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Remote Sensing of Animals

BIOACOUSTICAL MONITORING IN TERRESTRIAL ENVIRONMENTS

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Introduction

Many animal taxa—birds, frogs, and some mammals—conspicuously advertise their presence, identity, and behavioral status through vocalizations. In many environments, these species are more readily heard than seen. Accordingly, many bird and frog surveys obtain most of their data by listening rather than looking. Dramatic improvements in audio recorder technology have created compelling opportunities to make long duration environmental recordings with compact packages. This technology extends the spatial scope and temporal extent of acoustical monitoring and provides archival records of ecological conditions. Birdsong research experienced dramatic growth as recording and spectrogram analysis technology became practical.[1] Based on a sample of recent publications, environmental science may be on the cusp of similar growth in autonomous acoustical monitoring.[2-6]

"Autonomous acoustical monitoring is an emerging tool for terrestrial studies of ecology and animal behavior, and compelling results will be forthcoming as systems improve and researchers become familiar with their features and idiosyncrasies."

Strengths of acoustic sensors include long range, high fidelity, and passive operation. Compared with visual technologies like camera traps or video monitoring systems, audio systems offer omnidirectional coverage that is not immediately limited by the presence of obstructions or vegetation. Performance is not limited by available light. Audio data are more compact than video, and are comparatively easy to process automatically. There are numerous software packages that support detection and classification of animal signals. As the discussion of equipment will show, autonomous recording systems can be compact, presenting an unobtrusive visual footprint and negligible noise. Removal of the human from the system helps minimize disturbance to wildlife and other artifacts of direct observation.

Acoustical monitoring confronts several challenges. Increasing susceptibility to attenuation with frequency, the potential for refraction to limit detection range, and the distorting effects of scattering and multipath propagation—systems must be designed and placed to record signals of adequate strength and fidelity for analysis. While many animals have distinctive signatures, all biological signals are variable and waveform matched filtering will rarely be a successful approach. Classification methods must be able to distinguish within and between class variations. An additional complication is sorting out overlapping voices in dense choruses. Many species will produce most of their calls in this context—dawn choruses of birds, nocturnal choruses of insects and frogs.

Effective and efficient implementation of an acoustical monitoring project requires careful selection of equipment and software, a process that is best informed by a sampling plan that addresses explicit measurement objectives. Acoustical monitoring has been successfully utilized to measure habitat occupancy, local density, breeding phenology and success, activity schedules, habitat use and patterns of movement, and aggregate acoustical indicators of habitat characteristics. The kind of data collected, and the equipment best suited to collect it, will depend upon the objective. Nonetheless, some engineering considerations will likely be common to all applications. This paper reviews some of these issues, and illustrates the potential scale of terrestrial acoustical monitoring using examples from the authors' experience.

The typical acoustical monitoring system is made up of multiple components: microphone(s), windscreen, digital recorder, data storage, equipment housing and support hardware, and a power source. Although each component in an acoustical monitoring system may have particular features that must be considered, three factors should be evaluated for all system components: cost, size, and power consumption. Cost will usually limit the number of systems, and in many sampling plans a large number of systems will be needed to obtain adequate spatial coverage. Often the systems will have to be placed at locations far from a road. A compact, lightweight system is needed when deployment scenarios call for multiple systems to be placed during a single hike. Power consumption is often a primary determinant for cost, size and weight, because system batteries and possibly a renewable energy supply are usually the most bulky components and can be the most costly.

Microphones

The noise floor of these devices is critical for passive remote sensing. The noise floor limits the effective listening area of a system. As long as the instrument noise floor is higher than the background ambient sound level, every 3 dB reduction in noise floor doubles the signal capture area—assuming spherical spreading is the dominant source of attenuation. Dynamic range may be important because it will determine how close and loud an animal can be before the recording is distorted. Distorted recordings are undesirable, but loud, distorted sounds may still be identifiable.

