

BAYESIAN ACOUSTIC SOURCE TRACKING AND TRACK PREDICTION WITH ENVIRONMENTAL UNCERTAINTY

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1. OVERVIEW

This paper considers matched-field tracking and track prediction for a moving ocean acoustic source when properties of the environment (water column and seabed) are poorly known. The goal is not simply to estimate source locations, but to determine track uncertainty distributions, thereby quantifying the information content of the tracking process. The algorithm involves two stages. The first stage (referred to as the tracking stage) consists of probabilistic tracking by inverting acoustic recordings of the source at a sequence of past times. For this problem, a Bayesian formulation is applied in which the posterior probability density (PPD) is integrated over unknown environmental parameters to obtain a time-ordered sequence of joint marginal probability surfaces over source range and depth, referred to as probability ambiguity surfaces (PASs). Due to the strong nonlinearity of the matched-field problem, this inversion is carried out numerically using Markov-Chain Monte Carlo methods. In particular, Metropolis-Hastings sampling is applied to environmental parameters (rotated into principal components) and two-dimensional Gibbs sampling to source locations to take advantage of fast computation of conditional probability distributions over range and depth using normal mode methods. This approach provides a large ensemble of track realizations drawn from the PPD [1, 2].

The second stage (the prediction stage) consists of applying a probabilistic model for source motion to each of the track realizations in the PPD ensemble obtained in the tracking stage, thereby producing a sequence of source range-depth probability distributions for future times. The particular source motion model applied here is based on the assumption of constant source velocity. In this case, the dependence of source range with time, $R(t)$, can be modelled using the law of cosines [3], as illustrated in Fig. 1(a):

$$R(t) = \left[R_0^2 + (v_h t)^2 - 2R_0 v_h t \cos \theta_0 \right]^{1/2} \quad (1)$$

where R_0 and θ_0 are the range and the angle between receiver-to-source radial and direction of motion at an initial time $t_0 = 0$ and v_h is the horizontal velocity. Tracking using acoustic data measured at a vertical line array (VLA) cannot determine horizontal coordinates (x, y) , but only the range $R(t)$, as shown in Fig. 1(b). The closest point of approach (CPA) is defined to be the source position that minimizes

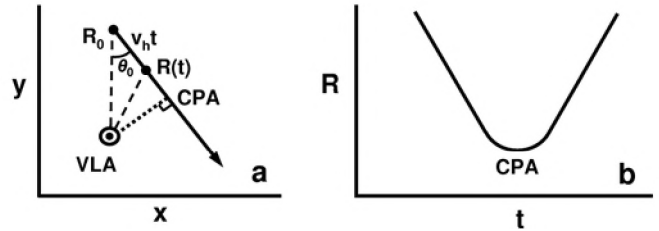


Figure 1. Track geometry in plan view (x - y) and range-time.

$R(t)$, as shown in Fig. 1(a) and (b). Equation (1) can be solved for track-parameter estimates $\hat{R}_0, \hat{v}_h, \hat{\theta}_0$ based on $R(t)$ values obtained by tracking inversion for a series of past times, and the uncertainty in the solution estimated using linearized inverse theory. These track parameter estimates can then be used to predict the source range at a series of future times using Eq. (1). Applying this procedure to every set of past ranges in the PPD ensemble from the tracking stage accounts for the uncertainty in the initial tracking, including the effects of environmental uncertainty. To account for uncertainty in the track prediction model, an ensemble of track predictions is drawn from the track-parameter uncertainty distribution for each set of past ranges. A similar procedure is applied to predict future source depths from past depth estimates (a simpler one-dimensional problem).

The result of the two stages described above is a very large ensemble of source tracks for future times, the variation of which quantifies the uncertainty in both past tracking and track prediction procedures. This ensemble can then be considered in terms of PASs for future times, and the most-probable track estimate/prediction (with uncertainties) can be extracted. Further, for incoming tracks, uncertainty distributions for range and time of CPA can be computed.

2. EXAMPLE

The section considers a simulated example of Bayesian track prediction. The unknown environment and source parameters of this example are illustrated in Fig. 2. Seabed geoacoustic parameters include the thickness h of an upper sediment layer with sound speed c_s , density ρ_s , and attenuation α_s , overlying a semi-infinite basement with sound speed c_b , density ρ_b , and attenuation α_b . The water depth is D , and the water-column sound-speed profile is represented by four parameters c_1 - c_4 at depths of 0, 10, 50,

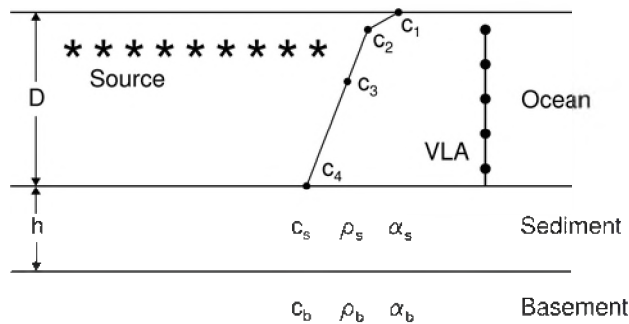


Figure 2. Experiment geometry and model parameters.

