Model-Based Ocean Acoustic Passive Localization

J.V. Candy
Lawrence Livermore National Laboratory
Livermore, CA 94550

E.J. Sullivan
Naval Undersea Warfare Center
Newport, RI 02841

Abstract—A model-based approach is developed (theoretically) to solve the passive localization problem. Here we investigate the design of a model-based identifier for a shallow water ocean acoustic problem characterized by a normal-mode model. In this problem we show how the processor can be structured to estimate the vertical wave numbers directly from measured pressure-field and sound speed measurements thereby eliminating the need for synthetic aperture processing or even a propagation model solution. Finally, we investigate various special cases of the source localization problem, designing a model-based localizer for each and evaluating the underlying structure with the expectation of gaining more and more insight into the general problem.

I. INTRODUCTION

The incorporation of ocean acoustic propagation models into signal processing schemes has long been the hope to improve overall processor performance. Current applications are concerned with the localization/detection of an acoustic source as well as environmental inversion. Proposed methods are based on bringing the predictions of a propagation model in concert with pressure measurements from an array. This is called the matched-field problem and much work has been accomplished [1,2]. Model-based techniques offer high expectations of performance, since a processor based on the predicted physical phenomenology that inherently has generated the measured signal must produce a better (minimum error variance) estimate than one that does not [3,4]. However, if the model embedded in this processor is inaccurate or for that matter incorrect, then the model-based processor can actually perform worse. Therefore, it is necessary, as part of the design procedure, to estimate/update the model parameters either through separate experiments or jointly (adaptively) while performing the required processing [5]. Note that the introduction of a recursive, on-line model-based processor (MBP) can offer a dramatic detection improvement in a tactical passive or active sonar-type system especially when a rapid environmental assessment is required [6].

Incorporating a propagation model into a signal processing scheme to solve the source localization problem was most probably initiated by the work of Hinich [7] in the development of a source depth estimator. The concept of matched-field processing (MFP), that is, comparing the measured pressure-field to that predicted by a propagation model was introduced by Bucker [8] in 1976. In MFP, the localization problem is solved by repeated model predictions at the array for an exhaustive search over assumed source positions. The final position estimate is that one related to maximum power. Many papers have been written exploiting and improving on the MFP and is best summarized in the text of Tolstoy [1] or the special issue of Doolittle [2].

With this background in mind, we investigate the development of a "model-based" localizer. That is, a localizer that incorporates a mathematical representation of the ocean acoustic propagation and estimates the position of the source. Clearly each of the methods described above can be classified as model-based, for instance, the MFP incorporates a fixed (parametrically) propagation model. However, in this paper we will investigate the state-space forward propagation scheme of Candy and Sullivan [5] and apply it to this problem. That is, we first develop a model-based identifier (MBI) and show how it can be used to estimate the critical wave number parameters from noisy measurement data and then investigate the model-based localizer (MBL) as an extension of this result.

Much of the formalism for this alternative to matched field processing has been worked out [5,6]. Model-based signal processing is concerned with the incorporation of environmental (propagation, seabed, sound speed, etc.), measurement (sensor arrays) and noise (ambient, shipping, surface, etc.) models along with measured data into a sophisticated processing algorithm capable of detecting, filtering (estimating) and localizing an acoustic source (target) in the complex ocean environment. This technique offers a well-founded statistical approach for comparing propagation/noise models to measured data and is not constrained to a stationary environment which is essential in the hostile ocean. Not only does the processor offer a means of estimating various quantities of high interest (modes, pressure-field, sound speed, etc.), but it also provides a means to statistically evaluate its performance on-line which is especially useful for model validation experiments [9,10]. Although model-based techniques have been around for quite a while, they have not.
yet found their way heavily into ocean acoustics. It is the purpose of this paper to investigate the theoretical feasibility of applying model-based processors to solve the source localization problem.

Model-based processing is a direct approach that uses in-situ measurements, that is, the actual acoustic and sound speed data. More specifically, the acoustic measurements are combined with a set of preliminary sound speed and other parameters to initialize the algorithm. The algorithm then uses the incoming data to recursively update the parameter set jointly with the acoustic signal processing. In principle, any propagation model can be included in this method; however, in this paper our designs are all based on the normal-mode model of propagation. In the following, we define the MBI as a nonlinear Kalman filter whose estimated states are the modal functions \( \phi(z_e) \) and states representing the estimated ocean acoustic parameters \( \theta(z_e) \) that have been augmented into the processor. The basic processor is shown in Figure 1. The inputs to the MBI can be either raw data \( \{p(z_e); \{c(z_e)\}\} \) or a combination of raw data and outputs \( \theta(z_e) \) of a modal solver [11].

