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Detection and Classification of Motor Vehicle Noise in a Forested Landscape

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Abstract Noise emanating from human activity has become a common addition to natural soundscapes and has the potential to harm wildlife and erode human enjoyment of nature. In particular, motor vehicles traveling along roads and trails produce high levels of both chronic and intermittent noise, eliciting varied responses from a wide range of animal species. Anthropogenic noise is especially conspicuous in natural areas where ambient background sound levels are low. In this article, we present an acoustic method to detect and analyze motor vehicle noise. Our approach uses inexpensive consumer products to record sound, sound analysis software to automatically detect sound events within continuous recordings and measure their acoustic properties, and statistical classification methods to categorize sound events. We describe an application of this approach to detect motor vehicle noise on paved, gravel, and natural-surface roads, and off-road vehicle trails in 36 sites distributed throughout a national forest in the Sierra Nevada, CA, USA. These low-cost, unobtrusive methods can be used by scientists and managers to detect anthropogenic noise events for many potential applications, including ecological research, transportation and recreation planning, and natural resource management.

Keywords Anthropogenic · Road · Noise · Soundscape ecology

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Introduction

Noise emanating from human activity has become a pervasive addition to natural soundscapes across the globe (Barber and others 2010). Noise is a rising threat to remote areas due to growth in air travel, motorized recreation, and exurban sprawl (Miller 2008). Anthropogenic sounds can spread from their sources in distances and directions (e.g., upslope) that many other human impacts cannot. Managing and protecting soundscapes in natural areas is an especially important issue for land and natural resource managers because of the potential impacts on wildlife and visitor experiences.

Modeling and monitoring studies have found that noise from motor vehicles can be detected across large spatial extents, demonstrating that roads are a major source of anthropogenic noise (Barber and others 2011). For example, 83 % of the land area of the continental United States is within 1,061 m of a road (Riitters and Wickham 2003). At this distance, noise from the average automobile can substantially exceed the natural sound level in many environments (Reijnen and others 1995).

Public and protected areas are not immune to the increase in noise. The U.S. Forest Service manages

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380,000 miles of roads. Recreational use of the U.S. Forest Service roads has grown ten-fold since the 1950s, to an average of 1.7 million vehicles each day (Coghlan and Sowa 1998). Many locations within the U.S. National Parks have degraded soundscapes because of high traffic on nearby roads (Lynch and others 2011). Noise impairs natural soundscapes, resources that are highly valued by park visitors: 72 % of Americans surveyed in 1998 believed that providing opportunities to experience natural quiet and the sounds of nature was a very important reason for having parks and preserves (Haas and Wakefield 1998). Research has documented physiological and psychological impacts of traffic noise on humans (Haralabidis and others 2008) as well as the benefits to human health associated with quiet or unimpaired soundscapes (Berglund and Lindvall 1995; Stansfeld and Matheson 2003).

Many wildlife species are negatively affected by noise associated with roads. Anthropogenic noise has been linked to a suite of physiological and behavioral responses for a variety of vertebrate taxa (Weisenberger and others 1996; Slabbekoorn and Peet 2003; Bee and Swanson 2007; Slabbekoorn and Ripmeester 2008; Barber and others 2010). It has been suggested that traffic noise in particular can disrupt or alter communication (Patricelli and Blickley 2006; Warren and others 2006; Parris and Schneider 2009); modify pairing and reproduction (Halfwerk and others 2011; Blickley and others 2012); increase stress responses (Creel and others 2002); and change density and occupancy patterns of species (Reijnen and others 1996; Bayne and others 2008; Francis and others 2009).

