On the accuracy and resolution of powersum-based sampling methods

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<td>As Published</td>
<td><a href="http://dx.doi.org/10.1109/TSP.2008.2007102">http://dx.doi.org/10.1109/TSP.2008.2007102</a></td>
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<tr>
<td>Publisher</td>
<td>Institute of Electrical and Electronics Engineers</td>
</tr>
<tr>
<td>Version</td>
<td>Final published version</td>
</tr>
<tr>
<td>Accessed</td>
<td>Thu Jan 10 02:44:43 EST 2019</td>
</tr>
<tr>
<td>Citable Link</td>
<td><a href="http://hdl.handle.net/1721.1/52382">http://hdl.handle.net/1721.1/52382</a></td>
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On the Accuracy and Resolution of Powersum-Based Sampling Methods

Julius Kusuma, Member, IEEE, and Vivek K Goyal, Senior Member, IEEE

Abstract—Recently, several sampling methods suitable for signals that are sums of Diracs have been proposed. Though they are implemented through different acquisition architectures, these methods all rely on estimating the parameters of a powersum series. We derive Cramér–Rao lower bounds (CRBs) for estimation of the powersum poles, which translate to the Dirac positions. We then demonstrate the efficacy of simple algorithms due to Prony and Cornell for low-order powersums and low oversampling relative to the rate of innovation. The simulated performance illustrates the possibility of superresolution reconstruction and robustness to correlation in the powersum sample noise.

Index Terms—Analog-to-digital conversion, Cramér–Rao bound (CRB), estimation, parametric modeling, Prony’s method.

I. INTRODUCTION

DIGITAL processing of continuous-time signals relies first and foremost on accurate data acquisition. In the classical paradigm, acquisition involves filtering a continuous-time signal and then measuring uniformly spaced samples; the samples are construed to specify a unique signal in a particular subspace of continuous-time signals. Importantly, the combination of Hilbert-space geometry and the representative signals forming a subspace makes the influence of noise, as measured by $L^2$ error, easy to analyze [1].

The focus of this paper is on signal acquisition for certain classes of signals that do not form subspaces. Through recently developed architectures and algorithms, these signals can be acquired from a small number of samples, but the greater geometric complexity of these signal sets makes the performance when samples are subject to noise more difficult to analyze. We provide a unification of the techniques of [2]–[4], showing that they each yield a powersum series fitting problem. We analyze the performance limits for powersum series fitting and the performance of several algorithms. Our analysis method is adapted for real-valued and complex-roots-of-unity cases, corresponding to these different sampling schemes. In particular, this enables comparison between architectures and highlights the importance of modeling sources of noise.

As a specific instance, we are interested in acquiring real-valued signals from the set

$$\mathcal{M}_K = \left\{ x : x(t) = \sum_{k=0}^{K-1} a_k \delta(t - t_k) \right\}$$ (1)

where the number of components $K$ is known.\(^1\) Sets of this type have been used to model many naturally occurring signals [5] and in ranging and wideband communication systems [6]. A signal in $\mathcal{M}_K$ is uniquely determined by $K$ pairs of parameters $\{(a_k, t_k)\}_{k=0}^{K-1}$, so it can be specified in various ways by $2K$ real numbers. One could hope that $N \geq 2K$ samples of $y(t) = h(t) * x(t)$ would suffice as such a representation. Indeed, it is shown in [2]—constructively through an algorithm that recovers $\{(a_k, t_k)\}$—that certain sampling kernels $h(t)$ do enable unique specification of $x(t)$ through samples of $y(t)$.

It is useful to separate the (approximate) acquisition of a signal from $\mathcal{M}_K$ into two interrelated phases: measurement and estimation. In the measurement phase, analog hardware takes $x(t)$ as an input and creates certain quantized samples. As described further in Section III, several architectures for measurement have been proposed. These each yield a powersum series fitting problem. In the estimation phase, some algorithm is applied to the samples to solve the fitting problem.

An important open question is: How robustly can a signal in $\mathcal{M}_K$ be estimated when the measurement process is subject to noise? Because of the form of $\mathcal{M}_K$, when the $t_k$s are fixed the estimation of the $a_k$s is a standard linear problem. The most interesting issue is thus the accuracy of estimating the $t_k$s. We address this question by explicitly exhibiting the Cramér–Rao bound (CRB) for the powersum series fitting problem and by comparing this bound numerically to the performance obtained with two practical algorithms.

We limit our attention to the $K = 1$ and $K = 2$ cases and hint at the infeasibility of an explicit approach for larger values of $K$. Note also that we are interested in the performance when the number of samples $N$ is at or near the minimum possible $(2K)$. A good understanding of the performance when the number of samples is large can be obtained by interpretation of results for spectral analysis [7]. As a final caveat, note that we consider Gaussian additive noise models. These are appropriate for cases in which thermal noise—rather than quantization noise, aperture uncertainty, and comparator ambiguity—is the dominant analog-to-digital conversion (ADC) impairment; this is the case for high-resolution ADC [8].

The remainder of the paper is organized as follows. We first introduce powersum series and solution for their parameters in

\(^1\)The use of a Dirac delta simplifies the discussion. It can be replaced by a known pulse $g(t)$ and then absorbed into the sampling kernel $h(t)$, yielding an effective sampling kernel $g(t) * h(t)$.

Manuscript received December 05, 2007; revised September 03, 2008. First published October 31, 2008; current version published January 06, 2009. The associate editor coordinating the review of this manuscript and approving its publication was Prof. Pierre Vandergheynst. This work was supported in part by the NEC Corporation Fund for Research in Computers and Communications and by the Texas Instruments Leadership University Consortium Program. This work was presented in part at the IEEE International Conference on Image Processing, Atlanta, GA, October 2006.

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Digital Object Identifier 10.1109/TSP.2008.2007102
the noiseless case in Section II. Then Section III shows how pow-
ersum series arise from several sampling architectures for signals of the class (1) and other signal classes. In particular, this puts ar-
chitectures from [2]–[4] into a common framework. In Section IV we
turn to algorithms for fitting powersum series which have noise. We focus on algorithms that are simple, work well for
small numbers of samples, and do not require initialization.
CRBs for powersum series estimation problems are developed in
Section V, where we give results for real-valued and complex-
roots-of-unity powersums. These are applied in Section VI, which
comprises various architectures and algorithms, using two
models for the sources of noise in the measurement architectures:
continuous-time white noise and powersum white noise.
The estimation error analysis presented here appeared first in
[9], and the architecture of Section III-C appeared first in [4].

II. POWERSUM SERIES

The nonlinear parameter estimation problems that we con-
sider in this paper are all reduced to estimation problems in-
volving a powersum series. We first introduce the powersum
series, before we review the estimation problems that are rel-
vant in Section III.

