist, M.K. 1995. Flexible bat echolocation: the influence of individual habitat and conspecifics on sonar signal design. Behavioral and Ecological Sociobiology 36:207–219.

Oliveira, M.C. 1998. Towards standardized descriptions of the echolocation calls of microchiropteran bats: pulse design terminology for seventeen species from Queensland. Australian Zoologist, 30:405–411.

Oswald, J.N., J. Barlow, and T.F. Norris 2003. Acoustic identification of nine delphinid species in the eastern tropical Pacific Ocean. Marine Mammal Science 19(1): 20-37.

Parsons, S. 2000. Identification of New Zealand bats (*Chalinolobus tuberculatus* and *Mystacina tuberculata*) in flight from analysis of echolocation calls by artificial neural networks. Journal of Zoology (London), 253: 447–456.

Parsons, S. 2004. Signal Analysis Techniques to Aid in Bat Species Identification, *in* Bat echolocation research: tools, techniques and analysis. Brigham, R. Mark; Kalko, Elisabeth K.V.; Jones, Gareth; Parsons, Stuart; Limpens, Herman J.G.A. [Eds]. Bat Conservation International, Austin, TX.

Parsons, S., and G. Jones 2000. Acoustic identification of twelve species of echolocating bat by discriminant function analysis and artificial neural networks. Journal of Experimental Biology, 203: 2641–2656.

Parsons, S., and J.M. Szewczak 2009. Detecting, Recording, and Analyzing the Vocalizations of Bats, in Ecological and Behavioral Methods for the Study of Bats, 2nd Edition, T.H. Kunz, ed. Johns Hopkins University Press (920 pp).

Placer, J. and C.N. Slobodchikoff 2000. A fuzzy-neural system for identification of species-specific alarm calls of Gunnison's prairie dogs. Behavioural Processes 52(1): 1-9.

Preatoni, D.G., M. Nodri, R. Chirichella, G. Tossa, L.A. Wauters, and A. Martinoli. 2005. Identifying bats from time-expanded recordings of search calls: comparing classification methods. Journal of Wildlife Management 69:1601–1614.

Queheillalt, D.M., J.W. Cain III, D.E. Taylor, M.L. Morrison, S.L. Hoover, N. Tuatoo-Bartley, L. Rugge, K. Christopherson, M.D. Hulst, M.R. Harris, and H.L. Keough. 2002. The exclusion of rare species from community-level analyses. Wildlife Society Bulletin 30:756-759.

Redgwell, R.D., J.M. Szewczak, G. Jones, and S. Parsons. 2009. Classification of echolocation calls from 14 species of bat by support vector machines and ensembles of neural networks. Algorithms 2:907-924.

Surlykke, A., & Kalko, E.K. 2008. Echolocating bats cry out loud to detect their prey. *PLoS one*, *3*(4), e2036.

Szewczak, J.M. 2000a. A tethered zip-line arrangement for reliably collecting bat echolocation reference calls. Bat Research News. 41:142.

Szewczak, J.M. 2000b. A consistent acoustic feature to discriminate *Myotis* species. Bat Research News. 41:141.

Szewczak, J.M. 2004. Advanced analysis techniques for identifying bat species, *in* Bat echolocation research: tools, techniques and analysis. Brigham, R. Mark; Kalko, Elisabeth K.V.; Jones, Gareth; Parsons, Stuart; Limpens, Herman J.G.A. [Eds]. Bat Conservation International, Austin, TX. 121-22.

Szewczak, J.M., and E.B. Arnett 2007. Acoustic Monitoring of Bats, *in* Methods and Metrics for Studying Impacts of Wind Energy Development on Nocturnal Species (Birds and Bats), T.H. Kunz, ed. National Wind Coordinating Committee (NWCC). Journal of Wildlife Management 71(8):2449–2486.

Tegeler-Amones, A.K., M.L. Morrison, J.M. Szewczak, and C. Stermer 2010. Assessing point count sampling in montane Meadows. California Fish and Game 96(3): 201-212.

Thomas, W. T., G.P. Bell, and M.B. Fenton 1987. Variation in echolocation call frequencies recorded from North American Vespertilionid bats: a cautionary note. Journal of Mammalogy, 68:842–847.

