Blind Estimation and Detection of Space-Time Trellis Coded Transmissions over the Rayleigh Fading MIMO Channel

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***Abstract*—We present a joint channel estimation and detection method of space-time trellis codes (STTC) in the context of an unknown flat fading multiple-input multiple-output (MIMO) channel. A combined state-space model for the space-time code and the Rayleigh fading MIMO channel is introduced, in order to use deterministic particle filtering at the receiver side. An important feature of the proposed method is that the fading rate need not be known to the receiver. Monte-carlo simulations show that the performances of the proposed scheme are close to decoding with perfect channel state information (CSI) using the Viterbi algorithm (VA).**

***Index Terms*—MIMO channel, space-time coding, joint channel estimation and decoding, particle filtering.**

I. Introduction

Using information theory, it has been shown that the capacity gains of MIMO channels can substantially improve the traffic of wireless communications [1]. Based on this result, space-time trellis codes were introduced in [2] as a technique which exploits both spatial and temporal diversity in order to combat fading channels efficiently. Later, algebraic STTC were designed to yield full diversity for binary phase shift keying (BPSK) and quadrature phase shift keying (QPSK) modulation [3].

The problem of blind detection of trellis coded MIMO systems has been addressed in [4], [5]. In [4], particle filtering [6] is applied to the problem of soft-input soft-output (SISO) symbol detection with an unknown MIMO channel. The trellis code is handled using an iterative (turbo) structure alternating between SISO symbol detection and SISO trellis decoding. Differential encoding/decoding is needed to remove phase ambiguities. In [5], particle filtering is used for joint symbol detection and trellis decoding with an unknown MIMO channel. Provided that a valid codeword can never be a phase shifted version of another valid codeword, no phase ambiguities exist. Removal of phase ambiguities in particle based MIMO receivers using pilot symbols has also been proposed in [7]. Note that in the aforementioned papers, the MIMO channel is modeled either as a block fading, as an autoregressive moving average (ARMA), or as an autoregressive (AR) process. Moreover, a stochastic form of particle filtering [8] (i.e. based on random draws) is used.

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Recently, it has been recognized that drawing randomly the data symbols from a discrete distribution during the prediction stage of particle filtering is inefficient since it introduces an unwanted approximation error [9]-[11]. Instead, a deterministic form of particle filtering performing recursively exploration for all data symbol hypotheses followed by a selection step, achieves better performances with a low number of particles.

In this letter, we consider an algebraic STTC with BPSK modulation, sent over a flat time-varying Rayleigh fading MIMO channel. We introduce a combined state-space model for the code and the time-varying channel, which is independent from the fading rate. This feature is useful since the velocity of the receiver is usually unknown. For instance, the ARMA channel model proposed in [5] needs perfect knowledge of the user velocity. A receiver structure based on deterministic particle filtering performs joint channel estimation and decoding.

Throughout the letter, bold letters indicate vectors and matrices, while the superscripts T and H denote the transpose and transpose conjugate operators, respectively. A complex Gaussian distribution is represented by $\mathcal{N}_{\mathcal{C}}(.)$.

This letter is organized as follows. In Sec. II, we recall the basic principles of deterministic particle filtering. Sec. III presents the communication model along with the channel model. Finally, Sec. IV presents the frame error rate (FER) performances of the proposed schemes, obtained by Monte Carlo simulations.

II. Sequence Estimation Using Deterministic Particle Filtering

We consider a discrete-time dynamical system of the form

$$\begin{cases} \boldsymbol{\zeta}_k = f_k\left(\boldsymbol{\zeta}_{k-1}, \mathbf{u}_k\right) \\ \mathbf{x}_k = \mathbf{F}_k(\boldsymbol{\zeta}_k)\mathbf{x}_{k-1} + \boldsymbol{\pi}_k \\ \mathbf{y}_k = \mathbf{H}_k(\boldsymbol{\zeta}_k)\mathbf{x}_k + \mathbf{n}_k. \end{cases} \quad (1)$$