In section II, we briefly develop the MBI and apply it to ocean acoustic problem. Next the localization problem is formulated in section III and various special cases solutions analyzed (theoretically). Here it is shown how to construct the localizer under different conditions. We summarize our results in the final section.

II. MODEL-BASED IDENTIFICATION FOR OCEAN ACOUSTICS

In this section we develop the model-based identifier which provides the basis of our eventual localizer design. System identification is typically concerned with the estimation of a model and its associated parameters from noisy measurement data. Usually the model structure is pre-defined (as in our case) and then a parameter estimator is developed to “fit” parameters according to some error criterion. The quality of the estimates must be evaluated to decide if the processor performance is satisfactory or equivalently the model adequately represents the data. There are various types (criteria) of identifiers employing many different model (usually linear) structures [12]. Since our efforts are primarily aimed at ocean acoustics in which the models and parameters are usually nonlinear, we will concentrate on developing a parameter estimator capable of on-line (shipboard) operations and nonlinear dynamics.

From our previous work [5,6], it is clear the the extended Kalman filter (EKF) identifier will satisfy these constraints nicely. We begin our analysis of the EKF as an identifier following closely the approach of Ljung [13]. The general nonlinear identifier or equivalently parameter estimator structure can be derived directly from the EKF algorithm [4] in discrete form.

To understand the internal structure of our processor and apply it to ocean acoustic problems, we first define the composite state-vector consisting of the original states \( x(z_e) \) and the “augmented” parameters, that is,

\[
\bar{x}(z_e) := \begin{bmatrix} \bar{z}(z_e) \\ \bar{\theta}(z_e) \end{bmatrix}
\]

where \( \ell \) is the general iteration—it could be time, depth, range etc. Substituting this augmented state vector into the EKF relations the MBI algorithm evolves easily when we define the following partitions [13]

\[
\tilde{P} := \begin{bmatrix} \tilde{P}_{zz} & \tilde{P}_{z\theta} \\ \tilde{P}_{\theta z} & \tilde{P}_{\theta\theta} \end{bmatrix} \quad \bar{K} := \begin{bmatrix} K_x \\ K_\theta \end{bmatrix}
\]

We note that this algorithm is not implemented in this fashion, it is implemented in the numerically stable UD-factorized form as in SSPACK-PC [14]. The simplified structure of the EKF parameter estimator is shown in Figure 2. Here we see the model-based identifier which consists of two distinct, yet coupled processors: a parameter estimator and a state estimator (filter). The parameter estimator provides estimates that are corrected by the corresponding innovations during each recursion. These estimates are then provided to the state estimator (extended Kalman filter) in order to update the model parameters used in the estimator. After both state and parameters estimates are calculated, a new measurement is processed and the procedure continues.

Next we consider the development of this processor applied to ocean acoustic problems. Here the model-based identifier incorporates an ocean acoustic propagation model into its internal structure which will eventually lead to formulations of the localization problem. Here we develop (theoretically) a model-based identifier for use with an ocean acoustic propagation model. For
Figure 2: MBI Processor Structure.

propagation in a shallow water environment we choose the normal-mode model which can easily be placed in state-space form (see Refr. 15 for details). We choose the “depth only” structure and assume a vertical array which yields a linear space-varying formulation.

By assuming that the horizontal range of the source $r_s$ is known a-priori, we can use the Hankel function $H_0(k_r(r_s))$ which is the source range solution. The Gauss-Markov model for this constrained problem is given by

$$\frac{d}{dz}\phi(z) = A(z)\phi(z) + B(z)u(z) + w(z)$$

(3)

with the pressure field measurement model given by

$$p(r_s, z) = C^T(r_s, z)\phi(z) + v(z)$$

(4)

where

$$C^T(r_s, z) = [\beta_1(r_s, z) \cdots \beta_M(r_s, z) \cdots 0]$$

(5)

with $\beta_i(r_s, z) = \frac{\phi_i(z)}{\phi_i(z)dz}$ and where $\kappa_r, \kappa_z$ are the respective wave numbers in the $r$ and $z$ directions with $c$ the depth-dependent sound speed profile and $\omega$ the harmonic source frequency. The random noise vectors $w$ and $v$ are assumed gaussian, zero-mean with respective covariance matrices, $R_w$ and $R_v$.