Definition 1 (Powersum Series): Samples \( \{x_n\}_{n=0}^{N-1} \) are
to be generated by a powersum series of order \( K \) with amplitudes
\( \{c_k\}_{k=0}^{K-1} \) and poles \( \{u_k\}_{k=0}^{K-1} \) when
\[
x_n = \sum_{k=0}^{K-1} c_k u_k^n, \quad n = 0, 1, \ldots, N - 1.
\]

Sequences of form (2) were first studied by G. C. M. R. de Prony
in 1795 as he attempted to find the decay rates of chemical pro-
cesses [10]. In de Prony’s original problem, the observations and
parameters are real-valued. This is sometimes called “real
exponential fitting” or “exponential analysis” in the natural sci-
ences literature [11], [12].
de Prony’s method is based an idea that is quite intuitive to
readers of this Transactions. Suppose \( x_n \) is of the powersum
form (2) for \( n \geq 0 \) and zero for \( n < 0 \). Then the \( z \)-transform
of this infinite sequence is given by
\[
X(z) = \sum_{k=0}^{K-1} c_k \frac{1}{1 - u_k z^{-1}}.
\]

Since \( X(z) \) has \( K \) poles, there is a monic annihilating filter
\( b_n \) supported on \{0, 1, \ldots, K\} such that \( d_n = x_n \ast b_n \) is zero
outside of \{0, 1, \ldots, K-1\}. This fact can be written in matrix
form as
\[
\begin{bmatrix}
x_K & x_{K-1} & \cdots & x_0 \\
x_{K+1} & x_K & \cdots & x_1 \\
\vdots & \vdots & \ddots & \vdots \\
x_{2K-1} & x_{2K-2} & \cdots & x_K \\
x_{2K+1} & x_{2K-1} & \cdots & x_{K-1}
\end{bmatrix}
\begin{bmatrix}
b_K \\
b_{K+1} \\
\vdots \\
b_{2K-1}
\end{bmatrix}
= \begin{bmatrix}
1 \\
0 \\
0 \\
0
\end{bmatrix}
\]
\[
\begin{bmatrix}
1 \\
b_1 \\
b_2 \\
\vdots \\
b_K
\end{bmatrix}
\]

where we have written \( K \) equations to have enough to solve
for the \( K \) unknowns \( \{b_k\}_{k=1}^{K} \). Looking at the matrix in (3), we
see that \( N = 2K \) samples of \( x_n \) are generally sufficient for
recovery of the \( b_k \). (If the solution is not unique, the data are fit
by a lower-order model.) Now factoring
\[
1 + \sum_{k=1}^{K} b_k z^{-k} \quad \Rightarrow \quad 1 - (1 - u_k z^{-1}),
\]

With the \( u_k \)s fixed, (2) describes a linear relationship between
\( (c_0, c_1, \ldots, c_{K-1}) \) and \( (x_0, x_1, \ldots, x_{K-1}) \); thus the \( c_k \)s are
easily determined.

We return to the fitting of powersum series—there in the pres-
ence of noise—in Section IV. That will be after we exhibit sev-
eral sampling architectures that generate powersum series.

III. SIGNAL MODELS AND ARCHITECTURES YIELDING
POWERSUM SERIES

As aforementioned, we are interested in signal estimation
problems involving powersum series. The form of powersum
series that arises depends on the signal model and the acquisi-
tion architecture. In this section, we consider the following three
scenarios in their order of publication:
1) a signal that is a periodic sum of Diracs, acquired using a
sinc sampling kernel and uniform sampling in time [2];
2) a sum of Diracs signal with a known local rate of innova-
tion, acquired using a sampling kernel that satisfies a
Strang-Fix condition and uniform sampling in time [3];
3) a sum of Diracs signal with a known local rate of innova-
tion, acquired using integrators and simultaneous sampling
in multiple channels [4], [9].

This is not an exhaustive review of the literature; in particular
other scenarios are presented in [2]. The coverage is selected
to include powersums with both real and complex poles and to
facilitate a comparison between 2) and 3) in Section VI.

A. Periodic Sum of Diracs Acquired With Sinc Kernel

Consider a signal \( x(t) \) that is a 1-periodic extension of
\[
\sum_{k=0}^{K-1} a_k \delta(t - t_k),
\]
where \( \{t_k\}_{k=0}^{K-1} \subset [0, 1) \). Because of the periodicity, \( x(t) \) can be represented using Fourier series
coefficients as
\[
x(t) = \sum_{m=-\infty}^{\infty} X_m \exp(j2\pi m t),
\]

For the given signal model, the Fourier series coefficients are
given by
\[
X_m = \sum_{k=0}^{K-1} a_k \exp(-j2\pi m t_k), \quad m \in \mathbb{Z}.
\]

The Fourier domain representation given in (5) has infinite
length, hence we say that this signal is not bandlimited. How-
ever, since (5) is a powersum series, it is possible to estimate
the coefficients from \( N \geq 2K \) samples of \( X_m \). In this case, the
poles of the powersum series are complex roots of unity.

Vetterli et al. [2] showed that Fourier series coefficient \( X_m \)
can be obtained by linear processing of uniform samples of the

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output of a $\sin(2Kt)$ sampling filter with input $x(t)$. Specifically, $X_m$ for $m \in \{-M, -M + 1, \ldots, M\}$ are obtained from $N \geq 2M + 1$ samples.

B. Aperiodic Sum of Diracs Acquired With Compactly Supported Kernel

The technique described in Section III-A is an idealized abstraction because it involves unrealizable filters and infinite periodic extension. Dragotti et al. [3] introduced more practical schemes that use compactly supported sampling kernels and causal sampling kernels with rational transfer functions. We concentrate here on sampling kernels $\phi(t)$ that satisfy the Strang-Fix conditions for polynomial reproduction up to degree $M$ for shifts by $1/N$.

