Classification of communication signals of the little brown bat

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Little brown bats, *Myotis lucifugus*, are known for their ability to echolocate and utilize their echolocation system to navigate, and locate and identify prey. Their echolocation signals have been characterized in detail but their communication signals are less well understood despite their widespread use during social interactions. The goal of this study was to develop an automatic classification algorithm for characterizing the communication signals of little brown bats. Sound recordings were made overnight on five individual male bats (housed separately from a large group of captive bats) for 7 nights, using a bat detector and a digital recorder. The spectral and temporal characteristics of recorded sounds were first analyzed and classified by visual observation of a call's temporal pattern and spectral composition. Sounds were later classified using an automatic classification scheme based on multivariate statistical parameters in MATLAB. Human- and machine-based analysis revealed five discrete classes of bat's communication signals: downward frequency-modulated calls, steep frequency-modulated calls, constant frequency calls, broadband noise bursts, and broadband click trains.
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I. INTRODUCTION

Echolocating bats are highly vocal animals and rely on a sonar system to locate, identify, and track moving prey, avoid obstacles, and orient in 3D space (Grinnell, 1995; Neuweiler 2000; Schuller and Moss, 2004). They possess an exquisite auditory system which analyzes the spectral and temporal characteristics of their sonar signals to reveal detailed information about their surroundings. During echolocation, they emit either a constant frequency (CF), or a frequency-modulated (FM), or a CF-FM combination signal (Fenton, 1984). Much research has focused on understanding their echolocation signals, which are known to vary both intra- and interspecifically (Griffin *et al.*, 1960; Masters *et al.*, 1995; Parsons and Jones, 2000). Much less is known about their communication calls in spite of these animals' extensive and complex social interactions (Kanwal *et al.*, 1994; Behr and von Helversen, 2004).

The communication calls of several species of echolocating bats have been characterized; vocal signals have been shown to convey information for courtship and mating (Barclay *et al.*, 1979; Thomas *et al.*, 1979), maternal reunion with offspring (Balcombe, 1990; Matsumura, 1979, 1981), avoiding predators, and defending or advertising feeding areas (Fenton, 1985; Wilkinson and Bohman, 1998). These studies show that communication calls may consist of several variations of CF and FM signals, such as a descending, rippled FM, or a long, quasi-CF (Kanwal *et al.*, 1994; Ohlemiller *et al.*, 1996; Kanwal *et al.*, 2004; Ma *et al.*, 2006). Most of the earlier studies relied on visual inspection of the call's spectrograms. Only more recently have rigorous statistical analyses been applied to characterize communication calls of a few bat species, as performed in songbirds (Mallett and Pepperberg, 2002), primates (Fisher and Hammerschmidt, 2002), cetaceans (Ford, 1989; Boisseau, 2005), and the bat's echolocation signals (Obrist, 1995; Burnett and Masters, 1999; Parsons and Jones, 2000; Kanwal *et al.*, 2001). In particular, the communication calls of the mustached bats *Pternotus parnellii parnellii* (Kanwal *et al.*, 1994), the lesser spear-nosed bat *Phyllostomus discolor* (Esser and Schubert, 1998), the greater spear-nosed bat *Phyllostomus hastatus* (Boughman and Schubert, 1998), and the greater horseshoe bat *Rhinolophus ferrumequinum* (Ma *et al.*, 2006) have now been parsed out using discriminant function analysis (DFA), principal components analysis (PCA), and spectrographic analysis.

In the little brown bat, *Myotis lucifugus*, analysis of their communication calls is limited to visual inspection of their call spectrograms (Fenton, 1976; Barclay *et al.*, 1979). These studies identified a variety of calls that included broadband and FM call signals, as summarized in Table I (Barclay *et al.*, 1979). Visual inspection is generally qualitative, difficult to conduct on large datasets, and thus subject to the interpretation of the investigators. In this study, we developed an automatic classification scheme for classifying the little brown bat's communication calls statistically. Classification and regression tree analysis (CART) and PCA were used to confirm the accuracy of the automatic classification algorithm. This

TABLE I. Summary of calls from *Myotis lucifugus* obtained through visual inspection of spectrograms. Values are means ± standard deviation (Barclay *et al.* 1979).