Identifying the sources of anthropogenic noise and measuring the duration and frequency of sound events are vital steps for understanding and managing the impacts of noise on wildlife and people. As storage capacity and battery life increase, inexpensive consumer digital audio recorders provide an increasingly efficient and accurate means to monitor soundscapes (Mennitt and Fristrup 2012). Digital audio recorders have revealed important information about animal acoustic signals and behaviors across variable spatial and temporal scales (Blumstein and others 2011) and have played central roles in extensive spatial surveys for rare or endangered species (Thompson and others 2010; Fristrup and Clark 2009). Field recordings can also obtain acoustic properties of anthropogenic noise while measuring effects on wildlife (Brown and others 2012). This study demonstrates the effectiveness of acoustic monitoring for documenting road traffic on landscape and regional scales.

Our approach applies consumer recorders to collect data, sound analysis software to automatically detect sound events within continuous recordings and measure their acoustic properties, and statistical classification methods to categorize sound events. We describe an application of this approach to detect motor vehicle noise on paved, gravel, and natural-surface roads and off-road vehicle trails in 36 sites distributed throughout a national forest in the Sierra Nevada, California, USA. These low-cost, automated methods can be used by scientists and managers to detect anthropogenic noise events for many potential applications, including ecological research, transportation and recreation planning, and natural resource management.

Methods

Field Data Collection

The detection and analysis methods we describe were developed to examine the relationships among motor vehicle activity, sound propagation patterns, and wildlife species distributions in Sierra National Forest, California (Reed and Dietz, unpublished data). We monitored 36 study sites over 2 years (2008–2009). The sites were located along paved, gravel, and natural-surface roads and off-road vehicle trails. The site locations were restricted to a single vegetation community (Sierran mixed conifer) within a fixed elevation range (1,300–2,600 m). Sierran mixed conifer forests are a heterogeneous mosaic of closed canopy forest, shrub patches, and open gaps, and they provide the primary habitat for more vertebrate species than any other Sierra forest type (North and others 2002). The monitoring sites had a mean canopy closure of 57 % (±23 %) and a mean basal area of 50 m^2 ha^{-1} (±11 m^2 ha^{-1}). The understory was relatively dense, such that the target motor vehicle route was visible at a distance of 25 m for a mean of 44 % of the field of view in one-third of the monitoring sites; no portion of the target motor vehicle route was visible in the remaining two-thirds of the sites. Monitoring surveys were limited to the summer dry season (June–August).

At each monitoring site, we established one sound recorder at 25 m from the target motor vehicle route to record sound propagated in the immediate vicinity of the road or trail. Sound recorders consisted of an MP3 recorder (iAudio 7, Cowon Systems, Inc., Seoul, Korea), powered by a 12 V, 10,000 mAh battery pack (Tenergy Corporation, Fremont, California), and a pair of stereo microphones (Super High Gain Micro Audio System, Supercircuits, Inc., Austin, Texas). MP3 recorders were set to line-in recording mode with a volume of 4 and audio quality of 64 kbps. We mounted the two microphones in trees, both oriented toward the target route, a mean of 0.8 m (±0.4 m) apart at a mean height of 1.4 m (±0.2 m) above the ground. Sound recorders were set to record continuously for a period of 10–14 days.

Detection of Sound Events

Stationary sound recorders produced sequential stereo Windows Media Audio (WMA) files that were 9.3 h in length. To facilitate storage and analysis of the data, we split the WMA files into 2-h increments (AsfBin 1.7.14, Radioactive Software, Dublin, Ireland) and converted them to waveform (WAV) format (SWITCH audio converter, NCH Software, Canberra, Australia). We used RAVEN PRO 1.4 (Cornell University, Ithaca, New York) to produce spectrograms, detect sound events, and quantify acoustic measurements from the WAV files.

Automated or computer-aided, detection methods are an alternative to browsing aurally or visually through long recordings to find specific sounds. Instead, a detection algorithm is applied to distinguish signals of interest from background sound. To detect motor vehicle sound events, we used RAVEN's band-limited energy detector, also known as a time–frequency energy detector (TFED). TFEDs identify user-defined signal characteristics associated with a particular sound event (e.g., a vehicle driving by or the call of a bird) within a continuous recording. Specifically, the TFED searches for sections of a recording that surpass a user-specified signal-to-noise ratio (SNR) threshold within a chosen frequency band and time interval.