The first equation is the *process* equation, where the system state $\boldsymbol{\zeta}_k$ at instant k takes discrete values and the process noise $\mathbf{u}_k$ takes values in a finite alphabet $\mathcal{A} = (\mathbf{a}_1, \dots, \mathbf{a}_Q)$. The second equation describes the evolution of the continuous part of the state, denoted by $\mathbf{x}_k$. The associated white Gaussian process noise $\boldsymbol{\pi}_k$ has a covariance matrix denoted by $\mathbf{Q}_k$. The third equation is the *measurement* equation, where the state dependent complex observations $\mathbf{y}_k$ are corrupted by white Gaussian measurement noise $\mathbf{n}_k$, with covariance matrix $\mathbf{R}_k$. $\mathbf{F}_k$ and $\mathbf{H}_k$ are matrices, in general nonlinearly depend on $\boldsymbol{\zeta}_k$. Additionally, it is assumed that $\mathbf{u}_k$, $\boldsymbol{\pi}_k$ and $\mathbf{n}_k$ are uncorrelated.

We seek the optimal maximum-likelihood (ML) sequence of discrete states $\boldsymbol{\zeta}_{1:k}$, given the sequence of noisy observations $\mathbf{y}_{1:k}$. Particle filtering approximates the posterior density $p(\boldsymbol{\zeta}_{1:k}|\mathbf{y}_{1:k})$ by a set of M weighted Dirac functions

$$\hat{p}(\boldsymbol{\zeta}_{1:k}|\mathbf{y}_{1:k}) = \sum_{i=1}^{M} w_k^{(i)} \delta\left(\boldsymbol{\zeta}_{1:k} - \boldsymbol{\zeta}_{1:k}^{(i)}\right), \quad (2)$$

where $\boldsymbol{\zeta}_{1:k}^{(i)}$ is the i-th discrete particle and $w_k^{(i)}$ the corresponding weight at instant k.

Assuming that the particle support $\{\boldsymbol{\zeta}_{1:k-1}^{(i)}, w_{k-1}^{(i)}\}_{i=1,\dots,M}$ is available, the deterministic particle filtering recursion at instant k is given by [9]-[11]:

1) Prediction: For each particle $\boldsymbol{\zeta}_{1:k-1}^{(i)}$ form the Q extensions $\{\boldsymbol{\zeta}_{1:k-1}^{(i)}, f_k(\boldsymbol{\zeta}_{k-1}^{(i)}, \mathbf{a}_j)\}$, for $j = 1, \dots, Q$
2) Correction: Compute the weight of each extension as
$$w_k^{(i,j)} \propto w_{k-1}^{(i)} p\left(\mathbf{u}_k = \mathbf{a}_j\right) \times p\left(\mathbf{y}_k|\boldsymbol{\zeta}_{1:k-1}^{(i)}, \mathbf{u}_k = \mathbf{a}_j, \mathbf{y}_{1:k-1}\right)$$
3) Resampling: Among the QM available extensions, the M most likely are retained to form the updated particle support $\{\boldsymbol{\zeta}_{1:k}^{(i)}, w_k^{(i)}\}_{i=1,\dots,M}$ and the others are discarded.

At the final instant $k = N$, the ML estimate $\hat{\boldsymbol{\zeta}}_{1:N}$ is the particle with maximum weight.

Note that the two last equations in (1) form a linear Gaussian dynamical system conditioned on $\boldsymbol{\zeta}_k$. Therefore using standard Kalman filtering techniques [12], we obtain

$$p\left(\mathbf{y}_k|\boldsymbol{\zeta}_{1:k-1}^{(i)}, \mathbf{u}_k = \mathbf{a}_j, \mathbf{y}_{1:k-1}\right) = \mathcal{N}_{\mathcal{C}}\left(\mathbf{H}_k(\boldsymbol{\zeta}_k^{(i)})\hat{\mathbf{x}}_{k|k-1}^{(i)}, \mathbf{H}_k(\boldsymbol{\zeta}_k^{(i)})\mathbf{P}_{k|k-1}^{(i)}\mathbf{H}_k(\boldsymbol{\zeta}_k^{(i)})^H + \mathbf{R}_k\right)$$