Since our array spatially samples the pressure-field, we choose to discretize the differential state equations using a finite (first) difference approach $\Delta z = z_{t+1} - z_t$. Therefore, substituting into the differential equation, we obtain

$$\phi_{m}(z_{t+1}) = [I + \Delta z A_m(z_t)] \phi_m(z_t) + \Delta z B_m(z_t)u(z_t)$$

(6)

Since we have a vertical line sensor array to measure the pressure-field, the measurement model for the $m^{th}$ mode becomes

$$p_m(r_s, z_t) = C_m^T(r_s, z_t)\phi_m(z_t) + v_m(z_t)$$

(7)

It is this model that we employ in our model-based identifier. Next suppose we assume that the vertical wave numbers, $\{\kappa_z(m)\}$, are unknown and we would like to estimate them directly from the pressure-field measurements. This is a crucial first step for any ocean acoustic processing requirement. By estimating the wave numbers directly from the noisy array measurements, not only do we obtain the parameters required for our subsequent model-based processor designs, but also we replace the need to perform the synthetic aperture processing which is the usual approach in obtaining the vertical numbers, that is, the horizontal wave numbers are estimated using a towed array and with known sound speed the vertical wave number are calculated from the dispersion relation. Note that this means that we are eliminating the need to solve the boundary value problem using a numerical eigenvalue solver [11]. It is well known that the wave numbers carry all of the essential information (boundary, temporal frequency etc.) directly - a powerful set of parameters! Thus, we define the basic vertical wave number identification problem as

GIVEN a set of noisy pressure-field measurements, $\{p(r_s, z_t)\}$, FIND the “best” (minimum error variance) estimate of the vertical wave numbers, that is, $\{\kappa_z(m)\}, m = 1, \cdots, M$.

The basic form of the coupled modal equations follows with $\kappa_z \rightarrow \theta$ and $m = 1, \cdots, M$

$$\phi_{m1}(z_t) = \phi_{m1}(z_{t-1}) + \Delta z \phi_{m2}(z_{t-1})$$
$$\phi_{m2}(z_t) = -\Delta z \theta_{m2}^2(z_{t-1})\phi_{m1}(z_{t-1}) + \phi_{m2}(z_{t-1})$$
$$\theta_m(z_t) = \beta_m(z_t)$$

(8)

(9)

with

$$\phi_m(r_s, z_t) = \beta_m(z_t)\phi_{m1}(z_t)$$

Thus, we have the following system functions identified from the above equations as

$$a_{m1}[\phi, \theta] = \phi_{m1}(z_{t-1}) + \Delta z \phi_{m2}(z_{t-1})$$
$$a_{m2}[\phi, \theta] = -\Delta z \theta_{m2}^2(z_{t-1})\phi_{m1}(z_{t-1}) + \phi_{m2}(z_{t-1})$$
$$a_{2M+1}[\phi, \theta] = \theta_1(z_t)$$

(10)

with corresponding jacobians given by

$$\frac{\partial a_{m1}}{\partial \phi} = 1, \frac{\partial a_{m1}}{\partial \theta} = \Delta z, \frac{\partial a_{m2}}{\partial \phi} = 0$$
$$\frac{\partial a_{m2}}{\partial \phi} = -\Delta z \theta_{m2}^2(z_t), \frac{\partial a_{m2}}{\partial \theta} = 1, \frac{\partial a_{2M+1}}{\partial \phi} = 0, \frac{\partial a_{2M+1}}{\partial \theta} = 1$$

(11)

For the measurement system we have that

$$c_m[\phi, \theta] = \beta(z_t)\phi_{m1}(z_t)$$

(12)
and the measurement jacobians are
\[ \frac{\partial c_m}{\partial \phi_m} = \beta(z_s), \quad \frac{\partial c_m}{\partial \theta_m} = 0, \quad \frac{\partial c_m}{\partial \phi_m} = 0 \] (13)

