

Blind Estimation of Direct Sequence Spread Spectrum Signals in Multipath

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Abstract—Self-recovering receivers for direct-sequence spread-spectrum signals with unknown spreading codes are discussed in this paper. Applications include signal interception, jamming, and low probability of intercept (LPI) communications. A multirate/multichannel, discrete-time model of the spread spectrum signal is introduced, which establishes links with array processing techniques. Borrowing blind channel estimation ideas, which were originally developed in the context of fractionally spaced equalizers or receivers with multiple antennas, linear solutions are obtained that are independent of the input distribution. The signal interception problem is further studied, and a zero-forcing (ZF) receiver/equalizer is proposed to recover the transmitted data. Its performance is analyzed, and some illustrative simulations are presented.

I. INTRODUCTION

SPREAD-SPECTRUM (SS) signals have been used for secure communications, command, and control for several decades [17]. For certain applications, their antijamming capabilities and low probability of intercept justify the price to be paid in increased bandwidth. In direct-sequence spread-spectrum (DS-SS) systems, the information signal is modulated by a pseudo-noise (PN) sequence prior to transmission resulting in a wideband signal resistant to narrowband jamming or multipath.

In multiuser CDMA systems, the PN spreading sequence is typically known to the receiver, where it is used to perform the matched filtering (or “despreading”) operation and recover the transmitted data (e.g., [14]). In single-user systems, however, there are cases where the receiver may have no knowledge of the transmitter’s PN sequence (e.g., when intercepting an unfriendly transmission in LPI communications). Then, all the related issues of synchronization, multipath equalization, and data detection become more challenging.

There is an abundance of references in the literature on the problem of synchronization or “code-delay acquisition” under various interference and multipath environments, when the PN sequence is known to the receiver [1]–[3]. However,

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the literature is not equally rich for the case where the PN sequence is unknown.

In [11] and [26], the problem of identifying the code-generating mechanism (i.e., the primitive generating polynomial) from a subset of noiseless or noisy chip sequence observations has been studied. However, these methods assume perfect chip synchronization and absence of multipath and data modulation, thereby limiting their applicability.

Contrary to these approaches, the combined effects of the unknown spreading code and multipath channel are estimated in this work without assuming a specific structure for the code generating mechanism. In particular, novel blind algorithms are developed for estimating the time-delay, multipath parameters, and spreading code of the received signal. The multirate nature of the spreading and despreading operations is exploited, and a multirate/multichannel discrete-time model of the DS-SS system is introduced. This model links the spread-spectrum signal estimation problem to recently developed methods for the estimation of multiple FIR channels [13], [18], [21], [28]. Multichannel methods obviate the use of higher order statistics and provide subspace-based algorithms with considerably improved performance.

The introduction of multirate/multichannel models for fractionally spaced equalizers has facilitated the development of fast blind algorithms for channel equalization applications [21]. Multirate models of CDMA systems have also been studied in order to improve interference suppression schemes [23], [24]. In this paper, the multirate spread-spectrum model is exploited to derive second-order-statistics-based, linear blind signal estimation methods. The signal parameters may be useful for purposes of intercepting or jamming the received spread-spectrum signal.

The focus of the present paper is on the interception/user acquisition problem, that is, on the recovery of the transmitted information data stream. Zero-forcing (ZF) linear receivers/equalizers are proposed based on the estimated signal parameters. Their performance is analyzed and compared with matched filter-based solutions. Optimal mean-square-error ZF receivers are also derived, and their performance is studied.

The rest of the paper is organized as follows. In the next section, the spread-spectrum signal estimation problem is stated in a discrete-time framework, whereas in Section III, the proposed algorithms are delineated, and identifiability issues are addressed. In Section IV, the receiver design problem is studied, and some linear solutions are proposed. The performance of these methods is evaluated in Section V,

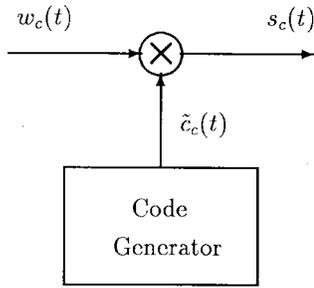


Fig. 1. Direct-sequence spread-spectrum modulation.

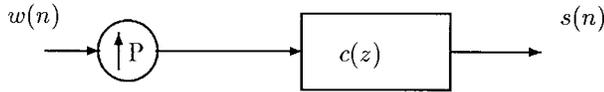


Fig. 2. Direct-sequence spreading operation.

whereas issues related to timing and bit rate estimation are discussed in Section VI. Finally, some illustrative simulation results and conclusions are presented in Sections VII and VIII, respectively.

II. DS/SS SIGNAL MODEL

In most studies of DS/SS systems, the continuous-time transmitted signal¹ $s_c(t)$ is modeled as a product of two waveforms (see Fig. 1)

$$s_c(t) = w_c(t)\tilde{c}_c(t) \quad (1)$$

where $w_c(t)$ is the information bearing signal before spreading, whereas $\tilde{c}_c(t)$ is the (periodically extended) spreading code waveform that is typically of much larger bandwidth than $w_c(t)$.

Despite its simplicity, this formulation does not reveal the multirate nature of the spreading operation and does not lend itself to the derivation of convenient discrete-time models. Since the spreading procedure is typically performed in discrete time, it will be useful in the sequel to describe it as a multirate convolution.

A. Multirate Framework

Let $c(k)$, $k = 0, 1, \dots, P - 1$ be a spreading code chip sequence of length P , and let the information sequence $w(k)$ modulate $c(k)$ with a spreading factor of P chips per information symbol. Then, the transmitted discrete-time signal at the chip rate is

$$s(n) = \sum_{k=-\infty}^{\infty} w(k)c(n - kP) \quad (2)$$

where $w(k)$ is oversampled by P and filtered by $c(k)$ (see also Fig. 2). This discrete-time model isolates the spectral spreading operation from the details of the modulation and transmission of the chip sequence $s(n)$.

In some DS/SS systems, a spreading code that is longer than the bit period is used. In this case, consecutive information

¹Subscript c is used to denote continuous time signals, and index t denotes continuous time.

symbols modulate different consecutive portions of the spreading code in a circular fashion. Equation (2) can be extended to cover this case, as we explain next.

Let $c(k)$, $k = 0, 1, \dots, KP - 1$ be a code sequence of length KP in a system with spreading factor P . Let $c(k; l)$, $k = 0, 1, \dots, K - 1$ be a family of sequences defined as $c(k; l) \triangleq c(kP + l)$ for $l = 0, 1, \dots, P - 1$ and, if k is not necessarily confined in the interval $[0, K - 1]$, define $\bar{c}(k; l) \triangleq c(k \bmod K; l)$, $k \in \mathbf{Z}$. Then, the transmitted discrete-time signal can be expressed as

$$s(n) = \sum_{k=-\infty}^{\infty} w(k)\bar{c}(k; n - kP) \quad (3)$$

where $w(k)$ is again oversampled but filtered through a periodically varying filter $\bar{c}(k; l)$. In the sequel, we focus on the description of (2), which makes the exposition simpler, whereas extensions to the case of (3) are discussed where appropriate.

The signal $s(n)$ is transmitted through a possibly dispersive channel at a chip rate $1/T_c$. Let $g_c(t)$ denote the complex baseband representation of the overall impulse response of the channel, including multipath effects and the transmitter and receiver spectral shaping filters. Then, the received signal at the receiver is

$$y_c(t) = \sum_{n=-\infty}^{\infty} s(n)g_c(t - nT_c - \tau) + v_c(t) \quad (4)$$

where τ is the propagation delay, and $v_c(t)$ is additive Gaussian noise. Substituting $s(n)$ from (2) to (4), we obtain

$$y_c(t) = \sum_{k=-\infty}^{\infty} w(k)h_c(t - kPT_c) + v_c(t), \quad (5)$$

$$h_c(t) \triangleq \sum_{n=0}^{P-1} c(n)g_c(t - nT_c - \tau) \quad (6)$$

where $h_c(t)$ is the combined impulse response of the channel and the spreading code. The summation limits in (6) come from the nonzero support of $c(n)$ over $[0, P - 1]$. If the received signal is sampled at the chip rate (every T_c seconds), then the discrete-time received signal is [cf. (5)]

$$y(n) = y_c(t)|_{t=nT_c} = \sum_{k=-\infty}^{\infty} w(k)h(n - kP) + v(n) \quad (7)$$

where $h(k) \triangleq h_c(kT_c)$ is the sampled impulse response, and $v(n) \triangleq v_c(nT_c)$. In addition, from (6), the overall impulse response is

$$h(k) = \sum_{n=0}^{P-1} c(n)g(k - n) \quad (8)$$

i.e., the convolution of the code and the channel impulse response. Following common practice in communication problems, we assume in the sequel that $g(k)$ is an FIR channel with

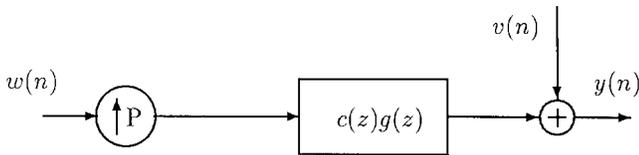


Fig. 3. Multirate model of DS/SS system.

order q_g . The discrete-time DS/SS formulation is depicted in Fig. 3.