Class	n	Duration (ms)	Max freq(kHz)	Min freq(kHz)
Squeak	73	28.7±28.3	29.8±10.7	20.9±5.4
Discontinuous double-note	116	30.2±7.3	67.7±10.5	34.1±5.5
Continuous double-note	14	28.9±7.5	65.4±14.3	35.0±6.0
Copulation call	38	61.3±14.8	11.4±2.6	9.5±2.2
Isolation call	283	21.0±8.8	38.6±17.2	22.2±5.1
Sine wave	9	242.8±50.5	51.6±5.7	30.3±3.6
Long squeak-straight FM	37	42.7±14.9	58.6±6.2	33.3±6.0
Long squeak-curved FM	13	89.0±24.0	57.7±10.4	33.9±8.2
Short squawk	50	62.6±61.8		
Long squawk	153	591±238		
Long squawk (buzz)	48	1040±251		
Audible buzz	216	2±1		

automatic classification scheme allows standardized analyses of large sound file datasets and identification of the most robust spectrographic features whose parameters can be adjusted to classify bat's communication signals.

II. METHODS

Adult male little brown bats, *Myotis lucifugus*, were collected from Starved Rock State Park in Utica, IL and kept in a flight cage $(1.9\times0.9\times0.9\text{ m})$, in an environmental room maintained at 27 °C and 60% relative humidity. Food (meal worms) and water were changed daily and made available *ad lib*.

A. Recordings of calls

Recordings were conducted between November 2004 and April 2005, after at least 1 month of captivity during which bats became accustomed to the new environment and diet. For recordings, a bat was housed in a recording cage placed 2.5 m in front of a bat detector with a frequency range of 10–120 kHz (D240X; Pettersson Elektronik AB, Uppsala, Sweden; Jones *et al.*, 2003; Ibanez *et al.*, 2001) linked to a Nagra ARES-BB digital recorder. The recording cage had a size of $30.5\times25.4\times20.3$ cm, which was confined to the maximal sound reception cone of the ultrasonic microphone of the bat detector. Calls from each bat were recorded overnight for 7 consecutive nights. Anechoic foam (7.62 cm thick) was placed behind the cage to eliminate echoes (Fig. 1). Additionally, calls from the entire group in the flight cage were recorded over a 7-night period to observe any novel call types that might emerge specifically in group settings.

B. Analysis of calls

1. Call features

Once recorded, calls were analyzed on a personal computer using BATSOUND PRO computer software (Peterrsson Elektronik AB) and later with MATLAB (Parsons and Jones, 2000; Jones *et al.*, 2003). We studied 15 spectrographic features as potential aids in classification: maximum frequency, maximum time, minimum frequency, minimum time, center frequency, center time, duration, kurtosis (freq), kurtosis (time), skew (freq), skew (time), spread (freq), spread (time), standard deviation (freq), and standard deviation (time). Features were chosen based on visual analysis of calls and/or usage in previous bat sound classification studies (Barclay *et al.*, 1979; Kanwal *et al.*, 1994).

Maximum frequency and time were defined as that corresponding to the 97th percentile of the signal's summed total magnitude. Minimum frequency and time were defined as that of the third percentile of the signal's summed total magnitude. Center frequency and time corresponded to the center of mass. To account for the variability within calls in this study, kurtosis, skew, spread, and standard deviation were chosen to describe both the frequency and time distributions of each call type. Kurtosis described the degree of peakedness of call's distribution. Skew described the degree of asymmetry of the call's distribution {[signal length * center – (signal length/2) −1]/(signal length/2)}. Spread delin-