Consider $x(t)$ as in (1) where $\{t_k\}_{k=0}^{K-1} \subset [0, 1)$. This is representative of having finite local rate of innovation normalized to $2K$. Let $r_{m,n}$ be coefficients for polynomial reproduction, such that

$$\sum_n r_{m,n}\phi\left(\frac{t-n}{N}\right) = d_m(t)$$

where $d_m(t) = t^n$, for $t \in [0, 1)$ and $m = 0, 1, \ldots, M$. Taking $N$ uniform samples of $x(t) * \phi(t)$ in $[0, 1)$ yields

$$x_n = \langle x(t), \phi\left(\frac{t-n}{N}\right) \rangle = \int \left(\sum_{k=0}^{K-1} a_k \delta(t-t_k)\right) \phi\left(\frac{t-n}{N}\right) \, dt$$

$$= \sum_{k=0}^{K-1} a_k \delta\left(\frac{t-n}{N}\right)$$

for $n = 0, 1, \ldots, N - 1$. Then we can compute

$$y_n = \sum_n r_{m,n} x_n$$

$$= \sum_n r_{m,n} \sum_{k=0}^{K-1} a_k \phi\left(\frac{t-k}{N}\right)$$

$$= \sum_{k=0}^{K-1} a_k \sum_n r_{m,n} \phi\left(\frac{t-k}{N}\right)$$

$$= \sum_{k=0}^{K-1} a_k \phi\left(\frac{t-k}{N}\right)$$

which is a powersum series. Hence, $x(t)$ can be perfectly reconstructed from $N \geq 2K$ samples $\{x_n\}_{n=0}^{N-1}$.

C. Aperiodic Sum of Diracs Acquired With Parallel Sampling

In [4], [9] we proposed a sampling architecture that is implemented by parallel integrators. Consider the same signal model as in Section III-B. Let $x_k(t)$ be the $k$th integral of $x(t)$; i.e., $x_0(t) = x(t)$ and $x_{k+1}(t) = \int_0^t x_k(\tau) d\tau$. Samples are taken simultaneously at the outputs of multiple channels: $y_n = x_{n+1}(1), n = 0, 1, \ldots, N - 1$.

To see how a powersum series is obtained, note that

$$x_1(t) = \int_0^t x(\tau) d\tau = \int_0^t \sum_{k=0}^{K-1} a_k \delta(t-t_k) d\tau$$

$$= \sum_{k=0}^{K-1} a_k H(t-t_k)$$

$$x_2(t) = \int_0^t x_1(\tau) d\tau = \int_0^t \sum_{k=0}^{K-1} a_k H(\tau-t_k) d\tau$$

$$= \sum_{k=0}^{K-1} a_k H(t-t_k)$$

and

$$x_3(t) = \int_0^t x_2(\tau) d\tau$$

$$= \int_0^t \sum_{k=0}^{K-1} a_k H(t-t_k) d\tau$$

$$= \sum_{k=0}^{K-1} a_k H(t-t_k)$$

etc., where $H(t)$ is the Heaviside (unit step) function. Thus $y_n = x_{n+1}(1) = (1/n!) \sum_{k=0}^{K-1} a_k (1-t_k)^n$, $n = 0, 1, \ldots, N - 1$.

IV. ALGORITHMS FOR POWERSUM ESTIMATION

Work on exponential fitting in signal processing has been concentrated in the areas of angle-of-arrival estimation and direction finding, often using multiple antennas or sensors. This body of work is focused on estimating the signal parameters by first estimating the signal covariance structure [7], [13]–[15], and on the case where we have large numbers of samples with multiple snapshots. Since the parameters of greatest interest are the angles of the coefficients of the powersum series—corresponding to frequencies of the series components—it is often assumed that the coefficients lie on the unit circle. Most of the publications in this area demonstrate the efficacy of their algorithms by Monte Carlo simulation and give the resulting mean-square error.

On the other hand, the papers on exponential fitting in the natural sciences often give proof of concept by using the proposed algorithms to estimate parameters in an experiment for which the correct answer is known [11], [12]. Moreover, the number of observations tends to be small. This is matched to our interest here, since we focus on signals with low local rate of innovation and sampling rates near the rate of innovation. However, where appropriate we still use Monte Carlo simulation and give the resulting mean-square error.

Throughout, we are interested in estimating the parameters of a powersum series in the presence of additive noise

$$y_n = \sum_{k=0}^{K-1} c_k u_k^n + w_n, \quad n = 0, 1, \ldots, N - 1. \quad (6)$$

We consider two classes of algorithms: algorithms based on Prony’s method and those based on the Matrix Pencil method,
also known as the Rotational Invariance Property [13], [14], [16]. These two classes of algorithms are closely related. (See [17] for a quick overview of their similarities and differences.) Several algorithms give performance close to the CRBs in the presence of additive white Gaussian noise (AWGN), such as the nonlinear least-squares algorithm [18] and a regularized maximum-likelihood algorithm [17]. However, while their performances can exceed those of the Prony- and Matrix Pencil-based methods, these algorithms require very good initial conditions and perform poorly when the number of samples \(N\) is small. These algorithms are often simulated and implemented using initial values obtained from the Prony and Matrix Pencil methods. A review of algorithms such as the annihilating filter, ESPRIT and MUSIC is given in [15].

We focus on the two methods less known within the signal processing community.

A. TLS-Prony

We briefly review the algorithm proposed by Rahman and Yu [19] and analyzed by Steedly and Moses [20] called total least squares-Prony (TLS-Prony). Suppose that we are given observations \(y_n, n = 0, 1, \ldots, N - 1\). Pick an integer \(L \geq K\), recommended to be around \(N/3\).

1) Form the Hankel matrix \(Y\) of size \((N - L) \times L\) from observations, where \([Y]_{i,j} = y_{j-i}\).

2) Compute the SVD of \(Y\) and reconstruct using only the \(K\) largest singular values. Call this reconstruction \(\hat{Y}\), and the first column \(\hat{y}\).

3) Compute the least-squares estimate \(\hat{b} = (\hat{Y})^T \hat{y}\), where \((\cdot)^T\) denotes the pseudo-inverse.

4) Find the \(L\) roots of polynomial representation \(\hat{b}(z)\), obtaining estimates \(\hat{u}_\ell\) for \(\ell = 0, 1, \ldots, L - 1\).

5) Do least-squares fitting to find amplitudes \(\hat{a}_\ell\) for each of the \(L\) estimates.

6) For each of the \(L\) estimates, compute energy

\[
E_\ell = \sum_n |\hat{a}_\ell y_n|^2.
\]

7) Pick \(K\) estimates with the largest energies.

B. Cornell’s Algorithm

Cornell [11] proposed a procedure for finding the coefficients of a powersum series from uniformly spaced observations based on segmenting the observations and computing partial sums. He gave simple formulas for the \(K = 1\) and \(K = 2\) cases. Petersson and Holmström [21] gave formulas for the \(K = 3\) and \(K = 4\) cases. These are dramatically more complicated, and to quote the authors, even for \(K = 3\) they found the formula “troublesome,” both due to the complexity of the algebraic expressions and their poor performance and instability in the presence of noise. Thus, in this paper we review and utilize only the simple formulas for \(K = 1\) and \(K = 2\).

Suppose that we are given observations \(y_n, n = 0, 1, \ldots, N - 1\). For convenience, let \(N = 4q\) for some integer \(q\).