The Jacobian matrices evolve to the following structure for the wave number identification problem are
\[ A_{\phi} = A(z_t, \theta) \] (14)

The associated wave number (parameter Jacobian) is given by
\[ A_{\theta, m} = \text{diag} \begin{bmatrix} 0 & \cdots & 0 \end{bmatrix} \] (15)
with \( A_{\phi} \in R^{2M \times 2M} \), and \( A_{\theta} \in R^{2M \times M} \) and the overall Jacobian matrix given by \( A(\phi, \theta) \in R^{3M \times 3M} \). The measurement Jacobian is much simpler for this problem
\[ C_{\theta}(\phi, \theta) = 0 \] (16)
and therefore the \( 1 \times 3M \) measurement Jacobian is
\[ C(\phi, \theta) = |C_{\phi}(\phi, \theta) | \] (17)

Using this information we can easily construct the overall parameter estimator. The prediction equations for the \( m^{th} \) mode and wave number are
\[ \phi_{m1}(z_t|z_{t-1}) = \phi_{m1}(z_{t-1}|z_{t-1}) + \Delta z_t \phi_{m2}(z_t|z_{t-1}) \]
\[ \phi_{m2}(z_t|z_{t-1}) = -\Delta z_t \phi_{m3}(z_t|z_{t-1}) \phi_{m1}(z_{t-1}|z_{t-1}) + \phi_{m1}(z_t|z_{t-1}) \]
and the corresponding innovations (parameterized by \( \theta \)) are given by
\[ e(z_t, \theta) = p(z, z_t) - \sum_{m=1}^{M} \beta_m(z_t) \phi_{m1}(z_t|z_{t-1}, \theta) \] (18)

with the correction equations
\[ \phi(z_t|z_t) = \phi(z_t|z_{t-1}) + K \phi(z_t) e(z_t) \]
\[ \theta_m(z_t|z_t) = \theta_m(z_t|z_{t-1}) + K \theta_m(z_t) e(z_t) \] (19)

So in this particular application we see how the model-based identifier can be employed to estimate the wave numbers (vertical) from noisy pressure-field and sound speed measurements evolving from a vertical array or hydrophones. This completes the section on applying the identifier to a ocean acoustic identification problem. Next we consider the localization problem.

III. MODEL-BASED LOCALIZATION

In this section we investigate (theoretically) the development of a model-based localization technique using the extended Kalman filter (EKF) identifier/parameter estimator of section II. In this framework, we can state (simply) the model-based localization problem as:

GIVEN a set of noisy pressure-field and sound speed measurements, \([p(r_s, z_s)], [c(z_s)]\) and the normal-mode propagation model, FIND the "best" (minimum error variance) estimate of the source position \((r_s, z_s)\), that is, find \( r_s \) and \( z_s \).

The approach we plan to take, is to investigate some special cases of the general two-dimensional localization problem to gain some insight into the structure and operation of the processor. We will define each problem under certain classes of assumptions and develop (theoretically) the model-based localizer for each.

Let us assume that we are operating in a shallow water environment \((r >> h)\) and we have a vertical array. We will investigate the development of a model-based identifier based on our "depth only" model of the previous section. Here we make the assumption that we have measurement/estimates of the pressure-field and sound speed as well as a set of vertical wave numbers along with the dispersion relation to obtain the horizontal wave numbers. With all of this information in hand, we investigate the construction of a model-based identifier to estimate (individually) the source depth and range. We construct the model-based identifier for the following cases:

- Case I: Depth known, range unknown
- Case II: Depth unknown, range known

If we use the normal mode propagation model, then in all of these cases the model-based identifier (MBI) can be constructed in a similar fashion with each being a special case. Examining the "depth only" state-space model, we see that the range and depth appear explicitly in the point source excitation, that is,
\[ u(z) = \delta(z - z_s) \] (20)

and in the measurement weighting equation
\[ \beta_m(r_s, z_s) = \frac{\phi_m(z_s)}{\int_{z_s}^{z} \phi^2(z) dz} H_0(\kappa_r(m) r_s) \] (21)