Following the same steps, it is not hard to develop a similar model for the spreading scenario of (3). The resulting input/output relationship is

$$y(n) = \sum_{k=-\infty}^{\infty} w(k)h(k; n - kP) + v(n) \quad (9)$$

$$h(k; n) = \sum_{l=0}^{q_g} g(l)\bar{c}(k; n - l) \quad (10)$$

and the system $h(k; n)$ becomes periodically time varying.

Based on the model of (7) and (8) [or (9) and (10)], the goal of this paper is to recover the information sequence $w(k)$ when both $c(k)$ and $g(k)$ are unknown, and no training samples are available. The following assumptions will be in effect throughout the rest of the paper.

- AS1) The bit period T_b , spreading factor P , and the code length KP for the case of (3) are known.
- AS2) The sequence $w(k)$, is a complex sequence taking values from a finite QAM constellation.
- AS3) $v(n)$ is a circular complex Gaussian white noise process, uncorrelated with $w(k)$, with zero mean and variance σ_v^2 .

Of the above assumptions, AS1) may be difficult to meet in some applications. If T_b are not available, algorithms exploiting the cyclostationary nature of the signal should be employed to estimate it (see, e.g., [4] and references therein). We defer discussion of this subject to Section V. AS2) is also not essential in the development of the proposed algorithms. It will only be utilized in the performance analysis section.

In order to exploit blind identification techniques available for multiple FIR channels, it will be useful in the sequel to provide equivalent multichannel descriptions of the models (7) and (8) or (9) and (10). This will be achieved by employing the polyphase decomposition of $y(n)$, which is a tool that is commonly used in multirate theory (e.g., [27]).

B. Multichannel Framework

Let $\mathbf{y}(n)$ be the length- P vector representation of $y(n)$

$$\mathbf{y}(n) \triangleq [y(nP), y(nP+1) \cdots y(nP+P-1)]^T \quad (11)$$

with vector z -transform $\mathbf{y}(z)$. Similarly, let us define $\mathbf{h}(z)$ and $\mathbf{v}(z)$. It can be shown that the operation of oversampling $w(n)$ by P and then filtering it through $h(z)$ (the interpolating filter in Fig. 3) is described in the polyphase domain by [27, ch. 4]

$$\mathbf{y}(z) = \sum_{k=-\infty}^{\infty} w(k)\mathbf{h}(z)z^{-k} + \mathbf{v}(z) \quad (12)$$

or in the z -domain by

$$\mathbf{y}(z) = \mathbf{h}(z)w(z), \quad (13)$$

Notice that $w(z)$ is a scalar quantity multiplying $\mathbf{h}(z)$ in (13) and that $\mathbf{h}(z)$ is an FIR $P \times 1$ vector system since the original $h(z)$ was FIR. Hence, (13) provides a single input/many outputs FIR model.

Following similar steps for the model of (9) and (10), we obtain

$$\mathbf{y}(n) = \sum_{k=-\infty}^{\infty} w(k)\mathbf{h}(k; n - k) + \mathbf{v}(n) \quad (14)$$

where $\mathbf{h}(k; n) \triangleq [h(k; nP), h(k; nP+1) \cdots h(k; nP+P-1)]^T$ is the polyphase representation of $h(k; n)$.

We close this subsection with the remark that the “multiple FIR channel model” of (13) is obtained due to the multirate nature of the DS/SS system and without requiring more than one receiving antenna. In the event, however, that an antenna array is available at the receiver, the system model is modified as follows.

Let $\mathbf{y}^{(r)}(z)$ be the polyphase representation of the signal received at array element r , $r = 1, \dots, R$. Then, by stacking all the polyphase vectors in a supervector, we obtain the description

$$\begin{bmatrix} \mathbf{y}^{(1)}(z) \\ \vdots \\ \mathbf{y}^{(R)}(z) \end{bmatrix} = \begin{bmatrix} \mathbf{h}^{(1)}(z) \\ \vdots \\ \mathbf{h}^{(R)}(z) \end{bmatrix} w(z) + \begin{bmatrix} \mathbf{v}^{(1)}(z) \\ \vdots \\ \mathbf{v}^{(R)}(z) \end{bmatrix} \quad (15)$$

with obvious notation. The algorithms discussed in the sequel apply to the scenarios of both (13) and (15).

The developments in this section can be extended to the multiuser case. See [23] for the use of such a multiuser framework in the derivation of optimal CDMA receivers. However, in the current work, we focus on signal estimation issues and limit ourselves to the single user case.

III. SIGNAL ESTIMATION

In this section, we are interested in the blind estimation of $h(k)$, i.e., of the combined effects of spreading and multipath on the transmitted information signal. Typically, blind channel estimation and equalization methods rely on higher order statistics to identify the channel’s impulse response (e.g., [16]). When multiple FIR channels are available, however, it can be shown that second-order statistics are sufficient to identify co-prime channels [21]. This result has triggered considerable interest in developing fast blind algorithms in the multichannel framework [10], [13], [18], [28]. Algorithms for the equivalent multirate setup [cf. (7) and Fig. (2)] have also been developed, exploiting the cyclostationary statistics of the signal [6], [8], [9], [22].

Given the equivalence between the spread-spectrum transmission and the multichannel/multirate framework, which was established in Section II, any of the above algorithms can, in principle, be employed to identify the combined spreading/multipath effects. Out of this plethora of methods, in the sequel, we will focus on the approach of [13]. Its main

advantage is that it does not require the input $w(k)$ to be i.i.d., and in the absence of noise, it yields exact results from finite data points. While the methods of [8], [20], [28] possess the same desirable properties, the approach of [13] appears to have better performance in the presence of noise.

Before discussing the details of the algorithms, it would be interesting to review the identifiability conditions both in the multichannel and the multirate case and examine how these conditions translate into requirements for the DS/SS system.

A. Identifiability

The identifiability conditions for the multichannel framework are summarized in the following proposition.

Proposition 1 [21] (see also [13]): The vector FIR channel $\mathbf{h}(k) = [h^{(0)}(k) \dots h^{(P-1)}(k)]^T$, $k = 0, \dots, q_h$ is uniquely identifiable from second-order statistics (within a complex scaling ambiguity), if we have the following:

- i) The polynomials $h^{(i)}(z)$, $i = 0, \dots, P-1$ have no common roots.
- ii) $h^{(i)}(0) \neq 0$ for at least one i , $0 \leq i < P$.
- iii) $h^{(i)}(q_h) \neq 0$ for at least one i , $0 \leq i < P$. \square

Of the above three conditions, only i) is indeed restrictive; ii) and iii) are always satisfied, provided that the vector channel order q_h has not been overestimated. Equivalently, these conditions can be expressed in the multirate setup as follows.

Proposition 2 [20]: The channel $h(k)$ in (7) is uniquely identifiable from second-order cyclostationary statistics (within a complex scaling ambiguity), if $h(z)$ has no P zeros equispaced on a circle by an angle $2\pi/P$. \square

Proposition 2 is easier to interpret in the context of DS/SS systems. The identifiability requirement amounts to not having P zeros of $h(z) = c(z)g(z)$, i.e., P combined zeros of the channel and the code sequence $c(z)$, equispaced on a circle.