For \(K = 1\), the steps are given by the following.

1) Compute partial sums of \(y_n\) as follows:

\[
S_1 = \sum_{n=0}^{N/2-1} y_n, \quad S_2 = \sum_{n=N/2}^{N-1} y_n.
\]

2) Compute \(W = S_2/S_1\).

3) Set estimate \(\hat{u}_0 = W^{N/2}\).

For \(K = 2\), the steps are given by the following.

1) Compute partial sums of \(y_n\) as follows:

\[
S_1 = \sum_{n=0}^{N/4-1} y_n, \quad S_2 = \sum_{n=N/4}^{N/2-1} y_n
\]

\[
S_3 = \sum_{n=N/2}^{3N/4-1} y_n, \quad S_4 = \sum_{n=3N/4}^{N-1} y_n.
\]

2) Compute

\[
L_1 = \frac{(S_1 S_4 - S_2 S_3)}{(S_1 S_3 - S_2^2)}
\]

\[
L_2 = \frac{(S_1 S_3 - S_2^2)}{(S_1 S_4 - S_2 S_3)}
\]

3) Find the roots \(W_0\) and \(W_1\) of \(z^2 - L_1 z + L_2 = 0\).

4) Set estimates \(\hat{u}_0 = W_0^{N/4}\) and \(\hat{u}_1 = W_1^{N/4}\).

Cornell showed that under the mild condition \(\mathbb{E}[\hat{u}_n] = 0\), this algorithm is a consistent estimator. Cornell’s algorithm has been extended by Agha [22] in order to avoid having to take powers of real numbers, although Agha’s modified algorithm gives similar performance for small sample sizes. Cornell’s algorithm has also been modified to allow for nonuniform spacing of samples by Foss [23].

V. CRAMÉR–RAO LOWER BOUNDS

In the derivation of CRBs we focus on the cases \(K = 1\) and \(K = 2\). We treat the complex-roots-of-unity and real-valued cases separately. We write the noisy powersum series as (6).

In this paper, we focus on the case where the additive noise \(w_n\) is i.i.d. zero-mean Gaussian with variance \(\sigma^2\), although we have results for additive Gaussian noise with arbitrary covariance given in [9].

The derivations of the CRBs are done via the Fisher information matrix (FIM), which is derived from the log-likelihood of the vector of parameters of interest [26]. Proofs of the theorems in this section appear in the Appendix.

A. \(K = 1\), Complex Roots of Unity

This case is applicable to the sampling scheme in Section III-A. Let the signal of (6) be periodic with period \(T_p\). The desired parameters are \(\theta = [c_0, \theta_0]^T\). The noiseless signal is given by

\[
X_m = c_0 \exp \left( j \frac{2\pi m}{T_p} \theta_0 \right).
\]
In the presence of additive noise, the signal is given by
\[ y(t) = c_0 \delta(t - t_0) + w(t) \]
\[ Y_m = c_0 \exp \left( j \frac{2\pi}{T_p} t_0 m \right) + W_m. \]  
\( (8) \)

Suppose that we observe \( N \) samples of \( Y_m, m = 0, 1, \ldots, N - 1 \). Define
\[ \Gamma_r = \frac{1}{N_{r+1}} \sum_{m=0}^{N-1} m^r. \]  
\( (9) \)

Further, let \( \tilde{x}[m] = \Re \{ X_m \} \) and \( \tilde{\omega}[m] = \Im \{ X_m \} \). In the presence of AWGN, the FIM is given by [26]
\[ J = \frac{2}{\sigma^2} \left[ \sum_m (\tilde{x}[m] \tilde{x}^H[m] + \tilde{\omega}[m] \tilde{\omega}^H[m]) \right] \]
\[ = \frac{2}{\sigma^2} \left( K \cdot L \cdot \begin{bmatrix} \Gamma_0 & 0 \\ 0 & \Gamma_1 \end{bmatrix} \cdot L \cdot K \right). \]
\( (10) \)

where we have
\[ \tilde{x}[m] = \begin{bmatrix} \cos \left( \frac{2\pi}{T_p} t_0 m \right) \\ -c_0 m \sin \left( \frac{2\pi}{T_p} t_0 m \right) \end{bmatrix} \]
\[ \tilde{\omega}[m] = \begin{bmatrix} \sin \left( \frac{2\pi}{T_p} t_0 m \right) \\ c_0 m \cos \left( \frac{2\pi}{T_p} t_0 m \right) \end{bmatrix} \]

Further let \( \Phi[m] = \Re \{ X_m \} \) and \( \Phi[m] = \Im \{ X_m \} \). The FIM is given by
\[ J = \frac{2}{\sigma^2} \left[ \sum_m (\Phi[m] \Phi^T[m] + \Phi[m] \Phi^T[m]) \right]. \]
\( (13) \)

For convenience, let \( c_0 = c_0(2\pi/T_p), c_1 = c_1(2\pi/T_p) \)
\[ \tilde{x}[m] = \begin{bmatrix} \cos \left( \frac{2\pi}{T_p} t_0 m \right) \\ c_0 \sin \left( \frac{2\pi}{T_p} t_0 m \right) \\ -c_1 \cos \left( \frac{2\pi}{T_p} t_1 m \right) \end{bmatrix} \]
\[ \tilde{\omega}[m] = \begin{bmatrix} \sin \left( \frac{2\pi}{T_p} t_1 m \right) \\ c_0 \cos \left( \frac{2\pi}{T_p} t_0 m \right) \\ -c_1 \sin \left( \frac{2\pi}{T_p} t_1 m \right) \end{bmatrix} \]

We obtain the following theorem:

**Theorem 1:** Consider the noisy powersum (8) where \( W_n \) is zero-mean white Gaussian noise with variance \( \sigma^2 \). Let \( c_0 = c_0(2\pi/T_p) \) and SNR = \( c_0^2/\sigma^2 \). Suppose that we obtain \( N \) samples of the signal after filtering using an antialiasing filter with bandwidth \( \pi/N \) rad. For convenience, let \( \delta t = |t_1 - t_0| \)
\[ \Gamma_r = \frac{1}{N_{r+1}} \sum_{m=0}^{N-1} m^r \]
\[ C_r = \frac{1}{N_{r+1}} \sum_{m=0}^{N-1} m^r \cos \left( \frac{2\pi}{T_p} \delta t \cdot m \right) \]
\[ S_r = \frac{1}{N_{r+1}} \sum_{m=0}^{N-1} m^r \sin \left( \frac{2\pi}{T_p} \delta t \cdot m \right) \]

