Cetacean Density Estimation from Novel Acoustic Datasets by Acoustic Propagation Modeling

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LONG-TERM GOALS

This project's long-term goal is the application and refinement of population density estimation methods based on detections of marine mammal vocalizations combined with propagation modeling. The density estimation method is applied to a novel acoustic data set, collected by a single hydrophone, to estimate the population density of false killer whales (*Pseudorca crassidens*) off of the Kona coast of the Island of Hawai'i.

OBJECTIVES

The objectives of this research are to apply existing methods for cetacean density estimation from passive acoustic recordings made by single sensors, to novel data sets and cetacean species, as well as refine the existing techniques in order to develop a more generalized model that can be applied to many species in different environmental scenarios. The chosen study area is well suited to the development of techniques that incorporate accurate modeling of sound propagation due to the complexities of its environment. Moreover, the target species chosen for this work, the false killer whale, suffers from interaction with the fisheries industry and its population has been reported to have declined in the past 20 years. Studies of abundance estimate of false killer whales in Hawai'i through mark recapture methods will provide comparable results to the ones obtained by this project. The ultimate goal is to contribute to the development of population density estimation methodologies that will be readily available to those involved in marine mammal research, monitoring, and mitigation.

APPROACH

Approach to Estimating Population Density

The methodology employed in this study to estimate the population density of false killer whales off Kona, Hawai'i, is based on the works of Zimmer *et al.* (2008), Marques *et al.* (2009), and Küsel *et al.* (2011). The density estimator formula given by Marques *et al.* (2009) is applied here for the case of one sensor, yielding the following formulation:

$$\widehat{\boldsymbol{D}} = \frac{\boldsymbol{n_c(1-\hat{c})}}{\boldsymbol{\pi w^2 \hat{P} T \hat{r}}}. \qquad (1)$$

In equation (1), n_c corresponds to the total number of auto-detected clicks in some time period T. The parameter $\hat{c}$ accounts for the rate of false positive detections. The maximum distance, beyond which we don't expect to detect any calls, is given by w. The cue production rate is dependent on available studies and information on animal acoustic behavior. More specifically, a cue is defined in this study as an echolocation click, which has been used as a preferred cue type for density estimation studies from single-sensor data sets. Finally, the most important parameter in equation (1) for our methodology is the average probability of detection, $\hat{P}$. Because detection distances are not realizable from single-sensor data, the average detection probability is estimated in a Monte Carlo simulation using the sonar equation along with transmission loss calculations to estimate the received signal-to-noise ratio (SNR) of tens of thousands of click realizations. In the Monte Carlo simulation, clicks are randomly distributed in 3D space inside a circular area of radius w around the sensor location. Simulated SNRs are then compared to those measured from the data set in a realization of the detection function, which gives a probability that the simulated SNR would be detected. The average probability of detection from all Monte Carlo realizations gives $\hat{P}$ to be used in equation (1). Finally, by combining the total number of detected clicks, the proportion of false positive detections, the total time of data analyzed, and the average click production rate to the average probability of detection we arrive at an estimate of the population. The density estimation methodology is illustrated in Fig. 1.

Potential Problems in the Estimation of Detection Probability

Continuous-wave (CW) analysis, that is, single-frequency analysis, is inherent to basic forms of the passive sonar equation. In the analysis detailed above it is typical to calculate transmission loss only at the center frequency of the click. This is then used to estimate received SNRs. However, many echolocation clicks can be very broadband in nature, with 10-dB bandwidths of 20 to 40 kHz or more. Recently Ainslie (2013) showed by means of analytical formulations that considering transmission loss by using CW analysis with the click's center frequency while disregarding its bandwidth introduces bias to detection probabilities and hence to population density estimates. He further suggested using a broadband correction factor in the passive sonar equation to avoid errors in estimates caused by huge call bandwidths.