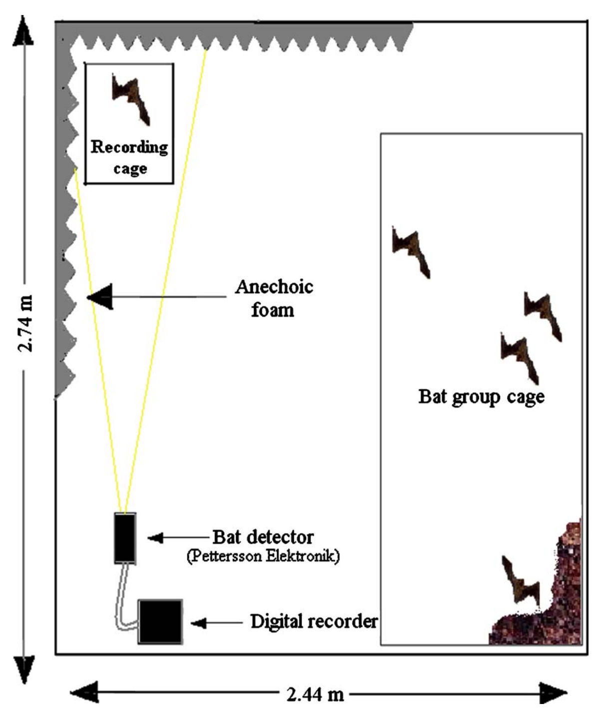

FIG. 1. Experimental setup for sound recordings from individual bats.

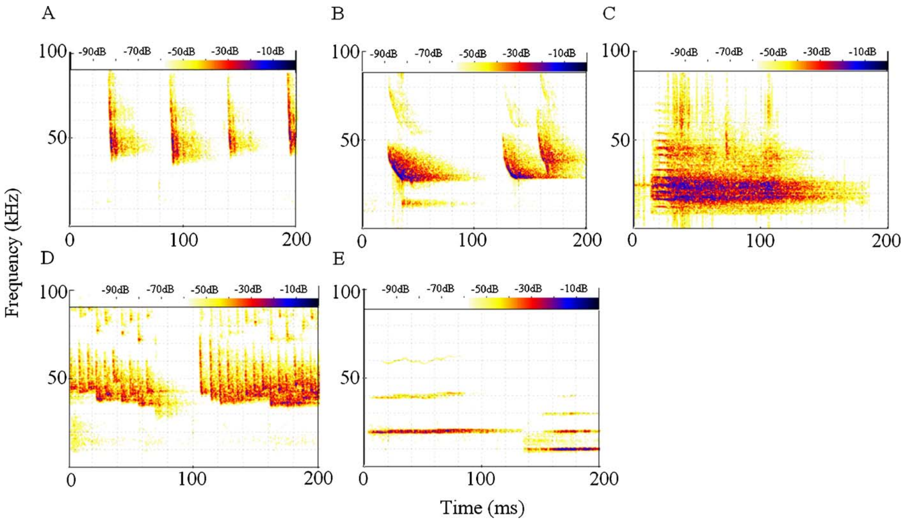

FIG. 2. Spectrograms of call types (FFT size 1024, Hamming window). (a) Steep frequency modulated; (b) downward frequency modulated; (c) broadband noise burst; (d) broadband click train; (e) constant frequency.

eated the range of a particular call [(max −min)/signal length]. Standard deviation showed the square root of the call's variance (Kenney and Keeping, 1962). Next, files were subjected to four types of analysis: manual classification, automatic classification, classification and regression tree analysis (CART), and principal components analysis (PCA).

2. Manual classification algorithm

First, a subset of call spectrograms (approximately 25%) was manually inspected and classified into five categories based on the call's spectrographic contours (Fig. 2) and Kanwal *et al.*'s (1994) classification scheme: steep FM (StFM), downward FM (DFM), broadband noise burst (BNB), broadband clicks train (BCT), and constant frequency (CF). Next, each manually classified call was plotted on a 3D graph (Fig. 3) whose axes consisted of different combinations of call features. Upper and lower boundaries were recorded for features that showed tight clustering of a particular call. For example, Fig. 3 shows that the boundaries of skew (time) for StFMs are −0.3 and −0.45. Different combinations of features were plotted until each call type could be distinguished by unique feature boundaries (Table II).