where $\hat{\mathbf{x}}_{k|k-1}^{(i)}$ and $\mathbf{P}_{k|k-1}^{(i)}$ are the predicted estimate and error covariance matrix of $\mathbf{x}_k$ conditioned on the sequence of discrete states $\boldsymbol{\zeta}_{1:k}^{(i)}$. Consequently, these quantities are obtained from the following recursions [12]

$$\begin{cases} \hat{\mathbf{x}}_{k|k-1}^{(i)} = \mathbf{F}_k(\boldsymbol{\zeta}_k^{(i)})\hat{\mathbf{x}}_{k-1|k-1}^{(i)} \\ \mathbf{P}_{k|k-1}^{(i)} = \mathbf{F}_k(\boldsymbol{\zeta}_k^{(i)})\mathbf{P}_{k-1|k-1}^{(i)}\mathbf{F}_k(\boldsymbol{\zeta}_k^{(i)})^H + \mathbf{Q}_k \end{cases}$$

with

$$\begin{cases} \mathbf{K}_k^{(i)} = \mathbf{P}_{k|k-1}^{(i)}\mathbf{H}_k(\boldsymbol{\zeta}_k^{(i)})^H \left(\mathbf{H}_k(\boldsymbol{\zeta}_k^{(i)})\mathbf{P}_{k|k-1}^{(i)}\mathbf{H}_k(\boldsymbol{\zeta}_k^{(i)})^H + \mathbf{R}_k\right)^{-1} \\ \hat{\mathbf{x}}_{k|k}^{(i)} = \hat{\mathbf{x}}_{k|k-1}^{(i)} + \mathbf{K}_k^{(i)}\left(\mathbf{y}_k - \mathbf{H}_k(\boldsymbol{\zeta}_k^{(i)})\hat{\mathbf{x}}_{k|k-1}^{(i)}\right) \\ \mathbf{P}_{k|k}^{(i)} = \mathbf{P}_{k|k-1}^{(i)} - \mathbf{K}_k^{(i)}\mathbf{H}_k(\boldsymbol{\zeta}_k^{(i)})\mathbf{P}_{k|k-1}^{(i)}. \end{cases}$$

Let d denote the dimension of the continuous part of the state $\mathbf{x}_k$, it is well known that the complexity of one recursion of the Kalman filter is $\mathcal{O}(d^3)$ [13]. Therefore, the complexity of one recursion of the particle filter is $\mathcal{O}(QMd^3)$.

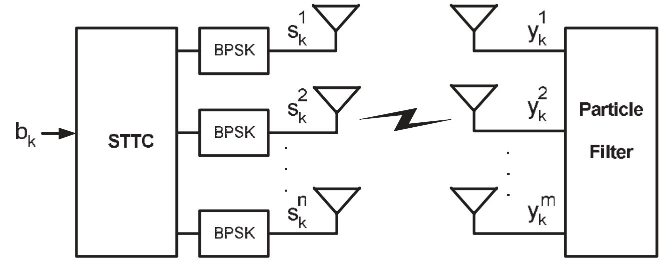

Fig. 1. Block diagram of the STTC system.

III. System Model

A. Communication system

We consider the communication system with n transmit and m receive antennas depicted in Fig. 1. The binary message $\{b_k\}$ is encoded with a memory-ν STTC. At time instant k, a STTC creates a vector of encoded bits mapped into BPSK symbols, denoted by $\mathbf{s}_k = \left[s_k^1, s_k^2, \dots, s_k^n\right]^T$, with $s_k^i \in \{-1, +1\}$, for $i = 1, \dots, n$. The received noisy observation at antenna j is given by

$$y_k^j = \sum_{i=1}^{n} c_k^{(ij)} s_k^i + n_k^j, \quad (3)$$

where $c_k^{(ij)}$ is the time-varying complex path gain from transmit antenna i to receive antenna j and n_k^j is a white Gaussian noise sample with single-sided power spectral density N_0. In vector notation, we have $\mathbf{y}_k = [y_k^1, y_k^2, \dots, y_k^m]^T$ and $\mathbf{n}_k = [n_k^1, n_k^2, \dots, n_k^m]^T$. The path gains are assumed to be independent flat Rayleigh fading coefficients. The noise samples on the receive antennas are also independent. At the receiver side, deterministic particle filtering is used to perform joint channel estimation and decoding.