The sequence $c(z)$ has only $P-1$ zeros, and they are typically not distributed around a circle (or can be designed that way). Moreover, since, typically, the order of $g(z)$ is such that $g(z)$ has less than P finite zeros, the identifiability condition is expected to be fulfilled in most cases. For example, if multipath is absent, $h(z) = Az^{-d}c(z)$, and the condition is valid for any code $c(z)$ of length P .

B. Subspace Methods

Let us briefly adapt in the sequel the SVD-based method of [13] to the present spread-spectrum setup. Define the supervector $\mathbf{y}_L(n) = [\mathbf{y}^{(0)}(n) \dots \mathbf{y}^{(0)}(n-L+1) \dots \mathbf{y}^{(P-1)}(n) \dots \mathbf{y}^{(P-1)}(n-L+1)]^T$. Then, using (12), $\mathbf{y}_L(n)$ can be written as

$$\mathbf{y}_L(n) = \mathcal{S}_L(\mathbf{h})\mathbf{w}_L(n) + \mathbf{v}_L(n) \quad (16)$$

where

$$\mathcal{S}_L(\mathbf{h}) = [\mathcal{T}_L^T[\mathbf{h}^{(0)}], \dots, \mathcal{T}_L^T[\mathbf{h}^{(P-1)}]]^T \quad (17)$$

is a Sylvester matrix, and

$$\mathcal{T}_L[\mathbf{h}^{(p)}] = \begin{bmatrix} h^{(p)}(0) & \dots & h^{(p)}(q_h) & & 0 \\ & \ddots & & \ddots & \\ 0 & & h^{(p)}(0) & \dots & h^{(p)}(q_h) \end{bmatrix} \quad (18)$$

is a Toeplitz matrix with L rows. Finally, $\mathbf{w}_L(n) = [w(n) \dots w(n-L+1)]^T$. From (16), the data correlation matrix $\mathbf{R}_{\mathbf{y}\mathbf{y}} = E\{\mathbf{y}_L(n)\mathbf{y}_L^*(n)\}$ can be expressed as

$$\mathbf{R}_{\mathbf{y}\mathbf{y}} = \mathcal{S}_L(\mathbf{h})\mathbf{R}_{\mathbf{w}\mathbf{w}}\mathcal{S}_L^*(\mathbf{h}) + \sigma_v^2\mathbf{I} \quad (19)$$

Under the identifiability conditions of Proposition 1, $\mathcal{S}_L(\mathbf{h})$ has column full rank $L + q_h$ (provided that the number of columns is less than the number of rows LP). If $\mathbf{R}_{\mathbf{w}\mathbf{w}}$ is also full rank, then $\text{range}\{\mathcal{S}_L(\mathbf{h})\} = \text{range}\{\mathcal{S}_L(\mathbf{h})\mathbf{R}_{\mathbf{w}\mathbf{w}}\mathcal{S}_L^*(\mathbf{h})\}$. Let us define the noise subspace of $\mathbf{R}_{\mathbf{y}\mathbf{y}}$ to be the space generated by the eigenvectors corresponding to the smallest eigenvalue, and let $\mathbf{U}_n = [\mathbf{u}_1 \dots \mathbf{u}_{LP-L-q_h}]$ be the matrix containing those eigenvectors. Then, \mathbf{U}_n spans the null space of $\mathcal{S}_L(\mathbf{h})\mathbf{R}_{\mathbf{w}\mathbf{w}}\mathcal{S}_L^*(\mathbf{h})$ and is orthogonal to its range space

$$\mathbf{U}_n^* \mathcal{S}_L(\mathbf{h}) = \mathbf{0} \quad (20)$$

Equation (20) is linear in the parameters $h(k)$ and can be equivalently written as

$$\mathcal{S}_{q_h+1}^* \mathbf{U}_n \mathbf{h} = \mathbf{0} \quad (21)$$

where

$$\mathbf{h} = [\mathbf{h}^{(0)}(0) \dots \mathbf{h}^{(0)}(q_h) \dots \mathbf{h}^{(P-1)}(0) \dots \mathbf{h}^{(P-1)}(q_h)]^T$$

and

$$\mathcal{S}_{q_h+1}(\mathbf{U}_n) = [\mathbf{S}_{q_h+1}(\mathbf{u}_1), \dots, \mathbf{S}_{q_h+1}(\mathbf{u}_{LP-L-q_h})]. \quad (22)$$

The matrix $\mathbf{S}_{q_h+1}(\mathbf{u}_i)$ is

$$\mathbf{S}_{q_h+1}(\mathbf{u}_i) = [\mathcal{T}_{q_h+1}^T[\mathbf{u}_i^{(0)}], \dots, \mathcal{T}_{q_h+1}^T[\mathbf{u}_i^{(P-1)}]]^T \quad (23)$$

where $\mathbf{u}_i^{(j)} = [u_i(jL+1), \dots, u_i(jL+L)]^T$. Under i)–iii) of Proposition 1, it was shown in [13] that the solution of (20) uniquely identifies $\mathbf{h}(k)$ (within a scaling ambiguity) if $L > q_h$.

Some remarks on the application of this method to the DS/SS setup are now in order:

- 1) The subspace identification method requires an SVD to be performed on a $PL \times PL$ matrix. In the DS/SS setup, the parameter L can be fairly small since L must only satisfy $L > q_h$, and q_h is a small integer. Even if the multipath delay spread is in the order of $T_b = PT_c$, the order increases only to $q_h = 2$. However, the spreading factor P (and, hence, the number of equivalent FIR channels) is large, typically in the order of hundreds of chips. To ease the computational burden and memory requirements, one could divide the problem into two (or more) with $P/2$ (or a fraction of P in general) channels in each subproblem. The subspace method can then be applied to each subproblem independently, reducing the computational complexity at the expense of some statistical efficiency. A different approach would be to

set the sampling rate equal to $1/2T_c$ (or less) instead of $1/T_c$ in this way resulting in a problem of smaller dimensionality.

- 2) The proposed method can estimate the convolution of the spreading code with the multipath channel and is useful when the code is unknown. It is still applicable, however, if the code $c(z)$ is known, and we are interested in the estimation of the multipath parameters $g(z)$. In this case, the relationship $h(z) = c(z)g(z)$ can be written in the time domain as

$$\begin{bmatrix} h(0) \\ \vdots \\ h(q_h) \end{bmatrix} = \mathcal{T}_{q_g+1}^T(\mathbf{c}) \begin{bmatrix} g(0) \\ \vdots \\ g(q_g) \end{bmatrix}. \quad (24)$$

Notice that the left-hand side of (24) coincides with \mathbf{h} after a permutation of its elements. Hence, after substituting \mathbf{h} in (21) from (24) [by accordingly permuting the rows of $\mathcal{T}_{q_g+1}^T(\mathbf{c})$], the former can be solved with respect to the parameters $g(k)$.

It is true that different approaches may be applicable if the spreading code is known. Even in the case of unknown $c(k)$, however, the decomposition of (24) together with the finite alphabet property of $c(k)$ may be useful² if we wish to recover $c(k)$ from $h(k)$. For example, the application of the iterative method of [19] to this problem may be an interesting research direction.

- 3) The signal estimation problem is considerably more difficult if the code length is a multiple of P (i.e., KP). In this case, each subchannel is periodically time varying, and the filtering matrix in (16) becomes

$$\overline{\mathcal{S}}_L(\mathbf{h}) = \left[\overline{\mathcal{T}}_L^T[\mathbf{h}^{(1)}], \dots, \overline{\mathcal{T}}_L^T[\mathbf{h}^{(P)}] \right]^T \quad (25)$$

where

$$\overline{\mathcal{T}}_L^T[\mathbf{h}^{(p)}] = \begin{bmatrix} h^{(p)}(0; 0) & \dots & h^{(p)}(0; q_h) & \dots & 0 \\ & \ddots & & \ddots & \\ 0 & & h^{(p)}(L-1; 0) & \dots & h^{(p)}(L-1; q_h) \end{bmatrix}. \quad (26)$$

Hence, the above method is not applicable.