3. Automatic classification

Second, all calls were classified automatically using the features and feature boundaries derived from the manual classification algorithm. Calls that were clipped were eliminated from the automatic classification. Features that did not provide unique information about a particular class, and thus not included in Table II, were removed from the automatic classification algorithm.

4. Classification and regression tree analysis (CART)

CART analysis (Brieman *et al.*, 1984) was used to verify the best features and boundaries chosen from 3D graph analysis. CART is a type of decision tree analysis which splits all of the dependent variables (call classes) using the optimal predictor variables (call features). The CART algorithm determines thresholds for the predictor variables, and

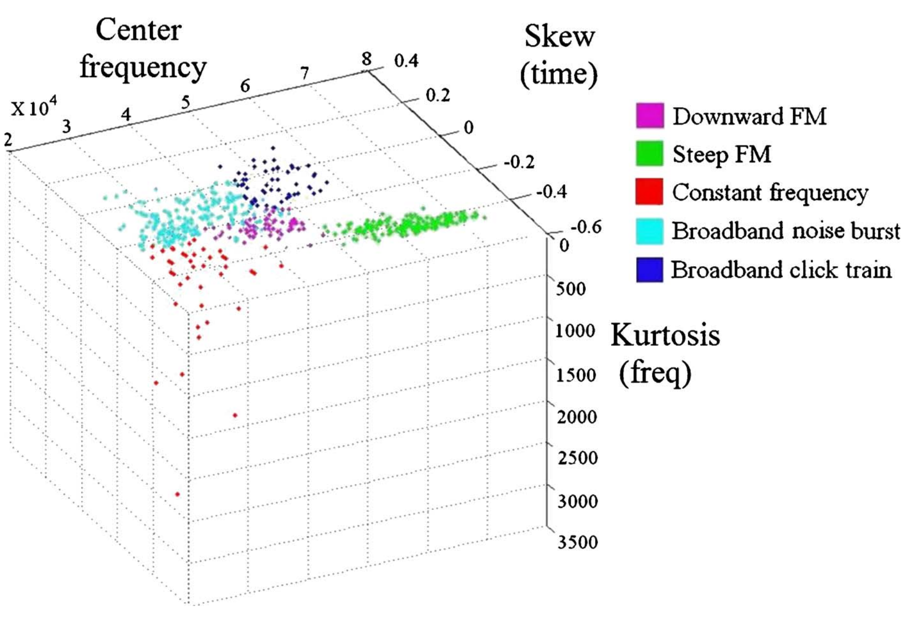

FIG. 3. Example of 3D plot used to determine the best feature set and feature boundaries for automatic classification. Features and feature boundaries that displayed clustering of individual classes were used in the automatic classification algorithm.

TABLE II. Manual classification parameters. A subset of call spectrograms (approximately 25%) was manually inspected and classified into five categories based on the call's spectrographic contours. Next, each classified call was plotted on a 3D graph (Fig. 3) whose axes consisted of different combinations of call features. Lower and upper boundaries were recorded for features that showed tight clustering of a particular call.

Class	Feature	Lower boundary	Upper boundary
Steep frequency modulated	Center frequency	50 kHz	75 kHz
	Kurtosis (freq)	N/A	100
	Skew (time)	−0.45	−0.3
Downward frequency modulated	Center frequency	35 kHz	50 kHz
	Kurtosis (freq)	N/A	100
	Skew (time)	−0.4	−0.15
	Duration	N/A	60 ms
Broadband click train	Center frequency	45 kHz	60 kHz
	Kurtosis (freq)	N/A	100
	Skew (time)	−0.15	0.15
Broadband noise burst	Kurtosis (freq)	N/A	250
	Skew (time)	−0.2	0.1
	Std (time)	N/A	0.03
Constant frequency	Center frequency	30 kHz	45 kHz
	Kurtosis (freq)	250	N/A
	Skew (time)	−0.3	−0.1

the branches are based on whether or not the values for the dependent variable are greater or less than these thresholds. The splitting continues until it reaches a leaf which corresponds to a labeled predictor variable. In this case, the *parent node* is the call feature which best splits the call classes into two groups. *Child nodes* continue to split the remaining call classes using the remaining robust call features until the CART algorithm terminates. The terminal nodes are typically mutually exclusive subgroups of the calls (Davuluri *et al.*, 2000; Bevilacqua *et al.*, 2003; Lemon *et al.*, 2003).

