AUTOMATIC SIGNAL DETECTION IN NOISE USING ENTROPY

Christine Erbe
JASCO Applied Sciences Australia Pty Ltd, Brisbane Technology Park, PO Box 4037, Eight Mile Plains, QLD 4113 Australia, Christine.Erbe@jasco.com

1. INTRODUCTION

Automatic detection of signals in noise is a common problem in many areas of acoustics. In the field of passive acoustic monitoring of marine mammals, the signals to be detected are vocalizations. The noise originates from natural (e.g. wind, waves, rain) and man-made sources (e.g. shipping, construction, seismic surveys). Signal characteristics vary broadly: frequency ranges from a few Hz to 200 kHz, duration from milliseconds to seconds to hours. Noise characteristics vary by similar orders of magnitude. While specific automatic detectors have been designed to successfully find specific calls in specific environments, the challenge is to find a large variety of calls in a large variety of noise. An exploitable difference between calls and noise is that most noise is a result of stochastic processes (wind, waves, rain, cavitating propellers and seismic airguns generate gas bubbles underwater of varying size and resonance frequency), while many animal signals are a result of deterministic processes (vibrating strings and cavities of predetermined and fixed size). As a result, Shannon entropy (also called information entropy) can be expected to differ between signal and noise. Shannon entropy quantifies the information contained in a data set. The concept was introduced by Claude E Shannon in his 1948 paper "A mathematical theory of communication" (Shannon 1948). The current article investigates whether entropy makes a "good" detector for animal calls in underwater ambient noise.

2. METHOD

Underwater acoustic recordings from the Arctic were used to test and compare automatic signal detectors. The species that were present in the recordings and their common call types are listed in Table 1.

Table 1. Selected arctic species and their call types

Species	Call Types
Bowhead whale	FM tones, song, pulsive calls
Gray whale	FM tones, moans, pulsive calls
Beluga whale	Whistles, pulsed calls, clicks
Walrus	Knocks, bell sounds, grunts
Bearded seal	FM signals
Ringed seal	Barks, yelps

Three different automatic detectors were tested and compared: 1) a broadband peak energy detector, 2) peak energy detection in a set of bandpass filters, and 3) a peak entropy detector. Each detector computed a statistical quantity s(t), a mean $\bar{s}$ and a standard deviation σ. For a given threshold γ, a signal was deemed present if $s(t) > \bar{s} + \gamma\sigma$. Two different windows were applied to the time series, an "averaging" window of 1 min length, over which the mean and standard deviation were computed, and a "detection" window of 100 ms length, over which the instantaneous statistic was computed for comparison to the mean. The detection window immediately preceded the averaging window and both were moved through the time series sample by sample.

Given a recorded pressure time series p(t), the broadband energy detector computed $p^2(t)$. The band-passed energy detector split the signal into multiple overlapping pass bands $p_f(t)$ before computing $p_f^2(t)$. This was done by Fourier transforming the time series over 100 ms long windows, and grouping the Fourier coefficients into octave bands covering the recorded bandwidth of 10 kHz. Moving the 100 ms window through the time series sample by sample yielded a time series of Fourier coefficients. Energy was computed in each band, and a signal was deemed present if the energy in any one band surpassed the mean by a preset threshold. A slightly different implementation of the band-passed energy detector and more detail about the entropy detector can be found in Erbe & King (2008).

The entropy detector also Fourier transformed the pressure time series over 100 ms windows and computed the power spectrum |P(f)|. The power spectrum was normalized so that the entropy did not depend on the absolute energy: $\sum P(f) = 1$. Shannon entropy was computed as $-\sum P(f) \cdot \log P(f)$. The 100 ms window was moved through the pressure time series sample by sample, yielding a time series of entropy.

3. RESULTS

Figure 1 shows an example of two marine mammal calls that were detected by the entropy detector. A spectrogram is plotted with entropy (not to scale) overlain as a thin black line.

