WIDE-BAND TARGET DEPTH ESTIMATION IN A SCATTERING OCEAN ENVIRONMENT

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ABSTRACT

This paper concerns target depth estimation using wideband active sonar multipath returns. Detailed full-field modeling of target returns is complicated by spectral amplitude and phase distortions induced by unknown target scattering, uncertainty in the bulk group delay, and unmodeled propagation effects. However, since the relative delays of the multipath return are relatively robust to modeling errors, the approach considered in this work consists of estimating a subset of the relative delays present in the data and using them with a depth-dependent likelihood function derived from ray-traces based on the ocean environment. This maximum-likelihood depth estimate (MLDE) algorithm is compared with an alternative full-field matched-field depth estimate (MFDE) approach in terms of results obtained with a real mid-frequency active sonar.

1. BACKGROUND

Matched-field processing (MFP) for active sonar is complicated by the fact that the complex target scattering function is unknown and introduces unknown phase and amplitude differences between scattered modes [1,2,3]. In an earlier work on depth estimation, a narrow-band matched-field processing algorithm called MFDE was developed which models the space-time target return at an array as a random complex sum of undistorted multipath signals [4,5].

In this paper, we consider depth estimation using wide-band signals, which have the potential to resolve some of the multipath arrivals scattered by the target. In particular, beamformed, match-filtered time series for successive pings contain multipath returns which are a function of target depth and range. A limitation of the ray acoustic models for wideband returns, however, is their inability to handle frequency dependent spectral distortion that is not explained by the usual linear superposition of scaled and delayed versions of the transmitted signal. These spectral distortions are partially due to the inability of the acoustic ray propagation code to model the unknown, frequency-dependent nature of the bistatic target scattering function. Further, bulk group delay jitter also distorts the phase spectrum of the observed multipath return.

In the following sections, we discuss two signal models for wideband multipath target returns and associated algorithms for the depth estimation problems they represent. The first is the wideband MFDE approach which extends the previous narrow-band MFDE. The second is a delay-based MLDE approach which uses measured delay differences from time-domain target returns.

2. MULTIPATH SIGNAL MODELS

For a given transmitter-target-receiver geometry, there generally are a multitude of possible paths between the transmitter and target and between the target and the receiver. If the bathymetry and sound velocity profiles are specified, the group delays of the various paths can be calculated via a ray-trace algorithm [6]. The delays predicted by the ray-tracer, as well as the number of delays, is generally a function of the hypothesized target depth. The depth estimation algorithms described in this paper attempt to exploit this dependence to arrive at a depth estimate, and so the ray-trace output (as a function of depth) is a key parameter set in the signal models.

2.1 MFDE signal model

The narrow-band MFDE signal model has been described more fully elsewhere, so only a brief indication of the wide-band model, which is a simple extension, will be given here [3]. In particular, the extension considered here is to divide the wideband return into a set of sub-bands. The sub-band widths should be large enough so that longer time delay spreads (corresponding to fast frequency fading due to multipath) can be captured in each sub-band but small enough to insure that small delay spreads (corresponding to target-induced scattering) do not affect the sub-band model up to a complex amplitude scaling. A linear signal model for the n^{th} observation and

m^{th} sub-band assumes a sum of delayed returns with random complex amplitudes and is modeled in the frequency domain as:

$$\mathbf{x}_{mn} = \mathbf{H}_{mn}\left(r_n, z, v_n\right)\mathbf{s}_{mn} + \boldsymbol{\eta}_{mn} \quad (1)$$