In this study, all 15 features were originally included in the CART analysis. The CART algorithm decided which of the 15 features provided unique information about a particular call type and then discarded the unused features in the final tree. Since this procedure is very similar to the manual classification algorithm in approach, CART results and manual classification results were compared, and K-fold cross validation was used to test the CART algorithm. In k-fold cross-validation ($k=10$), the data were divided into ten subsets of approximately equal size. The tree was trained ten times, each time leaving out one of the subsets from training, and using only the omitted subset to compute the accuracy of CART (Brieman *et al.*, 1984; Witten and Frank, 2005).

TABLE III. Percentage of calls. Totals were derived using the automatic classification algorithm. Calls that were clipped were removed from the dataset.

Class	Number of calls	Percentage
Broadband noise burst	2451	62.45%
Steep FM	655	16.69%
Downward FM	448	11.41%
Broadband click train	216	5.50%
Constant frequency	155	3.95%
Total	**3925**	**100.0**%

5. Principal components analysis (PCA)

Once the CART accuracy was computed, a custom-designed MATLAB program performed PCA to verify the number of features retained. PCA generates a set of uncorrelated variables (i.e., principal components) by computing linear combinations of the original variables (features). The first principal component is the linear combination of features that explains the most variance in the data. The last principal component is the remaining combination of features that explains the least variance in the data. Therefore, PCA allows one to verify if combinations of each of the features retained account for all of the variance (Wold *et al.*, 1987). Accuracy as a function of the number of principal components was also computed using CART and tenfold cross validation by first projecting the original feature vectors onto the principal components vectors (i.e., calculating their inner product).

III. RESULTS

A total of 3925 calls was recorded from five male bats (Table III). The group recordings were included in the total number of calls because they did not display any further variation.

A. Description of calls

Five features were derived from the manual classification scheme and included in the automatic classification

TABLE IV. Summary of calls from male *Myotis lucifugus* using the features and feature boundaries from the automatic classification algorithm. Values are means ± standard deviation.

Class	Center freq (kHz)	Duration (ms)	Kurtosis (freq)	Skew (time)	Std deviation (time)
Steep FM	60.0 ±0.24	39.10 ±1.20	34.81 ±0.98	−0.38 $\pm 1.6\times10^{-3}$	0.23 $\pm 7.2\times10^{-4}$
Downward FM	42.6 ±0.19	43.59 ±0.46	49.67 ±1.01	−0.27 $\pm 2.7\times10^{-3}$	0.24 $\pm 9.4\times10^{-4}$
Broadband noise burst	33.2 ±0.14	160.10 ±2.68	72.95 ±0.83	−0.11 $\pm 1.3\times10^{-3}$	0.26 $\pm 4.2\times10^{-4}$
Broadband click train	49.7 ±0.26	118.91 ±7.93	40.91 ±1.82	−0.06 $\pm 4.2\times10^{-3}$	0.26 $\pm 2.2\times10^{-3}$
Constant frequency	36.1 ±0.30	64.61 ±2.50	472.8 ±34.75	−0.20 $\pm 4.6\times10^{-3}$	0.24 $\pm 1.4\times10^{-3}$

TABLE V. Accuracy of automatic classification. A subset of manually classified calls was classified using the automatic classification algorithm and results were later compared to CART and PCA.