Since the point source is impulsive, it can be incorporated into the initial condition of the "forward" propagation model. So we see that within this framework, it is not obvious how to estimate either the range or depth, since they are implicit functions either of \( \phi \) or the initial condition vector, or \( \beta_m \) or \( \phi(z_s) \) or the Hankel function, \( H_0 \). The basic approach is to realize that at a given source depth these implicit functions are fixed, therefore, let us assume that \( \theta_i \) is a constant \((\theta = 0)\) or a random walk
with an underlying discrete Gauss-Markov model given by
\[ \theta(r_s, z_t) = \theta(r_s, z_{t-1}) + w_0(z_{t-1}) \]  
(22)

Thus, the normal mode model with augmented parameter space (as before) is:
\[ \phi_m(z_t) = \phi_m(z_{t-1}) + \Delta z_t \phi_m(z_{t-1}) \]
\[ \phi_m(z_t) = -\Delta z_t \kappa^2_m(z) \phi_m(z_{t-1}) + \phi_m(z_{t-1}) \]
\[ \theta_1(r_s, z_{t-1}) = \theta_1(r_s, z_{t-1}) \]
\[ \vdots \]
\[ \theta_M(r_s, z_t) = \theta_M(r_s, z_{t-1}) \]
(23)

with corresponding measurement model
\[ p(r_s, z_t) = \sum_{m=1}^{M} \gamma_m(r_s, z_t) \theta_m(r_s, z_t) \phi_m(z_t) \]
(24)

We choose this general representation where the set \( \{ \theta_m(r_s, z_t) \}, m = 1, \ldots, M \) is the unknown implicit functions of range and/or depth while the parameters, \( \{ \gamma_m(r_s, z_t) \} \) represent the known a-priori information that is included in the processor. The development of the localizer algorithm incorporates the design of the model-based identifier. The basic prediction estimates for the \( m \)th mode are
\[ \hat{\phi}_m(z_t|z_{t-1}) = \phi_m(z_{t-1}) + \Delta z_t \phi_m(z_{t-1}) \]
\[ \phi_m(z_t) = -\Delta z_t \kappa^2_m(z) \phi_m(z_{t-1}) + \phi_m(z_{t-1}) \]
\[ \hat{\theta}_1(r_s, z_{t-1}) = \theta_1(r_s, z_{t-1}) \]
\[ \vdots \]
\[ \hat{\theta}_M(r_s, z_{t-1}) = \theta_M(r_s, z_{t-1}) \]
(25)

and the corresponding innovations (parameterized by \( \theta \)) are given by
\[ e(z_t, \theta) = p(r_s, z_t) - \sum_{m=1}^{M} \beta_m(z_t) \hat{\phi}_m(z_t|z_{t-1}, \theta) \]
(26)

with the correction equations
\[ \hat{\phi}_m(z_t|z_{t-1}) = \phi_m(z_{t-1}) + K_m(z_t) e(z_t, \theta) \]
\[ \hat{\theta}(r_s, z_{t-1}) = \theta(r_s, z_{t-1}) + K_m(z_t) e(z_t, \theta) \]
(27)

The Jacobians are given by
\[ \frac{\partial \hat{\phi}_m(z_t|z_{t-1})}{\partial \theta} = \Delta z_t \phi_m(z_{t-1}) \]
\[ \frac{\partial \hat{\theta}(r_s, z_{t-1})}{\partial \theta} = 1 \]
\[ \frac{\partial \phi_m(z_t)}{\partial \theta} = -\Delta z_t \kappa^2_m(z_t) \phi_m(z_{t-1}) \]
\[ \frac{\partial \phi_m(z_{t-1})}{\partial \theta} = 1 \]
\[ \frac{\partial \phi_m(z_{t-1})}{\partial \theta} = 0 \]
(28)

For the measurement system we have that
\[ C(r_s, z_t) = \sum_{m=1}^{M} \gamma_m(r_s, z_t) \theta_m(r_s, z_t) \phi_m(z_t) \]
(29)

and the measurement Jacobians are
\[ \frac{\partial \gamma_m(r_s, z_t)}{\partial \theta} = \gamma_m \theta_m(r_s, z_t) \phi_m(z_t) \]
\[ \frac{\partial \gamma_m(r_s, z_t)}{\partial \theta} = 0 \]
(30)