To specify acoustic and temporal parameters for the TFED, we started with 2-h samples of motor vehicle traffic on each of three primary road and trail surfaces: paved, gravel, and natural-surface. We listened to the recordings and searched visually in their spectrograms for all motor vehicle noise events associated with each road type. Once a vehicle detection was verified, a selection was highlighted and saved. We recorded the following measurements for each selection: minimum and maximum frequency, minimum and maximum duration, minimum separation, block size, hop size, noise percentile, occupancy, and the SNR. Definitions of these parameters can be found in Table 1.

We followed the steps outlined in the RAVEN User's Manual (Charif and others 2007) using a trial-and-error approach to identify parameters to construct a TFED for vehicle events. To choose the frequency parameters, we documented the low and high frequencies of each sound event from the selection table. We recorded the lengths of time in seconds for short- (<1 s) and longer-duration events (<40 s) to choose values for the minimum and maximum duration parameters. For the minimum separation parameter, we found the closest distinct vehicle events and drew a selection between them and calculated a delta time measurement from the selection table. Next, we chose a block size that was three times longer than the maximum duration because the data being used for noise estimation should encompass both background noise and signal. The hop size parameter value should fall between the maximum duration and noise block size. For an appropriate value for the noise percentile parameter, we chose both high and low values. We accepted the default noise occupancy value provided by RAVEN. For the SNR, we measured the average power of our selections and the average power of a typical block of ambient sound without motor vehicle noise. The difference in average power was noted in decibels as the SNR ratio.

We manually specified the window type and size in RAVEN's Configure Spectrogram dialog to increase the accuracy of our detector. We chose a Hamming window function with a window size of 128 samples averaging between 500 and 1000 spectra. Because time resolution was not crucial for these long events, extensive averaging smoothed out the eccentricities of each vehicle while preserving the generic characteristics of most vehicles. We then tested several combinations of road type, TFED parameters, and average spectra to determine the best combination of values for our TFED (Table 2). We quantified the detector accuracy by recording the actual number of vehicle events from a known sample. The SNR, hop size, and minimum separation parameters needed the most adjustment before finding the best combination. Depending on road type, there were slight differences in the minimum separation parameter (e.g., ORV = 5 s, Gravel and Paved = 7.5 s). Besides this parameter, we found no differences between road type detectors. We tested the accuracy of the shorter minimum separation parameter on the gravel and paved road detectors and observed no change in the number of detections. Therefore, we used the ORV detector for all road surface types (Table 2).

For each 2-h sound file, RAVEN produced a list of detections that met the specified criteria. Detection is the process of finding particular sounds of interest within recordings (Charif and others 2007). Each detection was visually highlighted on the spectrogram (Fig. 1) and listed within a selection table, matching the list of selections identified by an auditory and visual search. The TFED produced detections of many anthropogenic and natural sound events, including the target motor vehicle sound events, as well as wind, thunder, aircraft, insects, and animal vocalizations. We applied the TFED analysis to both channels of the stereo recordings, and we eliminated duplicate detections (i.e., detections with overlapping durations) from the resulting dataset.

Classification Model

We used a statistical classification approach to distinguish the motor vehicle events from other types of detections (Cutler and others 2007). To build our classification model, we first created a dataset of known sound events. Our goal was to represent the full range of variability in the characteristics of both true and false positive motor vehicle

Table 1 Descriptions of temporal and acoustic measurements used by TFED to distinguish motor vehicle events from other sound events