Class	Automatic/Manual classification (# of calls)	Percent accurate
Steep FM	162/168	96.43
Downward FM	53/68	77.94
Broadband click train	97/114	85.09
Broadband noise burst	345/403	85.61
Constant frequency	33/38	86.84
Total	**690/791**	**87.23**

scheme: center frequency, duration, kurtosis (frequency), skew (time), and standard deviation (time). Means and standard deviations of calls were calculated for the five features (Table IV). Center frequencies of each class were in the ultrasonic range (33.2–60.0 kHz); however, their lowest frequencies were sometimes in the human audible range (Fig. 2). Total durations for communication calls were between 40–120 ms, much longer than the 1–10-ms range for the species' echolocation calls (Fenton, 1984).

The following are the mean values for call features (Table IV). Two types of FM signals were found. Steep FM (StFM) signals had a center frequency of ~60 kHz and duration of ~40 ms. Downward FM (DFM) signals had a center frequency of 43 kHz and duration of 44 ms. Two types of broadband signals were found. The broadband noise bursts (BNB) were the most common (Table III) with a center frequency of 33 kHz and a duration of 160 ms. BNBs are often associated with *Myotis lucifugus* agonistic calls and are similar to the *squawks* and *buzzes* found in Barclay *et al.* (1979) study. The broadband click trains (BCT) were a series of clicks with a center frequency of 50 kHz. The duration of the trains was ~119 ms long. Finally, constant frequency (CF) signals were found with a center frequency of ~36 kHz and duration of ~65 ms.

B. Automatic classification accuracy

A subset of approximately 800 manually classified calls was used to determine the accuracy of the automatic classification scheme (Table V). First, the calls were divided into different classes using visual observation. Then, each class was processed using the automatic classification scheme. The automatic classification scheme had approximately 87% accuracy overall. The confusion matrix (Table VI) displays the number and call class of inaccurately classified calls.

TABLE VI. Confusion matrix. The call classes that were misclassified are shown.

Class	Steep FM	Downward FM	Broad-band click train	Broad-band noise burst	Constant frequency
Steep FM	162	1	2	3	0
Downward FM	1	53	4	10	0
Broadband click train	0	7	97	10	0
Broadband noise burst	3	14	29	345	12
Constant frequency	0	1	0	4	33

C. CART and PCA

The CART algorithm, as implemented in MATLAB, was used to confirm the accuracy of best features and boundaries included in the automatic classification algorithm. The features and feature boundaries chosen by CART were slightly different from those chosen in manual classification (Fig. 4), including minimum frequency, center frequency, center time, kurtosis (frequency), kurtosis (time), skew (time), spread (frequency), and maximum time in its feature set. Using tenfold cross validation, CART results showed an average accuracy of 89.71% (±3.37). Figure 5 shows CART analysis using the five features derived from manual classification alone [i.e., center frequency, duration, kurtosis (frequency), skew (time), and standard deviation (time)]. An average accuracy of 86.57% (±3.23) was calculated using tenfold cross validation.

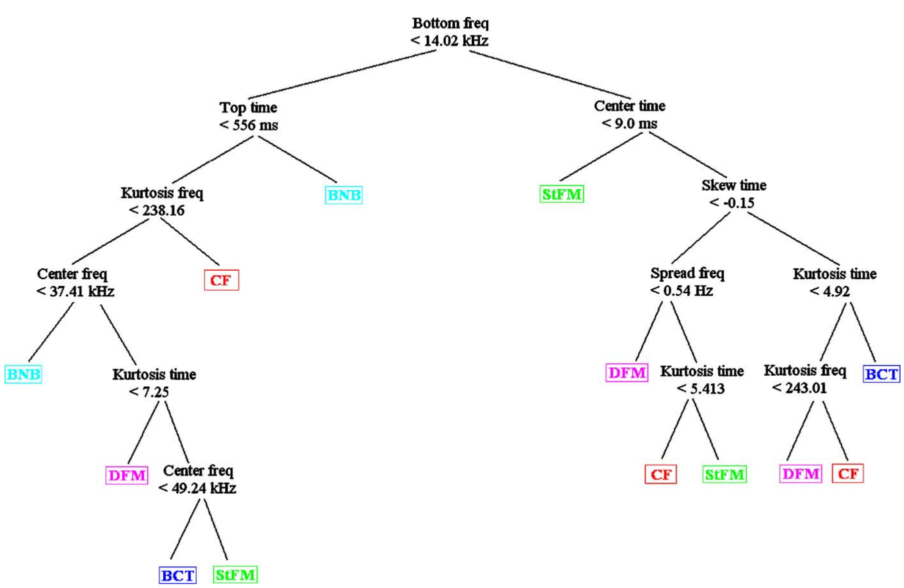

FIG. 4. Pruned tree generated by CART using all 15 features.