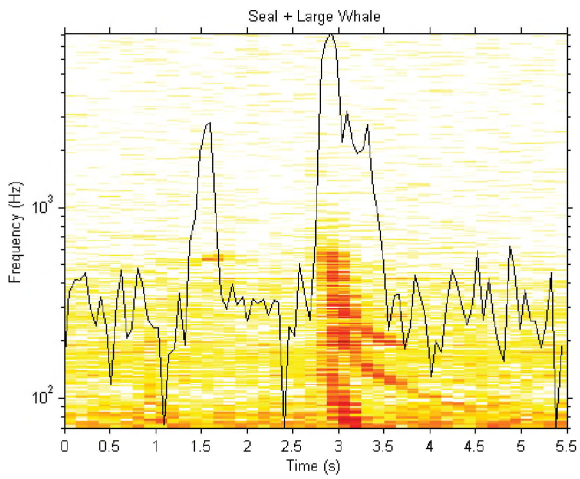

Fig. 1. Spectrogram of a 5.5 s recording showing a faint pinniped call and an FM call of a baleen whale. Entropy is shown as a black line unscaled.

To compare the three detectors, receiver-operating-characteristics (ROC) were computed. An automatic detection task is a binary classification problem with four possible outcomes (hit, miss, false alarm, correct rejection). With P_{FA} as the probability of false alarm and P_{CD} as the probability of correct detection (determined by comparing automatic detections to manual detections), ROC curves are computed by varying the threshold γ. As γ is increased, the number of false alarms decreases at the cost of the number of correct detections, because the number of misses increases. An ideal detector would have a probability of false alarm of 0 and a probability of correct detection of 1. The "best" detector in a comparison of detectors is the one approaching (0|1) most closely, in this case the entropy detector.

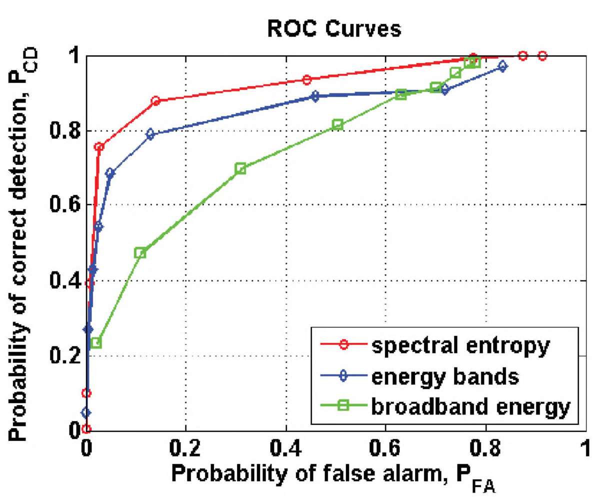

Fig. 2. Comparison of the performances of the three detectors using receiver-operating characteristics (ROC). Each data point corresponds to a set threshold γ.

4. DISCUSSION

All of the animals in Table 1 made calls with tonal components (whistles or frequency modulated (FM) tones). Shannon entropy was significantly higher for these than for ambient noise and these calls were therefore detected very well. The broadband clicks of animals were not detected well by the entropy detector.

Ambient noise can have tonal components (e.g. ice noise and shipping), but these did not cause a significant number of false alarms in the tested data set. The largest number of false alarms was due to ringing bubbles. These were believed to be biological in origin, but the animal making them could not be identified.

For calls of constant frequencies plus harmonics, the band-passed energy detector worked well if the condition was set that energy had to be detected simultaneously in more than two and less than four frequency bands.

Comparing the instantaneous value of the statistic to the median instead of the mean improved performance as ambient noise can have large yet brief (transient) outliers which affect the mean but not the median.

Choosing the window lengths depends on the ultimate goal. If individual calls need to be counted, then the detection window should be short and ideally of the length of typical calls. If a mere species present/absent outcome is desired, window lengths are not critical and can be longer, grabbing more than one call at a time. The length and placement of the averaging window can be made adaptive. E.g. if a group of vocalizing belugas is encountered, the averaging window would ideally remain fixed in time before the vocalizations start rather than moving into the animal sounds and averaging them into ambient noise. Once the vocalizations have stopped, the averaging window can be jumped forward to the end of the vocalizations and continue to move through the data.

Altogether, the entropy detector worked well to find sounds of the target species in their arctic acoustic environment. The entropy detector should be considered a first step in a series of automatic analysis tools. As a second step, all detected signals need to be classified to species, which was not attempted in the current study.

REFERENCES

Erbe, C., and A.R. King (2008). Automatic detection of marine mammals using information entropy. J. Acoust. Soc. Am. 124, 2833-2840.

Shannon, C.E. (1948). A mathematical theory of communication. Bell Syst. Tech. J. 27, 379-423.