Tracking of geoacoustic parameters using Kalman and particle filters

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This paper incorporates tracking techniques such as the extended Kalman, unscented Kalman, and particle (PF) filters into geoacoustic inversion problems. This enables spatial and temporal tracking of environmental parameters and their underlying probability densities, making geoacoustic tracking a natural extension to geoacoustic inversion techniques. Water column and seabed properties are tracked in simulation for both vertical (VLA) and horizontal (HLA) line arrays using the three tracking filters. Filter performances are compared in terms of filter efficiencies using the posterior Cramér–Rao lower bound. Tracking capabilities of the geoacoustic filters under slowly and quickly changing environments are studied in terms of divergence statistics. Geoacoustic tracking can provide continuously environmental estimates and their uncertainties using only a fraction of the computational power of classical geoacoustic inversion schemes. Interfilter comparison show that while a high-particle-number PF outperforms the Kalman filters, there are many cases where all three filters perform equally well depending on the inversion configuration (such as the HLA versus VLA and frequency) and the tracked parameters.

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I. INTRODUCTION

Geoacoustic inversion is a technique used to extract information about the ocean environment by analyzing the acoustical field propagation in that medium. Typically, water column and seabed parameters such as sound speed profiles (SSPs), sediment densities, layer thicknesses, and attenuations are estimated by finding an environmental model that generates an acoustic field that matches closely the measured field. There are different configurations that are typically used in geoacoustic inversion, each with its own advantages and drawbacks. Some of the most commonly used ones include vertical (VLA) or horizontal (HLA) line arrays, bottom moored or towed arrays, and active or passive source configurations that use either a separate towed source or ship self-noise for inversion. 1–7 While some of the inversion techniques focus on obtaining the optimum solution with minimum computation time using efficient global optimizers such as genetic algorithms 8 or simulated annealing, 9 the others estimate the probability densities of the environmental parameters to compute the uncertainty in the estimated parameters. 10,11 This enables them to project this environmental uncertainty into parameters-of-interest such as the uncertainties in transmission loss and statistical sonar performance prediction. 12

This paper reformulates the geoacoustic inversion algorithms that estimate the geoacoustic environment between the source and the receiver array at a given time into tracking the evolution of these parameters and their associated uncertainties in space and time. This is achieved by merging geoacoustic inversion techniques with tracking algorithms such as the Kalman and particle filters (PFs). These filters have been used previously in estimation 13 and temporal tracking 14 of the ocean SSP and similar acoustic applications. 15,16

Here, the geoacoustic tracking problem is formulated in a Kalman framework, and depending on the source/receiver configuration, the acoustic field is calculated using either the normal mode code SNAP (Ref. 17) or the complex normal mode code ORCA (Ref. 18) for near-field calculations. This interaction between the environmental parameters and the acoustic field can involve a high level of nonlinearity. In addition, it is known from previous studies 19–23 that the posterior probability densities (PPDs) of geoacoustic parameters can be non-Gaussian. Therefore, geoacoustic tracking is a challenging task and requires tracking filters that can handle nonlinear, non-Gaussian systems. This paper studies the suitability of three such filters, namely, the extended Kalman filter 22 (EKF), the unscented Kalman filter 23 (UKF), and the PF (Ref. 24) in geoacoustic tracking. All three filters use different schemes to deal with such complex systems. The EKF extends the best possible filter in a linear/Gaussian system, i.e., the Kalman filter (KF), into the nonlinear/non-Gaussian domain by analytical linearization of the problem. Instead, the UKF uses statistical linearization with unscented transform. Finally, the PF propagates a large number of particles to represent the evolving probability density function (PDF) of the environmental parameters. In this paper, the tracked parameters are restricted to environmental parameters since detection and tracking of a target/source using tracking filters are already well-studied fields in applications involving sonar and radars.

Most cases that require consecutive geoacoustic inversions to obtain the spatial/temporal variation of geoacoustic parameters effectively can be reformulated as tracking prob-
lems. Three examples are shown in Fig. 1:

(a) Figure 1(a) shows a typical fixed hydrophone array (VLA or HLA) configuration and a separate towed source with the aim of capturing the environment between the moving source and the receiver array. The two dimensional environment between the source and the array changes as the source is towed, resulting in an evolution of the range-independent model in time, as shown in the figure as step indices \( k \). For example, such a scenario could transform the following geoacoustic inversion approaches into geoacoustic tracking:

- a towed source and fixed VLA [e.g., SWARM’95 (Ref. 21)],
- a towed source and fixed HLA [e.g., SWAMI’98 (Ref. 2) and Barents Sea’03 (Ref. 6)],
- the test cases used in the Geoacoustic Inversion Techniques Workshop with a moving source and fixed HLA (Ref. 25), and
- a single hydrophone mounted on seafloor receiving transmission from a towed source [e.g., SCARAB’98 (Ref. 26)].

(b) Figure 1(b) represents the type of configuration that is designed to capture range-dependent environmental parameters at small range increments. The illustration given in the figure uses a HLA and a source close to the array, both towed by the same ship. Hence, the HLA captures the near-field acoustic field that is affected only by a small section of the water column and seabed. It is possible to take each of these sections as a step index in range and assume that the environment is constant within each \( k \), and therefore turn it into a range-dependent environment tracking problem. The update rate can be increased using overlapping blocks but for the sake of simplicity, a nonoverlapping scheme is shown here. This type of geoacoustic tracking could be used in

- a towed source and HLA [e.g., MAPEX2000 (Refs. 1, 5, and 7)],
- tow-ship self-noise data acquired via a towed HLA [e.g., MAPEX2000 (Ref. 3)], and
- passive fathometer using the ocean ambient noise field measured by a drifting VLA [e.g., ASCOT’01 and Boundary’03 (Ref. 27)].

(c) The last example, given in Fig. 1(c), estimates the evolution in time of the water column SSP along a fixed path. Such a scenario could be implemented in the following examples:

- a fixed source and fixed VLA [e.g., Yellow Shark’94 (Ref. 28)] and
- KFs used to track the SSP in a similar configuration during the MREA/BP’07 experiment (Ref. 14)

The main objective of this paper is to incorporate tracking filters into the geoacoustic inversion problem and test the effectiveness of each filter in geoacoustic parameter tracking.

II. GEOACOUSTIC ESTIMATION AS A TRACKING PROBLEM

Geoacoustic inversion requires a measurement equation relating the simulated acoustic field to the observed data through a forward model. This is represented using

\[
d_{\text{obs}} = s d(m) + e, \tag{1}
\]

where \( d_{\text{obs}} \) represents the complex-valued acoustic data vector along the array, \( s \) is the complex source magnitude, \( d(m) \) is the simulated field obtained using the acoustic propagation model for an environment represented by the environmental model \( m \), and \( e \) is complex Gaussian noise. Using Eq. (1), a geoacoustic inversion algorithm defines an objective function to be used in the inversion to obtain the best possible model \( \hat{m} \).

