# Bird flight call discrimination using machine learning

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1:30

**4pAB2. Quantitative analysis of dolphin sounds.** Peter L. Tyack (Dept. of Biol., Woods Hole Oceanogr. Inst., Woods Hole, MA 02543)

Most analyses of acoustic communication in animals lump sounds into qualitative categories. These are usually based upon aural impressions for human listeners or visual inspection of spectrograms. Quantitative analysis of acoustic features from beluga whale sounds raise serious questions about how discrete and robust the traditional categories of beluga calls are. Other categories, such as the contour of a dolphin whistle, use features that need not relate directly to absolute measure of time and frequency. Studies of vocal development and vocal imitation often benefit from a quantitative measure of similarity between sounds and putative models. Several different methods are compared to analyze whistle contours, including multivariate analysis of time-frequency features, dynamic time warping, and a signal compression approach. Ultimately, all such techniques need to be validated by studies of how each species perceives its own signals.

1:55

**4pAB3. Comparison of the whistle structure of six species of dolphin.** William E. Evans (Texas Inst. of Oceanogr., Texas A&M Univ., P.O. Box 1675, Galveston, TX 77553), Wang Ding (Inst. of Hydrobiol., Chinese Acad. of Sci., People's Republic of China), and Bernd Würsig (Texas A&M Univ., Galveston, TX 77553)

Spectral and statistical analyses were used to compare the whistle structure of six species of dolphin; *Stenella longirostris, Stenella frontalis, Stenella attenuata, Lagenorhynchus obscurus, Tursiops truncatus,* and *Sotalia fluviatilis.* A consistent pattern existed in the various coefficients of variation calculated for the different species. In general, the frequency variables had the lowest coefficients of variation (cv). The values of cv for maximum frequency were usually the lowest. Compared to other species *Tursiops* had relatively large coefficients of variation of the frequency variables indicating that the frequencies of *Tursiops* whistles were more diverse. The other five species had similar frequency ranges which had higher upper frequencies than *Tursiops*. The results of discriminate analysis indicated that here were significant differences between the whistle structures of the different species, and that these differences were related to taxonomic relations, body size, and habitat. The magnitude of the differences in whistle structure correlated with taxonomic relationships of the various species studied. The pelagic species emitted whistles in a relatively higher frequency range and greater frequency modulation than the coastal or riverine species.

2:20

**4pAB4. Automatic detection and classification of nocturnal migrant bird calls.** Harold Mills (Cornell Lab. of Ornithol., 159 Sapsucker Woods Rd., Ithaca, NY 14850)

Computer software was developed to detect the nocturnal flight calls of nine species of migrating warblers in digitized field recordings, and to classify the calls by species. The calls are frequency-modulated tones in the 5- to 9-kHz frequency band, and between 50 and 100 ms in duration. Detection was accompanied by locating temporal peaks in call band energy. Some false detections of insect calls were prevented by rejecting certain types of peaks. Classification is approached by tracking the frequencies of the calls over time and classifying the frequency tracks with an artificial neural network.

## *Contributed Papers*

2:45

**4pAB5. Bird flight call discrimination using machine learning.** Andrew Taylor (Comp. Sci. and Eng., Univ. of NSW, Sydney 2052, Australia)

The development of a software system which can detect and identify the flight calls of migrating birds is reported. The system first produces a spectrogram using a DFT. Calls are detected in the spectrogram using an *ad hoc* combination of local peak-finding and a connectedness measure. Attributes are extracted both globally from the call and from a window moved incrementally through the call. Decision trees are then used to determine the bird species. These decision trees are induced from a training set using Quinlan's C4.5 system [J. R. Quinlan, C4.5: Programs for Machine Learning, Morgan Kauffman (1993)]. The system has been tested on a set of 138 nocturnal flight calls from nine species of birds [W. R. Evans, personal communication]. Some calls are faint, and interfering insect noise is present in others. Tenfold resampling was used to classify the calls unseen. Seventy-eight percent of calls were identified correctly, 4% incorrectly and 18% were placed in an "uncertain" category. Neural network-based classifiers are commonly used in this general domain and would likely produce similar accuracy, but use of symbolic machine learning offers two important advantages: Training time is linear in the number of examples and the resulting classifier is less opaque. Both significantly ease classifier construction.

3:00

**4pAB6. Vocal learning in Budgerigars (*Melopsittacus undulatus*) using food reward.** Kazuchika Manabe and Robert J. Dooling (Psych. Dept., Univ. of Maryland, College Park, MD 20742)

Budgerigars (parakeets) are small, highly social, Australian parrots capable of vocal learning throughout adulthood. These birds readily produce short (200 ms), whistled, frequency-modulated contact calls when separated from one another. In this experiment, birds were trained twice daily in 10 min sessions to produce or modify contact-call-like vocalizations using food reward. Calls were analyzed in real time using serial FFTs and each production was compared to a digitally stored "template." Call productions which exceeded a predetermined criterion of similarity were rewarded, while those below criterion were not. Results show that budgerigars can learn to modify the intensity and spectro-temporal pattern of their species-typical calls within several days. Aside from human language, bird vocalizations have provided the only other clear example of learning in the acquisition and maintenance of a vocal repertoire. While song learning in birds has led to a number of important insights into the neurobiology of learning, such learning typically occurs over a time frame of months to years. The present results demonstrating call learning over a period of several days more closely parallel the time course of other more common forms of vertebrate learning. [Work supported by NIH Grants DC00198 and MH00982.]