Further, let \( M = \begin{bmatrix} \Gamma_2 (\Gamma_0^2 - C_0^2) - S_0^2 \Gamma_0 & C_2 (\Gamma_0^2 - C_0^2) - S_2^2 \Gamma_0 \\ C_2 (\Gamma_0^2 - C_0^2) - S_2^2 \Gamma_0 & \Gamma_2 (\Gamma_0^2 - C_0^2) - S_0^2 \Gamma_0 \end{bmatrix} \)
\[ P = \frac{1}{\Gamma_0^2 - C_0^2} M. \]

Then the CRB is given by
\[ \mathbf{E} \left[ (\hat{t}_k - t_k)^2 \right] \geq \frac{1}{\text{SNR}_k N^3} \left| \mathbf{P} \right|_{k,k}. \]
\( (14) \)

The bound of Theorem 2 scales as \( 1/N^2 \), consistent with previously known results in line spectrum estimation and with Theorem 1. Further, the formula obtained in (14) is similar to that of Dilaveroglu [24, Theorem 2].
C. $K = 1$, Real-Valued Case

This case is applicable to the sampling schemes of Section III-B (where $u_k = t_k$) and Section III-C (where $u_k = 1 - t_k$). Consider the simplest case where $\delta t$ is white Gaussian with variance $\sigma^2$. Define the finite summation

$$G_r(x) = \frac{1}{N^r + 1} \sum_{n=0}^{N-1} n^r x^n.$$  \hspace{1cm} (15)

We can write the FIM as

$$J = \frac{2}{\sigma^2} \left[ \begin{array}{ccc} \sqrt{N} & 0 & 0 \\ 0 & N \sqrt{N} & 0 \\ G_0(u_0^2) & G_1(u_0^2) & G_2(u_0^2) \end{array} \right] \left[ \begin{array}{c} 1 \\ 0 \\ 0 \end{array} \right] \left[ \begin{array}{c} \sqrt{N} \\ 0 \\ N \sqrt{N} \end{array} \right].$$

We are interested in finding the CRB for $u_0$, which is the last entry of the inverse of the FIM. This can be obtained by using direct matrix inversion.

Theorem 3: Let a noisy real-valued powersum be given by $y_n = \alpha_0 u_0^n + \eta_n$, for $n = 0, 1, \ldots, N - 1$, where $\eta_n$ is zero-mean white Gaussian noise with variance $\sigma^2$. Then the CRB for estimation of $u_0$ from $\{y_n\}_{n=0}^{N-1}$ is given by

$$E[(\hat{u}_0 - u_0)^2] \geq \frac{\sigma^2}{\text{SNR} N^3 (G_0(u_0^2) G_2(u_0^2) - G_1(u_0^2) G_1(u_0^2)^2)}$$  \hspace{1cm} (16)

where $\text{SNR} = \frac{\sigma^2}{\alpha_0^2 u_0^2}$.

The bound of (16) scales as $1/N^2$, consistent with the behavior of frequency estimates in line spectrum estimation [15].

Suppose for now that the signal of interest consists of complex-valued poles, not necessarily complex roots of unity. This case was studied by Steedly and Moses in [20]. The magnitude of the poles in that case corresponds to the damping coefficient of the signal. They showed that the CRB for the estimation of this parameter is minimized around the unit circle. By contrast, (16) is not minimized by $u_0 = 1$. We will revisit this comparison later in Section VI-A.

When the poles are complex-valued, the lack of knowledge of the exact pole angle leads to large errors in the estimate of the pole magnitude: a small error in the phase estimate of the pole will be amplified by the magnitude of the pole, as shown in Fig. 2 of [20]. Hence, in the complex case, the variance in a pole magnitude estimate is best near unit magnitude and becomes worse as the true pole magnitude increases. In our case, the poles have positive real values. The variance in the pole estimate decreases as the pole magnitude is increased, as there is no phase ambiguity.

D. $K = 2$, Real-Valued Case

Finally, we examine the case with $K = 2$ and real-valued poles. Let $\theta = [c_0, c_1, t_0, t_1]^T$ be the vector of unknown parameters. We wish to derive the CRB for the estimation of $t_0$ and $t_1$ in terms of $\delta t = t_1 - t_0$ when the observations are subjected to AWGN.

Consider two-term noisy powersum $y_n = \alpha_0 (u_0^n + c_1 (u_1^n) + \eta_n$, where $\eta_n$ is white Gaussian noise. For convenience, let

$$A = \begin{bmatrix} G_0(u_0^2) \\ G_0(u_0 u_1) \\ G_0(u_1^2) \end{bmatrix}, \quad B = \begin{bmatrix} G_1(u_0^2) \\ G_1(u_0 u_1) \\ G_1(u_1^2) \end{bmatrix}, \quad C = \begin{bmatrix} G_2(u_0^2) \\ G_2(u_0 u_1) \\ G_2(u_1^2) \end{bmatrix}$$

where $G_r(x)$ is as given in (15). Then the CRB can be found via the Schur complement, yielding the following theorem.

Theorem 4: Consider the estimation of $\{u_0, u_1\}$ from $N$ observations of a two-term noisy powersum subject to AWGN with variance $\sigma^2$. Let $\text{SNR}_k = \frac{\sigma_k^2}{\sigma^2}, k = 1, 2$. Then the CRB is given by

$$E[\{\hat{\delta t} - \delta t\}^2] \geq \frac{\text{SNR}_k}{\text{SNR}_1 N^3} \left[ (C - BA^{-1}B)^{-1} \right]_{kk}$$

where $A, B, C$ are as given above.

VI. PERFORMANCE EVALUATION

In this section, we first compare the performance of the schemes of Section IV against the CRBs of Section V, suitable for the cases where the powersum series is subjected to AWGN.

Then we consider the case of signal parameter estimation in the presence of continuous-time AWGN, where the different sampling schemes yield different noise structures in the powersum. We compare the powersum-based sampling schemes with the conventional method of applying an antialiasing filter, taking uniform samples, and estimating the signal pulse delay by finding the maxima of the cross correlation.

A. Powersum AWGN

It is known from the line spectrum estimation literature that both the Prony method and rotational invariance algorithms work well in the presence of AWGN when powersum poles are complex roots of unity, and that both algorithms have a superresolution property. Further, the performances of the algorithms are independent of the actual values of the powersum poles. We show this in Fig. 1 for the estimation of one Dirac, and in Fig. 2 for the case of two Diracs. We compare the two algorithms with the derived CRB from Theorem 1 and Theorem 2. In this set of simulations, we set the period of the signal to be $T_p = 1$. The results of the Cornell algorithm are not shown as they are similar to the results of the TLS-Prony algorithm.

The real-valued case is less known. From Fig. 3 we see that the performance depends on the actual value of the powersum poles. The TLS-Prony algorithm outperforms the Cornell algorithm, except when the poles are small and the number of samples is very small, e.g., $N = 2$.