Geoacoustic tracking, on the other hand, uses two dynamic equations to characterize the system:

- An equation modeling the evolution of the environmental model parameters governed by the physical processes in the medium such as ocean currents and mixing, bathymetry, and the expected rate of change in seabed parameters in range.
- An acoustic measurement equation similar to Eq. (1). However, this is a dynamic equation that includes a continuous stream of data \( d_{\text{obs}} \), where \( k \) represents the temporal or spatial step index.

Following standard KF notation, the error \( e \) in the measurement equation, the environmental model \( m \), and the acoustic field across the hydrophone array \( d_{\text{obs}} \) at step \( k \) henceforth will be denoted by \( w_k \), \( x_k \), and \( y_k \), respectively. Therefore, the set of equations at step \( k \) are
The most commonly used propagation models are normal mode
555 and the available computational power. The most
567 observed across the receiver array for a given environmental
579 model that propagates acoustic fields and simulates the field
591 This process involves the selection of a suitable forward
593 model parameters to acoustic measurements. Even though many geoacoustic parameters such as
601 are not included in the evolution model. For example, the
613 is assumed complex Gaussian with covariance $R_k$ obtained from the array signal-to-noise ratio (SNR) [see Eq. (9)].
Since the synthetic data used here are generated using the same forward model and environmental parameters, there is no modeling error in the examples. Working with real data will include unavoidably the modeling uncertainty, resulting in an increase in the noise term.

The KFs necessitate a linear/Gaussian framework, whereas any distribution can be used for the PF. This means that the prior PDF $p(x_0)$, the state variables, state, and measurement noise all have to be Gaussian to run any KF algorithm as a geoacoustic tracking filter. PFs can work with any PDF. However, in order to compare these two types of filters under identical initial conditions, the prior densities at $k=0$ are taken as Gaussian PDF in this paper. The results of the KFs will all be Gaussian, while the PF densities can be of any distribution.

### III. THEORY

For a system with linear state and measurement equations and Gaussian PDFs the KF (Ref. 22) is the optimal filter in a minimum mean square error (MSE) sense. However, for nonlinear, non-Gaussian problems such as geoacoustic tracking, it may not be possible to find an optimal estimator. Therefore, three suboptimal filters are investigated:

- EKF that uses analytical linearization where the measurement equation is linearized using the first order Taylor series expansion,
- UKF that uses statistical linearization where the nonlinearity in the parabolic equation is kept but PDFs are restricted to be Gaussian, and
- PF or sequential Monte Carlo (SMC), which uses a sequential importance resampling (SIR) or bootstrap filter to track the nonlinear, non-Gaussian system.

Each of these algorithms has its advantages and drawbacks for different tracking applications. See Appendix A for filter descriptions and implementation details.

The filters can be compared to each other using the root mean square (RMS) error between the true environment $x_k$ and the filter estimate $\hat{x}_k$. However, this only shows if one filter is doing better than the others, giving no indication about whether and to what extent the information available through previous states and current measurements are exploited by the filter, especially given the fact that all three of these filters are suboptimal. Therefore, it is desirable to have a tool that can not only assess the performances of these techniques but also provide a limit to achievable performance for a given environment.

This is done by using the posterior or Bayesian Cramér–Rao lower bound (PCRLB) introduced by van Trees (30) (see Appendix B). PCRLB is the Bayesian counterpart of the
classical Cramér-Rao lower bound (CRLB) defined in a non-
Bayesian framework as the inverse of the Fisher information
matrix. There are studies on the calculation of both the
CRLB (Ref. 31) and the PCRLB (Ref. 32) for geoaoustic
inversion problems. Any filter that achieves a MSE equal to
the CRLB is called an efficient estimator. For a linear and
Gaussian system, the KF is an efficient estimator. It may not
be possible to attain the PCRLB for a nonlinear, non-
Gaussian system.

The performance metrics used in this paper are

\[
\text{RMS}_k(i) = \left[ \sum_{j=1}^{n_{MC}} \left( \frac{x_j^k(i) - \hat{x}_j^k(i)}{n_{MC}} \right)^2 \right]^{1/2},
\]

(5)

\[\eta_j(i) = J_k^{1/2}(i,i)/\text{RMS}_k(i),\]

(6)

\[
\text{RTAMS}(i) = \left[ \sum_{k=k_1}^{k_2} \sum_{j=1}^{n_{MC}} \left( \frac{x_j^k(i) - \hat{x}_j^k(i)}{n_{MC}} \right)^2 \right]^{1/2},
\]

(7)

\[
\text{Improv} = \frac{\text{RTAMS}_{\text{EKF}} - \text{RTAMS}_{\text{filter}}}{\text{RTAMS}_{\text{EKF}}},
\]

(8)

where \(x_j^k(i)\) is the \(i\)th parameter of the true state vector \(x\) at
time index \(k\) for the \(j\)th MC run, \(\text{RMS}_k\), \(J_k\), and \(\eta_k\) are the
root mean square error, the Fisher information matrix (in-
verse of the PCRLB), and the filter efficiency, respectively, at
step \(k\). RTAMS is the root time averaged mean square error,\(^{29}\)
calculated for the interval \([k_1,k_2]\), and Eq. (8) calculates the
performance improvement of a filter with respect to the EKF.

IV. EXAMPLES

This section is composed of three geoaoustic tracking
examples that either spatially or temporally track the evolving
environment and the PPD. The first two use the configu-
ration in Fig. 1(a), and the last one uses the one in Fig. 1(b).
The simulation parameters such as the array structure, water
depth, and source frequencies are selected similar to the ones
that are used in Refs. 1 and 20. Each example evaluates and
compares different aspects of the tracking algorithms. These
three examples are

1. Temporal tracking. Filter efficiencies, PCRLB calcula-
tions, performance limitation analysis, computational
costs, effects of increasing the particle size in PF, and
interfilter comparison of uncertainty propagation are
studied using temporal tracking of an effective range-
dependent environment (with \(n_s=4\) unknown param-
eters at each step \(k\)).

2. Divergence analysis. For both slowly varying and
abruptly changing environments, a divergence analysis is
carried out using \(n_s=7\) unknown parameters at each step
\(k\).

3. Spatial tracking. The effects of selection of geoaoustic
setup on filters and tracking performance of individual
geoacoustic parameters are investigated using spatial
tracking of a range-dependent environment represented
by \(n_s=7\) unknown parameters at each spatial step \(k\).