As in many other data collection systems, autonomous recordings are only as good as the sensors they use to transduce environmental quantities into electrical signals. The noise floor of an acoustical monitoring system will likely be determined by the microphone. Table 1 compares a representative selection of commercially available electret microphones, all costing less than $20. These sensors have noise floors that are 14-37 dB above the 1 kHz hearing threshold of a healthy human listener. Therefore, many autonomous recorders cannot detect sounds as effectively as an experienced naturalist. In some studies, it might be desirable for autonomous recorders to exceed human hearing performance. Some terrestrial vertebrates have hearing thresholds that are up to 20 dB lower than human thresholds.[7-9] To understand their behavior, especially in relation to the masking effects of noise,[10] instruments are needed that can outperform their hearing. In addition to noise floor, selection and deployment of microphones should consider sensitivity, frequency response, directivity, and robustness.

Microphone power consumption merits brief consideration. For a 30 day continuous deployment, these microphones would require between 12 and 432 mAh of battery capacity, which is likely to be a negligible fraction of the overall system power budget. However, if an independent power source is provided for the microphones, which may improve the overall system noise floor, then current drain may be a factor. The microphone with the highest consumption could be powered by a single alkaline 9 volt battery, while the microphone with the lowest consumption could be powered by a small coin battery.

One tactic to improve system performance is to physically amplify incoming sound before it reaches the microphone element.[11] Parabolic reflectors are widely used to make focused recordings of vocal animals, but these devices realize their gain inside a very small solid angle, so they do not substantially expand the spatial coverage of a microphone. For a conical or exponential horn, gain is realized by the concentration of energy as sounds are confined by the progressively smaller cross sectional area of the horn. Consider a horn of length L, mouth area S_m and throat area S_t. At high frequencies, the gain relative to a free field microphone is approximated by $10\log_{10}(S_m/S_t)$. For a given mouth size, a smaller microphone element will realize greater horn gain. This approximate formula for the gain of a horn applies above the specified cutoff frequency, which is determined by the flare rate of the horn. $F_c = ca/(4\pi)$,where c is the speed of sound in meters per second and a is the flare rate, equal to $\ln(S_m/S_t)/L$. This formula is easily inverted to calculate the flare rate needed to insure a desired cutoff frequency. Note that this simplified analysis neglects the constructive and destructive interference that occurs within the horn and other effects that arise when the incoming wavefronts are not parallel to the mouth of the horn. These factors complicate the frequency response function and present challenges for calibration of measured sound pressure levels.

What limits the size of the mouth area? The larger the mouth becomes, the more directional the sensor becomes. To a first approximation, the directivity of the horn microphone

Table 1. Representative specifications for Original Equipment Manufacturer (OEM) electret capsules

Electret microphone capsule	Current drain in mA	Sensitivity in dB re 1V/Pa	Noise floor in dB re 20 uPa @ 1 kHz	Diameter in mm	20 mm horn noise floor in dB
Analog Devices ADMP504	0.2	-38	29	0.25	-9.1
Sonion 6290	0.017	-34	24	0.56	-7.1
Sonion 1PO24	0.035	-30	21	1.4	-2.1
AAC SDM0401BL-383	0.2	-38	32	0.5	0.0
Knowles EK23133	0.05	-53	26	1.6	4.1
Knowles SPY0824R5H-QB	0.12	-38	32	0.95	5.5
Wolfson WM7120A	0.14	-42	37	0.55	5.8
Knowles SPM0406HE3H-SB	0.5	-22	35	0.838	7.4
Infineon SMM310	0.08	-42	35	0.84	7.5
Primo EM-172	0.6	-37	14	10	8.0
Primo EM-158	0.5	-31	19	5.8	8.2
Knowles SPM0408LE5H-TB	0.35	-18	35	1.016	9.1
Panasonic WM61-A	0.5	-35	32	6	21.5
Roland R05 internal microphones	NA	NA	35	NA	NA

system will be similar to a solid disk of the same size mounted in a baffle. For frequencies such that the transducer diameter corresponds to multiple wavelengths, the horn microphone will be highly directional. In Table 1, a 20 mm mouth diameter was assumed, which implies highly directional response at about 16.5 kHz.[12] The performance gain of a horn comes with a cost—nonuniform gain across frequency. In general, horns deemphasize low frequency sounds, with the cutoff frequency for maximum gain being determined by the flare rate of the horn. This low frequency deemphasis can be advantageous for two reasons—background sound level spectra are often red,[13] and high frequency sounds experience greater atmospheric absorption. Horns can supply more gain to extend high frequency detection capability while suppressing the ability of low frequency noise to saturate the system.