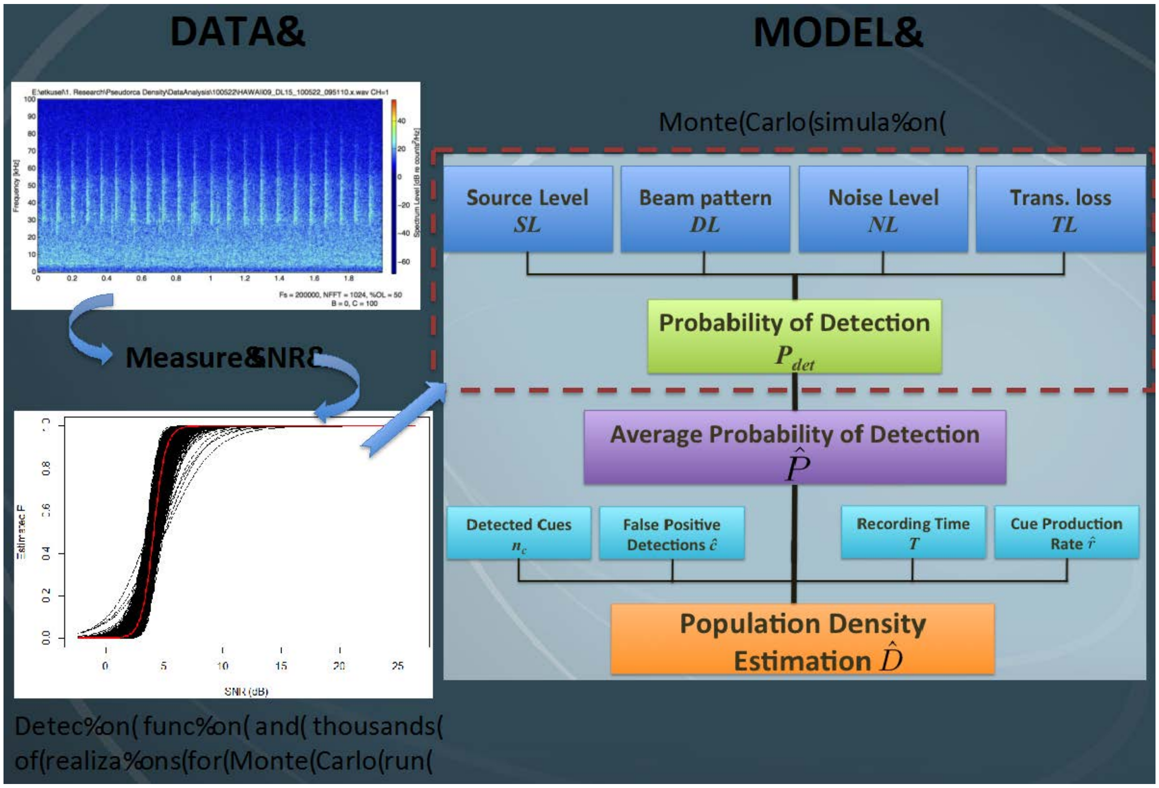

Figure 1. Summary of single-sensor population density estimation methodology.

In view of the potential issue described above, we examine the methodology that has been used to estimate detection probabilities of highly broadband clicks recorded by single instruments. Using simple modeling experiments based on synthetic and real data sets that have highly broadband signals, we quantify the bias in the sonar equation estimates of detection probability and its effect on density estimates. Furthermore, we discuss the usage of transmission loss as an appropriate measure for calculating the SNR of received clicks, as well as the usage of complex propagation models that require, most often nonexistent, detailed environmental information. Lastly we also look into the effects of including multipath clicks in density estimates.

Population Density Estimation of False Killer Whales off Kona, Hawai'i

A test case using a real data set containing highly broadband false killer whale (*Pseudorca crassidens*) clicks recorded off the Kona coast of Hawai'i was used to further investigate the single-sensor density estimation methodology. In this case, whale acoustic and diving behaviors were also incorporated into the model. From literature information on the target species' diving behavior when emitting sounds, a 3D random distribution of simulated animals was created (Fig. 2), taking into account their orientations with respect to the hydrophone. The simulated animals are placed inside a circle in which the center is the hydrophone location and the radius corresponds to the maximum estimated detection distance for false killer whale clicks in the local environment, which, for simulation purposes, is taken to be 10 km. Source level is taken as a distribution based on minimum and maximum on-axis values reported in the literature (Madsen *et al*., 2004). Information on directionality loss due to the animal's beam pattern is also taken from the literature (Au *et al*., 1995). Ambient noise levels were measured from the acoustic data set. Transmission loss is calculated here as has been done before (Küsel *et al*., 2011), that is, using an acoustic propagation model, and also by calculating arrival times and amplitudes and convolving with a false killer whale source click, as is described above in creating a synthetic data set. Information on source level, directionality loss, ambient noise and transmission loss is then combined in the sonar equation to estimate SNRs of thousands of click realizations. The remainder of the analysis follows that described above in the section *Approach to Estimating Population Density*.