A. Example 1: Temporal tracking using a VLA

This example compares the performance of the EKF,
UKF, and PF with the best possible limit given by the
PCRLB in terms of the RMS error and the filter efficiency.
The range-independent environment model used is given in
Fig. 2. Note that the selection of the environmental model is
arbitrary, and multiple more complex models can be incor-
porated into filters such as the multiple model particle filter
(MMPF).\(^{29}\)

Only the four parameters representing the sediment
layer, namely, sound speed, thickness, attenuation, and den-
sity, are tracked in this example. A sandy silt with medium-
fine to fine sand sediment is used in the tracking.\(^7\) A VLA
spanning the entire 100 m water column with 20 hydro-
phones is used. A frequency of 250 Hz is selected. All the
environmental constants, state variables, their initial means
and covariances, and the filter parameters are given in Table
I. The covariance of the measurement error term \(R = \nu I\)
is computed from the array SNR (Ref. 20) defined as

\[
\text{SNR} = 10 \log \frac{\text{var}(\nu_x) / \text{var}(\nu_x)}{\nu}.
\]

(9)

The PCRLB and the filter performances are calculated
using the Monte Carlo (MC) analysis as discussed in Appen-
dix B. First, \(n_{MC}=100\) evolving environments (each one a
MC trajectory) are created using the state equation, with
starting values selected from a Gaussian with a mean of \(x_0\)
and covariance \(P_0\). These trajectories are given in Fig. 3(a).
Then the PCRLB is computed using Eq. (B2) where the first
term (\(D_{x_1}^{x_2}\)) is estimated using Eq. (B8). Each of these 100
trajectories is also tracked by the EKF, UKF, and PFs using
200, 2000, and 10 000 particles designated by PF-200, PF-
2000, and PF-10 000, respectively. The normal mode code
SNAP is selected as the forward model.

The evolution of the RMS error in Eq. (5) of each pa-
rameter is computed for each filter and is given in Fig. 3(b)
as a function of step index \(k\). Note that the region below the
square root of the PCRLB is shaded as unattainable RMS
values. Also note that the filter RMS error estimates can
initially get lower than this limit before they increase and
stabilize to their real values. Hence, this region is discarded
in the calculations by setting the \([k_1,k_2]\) interval as
\([100,150]\) min for the RTAMS in Eq. (7) and their following
improvement-over-EKF computations in Eq. (8).
The results given in Fig. 3 show that the PFs perform better than the EKF and the UKF. While sediment thickness and sound speed tracking using PF is clearly superior to the KF variants, only PF with a large number of particles outperforms the EKF and UKF tracking of the sediment density, and all three types of filters perform well for attenuation tracking, closely following the theoretical limit set by the PCRLB. The RMS errors in sediment parameters, the average efficiency after 2.5 h of tracking, RTAMS values, and improvement-over-EKF percentages are given in Table II. Due to its inherent limitations, the EKF achieves an average filter efficiency of 52%. The UKF performs only slightly better with a 2% improvement over the EKF. With an efficiency of 63%, the PF-200 is 19% better than the EKF. Increasing the particle number improves performance to 80% efficiency in the PF-2000. The PF-10 000 results show that further increase in the particle number does not result in an increase in the performance, with a 37% improvement over the EKF out of a theoretical upper limit of 48% dictated by the PCRLB. PF-10 000 results are not shown in Fig. 3 but are given in Table II.

Even though PF performs better than the KFs in terms of RMS errors, it is also important to compare the computational cost of each algorithm both with each other and with


**FIG. 3.** (Color online) Example 1: Comparison of the tracking algorithms: (a) Evolution of 100 different environments (Monte Carlo trajectories), and (b) RMS errors for the EKF, UKF, 200-point PF, and 2000-point PF obtained from tracking each of these 100 trajectories along with the theoretical lower limit for the RMS error, the square root of the posterior CRLB.

**TABLE I.** Environmental and simulation parameters used in example 1.

<table>
<thead>
<tr>
<th>Environment</th>
<th>State variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constants</td>
<td>x</td>
</tr>
<tr>
<td>cₑₑₑ</td>
<td>1480 m/s</td>
</tr>
<tr>
<td>cₑₑₑ</td>
<td>1460 m/s</td>
</tr>
<tr>
<td>hₑₑₑ</td>
<td>100 m</td>
</tr>
<tr>
<td>cₑₑₑ</td>
<td>1700 m/s</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Simulation parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Source depth</td>
</tr>
<tr>
<td>Source range</td>
</tr>
<tr>
<td>Receiver type</td>
</tr>
<tr>
<td>No. of hydrophones</td>
</tr>
<tr>
<td>Array start, Δz</td>
</tr>
</tbody>
</table>
Divergence is an important issue in tracking problems. There are many reasons a track will diverge, such as the limitations in the filter (e.g., a KF structure in a highly non-Gaussian problem), errors in the forward model, and incorrect assumptions about the state and/or measurement noise. A frequently encountered problem is the error in the state equation model. The state equation models how we expect the state parameters to behave with $k$. If the real values of the state parameters evolve differently from this state evolution model, the filter may be unable to track these changes. Even though the measurement equation may tell the filter that the parameters are changing in an unexpected way, the filter may ignore the measurement information coming from Eq. (3) if this contradicts the state evolution model in Eq. (2). The filter type selected will affect the level of state modeling error that can be handled without resulting in divergence.

Geoacoustic tracking is no different. The state model used here assumes that the environment is evolving slowly. Therefore, comparing filter behavior under both slowly and fast changing environments is desirable. The environment in Fig. 2 is selected with $n_e=7$ environmental parameters to track, with the same VLA configuration and forward model as in the previous example. The simulation and measurement configuration parameters are selected from the sensitivity

\[
\begin{array}{cccccc}
\text{Method} & \text{$c_{\text{ed}}$ (m/s)} & \text{$h_{\text{ed}}$ (m)} & \text{$\alpha_{\text{ed}}$ (dBA)} & \text{$\rho_{\text{ed}}$ (g/cm$^3$)} & \text{Avg.} \\
\text{EKF} & 0.43 & 0.77 & 6.5 \times 10^{-3} & 10.7 \times 10^{-3} & 52 \\
\text{UKF} & 0.45 & 0.80 & 5.0 \times 10^{-3} & 11.1 \times 10^{-3} & 55 \\
\text{PF-200} & 0.30 & 0.53 & 5.8 \times 10^{-3} & 9.9 \times 10^{-3} & 63 \\
\text{PF-2000} & 0.22 & 0.39 & 4.2 \times 10^{-3} & 9.3 \times 10^{-3} & 80 \\
\text{PF-10000} & 0.22 & 0.39 & 4.2 \times 10^{-3} & 9.3 \times 10^{-3} & 81 \\
\text{\%PCRLB} & 0.22 & 0.16 & 3.5 \times 10^{-3} & 8.8 \times 10^{-3} & 100 \\
\end{array}
\]

(b) Filter Efficiency (%)

\[
\begin{array}{cccccc}
\text{RMS at } t=150 \text{ min} & \text{Avg.} & \text{RTAMS (100–150 min)} & \text{Avg.} & \text{Improv.} \\
\hline
\text{EKF} & 0.44 & 0.82 & 6.1 \times 10^{-3} & 11.3 \times 10^{-3} & 0 \\
\text{UKF} & 0.46 & 0.84 & 4.9 \times 10^{-3} & 11.8 \times 10^{-3} & 2 \\
\text{PF-200} & 0.31 & 0.54 & 5.8 \times 10^{-3} & 10.4 \times 10^{-3} & 19 \\
\text{PF-2000} & 0.24 & 0.39 & 3.9 \times 10^{-3} & 9.6 \times 10^{-3} & 36 \\
\text{PF-10000} & 0.24 & 0.39 & 3.9 \times 10^{-3} & 9.6 \times 10^{-3} & 37 \\
\text{\%PCRLB} & 0.22 & 0.17 & 3.5 \times 10^{-3} & 8.8 \times 10^{-3} & 48 \\
\end{array}
\]