In principle, one could employ existing methods, which are capable of identifying linear periodically time-varying channels [5], [25], but that may be impractical when K is large. Due to the inherent difficulty of the problem, it is common practice when dealing with long spread-spectrum codes to focus on identifying the parameters of the code-generating mechanism (e.g., code-generating polynomial) rather than in estimating the entire code sequence [26]. In this approach, the parameter space is systematically searched, and each generating polynomial candidate is tested against the given data. Although in the presence of multipath and bit modulation the method of [26] is not applicable, the idea of testing each candidate code can still be applied. In this framework, (24)

can be extended to describe $h(n; k)$

$$\begin{bmatrix} h(n; 0) \\ \vdots \\ h(n; q_h) \end{bmatrix} = \mathcal{T}_{q_g+1}^T(\mathbf{c}_n) \begin{bmatrix} g(0) \\ \vdots \\ g(q_g) \end{bmatrix}. \quad (27)$$

The linear equations in (20) now involve the time-varying parameters $h(n; k)$, $n = 0, \dots, L-1$, $k = 0, \dots, q_h$. Hence, they can be written in an equivalent matrix form as

$$\mathcal{U}[h(0; 0) \dots h(0; q_h) | \dots | h(L-1; 0) \dots h(L-1; q_h)] = \mathbf{0} \quad (28)$$

where \mathcal{U} contains the elements of \mathbf{U}_n appropriately permuted. From (28) and (27), we obtain the equations

$$\mathcal{U} \begin{bmatrix} \mathcal{T}_{q_g+1}^T(\mathbf{c}_0) \\ \vdots \\ \mathcal{T}_{q_g+1}^T(\mathbf{c}_{L-1}) \end{bmatrix} \begin{bmatrix} g(0) \\ \vdots \\ g(q_g) \end{bmatrix} = \mathbf{0}. \quad (29)$$

Equation (29) is the basis for testing the validity of a candidate sequence $\mathbf{c}_0, \dots, \mathbf{c}_{L-1}$. If the candidate sequence coincides with the true one, there exists a non-trivial solution of (29). Hence, the smallest eigenvalue of $\mathcal{U}[\mathcal{T}_{q_g+1}^T(\mathbf{c}_0) \dots \mathcal{T}_{q_g+1}^T(\mathbf{c}_{L-1})]^T$ should be zero, and the solution is given by the corresponding eigenvector. Thus, a test on the smallest singular value (against zero) provides a means of determining the validity of a candidate code sequence. This test should be used in connection with a systematic search of the parameter space of the generating polynomial. Uniqueness questions regarding the solution of (29), as well as identifiability conditions for this case, however, will not be pursued here any further.

IV. RECEIVER DESIGN

The estimated signal parameters $h(k)$ may be of importance in a variety of different tasks ranging from signal interception to jamming or interference suppression. In the rest of the paper, we focus on the signal interception problem, i.e., on methods to recover the transmitted information $w(n)$ from the received data $y(n)$.

It is well known that in a multipath environment, the maximum likelihood receiver can be implemented using the Viterbi algorithm (e.g., [15]). Due to its computational complexity, however, considerable interest exists for simpler, linear solutions. In this section, we are interested in developing linear receivers $\mathbf{f}(z)$ such that the estimated sequence

$$\hat{w}(z) = \mathbf{f}^T(z)\mathbf{y}(z) \quad (30)$$

has certain desirable properties and is close to $w(z)$ in some sense. Although simpler solutions may be possible if more than one sample per chip is available (e.g., RAKE receivers), we will not pursue this direction here.

In the special case where no multipath is present, the matched filter followed by a hard limiter is known to be the optimal way to process and decode the received data (e.g., [15]). Hence, in this case, $\mathbf{f}(z)$ should be chosen as

$$\begin{aligned} \mathbf{f}(z) &= \mathbf{h}^*(z^{-1}), \\ \hat{w}(z) &= \mathbf{h}^{*T}(z^{-1})\mathbf{y}(z), \end{aligned} \quad (31)$$

²We wish to thank the anonymous reviewer who pointed out this direction.

This approach may provide satisfactory performance even when mild ISI is present, but different techniques should be applied when the ISI is severe.

A. Zero-Forcing Receivers

A simple linear design that can completely eliminate ISI is the ZF receiver [9], [18]. In this approach, the receiver $\mathbf{f}(z)$ is chosen such that in the absence of noise, $\hat{w}(z)$ in (30) is identical to $z^{-l}w(z)$, i.e., the transmitted signal is perfectly recovered within a possible delay of l bits. From (30) and (13) [with $\mathbf{v}(z) = \mathbf{0}$], the ZF receiver must satisfy

$$\mathbf{f}^T(z)\mathbf{h}(z) = z^{-l}. \quad (32)$$

It can be shown that in the multiple FIR channels framework, there exist FIR ZF receivers as long as the identifiability condition of Proposition 1 is satisfied [18]. We should point out here that bit synchronization is not a requirement for the existence of ZF solutions. The identifiability conditions of Proposition 1 are satisfied even if $h(k)$ has a number of leading zeros (less than P).

Let $\mathbf{f}_M(z)$ be an FIR vector receiver of order $M - 1$ with elements $f_M^{(p)}(z) = f_M^{(p)}(0) + z^{-1}f_M^{(p)}(1) + \dots + z^{-(M-1)}f_M^{(p)}(M-1)$, $p = 0, 1, \dots, P-1$. Then, the ZF constraint of (32) can be written in the time domain as

$$\mathbf{f}_M^T \mathcal{S}_M(\mathbf{h}) = \mathbf{1}^T \quad (33)$$

where the super vector $\mathbf{f}_M = \{[\mathbf{f}_M^{(1)}]^T \dots [\mathbf{f}_M^{(P)}]^T\}^T$, and each vector $\mathbf{f}_M^{(p)} = [f_M^{(p)}(0) \dots f_M^{(p)}(M-1)]$. The Sylvester matrix $\mathcal{S}_M(\mathbf{h})$ is given by (16), (18), and $\mathbf{1} = [0, \dots, 0, 1, 0, \dots, 0]^T$ with one in the $l+1$ st position. Under the conditions of Proposition 1, $\mathcal{S}_M(\mathbf{h})$ has full rank [18]. Hence, if $M > q_{\mathbf{h}}$, (33) represents an exact or underdetermined system of equations and, therefore, admits an exact solution.

As an example, consider a system where $q_{\mathbf{h}} = 1$. If we consider a receiver of order $M - 1 = 0$, i.e., a constant vector $\mathbf{f}(z) = \mathbf{f}\forall z$, then (32) with $l = 0$ is equivalent to

$$\mathbf{f}^T[\mathbf{h}(0) \ \mathbf{h}(1)] = [1 \ 0]. \quad (34)$$

An exact solution of (34) can be found if $P \geq 2$ and if $[\mathbf{h}(0) \ \mathbf{h}(1)]$ has full rank.

If M is chosen greater than 1 or if $P > 2$ (as is usually the case), (34) represents an underdetermined system and admits an infinity of different solutions. Since all of these solutions are equivalent in the absence of noise, it is natural to select the one that, on top of the ZF property, minimizes the noise interference. This problem is discussed next.

B. Optimal ZF Receivers

Let us consider the optimal receiver $\mathbf{f}(z)$ that minimizes the mean square error (MSE)

$$\text{MSE} = E\{|w(n-l) - \hat{w}(n)|^2\} \quad (35)$$

where $\hat{w}(z)$ is given by (30), subject to the ZF constraint of (32). This problem was addressed in [23] in the more general context of multiuser systems. The solution (which has been

adapted to the current scenario) for an FIR receiver of order $M - 1$ is summarized in the following proposition.

Proposition 3: Under the identifiability conditions of Proposition 1, and with M such that (33) has at least one solution, the parameter vector \mathbf{f}_M that minimizes (35) subject to (33) is

$$\mathbf{f}_M^T = \mathbf{1}^T [\mathcal{S}_M^{*T}(\mathbf{h}) \mathbf{R}_{\mathbf{vv}}^{-1} \mathcal{S}_M(\mathbf{h})]^{-1} \mathcal{S}_M^{*T}(\mathbf{h}) \mathbf{R}_{\mathbf{vv}}^{-1} \quad (36)$$

where $\mathbf{R}_{\mathbf{vv}} = E\{\mathbf{v}(n)\mathbf{v}^{*T}(n)\}$, and the supervector $\mathbf{v}(n) = [v^{(1)}(n) \dots v^{(1)}(n-M+1); \dots; v^{(P)}(n) \dots v^{(P)}(n-M+1)]^T$. \square

Proof: See [23].