B. Classical state-space representation

We first recall the state-space model introduced in [5]. Consider an approximate model for a mobile Rayleigh fading channel using an autoregressive model of order P (AR(P)) [14]. The time-varying channel gain for transmit antenna i and receive antenna j is written as

$$c_k^{(ij)} = \sum_{p=1}^{P} \phi_p c_{k-p}^{(ij)} + \pi_k^{(ij)}, \quad (4)$$

where $\phi_1, \dots, \phi_P$ are non-zeros constants *depending on the fading rate* and the $\pi_k^{(ij)} \sim \mathcal{N}_{\mathcal{C}}(0, q)$ are independent driving noise terms.

We define the P-dimensional vector

$$\mathbf{x}_k^{(ij)} = \left[c_k^{(ij)}, c_{k-1}^{(ij)}, \dots, c_{k-P+1}^{(ij)}\right]^T,$$

by (4) we have

$$\mathbf{x}_k^{(ij)} = \boldsymbol{\Phi}\mathbf{x}_{k-1}^{(ij)} + \boldsymbol{\pi}_k^{(ij)},$$

where

$$\boldsymbol{\Phi} = \begin{bmatrix} \phi_1 & \phi_2 & \dots & \phi_{P-1} & \phi_P \\ 1 & 0 & \dots & 0 & 0 \\ 0 & 1 & \dots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \dots & 1 & 0 \end{bmatrix},$$

and $\boldsymbol{\pi}_k^{(ij)} = [\pi_k^{(ij)}, 0, \ldots, 0]^T$. Consequently, for the Pnm-dimensional stacked vector of channel gains

$$\mathbf{x}_k = \left[\mathbf{x}_k^{(11)^T}, \ldots, \mathbf{x}_k^{(n1)^T}, \ldots, \mathbf{x}_k^{(1m)^T}, \ldots, \mathbf{x}_k^{(nm)^T} \right]^T,$$

we have

$$\mathbf{x}_k = \mathbf{F}\mathbf{x}_{k-1} + \boldsymbol{\pi}_k$$

where state transition matrix is given by

$$\mathbf{F} = \begin{bmatrix} \boldsymbol{\Phi} & \mathbf{0} & \ldots & \mathbf{0} \\ \mathbf{0} & \boldsymbol{\Phi} & \ldots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \ldots & \boldsymbol{\Phi} \end{bmatrix},$$

and the process noise vector is given by

$$\boldsymbol{\pi}_k = \left[\boldsymbol{\pi}_k^{(11)^T}, \ldots, \boldsymbol{\pi}_k^{(n1)^T}, \ldots, \boldsymbol{\pi}_k^{(1m)^T}, \ldots, \boldsymbol{\pi}_k^{(nm)^T} \right]^T.$$

We also define the Pn-dimensional vector obtained by inserting $P-1$ zeros between the elements of the vector of transmitted symbols $\mathbf{s}_k = \left[s_k^1, s_k^2, \ldots, s_k^n\right]^T$

$$\mathbf{r}_k\left(\mathbf{s}_k\right) = [s_k^1, 0, \ldots, 0, s_k^2, 0, \ldots, 0, \ldots, s_k^n, 0, \ldots, 0].$$

Then from (3), we have a state-space description of our communication system as

$$\begin{cases} \boldsymbol{\zeta}_k = f_k\left(\boldsymbol{\zeta}_{k-1}, b_k\right) \\ \mathbf{x}_k = \mathbf{F}\mathbf{x}_{k-1} + \boldsymbol{\pi}_k \\ \mathbf{y}_k = \mathbf{H}_k(\boldsymbol{\zeta}_k)\mathbf{x}_k + \mathbf{n}_k, \end{cases}$$

where $\boldsymbol{\zeta}_k$ is the STTC state at instant k, f_k is the STTC state transition function and $\mathbf{H}_k(\boldsymbol{\zeta}_k)$ is the $m \times Pnm$ observation matrix given by

$$\mathbf{H}_k(\boldsymbol{\zeta}_k) = \begin{bmatrix} \mathbf{r}_k\left(\mathbf{s}_k\right) & \mathbf{0} & \ldots & \mathbf{0} \\ \mathbf{0} & \mathbf{r}_k\left(\mathbf{s}_k\right) & \ldots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \ldots & \mathbf{r}_k\left(\mathbf{s}_k\right) \end{bmatrix},$$

where $\mathbf{s}_k$ is the modulated STTC output, given the current STTC state $\boldsymbol{\zeta}_k$.