Fig. 4. (Color online) Example 1: Performance improvement of PF as a function of number of particles expressed in terms of (a) filter efficiency, and (b) improvement over the EKF. The dashed line shows the attainable improvement limit.
plots at $t=0$, given in Fig. 5. These plots are obtained by varying one parameter at a time from their values at $t=0$, while the other six are the same as those of $x_0$. The normalized objective function used here is similar to ones used in Refs. 20 and 10 as a MSE metric. It is given as

$$\Phi_n(x) = 1 - \frac{1}{Y_k} \frac{\|y_k - d(x_k)/d(x_k)\|^2}{\|d(x_k)\|^2}.$$  (10)

The objective functions in Fig. 5 are given for three different frequencies at 50, 100, and 250 Hz, respectively. Note that the penetration depth of the field decreases as the frequency is increased. Since the source and VLA are separated by 5 km, most of the high-incidence angle deep penetrating modes have attenuated at longer ranges and may not be detected by the receiver array. Note that $\Phi_n(x)$ for sediment thickness becomes insensitive after a certain value, which decreases with increasing frequency. The same also applies to the bottom sound speed. For the given environment, most of the signal is restricted to the sediment, not penetrating deep enough; hence $\Phi_n(x)$ is not sensitive to the bottom parameters.

Simulation parameters different from the previous example are provided in Table III. The tracking is carried out for 200 min with one update every 2 min. A frequency of 250 Hz is selected for the tracking problem. At this frequency, the bottom parameters give an entirely flat sensitivity plot, and sediment thickness above around 20 m is poorly determined. The evolutions of the seven parameters are given as solid lines in Fig. 6. These variations include a fluctuation in the top water sound speed, simultaneous gradual variations in all seven parameters, and a simultaneous sudden jump in two sediment parameters, sediment thickness from 30 to 20 m followed by a similar increase in the sediment sound speed. Note that one of the two environmental parameter jumps is in the sediment, a poorly determined parameter. Therefore, the filters are expected to give high divergence percentages due to the selection of such an environment and frequency, enabling a comparison between them under conditions difficult for tracking purposes. The evolving environment is tracked using the EKF, UKF, and PF that use 200, 2000, and 5000 particles, respectively. PF-2000 results are not shown in Fig. 6 but are given in Table IV.

The corresponding temporal evolution of the amplitude of the vertical acoustic field at 5 km as a function of time is given in Fig. 7. Note how the vertical mode structure evolves with time. Also note that only a sampled version of this field is used in tracking, as shown in the figure as circles representing the vertical hydrophone locations of the VLA. A lower spatial sampling frequency of the vertical field may result in the loss of some of the evolving trends in the field and higher divergence rates.

A typical track result for each filter is given in Fig. 6 along with the true trajectories of the parameters, and the results are summarized in Table IV. Some of the important

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**Table III. Simulation parameters for example 2.**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>$c_{sw}$</th>
<th>$c_{sb}$</th>
<th>$c_{sed}$</th>
<th>$h_{sed}$</th>
<th>$\alpha$</th>
<th>$\rho$</th>
<th>$c_{shad}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>State noise $Q_k^{1/2}$</td>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
<td>1.0</td>
<td>0.002</td>
<td>0.02</td>
<td>1.5</td>
</tr>
<tr>
<td>Initial cov. $P_0^{1/2}$</td>
<td>1.0</td>
<td>1.0</td>
<td>1.0</td>
<td>1.0</td>
<td>0.002</td>
<td>0.02</td>
<td>3.0</td>
</tr>
<tr>
<td>Divergence threshold</td>
<td>1.0</td>
<td>1.0</td>
<td>1.0</td>
<td>1.0</td>
<td>0.01</td>
<td>0.05</td>
<td>10.0</td>
</tr>
</tbody>
</table>
The features in this figure are as follows:

- All four filters are sensitive to the water column sound speed parameters and are able to track them. Water column parameters only start to diverge after the jump at \( t = 140 \) min for the EKF, UKF, and PF-200 because these filters are unable to track some of the sediment parameters that are coupled to the water column sound speed values. The PF-5000 is able to track these parameters perfectly both during slow \((t < 140 \text{ min})\) and rapid \((t > 140 \text{ min})\) changes. Although the PF-200 could track the slowly changing sound speed values, the track is much noisier than the KF filters and the high-particle PF. A similar pattern emerges for the sediment density.

- All four filters are mostly able to track the sediment sound speed parameters. The PF-5000 is able to track these parameters perfectly both during slow \((t < 140 \text{ min})\) and rapid \((t > 140 \text{ min})\) changes. Although the PF-200 could track the slowly changing sound speed values, the track is much noisier than the KF filters and the high-particle PF. A similar pattern emerges for the sediment density.

**TABLE IV. Results for example 2.**

<table>
<thead>
<tr>
<th>Method</th>
<th>After 140 min</th>
<th>After 200 min</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>RTAMS</td>
<td>% Imp. ( h_{sed} ) (m)</td>
</tr>
<tr>
<td>EKF</td>
<td>0.75</td>
<td>10.6</td>
</tr>
<tr>
<td>UKF</td>
<td>0.71</td>
<td>11.2</td>
</tr>
<tr>
<td>PF-200</td>
<td>2.92</td>
<td>9.2</td>
</tr>
<tr>
<td>PF-2000</td>
<td>0.83</td>
<td>4.8</td>
</tr>
<tr>
<td>PF-5000</td>
<td>0.82</td>
<td>3.1</td>
</tr>
</tbody>
</table>

The PF-5000 is able to track these parameters perfectly both during slow \((t < 140 \text{ min})\) and rapid \((t > 140 \text{ min})\) changes. Although the PF-200 could track the slowly changing sound speed values, the track is much noisier than the KF filters and the high-particle PF. A similar pattern emerges for the sediment density.
speed, including the sudden jump in the parameter. Again, the track given by PF-5000 is superior to the other three.

- As expected, the first three filters fail to track the sudden jump in the sediment thickness. Only PF-5000 is able to track the true trajectory. Also note how noisy the track is even for the PF-5000 due to the low sensitivity predicted in Fig. 5.
- Attenuation is the only parameter where there is a marked difference between the EKF and the UKF. The improvements introduced by the UKF over the linearized EKF enable it to track the attenuation, whereas the EKF divergence rates are much higher. PF-200 performance lies somewhere between the two KFs, and PF-5000 performance is very similar to the UKF performance, except for the superior performance after the jump due to divergence of other parameters in the UKF.
- All four filters are unable to track the bottom sound speed. This is an expected result, taking into account the entirely flat sensitivity curve given in Fig. 5.

