ADAPTIVE PRECODING IN MIMO WIRELESS COMMUNICATION SYSTEMS USING BLIND CHANNEL PREDICTION OVER FREQUENCY SELECTIVE FADING CHANNELS

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ABSTRACT

This paper investigates the feasibility of Tomlinson–Harashima precoding when transmitting over multiple–antenna radio interfaces. In particular, we focus on the robustness of adaptive methods with respect to channel estimation errors. Two approaches are investigated to obtain predictions of the channel impulse response required to select the precoding parameters: Kalman filtering and particle filtering. Kalman filtering exhibits good performance but requires knowledge of the transmitted symbols in advanced. The particle filtering method considered in this work, on the other hand, is a blind technique that provides higher spectral efficiencies with a small loss in performance.

1. INTRODUCTION

In recent years, transmission over Multiple–Input/Multiple–Output (MIMO) channels arising from the utilization of multiple antennas at both transmission and reception has attracted a lot of attention due to the high capacity of these communications links [1]. One way to increase performance over MIMO channels is the utilization of *precoding techniques* that allow the separation of the parallel data streams at the receiver by means of channel pre–equalization at the transmitter side [2]. The problem to implement precoding methods is that Channel State Information (CSI) should be available at transmission. While this assumption is reasonable at the receiver, knowing the channel at the transmitter implies the transmission of CSI through a reverse feedback channel. In time varying channels, feedback delay is a source of errors since the precoder is designed with a past channel estimate that does not exactly correspond to the present channel. Thus, in addition to channel estimation errors, practical implementations of precoding methods are also affected by channel prediction errors.

In this work, however, we show that Tomlinson-Harashima Precoding (THP) methods [3] are robust to channel estimation and prediction errors. Even though they are designed with an erroneous channel, we show that THP techniques are able to correct most of the channel Intersymbol Interferences (ISI) whereas the remaining ISI is easily corrected with a linear equalizer at the receiver. This is more efficient than correcting all the ISI at the receiver. A straighforward way to acquire the CSI is to transmit training sequences that are known *a priori* by the transmitter and the receiver. This approach, however, results in a spectral efficiency loss because pilot symbols do not convey information. On the other hand, blind methods do not need explicit knowledge of the transmitted symbols and thus can track channel variations continuously during the transmission of information data. Along this work we will focus on two channel prediction methods, namely Kalman filtering and Sequential Importance Resampling (SIR). The first is a supervised method that needs knowledge about the true transmitted symbols and the latter is a blind one, since only assumptions about the probablility distributions are made [4]. Nevertheless, our computer experiments show that, although Kalman filter performs better, only a small loss in performace takes place when the SIR algorithm is employed.

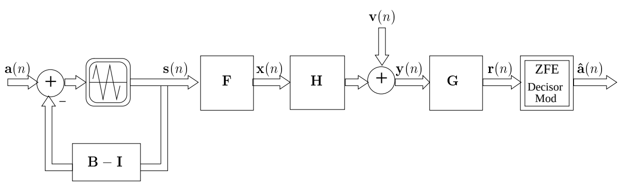

Fig. 1. THP System.

The remaining of this paper is organized as follows. Section 2 describes the signal model for THP over time varying channels. In Section 3, the standard Kalman filtering and the SIR algorithm are introduced and applied to the problem of estimating and predicting an unknown channel. Section 4 is devoted to analyze the performance of the considered precoding techniques by means of deriving expressions of the Signal to Noise Ratio (SNR) at the receiver

[*]This work has been supported by Ministerio de Ciencia y Tecnología of Spain and FEDER funds from the European Union, under grant number TEC2004-06451-C05-01.

input. Illustrative computer simulations are presented in Section 5 and some concluding remarks are made in Section 6.

2. THP FOR TIME VARYING CHANNELS

Although originally proposed for Single–Input/Single–Output (SISO) systems, the principle of THP can be directly extended to $n_t \times n_r$ MIMO time varying channels [5]. Figure 1 shows the block diagram of a MIMO communication system with THP. We will assume that the transmitted symbols belong to a BPSK constellation $a(n) \in \mathcal{A} = \{\pm 1\}$, $n = 0, 1, 2 \ldots$, and gathered in frames of length $N + 1$. We also assume that we transmit over a time varying frequency–selective Rayleigh fading channel with a coherence time T_C. Information about the channel is available at the transmitter because there exists a feedback channel that sends CSI from the receiver to the transmitter. Nevertheless, feedback introduces some delay δ so for the CSI be available at the transmitter we need $\delta << T_C$.