Therefore, the deterministic particle filtering technique developed in Sec. II is readily applicable.

C. Proposed state-space representation

An alternative model for mobile Rayleigh fading channels uses an exponential basis expansion with L bases (EBE(L)) [15]. Let T be the symbol duration. The time-varying channel gain for transmit antenna i and receive antenna j is modeled as

$$c_k^{(ij)} = \sum_{l=1}^{L} \alpha_l^{(ij)} e^{j2\pi F_l kT}, \tag{5}$$

where the $\alpha_l^{(ij)}$ are unknown but constant coefficients to be estimated. Obviously, the channel time variations are captured by the time-dependent complex exponentials. The frequencies F_l, $l = 1, \ldots, L$ are fixed parameters *independent from the fading rate*.

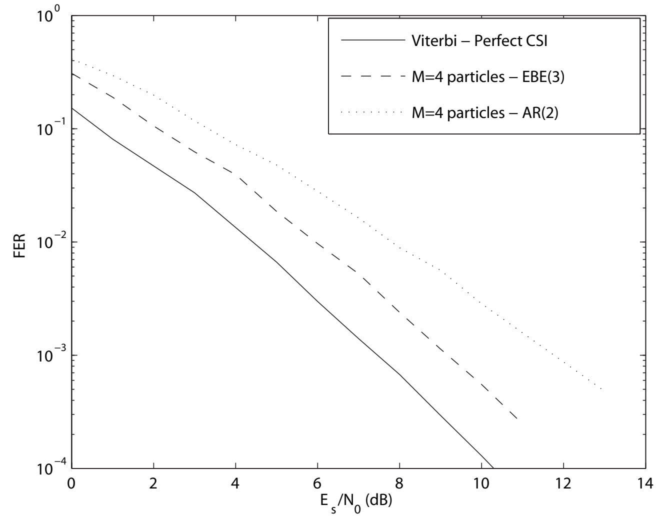

Fig. 2. FER vs. E_s/N_0 for a MIMO channel with $B_dT = 10^{-4}$.

We define the Ln-dimensional vector of stacked channel coefficients corresponding to receive antenna j, $j = 1, \ldots, m$

$$\boldsymbol{\alpha}^j = \left[\alpha_1^{(1j)}, \ldots, \alpha_L^{(1j)}, \ldots, \alpha_1^{(nj)}, \ldots, \alpha_L^{(nj)}\right]^T,$$

and the Ln-dimensional vector depending on the transmitted symbols $\mathbf{s}_k = \left[s_k^1, s_k^2, \ldots, s_k^n\right]^T$

$$\mathbf{v}_k\left(\mathbf{s}_k\right) = [e^{j2\pi F_1 kT} s_k^1, \ldots, e^{j2\pi F_L kT} s_k^1, \ldots, e^{j2\pi F_1 kT} s_k^n, \ldots, e^{j2\pi F_L kT} s_k^n].$$

It follows from (5) that (3) can be rewritten as

$$y_k^j = \mathbf{v}_k\left(\mathbf{s}_k\right)\boldsymbol{\alpha}^j + n_k^j.$$

Now define the Lnm-dimensional channel state as

$$\mathbf{x}_k = \begin{bmatrix} \boldsymbol{\alpha}^1 \\ \vdots \\ \boldsymbol{\alpha}^m \end{bmatrix}.$$