The divergence percentages are given in Table IV for slowly changing (before \( t = 140 \) min) and fast changing (after \( t = 140 \) min) environments. A parameter track is declared diverged if the RMS error is greater than the corresponding threshold given in Table III for any 30 consecutive min (i.e., 15 samples). All the average values in Table IV are computed using the first six parameters, excluding the bottom sound speed, which always diverge. Note how the KFs have low RTAMS for the sediment thickness compared to the RTAMS of PFs before the jump. The average improvement over EKF is 20% for PF-5000, and overall, the UKF performs best in this region. The UKF, PF-2000, and PF-5000 almost always successfully track the trajectory, while the average divergence rates are 16% and 39% for the EKF and PF-200, respectively.

However, both KFs have difficulties at the jump in the sediment thickness. The UKF still outperforms the EKF by 15%, but the improvement goes up to 60% for the PF-5000 (Table IV). The average divergence in the water column and sediment layer sound speed values (designated as \( c_{s,\text{sed}} \)) are given after the jump. The UKF diverges less than the EKF in sound speed tracking and more in attenuation tracking, both filters have a 100% divergence for the sediment thickness, and the UKF still tracks the attenuation whereas the EKF diverges 68% of the time after the jump. The PF-5000, on the other hand, diverges only 19% of the time for the hard-to-track sediment thickness, and overall, the PF performs much better than the KF structures after the jump.

It is also of interest to observe the underlying PDFs of the evolving parameters and examine how the uncertainty in parameters change with filter. The evolving PPD of the sediment thickness as a function of time is given for a PF-10 000 and the EKF in Fig. 8. They start with the same initial Gaussian PDF as seen at \( t = 0 \). Both filters are able to follow the parameter until the sudden decrease in the sediment thickness. Note that the PDF of the EKF is always a Gaussian (due to the initial Gaussian assumption and linearization), whereas the PF density can take different forms, which enables the filter to simultaneously follow multiple regions in the state space with high likelihoods (such as at \( t = 116 \) and 152 min. As the parameter starts to evolve quickly, the EKF is unable to follow, and it diverges, as can be seen from the large error in the PDFs given after \( t = 140 \) min between the PF and the EKF. Note how stable the PDF evolution in Fig. 8(b) is at \( h_{\text{sed}} = 20 \) m compared to the 30 m sediment thickness region due to the flat sensitivity curve for larger sediment thickness values.

C. Example 3: Spatial tracking using a HLA

The final example uses a HLA towed together with the source to map the spatially evolving environment. The configuration in Fig. 1(b) is used with a HLA of 254 m and a distance of 300 m from the source. A nonoverlapping spatial partitioning with each step \( k \) representing 500 m is selected. Since the source and HLA are close to each other, the complex normal mode code ORCA capable of computing the near field is used as the forward model. The simulation parameters different from the previous examples are summarized in Table V. The seven-parameter environment in Fig. 2 is used. To compare the effects of different configurations on an identical geoacoustic tracking problem, the evolution of the environmental parameters is the same as in the previous example.

A typical track for each type of filter is shown in Fig. 9. Note how the tracking capabilities of the filters for individual parameters change from the previous long-range VLA configuration to the short-range HLA configuration used here. Geoacoustic tracking behaves very similarly to previous studies comparing geoacoustic inversions using HLA versus VLA in that a parameter that is not readily estimated by geoacoustic inversion will also be poorly tracked. The major difference of a source close to the receiver is the ability of the receiver to detect higher order modes with large incidence angles that can penetrate deeper into the sediment since the signal does not propagate enough to attenuate these fields. This means that the field across the HLA is much more sensitive to some of the sediment and bottom parameters such as the bottom sound speed and sediment thickness. Notice how all four filters are able to track, in general, the

![Image](https://example.com/image.png)
bottom sound speed, sediment thickness, sediment sound speed, and density both in slowly and fast changing environments. Since the field is not that sensitive to the attenuation, it is now a relatively poorly determined parameter and the EKF fails to track it, while the UKF and PF-500 are able to maintain the track, albeit a noisy one. Similarly, the filters are unable to track the top sound speed value most of the time. Only PF is able to track this parameter on occasion.

The improvement percentages of the filters are obtained by repeating the track using 100 MC realizations. The results are given in Table V. The improvement of the UKF over EKF is similar to the previous example with 25% and 33% for slowly and fast changing regions, respectively. PF-200 performs poorly due to an insufficient number of particles used in tracking. On the other hand, the PF-5000 outperforms the EKF by 60%.

V. DISCUSSION

It is possible to extend the state space from just the environmental parameters by appending other parameters-of-interest such as the source range, depth, and speed. Also a single frequency is used throughout the paper. However, multiple frequencies are frequently employed for geoacoustic inversion due to the varying levels of sensitivities to different frequencies and robustness. It is possible to include multiple frequencies by appending the array data at different frequencies forming a long measurement vector \( y_k \) and a forward model \( h(x_k) \) composed of multiple normal mode runs at different frequencies.

The filter performance strongly depends on where \( x \) is in the state space. The most common scenario is where the performance improves from the EKF to the UKF to a PF with enough particles. However, there are regions in the state space where the KFs give better tracking results depending on the local linearity of the forward model and the Gaussian nature of the densities involved.

Although not given here, there are some special cases in geoacoustic tracking that can result in track divergence. One example observed during spatial tracking using the HLA configuration (example 3) is when a layer gets thin and then

### Table V. Simulation parameters and percent improvement of filters for example 3.

<table>
<thead>
<tr>
<th>Simulation parameters</th>
<th>35 km</th>
<th>50 km</th>
</tr>
</thead>
<tbody>
<tr>
<td>Source depth</td>
<td>20 m</td>
<td>100 Hz</td>
</tr>
<tr>
<td>Receiver type</td>
<td>HLA</td>
<td>40 dB</td>
</tr>
<tr>
<td>Receiver depth</td>
<td>26 m</td>
<td>300 m, 2 m</td>
</tr>
<tr>
<td>No. of hydrophones</td>
<td>128</td>
<td>50 km (k=100)</td>
</tr>
<tr>
<td>MC runs</td>
<td>100</td>
<td>1 meas./500 m</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Method</th>
<th>% Imp. over EKF</th>
</tr>
</thead>
<tbody>
<tr>
<td>EKF</td>
<td>0</td>
</tr>
<tr>
<td>UKF</td>
<td>25</td>
</tr>
<tr>
<td>PF-200</td>
<td>-12</td>
</tr>
<tr>
<td>PF-5000</td>
<td>60</td>
</tr>
</tbody>
</table>
thickens again. When the layer gets thin, other parameters such as the sound speed, attenuation, and density characterizing the layer have little or no effect on the acoustic field across the array, temporarily making the field insensitive to that layer’s parameters. This results in deviations from their true values for these parameters, and when the layer starts to thicken again the filters diverge since the starting points for the layer parameters other than the layer thickness are too far from their current true values.

