Cloud Radio-Multistatic Radar: Joint Optimization of Code Vector and Backhaul Quantization

Shahrouz Khalili, Osvaldo Simeone, Senior Member, IEEE, Alexander M. Haimovich, Fellow, IEEE

Abstract—A multistatic radar set-up is considered in which distributed receive antennas are connected to a Fusion Center (FC) via limited-capacity backhaul links. Similar to cloud radio access networks in communications, the receive antennas quantize the received baseband signal before transmitting it to the FC. The problem of maximizing the detection performance at the FC jointly over the code vector used by the transmitting antenna and over the statistics of the noise introduced by backhaul quantization is investigated. Specifically, adopting the information-theoretic criterion of the Bhattacharyya distance to evaluate the detection performance at the FC and information-theoretic measures of the quantization rate, the problem at hand is addressed via a Block Coordinate Descent (BCD) method coupled with Majorization-Minimization (MM). Numerical results demonstrate the advantages of the proposed joint optimization approach over more conventional solutions that perform separate optimization.

Index Terms—Multistatic radar, Cloud processing, Quantization, Information-theory, Detection.

I. INTRODUCTION

Waveform design has been a topic of great interest to radar designers, see, e.g., [1], [2], [3]. In particular, for the problem of signal detection, the shape of the transmitted waveform may greatly affect detection performance when the radar operates in a clutter environment in which detection is subject to signal-dependent interference. The optimal waveform in the Neyman-Pearson (NP) sense is studied for monostatic radars in [4], [5]. With multistatic radars, the NP criterion affords little insight into optimal waveform design, and information-theoretic criteria, such as Kullback-Leibler divergence [6] and Bhattacharyya distance [7], have served in the literature as tractable alternatives [8].

Existing waveform design techniques such as those discussed in [6], [8], assume infinite-capacity links between a set of distributed radar elements and a Fusion Center (FC) that performs target detection (see Fig. 1). In scenarios in which the receive antennas are distributed over a large geographical area to capture a target’s spatial diversity [9] and no wired backhaul infrastructure is in place, this assumption should be revised. In fact, in such cases, including deployments in hostile environments or with moving sensors, the antennas would be typically connected to the FC through limited-capacity backhaul links, e.g., microwave radio channels.

In order to cope with the capacity limitations of the backhaul links, inspired by the cloud radio access architecture in cellular communication systems [10], we assume that the receive sensors quantize the received baseband signal prior to the transmission to the FC. Hence, the FC operates on the quantized received baseband signals. We refer to this system as Cloud Radio-Multistatic Radar (CR-MR). We formulate and tackle the problem of jointly optimizing over the code vector and over the operation of the quantizers at the receive antennas by adopting information-theoretic criteria in Sec. III and Sec. IV respectively. We observe that, while the impact of quantization on FC-based sensing systems has been widely investigated (see, e.g., [11]), ours seems to be the first work to address the joint optimization of code vector and quantization for multistatic radars. Numerical results are reported in Sec. V.

Notation: Bold lowercase letters denote column vectors and bold uppercase letters denote matrices; $|X|$ denotes the determinant of matrix $X$. $I(X;Y)$ represents the mutual information between random variables $X$ and $Y$. $\mathcal{CN}(\mu, \mathbf{Q})$ is the complex Gaussian distribution with mean vector $\mu$ and covariance matrix $\mathbf{Q}$. $\mathbf{1}$ is a column vector with all elements equal to one and $[\mathbf{X}]_{m,n}$ denotes the $(m,n)$ element of matrix $\mathbf{X}$. $\mathbf{S}_m^N$ denotes the set of symmetric positive semidefinite $N \times N$ matrices.

II. SYSTEM MODEL

We focus on the CR-MR system shown in Fig. 1 in which a transmitter and $N$ receive antennas form a system seeking to detect the presence of a single stationary target over a clutter field. The receive antennas are connected to a FC via limited-capacity backhaul links. While the presented framework is sufficiently general to accommodate arbitrary backhaul capacity limitations, in this letter, for simplicity, we adopt the constraint that the total capacity available for communication between the $N$ receive antennas and the FC is $C$ bit per received (complex) sample. This scenario captures...
in a simple way a backhaul channel that is shared by the receiving antennas.