Examples of the theoretical on-axis frequency response for two exponential and conical flared horns are shown in Fig. 1. The dimensions are as for the first example in Table 1 (i.e., a throat diameter of 0.25 mm and mouth diameter of 20 mm) and the length is varied to achieve varying cutoff frequencies. The gain of the conical shaped horn approaches the maximum at a more gradual rate than the exponential. The marked peaks and troughs in the response functions can be minimized by adjusting the dimensions of the horn such that the mouth impedance is matched to the radiation impedance.[14] As a result, a smooth frequency response is achieved, e.g. the exponential horn in Fig. 1 with f_c = 5.5 kHz.

Fig. 1. A National Park Service (NPS) acoustical monitoring system deployed in Zion National Park. Through many generations of NPS systems, wind speed logging has been a consistent component, to identify times when pseudonoise generated by airflow around the wind screen would inflate the spectrum measurements.

Recorders

The increasing capabilities of consumer digital audio recorders (DAR), especially increases in storage capacity and reductions in power consumption, enable continuous audio recordings exceeding one month in duration with packages that are relatively small and inexpensive. These devices utilize integrated circuits for signal conditioning, analog-to-digital conversion, and data storage, reducing the cost and complexity of assembly. Most DARs are designed for the purpose of speech or music recording rather than unattended monitoring of natural sounds and biological studies. Accordingly, many DAR features are superfluous–such as equalization or special effects—or detrimental—such as a visual interface that continually draws power. Nonetheless, the core function is to record high fidelity acoustic signals to memory and most DARs can be repurposed for unattended recording in harsh environments by enclosing them in a rugged weatherproof housing, providing a supplemental battery power supply, and shrouding the microphones with a wind fairing and splash protection.

Selecting a DAR involves consideration of several characteristics. In terms of cost and power consumption, the DAR will almost always be the most critical selection. The DAR will rarely be larger and heavier than the power subsystem, but the DAR power consumption largely determines the power requirements. Except for applications that demand enormous data storage capacity, DARs that use solid state memory will be preferable, due to significant reductions in power consumption and greater tolerance of environmental shocks relative to spinning hard disks. Intrinsic noise levels, dynamic range, bandwidth limits, sensitivity to environmental conditions, and build quality are other features of interest. The suitability of any DAR for acoustic measurements will depend upon the application and the environment. In some situations an extremely inexpensive unit may be the best choice, despite the limitations this imposes on the accuracy of the measurements.

The capabilities of consumer audio recorders to record accurate time histories of acoustic signals have been documented.[15] Compressed audio (MP3) can be calibrated and used to calculate sound level metrics from audio data.[16] There are many consumer recorders to choose among, and capabilities are evolving rapidly as technology progresses. Table 2 displays specifications for a representative set of DARs including power draw, storage capacity given memory type, and equivalent input noise (EIN).

Power consumption is fairly straightforward to compare. The Centon would require less than 15 Amp-hours of battery to run for 30 days; it could run for a month on a single D size alkaline battery. The Roland R-26 requires nearly 190 Amp-hours, and might be powered by an array of 128 Watt-hour rechargeable prismatic LiFePO4 batteries, each weighing 1.4 kg. The Centon delivers compromised recordings designed for human speech, while the R-26 delivers up to 6 channels of high definition audio.

The maximum recording time of a recorder is a function of storage capacity and recording bit rate. Many of these units use high capacity secure digital (SDHC) memory cards to store audio data. SDHC cards have a current maximum capacity of 32 GB in a package that is 32 mm × 24 mm × 2.1 mm. The SCXC standard, which shares the same physical dimensions, has a maximum capacity of 2 TB, and 128 GB cards are currently available. Two channels of CD quality audio (44.1 kHz sample rate, 16 bit data) will fill up a 32 GB card in about 50 hours. Compressed audio storage significantly extends recording time, and also reduces power consumption because of reduced energy consumption for writing to memory. In a 128 kbps MP3 format, that 32 GB card will last almost 23 days.

Digital audio recorders are often equipped with microphones and one example is included in Table 1. In cases where external microphones are preferred, the preamplifier and recording sections can be utilized separately. Microphone preamplifier noise levels are often so low they are difficult to measure accurately. EIN is an equivalent input noise estimate given the output impedance of a typical microphone, usually 150 ohms. A comparison between the recorder EIN and microphone self noise reveals that the recorder noise is often insignificant and the microphone will be the limiting factor.