If the noise $v(n)$ is white, hence, $\mathbf{R}_{\mathbf{vv}} = \sigma_v^2 \mathbf{I}$, (36) simplifies to

$$\mathbf{f}_M^T = \mathbf{1}^T [\mathcal{S}_M^{*T}(\mathbf{h}) \mathcal{S}_M(\mathbf{h})]^{-1} \mathcal{S}_M(\mathbf{h}). \quad (37)$$

Notice that both (36) and (37) do not rely on the i.i.d. assumption for $w(n)$ and can tolerate colored inputs. Moreover, contrary to Wiener solutions, they do not depend on the power of the additive noise. For this reason, an optimal ZF solution may be preferable to the MMSE one in a blind scenario, where the noise power may not be available.

Optimal ZF equalizers in a cyclostationary setup were studied in [9], whereas extensions to multiuser systems were presented in [23] and [24]. The contribution of the current work lies in their adoption for the recovery of distorted DS-SS signals. In addition, similar results for the special case of white noise and under a different communications setup were independently obtained in [7]. These results were brought to our attention by the reviewers of the current paper.

V. PERFORMANCE ANALYSIS

In Section IV, we presented two alternatives for the receiver structure, namely, the matched filter and the ZF receiver. Depending on the severity of multipath effects and ISI, either of the two could be best suited for a particular setup. It would be informative, therefore, to study the performance of the two schemes as a guide in selecting the appropriate structure. In the sequel, we consider the output SNR and the probability of error for each structure. We focus on BPSK modulation for reasons of simplicity and clarity of presentation.

Let $w(n)$ be an i.i.d. BPSK signal with variance σ_w^2 , and let, without loss of generality, $\|\mathbf{h}\| = 1$ (the channel has unit energy). Let also $v(n)$ be white Gaussian noise of variance σ_v^2 . If a matched filter (MF) receiver is used, then the overall response of the system is given by [cf., (12), (31)]

$$r_h(k) = \sum_n \mathbf{h}^{*T}(n)\mathbf{h}(n+k) \quad (38)$$

and

$$\hat{w}(n) = \sum_{k=-q_r}^{q_r} r_h(k)w(n-k) + \tilde{v}(n) \quad (39)$$

where $\tilde{v}(n) = \sum_{k=0}^{q_{\mathbf{h}}} \mathbf{h}^{*T}(k)\mathbf{v}(n+k)$.

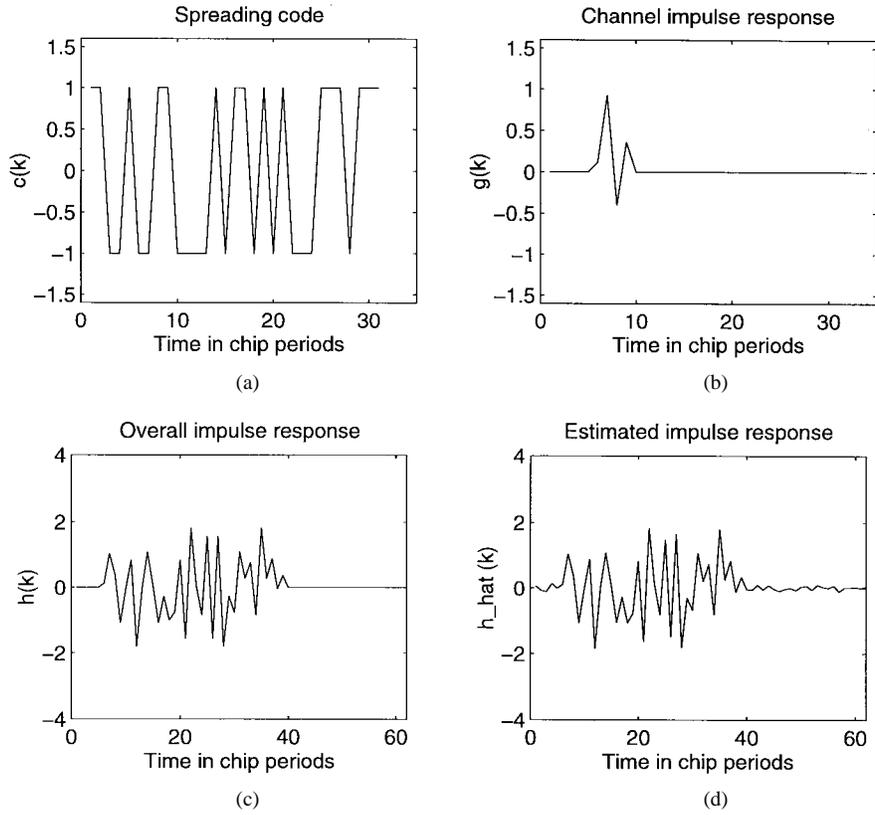


Fig. 4. Spreading code and multipath effects.

If no multipath is present, then $r_h(k) = \delta(k)$, and the MF receiver is optimum with a probability³ of error⁴ (e.g., [15, ch. 8])

$$\begin{aligned} P_{e,opt} &= Q\left(\sqrt{\text{SNR}_{opt}}\right) \\ &= Q\left(\sqrt{\frac{P\sigma_w^2}{\sigma_v^2}}\right). \end{aligned} \quad (40)$$

In the general case, however, (39) may be written as

$$\hat{w}(n) = w(n) + \text{ISI}(n) + \tilde{v}(n) \quad (41)$$

where

$$\begin{aligned} \text{ISI}(n) &= \sum_{k=-q_r}^{-1} r_h(k)w(n-k) \\ &\quad + \sum_{k=1}^{q_r} r_h(k)w(n-k) \end{aligned} \quad (42)$$

and $[-q_r, q_r]$ denotes the nonzero support of $r_h(k)$ in (38). Then, the probability of error can be computed by evaluating all the possible patterns of ISI, yielding

$$\begin{aligned} P_{e,mf} &= \frac{1}{2^{2q_r}} \sum_{w(n-k), k \neq 0} \left\{ \frac{1}{2} Q\left[\frac{\sigma_w\sqrt{P} + \text{ISI}(n)}{\sigma_v}\right] \right. \\ &\quad \left. + \frac{1}{2} Q\left[\frac{\sigma_w\sqrt{P} - \text{ISI}(n)}{\sigma_v}\right] \right\}. \end{aligned} \quad (43)$$

If a ZF receiver of length M is employed, i.e., $\mathbf{f}(z)$ satisfies (32), then

$$\hat{w}(z) = w(z) + \tilde{v}(z) \quad (44)$$

where the noise component is $\tilde{v}(n) = \mathbf{f}^T(z)\mathbf{v}(z)$. The output noise power is

$$\sigma_{\tilde{v}}^2 = \mathbf{f}_M^T \mathbf{R}_{\mathbf{v}\mathbf{v}} \mathbf{f}_M^*. \quad (45)$$

If \mathbf{f}_M is the optimal ZF equalizer, which is given by (36), then

$$\sigma_{\tilde{v}}^2 = \mathbf{1}^T [\mathcal{S}_M^{*T}(\mathbf{h}) \mathbf{R}_{\mathbf{v}\mathbf{v}}^{-1} \mathcal{S}_M(\mathbf{h})]^{-1} \mathbf{1} \quad (46)$$

³The function $Q(x)$ is defined as $Q(x) = (1/2\pi) \int_x^\infty e^{-x^2/2} dx$.

⁴The SNR at the chip rate in that case is σ_w^2/σ_v^2 , assuming that $c(k)$ takes values $\{\pm 1\}$. Due to the coherent combination of P chips, however, the SNR at the output of the MF is $\text{SNR}_{opt} = P\sigma_w^2/\sigma_v^2$.