The radar waveform is a coherent train of $K$ standard pulses with complex amplitudes forming a code $\mathbf{a} = [a_1, ..., a_K]^T$. The pulse repetition intervals are sufficiently large such that the returns in each pulse interval are due to a single transmitted pulse. The code design controls the spectral properties of the waveform, and thus the response of the radar system to the target and clutter. With respect to each sensor, the target is assumed to obey a Swerling Type 1 model, i.e., the return has a Rayleigh envelope, which is fixed over the observation interval. The parameters of the target Rayleigh envelope are assumed known, and the returns observed by different sensors are independent. The clutter is assumed homogeneous over the range of interest, complex-valued Gaussian, with zero-mean and known variance, fixed over the observations interval and independent between sensors. Finally, the additive Gaussian noise is assumed to have a known temporal covariance matrix for each sensor.

Based on the mentioned assumptions, the $K \times 1$ discrete-time signal received by the $n$-th antenna, after matched filtering and symbol-rate sampling, is given by [8]

$$
\mathcal{H}_0 : \mathbf{r}_n = \mathbf{c}_n + \mathbf{w}_n
$$

$$
\mathcal{H}_1 : \mathbf{r}_n = \mathbf{s}_n + \mathbf{c}_n + \mathbf{w}_n \quad n = 1, ..., N,
$$

where the hypotheses $\mathcal{H}_0$ and $\mathcal{H}_1$ respectively, represent the absence and presence of a target in a given range resolution cell; $\mathbf{s}_n = \rho_n \mathbf{a}$ is the useful part of the received signal, with $\rho_n$ being the random clutter complex amplitude of the target return; $\mathbf{c}_n$ is the clutter, with $\rho_n$ being the random clutter complex amplitude; and $\mathbf{w}_n$ is Gaussian noise, accounting for thermal noise, interference and jamming, which is assumed to be distributed as $CN(0, \mathbf{M}_n)$ for some covariance matrix $\mathbf{M}_n$. The complex amplitudes $\sigma_n$ and $\rho_n$ are independent and distributed as $CN(0, \sigma_n^2)$ and $CN(0, \rho_n^2)$, respectively. All variables $\mathbf{w}_n$, $\sigma_n$, $\rho_n$ and $\mathbf{M}_n$ are assumed to be known to the FC for all $n = 1, ..., N$, e.g., from prior measurements or prior information [8].

Each receiver quantizes the received vector $\mathbf{r}_n$, and sends the quantized vector $\tilde{\mathbf{r}}_n$ to the FC. Note that, since the receiver does not know whether the target is present or not, the quantizer cannot depend on the correct hypothesis $\mathcal{H}_0$ or $\mathcal{H}_1$. In order to facilitate analysis and design, we follow the standard approach of modeling the effect of quantization by means of an additive quantization noise (see, e.g., [12] [13]). The signal received by the FC from the $n$-th antenna is hence given by

$$
\mathcal{H}_0 : \tilde{\mathbf{r}}_n = \mathbf{c}_n + \mathbf{w}_n + \mathbf{q}_n
$$

$$
\mathcal{H}_1 : \tilde{\mathbf{r}}_n = \mathbf{s}_n + \mathbf{c}_n + \mathbf{w}_n + \mathbf{q}_n,
$$

where $\mathbf{q}_n \sim CN(0, \mathbf{Q}_n)$ is the quantization error vector, which is assumed to be Gaussian for the sake of tractability. Note that the covariance matrix $\mathbf{Q}_n$ defines the shape of the quantization regions and determines the bit rate required for backhaul communication between antenna $n$ and the FC [12] [13]. To set the problem [3] in a standard form, the signal received at the FC is whitened with respect to the overall additive noise $\mathbf{c}_n + \mathbf{w}_n + \mathbf{q}_n$, and the returns from all sensors are combined leading to