where $\mathbf{H}_{mn}(r_n, z, v_n)$ is the frequency-domain replica matrix for a target at range r_n, depth z, and velocity v_n. The number of columns in $\mathbf{H}_{mn}(r_n, z, v_n)$ is equal to the number of paths that make up the sonar return, and each column of $\mathbf{H}_{mn}(r_n, z, v_n)$ corresponds to the in-subband complex spectrum of the signal returning on a particular path. The complex vector $\mathbf{s}_{mn}$ describes the scattering on each multipath, and $\boldsymbol{\eta}_{mn}$ is complex additive noise. The parameters r_n and v_n are assumed to be known or previously estimated, and the depth parameter z is assumed to have the same value for all observations $\mathbf{x}_{mn}$. The vectors $\mathbf{s}_{mn}$ and $\boldsymbol{\eta}_{mn}$ (over all values of m and n) are assumed to be jointly Gaussian, zero mean, and independent, with covariance matrices are $\mathbf{I}_s$ and $\sigma_\eta^2\mathbf{I}_\eta$, respectively.

2.2. MLDE signal model

Dividing the frequency band of the signal into K bands, the in-phase-and-quadrature (I&Q) impulse response of the k^{th} sub-band matched filter will be denoted by the function $m_k(t)$. Let the function $q(t)$ be the time series of the transmitted signal. Denote the i^{th} multipath delay due to a target at range r_n and depth z as $\tau_{n,i}(z)$. Let the function $\phi_i(t)$ denote the impulse response of the target for the i^{th} multipath. Then the output of the k^{th} sub-band matched filter with the n^{th} observation as the input can be written as

$$y_{kn}(t,z) = \sum_i a_{kn}(m_k(t) * \phi_i(t) * q(t - \tau_{n,i}(z))) + \nu_{kn}(t) \quad (2)$$

where the symbol "* " indicates convolution. The complex scalars a_{kn} are complex amplitudes of each multipath and $\nu_{kn}(t)$ is zero-mean Gaussian noise. The amplitudes a_{kn} are treated as non-random, unknown parameters. Unlike the MFDE algorithm, the variance for the noise does not play an explicit role in the application of the MLDE algorithm.

3. MFDE AND MLDE METHODS

One approach to handling distorted returns is to divide the wide-band spectrum of the signal into a number of narrow sub-bands, perform narrow-band MFDE on each sub-band, and incoherently accumulate the resulting likelihood over sub-bands. However, for surface targets this model does not seem to address the variability seen in real returns.

Another approach to the problem is to estimate delay differences between arrivals in a multipath return and use these time differences to estimate the target depth. The MLDE algorithm described in this paper employs this strategy, and is applied to real data. The results are compared to the corresponding results with the MFDE algorithm.

3.1. MFDE algorithm

Since the observation $\mathbf{x}_{mn}$ is zero-mean Gaussian by the assumptions of the signal model, the covariance matrix is given by

$$\mathbf{R}_{mn}(z) = \mathbf{H}_{mn}\left(z\right)\mathbf{H}_{mn}^H\left(z\right) + \sigma_\eta^2\mathbf{I}_\eta \quad (3)$$

Then the log-likelihood function is given by

$$L_k(z \mid \mathbf{x}_{mn}) = -\ln(\pi^W \det(\mathbf{R}_{mn}(z))) - \mathbf{x}_{mn}\mathbf{R}_{mn}^{-1}(z)\mathbf{x}_{mn}^H \quad (4)$$

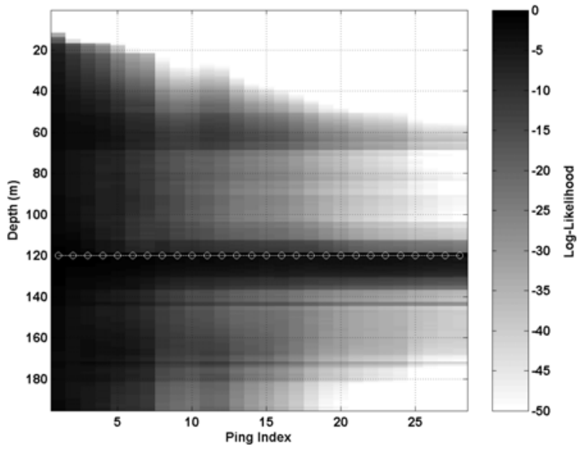
Summing the likelihood over all observation and sub-band indices, the MFDE is

$$\hat{z}_{\text{MFDE}} = \arg\max_z\left(\sum_{m,n} L_{mn}(z \mid \mathbf{x}_{mn})\right) \quad (5)$$