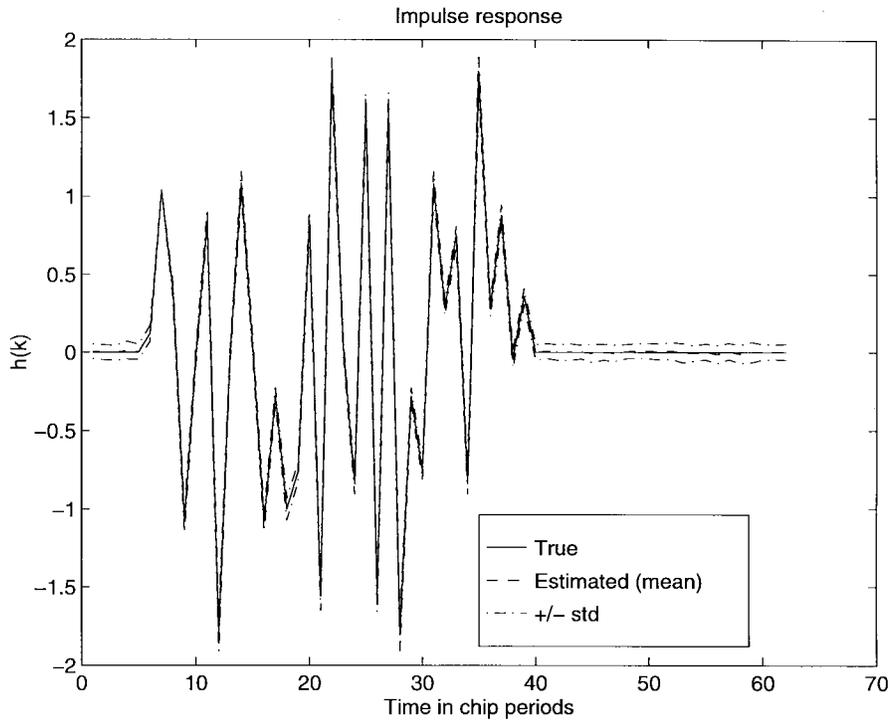


Fig. 5. Monte Carlo results on estimated impulse response.

which for white noise reduces to

$$\begin{aligned} \sigma_v^2 &= \rho \sigma_w^2, \\ \rho &\triangleq \mathbf{1}^T [\mathbf{S}_M^{*T}(\mathbf{h}) \mathbf{S}_M(\mathbf{h})]^{-1} \mathbf{1}. \end{aligned} \quad (47)$$

Hence, the output SNR for the ZF receiver is $\text{SNR}_{zf} = \sigma_w^2 / (\rho \sigma_v^2)$, and the probability of error is given by

$$\begin{aligned} P_{e,zf} &= Q\left(\sqrt{\text{SNR}_{zf}}\right) \\ &= Q\left(\sqrt{\frac{\sigma_w^2}{\rho \sigma_v^2}}\right). \end{aligned} \quad (48)$$

Comparing (48) with (40), we infer that $\text{SNR}_{zf} = \text{SNR}_{opt}/P\rho$. Hence, the factor $P\rho$ (in decibels) represents the SNR loss with respect to the optimal nondispersive setup.

By using (43) and (48), the performance of the two alternative solutions can be evaluated, and the best can be selected.

VI. BIT RATE ESTIMATION

The discussion up to this point has assumed that the bit period T_b is known to the receiver. This information is crucial since the receiver has to obtain a sample every T_b/P s. Although the proposed method does not require the receiver filter to be bit-synchronized, still, T_b is needed so that the sampling rate is in accordance with the transmitter bit (and hence chip) rate.

In this section, we address the problem of estimating T_b . As is typically done in synchronization problems, we will exploit the cyclostationary nature of the received signal to obtain an estimate for T_b [4], [12].

The correlation of the received (continuous-time) signal can be expressed as [cf., (5)]

$$\begin{aligned} r_{y_c}(t; \tau) &= E\{y_c(t)y_c^*(t+\tau)\} \\ &= \sigma_w^2 \sum_{k=-\infty}^{\infty} h_c(t - kPT_c)h_c^*(t + \tau - kPT_c) \\ &\quad + r_v(\tau). \end{aligned} \quad (49)$$

Notice that $r_{y_c}(t; \tau)$ depends explicitly on time t since $y_c(t)$ is nonstationary. It is clear from (49) that $r_{y_c}(t; \tau)$ is a periodic function of time t with period PT_c . Hence, for fixed τ , it admits a Fourier series representation with coefficients R_{y_c} , which are called cyclic correlations. As commonly done in Fourier series analysis, the cyclic correlation may be defined for every frequency ω , using delta functions as

$$\mathcal{R}_{y_c}(\omega; \tau) = \sum_{l=-\infty}^{\infty} R_{y_c}(l; \tau) \delta\left(\omega - \frac{2\pi}{PT_c} l\right). \quad (50)$$

Clearly, the estimation of the line frequencies in this spectral representation provides information about the bit (or chip) periods.

Let us now consider the case where the receiver operates at a sampling rate $\omega_s = 1/\alpha T_c$, where $\alpha \neq 1$, i.e., is not synchronized with the transmitting rate $1/T_c$. In general, α

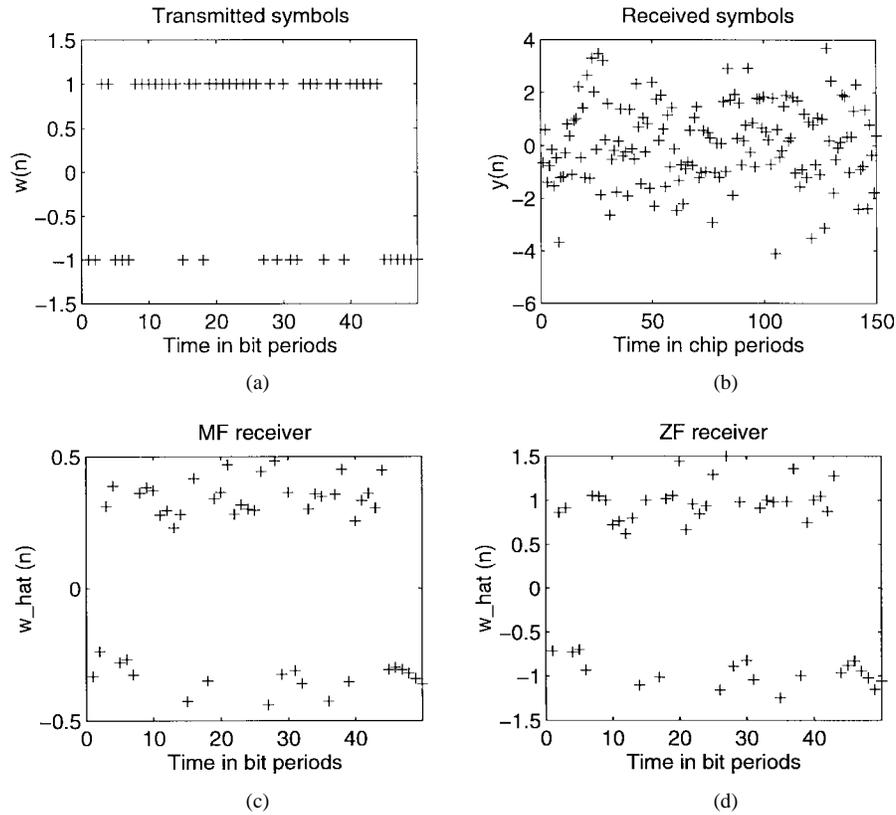


Fig. 6. Received and equalized symbols.

will be close to 1, but we assume it is not exactly equal to one. The correlation of the sampled system is

$$\begin{aligned} r_y(n; k) &= E\{y_c(n\alpha T_c)y_c^*[(n+k)\alpha T_c]\} \\ &= r_{y_c}(n\alpha T_c; k\alpha T_c). \end{aligned} \quad (51)$$

Although $r_{y_c}(t; \tau)$ is a periodic function of t , the sampled version $r_y(n; k)$ is not necessarily periodic. It is, however, almost periodic and admits a Fourier series representation. From (50) and the sampling theorem, we obtain

$$\begin{aligned} \mathcal{R}_y(\omega; k) &= \frac{1}{\alpha T_c} \sum_{m=-\infty}^{\infty} \sum_{l=-\infty}^{\infty} R_{y_c}(l; k\alpha T_c) \\ &\quad \times \delta\left(\frac{\omega}{\alpha T_c} - \frac{2\pi}{PT_c}l - \frac{2\pi}{\alpha T_c}m\right) \end{aligned} \quad (52)$$

where the summation over m accounts for possible aliasing effects. Equation (52) shows that $\mathcal{R}_y(\omega; k)$ exhibits a peak at the frequency $2\pi/PT_c$, assuming that the aliasing effects are not severe (note that if $\alpha \approx 1$, then $\alpha \ll P$, and $2\pi/\alpha T_c \gg 2\pi/PT_c$). Hence, an estimate of the spectral peaks can be used to provide information about T_b .