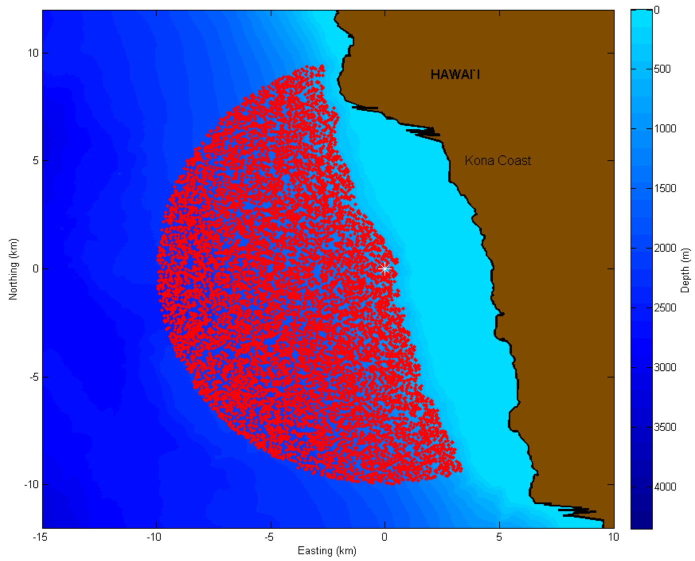

Figure 2. Kona Coast of Hawai'i showing location of HARP deployment (white dot in the center of semi-circle) and random distribution of 10,000 simulated whale locations (red dots) around the hydrophone where bathymetry is deep enough for them for perform foraging dives and hence produce echolocation clicks.

WORK COMPLETED

The work completed in 2014 includes, 1) Estimation of false positive detections from the Hawai'i data set, 2) Design and execution of modeling experiments to understand the effect of modeling broadband calls by using its center frequency on the estimation of detection probability.

Outstanding actions for this project include, 1) Finishing the density estimation analysis of the Hawai'i data set containing false killer whale echolocation clicks, in view of the results from the modeling experiments. This entails, running Monte Carlo simulations for the estimation of the average probability of detection ($\hat{P}$ in Eq. (1)), and estimating density of false killer whales for the period of the data set being used. The probability of detection estimation will be performed by using the clicks center frequency, and also by taking the full bandwidth into consideration. Density estimates based on these approaches will be compared.

1) Estimation of false positive detections from the Hawai'i data set

The proportion of false positive detections was estimated by manually checking every 30th auto-detection made through the software *Ishmael* against the data set. During the manual check, auto-detections of reverberated clicks, which often spanned several detections, were considered as false positives. Clicks that were observed to be part of a buzz sequence were also treated as false positives.

Finally, clicks that looked clipped, that is, that were observed across the entire bandwidth in the spectrogram, were also considered false positives.

2) Design and execution of modeling experiments for population density estimation

A series of modeling experiments were devised with increasing degrees of complexity to examine the effect of high frequency and highly broadband calls on density estimates. All experiments were based on the single-sensor density estimation formula (Eq. (1)). First, a simple experiment was conducted where 1000 points were randomly distributed inside circular areas of radius 10 and 20 km. Different detection circles were assumed inside both circular areas, and were defined by the radius where transmission loss equaled noise levels. The synthetic data was created using a single frequency and the estimation of detection probabilities was performed by using a higher frequency than the data. The objective was to show that by using a different frequency in the calculations than that of the original data, the detection circle would change and density estimates would be consequently under or overestimated. Usually the parameter w in Eq. (1) can be taken as something larger than the expected detection range. By taking the large radius of 20 km, increasing radius of detection circles are investigated through 20 different realizations of synthetic data and the effect on the variance of density estimates.