Variable	Description
Agg entropy	The total amount of disorder in sound over the entire detection
Avg entropy	The amount of disorder in sound averaged for each time–frequency frame in the detection
Avg power	Value of the spectrogram's power spectral density averaged over the detection (dB)
Block size	Duration of noise block used to calculate the background noise
Center time	Duration of time between the beginning of the detection and the median cumulative acoustic energy (s)
Center freq	Frequency that divides the detection at the median of cumulative acoustic energy (Hz)
Duration	Total duration of the detection (s)
Hop size	The parameter that determines how much smoothing is performed in the noise estimation computation
Max power	Maximum power within the detection (dB)
Min/Max duration	The minimum and maximum duration (s) of a selection
Min/Max freq	The minimum and maximum frequencies of a selection
Min Separation	The amount of time between selection(s)
Noise Percentile	The percentage of the ranked noise that is counted as background noise
Peak freq	Frequency at which maximum power occurs within the detection (Hz)
Occupancy	Proportion of samples within a selection where a signal exceeds the background noise by the (SNR)
Q1 Freq	Frequency that divides the detection at the first quartile (25 %) of cumulative acoustic energy (Hz)
Q3 Freq	Frequency that divides the detection at the third quartile (75 %) of cumulative acoustic energy (Hz)
Q1 Time	Time duration between the beginning of detection and first quartile (25 %) of acoustic energy(s)
Q3 Time	Time duration between the beginning of detection and third quartile (75 %) of acoustic energy(s)
SNR	The level above background noise that the sample must exceed

detections. We selected 13 sites from across the Sierra National Forest study area to represent a range of road surfaces (paved, gravel, and natural) and motor vehicle types (automobile, truck, motorcycle, and all-terrain vehicle). We excluded the first 15 min of recording at each site to avoid including detections of sounds produced by the field technicians installing the acoustic monitoring equipment. We then selected the first 100 or all unique detections, if fewer than 100, recorded at each of the 13 sites. Because the sites were established at different times of day and on different days of the week, and because the sites had highly variable detection rates over time, the selected detections were well distributed during both day and nighttime hours throughout the study period. This selection process yielded a dataset of 1,281 known detections, or a mean of 98.5 ($\pm$5.3) detections per site.

A trained technician listened to all of the selected detections using RAVEN and Shure SRH840 headphones (Shure Incorporated, Niles, IL) and coded each as a true (1) or false (0) motor vehicle detection. Overall, the classification model dataset comprised 32.9 % motor vehicle events and 67.1 % false detections. False detections typically consisted of wind, animal/insect vocalizations, and aircraft noise. We saw no evidence of false detections masking true detections during the coding process.

We used RAVEN to extract several acoustic and temporal measurements from the selected detections that were likely to be useful for distinguishing the motor vehicle events from other sound events (Table 1). These included the duration, center, first and third quartile times; peak, center, first and third quartile frequencies; average and aggregate measures of entropy; average and maximum powers; and occupancy of each sound event. We calculated the acoustic measurements based on RAVEN's default spectrogram parameters within the frequency range of the TFED (1–2 kHz).

We randomly selected 20 % ($n = 256$) of the known detections to reserve as a validation dataset. We used the remaining 80 % ($n = 1{,}025$) of the known detections and the 13 predictor variables to build a classification model using the Random Forests (RF) package of R statistical software (Breiman 2001). Based on a preliminary exploration of the data, we used the default number of variables available for splitting at each node (mtry = 3) and the default number of trees (ntree = 500) to build the model in RF.

We applied the RF classification model to detections in the validation dataset, and we calculated three measures of the accuracy of our classification model for both the model and validation datasets: the percentage of detections classified correctly (PCC), the percentage of motor vehicle events classified correctly (sensitivity), and the percentage of non-motor vehicle events classified correctly (specificity). We also calculated the importance of individual

