

# BAYESIAN SOURCE TRACK PREDICTION IN AN UNCERTAIN ENVIRONMENTAL INVERSION

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## 1. INTRODUCTION

This paper considers probabilistic prediction of the future locations of a moving acoustic source in the ocean based on past locations as determined by Bayesian source tracking in an uncertain environment [1, 2]. The Bayesian tracking approach considers both source and environmental parameters as unknown random variables constrained by noisy acoustic data and prior information, and integrates the posterior probability density (PPD) over the environmental parameters to obtain a time-ordered series of joint marginal probability surfaces over source range and depth. The integration is carried out using Markov-chain Monte Carlo (MCMC) methods which provide a large sample of track realizations drawn from the PPD. Applying a probabilistic model for source motion to each of these realizations produces a sequence of source range-depth probability distributions for future times. These predictions account for both the uncertainty of the source-motion model and the uncertainty in the state of knowledge of past source locations, which is itself dependent on environmental uncertainty. The approach is illustrated for range-depth tracking using a vertical sensor array for two source-motion models which differ in the degree of confidence assigned to future predictions based on past localizations.

## 2. TRACK PREDICTION EXAMPLES

The example illustrates tracking/track prediction for a quiet submerged source in shallow water with little knowledge of environmental parameters. The unknown environment and source parameters are illustrated in Fig. 1. Seabed geoacoustic parameters include the thickness  $h$  of an upper sediment layer with sound speed  $c_s$ , density  $\rho_s$ , and attenuation  $\alpha_s$ , overlying a semi-infinite basement with sound speed  $c_b$ , density  $\rho_b$ , and attenuation  $\alpha_b$ . 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, and  $D$  m. Wide uniform prior distributions (search intervals) are assumed for all parameters. Acoustic data are measured at 300 Hz at a vertical array consisting of 24 sensors at 4-m spacing from 26- to 118-m depth (simulated acoustic fields are computed using a normal-mode propagation model). The track consists of an acoustic source at 30-m depth moving toward the array at a constant radial velocity of 5 m/s (~10 kts). Acoustic data are collected at the array once per minute for 9 minutes, corresponding to source-receiver ranges of 6.4, 6.1, ..., 4.0 km. Random complex-Gaussian

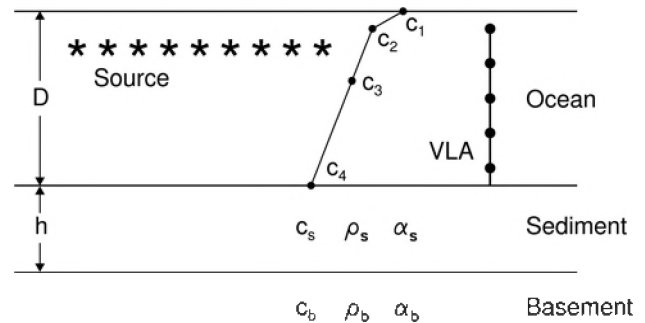


Fig. 1. Experiment geometry and model parameters.

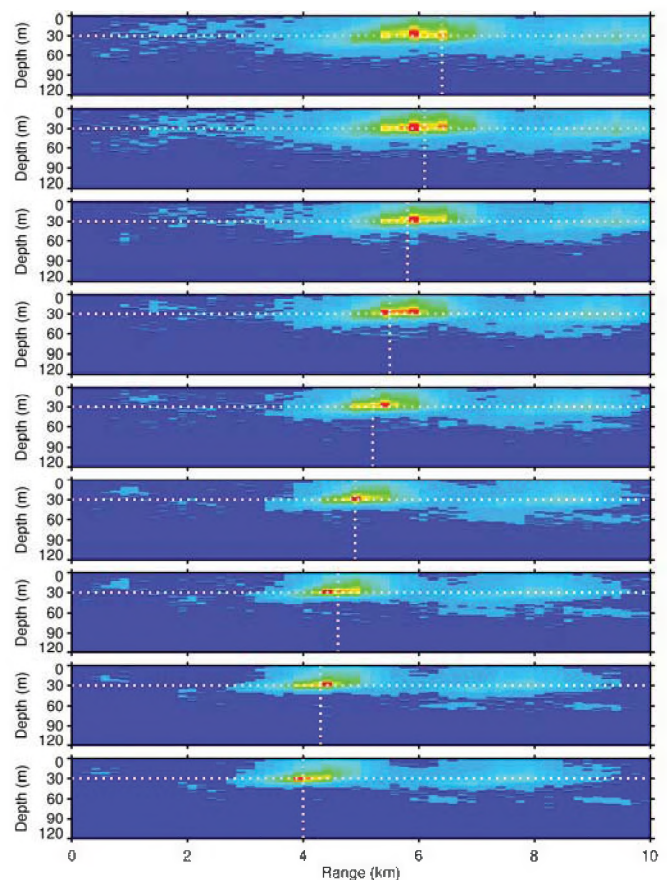


Fig. 2. Joint marginal probability distributions for source location computed via Bayesian tracking (time advances by 1 min/panel from top to bottom). Dotted lines indicate the true source depth and range. (Each panel normalized independently.)