A more complex synthetic data set was then created by calculating arrival amplitudes for each of the 100 points randomly distributed inside an 8 km circular area. Arrival amplitudes were convolved with a synthetic and highly broadband signal. Realistic ambient noise data was also added to the received signals. Analysis of this synthetic data set and its modeling was performed following four distinct cases. Case 1 considered a 5 kHz bandwidth centered on the signal's center frequency (35 kHz) and disregarded all multipath arrivals. Case 2 considered the full bandwidth of the signal but still disregarded multipath arrivals. Case 3 considered both the full bandwidth and the multipath arrivals. Finally, case 4 considered the 5 kHz narrow band around the center frequency and multipath arrivals. By knowing the exact number of points, or animals, we could investigate how well the density estimator performed and the effect of choosing different frequency bands for the detection and modeling components of the analysis.

RESULTS

1) Results on the estimation of false positive detections from the Hawai'i data set

Checking every 30^{th} auto-detection from the total of 260,973 clicks detected in 2.5-hour period of continuous data being analyzed, yielded a rate of false positive detections equivalent to 30.84%. This corresponds to parameter $\hat{c}$ in Eq. (1).

2) Results on the modeling experiments

For the simple modeling experiment, the expected probability of detection is given by the ratio of the detection area by the total area. For example, considering a 5 km detection radius inside of a 20 km circle, results in an expected detection probability of 0.0625. The total number of animals divided by the total area considered gives the expected density. So, for the case of 1000 animals inside the 20 km circle the expected density is 0.7958. We observed from the results that when the same data frequency was used in the calculations, expected and simulated probability of detection and density estimate agreed well. On the other hand, by using a higher frequency in the Monte Carlo simulation, the probability of detection is underestimated and consequently the density estimate is overestimated. These results can be better visualized through Figs. 3 and 4. The synthetic data used in this simple example is shown in Fig. 3 along with the detection range of 5 km at 20 kHz and the corresponding detection circle for a frequency of 40 kHz. By increasing the frequency, the detection radius and consequently the number of animals inside the circle decreases.

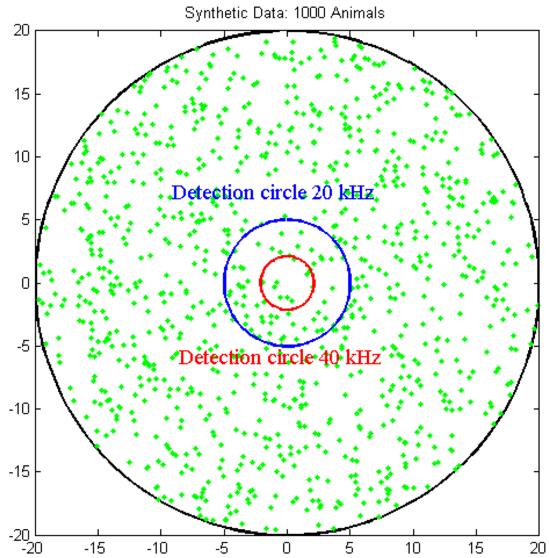

Figure 3. Synthetic data created for simple modeling experiment on density estimation with 1000 animals uniformly distributed inside a circular area of radius 20 km. Detection circle of 5 km at 20 kHz is shown as the blue curve. The red circle represents the corresponding detection circle at 40 kHz.

Figure 4 assumes a source level of 155 dB re 1 μPA^2/Hz. Source level minus transmission loss for sources of frequency 20 and 40 kHz are then plotted against range. Corresponding noise levels at the two frequencies considered are also plotted (straight blue and red lines) and the distance where a detection occurs is indicated by the dashed black vertical lines. As the frequency increases, the detection range decreases. For the case of 1000 animals inside an area of radius 20 km and detection circle of 5 km at 20 kHz, by estimating density using a 40 kHz frequency, instead of approximately 0.8 animals/km^2, the calculated density is approximately 3.5 animals/km^2.