We will represent the channel by the $n_r \times n_t L$ matrix $\mathbf{H}(n)$, where L is the maximum channel length of all component $n_r n_t$ SISO links. The channel beetween the ith receiver antenna and the jth transmit antenna is given by $\mathbf{h}_{ij}(n) = [h_{ij}^0(n), \ldots, h_{ij}^{L-1}(n)]$, $(i = 1, 2, \ldots, n_r,\ j = 1, 2, \ldots, n_t)$. Therefore, the channel matrix $\mathbf{H}$ may be expressed as,

$$\mathbf{H}(n) = \begin{bmatrix} \mathbf{h}_{11}(n) & \cdots & \mathbf{h}_{1n_t}(n) \\ \vdots & \vdots & \vdots \\ \mathbf{h}_{n_r 1}(n) & \cdots & \mathbf{h}_{n_r n_t}(n) \end{bmatrix} \tag{1}$$

Let us further stack the matrix $\mathbf{H}$ into a column vector with $n_t n_r L$ coefficients

$$\begin{aligned} \mathbf{h}(n) \quad = \quad & [h_{11}^0(n) \ldots h_{n_r 1}^0(n) \ldots h_{1n_t}^0(n) \ldots h_{n_r n_t}^0(n) \ldots \\ & h_{11}^{L-1}(n) \ldots h_{n_r 1}^{L-1}(n) \ldots h_{1n_t}^{L-1}(n) \ldots h_{n_r n_t}^{L-1}(n)]^T \end{aligned} \tag{2}$$

The channel varies in time according to the Wide Sense Stationary and Uncorrelated Scattering (WSSUS) model of Bello [6], i.e.,

$$E\{h_{ij}^k(n_1) h_{ij}^k(n_2)\} \sim J_o(2\pi f_{d_{ij}}^{\,k} T\tau) \tag{3}$$

where $f_{d_{ij}}^{\,k} = f_d$ is the Doppler frequency of the kth tap between the jth transmit antenna and the ith receiver antenna, T is the frame time, J_o is the zero-order Bessel function of the first kind and $\tau = |n_1 - n_2|$. MIMO channel variations will be approximated by a first–order Gauss–Markov process, i.e.,

$$\mathbf{h}(n) = \mathbf{A}\mathbf{h}(n-1) + (\mathbf{I} - \mathbf{A})\mathbf{w}(n), \quad n \geq 0 \tag{4}$$

where $\mathbf{h}(n)$ is given by equation (2), $\mathbf{A}$ is a known $n_t n_r L \times n_t n_r L$ matrix and $\mathbf{w}(n)$ is a zero–mean, i.i.d., circular complex Gaussian vector process with covariance matrix $\mathbf{Q} = \sigma_w^2 \mathbf{I}$. The channel impulse response (CIR) vector $\mathbf{h}(n)$ will be independent of $\mathbf{w}(n)$ for all $n \geq 0$ and has a prior Gaussian distribution with a zero mean vector, i.e., $\bar{\mathbf{h}}(-1) = \mathbf{0}$ and an identity covariance matrix, i.e., $\mathbf{C}(-1) = \mathbf{I}$. Due to the WSSUS assumption, we can let $\mathbf{A}$, $\mathbf{Q}$ and $\mathbf{C}(-1)$ be diagonal matrices. Model inaccuracies can be made arbitrarily small by increasing the Gauss–Markov process order. Nevertheless, low-order models can capture most of the channel tap dinamics and lead to effective tracking algorithms [7].