Thomas, D.W., and S.D. West. 1989. Sampling methods for bats. U.S. Department of Agriculture Forest Service, General Technical Report PNW-GRR-243, Pacific Northwest Research Station, Portland, Oregon, USA. http://treesearch.fs.fed.s/pubs/9090. Accessed 10 Feb 2007.

Appendix A. Supporting Data

Table of eastern US bat echolocation call characteristics:

http://www.sonobat.com/download/EasternUS_Acoustic_Table_Mar2011.pdf

Table of western US bat echolocation call characteristics:

http://www.sonobat.com/download/WesternUS_Acoustic_Table_Mar2011.pdf

Eastern US Classification notes:

http://www.sonobat.com /download/SonoBat_Classification_Note-NE-v304.pdf

http://www.sonobat.com/download/MysoMyluClassificationNote-NE-v3.1.pdf

Western US Classification notes:

http://www.sonobat.com /download/SonoBat_Classification_Note-NW-v304.pdf

Appendix B. List of Scientific/Technical Publications

Articles in peer-reviewed journals

Rognan, C.B., Szewczak, J.M., & Morrison, M.L. 2012. Autonomous Recording of Great Gray Owls in the Sierra Nevada. *Northwestern Naturalist*, 93(2): 138-144.

Rodhouse, T.J., P.C. Ormsbee, K.M. Irvine, L.A., J.M. Szewczak, and K.T. Vierling 2012. Assessing the status and trend of bat populations across broad geographic regions with dynamic distribution models. *Ecological Applications*, 22(4): 1098–1113.

Tegeler-Amones, A.K., M.L. Morrison, and J.M. Szewczak 2011. Using long-term audio recordings to survey avian species. *Wildlife Society Bulletin*, 36: 21–29.

Tegeler-Amones, A.K., M.L. Morrison, J.M. Szewczak, and C. Stermer 2010. Assessing point count sampling in montane Meadows. *California Fish and Game* 96(3): 201-212.

Redgwell, R.D., J.M. Szewczak, G. Jones, and S. Parsons. 2009. Classification of echolocation calls from 14 species of bat by support vector machines and ensembles of neural networks. *Algorithms* 2: 907-924.

Rognan, C.B., J.M. Szewczak, and M.L. Morrison 2009. Vocal individuality of great gray owls in the Sierra Nevada. *Journal of Wildlife Management*. 73(5): 755–760.

Szewczak, J.M., and E.B. Arnett 2007. Acoustic Monitoring of Bats, *in* Methods and Metrics for Studying Impacts of Wind Energy Development on Nocturnal Species (Birds and Bats), T.H. Kunz, ed. National Wind Coordinating Committee (NWCC). *Journal of Wildlife Management* 71(8): 2449–2486.

Technical reports

Szewczak, J.M. 2011. A call in the night. *United States Fish and Wildlife Service Endangered Species Bulletin*. 3:42-43.

Conference or symposium proceedings scientifically recognized and referenced

Szewczak, J.M. 2004. Advanced analysis techniques for identifying bat species, *in* Bat echolocation research: tools, techniques and analysis. Brigham, R. Mark; Kalko, Elisabeth K.V.; Jones, Gareth; Parsons, Stuart; Limpens, Herman J.G.A. [Eds]. Bat Conservation International, Austin, TX. 121-22.

Conference or symposium abstracts

Rodhouse, T.J., P.C. Ormsbee, K.M. Irvine, L.A. Vierling, J.M. Szewczak, and K.T. Vierling 2012. Annual turnover in bat occupancy patterns: predictions from life history theory and implications for conservation and monitoring. Ecological Society of America, Portland, OR, August 5–12, 2012.

Szewczak, J.M. 2012. Overlapping call characteristics of Myotis. Northeast Bat Working Group, Carlisle, PA, January 11–13, 2012.

Szewczak, J.M. 2011. SonoBat automated bat classification. North American Symposium for Bat Research, Toronto, Ontario, October 25-29, 2011.

Kennedy, J.P., and J.M. Szewczak 2010. Bat activity across the vertical gradient of an old-growth redwood forest. North American Symposium for Bat Research, Denver, CO, October 27-30, 2010.

G. Reyes, and J.M. Szewczak 2010. The behavioral function of social calls in the migratory hoary bat *Lasiurus cinereus.* North American Symposium for Bat Research, Denver, CO, October 27-30, 2010.