Then we have a new state-space description of our communication system as

$$\begin{cases} \boldsymbol{\zeta}_k = f_k\left(\boldsymbol{\zeta}_{k-1}, b_k\right) \\ \mathbf{x}_k = \mathbf{x}_{k-1} \\ \mathbf{y}_k = \mathbf{H}_k(\boldsymbol{\zeta}_k)\mathbf{x}_k + \mathbf{n}_k, \end{cases}$$

where the $m \times Lnm$ observation matrix is given by

$$\mathbf{H}_k(\boldsymbol{\zeta}_k) = \begin{bmatrix} \mathbf{v}_k\left(\mathbf{s}_k\right) & \mathbf{0} & \ldots & \mathbf{0} \\ \mathbf{0} & \mathbf{v}_k\left(\mathbf{s}_k\right) & \ldots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \ldots & \mathbf{v}_k\left(\mathbf{s}_k\right) \end{bmatrix},$$

where $\mathbf{s}_k$ is again the modulated STTC output, given the current STTC state $\boldsymbol{\zeta}_k$.

IV. Simulation Results

In all simulations, we employ a MIMO channel with $n = 2$ transmit antennas and $m = 2$ receive antennas. We consider block transmissions, where the binary message $\{b_k\}$ is organized in length-N frames. In our simulations $N = 100$.

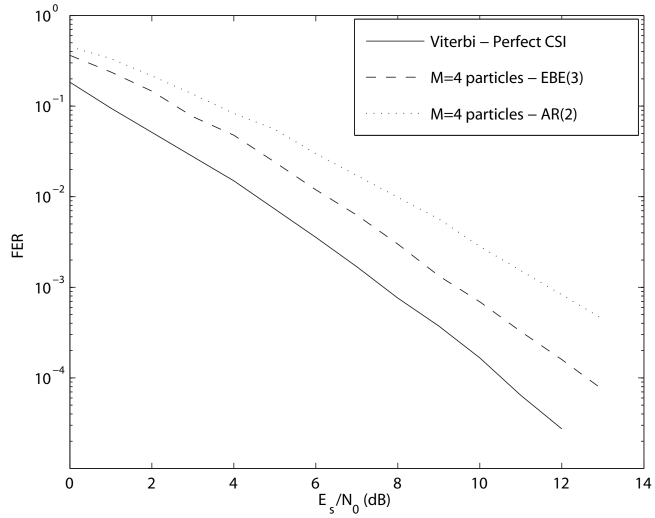

Fig. 3. FER vs. E_s/N_0 for a MIMO channel with $B_dT = 0.003$.

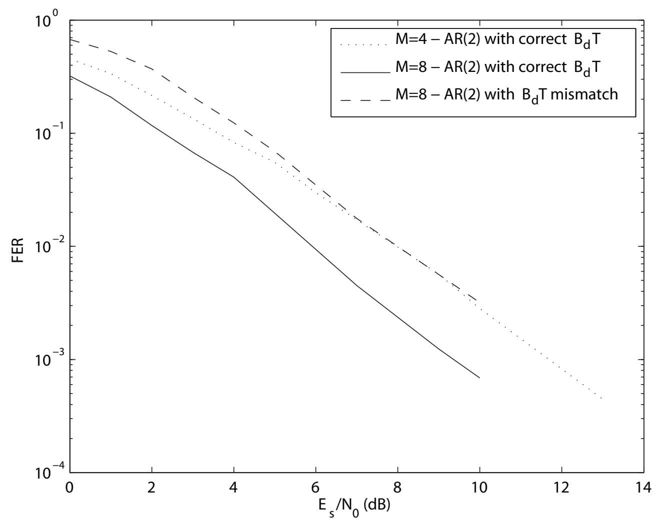

Fig. 4. FER vs. E_s/N_0 for a MIMO channel with $B_dT = 0.003$: with knowledge of the true fading rate (solid and dotted) and with fading rate mismatch (dashed).

The encoder is the memory-2 algebraic STTC for BPSK modulation with connection polynomials $(5, 7)$ in octal [3]. The energy per transmitted BPSK symbol (or equivalently per transmit antenna) is denoted by E_s. The STTC state is reset to zero at the end of each frame.