There is a loss of information and addition of artifacts when audio compression reduces the storage requirements of a signal, though the psychoacoustic perception algorithm underlying MP3 encoding seeks to minimize the salience of these defects. Acoustic sources and animal calls are still readily recognized by active listeners and automatic detection and classification software should be effective with compressed audio of this quality. A recent study has shown that the energy of the signal is preserved through the audio compression in a one-third octave band sense.[16] This allows for calibrated sound pressure levels to be calculated, although the accuracy of these measurements will be less than the reference instrument used to develop the calibration.

Software for automated detection, characterization, and classification

The information presented above can help inform development of acoustical monitoring systems with high performance/price ratios, but efficient data collection is moot without

Table 2. Specifications of a representative sample of digital audio recorders (DAR)

Recorder	Power	Storage Capacity Gb	Minimum Sample/ Data Rate	Schedule	Max days	Watt-hours for 30 days	EIN (150 ohms)
Centon moVex and similar	20 ma @ 1.5 v	8	4400/6.4 kbps ACT	No	116	22	NA
Olympus DM-420	30 ma @ 3 v	32	8 kbps mono WMA	Yes	370	65	-114 dBu
Olympus LS-7	35 ma @ 3 v	32	8 kbps mono WMA	Yes	370	76	-115 dBu
Roland R-05	60 ma @ 3v	32	128 kbps MP3	No	23	130	-120 dBu
Roland R-26	260 ma @ 6v	32	128 kbps MP3	No	23	1123	-122 dBu
Wildlife Acoustics SM2+	85 ma @ 6v	128	4000	Yes	370	367	NA

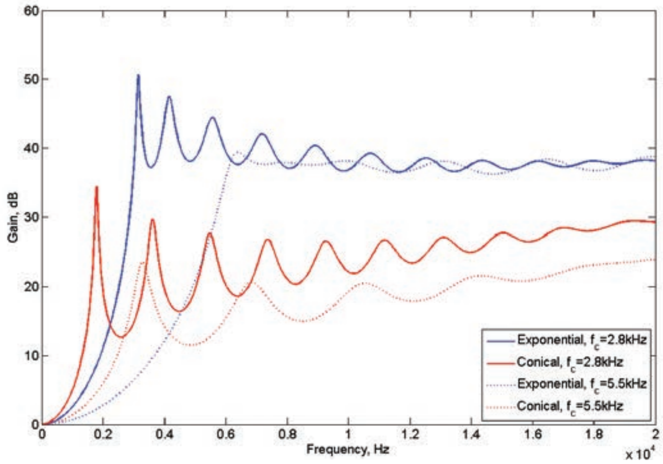

Fig. 2. Theoretical on-axis gain of conical and exponential horns relative to a free-field microphone. Two lengths are represented: 88 mm for f_C = 2777 Hz, and 44 mm for f_C = 5554 Hz.

an effective plan for processing the data. In the authors' experience, many projects have encountered significant bottlenecks in this phase. There are many potential software tools to automate processing, but the difficulty seems to lie in selecting the appropriate tool, and gaining sufficient experience with its use to maximize its performance.

Automated bioacoustical monitoring can be envisioned as a three step process: detecting and delimiting events of interest, characterizing the structure of the event, and classifying the event to a species or other class of signals. In some processing schemes, a highly selective detector serves all three processes. Examples are matched filtering[17] and spectrogram correlation.[18] Matched filtering is an optimal detector when the signal is known exactly, a situation that will rarely obtain for biological sources. In fact, it is not an exaggeration to suggest that no animal sound is ever replicated exactly. The limited time-frequency resolution of spectrograms helps diminish small differences among acoustical signals, so spectrogram correlation is not as narrowly selective as waveform matched filtering. Nonetheless, the authors' experience has shown that successful use of spectrogram correlation for some classes of sounds may require tens of templates to achieve adequate coverage. Less selective detectors[19] defer the decisions about classification, and offer researchers opportunities to study a wide range of signals that share some structural similarity with the signals of interest. This flexibility comes at a cost—the detection software may need to manage millions of detections, and subsequent analysis will chal-