The corresponding jacobian matrices follow identically for \( A_\theta \) with \( \kappa_s(m) \rightarrow \theta_m \) and \( A_\theta = 0 \), but the measurement Jacobians become
\[ C_\theta(\phi, \theta) = |\gamma_1(r_s, z_t)\phi_1(z_t)| \cdots |\gamma_M(r_s, z_t)\phi_M(z_t)| \]
(31)

and
\[ C_\theta(\phi, \theta) = |\gamma_1(r_s, z_t)\phi_1(r_s, z_t) | \cdots |\gamma_M(r_s, z_t)\phi_M(z_t)| \]
(32)

Now let us examine the special cases and see how they effect this general design. The key idea here is that the model-based identifier is used to estimate the implicit function \( \{ \theta_m \} \) which is then solved for the parameters of interest (depth, range). For Case I with known depth and range unknown, we have (known)
\[ \gamma_m(r_s, z_t) = \gamma_m(z_t) = \frac{\phi_m(z_t)}{\int_0^\infty \phi^2(z)dz} \]
(33)

and now for the Hankel function we can approximate it using the far-field condition \( (\kappa_r > 1) \) by
\[ H_0(\kappa_r(m)r_s) \approx \frac{e(-\alpha_r(m)r_s)}{\sqrt{\kappa_r(m)r_s}} \]
(34)

Since our pressure-field measurement is real and evaluated at \( r = r_s \), we have
\[ \theta_m(r_s) := \Re[H_0(\kappa_r(m)r_s)] = \frac{e(-\alpha_r(m)r_s)}{\sqrt{\kappa_r(m)r_s}} \]
(35)

Solving for \( r_s \), we have
\[ \theta^2_m(r_s)\kappa_r(m)r_s(m) = e^{-2\alpha_r(m)r_s} \]
(36)

and using a one-term power series expansion for the exponential we have
\[ r_s(m) \approx 1 \]
\[ \theta^2_m(r_s)\kappa_r(m) + 2\alpha_r(m) \]
(37)

which is used in the maximum likelihood estimator of the range
\[ \hat{r}_s = \sum_{m=1}^{M} r_s(m) \]
(38)

Examining Case II with depth unknown and range known, we have \( \beta_m \) as before with the known components given by
\[ \gamma_m(r_s, z_t) = \gamma_m(r_s) = \frac{qH_0(\kappa_r(m)r_s)}{\int_0^\infty \phi^2(z)dz} \]
(39)

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and now we have

$$\hat{\theta}(r_s, z_s) = \hat{\phi}(z_s)$$  \hspace{1cm} (40)$$

Suppose we assume that we can subdivide the ocean medium into small layers in depth such that \( \Delta z = \Delta z_s / N_s \), for \( N_s \) the number of subdivisions (between each depth). Further assume that over this small layer the sound speed is piecewise constant. Clearly, if we make the layers small enough this assumption will hold true. This being the case, we have a closed form solution for the modal function, that is, we know that at \( z_s = z_s \), we have

$$\hat{\phi}_{m1}(z_s) = \hat{\phi}_{m1}(z)|_{z=z_s} = \sin \kappa(z_s)(z_s - z_0)$$  \hspace{1cm} (41)$$
or solving for \( z_s \) we obtain

$$z_s(m) = \frac{\arcsin \left( \frac{\theta_m(r_s, z_s)}{\kappa_s(m)} \right)}{\kappa_s(m)} + z_0, \quad m = 1, \ldots, M$$  \hspace{1cm} (42)$$

As before, performing the maximum likelihood estimation on the depth we have

$$\hat{z}_s = \frac{1}{M} \sum_{m=1}^{M} z_s(m)$$  \hspace{1cm} (43)$$

This completes the theoretical development of potential range and depth estimators using the model-based localizer, that is, a model-based identifier plus a coordinate estimator.

IV. DISCUSSION

In this paper we have developed an on-line, adaptive, model-based solution to the localization problem, that is, a source position location estimation scheme based on coupling the normal-mode propagation model to a functional model of position. The algorithm employed is the nonlinear extended Kalman filter identifier/parameter estimator in predictor/corrector form which evolved as the solution to the minimum variance estimation problem when the models were placed in state-space form.

It was shown that the model-based localizer follows quite naturally from the model-based identifier. In fact, a vertical wave number identifier was constructed (theoretically) to investigate the underlying structure of the processor. Using this structure the localizer was also theorized based on various implicit function solutions to the source position.

References


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