It has been shown in [4] that the cyclic correlation (or the strength of the spectral peaks) can be consistently estimated by

$$\hat{\mathcal{R}}_y(\omega; k) = \frac{1}{N} \sum_{n=0}^{N-1} y(n)y^*(n+k)e^{-j\omega n}. \quad (53)$$

Motivated by these results, in this paper, we propose to use (53) to estimate the unknown frequency $2\pi/PT_c$. The Fourier transform in (53) should be computed in the neighborhood

of the “assumed” bit rate $\omega_b = \omega_s/P = 2\pi/P\alpha T_c$ (i.e., for $|\omega - \omega_b| < B$ for some B), and the maximum should be selected. Then, α can be estimated as

$$\hat{\alpha} = (\omega_b)^{-1} \arg \max_{\omega, |\omega - \omega_b| < B} |\hat{\mathcal{R}}_y(\omega; k)|. \quad (54)$$

Once α has been estimated, the receiver has to adjust to the estimated bit rate.

The synchronization problem is a very important future research topic. Due to lack of space, however, no further details on performance and implementation issues will be discussed here.

VII. SIMULATIONS

In this section, we present some simulation examples to illustrate the feasibility of our approach. A spread-spectrum signal was generated by spreading a BPSK sequence $w(n)$ using (2), where the spreading code $c(n)$ was a Gold sequence of length 31 [see Fig. 4(a)]. The chip rate signal was then modulated using a rectangular spectral pulse

$$p(t) = \begin{cases} \sqrt{\frac{1}{T_c}} & 0 \leq t < T_c \\ 0 & T_c \leq t \end{cases} \quad (55)$$

and transmitted through a multipath channel (with three distinct paths), with impulse response

$$\begin{aligned} g_{mult}(t) &= 1.2\delta(t - 4.9T_c) - 0.8\delta(t - 5.8T_c) \\ &\quad + 0.6\delta(t - 6.6T_c), \end{aligned} \quad (56)$$

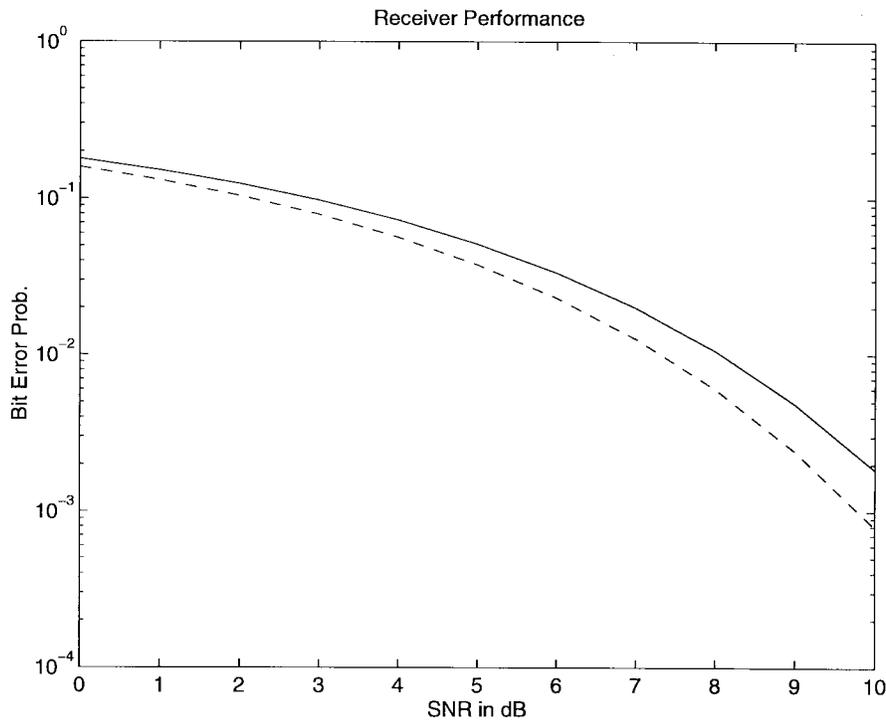


Fig. 7. Performance of matched filter and ZF receiver.

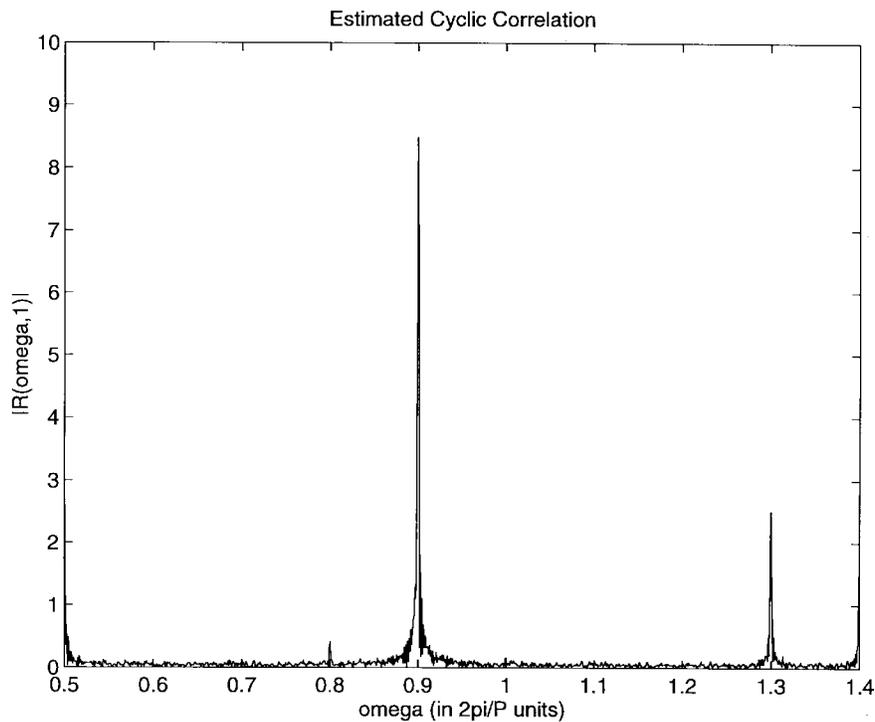


Fig. 8. Bit period estimation.

The path delays are $4.9T_c$, $5.8T_c$, and $6.6T_c$, respectively. where
 The impulse response of the channel, including the transmitter spectral pulse and the receiver matched filter, is

$$g_c(t) = 1.2p_2(t - 4.9T_c) - 0.8p_2(t - 5.8T_c) + 0.6p_2(t - 6.6T_c) \quad (57)$$

$$p_2(t) = \int p(\tau)p(t + \tau) d\tau. \quad (58)$$

By sampling (57) every T_c s, we obtain the discrete-time channel impulse response depicted in Fig. 4(b). Notice that the channel of Fig. 4(b) introduces a delay of five chip periods and has a memory spread of four chip periods. The overall impulse

response $h(k)$, i.e., the convolution of $c(k)$ and $g(k)$, is shown in Fig. 4(c) (with order $q_h = 38$).

Test Case 1: The subspace method of (19) and (20) was used to estimate the unknown impulse response $h(k)$, whereas T_b was assumed known. White Gaussian noise was added to the received signal with SNR = 0 dB, where $\text{SNR} = 10 \log_{10} E\{\|y(n) - v(n)\|^2\} / P\sigma_v^2$. Fig. 4(d) shows the estimated $\hat{h}(k)$ using a data record of 500 bits. Since the system was not bit synchronous and, hence, the delay introduced by $g(k)$ was unknown, the order of $\hat{h}(k)$ was not known. For this reason, $\hat{q}_h = 61$ was used (equivalent to two bit periods), in this way overestimating the actual channel order of $q_h = 38$. The overestimation can be seen in Fig. 4(d), where $\hat{h}(k)$ possesses a number of trailing “zeros.”

In order to obtain a quantitative measure of the proposed algorithm's performance, we ran 100 Monte Carlo iterations of the above experiment ($N = 500$ bits, SNR = 0 dB). Fig. 5 shows the true $h(k)$ (solid line), as well as the mean (dashed line) \pm the standard deviation (dashed-dotted line) of the 100 runs. We observe a reasonable estimation accuracy despite the low SNR.