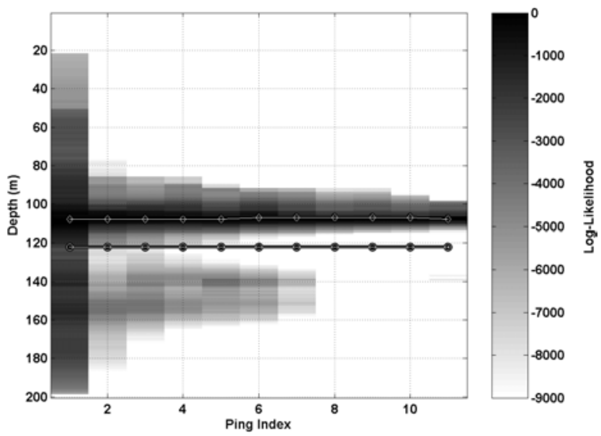
3.2. MLDE algorithm

Since target depth is encoded in relative multipath delays, given sufficient bandwidth to resolve at least some of the multipath delays, the depth estimation problem is split into two stages: 1) multipath delay difference estimation in a scattering environment, and 2) maximum likelihood depth estimation using multipath delays.

Ideally, the delay difference estimator should be insensitive to bulk group delay, robust to uncertainty in multipath phase and amplitude scaling, and robust to target and bottom scattering distortions. The delay difference estimation approach employed here is to measure the time difference between the two strongest peaks in the sub-band matched filter output. Denote this measurement for the m^{th} sub-band and n^{th} observation $y_{kn}(t,z)$ by $\Delta\tau_{mn}$. Since the functions $\phi_i(t)$ are not generally impulse functions, the data model in Eq. (2) will not exhibit differential delays between its peaks that match exactly those predicted by the distortionless model



(a)



(b)

Figure 1. Real data results from an echo repeater at a depth of 122 m: (a) MLDE depth is 120 m, (b) MFDE depth is 108 m.

(i.e., when $\phi_i(t) = \delta(t)$ for all i, where $\delta(t)$ is the Dirac delta function).

The set of relative multipath delays $\Delta\tau_{mn}$ estimated from this process can be then used as the input to a maximum likelihood depth estimator. Specifically, at a hypothesized depth z_{hyp}, a depth-dependent likelihood function may be calculated in the following manner: given a set of multipath delays $\tau_{n,i}(z_{\text{hyp}})$ (the index i runs from 1 to the number of delays) calculate all possible delay differences $d_{ijn}(z_{\text{hyp}}) = |\tau_{n,i}(z_{\text{hyp}}) - \tau_{n,j}(z_{\text{hyp}})|$, and form the likelihood function

$$l_n(z_{hyp} \mid \Delta\tau_{mn}) = C \sum_{\substack{i,j \\ i \neq j}} g(\Delta\tau_{mn} - d_{ijn}(z_{hyp})) \qquad (6)$$

where the function g is a histogram-smoothing kernel and C is a normalization constant chosen so that $\int l_n(z_{hyp} \mid x)dx = 1$. Then the MLDE becomes

$$\hat{z}_{\text{MLDE}} = \arg\max_z \left(\sum_n l_n(z \mid \Delta\tau_{mn})\right) \qquad (7)$$