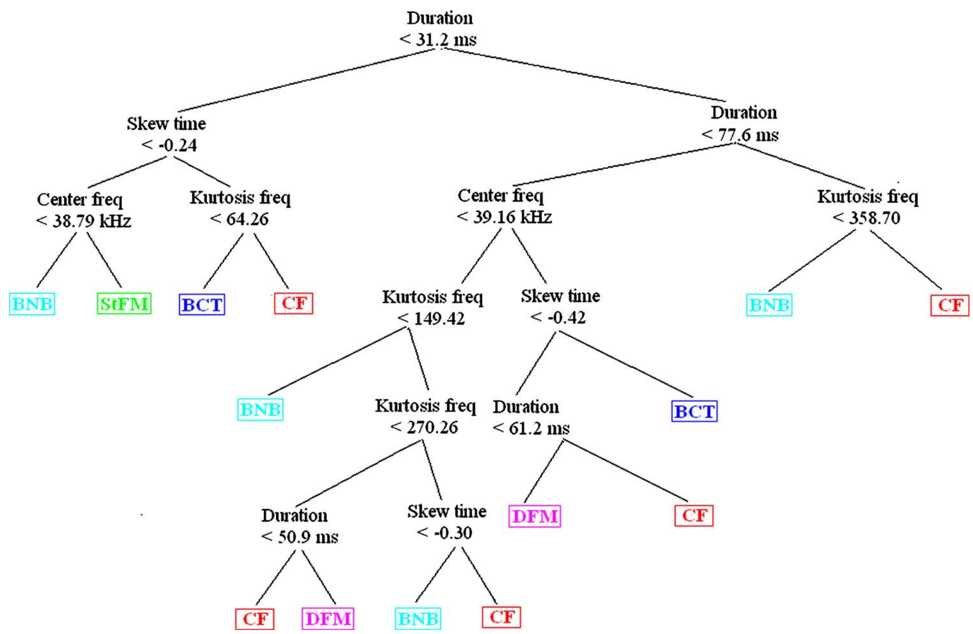

FIG. 5. Pruned tree generated by CART using the five features derived from manual classification.

PCA was then used to analyze the amount of variance explained by all 15 features (Fig. 6). PCA showed that six linear combinations (i.e., principal components) of all 15 features were most useful in explaining the data. The original feature vectors were then projected (inner product) onto the principal components vectors, and accuracy as a function of the number of principal components was assessed using CART and tenfold cross validation (Fig. 7). Accuracy remained above approximately 80% using six or more principal components.

IV. DISCUSSION

The communication repertoire of *Myotis lucifugus* was previously studied by Fenton and colleagues in the late 1970's. Since then, much progress has been made in sound classification technology. For example, programs such as MATLAB and WEKA (Witten and Frank, 2005) can be used to automatically classify large datasets in little time. Automatic classification parameters can also be easily manipulated to

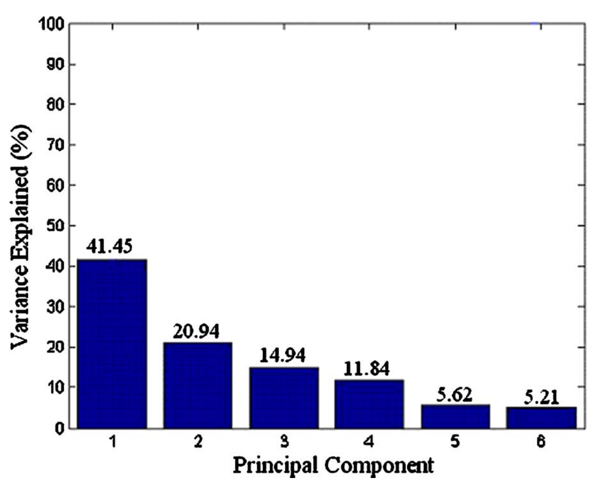

FIG. 6. Principal components analysis of all 15 features, showing the amount of variance in the data that is explained by each principal component.