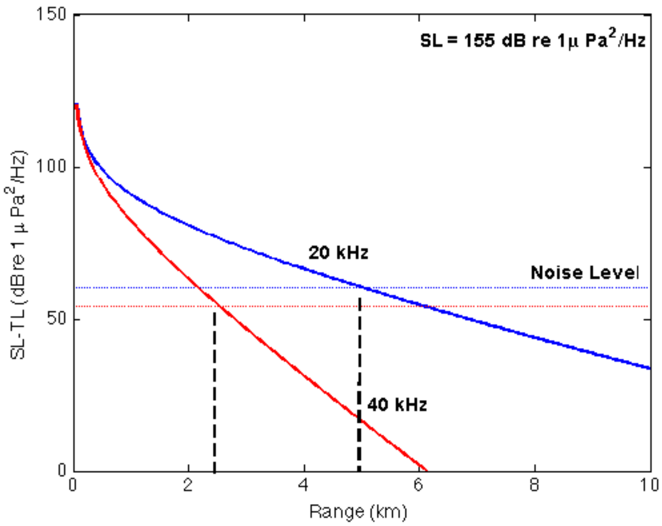

Figure 4. Source level minus transmission loss curves assuming a source level of 155 dB re 1 µPA^2/Hz at 20 (blue curve) and 40 kHz (red curve). Detection distances are indicated by black dashed lines.

Finally, taking the 20 km radial area, increasing values of detection circle were assumed (2, 5, 10, 15 and 18 km) and up to 20 different realizations of synthetic data were assumed. For each data realization a density estimate was calculated and the variance of all estimates was taken. It was observed that the closer the detection range was from the actual range where animals were considered the better the density estimate with lower variance given all realizations of the synthetic data. Such result suggests that the parameter w in Eq. (1) should not be arbitrarily big, but within a short margin of the expected detection distance.

The analysis process on the complex synthetic data set was the same as would be done with measured data. Results of the density estimation calculations, shown in Table 1, indicate good agreement between the expected density estimate and the calculated estimate using a narrow bandwidth (5 kHz) around the center frequency and no multipath detections. By considering the full bandwidth of the synthetic signal (10-60 kHz) in case 2 caused the density estimate to increase. Case 3, which considered both full bandwidth and multiple arrivals, yielded a density estimate that was approximately double from that of case 2. A close look at transmission loss indicate that this parameter could be calculated using the simpler spherical spreading law plus high frequency attenuation for the purpose of estimating population density. Moreover, each detected click corresponds to one arrival and transmission loss is the sum of all the arrivals. Therefore, another alternative would be to use a ray model calculation of arrival times and amplitudes for the specific environment and convolve it with a source "click" in the same manner as the synthetic data set was created. That way, the full spectrum of the call would be taken into account when estimating density, and multipath could also be taken into account. It is also worth noting that multiple arrivals can be taken into account in the calculation of $\hat{P}$.

From the simple modeling examples it is clear that the $\hat{P}$ estimate should be consistent with detected clicks, or what is being measured. However, real measured data present a series of complexities that also need to be taken into account such as no ground truth for comparison, clicks are also distributed in depth and usually have a narrow beam pattern that needs to be taken into account, for some environments reverberation could be present causing clicks to be non-distinctive and finally the click production rate might not be known for the species of interest.

Table I. Results of density estimation analysis on synthetic data set with 100 animals uniformly distributed inside a circular area of radius 8 km. Expected density is 497 animals/1000 km^2. Transmission loss was calculated using Bellhop and results were taken at 600 m.

	n_c#	$\hat{P}$	$\hat{D}$
Case 1: - 32.5-37.5 kHz - No Multipath	9	0.1194	375
Case 2: - 10-60 kHz - No Multipath	33	0.1079	1520.8
Case 3: - 10-60 kHz - Multipath	71	0.1128	3131.3
Case 4: - 32.5-37.5 kHz - Multipath	19	0.1072	881.1

IMPACT/APPLICATIONS

The application of recently developed density estimation methods to different data sets and marine mammal species provides opportunities to test the methodology and make it more general. It was noted however that such methodology is not a “one size fits all,” since, as observed in the present study, the frequency band of calls will influence, for example, how to appropriately simulate them. When studying species that are considered threatened or endangered in any way, as is the case with false killer whales in Hawai’i, it is hoped that density estimation methods from passive acoustics can become a tool to help monitor, study and protect those populations. Development of more efficient and accurate propagation modeling practices, by performing convergence tests and propagating the field straight to each simulated animal instead of performing interpolation, to be used in estimating the probability of detection of marine mammal calls is also an interesting component of this project. The ultimate goal is to develop easy-to-use software to make density estimation readily available to the Navy and to those involved in marine mammal research, monitoring, and mitigation. By improving our capabilities for monitoring marine mammals we hope to contribute to minimizing and mitigating the impacts of man-made activities on these marine organisms.

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