The smoothing kernel g may be chosen to represent the degree of uncertainty in the measured differential delays, which is induced by the unknown functions $\phi_i(t)$ in Eq. (2). The kernel used in this paper had the same form as the density function for a Gaussian random variable:

$$g(x) = (2\pi\beta^2)^{-1/2} \exp(-x^2/(2\beta^2)) \qquad (8)$$

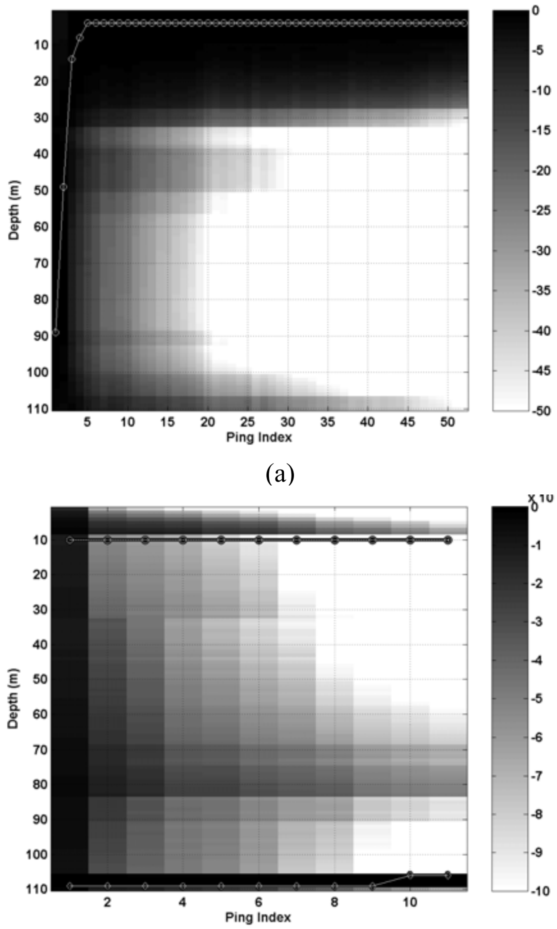
where β was set to 5 ms. The likelihood in Eq. (2) is written in terms of a single relative delay estimate per ping, but it could be generalized to multiple relative delay estimates per ping, potentially yielding better estimation performance.

4. REAL DATA RESULTS

Both the MFDE and MLDE algorithms have been applied to real data, and results are presented here for both a surface target and an echo repeater. The surface target was a target of opportunity. The transmitted signal for the surface target was an HFM with a bandwidth of 400 Hz (which was split into five sub-bands for processing), and the signal employed for the echo repeater was an 800 Hz HFM (which was split into eight bands). The signal to noise ratio for the data from both targets was approximately 20 to 25 dB.

Fig. 1(a) shows the accumulated log-likelihood surface from the MLDE for the echo repeater data (true depth was 122 m), where the vertical axis is hypothesized depth (in meters) and the horizontal axis is ping index. The accumulated log-likelihood is indicated by the intensity, with darker shades corresponding to greater likelihood. The estimate after 28 pings of data was 120 m. Fig. 1(b) shows the accumulated log-likelihood surface from the MFDE. The estimate after 11 pings was 108 m.

Fig. 2(a) shows the accumulated log-likelihood surface for the MLDE with the surface target (true depth was 5 to 10 meters). The estimate after 52 pings of data was 4 m. Fig 2(b) shows the accumulated log-likelihood surface from the MFDE. The estimate after 11 pings was 107 m, which was very near to the ocean bottom.



(a)

(b)

Figure 2. Real data results from a surface target, (true depth of 5-10 m): (a) MLDE depth is 4 m, (b)MFDE depth is 107 m.

5. REMARKS

The MFDE and MLDE both seem to perform well with the echo repeater target, while only the MLDE gives a good result with the surface target. This may be due to the fact that the echo repeater may not contribute large spectral distortions to the received signal spectrum, while the surface target (a ship's hull) probably does induce larger spectral distortions.

One key assumption that is made in this work is that the spectral distortion is not so severe that the matched filters used in the MLDE algorithm is incapable of producing strong peaks to enable the algorithm to register the arrival times along the two strongest paths. In the case that the distortion is great enough to preclude this approach, a more robust method of estimating delay differences is required. This is a direction for future study.

Another area for future study are methods for determining the number of sub-bands to use with these algorithms.

6. ACKNOWLEDGEMENTS

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6. REFERENCES

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