Table 3. Web links to software for bioacoustical data processing

software	Website
Freely available software	
Ishmael	http://www.bioacoustics.us/ishmael.html
Pamguard	http://www.pamguard.org/
XBAT	http://code.google.com/p/xbat-devel/
Sound Analysis Pro	http://soundanalysispro.com/
PRAAT	http://www.fon.hum.uva.nl/praat/
TRITON	http://cetus.ucsd.edu/technologies_Software.html
Commercial products	
Raven	http://www.birds.cornell.edu/brp/raven/RavenOverview.html
SoundID	http://www.soundid.net/
SongScope	http://www.wildlifeacoustics.com/products/analysis-software
SonoBat	http://www.sonobat.com/
Avisoft SASlab Pro	http://www.avisoft.com/soundanalysis.htm
Signal Event	http://www.engdes.com/sigwin/products/products.html
Machine learning and data mining	
R	http://cran.r-project.org/
RapidMiner	http://rapid-i.com/
Weka	http://www.cs.waikato.ac.nz/ml/weka/
mlpy	http://mlpy.sourceforge.net/
scikit-learn	http://scikit-learn.org/stable/
Apache Mahout	http://mahout.apache.org/
orange	http://orange.biolab.si/
Shogun	http://www.shogun-toolbox.org/
ELKI	http://elki.dbs.ifi.lmu.de/

Fig. 3. National Park Service (NPS) landscape scale soundscape survey in Rocky Mountain National Park. This system utilized a digital audio recorder (Zoom H2) and relied upon its internal microphones. The electronics were protected underneath an enclosure that served as both a wind fairing and weather protection.

Fig. 4. The recording system utilized by Joe Medley (U. C. Davis) to monitor great grey owls in the Sierra Nevada mountains of California. Two preamplified electret microphones (SuperCircuits PA3) were inserted into the throats of laboratory funnels, which served as conical horns. The rectangular case contained rechargeable NiMH D cells and a Cowon iAudio 7 solid state recorder.

lenge algorithms and visualization schemes.

An online guide to bioacoustical software can be found at: http://zeeman.ehc.edu/envs/Hopp/sound.html. Table 3 provides links to several software packages that are designed to expedite processing of large bioacoustical data sets. This includes references to software that supports machine learning models, which offer a diverse array of tools for classifying sounds.

Examples illustrating potential scale

The authors have been involved in several large scale projects to monitor natural sounds. The National Park Service Natural Sounds and Night Skies Division has monitored acoustic resource conditions at hundreds of sites in park units across the United States. These data include 1/3rd octave, 1-second equivalent continuous noise level (L_{eq}) measurements to characterize ambient sound levels, and audio recordings to help identify common sounds and document their prevalence. In recent systems, a Roland R-05 has been used to obtain continuous audio recordings. Figure 1 illustrates a recent deployment in Zion National Park. An area of ongoing research is developing models that help generalize these point measurements of acoustical conditions into park and regional maps that illustrate the distribution of spatially varying acoustical conditions.

Many other acoustical monitoring projects will seek to automatically identify particular sounds of interest. Table 4 illustrates the size and eventual classification accuracy that was obtained in the course of those analyses. Three of the projects used Raven, a commercial product one of the authors helped initiate by securing a National Science Foundation grant to fund its development. The fourth utilized XBAT, a Matlab library one of the authors helped fund to pursue the project listed in the table. Raven was a logical choice for the first three projects because of its flexible tools for displaying large volumes of acoustical data and its extensive user manual—a real benefit for collaborators who are analyzing large quantities of recordings for the first time. XBAT was used for the fourth project because more selective detection was required to distinguish the sounds of the species of interest. The authors' familiarity with these programs was an overriding consideration; other packages could have been equally effective. Raven and XBAT were used to detect and extract standardized measurements from the sounds, and Random Forest[20] classifiers were trained to discriminate between true and false detections.