Another case is the coupling between the parameters. When the sediment thickness increases, less signal reaches the bottom layer, resulting in degrading performance of these bottom parameters similar to the previous case and may cause divergence as the sediment gets less thick again. In general, PFs show more robust tracking under such conditions.

Also the seabed can have spatial layer changes. While one sediment layer and a semi-infinite bottom are adequate initially, a second sediment layer can form. Or the sediment type becomes sand, whereas the model given to the PF assumed that the region is clay, limiting the possible parameter values via priors. Such environments can be tracked using multiple environmental models, one for each possible scenario. This will require Gaussian sum filters such as the interactive multiple model EKF/UKF that involves a filter bank composed of multiple KFs running in parallel for each possible model.29,36 Similarly, this can be accomplished using their PF counterpart, the MMPF. 37

One interesting observation from the simulations is the KFs ability to continue to track some parameters while other parameters diverge and can only be tracked by the PF. This means that the marginal densities for these parameters are close to Gaussian and the measurement equations connecting those parameters to the acoustic field are close to being linear. This is unlike many other tracking problems such that when one parameter starts to diverge, so do all the others, usually resulting in a total divergence. However, there are many cases where such marginal Gaussian densities occur. In these cases, one common approach is to use a Rao–Blackwellized particle filter also known as the marginalized

![Graphs showing tracking results of EKF, UKF, PF-200, and PF-5000 for the seven-parameter environment given in Fig. 1 using the short range HLA configuration. True trajectories (dashed) are provided along with the tracking filter estimates (solid).](image)
particle filter that groups the state parameters into linear/Gaussian and nonlinear/non-Gaussian ones and uses a mixed EKF/PF approach, reducing the dimension of the state space that the PF has to sample, which, in return, reduces significantly the required number of particles for a desired accuracy.29,38

VI. SUMMARY

Tracking of geoacoustic environmental parameters has been addressed. Spatial and temporal evolutions of the water column and seabed parameters were estimated using EKFs, UKFs, and PFs with acoustic measurements as inputs. These tracking filters enabled providing real-time, continuously updated estimates of the geoacoustic parameters and their uncertainties, requiring far fewer forward model runs compared to alternatives such as successively running geoacoustic inversion algorithms.

This paper investigated how the three filters behaved for the nonlinear, non-Gaussian geoacoustic tracking problem using three examples with both the VLA and HLA simulated data. An efficient way of computing the local PCRLB to compute the filter efficiencies was shown. The results showed that all three filters performed well in geoacoustic applications. It was found that a PF with enough particles could typically achieve 80% filter efficiency in geoacoustic tracking while providing PPD evolutions for the environmental parameters. Even though KFs had less efficiency and high divergence rates and were unable to track some parameters while the PF was still able to maintain track, they also showed robust tracking in many cases. Since they are computationally very fast compared to the PF, they can be used in many applications where the performances are similar. The UKF outperformed the EKF in most of the simulations, but the improvement-over-EKF values of the UKF were modest compared to the PF. The PF was able to maintain track in environments that include sudden changes such as the sediment thickness. The two KFs used here showed mixed success in tracking sudden jumps in the parameter values.

PFs proved to be very promising in the nonlinear, non-Gaussian geoacoustic tracking problem. It was shown that the performance could degrade below that of the EKF if a small number of particles were used. However, in this paper, the PF with enough particles showed robust tracking in a number of cases involving different measurement configurations that use HLA and VLA data, slowly and quickly changing environments, and environmental parameters with relatively flat sensitivity curves. The limitations of all three filters were discussed using an example of tracking a quickly changing environment with parameters having medium to totally flat sensitivity curves.

ACKNOWLEDGMENT

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APPENDIX A: FILTER EQUATIONS

1. Extended Kalman filter

The first filter choice is the EKF (Ref. 22). Since KF is the best possible linear tracking filter, its extended version that can operate on nonlinear systems can still be near optimal. The EKF works by converting the system into a form over which the KF can operate. This is done by locally linearizing the equations using the first terms in the Taylor series expansions of the nonlinear transformations (such as the normal mode code in h) and assuming that the nonlinearities are small so that EKF will perform well. Once the equations are linearized, starting with a Gaussian PDF for x0 will ensure that the evolving parameters will remain Gaussian, and it is necessary to propagate only the mean and covariance as in the KF. However, due to this approximation, the EKF cannot claim the optimality enjoyed by the KF for linear-Gaussian systems. The EKF has been implemented successfully in a large number of applications such as radar and sonar target tracking applications, and its speed and ease of implementation make the EKF the filter of choice.

In geoacoustic tracking, the complex source magnitude sk is usually not known. Therefore, the EKF equations are modified by inserting a maximum likelihood (ML) estimator that estimates the source every time the forward normal d(x0) is run.10 This is done by writing the likelihood function at step k as

\[
\mathcal{L}(x_k) = \frac{1}{\pi n_H R^H R^{-1}} \exp\left[-\frac{\|y_k - s_k d(x_k)\|^2}{\nu}\right],
\]

(A1)

where n_H is the number of hydrophones. Assuming that the complex Gaussian noise w_k is uncorrelated with the same variance along the array \( R = n I \),

\[
\mathcal{L}(x_k) = \frac{1}{(\pi \nu)^{n_H}} \exp\left(-\frac{\|y_k - s_k d(x_k)\|^2}{\nu}\right).
\]

(A2)

The ML estimate for the source s_k is then obtained by solving for \( \partial \mathcal{L} / \partial s_k = 0 \), giving

\[
\hat{s}_k = \frac{d(x_k)^H y_k}{||d(x_k)||^2}.
\]

(A3)

This source estimate is used in the following EKF equations both for the calculation of h and during the linearization of h to obtain the matrix H:

\[
\hat{x}_k|_{k-1} = F \hat{x}_{k-1}|_{k-1},
\]

(A4)

\[
P_{\hat{x}|k-1} = Q_{k-1} + F P_{\hat{x}|k-1} F^T,
\]

(A5)

\[
\hat{x}_k|k = \hat{x}_k|_{k-1} + K_k (y_k - h(\hat{x}_k|_{k-1})),
\]

(A6)

\[
P_{\hat{x}|k} = P_{\hat{x}|k-1} - K_k S_k K_k^T,
\]

(A7)

where

\[
S_k = H_k P_{\hat{x}|k-1} H_k^T + R_k,
\]

(A8)

\[
K_k = P_{\hat{x}|k-1} H_k^T S_k^{-1},
\]

(A9)
\[
\begin{align*}
\mathbf{h}(\mathbf{\hat{x}}_{k|k-1}) &= \frac{\mathbf{d}(\mathbf{\hat{x}}_{k|k-1})^T \mathbf{y}_k \mathbf{d}(\mathbf{\hat{x}}_{k|k-1})}{||\mathbf{d}(\mathbf{\hat{x}}_{k|k-1})||^2}, \\
\hat{\mathbf{H}}_k &= [\nabla_x \mathbf{h}^T(\mathbf{\hat{x}}_{k|k-1})]^T.
\end{align*}
\]

(A10)

Equations (A4) and (A5) are the prediction steps that give the environmental model estimate \( \mathbf{\hat{x}}_k \) and its associated uncertainty in terms of the covariance matrix \( \mathbf{P}_k \) at step index \( k \) given the previous history \( \{\mathbf{x}_0, \mathbf{x}_1, \ldots, \mathbf{x}_{k-1}\} \). Eqs. (A6) and (A7) are the correction equations that give \( \mathbf{\hat{x}}_k \) and \( \mathbf{P}_k \) at step index \( k \) given its previous history \( \{\mathbf{x}_0, \mathbf{x}_1, \ldots, \mathbf{x}_{k-1}\} \) and the set of measurements \( \{\mathbf{y}_1, \mathbf{y}_2, \ldots, \mathbf{y}_k\} \), and \( \mathbf{K} \) is the Kalman gain.