Suppose for now that the signal of interest consists of complex-valued poles, not necessarily complex roots of unity. The results shown in Fig. 3 are very different from those of Steedly and Moses in [20], where the poles are complex-valued but are not necessarily roots of unity. The magnitude of the poles in that case corresponds to the damping coefficient of the signal. They
showed that the CRB for the estimation of this parameter is minimized when the poles are on the unit circle. By contrast, neither the bound (16) nor the MSE performance of the algorithms in Fig. 3 is minimized by $u_0 = 1$. This illustrates that translating the results from the complex-valued case to the real-valued case is not straightforward and can be misleading.

Now we examine the superresolution property of the proposed multichannel sampling method in Fig. 4. Smith proposed in [25] that the minimum requirement to resolve two signals is that

$$\text{RMS of source separation} \leq \text{source separation}, \quad (17)$$

The **statistical resolution limit** is then defined as the source separation at which (17) is achieved with equality. Consider a signal with two components: $y_n = c_0(u_0)^n + c_1(u_1)^n + w_n$. Let the desired parameters be $\theta = (u_0, u_1)^T$. We are interested in how the estimate of $\theta$ depends on $\delta u = |u_0 - u_1|$. It can be seen that in some cases, the performance of the proposed system exceeds the resolution limit of the classical system. The performance depends on the actual locations of the
poles. The Cornell algorithm for \( K = 2 \) shows performance that is far superior to that of the TLS-based algorithm. We show the mean-square error result from the Cornell algorithm in Fig. 4 and omit the results from the TLS-based algorithm.

We also demonstrate that the algorithms considered perform well for larger values of \( K \). We show the case where \( K = 4 \) and SNR is at 40 dB in Fig. 5. As expected, the performance of the TLS-Prony algorithm is worse for the poles that are closer together, and in the real-valued case for poles with smaller magnitudes.

B. Continuous-Time AWGN

The problem of delay estimation in the presence of AWGN from uniformly spaced samples is a well-known estimation problem [26]. Let the energy of the signal be \( \xi_s \). Given \( N \) samples of a signal with bandwidth \( B \), it is known that the optimal estimate is the one that maximizes the cross-correlation, and its performance is bounded by

\[
\text{var}(\hat{\tau}) \geq \frac{1}{\text{SNR} \cdot F^2} \tag{18}
\]

where

\[
F^2 = \frac{\int s(t)^2 dt}{\int s^2(t) dt}, \quad \text{SNR} = \frac{\xi_s}{(2\pi)}.
\]

The sampling rate is \( \Delta = 1/(2B) \) and \( \sigma^2 = N_0B \). In this case we must choose \( s(t) \) the lowpass sampling filter to be commensurate to our desired sampling rate. When the original pulse is a Dirac, it is well-known that the resulting mean square-error decays as the square of the sampling rate. Finally, by brute-force search of the cross-correlation peak, it is known that the bound of (18) is achievable.

1) Vetterli-Marziliano-Blu: For this case, in Section III-A we have derived that the operation of lowpass filter—sample—Discrete Fourier Transform is equivalent to projection of the input signal into an orthonormal basis. Hence, white continuous-time AWGN becomes AWGN powersum noise, which we considered in Fig. 1 for the estimation of one Dirac and in Fig. 2 for the case of two Diracs.

2) Dragotti-Vetterli-Blu: In Sections III-B and III-C we saw that the sampling scheme of Dragotti et al. is equivalent to the multichannel sampling scheme except for the sampling kernels used. The span of the union of kernels of the former is larger than that of the kernels of the latter. More importantly, the extraneous span falls outside the interval where the desired signal is located [9].

The performance of the Dragotti scheme in the presence of powersum AWGN is identical to that of the multichannel scheme, which we consider in Section VI-B-3).

Now consider the noise characterization when the noise in the system arises from continuous-time AWGN. In this case, \( \xi_n \) will be correlated. When the sampling kernel is a first-order B-spline, the covariance matrix has a tridiagonal form. The diagonal entries are given by

\[
E[u_n u_m] = \frac{N_0}{2} \frac{1}{N^2} \int_{-\infty}^{1} t \cdot dt = \frac{N_0}{2} \frac{1}{N^2}
\]

and the off-diagonal entries are given by

\[
E[u_n u_m] = \frac{N_0}{2} \frac{1}{N^2} \int_{-\infty}^{1} (1-t) t \cdot dt = \frac{N_0}{2} \frac{1}{N^2} \frac{1}{6}.
\]

Simulation results are shown in Fig. 6. In this simulation, we show the effect of different numbers of samples \( N \). The kernel used is a simple first-order B-spline, which can reconstruct \( \theta^0 \) and \( \theta^1 \) within the interval of interest. For the scheme of Dragotti, we used a B-spline of order 1 as the sampling kernel. In this comparison we plot the estimate of \( (1 - \theta^0) \) from the multichannel scheme versus the estimates of \( \theta^0 \) of the Dragotti scheme for consistency. Clearly, the performance of the Dragotti scheme is strictly worse than that of the multichannel scheme, due to the difference in the footprints of the sampling kernels. In the Dragotti scheme, the width of the B-spline is
Fig. 6. Performance results for estimation of one Dirac using a first-order B-spline. The system is implemented using the simple Cornell algorithm. The plot shows different number of samples \( N \), but the reconstruction first forms a length-2 powersum series. The AWGN is added in the continuous-time domain, with spectral density \( N_0 = 0.1 \). DVB refers to the Dragotti-Vetterli-Blu architecture and KG refers to the architecture proposed by the authors.

Fig. 7. Performance results for estimation of two Diracs using a first-order B-spline. The reconstruction first forms a length-4 powersum series. The AWGN is added in the continuous-time domain, with spectral density \( N_0 = 0.1 \).

Scaling inversely to the number of samples to be taken. Hence, as the number of samples and the sampling rate \( N \) grows, the extraneous support of the kernels become smaller and approach that of the multichannel sampling scheme.

For the discrimination of two Diracs, we show the results in Fig. 7. From the figure we can see that in some regime the RMS error of the estimate is below the spacing of the two Diracs, and hence the system under consideration has a superresolution property.

3) Kusuma-Goyal: We finally come to the case where the noise is induced in the continuous-time domain. We focus on the case of continuous-time AWGN. Due to the structure of the multichannel sampling scheme, the sample domain noise will be correlated additive Gaussian noise. We derive the covariance structure in the following.