Test Case 2—Receiver Design: Based on the estimated $\hat{h}(k)$, both the matched filter and the ZF vector receiver (of order $M - 1 = 1$) were implemented [using (31) and (33), respectively]. Fig. 6(a) shows the transmitted BPSK sequence $w(n)$, whereas Fig. 6(b) shows the received data $y(n)$, which are corrupted by ISI and additive noise. In Fig. 6(c) and (d), the estimated $\hat{w}(n)$ is shown using the matched filter and the ZF structures, respectively. Both receivers manage to equalize the data adequately, as shown in the figures. The remaining fluctuations at the output of the matched filter are due to residual ISI, whereas those at the output of the ZF receiver are due to noise effects.

A better picture of the performance of the two schemes is obtained by the results of Section V. The probability of error for the two alternatives was evaluated using (43) and (48) and is plotted in Fig. 7 versus SNR. The matched filter receiver (dashed line) is slightly superior to the ZF receiver (solid line) in this example, indicating that the ISI removal of the ZF approach does not outweigh the noise enhancement. In other cases of more severe ISI, the ZF solution is expected to outperform the matched filter receiver.

Test Case 3—Bit Period Estimation: In this experiment, we show how the receiver may be synchronized to the transmitter bit rate, according to the developments of Section VI. The same multipath channel of (57) was used, but the receiver was assumed to sample every $0.9T_c$ s (i.e., $\alpha = 0.9$ in this case). This effect was simulated by oversampling the channel's continuous-time impulse response by a factor of 10 and then undersampling the filtered signal by a factor of 9.

Fig. 8 shows the estimated cyclic correlation (for $k = 1$) using (53) with a record of 50 bits. The x -axis is labeled in multiples of $\omega_b = 2\pi/P\alpha T_c$ so that the peak at $2\pi/PT_c$ is exactly positioned at $\alpha = 0.9$.

VIII. CONCLUSIONS

A discrete-time multirate framework for spread-spectrum signals was introduced in this paper, leading to novel algo-

gorithms for blind estimation of the signal parameters and for signal interception. Extensions to the cases where very long spreading codes are used present an interesting future topic.

REFERENCES

- [1] K. K. Chawla and D. V. Sarwate, “Parallel acquisition of PN sequences in DS/SS systems,” *IEEE Trans. Commun.*, vol. 42, pp. 2155–2163, May 1994.
- [2] ———, “Acquisition of PN sequences in chip synchronous DS/SS systems using a random sequence model and the SPRT,” *IEEE Trans. Commun.*, vol. 42, pp. 2325–2333, June 1994.
- [3] U. Cheng, W. J. Hurd, and J. I. Statman, “Spread-spectrum code acquisition in the presence of Doppler shift and data modulation,” *IEEE Trans. Commun.*, vol. 38, pp. 241–249, Feb. 1990.
- [4] A. V. Dandawate and G. B. Giannakis, “Statistical tests for presence of cyclostationarity,” *IEEE Trans. Signal Processing*, vol. 42, pp. 2355–2369, Sept. 1994.
- [5] ———, “Modeling (almost) periodic moving average processes using cyclic statistics,” *IEEE Trans. Signal Processing*, vol. 44, pp. 673–684, Mar. 1996.
- [6] Z. Ding and Y. Li, “On channel identification based on second-order cyclic spectra,” *IEEE Trans. Signal Processing*, vol. 42, pp. 1260–1264, May 1994.
- [7] D. Gesbert, P. Duhamel, and S. Mayrargue, “Subspace-based adaptive algorithms for the blind equalization of multichannel FIR filters,” in *Proc. EUSIPCO*, 1994, pp. 712–715.
- [8] G. B. Giannakis, “A linear cyclic correlation approach for blind identification of FIR channels,” in *Proc. 28th Asilomar Conf. Signals Syst. Comput.*, Pacific Grove, CA, Oct. 31–Nov. 2, 1994, pp. 420–424.
- [9] G. B. Giannakis and S. Halford, “Blind fractionally-spaced equalization of noisy FIR channels: Adaptive and optimal solutions,” in *Proc. Int. Conf. Acoust., Speech, Signal Processing (ICASSP'95)*, Detroit, MI, May 8–12, 1995, vol. 3, pp. 1972–1975.
- [10] Y. Hua, “Fast maximum likelihood for blind identification of multiple FIR channels,” in *Proc. 28th Asilomar Conf. Signals, Syst., Comput.*, Pacific Grove, CA, Oct. 31–Nov. 2, 1994, pp. 415–419.
- [11] J. L. Massey, “Shift register synthesis and BCH decoding,” *IEEE Trans. Inform. Theory*, vol. IT-15, pp. 122–127, Jan. 1969.
- [12] J. E. Mazo, “Jitter comparison of tones generated by squaring and by fourth-power circuits,” *Bell Syst. Tech. J.*, pp. 1489–1498, May/June 1978.
- [13] E. Moulines, P. Duhamel, J. Cardoso, and S. Mayrargue, “Subspace methods for the blind identification of multichannel FIR filters,” *IEEE Trans. Signal Processing*, vol. 43, pp. 516–525, Feb. 1995.
- [14] R. L. Pickholtz, D. L. Schilling, and L. B. Milstein, “Theory of spread-spectrum communications,” *IEEE Trans. Commun.*, vol. COMM-30, pp. 855–884, May 1982.
- [15] J. G. Proakis, *Digital Communications*. New York: McGraw-Hill, 1989.
- [16] O. Shalvi and E. Weinstein, “New criteria for blind deconvolution of nonminimum phase systems (channels),” *IEEE Trans. Inform. Theory*, vol. 36, pp. 312–321, Mar. 1990.
- [17] R. A. Sholtz, “The origins of spread-spectrum communications,” *IEEE Trans. Commun.*, vol. COMM-30, pp. 822–854, May 1982.
- [18] D. T. M. Slock, “Blind fractionally-spaced equalization, perfect-reconstruction filter banks and multichannel linear prediction,” in *Proc. Int. Conf. Acoust., Speech, Signal Processing*, Adelaide, Australia, 1994, vol. IV, pp. 585–588.
- [19] S. Talwar, M. Viberg, and A. Paulraj, “Blind estimation of multiple co-channel digital signals using an antenna array,” *IEEE Signal Processing Lett.*, vol. 1, pp. 29–31, Feb. 1994.
- [20] L. Tong, G. Xu, B. Hassibi, and T. Kailath, “Blind channel identification based on second-order statistics: A frequency domain approach,” *IEEE Trans. Inform. Theory*, vol. 41, pp. 329–334, Jan. 1995.
- [21] L. Tong, G. Xu, and T. Kailath, “Blind identification and equalization based on second-order statistics: A time-domain approach,” *IEEE Trans. Inform. Theory*, vol. 40, pp. 340–349, Mar. 1994.
- [22] L. Tong and H. Zeng, “Blind channel identification using cyclic spectra,” in *Proc. 28th Conf. Inform. Sci. Syst.*, Princeton Univ., Princeton, NJ, Mar. 1994, pp. 711–716.
- [23] M. K. Tsatsanis and G. B. Giannakis, “Optimal decorrelating receivers for DS-CDMA systems: A signal processing framework,” *IEEE Trans. Signal Processing*, vol. 44, pp. 3044–3055, Dec. 1996.
- [24] ———, “Multirate filter banks for code division multiple access systems,” in *Proc. Int. Conf. Acoust., Speech, Signal Processing*, Detroit, MI, May 8–12, 1995, vol. 2, pp. 1484–1487.

- [25] ———, "Blind identification of rapidly fading channels using second order statistics," in *Proc. 29th Asilomar Conf. Signals, Syst., Comput.*, Pacific Grove, CA, Oct. 1995.
- [26] D. A. Wright and L. B. Milstein, "Sequence generator identification from noisy observations using three way recursions," in *Proc. Conf. Ant. Comm. (NTECH-86)*, Sept. 29–Oct. 1, 1986, pp. 191–195.
- [27] P. P. Vaidyanathan, *Multirate Systems and Filter Banks*. Englewood Cliffs, NJ: Prentice-Hall, 1993.
- [28] G. Xu, H. Liu, L. Tong, and T. Kailath, "A least-squares approach to blind channel identification," *IEEE Trans. Signal Processing*, vol. 43, pp. 2982–2993, Dec. 1995.



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