Table 2 Parameter settings associated with the TFED

Road type	Min freq	Max freq	Min dur	Max dur	Min sep	Block	Hop	Percentile	Occupancy	SNR	Spectogram configuration
Default											Hann, 256 samples, avg 1 spectra
Gravel	1,000	2,000	10	40	5	20	10	20	60	2	Hamming, 128 samples, avg, 1,000 spectra
	1,000	4,500	10	40	5	20	10	20	60	2	Hamming, 128 samples, avg 1,000 spectra
	1,000	2,000	10	40	5	20	10	20	60	4	Hamming, 128 samples, avg 1,000 spectra
	1,000	2,000	10	40	5	20	10	20	60	6	Hamming, 128 samples, avg 1,000 spectra
	1,000	2,000	10	40	5	20	10	20	60	5	Hamming, 128 samples, avg 1,000 spectra
	1,000	2,000	10	40	10	20	10	20	60	5	Hamming, 128 samples, avg 1,000 spectra
	1,000	**2,000**	**10**	**40**	**7.5**	**20**	**10**	**20**	**60**	**5**	**Hamming, 128 samples, avg 1,000 spectra**
ORV	1,000	2,000	10	40	5	20	10	20	60	5	Hamming, 128 samples, avg 1,000 spectra
	1,000	2,000	10	40	5	20	10	20	60	5	Hamming, 128 samples, avg 500 spectra
	1,000	2,000	10	40	5	20	10	20	60	2	Hamming, 128 samples, avg 1,000 spectra
	1,000	2,000	10	40	7.5	20	10	20	60	7	Hamming, 128 samples, avg 1,000 spectra
	1,000	2,000	10	40	7.5	20	10	20	60	10	Hamming, 128 samples, avg 1,000 spectra
	1,000	2,000	10	40	5	20	10	20	60	3.5	Hamming, 128 samples, avg 1,000 spectra
	1,000	2,000	10	40	10	20	10	20	60	4	Hamming, 128 samples, avg 1,000 spectra
	1,000	2,000	10	40	10	80	60	20	60	4	Hamming, 128 samples, avg 1,000 spectra
	1,000	2,000	10	40	10	40	20	20	60	4	Hamming, 128 samples, avg 1,000 spectra
	1,000	2,000	10	40	10	20	10	20	60	5	Hamming, 128 samples, avg 1,500 spectra
	1,000	4,500	10	40	10	20	10	20	60	5	Hamming, 128 samples, avg 1,500 spectra
	1,000	2,000	10	40	5	20	10	20	60	5	Hamming, 128 samples, avg 500 spectra
[a]	**1,000**	**2,000**	**10**	**40**	**5**	**20**	**10**	**20**	**60**	**5**	**Hamming, 128 samples, avg 1,000 spectra**
	1,000	2,000	10	40	5	20	10	20	60	3.5	Hamming, 128 samples, avg 500 spectra
	1,000	2,000	10	40	5	20	10	20	70	5	Hamming, 128 samples, avg 500 spectra
	1,000	2,000	10	40	5	20	10	20	50	5	Hamming, 128 samples, avg 500 spectra
	1,000	2,000	10	40	5	60	40	20	60	5	Hamming, 128 samples, avg 500 spectra
	1,000	2,000	10	40	5	10	5	20	60	5	Hamming, 128 samples, avg 500 spectra
Paved	1,000	2,000	10	40	10	20	10	20	60	4.5	Hamming, 128 samples, avg 1,000 spectra
	1,000	2,000	10	20	5	20	10	20	60	5	Hamming, 128 samples, avg 1,000 spectra
	1,000	2,000	10	40	5	20	10	20	60	5	Hamming, 128 samples, avg 1,000 spectra
	1,000	**2,000**	**10**	**40**	**7.5**	**20**	**10**	**20**	**60**	**5**	**Hamming, 128 samples, avg 1,000 spectra**
	1,000	2,000	10	40	7.5	20	10	20	60	4	Hamming, 128 samples, avg 1,000 spectra
	1,000	2,000	10	40	7.5	20	10	20	60	5.5	Hamming, 128 samples, avg 1,000 spectra

Rows which are in bold designate the best combination of parameters for road type

[a] Designates the top combination of parameters used for all road types

variables to the classification as the permutation-based mean decrease in accuracy.

Results

During the 2008 and 2009 summer field seasons, we recorded a total of 866.4 days (20,798 h) of sound. We recorded a mean of 12.0 days (289 h) per year at each of the 36 monitoring sites, and a mean of 7.0 days (169 h) per year on each acoustic monitor within the sites. Across all the 13 sites selected to create the model and validation datasets, the recordings yielded a mean of 5.9 detections per hour, 1.9 detections per hour (32.9 %) of which were motor vehicle events.

