UNDERWATER 3-D PASSIVE ACOUSTIC BAYESIAN TRACKING OF PACIFIC WALRUS

Brendan Rideout[1], Stan E. Dosso[1], and David Hannay[2]

[1]School of Earth and Ocean Sciences, University of Victoria, 3800 Finnerty Rd., Victoria, BC, Canada, V8P 5C2, bprideou@uvic.ca

[2]JASCO Research Ltd., 2101-4464 Markham St., Victoria, BC, Canada, V8Z 7X8

1. INTRODUCTION

This paper describes an MSc thesis research project aimed at three-dimensional (3-D) passive acoustic localization and tracking of vocalizing Pacific Walrus. Passive acoustic localization, in this context, is the process of determining the location of an underwater marine mammal without producing artificial sounds; only the natural sounds of the animal itself are used. Tracking, in this case, is the process of determining a sequence of underwater positions for a sequence of calls. The primary goal of this work is to develop a method for gathering behavioral data on marine mammals without the need to physically attach devices to the animal.

Experimental error is an important part of any scientific endeavor, and must be addressed for the results to be of greatest use. In the context of localization, experimental error is present in the data collection process, both in measuring arrival times for underwater calls and in knowledge of the experiment geometry and characteristics of the acoustic propagation environment (i.e. water depth and sound speed). Quantifying the effect these errors have on the reliability of the location is critical to interpreting the localization results. This work includes uncertainty in the measured data as well as in the sensor locations and the environmental parameters in an attempt to develop a comprehensive picture of localization uncertainty. Without knowing how uncertain the individual call localizations within a track are, it is not possible to say how much more likely the given track is compared with other possible tracks, and therefore how much significance to ascribe to features of the track (such as variations in depth or apparent swim speed of the calling animal).

2. BACKGROUND THEORY

Localization, as implemented in this paper, is similar in principle to triangulation. Triangulation typically only uses energy which travels directly from the unknown source location to the receivers. Because sound bounces off the sea surface and bottom, additional information is available for underwater localization in the form of multipath arrivals (energy which has bounced one or more times off the surface and/or bottom prior to reaching the recorder).

The following derivation describes the approach used to calculate a track for a sequence of calls [1]. To account for all possible sources of error, the set of unknown model parameters **m** includes 3-D locations and times for each call in the track, 3-D hydrophone locations, sound speed, water depth and inter-hydrophone time synchronization factors. Arrival times for all direct and multipath arrivals from each hydrophone and call are arranged into the vector **t**. The relationship between **t** and **m** is non-linear, but can be linearized about an arbitrary starting model $\mathbf{m_0}$ by retaining the first order term from the Taylor expansion:

$$\mathbf{t} = \mathbf{t}(\mathbf{m}) = \mathbf{t}(\mathbf{m}_0 + \delta\mathbf{m}) \approx \mathbf{t}(\mathbf{m}_0) + \mathbf{J}\delta\mathbf{m} \qquad (1)$$

where **J** is the Jacobian matrix composed of partial derivatives evaluated at $\mathbf{m_0}$. Rearranging **(1)** and taking $\mathbf{m}$-$\mathbf{m_0}$=$\boldsymbol{\delta}\mathbf{m}$ yields:

$$\mathbf{d} \equiv \mathbf{t} - \mathbf{t}(\mathbf{m}_0) + \mathbf{J}\mathbf{m}_0 = \mathbf{J}\mathbf{m} \qquad (2)$$

This inverse problem is linear but, because hydrophone and source positions are both unknown, is ill-conditioned. Regularization is used to add additional information to the problem in the form of a preference for a smooth track, and prior estimates (with approximate uncertainties) for sound speed, water depth, and hydrophone positions. Specifically, the objective function minimized to fit the data and prior information takes the form:

$$\psi = [\mathbf{d} - \mathbf{J}\mathbf{m}]^T \mathbf{C}_\mathbf{d}^{-1}[\mathbf{d} - \mathbf{J}\mathbf{m}] + \mu_1 \mathbf{m}^T \mathbf{R}\mathbf{m} + \mu_2[\mathbf{m} - \hat{\mathbf{m}}]^T \mathbf{C}_{\hat{\mathbf{m}}}^{-1}[\mathbf{m} - \hat{\mathbf{m}}], \qquad (3)$$

where $\mathbf{C_d}$ is the data covariance matrix, **R** is a 3-D roughening matrix applied to the track locations such that $\mathbf{m}^T\mathbf{R}\mathbf{m}$ represents the L_2 norm of the second derivative (curvature) of the track, $\hat{\mathbf{m}}$ is a vector of prior estimates of model parameters in **m**, $\mathbf{C}_{\hat{\mathbf{m}}}$ is a matrix of prior uncertainties, and μ_1 and μ_2 are trade-off parameters. Minimizing ψ yields the equation:

$$\mathbf{m} = \left[\mathbf{J}^T \mathbf{C}_\mathbf{d}^{-1}\mathbf{J} + \mu_1\mathbf{R} + \mu_2\mathbf{C}_{\hat{\mathbf{m}}}^{-1}\right]^{-1}\left[\mathbf{J}^T\mathbf{C}_\mathbf{d}^{-1}\mathbf{d} + \mu_2\mathbf{C}_{\hat{\mathbf{m}}}^{-1}\hat{\mathbf{m}}\right] \qquad (4)$$

Due to the linearization step, the solution converges over multiple iterations of (4). Values for the trade-off parameters are selected such that the data and prior estimates are fit to a statistically appropriate level according to the χ^2 criterion [1]. The resulting track is one which maximizes smoothness while still fitting the data to within the data uncertainty. In other words the degree of smoothing, and the closeness of the final solution to the prior estimates, is proportional to the uncertainty in the data. If the data have large uncertainty the resulting track will tend to become smoother and the model parameters become more similar to their prior estimates.