and D m. Wide uniform prior distributions (search intervals) are assumed for all parameters. Synthetic acoustic data were computed at a frequency of 100 Hz for 9 source locations at 2-minute intervals along an inbound track with a constant depth of 30 m and ranges defined by $R_0=14$ km, $\theta_0=14^\circ$, and $v_h=8.5$ m/s. These ranges and depths are shown in the left column of Fig. 3 (dotted lines). The data were computed at a VLA with 24 receivers at 4-m spacings from 26.120-m depth in 130-m of water. Random Gaussian errors of fixed variances were added to the synthetic data to achieve a mean SNR over the track of -2 dB.

Bayesian source tracking was applied to these data for a source search region of 0-20 km range and 0-129 m depth, with constraints on maximum allowable horizontal and vertical source velocities of 10 and 0.33 m/s, respectively. The resulting PASs are shown in the left column of Fig. 3. The track marginal distributions are multi-modal, with three distinct tracks of relatively high probability and at least one other with lower probability. These tracks differ in range, but are fairly consistent in source depth (near or slightly shallower than the true depth) and velocity. Interestingly, for this noise realization, the track that corresponds most closely to the true track is not the highest probability track, but the second highest. This example illustrates the power of sampling the PPD in the Bayesian approach, since algorithms based on estimating the highest-probability track would miss this important secondary track.

Probabilistic track prediction was subsequently applied for 9 future source locations at 4-minute intervals (i.e., twice the time interval for tracking), producing the sequence of PASs shown in the right column of Fig. 3. The track prediction results initially include peaks for the four distinct tracks estimated from acoustic inversion, but these coalesce within the first three time samples. Beyond this the PAS peaks occur at somewhat longer ranges and shallower depths than the true track, although the true track is encompassed by the high-probability regions.

3. SUMMARY

This paper developed and illustrated a probabilistic approach to the prediction of future locations of a moving ocean acoustic source based on probability distributions for

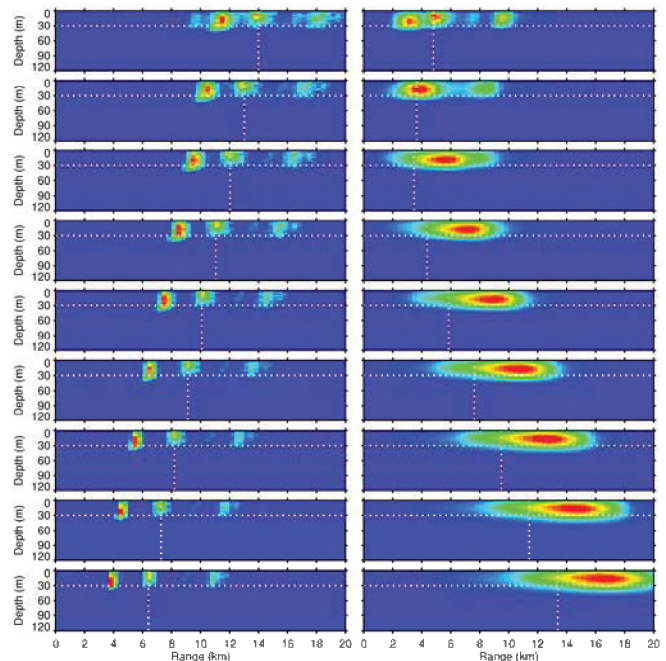


Figure 3. PASs for source tracking (left column) and track prediction (right column) for the synthetic example. Dotted lines indicate the true source range and depths.

past source locations, as estimated by a Bayesian acoustic tracking algorithm which accounts for environmental uncertainty. Markov-chain Monte Carlo methods were employed to sample the posterior probability density over unknown environmental parameters and past source locations, and a probabilistic prediction model for constant-velocity source motion based on the law of cosines was applied to each track-estimate realization in the ensemble to produce probability distributions for future source locations. The results were presented in terms of probability ambiguity surfaces (joint marginal PPDs over source range and depth), which quantify the information content of data and prior for track estimation and prediction.

REFERENCES

- [1] Dosso, S.E. and M. J. Wilmut, 2008. Uncertainty estimation in simultaneous Bayesian tracking and environmental inversion, *J. Acoust. Soc. Am.*, vol. 124, 82-97.
- [2] Dosso, S.E. and M. J. Wilmut, 2009. Comparison of focalization and marginalization for Bayesian tracking in an uncertain ocean environment, *J. Acoust. Soc. Am.*, vol. 125, 717-722.
- [3] M. J. Wilmut, J. M. Ozard, and M. L. Yeremey, 1997. Tracking in range versus time with applications to matched-field processing of vertical line array data, *Canadian Acoustics*, vol. 25, 21-27.