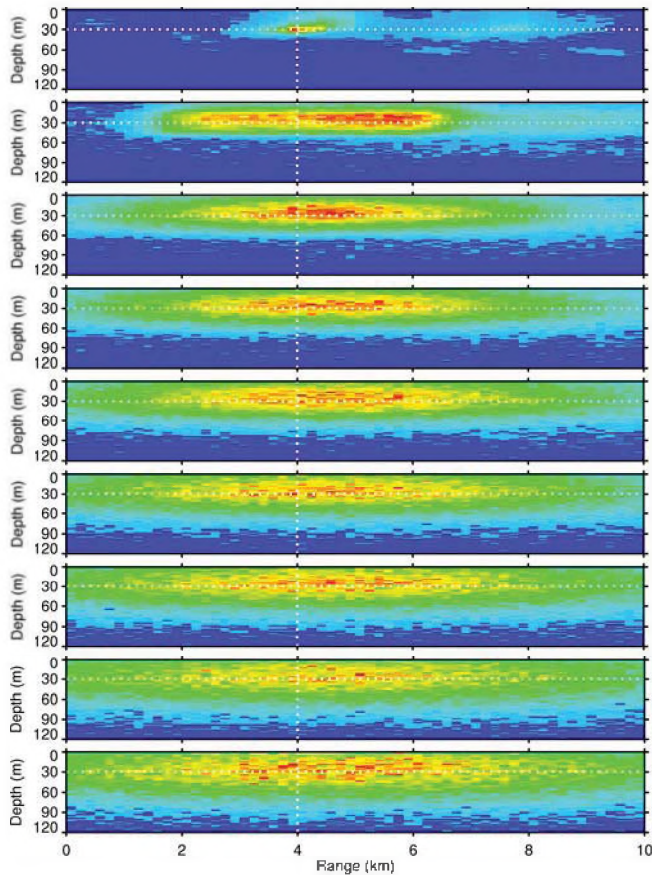


Fig. 3. Probability distributions for predicted source locations using uniform track-prediction model (time advances by 4 min/panel from top to bottom). Dotted lines indicate source depth and range at last tracked location.

errors are added to the data to achieve a signal-to-noise ratio (SNR) that varies from  $-14$  to  $-8$  dB with decreasing range along the track. Figure 2 shows joint marginal probability distributions for source range and depth integrated over all unknown environmental parameters via MCMC, with the additional constraint (prior information) of a maximum source velocity of 10 m/s in the radial and 0.06 m/s in the vertical. Figure 2 shows a strong probability maximum near the true source locations, although weaker secondary maxima are also evident.

The first track-prediction example is based on the pessimistic assumption that estimates of past source motion have no bearing on future motion; source motion is constrained only by the limits on radial and vertical velocity. Under these assumptions, future source positions are modelled as random variables uniformly distributed over the range-depth region allowed by the source velocity constraints. Figure 3 shows the track-prediction results for this source-motion model. The first panel in this figure repeats the last computed source localization probability distribution of Fig.2 (i.e., the take-off point for track prediction); the following panels represent predicted source

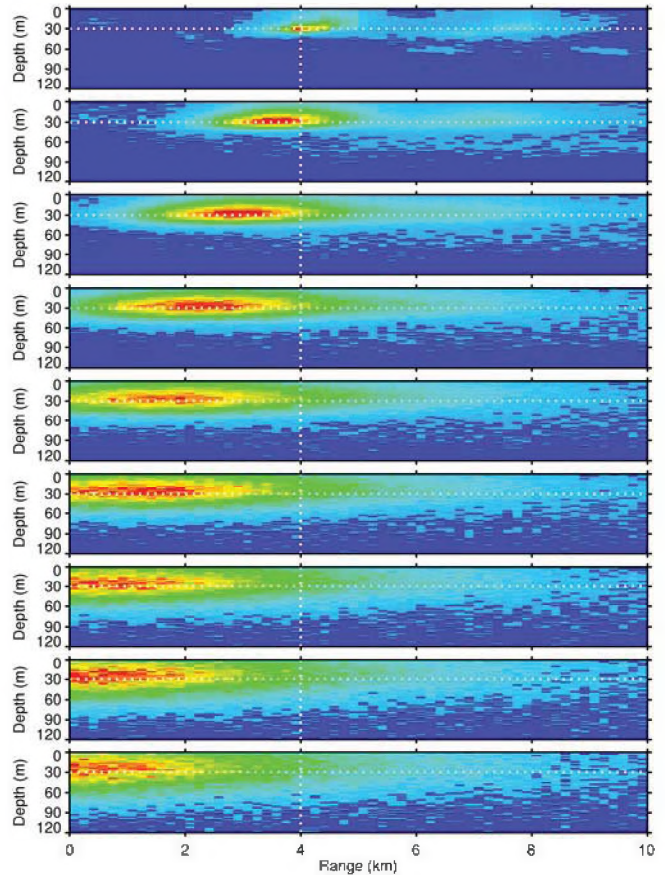


Fig. 4. Probability distributions for predicted source locations using Gaussian track-prediction model (time advances by 4 min/panel from top to bottom). Dotted lines indicate source depth and range at last tracked location.

location probability distributions at time intervals of 4 mins. The second example is based on the more optimistic assumption that estimates of past source motion provide useful information in predicting future motion. In this case the source motion is modelled as a Gaussian-distributed random variable with mean and standard deviation computed from the source locations along the particular track realization of the MCMC sample. The results of this procedure, shown in Fig. 4, generally extend the inward radial source motion detected in tracking results of Fig. 2, although the probability distributions disperse with time due to the uncertainty in the tracking results and the source-motion model

## REFERENCES

- [1] Dosso, S.E. and M. J. Wilmut, 2008. Uncertainty estimation in simultaneous Bayesian tracking and environmental inversion. *J. Acoust. Soc. Am.*, **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.*, **125**, 717-722.