The screech owl study[21] sought to detect a wide range of sounds originating in the nest boxes, produced by adults, nestlings, and embryos. The proximity of the microphone provided favorable signal-to-noise ratios for most classes of signals, but the diversity of sounds called for generalized detection based on frequency bandlimited acoustic energy. Kozlowski reviewed and identified tens of thousands of sounds to provide the data set that trained the classifier. The black-capped vireo study[22] utilized more than 80 spectrogram templates to detect 5 types of notes. Several other bird species at the study site produced sounds that closely resembled each of these note types, so it was difficult to achieve a manageable false alarm rate. Spectrogram selection involved an iterative process of identifying missed detections, and selecting templates to capture those signals, and eliminating templates that became redundant. The last two projects document the success of collaborators who pursued their analyses with limited guid-

Table 4. Examples of large scale automated acoustic classification

Project	Investigator	Software	Scale	Classification accuracy
Screech Owl Nest Sounds	Corinne Kozlowski, Cornell University	Raven	1.7 million sounds	0.93
Fort Hood Black-capped Vireo	Kurt Fristrup, Anne Warde, Cornell University	XBAT	Over 5 million sounds	0.98
Off-highway vehicles in Sierra National Forest	Sarah Reed, Colorado State University	Raven	36 sites, many days per site	0.97
California Great Grey Owl	Joe Medley, U. C. Davis	Raven	more than 50 sites; 50,000 GGOW sounds detected	0.94

ance from one of the authors. They represent relatively favorable scenarios. The great grey owl study had the advantage of a limited number of other sounds that could occur within the frequency bands of interest at night. The vehicle study was able to utilize a generalized template for low resolution spectrogram correlation to detect a wide range of vehicles.

When standardized measurements are used to characterize the structure of sounds, several principles should guide the design and implementation of these measurements. Measurements must be relevant to the classification task, and analysis and presentation will be eased if the values are readily interpreted, if they summarize salient physical or spectrographic features. In order to minimize "the curse of dimensionality"[23] and unintentional weighting of particular characteristics, measurements should be at least partially uncorrelated across the sample. Lastly, measurements should be robust, yielding similar values when there are modest changes in the acoustical background behind the signal of interest. It may be fruitful to consider measurements as extremely lossy data compression, to evaluate the relative merits of alternative sets of measurements in terms of the accuracy of signal reconstruction.

Perhaps the most challenging aspect of automated detection is quantifying the fraction of events that the detection and classification regime failed to capture. The straightforward practice is extensive review of a randomized sample of the raw data, but this will be laborious and inefficient when signals of interest are rare. Another option is to utilize multiple methods in conjunction with an approach analogous to multisensory data fusion[24] or mark-recapture analysis[25] to estimate the fraction of signals that have been missed by all methods.

Conclusion

Autonomous acoustical monitoring is an emerging tool for terrestrial studies of ecology and animal behavior, and compelling results will be forthcoming as systems improve and researchers become familiar with their features and idiosyncrasies. In terms of data collection, there are numerous commercial options for microphones and recorders, orders of magnitude differences in performance, and more than an order of magnitude difference in price. Brent Hetzler of the National Park Service[26] has conducted extensive acoustical surveys for Mexican spotted owls using $20 voice recorders that he modified for long-term operation. Digital audio recorders capable of broadband, high fidelity recording generally cost $200 or more, and specialized acoustical monitoring equipment can cost $2000 or more.

The right recorder will rarely be the most expensive unit, and it may not be the unit with the highest performance/price ratio. Spreading and absorptive losses combine with refraction in atmospheric sound propagation to present severe limits to the maximum range of detection. Distributed sensing allows for effectively higher signal to noise ratios through an abundance of vantage points, especially when the location of the source of interest is unknown. In addition, acoustical sampling may need to span a wide range of environmental conditions and a single sensor is less robust to component failure. Accordingly, many units that are less capable may yield more useful information than a few units with more impressive performance.[27]

Bioacoustical monitoring can document many parameters of interest—occupancy, temporal activity patterns, spatial patterns of movement, population density, breeding activity, and possibly—when long-term individual recognition is possible—individual survivorship and reproductive output. The extent and nature of the necessary acoustical data, as well as supplemental information, depends upon the parameter of interest and the scope of the study. Useful information will undoubtedly emerge from any study that collects good recordings, but efficiency and effectiveness will be greatly improved by developing an explicit sampling plan that addresses one or more parameters for estimation. Focused monitoring effort will yield more decisive results with less effort than undirected effort.[28] **AT**

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Daniel Mennitt is a Research Scientist in the Department of Electrical and Computer Engineering at Colorado State University. He received his Ph.D. in Mechanical Engineering from Virginia Tech while studying multiarray passive acoustic localization and tracking. Current topics of interest include acoustic propagation and modeling, auditory scene analysis, and the spatial variation of ambient sound pressure levels.