$$
\mathcal{H}_0 : \mathbf{y} \sim CN(0, \mathbf{I})
$$

$$
\mathcal{H}_1 : \mathbf{y} \sim CN(0, \mathbf{DSD} + \mathbf{I}),
$$

where $\mathbf{y} = [\mathbf{y}_1^T, ..., \mathbf{y}_N^T]^T$, $\mathbf{y}_n = \mathbf{D}_n \tilde{\mathbf{r}}_n$, $\mathbf{D}_n$ is the whitening matrix associated with the $n$-th radar element, $\mathbf{D}_n \triangleq (\sigma_n^2, \mathbf{a}\mathbf{a}^H + \mathbf{M}_n + \mathbf{Q}_n)^{-1/2}$, $\mathbf{D}$ is the block diagonal matrix $\mathbf{D} = diag[\mathbf{D}_1, ..., \mathbf{D}_N]$, and $\mathbf{S}$ is the block diagonal matrix $\mathbf{S} = diag[\sigma_1^2, \mathbf{a}\mathbf{a}^H, ..., \sigma_N^2, \mathbf{a}\mathbf{a}^H]$. The detection problem described by [3] has the standard solution given by the test $\mathbf{y}^H \tilde{\mathbf{s}} \geq \gamma_{\mathcal{H}_0}$, where $\tilde{\mathbf{s}} = \mathbf{DSD}^{-1} \mathbf{y}$ and the threshold $\gamma$ is determined from the tolerated false alarm probability [14].

### III. PROBLEM FORMULATION

In this section, we aim at finding the optimum code vector $\mathbf{a}$ and quantization error covariance matrices $\mathbf{Q}_n$, $n = 1, ..., N$, for a given backhaul capacity constraint $C$. To this end, for the sake of tractability, we resort to information-theoretic metrics for both the detection performance and the backhaul capacity requirements. Specifically, as in [7] and [8] (see also references therein), we adopt the Bhattacharyya distance between the distributions of the quantized received signal [2] under the two hypotheses to evaluate the performance in terms of detection; moreover, we leverage rate-distortion theory to account for the backhaul capacity requirements [13]. For two zero-mean Gaussian distributions with covariance matrix of $\Sigma_1$ and $\Sigma_2$, the Bhattacharyya distance $B$ is given by $B = |0.5(\Sigma_1 + \Sigma_2)|/\sqrt{|\Sigma_1||\Sigma_2|}$ [7]. Therefore, for the signal model (3), the Bhattacharyya distance can be calculated as $B = \sum_{n=1}^N B_n(a, \mathbf{Q}_n)$ with [8]

$$
B_n(a, \mathbf{Q}_n) = \log \left( 1 + 0.5\lambda_n \sqrt{1 + \lambda_n} \right),
$$

where we have made explicit the dependence on $\mathbf{a}$ and $\mathbf{Q}_n$, and we have defined

$$
\lambda_n = \sigma_n^2 \mathbf{a}^H (\sigma_n^2, \mathbf{a}\mathbf{a}^H + \mathbf{M}_n + \mathbf{Q}_n)^{-1} \mathbf{a}.
$$

We observe that (4) is valid under the assumption that the effect of the quantizers can be well approximated by an additive Gaussian noise as per [2]; in a suitable asymptotic regime, this can be argued by using rate-distortion theory as briefly discussed below.

The backhaul rate requirement on each $n$th backhaul link is quantified here by means of the mutual information $I(\mathbf{r}_n; \tilde{\mathbf{r}}_n)$. Rate-distortion theory guarantees the existence of a vector quantizer operating over a large number of measurement vectors [1] with a rate asymptotically equal to $I(\mathbf{r}_n; \tilde{\mathbf{r}}_n)$ and such that the empirical distribution of the corresponding sequences $(\mathbf{r}_n, \tilde{\mathbf{r}}_n)$ is close to the joint distribution described by (2) with high probability [13]. While the mutual information $I(\mathbf{r}_n; \tilde{\mathbf{r}}_n)$ depends on the actual hypothesis $\mathcal{H}_0$ or $\mathcal{H}_1$, it is easy to see that $I(\mathbf{r}_n; \tilde{\mathbf{r}}_n)$ is larger under hypothesis $\mathcal{H}_1$. Based on this, the mutual information $I(\mathbf{r}_n; \tilde{\mathbf{r}}_n)$ evaluated under $\mathcal{H}_1$ is...
adopted here as the measure of the bit rate required between 
n-th receive antenna and the FC. This can be easily calculated as 
I(r_n, α_n) = I_m(a, Q_n), with

\[ I_m(a, Q_n) = \log \left| 1 + (Q_n^{-1} M_n) \right| \]
\[ + \log \left( 1 + (\sigma^2_{e,n} + \sigma^2_n) a^H (Q_n + M_n)^{-1} a \right), \quad (6) \]

where again we have made explicit the dependence of mutual 
information on a and Q_n.