We found a high degree of classification accuracy (>94 %) for true and false positive motor vehicle detections for both the model and validation datasets (Table 3). Variables related to the intensity (i.e., power), entropy (i.e., disorder), and duration of the noise events were more important than frequency characteristics for discriminating motor vehicles from other types of detections (Fig. 2).

Motor vehicle noise events were characterized by a relatively long duration (18.7 ± 6.9 s) and high peak (96.1 ± 6.3 dB) and average power (78.1 ± 5.8 dB) at relatively low frequencies (IQR: 1,183–1,411 Hz). It is

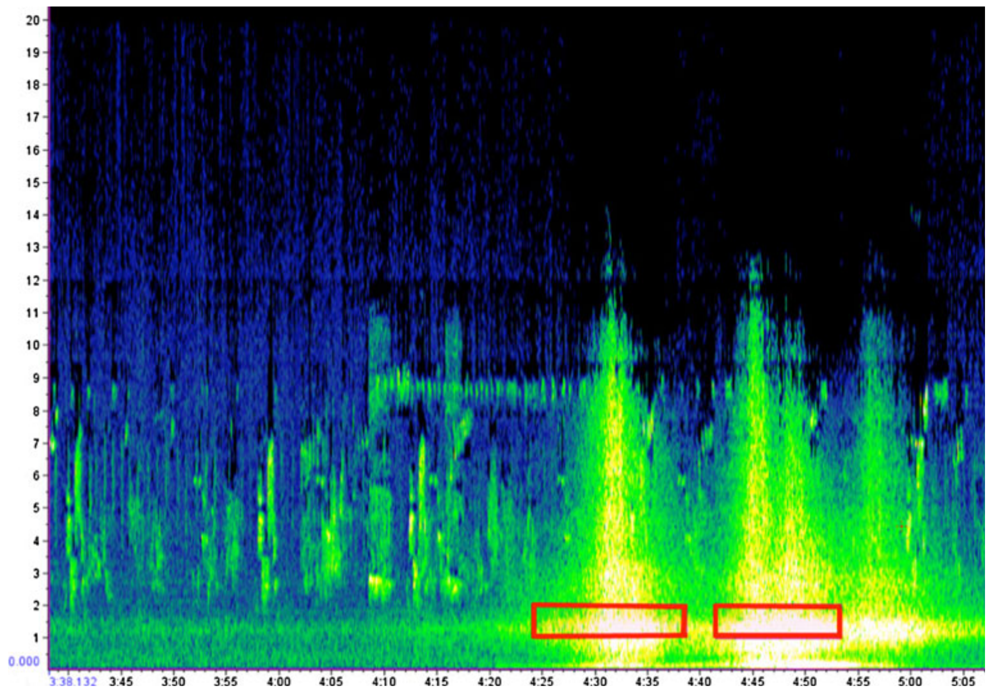

Fig. 1 Motor vehicle detections along a paved road generated by a TFED (RAVEN 1.4). The spectrogram consists of a series of spectra of successive records plotted in a parallel shape with the y-axis representing frequency in kilohertz (KHz), whereas the x-axis represents time in minutes and seconds (m:s). Amplitude at each frequency is represented by color. Here, warmer colors characterize greater amplitudes

important to note that these measurements were recorded for the frequency range of the TFED (1–2 kHz), although we also found them to be relatively consistent with measurements made over a broader frequency range (0.5–4 kHz). The true positive motor vehicle detections were distinguished from false positive detections, which had a shorter duration (8.5 ± 5.7 s) and lower peak (77.5 ± 9.0 dB) and average power (59.3 ± 6.8 dB) measurements (Table 4).