J.M. Szewczak 2009. Automated survey and monitoring of bird and bat populations. Statewide Tri-Agency Biologist Training and Workshop and Road Ecology Meeting. Walnut Creek, CA, February 24-26, 2009

Szewczak, J.M. 2008. Automated Acoustic Monitoring of Bat and Bird Populations. Partners in Environmental Technology Symposium, Washington, D.C., December 2-4, 2008.

J.M. Szewczak 2008. Automated monitoring and assessment of bat and bird populations on military lands. The Western Section of The Wildlife Society Annual Conference, Redding, CA, February 6-8, 2008.

Tegeler-Amones, A., J.M. Szewczak, H. Mathewson, M.L. Morrison, and C. Stermer 2008. Assessing Monitoring Techniques for Bird Populations in Sierra Nevada Montane Meadows. The Western Section of The Wildlife Society Annual Conference, Redding, CA, February 6-8, 2008.

Szewczak, J.M. 2007. Automated Monitoring and Assessment of Bat and Bird Populations. Partners in Environmental Technology Symposium, Washington, D.C., December 3-5, 2007.

Corcoran, A.J., and J.M. Szewczak 2007. Automated Acoustic Identification of Nine Bat Species of the Eastern United States. XIV International Bat Research Conference, Merida, Mexico, August 19-20, 2007.

Szewczak, J.M. 2006. Developing an automated system for monitoring and assessing bat populations. Partners in Environmental Technology Symposium, Washington, D.C., November 28-30, 2006.

Corcoran, A J. and J.M. Szewczak 2006. Fully Automated Identification of Three Bat Species: *Lasiurus borealis*, *Nycticeius humeralis*, and *Pipistrellus subflavus* Using Full-Spectrum Acoustic Data. North American Symposium for Bat Research, Wilmington, NC, October 18-21, 2006.

Szewczak, J.M. 2005. Progress toward an automated system for monitoring and assessing bat populations. Partners in Environmental Technology Symposium, Washington, D.C., November 29-December 1, 2005.

Berry, R. D. and J.M. Szewczak 2005. A field recording technique to passively collect and time tag echolocation calls from free flying bats Western Bat Working Group Biennial Meeting, Portland, OR. March 30 – April 2, 2005.

Szewczak, J.M. 2005. Monitoring bats in a restored montane willow meadow. The Western Section of The Wildlife Society Annual Conference, Sacramento, CA, January 19-21, 2005.

Szewczak, J.M. 2004. Advances in the acoustic monitoring of bats. American Society of Mammalogists. Arcata, CA. June 16, 2004.

Szewczak, J.M. 2004. Bat Monitoring and Assessments. Partners in Environmental Technology Symposium, "Preserving our Critical Natural Resources." Washington, D.C., December 2, 2004.

Text books or book chapters

Parsons, S., and J.M. Szewczak 2009. Detecting, Recording, and Analyzing the Vocalizations of Bats, in Ecological and Behavioral Methods for the Study of Bats, 2nd Edition, T.H. Kunz, ed. Johns Hopkins University Press (920 pp).

Graduate dissertations

Corcoran, Aaron J. *Automated acoustic identification of nine bat species of the eastern United States*. Diss. Humboldt State University, 2007.

Amones, Amy Kay Tegeler. *Assessing monitoring techniques for bird populations in Sierra Nevada montane meadow and aspen communities*. Diss. Humboldt State University, 2008.

Kennedy, Jean-Paul. *Bat activity across the vertical gradient of an old-growth redwood forest*. Diss. Humboldt State University, 2011.

Rognan, Cameron B. *Bioacoustic techniques to monitor great gray owls (Strix nebulosa) in the Sierra Nevada*. Diss. Humboldt State University, 2007.

Loman, Zachary. *Response of a North American wood warbler, the golden-cheeked warbler (Dendroica chrysoparia) to anthropogenic noise*. Diss. Humboldt State University, 2010.

Scientific or technical awards or honors

2009 recipient of the United States Forest Service *Wings across the Americas* award for outstanding achievement in bat conservation.

2010 Certification of Appreciation from the United States Forest Service *Wings across the Americas* award for contributing to bat conservation.