Let \( u(t) \) be white Gaussian noise with spectral density \( N_0/2 \), and let the continuous-time signal be:

\[
y(t) = \alpha_0 \delta(t - t_0) + u(t).
\]

Following Section III-C, let the sampled signal be:

\[
y_k = \alpha_0 (1 - t_0) \delta_k + w_k
\]

where \( w_k \) is the additive noise term. The covariance of the noise term \( w_k \) can be written as

\[
E[w_k w_k^\ast] = \frac{1}{2} \sum_{k} \frac{N_0}{2k+1} T^{k+1}. \tag{20}
\]

C. Comparison of the Sampling Schemes Using Continuous-Time AWGN

Although the scheme of Section III-A is suitable for a periodic signal, it is possible to apply this scheme to an aperiodic signal by applying a lowpass filter, taking samples uniformly within the time interval of interest, and computing the Discrete Fourier Transform instead of the Fourier series coefficients. By this method, we can compare the three architectures together as applied to an aperiodic signal. In the previous, we have compared the multichannel scheme and the Dragotti scheme and showed that the former is strictly better than the other in the presence of continuous-time AWGN. Further, when white sampling noise is present, the Dragotti scheme suffers from noise amplification.

Using the same continuous-time AWGN model we compare the periodic sinc scheme, the multichannel scheme, and the conventional scheme based on cross-correlation in Fig. 8. Since the
performance of the multichannel scheme is dependent on the actual location of the pulse, we show the mean-square error of the best-case and worst-case parameters when the pulse is located in \( t \in [0, 1) \). The conventional scheme gives the best result for the estimation of a single pulse, but it requires either a brute-force search or a gradient search to find the peak of the correlation.

VII. CLOSING REMARKS

We examined several sampling architectures that are based on estimating the parameters of a powersum series. We introduced less-known algorithms that are suitable for small sample sets, do not require initialization, and give superresolution properties. We derived CRBs for when the powersum series is subjected to additive white Gaussian noise. For cases where the number of components is \( K = 1 \) or \( K = 2 \), we showed that the proposed algorithms work well even when the noise in the powersum is correlated.

In the real-valued case, although the TLS-Prony method gives superior performance for estimating single or well-spaced Diracs when \( N > 2 \), the Cornell algorithm is better for separating two closely spaced Diracs. This is also true for continuous-time white noise [9]. Further, the bounds and performances depend on the true values of the parameters.

In the complex-valued case, TLS-Prony and Cornell algorithms give nearly identical performance. For separating two closely spaced Diracs, both algorithms again give very similar results. Unlike the real-valued cases, the performance of the system does not depend on the true values of the parameters.

We used a continuous-time white Gaussian noise model to compare the three measurement architectures considered. For the estimation of a single Dirac, the conventional scheme of using a lowpass filter and using a correlation gives the best mean-square error performance. However, estimating multiple Diracs requires a multi-dimensional peak finding algorithm. By contrast, the proposed parametric schemes can give simultaneous solutions. Further, the parametric sampling schemes have a superresolution property.

Finally, we showed that the performance of the multi-channel scheme is strictly better than that of the scheme based on Strang-Fix kernels. It also compares favorably with the standard method and the scheme for periodic Diracs via periodic approximation.

We have also considered several hardware-centric noise models that depend on the topology of the system in [9]. We demonstrated that the systems and algorithms proposed work well even in the presence of correlation in the noise term of the powersum series. Some of the CRBs derived in this paper can also be extended to white Gaussian noise with arbitrary covariance, which is suitable for these hardware-centric models.

APPENDIX

In this appendix we derive the performance limits of Section V. We are interested in estimating parameters \( \{u_k\} \) and \( \{c_k\} \) from observations of the noisy powersum

\[
y_n = \sum_{k=1}^{K-1} c_k (u_k)^n + w_n, \quad n = 0, 1, \ldots, N - 1. \tag{21}
\]

The additive noise \( w_n \) has covariance matrix \( \Sigma \). In vector notation, let 
\[
c = [c_0, c_1, \ldots, c_{K-1}]^T \quad \text{and} \quad u = [u_0, u_1, \ldots, u_{K-1}]^T.
\]

The rows of the Vandermonde matrix \( U \) are defined to contain scalar powers of \( u^T \). Then we can write (21) in vector notation as:

\[
y = Uc + w.
\]

Suppose that additive noise \( w \) is zero-mean Gaussian with covariance matrix \( \Sigma \). Then the likelihood is:

\[
L = \frac{1}{\sqrt{|\Sigma|^{1/2}}} \exp \left( - \frac{1}{2} (y - Uc)^H \Sigma^{-1} (y - Uc) \right) \tag{22}
\]

where \( U \) is a Vandermonde matrix containing powers of the poles \( \{u_k\} \). While it is possible to derive a CRB for additive Gaussian noise with arbitrary covariance matrix \( \Sigma \) (see [9]), in this paper we focus on the white noise case.

When the noise is white we obtain a simpler expression for the FIM (for example see [26]). For convenience, let \( \theta \) be the vector of parameters and let \( x[n; \theta] \) be the noiseless signal given by \( \theta \). In this case,

\[
- \ln L = \text{constant} + \frac{1}{2\sigma^2} \sum_n (y_n - x[n; \theta])^2.
\]

The partial derivative is particularly simple:

\[
- \frac{\partial}{\partial \theta} \ln L = \frac{2}{\sigma^2} \sum_n (y_n - x[n; \theta]) \frac{\partial}{\partial \theta} x[n; \theta].
\]

Then,

\[
J = \frac{1}{\sigma^2} \left[ \left( \frac{\partial}{\partial \theta} \ln L \right)^H \left( \frac{\partial}{\partial \theta} \ln L \right) \right]
\]

\[
= \frac{1}{\sigma^2} \sum_n \left[ \left( \frac{\partial}{\partial \theta} x[n; \theta] \right)^H \left( \frac{\partial}{\partial \theta} x[n; \theta] \right) \right].
\]

Let \( p[n] = [(u_0)^n, \ldots, (u_{K-1})^n, 0, \ldots, (u_0)^{n-1}, \ldots, c_{K-1} \cdot n \cdot (u_{K-1})^{n-1}]^T \). Then we can write the FIM compactly as

\[
J = \frac{1}{\sigma^2} \left[ \sum_n p^T[n] p[n] \right]. \tag{23}
\]

Complex Poles on the Unit Circle

In this section, we examine the case when the poles of the powersum series are complex roots of unity. This is suitable for the sampling scheme of Vetterli, Marziliano, and Blu, which we reviewed in Section III-A.

Single-Component Case: We prove Theorem 1. Recall the FIM from (10). The inverse of the FIM is given by

\[
J^{-1} = \frac{\sigma^2}{2} \left[ \begin{array}{cc}
\frac{1}{N} & \frac{1}{N} \\
\frac{1}{N^2} & \frac{1}{N^2} \end{array} \right]. \tag{24}
\]

Since the desired estimation bound is for \( u_0 \), we have obtained Theorem 1 from the bottom right corner of \( J^{-1} \).