If the n_r– dimensional received signal is sampled at symbol rate, we will have the following discrete–time model,

$$\mathbf{y}(n) = \mathbf{X}(n)\mathbf{h}(n) + \mathbf{v}(n) \tag{5}$$

where $\mathbf{h}(n)$ is given by the Equation (2), $\mathbf{X}(n)$ is a $n_r \times n_r n_t L$ channel input symbols matrix, defined as

$$\begin{aligned} \mathbf{X}(n) \quad = \quad & [x_1(n)\mathbf{I}_{n_r} \ldots x_{n_t}(n)\mathbf{I}_{n_r} \ldots \\ & x_1(n-L+1)\mathbf{I}_{n_r} \ldots x_{n_t}(n-L+1)\mathbf{I}_{n_r}] \end{aligned} \tag{6}$$

and $\mathbf{v}(n) = [v_1(n) \cdots v_{n_r}(n)]^T$ is the zero mean spatio–temporally Additive White Gaussian Noise (AWGN) vector with covariance matrix $\mathbf{R} = \sigma_v^2 \mathbf{I}$. If we employ the notation given by the equation (1), the received signal may be expressed as $\mathbf{y}(n) = \mathbf{H}(n)\mathbf{x}(n) + \mathbf{v}(n)$, where $\mathbf{x}(n)$ is a $n_r n_t L \times 1$ vector defined as

$$\begin{aligned} \mathbf{x}(n) \quad = \quad & [x_1(n), \ldots, x_1(n-L+1), \ldots \\ & x_{n_t}(n), \ldots, x_{n_t}(n-L+1)]^T \end{aligned} \tag{7}$$

Regarding the discrete–time model already given, we must calculate the optimum feedforward and feedback matrices to select the precoding parameters. We define the z–transform of the channel matrix as

$$\mathbf{H}(z; n) = \sum_{k=0}^{L-1} \mathbf{H}^k(n) z^{-k} \tag{8}$$

where the matrices $\mathbf{H}^k(n)$ will be given by

$$\mathbf{H}^k(n) = \begin{bmatrix} h_{11}^k(n) & \cdots & h_{1n_t}^k(n) \\ \vdots & \vdots & \vdots \\ h_{n_r 1}^k(n) & \cdots & h_{n_r n_t}^k(n) \end{bmatrix} \tag{9}$$

definition. Solving the *spectral factorization problem* [8, 9],

$$\mathbf{H}(z; n)\mathbf{H}^H(z^{-*}; n) = \mathbf{L}(z; n)\mathbf{L}^H(z^{-*}; n) \tag{10}$$

it is obtained a time–domain matrix $\mathbf{L}(n)$ corresponding to $\mathbf{L}(z; n) = \sum_{k=0}^{L-1} \mathbf{L}^k(n) z^{-k}$ strictly causal (i.e., $\mathbf{L}^k(n) =$

$\mathbf{0}, k < 0$), minimum phase (i.e., $\det(\mathbf{L}(z;n)) \neq 0$, $|z| \geq 1$), and where $\mathbf{L}^0(n)$ is lower triangular. The feedforward matrix is then given as

$$\mathbf{F}(z;n) = \mathbf{H}^H(z^{-*};n)\mathbf{L}^H(z^{-*};n)^{-1} \tag{11}$$

and the feedback matrix reads

$$\mathbf{B}(z;n) = \mathbf{G}(n)\mathbf{L}(z;n) \tag{12}$$

where $\mathbf{G}(n)$ is an $n_r \times n_t$ scale matrix obtained from $\mathbf{L}(z)$ by means of the inverse of the main diagonal of $\mathbf{L}^0(n)$ and, therefore, $\mathbf{B}^0(n)$ will be a unit–diagonal lower triangular matrix ("monic" matrix polynomial $\mathbf{B}(z;n)$).

In this paper we will assume that matrix **B**(z) is calculated from channel estimates obtained at the receiver. We will explain in the following section how to estimate the channel by means of Kalman filtering and Sequential Importance Sampling (SIS) techniques.

3. CHANNEL TRACKING

Kalman filtering is the most widely used method for estimating and predicting the channel impulse response of time varying channels. Kalman filtering, however, needs the estimation of true data symbols or estimating the channel only during the time intervals where training symbols are transmitted. On the other hand, particle filtering techniques, such as standard Sequential Importance Resampling [10, 11], are blind methods that do not need explicit knowledge of the transmitted symbols but require the knowledge of the distribution of the hidden and observed process, although recent techniques do not need to make such assumptions [12]. Thus, we will be able to track channel variations while the data transmission progresses.