Note that the insertion of the ML estimate of the source in Eq. (A3) into the Kalman update equation violates the Kalman formulation. This is true for Eq. (A6) where the Kalman gain is applied to the measured minus predicted data \( \mathbf{y}_k - \mathbf{y}_{\text{pred}} \) since the predicted data include \( \mathbf{y}_k \) itself due to the ML source estimate in Eq. (A3). However, the ML estimator in Eq. (A3) simply normalizes the amplitude of the predicted data so that the acoustic field variation across the array is compared, not the actual amplitudes, eliminating the effects of the unknown source amplitude. Moreover, the averaging inherent in the inner product in Eq. (A3) over the array elements makes the source estimate less noisy and more robust relative to the environmental parameters. Finally, the performance calculations of the KFs used here are not affected since the synthetic data enable us to compute the true filter RMS error \( \overline{E}[\mathbf{x}_{k|k} - \mathbf{\hat{x}}_{k|k}]^2 \) instead of the conventional performance metric for the KF (covariance matrix \( \mathbf{P}_{k|k} \)). An alternative approach would be to include the unknown source term into the state model \( \mathbf{x}_k \). However, this will increase the dimension of the state space for a nuisance parameter in which we are not interested.

2. Unscented Kalman filter

The analytical linearization used in the EKF results in poor estimates of the mean and covariance as the nonlinearity in the forward model increases. To mitigate this the UKF\(^{33,39}\) has been introduced. Instead of analytical linearization, the UKF uses a concept called statistical linearization in which the filter enforces Gaussianity and keeps the nonlinearity. Enforcing Gaussian PDFs enables the filter to carry all the necessary information by propagating only the mean and covariance as does the KF. This is achieved by the UT that enables the propagation of the mean and variance through nonlinear functions. The UKF represents initial densities using only a few predetermined particles called sigma points. These points are chosen deterministically by the UT algorithm, and they describe accurately the mean and covariance of a PDF. As the random variable undergoes a nonlinear transformation, these points are propagated through the nonlinear function and used to reconstruct the new mean and covariance using the UT weights. Hence, unlike the EKF, they can compute accurately the mean and covariance to at least second order (third if the initial PDF is Gaussian) of the nonlinearity.

Similar to the EKF, the UKF algorithm used here incorporates a ML estimator for the unknown source term. The UKF uses the following recursive formulation where \( 2n_x + 1 \) sigma points \( \{\mathbf{\lambda}_i\}_{i=0}^{2n_x} \) and their corresponding weights \( \mathbf{W} \) are generated and used with the UT algorithm to perform the mean \( \langle \mathbf{\lambda} \rangle \) and covariance \( \mathbf{P} \) calculations required in the Kalman framework. The UT weights are given in terms of the scaling parameter \( \kappa = \alpha^2 (n_x + \kappa) - n_x \), and prior knowledge parameter \( \beta \), where \( \alpha \) is used to control the spread of the sigma points around the mean and \( \kappa \) is the secondary scaling parameter. \( \alpha \), \( \beta \), and \( \kappa \) are taken as 0.1, 2, and 0, respectively.

UT weights and sigma points are generated using

\[
\begin{align*}
\lambda_0^k & = \hat{x}_{k|k-1}, \\
W_0 & = \frac{\lambda}{n_x + \lambda}, \quad W_{\text{cov}}^0 = W_0 + \beta + 1 - \alpha^2, \\
\lambda^i_k & = \hat{x}_{k|k-1} + (\sqrt{Q(n_x + \kappa)P_{k-1|k-1}})_i, \\
W_m^i & = W_{\text{cov}}^i = 0.5, \quad i = 1, 2, \ldots, 2n_x, \\
W_{m+cov}^i & = 0.5, \quad i = 1, 2, \ldots, 2n_x, \\
X_{k|k-1} & = Q_{\text{cov}} + \sum_{i=0}^{2n_x} W_{m+cov}^i \mathbf{\lambda}^i_{k|k-1} = \sum_{i=0}^{2n_x} W_{m+cov}^i \mathbf{\lambda}^i_{k|k-1} - \hat{x}_{k|k-1} - \mathbf{\hat{x}}_{k|k-1}^T, \\
\end{align*}
\]

(A12)

(A13)

where \( (\sqrt{\mathbf{\lambda}})_i \) is the \( i \)th column of the matrix square root. The prediction step is composed of

\[
\begin{align*}
X_{k|k-1} & = \mathbf{F}X_{k-1}, \quad Y_{k|k-1} = \frac{\mathbf{d}(\mathbf{\lambda}^i_{k|k-1})^T \mathbf{y}_k \mathbf{d}(\mathbf{\lambda}^i_{k|k-1})}{||\mathbf{d}(\mathbf{\lambda}^i_{k|k-1})||^2}, \\
\hat{x}_{k|k} & = \sum_{i=0}^{2n_x} W_{m+cov}^i \mathbf{\lambda}^i_{k|k-1}, \quad \hat{y}_{k|k} = \sum_{i=0}^{2n_x} W_{m+cov}^i \mathbf{\lambda}^i_{k|k-1}, \\
\mathbf{P}_{k|k-1} & = Q_{k-1} + \sum_{i=0}^{2n_x} W_{m+cov}^i [\mathbf{\lambda}^i_{k|k-1} - \hat{x}_{k|k-1}] [\mathbf{\lambda}^i_{k|k-1} - \hat{x}_{k|k-1}]^T, \\
\end{align*}
\]

(A14)

and the update step uses

\[
\begin{align*}
\mathbf{P}_{xy} & = \sum_{i=0}^{2n_x} W_{m+cov}^i [\mathbf{\lambda}^i_{k|k-1} - \hat{x}_{k|k-1}] \mathbf{y}_k - \hat{y}_{k|k-1}]^T, \\
\mathbf{P}_{yy} & = \sum_{i=0}^{2n_x} W_{m+cov}^i [\mathbf{\lambda}^i_{k|k-1} - \hat{y}_{k|k-1}] [\mathbf{\lambda}^i_{k|k-1} - \hat{y}_{k|k-1}]^T, \\
\mathbf{K}_k & = \mathbf{P}_{xy} \mathbf{P}_{yy}^{-1}, \\
\hat{x}_{k|k} & = \hat{x}_{k|k-1} + \mathbf{K}_k (\mathbf{y}_k - \hat{y}_{k|k-1}), \\
\mathbf{P}_{k|k} & = \mathbf{P}_{k|k-1} - \mathbf{K}_k (\mathbf{P}_{xy} + \mathbf{R}_k) \mathbf{K}_k^T.
\end{align*}
\]

(A15)

(A16)

(A17)

Although it is fast relative to more advanced techniques, derivative-free, and an improvement over the EKF, there still are two weaknesses. The first is that the nonlinearity may be so severe that it may require an even higher order accuracy than the UKF can provide to correctly capture the mean and
covariance. The other is that the densities may be highly non-Gaussian so that the first two moments will not be sufficient even if they can be calculated correctly.