Resolution of FRI Method: Now we consider Theorem 2. For convenience define

\[
K = \text{diag}(\sqrt{N}, \sqrt{N}, N\sqrt{N}, N\sqrt{N})
\]

\[
L = \text{diag}(1, 1, \alpha_0, \alpha_1). \tag{25}
\]
We segment the FIM as follows:

\[
J = \frac{2}{\sigma^2} \left( K \cdot L \cdot \begin{bmatrix} E & W \end{bmatrix} \cdot W^T \cdot Q \cdot L \cdot K \right). \tag{26}
\]

After some algebra, we obtain

\[
E = \begin{bmatrix} \Gamma_0 & C_0 \\ C_0 & \Gamma_0 \end{bmatrix}, \quad W = \begin{bmatrix} 0 & -S_1 \\ S_1 & 0 \end{bmatrix},
\]

\[
Q = \begin{bmatrix} \Gamma_2 & C_2 \\ C_2 & \Gamma_2 \end{bmatrix}.
\]

The CRB is found by computing the inverse of the FIM:

\[
J^{-1} = \frac{2}{\sigma^2} \left( K^{-1} \cdot L^{-1} \cdot \begin{bmatrix} E & W \end{bmatrix} \cdot W^T \cdot Q \cdot L^{-1} \cdot K^{-1} \right). \tag{27}
\]

We are interested in the bound on the estimates of \( t_0 \) and \( t_1 \), which we obtain via the inverse of the Schur complement of \( c \) in \( J \):

\[
P = Q - W^T E^{-1} W = \begin{bmatrix} \Gamma_2 & C_2 \\ C_2 & \Gamma_2 \end{bmatrix} - \frac{1}{\Gamma_0^2 - C_0^2} \begin{bmatrix} S_1^2 \Gamma_0 & S_1^2 C_0 \\ S_1^2 C_0 & S_1^2 \Gamma_0 \end{bmatrix}.
\]

\[
M = \begin{bmatrix} \Gamma_2 (\Gamma_2^2 - C_0^2) - S_1^2 \Gamma_0 & C_2 (\Gamma_2^2 - C_0^2) - S_1^2 C_0 \\ C_2 (\Gamma_2^2 - C_0^2) - S_1^2 C_0 & \Gamma_2 (\Gamma_2^2 - C_0^2) - S_1^2 \Gamma_0 \end{bmatrix}.
\]

\[
P = \frac{1}{\Gamma_0^2 - C_0^2} M, \quad P^{-1} = (\Gamma_0^2 - C_0^2) M^{-1}.
\]

Finally, we define \( \text{SNR}_{k} = 2\alpha_k^2 / \sigma^2 \) and obtain

\[
E[(\hat{t}_k - t_k)^2] \geq \frac{1}{\text{SNR}_{k}} \frac{1}{N^3} |P|_{k,k}
\]

proving Theorem 2.

**Real-Valued Poles**

We now examine the case when the poles are real-valued. This is suitable for the sampling schemes of the Dragotti, Vetterli, and Blu—reviewed in Section III-B—and that of the authors, reviewed in Section III-C.

To examine the resolution limit, following Dilaveroglu [24] we wish to derive the performance for \( K = 2 \) in terms of \( \delta u = u_1 - u_2 \). However, Dilaveroglu only considered the undamped line spectra case, which contains complex exponentials on the unit circle, say \( \exp(j\omega_1) \) and \( \exp(j\omega_2) \). He used trigonometric identities to decompose the parameters into the desired form. In his case, the final result gives a CRB for \( \omega_1 \) and \( \omega_2 \) that depends on \( \delta \omega = \omega_1 - \omega_2 \), but independent of absolute terms \( \omega_1 \) and \( \omega_2 \). By contrast, we do not obtain such convenient decompositions and have to rely on numerical evaluation.

**Single-Pole Case**: We now use the result to consider the simplest case when there is only one pole in the signal, as in Theorem 3. First consider the case when \( \eta_1 \) is white Gaussian with variance \( \sigma^2 \).

We can write the FIM as:

\[
J = \frac{2}{\sigma^2} \begin{bmatrix} \sqrt{N} & 0 \\ 0 & N \sqrt{N} \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & (\alpha_0) \end{bmatrix} \begin{bmatrix} G_0(u_0^2) \\ G_1(u_0^2) \\ G_2^2(u_0^2) \\ G_1^3(u_0^2) \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & (\alpha_0) \end{bmatrix} \begin{bmatrix} \sqrt{N} & 0 \\ 0 & N \sqrt{N} \end{bmatrix}.
\]

We are interested in finding the CRB for \( (\hat{u}_0 - u_0)^2 \), which is the last entry of the inverse of the FIM \( J^{-1} \). This can be obtained by using direct matrix inversion:

\[
E[(\hat{u}_0 - u_0)^2] \geq \frac{\sigma^2}{N^3} \begin{bmatrix} (\alpha_0) \\ (\alpha_1) \end{bmatrix} \begin{bmatrix} G_0(u_0^2) & G_1(u_0^2) \\ G_0(u_0^2) & G_1(u_0^2) \end{bmatrix} \begin{bmatrix} (\alpha_0) \\ (\alpha_1) \end{bmatrix}.
\]

**Two-Pole Case**: We now consider the case when \( K = 2 \) as in Theorem 4. For convenience, we define the following:

\[
R = \text{diag}(\sqrt{N}, \sqrt{N}, N \sqrt{N}, N \sqrt{N}), \quad S = \text{diag}(1, 1, (\alpha_0), (\alpha_1))
\]

and

\[
G_r(x) = \frac{1}{N^{r+1}} \sum_{n=0}^{N-1} n^r (x)^n. \tag{28}
\]

Recall the definitions from Section V-D. Then the FIM can be written as

\[
J = \frac{1}{\sigma^2} \cdot R \cdot S \cdot \begin{bmatrix} A & B \\ B^T & C \end{bmatrix} \cdot S \cdot R.
\]

By defining \( \text{SNR}_k = \epsilon_k^2 / \sigma^2 \), then the CRB is given by

\[
E[(\hat{t}_k - t_k)^2] \geq \frac{\sigma^2}{\text{SNR}_k \cdot N^3} \begin{bmatrix} (C - B^T A^{-1} B)^{-1} \end{bmatrix}_{k,k}.
\]

Unfortunately, no further simplification has been found in finding the inverse of the FIM, and we obtain the CRB by numerical evaluation instead.

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