Discussion

This approach is ideal for monitoring acoustic events in remote locations that require extended or continuous recording to capture a sufficient sample of intermittent sounds. Logistically, our compact recording units can be easily transported across areas that are remote or difficult to access. Battery life allows units to continuously record for 10–14 days in the field without maintenance, requiring little effort of researchers and introducing minimal disturbance to the subjects of the study. The relatively low cost of a unit (~$350 USD) enables broad coverage across numerous sites.

The detection process allowed us to search and select for motor vehicle noise within a very large dataset (more than 2 years' time of continuous recordings). The TFED algorithm generated several false detections, but a subsequent random forest classification process accurately sorted vehicle events from false detections. At the onset of our analysis, we expected to develop one detector for each vehicle type and each associated road type. However, our approach yielded one detector that could be used for all motor vehicles and sampled road types. The ease and success of classification of candidate detections suggests that the most efficient approach for similar datasets is to first minimize the false negatives in the detector algorithm and then to remove false positives via a classification model.

Our TFED parameters (Table 2) were customized for the environmental conditions and vehicle mix of our study area. Background sound levels in all environments can vary quite widely. Many environmental factors, including elevation, temperature and wind gradients, and vegetation structure, influence patterns of sound propagation (Reed and others 2012), and future researchers will likely need to customize TFED parameters for application in other locations. Researchers should consider the tradeoffs between the time required for customization of the TFED parameters and the highly efficient runtime for analysis. We acknowledge that other applications may require some experimentation to select spectrogram and TFED parameters that exploit consistent features of the signals of interest while suppressing irrelevant variation. It is also important

Table 3 Accuracy of classification model for motor vehicle detections

Accuracy metric	Model data ($n = 1,025$)	Validation data ($n = 256$)
PCC	96.5	97.3
Sensitivity	94.6	98.8
Specificity	97.4	96.5

to note that selection of a representative set of sound events for the detection and classification process is of equal or greater importance than a highly accurate detector. A diverse sample of sound events can minimize false negatives in the detector, minimize false positives in the classification model and reduce TFED parameter customization time. After model customization (30–40 h), each 9.3-h file required 6.5 min of processing time, and thus 1 week of monitoring (168 h) required 7.9 h of computing time, with minimal supervision by a technician. This automated approach is roughly twice as fast as the most efficient spectrogram review process (E. Lynch, pers. comm), which requires dedicated effort by a technician. The TFED algorithm runs more slowly as the frequency of vehicle events increases, but it remains faster than visual review and annotation. However, spectrogram review by an experienced technician will be the most favorable in a complicated noise environment with overlapping events from a variety of noise sources.

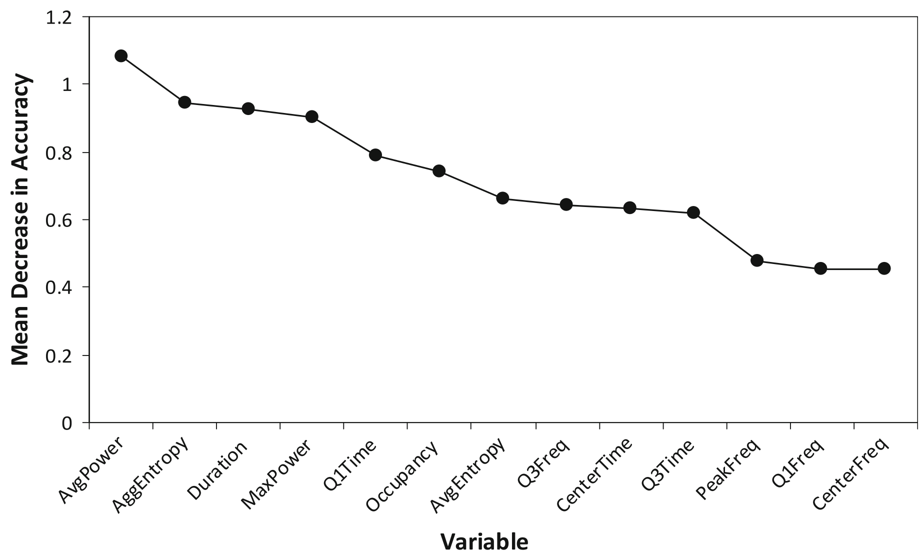

Fig. 2 Variable importance plots for temporal and acoustic measurements used to distinguish motor vehicle events from other detections in the RF classification model. Higher values of mean decrease in accuracy indicate variables that are more important to the classification