The problem of maximizing the metric (4) over the code 
vector a and the covariance matrices Q_n, for n = 1, ..., N
under total backhaul capacity constraint is stated as

\[ \text{minimize} \quad \sum_{n=1}^{N} B_n(a, Q_n) \triangleq - \sum_{n=1}^{N} \log \left( 1 + 0.5 \lambda_n \right) \quad (7a) \]
\[ \text{subject to} \quad \lambda_n = \sigma^2_{t,n} a^H (\sigma^2_{e,n} a^H + M_n + Q_n)^{-1} a \quad (7b) \]
\[ Q_n \succeq 0 \text{ for all } n = 1, ..., N \quad (7c) \]
\[ ||a||^2 \leq P \quad (7d) \]
\[ \sum_{n=1}^{N} I_m(a, Q_n) \leq C , \quad (7e) \]

where we have formulated the problem as the minimization of
the negative distance \(\sum_{n=1}^{N} B_n(a, Q_n)\), with \(B_n(a, Q_n) = -B_n(a, Q_n)\), following the standard convention in [15]. The 
power of the code a is constrained not to exceed a value P.
Note that the constraint (7c) ensures that the total transmission 
rate between the receive antennas and the FC is smaller than 
C according to the adopted information-theoretic metrics.

IV. Solution of the Optimization Problem

The optimization problem in (7) is not convex, and is 
hence difficult to solve to obtain a global optimum. Aiming at 
attaining a locally optimal solution, we approach the joint 
optimization of a and Q_n, for n = 1, ..., N in (7) via BCD. Accordingly, at the m-th iteration of the BCD method, 
the optimum code vector \(a^{(m)}\) is obtained by solving (7) 
for matrices \(Q_n\) fixed at given values \(Q^{(m-1)}_n\) obtained at
the previous iteration; subsequently, the matrices \(Q^{(m)}_n\) are 
calculated by solving (7) with \(a = a^{(m)}\). The steps of BCD 
algorithm are summarized in Table I.

| Step | Description |
|------|-------------|
| 0    | Initialize \(a^{(0)} \in C^N\) and \(Q^{(0)}_n \in S^N\) for \(n = 1, ..., N\) for feasible values and set \(m = 1\). |
| 1    | Find \(a^{(m)}\) by solving the optimization problem in (7) when \(Q_n = Q^{(m-1)}_n\) via the MM algorithm (Sec. IV-A eq. (13)). |
| 2    | Find \(Q^{(m)}_n\) for \(n = 1, ..., N\) by solving the optimization problem in (7) when \(a = a^{(m)}\) via the MM algorithm (Sec. IV-B eq. (16)). |
| 3    | Set \(m = m + 1\). |
| 4    | Repeat step 1 and 2 until the convergence is attained. |

Steps 2 and 3 of Table I still require to solve non-convex 
problems. Similar to [8], we resort to successive convex 
approximations by means of the MM technique [16]. Note 
that this algorithm, which combines BCD and MM, coincides
with the general-purpose optimization scheme studied in [17].
The MM algorithm converges to a local optimum, and is based 
on approximating non-convex functions via convex functions 
that are locally tight global upper bounds at the current iterate.

Note that in (7) both functions \(B_n(a, Q_n)\) and \(I_m(a, Q_n)\) are 
non-convex in a and Q_n. Given a non-convex function \(f(x)\) 
of a generic variable x, the MM algorithm at the l-th iteration 
substitutes the function \(f(x)\) with a convex approximation 
\(f(x|x^{[l-1]}|)\) of \(f(x)\) at the current solution \(x^{[l-1]}\) that satisfies 
the global upper bound property

\[ f(x|x^{[l-1]}|) \geq f(x), \quad (8) \]

for all x in the domain, along with the local tightness condition 
\(f(x^{[l-1]}|x^{[l-1]}|) = f(x^{[l-1]})\). (9)

properties guarantee the feasibility of all iterates and convergence 
to a local optimum [16]. We emphasize that we are 
using superscript \((m)\) to identify the iterations of the outer 
loop described by Table I and the superscript \([l]\) as the index of 
the inner iteration of the MM algorithm. In Sec. IV-A and 
Sec. IV-B we discuss the application of the MM algorithm to 
perform Step 1 and Step 2 in Table I.