United States
Department of Agriculture

Certificate of Appreciation

Awarded to

Joe Szewczak

Humboldt State University

Significant Contribution to the following program:
Bat Blitzes in the Southeastern United States:
A Partnership Program Between the US Forest Service
Southern Region and the Southeastern Bat Diversity Network

U.S. Forest Service Wings Across the Americas

Date March 2010

Thomas L. Tidwell

Tom Tidwell
Chief, U.S. Forest Service

Appendix C. Other Supporting Materials

Protocols/User Guides

Quick start guides to using SonoBat:

http://www.sonobat.com/download/SonoBatBasicOperations.ppt

http://www.sonobat.com/download/SonoBat_3.ppt

http://www.sonobat.com/download/SonoBatUtilities.pdf

http://www.sonobat.com/download/OpeningAndUsingSonoBatchFilesv313.ppt

http://www.sonobat.com/SonoBatch_Output_Descriptors.htm

http://www.sonobat.com/SonoBat parameters.html

http://www.sonobat.com/SonoBat_batch_workflow.pdf

User's Guide:

http://www.sonobat.com/download/SonoBat_userguide_Aug2008.pdf

Addendum to User's Guide:

http://www.sonobat.com/download/SonoBatEnhancementsSinceUsersGuide.pdf

Background information on full-spectrum analysis:

http://www.sonobat.com/download/FullSpect_and_Zero-Crossing.ppt

Recording and classification notes:

Eastern North America:

http://www.sonobat.com/download/SonoBatClassificationNote-NE-v3.1.pdf
http://www.sonobat.com/download/MysoMyluClassificationNote-NE-v3.1.pdf

Western North America:

http://www.sonobat.com/download/SonoBatClassificationNote-NW-v3.1.pdf

Tables of species' acoustic characteristics:

Eastern US bat echolocation call characteristics:

http://www.sonobat.com/download/EasternUS_Acoustic_Table_Mar2011.pdf

Western US bat echolocation call characteristics:

http://www.sonobat.com/download/WesternUS_Acoustic_Table_Mar2011.pdf

Arizona region bat echolocation call characteristics:

http://www.sonobat.com/download/AZ_Acoustic_Table-Mar08.pdf

Rocky Mountain region bat echolocation call characteristics:

http://www.sonobat.com/download/RockyMtn_Acoustic_Table-Mar08.pdf

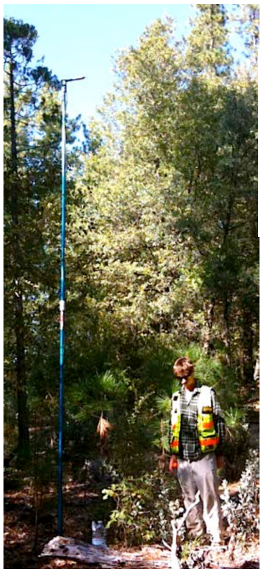
Guides to using SonoBird:

http://www.sonobird.com/download/SonoBirdBasicOperations-1.6.ppt

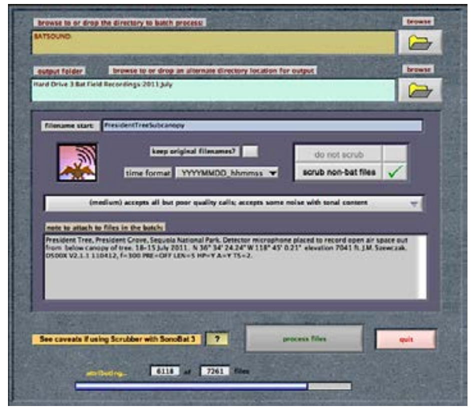
http://www.sonobird.com/download/SonoBirdSearches-v1.6.ppt

http://www.sonobird.com/download/SonoBirdSearches-v1.6-tutorial.ppt

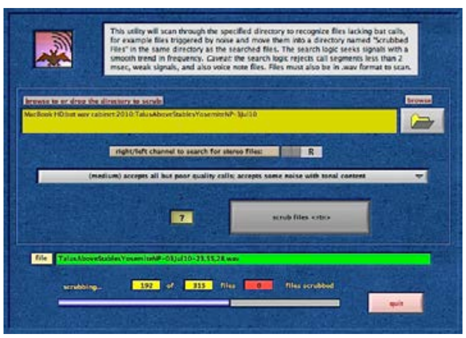
Bat echolocation call recording and analysis workflow:



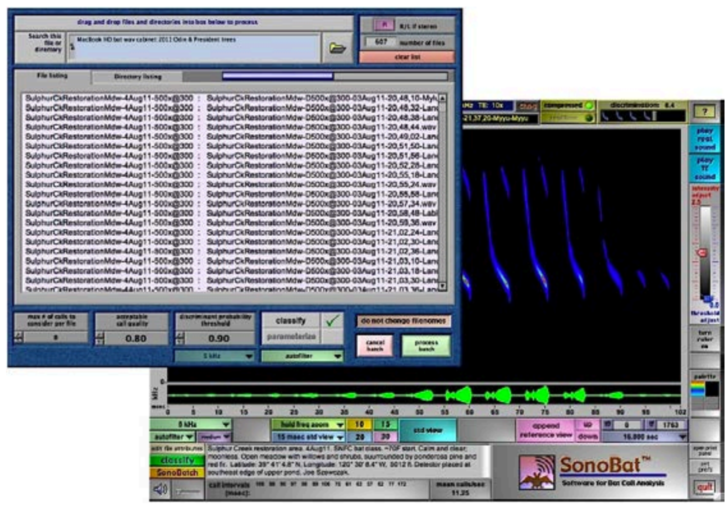
Record bats in the field.



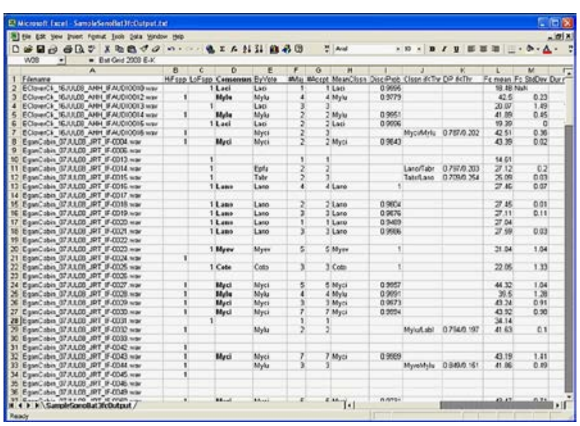
Transfer field data to store and process using a hardware-specific SonoBat Attributer utility to name files and embed metadata for data management.



As an option during attributing, or as a separate operation with the SonoBat Scrubber utility, remove non-bat noise-triggered files.



Set up a batch processing job to analyze and classify recorded sequences to species and execute.



Inspect output, sort, and manually confirm results as needed for acoustically ambiguous species following recommendations in Echolocation Call Characteristics Tables and Classification Notes.

Appendix D. Addendum

Preliminary field test of discriminating Indiana bats (*M. sodalis*)

Abstract from presentation at the Northeast Bat Working Group meeting, Albany, NY January 10, 2013:

A FIELD TEST OF TWO ACOUSTIC CLASSIFICATION SYSTEMS TO DISCRIMINATE INDIANA BATS (*MYOTIS SODALIS*)

Joseph M. Szewczak[1] and Leila S. Harris[2], [1]*Humboldt State University, Arcata, CA 95521*, [2]*ICF International, Sacramento, CA 95814*

(Oral presentation)

With the proposed US Fish and Wildlife Service Indiana bat summer protocol, interest and concern has grown regarding the effectiveness of different hardware and software systems for acoustic recognition for this species. As management decisions depend upon the assessed presence of Indiana bats, determining the rates of false positives from various systems becomes imperative. Field recordings of free-flying bats made outside the expected range of Indiana bats, but in the presence of acoustically similar species as Indiana bats, e.g., little brown bats (*M. lucifugus*), can provide a direct means for testing and comparing the rates of Indiana bat false positives. We had the opportunity to perform a preliminary test of this approach on three overnight recording sets from a site near a known little brown bat roost in southern Maine approximately 100 miles beyond the reported range of Indiana bats. We analyzed full-spectrum data acquired from Pettersson D500X detectors using SonoBat 3.1 NE and converted the recordings to Anabat format using Myotisoft ZCANT for analysis using EchoClass 1.1. The three recording sets yielded 112, 177, and 73 high frequency bat passes. Despite an expectation of no Indiana bats at these sites, EchoClass reported twice as many Indiana than little brown bats at site one, 10 times as many at site two, and 1.7 times as many at site three, and concluded >= 99% probability of presence for Indiana bats at all sites. In contrast, SonoBat reported 4% Indiana to 88% little brown bats at site one, and only little brown bats and no Indiana bats at sites two and three. As the 4% Indiana bat result lies within the expected 8–10% Indiana to little brown bat error rate by SonoBat, the SonoBat results would indicate that Indiana bats do not likely occur at these sites.