Table 4 Mean (±SD) temporal and acoustic characteristics of true and false positive motor vehicle detections

	True positive detections ($n = 421$)		False positive detections ($n = 860$)	
Measurement	Mean	SD	Mean	SD
Duration (s)	18.7	6.9	8.5	5.7
Center time (s)	8.5	4.4	4.0	3.3
Q1 time (s)	6.6	4.1	2.2	2.1
Q3 time (s)	10.5	4.9	5.8	4.4
Center frequency (Hz)	1,254.6	77.6	1,350.9	194.1
Peak frequency (Hz)	1,246.0	106.7	1,385.9	310.1
Q1 frequency (Hz)	1,183.0	58.6	1,186.2	153.1
Q3 frequency (Hz)	1,411.3	68.0	1,536.0	217.7
Aggregate entropy	2.3	0.1	2.2	0.2
Average entropy	2.0	0.1	1.9	0.1
Average power (dB)	78.1	5.9	59.3	6.8
Maximum power (dB)	96.1	6.3	77.5	9.0
Occupancy	0.9	0.1	0.9	0.2

A potential improvement on our approach would be to use a recorder that produces compressed audio files that can be processed directly by the sound analysis program. This would eliminate the need to split and translate the recorded data into WAV format. The WAV files were about ten times as large as the WMA files, and so acoustic data were archived in compressed form, and only converted to WAV format for processing.

Our approach can be used, at minimum, to unobtrusively monitor traffic, including information on vehicle types and speeds. Other techniques for monitoring vehicle traffic (e.g., active infrared or magnetic sensors) also require calibration or post-processing of data to minimize false counts and accurately distinguish vehicle types (Cessford and others 2002); yet alternative traffic monitoring technologies which are capable of classifying vehicles by type range from 1.4 (e.g., inductive loop) to 74.3 times (e.g., video image processor) as expensive as the recording units that we deployed (Mimbela and Klein 2007). Although our recorders were located close to roads, acoustic monitoring can plausibly detect vehicles at considerable distances in all directions and monitor traffic that is not confined to roads. To maximize detectability, practitioners should place recording units in close proximity to the sound source to minimize the effects of atmospheric and environmental conditions on sound propagation. If a practitioner wants to measure propagation effects, then positioning recording units at a range of distances is critical. However, a higher rate of false detection would be expected at more distant sites where the level of vehicle noise is closer to background sound levels.

Our acoustic monitors allow researchers the flexibility to customize settings to fit research needs and questions. Adapting our methods for snowmobiles or aircraft, for example, should be straightforward, as long as noise events do not generally overlap in time. RAVEN's detector performed more reliably when the spectrogram parameters were configured to reduce the time–frequency resolution to minimize variations among the events of interest while preserving sufficient temporal resolution to distinguish between successive events. The same principle would apply for the development of detectors for animal vocalizations. With properly customized parameters, acoustic recordings can also validate predictions of noise mapping software, and record acoustic indications of wildlife responses to noise.

There is an emergent need to develop a standardized approach to monitor, analyze, document, and share information in the fields of bioacoustics and acoustic ecology (Blumstein and others 2011). Acoustic methods provide opportunities to monitor human activities and their effects on ecosystems at broad spatial and temporal time scales relevant to land use and management decisions. Accessible, efficient, and affordable, the methods we demonstrate in this article can be used for a wide variety of management and research applications, including ecological research, transportation and recreation planning, and natural resource management, as well as the development of a common framework for collecting and analyzing data in the emerging field of soundscape ecology.

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