classify other calls in the species' repertoire by adding new features and feature boundaries when needed (e.g., interpulse interval duration or repetition rate). Such programs reduce subjectivity and therefore allow replicable results across researchers. In addition to newer technology, there is also a new understanding of the importance of studying bat communication calls. Several studies (Fenton, 1985; Kanwal *et al.*, 1994; Wilkinson and Bohman, 1998) show that bat communication calls are more spectrographically complex than echolocation calls, and thus may require more complex auditory processing. Although this study was limited to only male *Myotis lucifugus* due to permit restrictions, it nonetheless reveals the diversity of the species' communication calls.

Five primary communication call types were found: downward FM, steep FM, broadband noise burst, broadband click train, and constant frequency. As shown in Table VI, there was some overlap in the classification of call types because different calls may share similar acoustic features. For example, the DFM calls were sometimes misclassified as BNBs. This is understandable since DFM calls do have components similar to BNBs (e.g., broad bandwidth) (Fig. 2). The machine is therefore unable to "ignore" features which may not aid in defining its overall shape in a small number of cases. Two other class variations were also identified, upward FM (UFM) and brief broadband noise burst (bBNB). However, UFM and bBNB signals occurred infrequently and were thus removed from the dataset. The UFM signals were similar to the copulation calls found by Barclay *et al.* (1979), and would presumably occur more frequently in the presence of females. The bBNB signals were similar to the audible buzzes included in Barclay *et al.*'s (1979) study. Many other calls recorded by Barclay *et al.* are also expected to occur only in the presence of females, such as in mother-young interactions or during pair bonding. For example, the *double-note* and *isolation calls* (Table I) were recorded within a nursery colony, as juveniles sought communication with their mothers. *Copulation* calls were emitted by males during copulation or attempted copulation (Barclay *et al.*, 1979).

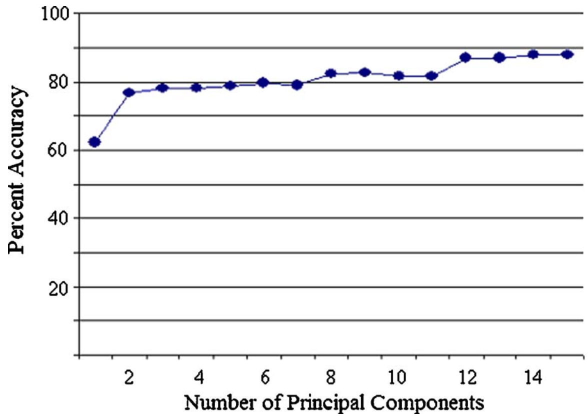

FIG. 7. Accuracy as a function of the number of principal components computed using CART and tenfold cross validation.

In terms of classification schemes, CART is robust and functions by continually splitting large groups into two subgroups based on features until the terminal groups are mutually exclusive. In this study, CART started with the entire bat call repertoire and all 15 features, then split it into individual classes, which served as the terminal groups. CART performed as well as full PCA (accuracy ~89% for both), suggesting that eight features used by CART (Fig. 4) were completely sufficient for classification. When five features were used in manual classification (Table II), there was approximately 87% accuracy, suggesting that five features can classify nearly all of the data. When only these five features were included in CART analysis, the accuracy was nearly identical (~87%). The five features had a higher accuracy than PCA with five (Fig. 7), suggesting that this specific set of features captures essentially all of the information useful for classification.

As is the case in most animal communication studies, the main goal is to determine the behavioral relevance of different call types. Follow-up studies will be conducted to determine the behavior that is associated with each class identified in this study.

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