A. Step 1

At Step 1, the goal is to obtain the optimal value of \(a^{(m)}\) for 
problem (7) given \(Q_n = Q^{(m-1)}_n\) for all \(n = 1, ..., N\). To 
this end, we apply the MM algorithm as follows. A convex locally 
tight upper bound \(B(a, Q_n, a^{[l]})\) of \(B_n(a, Q_n)\) was derived 
in [8] and is given by

\[ B_n(a, Q_n, a^{[l]}) = \phi^{[l]}_n a^H ((M_n + Q_n)^{-1} - a - \mathcal{N} \left( (d_n^{[l]})^H a \right), \quad (10) \]

where \(\gamma_n = \sigma^2_{t,n}/\sigma^2_{e,n}, \quad \beta_n = \sigma^2_{e,n}, \quad \lambda_n = \gamma_n - \gamma_n/(1 + \beta_n a^{[l]} ((M_n + Q_n)^{-1} a^{[l]})\)

\[ \phi^{[l]}_n = \frac{\beta_n}{1 + \beta_n a^{[l]} ((M_n + Q_n)^{-1} a^{[l]})} + 0.5 \gamma_n + \frac{\beta_n}{1 + \beta_n a^{[l]} ((M_n + Q_n)^{-1} a^{[l])}^2} \]

\[ d_n^{[l]} = \frac{\beta_n}{1 + \beta_n a^{[l]} ((M_n + Q_n)^{-1} a^{[l]})} \]

\[ x^{[l]} = (\sigma^2_{e,n} + \sigma^2_{e,n} a^{H}) ((M_n + Q_n)^{-1} a^{[l]}, \quad (11) \]

with \(a^{[l]}\) being the value of a obtained at the \(l\)-th iteration of 
the MM algorithm and \(y_n^{[l]} = (a^{[l]})^H ((M_n + Q_n)^{-1} a^{[l]}\) A 
bound with the desired property can also be easily derived for 
\(I_m(a, Q_n)\) by using the inequality \(\log (1 + x) \leq \log (1 + x^{[l]}) + 1/(1 + x^{[l]}) (x - x^{[l]})\), for \(x = (\sigma^2_{e,n} + \sigma^2_{e,n} a^H ((Q_n + M_n)^{-1} a^{[l]}\),
leading to

\[ I_m(a, Q_n, a^{[l]}) = \log \left| 1 + (Q_n^{-1} M_n) \right| + \log (1 + x^{[l]}) + 1/(1 + x^{[l]}) (\sigma^2_{e,n} + \sigma^2_{e,n} a^H ((Q_n + M_n)^{-1} a^{[l]})^2 \]

\[ + \left( \sigma^2_{e,n} + \sigma^2_{e,n} a^H ((Q_n + M_n)^{-1} a^{[l]})^2 - x^{[l]} \right). \quad (12) \]

MM algorithm then prescribes the solution of the following 
convex optimization problem iteratively, until convergence is
tained:
\[ a^{[l]} = \arg \min_{a} \sum_{n=1}^{N} \mathcal{B}_n(a, Q_n^{(m-1)}) a^{[l-1]} \] (13a)

subject to \( ||a||_2^2 \leq P \) (13b)

\[ \sum_{n=1}^{N} \mathcal{I}_n(a, Q_n^{(m-1)}) a^{[l-1]} \leq C. \] (13c)

**B. Step 2**

At Step 2, the matrices \( Q_n^{(m)} \) are obtained for a given \( a = a^{(m)} \). Similar to (12), upper bounds with the desired properties are derived for functions \( \mathcal{I}_n(a, Q_n) \) and \( \mathcal{B}_n(a, Q_n) \) as follows:

\[
\begin{align*}
\mathcal{I}_n(a, Q_n | Q_n^{[l]}) &= \log |Q_n^{[l]}| + (\sigma_{c,n}^2 + \sigma_{t,n}^2) a a^H + M_n| \\
&- \log |Q_n| + \sum_{k=1}^{N} \text{Tr} \left( (Q_n^{[l]} + (\sigma_{c,n}^2 + \sigma_{t,n}^2) a a^H + M_n)^{-1} (Q_n - Q_n^{[l]}) \right) \\
&+ M_n \right) \right) \\
&+ 0.5 \text{Tr} \left( (Q_n^{[l]} + (\sigma_{c,n}^2 + \sigma_{t,n}^2) a a^H + M_n)^{-1} Q_n \right) \\
&+ 0.5 \text{Tr} \left( (Q_n^{[l]} + (\sigma_{c,n}^2 + \sigma_{t,n}^2) a a^H + M_n)^{-1} Q_n \right).
\end{align*}
\] (14)