The time-varying Rayleigh fading MIMO channel is simulated with the method described in [17]. Let B_d denote the maximum Doppler shift, then the channel autocorrelation for $i = 1, \ldots, n$ and $j = 1, \ldots, m$ is given by

$$E\left[c_k^{(ij)} {c_{k-n}^{(ij)}}^*\right] = J_0(2\pi n B_d T),$$

where J_0 is the zero-order Bessel function of first kind. A good approximation of the channel statistics is obtained with the order $P = 2$ autoregressive model (AR(2)) of Sec. III-B by letting

$$\phi_1 = 2r\cos(\omega), \quad \phi_2 = -r^2, \tag{6}$$

where $r = 0.809^{2\pi B_d T}$ and $\omega = 0.781 \times 2\pi B_d T$. In order to normalize the channel gain variance to one, the variance of the noise terms $\pi_k^{(ij)}$ must be chosen as [16]

$$q = \frac{1+\phi_2}{1-\phi_2}[(1-\phi_2)^2 - \phi_1^2].$$

Regarding the receiver of Sec. III-C, we use an exponential basis expansion of the channel gains proposed by the authors in [11], with $L = 3$ frequencies (EBE(3))

$$F_1 = -\frac{1}{sNT}, \quad F_2 = 0, \quad F_3 = \frac{1}{sNT},$$

where s is an small integer and NT is the duration of the frame. We found that setting $s = 3$, any correlated Rayleigh fading process such that $0 < B_dT \lesssim \frac{1}{sN}$ is well approximated by (5). In the simulations, we consider slow fading with $B_dT = 10^{-4}$ and moderately fast fading with $B_dT = 0.003$, therefore the model given by (5) is valid, since $N = 100$.

Fig. 2 shows the FER performances of the considered system for a fading rate of $B_dT = 10^{-4}$. We compare the blind deterministic particle receiver for the EBE(3) and AR(2) channel models with $M = 4$ particles. We observe that at high E_s/N_0, the receiver with EBE(3) (resp. AR(2)) channel model is approximately 1.5dB (resp. 4.5dB) less power efficient than the VA with perfect CSI. Fig. 3 shows a similar behavior for a fading rate of $B_dT = 0.003$.

The dotted and the solid curve in Fig. 4 shows the influence of the number of particles on the blind receiver with the AR(2) channel model at $B_dT = 0.003$. Comparing with Fig. 3, we see that the receiver with AR(2) model and $M = 8$ reaches the same FER as the receiver with EBE(3) model and $M = 4$ (for instance FER=10^{-3} at $E_s/N_0 = 10$dB for both receivers). Our interpretation is that an AR model capturing the short term variations of the channel as well as a simple EBE model with only 3 bases, would in general require a large order P. Consequently, the EBE(3) model is able to predict the channel gains more accurately than its AR(2) counterpart, during the prediction stage of particle filtering. This disadvantage of the AR(2) based receiver can be compensated only by doubling the number of particles, at the cost of increased complexity.

Up to now, all simulations assumed that the coefficients of the AR(2) based receivers given by Eq. (6), were generated with the true value of the fading rate B_dT. In order to study the sensitivity of an AR(2) based receiver to a fading rate mismatch, the dashed curve in Fig. 4 represents the performances of a blind receiver with $M = 8$ particles at true $B_dT = 0.003$, but with coefficients in Eq. (6) generated for $B_dT = 0.03$. This corresponds to the situation where the receiver grossly overestimates the unknown user's velocity. It appears that the fading rate mismatch induces a loss of 2dB in terms of power efficiency. Clearly this drawback disappears when the EBE model is used, since in this case the fading rate need not be known to the receiver.

V. Conclusion

In this letter, we considered joint estimation and decoding of space-time trellis codes with BPSK modulation on a unknown flat Rayleigh fading MIMO channel. A conditionally linear Gauss-Markov state-space model of the channel was introduced, which is independent of the fading rate. A corresponding receiver structure based on ML deterministic particle filtering was proposed. It was shown through simulations that, even with a small number of particles, the performances of the blind receiver can approach the perfect CSI case. The main advantage of the proposed technique is its independence from the unknown fading rate for quasi-static to moderately fast fading MIMO channels.

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