3. Particle filter

The third algorithm used in this paper is the SMC commonly known as the PF. Rapid increases in the available computational power have made the PF very popular for many nonlinear, non-Gaussian tracking problems. Unlike the Kalman framework, neither Gaussian nor linearity assumptions are necessary for the PF. However, this means that propagating only the mean and covariance is not sufficient anymore. Instead, the PF propagates an ensemble of particles to represent the densities. These particles are selected randomly by MC runs. Compared with the sigma points of the UKF, a much larger number of particles are needed to represent the PDF. Therefore, the PF can perform much better than its KF variants, but it does this with an order of magnitude increase in the required computational resources. There are many different variants of the PF such as the regularized particle filter, Markov chain MC step PF, and auxiliary and classical SIR PFs. The SIR (Ref. 40) algorithm is used throughout this work. Normally, degeneracy can be a problem for the SIR algorithm, especially for low process noise systems. However, due to the environmental uncertainty in the model, \( Q_k \) is selected to be relatively large, thus mostly eliminating the need for more complex PFs with improved sample diversity.

The SIR algorithm uses \( n_p \) particles \( \{x_{k|k-1}^{p}\}_{p=1}^{n_p} \) to represent the PDF at each step \( k \). The filter has the predict and update sections just as in a KF, but the SIR filter will use these sections to propagate the particles instead of mean and covariance calculations. The initial set of particles \( \{x_{0|k-1}^{p}\}_{p=1}^{n_p} \) are sampled from the prior \( p(x_0) \). The SIR filter uses the importance sampling density as the transitional prior \( p(x_k|x_{k-1}) \). Although this is a suboptimal choice, it is easy to sample from this density. This selection results in particle weights proportional to the likelihood \( W_k \sim p(y_k|x_k) \).

The prediction step consists of sampling from the prior. Then the normalized weight \( W_k \) of each particle is calculated from its likelihood function. As with the KFs, the source term is estimated with a ML estimator during the likelihood calculation of each particle in the ensemble. The update step includes the resampling section where a new set of \( n_p \) particles is generated from the parent set according to the weights of the parent particles, with high likelihood particles generating more particles than the low likelihood ones. Hence, a single iteration of the recursive SIR algorithm can be summarized as

\[
\begin{align*}
\{x_{k|k-1}^{p}\}_{p=1}^{n_p} & \sim p(x_k|x_{k-1}), \\
W_k & = \frac{p(y_k|x_{k|k-1})}{\sum_{p=1}^{n_p} p(y_k|x_{k|k-1}^{p})}, \\
\{x_{k|k}^{p}\}_{p=1}^{n_p} & = \text{Resample}[W_k, \{x_{k|k-1}^{p}\}_{p=1}^{n_p}], \\
\text{such that } P(x_k|x_{k-1}) & = W_k
\end{align*}
\]  
(A18, A19, A20)

APPENDIX B: POSTERIOR CRAMÉR–RAO LOWER BOUND

One issue with the tracking problems is that the computation of the full PCRLB is not feasible. Unlike geoaoustic inversion where there is a fixed number \( n_k \) of random variables in the model vector \( x \), geoaoustic tracking introduces \( n_k \) new random variables with every new step \( k \). Therefore, we will use a \( (n_k \times n_k) \) matrix PCRLB \( B_k \) instead of the full PCRLB matrix. PCRLB \( B_k \) is defined as the inverse of the filtering information matrix \( J_k \) so that the MSE of any filter estimate at tracking step index \( k \) will be bounded as

\[
E[(\hat{x}_{k|k} - x_k)(\hat{x}_{k|k} - x_k)^T] \approx J_k^{-1}. \quad (B1)
\]

A computationally efficient way of computing this PCRLB recursively for discrete-time nonlinear filtering problems is given in Ref. 42,

\[
J_k = D_{k-1}^{12} - [D_{k-1}^{12}]^T (J_{k-1} + D_{k-1}^{11})^{-1} D_{k-1}^{12}, \quad (B2)
\]

where

\[
D_{k-1}^{11} = -E[\nabla x_{k-1} \log p(x_k|x_{k-1})]^T, \quad (B3)
\]

\[
D_{k-1}^{12} = -E[\nabla x_{k-1} \log p(x_k|x_{k-1})], \quad (B4)
\]

\[
D_{k-1}^{22} = -E[\nabla x_{k} \log p(x_k|x_{k-1})]^T - E[\nabla x_{k} \log p(y_k|x_k)^T]. \quad (B5)
\]

It is important to note that the computations only require \( (n_k \times n_k) \) matrices, and the computation cost is independent of the step index \( k \). The geoaoustic tracking problem with the system of equations defined in Eqs. (2) and (3) has a linear state equation, and both of the random noise sequences \( v \) and \( w \) are additive and Gaussian. Therefore, the above equations can be reduced to

\[
D_{k-1}^{11} = F^T Q_{k-1}^{-1} F, \quad (B6)
\]

\[
D_{k-1}^{12} = -F^T Q_{k-1}^{-1}, \quad (B7)
\]

\[
D_{k-1}^{22} = Q_{k-1}^{-1} + E[\nabla h(x_k)^T R_0^{-1} H_k], \quad (B7)
\]

where \( H_k \) is the jacobian of \( h(x) \) computed similar to Eqs. (A10) and (A11) at its true value \( x_k \). Unfortunately, the expectation in Eq. (B7) has to be evaluated numerically using a MC analysis. \( D_{k-1}^{22} \) is computed as

\[
D_{k-1}^{22} = Q_{k-1}^{-1} + \frac{1}{n_{MC}} \sum_{j=1}^{n_{MC}} \nabla h(x_j)^T R_0^{-1} [\nabla h(x_j)]^T, \quad (B8)
\]

where \( n_{MC} \) is the number of MC trajectories, assuming a Gaussian prior PDF with a covariance matrix \( P_0 \). The recursion in Eq. (B2) is initiated with

\[
J_0 = -E[\nabla x_0 \log p(x_0)]^T = P_0^{-1}. \quad (B9)
\]

Once the PCRLB, the inverse of \( J_k \) in Eq. (B2), is computed, the filters can be compared with each other and the CRLB.