and

\[
\begin{align*}
\mathcal{B}_n(a, Q_n | Q_n^{[l]}) &= -\log |(\sigma_{c,n}^2 + 0.5 \sigma_{t,n}^2) a a^H + Q_n + M_n| \\
&+ 0.5 \text{Tr} \left( (\sigma_{c,n}^2 + 0.5 \sigma_{t,n}^2) a a^H + Q_n + M_n)^{-1} Q_n \right) \\
&+ 0.5 \text{Tr} \left( (\sigma_{c,n}^2 + 0.5 \sigma_{t,n}^2) a a^H + Q_n + M_n)^{-1} Q_n \right).
\end{align*}
\] (15)

The MM algorithm then evaluates the matrices \( Q^{[m]} = [Q_1^{[m]}, \ldots, Q_N^{[m]}] \) by solving the following convex optimization problem iteratively, until convergence is attained:

\[
\begin{align*}
Q^{[l]} &= \arg \min_{Q} \sum_{n=1}^{N} \mathcal{B}_n(a^{(m)}, Q_n | Q_n^{[l-1]}) \\
\text{subject to} \sum_{n=1}^{N} \mathcal{I}_n(a^{(m)}, Q_n | Q_n^{[l-1]}) \leq C \\
Q_n \succeq 0 \text{ for all } n = 1, \ldots, N.
\end{align*}
\] (16a)

**V. NUMERICAL RESULTS AND CONCLUSION REMARKS**

In this section, the performance of the proposed algorithm that performs joint optimization of the code vector \( a \) and of the quantization noise covariance matrices \( Q_n \), for \( n = 1, \ldots, N \) is investigated via numerical results. For reference, we consider the performance of the following strategies: (i) No optimization: Set \( a = \sqrt{P/K} 1 \) and \( Q_n = \mathcal{I} \), for \( n = 1, \ldots, N \), where \( \epsilon \) is a constant that is found by satisfying the constraint \( \epsilon \) with equality; (ii) Code vector optimization: Optimize the code vector \( a \) by using the algorithm in (8), which is given in Table 1 by setting \( Q_n = 0 \) for \( n = 1, \ldots, N \), and set \( Q_n = \mathcal{I} \), for \( n = 1, \ldots, N \), as explained above. Quantization noise optimization: Set \( a = \sqrt{P/K} 1 \) and optimize the covariance matrices \( Q_n \) as per Step 2 in Table 1 (iv) Joint optimization of code vector and quantization noise: The code vector \( a \) and the covariance matrices \( Q_n \) are optimized jointly by using the algorithm in Table 1. Throughout, we set the number of receive antennas as \( N = 3 \), the length of the code vector as \( K = 6 \), the variance of the target amplitudes as \( \sigma_{c,n}^2 = 1 \), for \( n = 1, \ldots, N \), the variance of the clutter amplitudes as \( \sigma_{c,1}^2 = 0.125 \), \( \sigma_{c,2}^2 = 0.25 \), and \( \sigma_{c,3}^2 = 0.5 \), and \( [M_n]_{m,k} = (1 - 0.15n)(m-k) \) and \( C = 15 \) bit/sample.

Fig. 2 plots the Bhattacharyya distance versus the detection probability \( P_{fa} \), for \( P = 10 \) dB and the noise variance matrices as \( [M_n]_{m,k} = (1 - 0.15n)(m-k) \) as in (8). In Fig. 2 the Bhattacharyya distance is plotted versus the available backhaul capacity \( C \). For sufficiently large values of \( C \), optimizing the code vector only has significant gains as discussed in [8]. However, for intermediate values of \( C \), it is more advantageous to properly design the quantization noise. The proposed joint optimization of code vector and quantization noise is seen to be beneficial over the separate optimization strategies across all values of \( C \).

Fig. 3 plots the Receiving Operating Characteristic (ROC), i.e., the false alarm probability \( P_{fa} \) versus the detection probability \( P_d \), for \( C = 15 \) bit/sample. The curve was evaluated via Monte Carlo simulations by implementing the optimum test detector [8]. It is seen that the proposed joint optimization method provides remarkable gains, while, given the backhaul limitations, optimizing only the code vector leads to significantly smaller advantages.
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