To calculate uncertainties for the track resulting from (4), the model covariance matrix is calculated for the final solution. The general equation for the model covariance matrix (whose diagonal terms are the variances for the Gaussian distributions which represent the model parameter uncertainties) is:

$$\mathbf{C}_\mathbf{m} = \left\langle \left(\mathbf{m} - \langle\mathbf{m}\rangle\right)\left(\mathbf{m} - \langle\mathbf{m}\rangle\right)^T \right\rangle \qquad (5)$$

By substituting the value for **m** calculated in (4), (5) yields the following formula for C_m for the case of additive data noise:

$$\mathbf{C_m} = G^{-1}\mathbf{J}^T\mathbf{C_d}^{-1}\mathbf{J}\left(G^{-1}\right)^T, where$$
$$G = \mathbf{J}^T\mathbf{C_d}^{-1}\mathbf{J} + \mu_1\mathbf{R} + \mu_2\mathbf{C}_{\hat{\mathbf{m}}}^{-1} \quad (6)$$

3. FIELD STUDY

In August 2009, three ocean bottom hydrophone (OBH) recorders were deployed near the Hanna Shoal in the northeastern Chukchi Sea in a roughly equilateral triangle (~400 m on a side). Due to the shallow water (30 m) and flat bottom in this part of the Chukchi, the acoustic propagation environment is well suited for carrying out localization work. Additionally, the Hanna Shoal is known to be a common feeding ground for female and juvenile Pacific Walrus during the summer months. The OBHs recorded with a 16 kHz sampling frequency at 24 bits/sample for 2.5 months. Following retrieval, an automatic marine mammal vocalization detection and classification algorithm (developed by JASCO Research Ltd.) identified a segment of the data containing a high concentration of probable walrus knocks (impulsive calls). The calls in this segment were further processed using a semi-autonomous frequency domain-based edge detector to pick out the direct and multipath arrival times for each call at each OBH. Figure 1 shows time synchronized recordings of a single walrus knock recorded on each hydrophone. Note that the call arrives at each hydrophone at a different time and that the time delays between the various multipath arrivals also differ. These inter-OBH differences represent the information used to locate the point of origin for the knock.

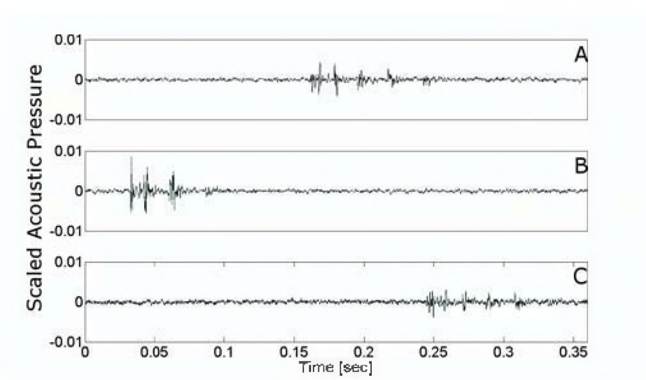

Figure 1 - Time synchronized walrus knock recorded on Hanna Shoal OBH A, B, and C.

4. SYNTHETIC EXAMPLE

Because 3-D localization using real data was not fully implemented at the time of writing, a simulation is used here to illustrate the inversion results. Figure 2 shows a comparison between true source positions and locations calculated using the linearized, regularized tracking algorithm. For each of the true source positions, simulated arrival times were calculated for each of the three hydrophone locations. Zero mean Gaussian noise was added to these arrival times, with standard deviations on the order of 0.0005 s. The measured data is expected to have a similar noise standard deviation. The noisy data were processed using the tracking algorithm. For this plot, only prior estimate regularization was used (no smoothing was done). The top panel shows a plan (*x*-*y*) view of the track. The bottom panel shows source depth (*z*) as a function of *x*. Each call's (x,y,z) position uncertainty is taken to be Gaussian distributed. Standard deviations for these uncertainties are shown in Figure 2 for the *y* and *z* coordinates for each call location. Hydrophone coordinates and uncertainties were also calculated, but are not shown. If data and environmental uncertainties were reduced (indicating that the data is more informative and the environment better understood), call location uncertainties would also be reduced.

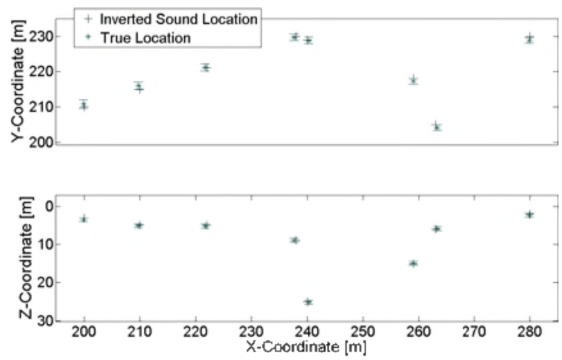

Figure 2 - True and localized 3-D track for synthetic data.

REFERENCES

[1] Dosso, S. E. *et al.* (1998). High-precision array element localization for vertical line arrays in the Arctic Ocean. IEEE J. Oceanic Eng., 23, 365-379.

ACKNOWLEDGEMENTS

This work has been partly funded by the Natural Sciences and Engineering Research Council (NSERC) of Canada, JASCO Research Ltd., the Province of British Columbia's Ministry of Advanced Education, and the University of Victoria.