3.1. Kalman Filtering

Taking into account the data model of (5), so called the *observation or measurement* equation, and the state model of (4) the vector Kalman filter equations can be summarized as follows,

$$\begin{aligned}
\mathbf{P}(n|n-1) &= \mathbf{A}\mathbf{P}(n-1|n-1)\mathbf{A}^T + \mathbf{Q} \\
\mathbf{K}(n) &= \mathbf{P}(n|n-1)\mathbf{X}(n)(\mathbf{X}^T(n)\mathbf{P}(n|n-1)\mathbf{X}(n) + \mathbf{R})^{-1} \\
\mathbf{c}(n) &= \mathbf{y}(n) - \mathbf{X}^T(n)\mathbf{A}\hat{\mathbf{h}}(n-1) \\
\hat{\mathbf{h}}(n) &= \mathbf{A}\hat{\mathbf{h}}(n-1) + \mathbf{K}(n)\mathbf{c}(n) \\
\mathbf{P}(n|n) &= \mathbf{P}(n|n-1) - \mathbf{K}(n)\mathbf{X}^T(n)\mathbf{P}(n|n-1)
\end{aligned} \tag{13}$$

where $\mathbf{P}(n|n-1)$ is the prediction error covariance matrix, $\mathbf{P}(n|n)$ is the correction error covariance matrix, $\mathbf{K}(n)$ is the Kalman gain and $\mathbf{c}(n)$ is the innovation process. The kalman filter will be initialized by $\hat{\mathbf{h}}(-1) = \bar{\mathbf{h}}(-1) = \mathbf{0}$ and $\mathbf{P}(-1|-1) = \mathbf{C}(-1) = \mathbf{I}$.

Although the true symbols could have been estimated from data leading to blind techniques using Kalman filters, for simplicity we have assumed that the true symbols are known by means of including some pilot symbols in each frame that will allow us to estimate and predict the channel behavior according to this algorithm.

3.2. Sequential Importance Resampling

Sequential Importance Sampling (SIS) is one of the most popular Monte Carlo (MC) methods. It consists of drawing M samples, usually called *particles* and denoted by $x^{(i)}$, from a trial probability mass function (pmf) $q(x)$ in order to get an empirical approximation of the pmf $p(x)$. These particles are weighted according to $w^{(i)} \propto p(x^{(i)})/q(x^{(i)})$, with $\sum_{i=1}^{M} w^{(i)} = 1$. The set of particles and their associated normalized weights then becomes a discrete estimate of the desired pmf, $p(x)$.

Taking into account that the channel impulse response (CIR) vector has a prior Gaussian distribution, as we have explained in Section II, the posterior channel probability density function is also Gaussian (c.f. [4]),

$$p[\mathbf{h}|\mathbf{x}_{0:n}, \mathbf{y}_{0:n}] = \mathcal{N}(\bar{\mathbf{h}}(n), \mathbf{C}(n)) \tag{14}$$

where the transmitted symbols vectors in a single frame are given by $\mathbf{x}_{0:n} = \{\mathbf{x}(0), \mathbf{x}(1), \ldots, \mathbf{x}(n)\}$ and where $\mathbf{y}_{0:n} = \{\mathbf{y}(0), \mathbf{y}(1), \ldots, \mathbf{y}(n)\}$ are the received symbols vectors. The distribution parameters $\bar{\mathbf{h}}(n)$ and $\mathbf{C}(n)$ can be updated recursively according to

$$\mathbf{C}^{-1}(n) = \frac{\mathbf{x}(n)\mathbf{x}(n)^T}{\sigma_v^2} + \mathbf{C}^{-1}(n-1) \tag{15}$$

$$\bar{\mathbf{h}}(n) = \mathbf{C}(n)\left(\frac{\mathbf{x}(n)\mathbf{y}^T(n)}{\sigma_v^2} + \mathbf{C}^{-1}(n-1)\bar{\mathbf{h}}(n-1)\right) \tag{16}$$

for all $n \geq 0$. Using the particle filter approximation of the *a posteriori* pmf of the symbols, the posterior channel distribution associated to the highest importance weighted particle, $\mathcal{N}\left(\bar{\mathbf{h}}(n)^{(i_{max})}, \mathbf{C}(n)^{(i_{max})}\right)$, provides a Bayesian estimate of the CIR and, therefore, predictions can be obtained in a straightforward manner.

Next, we explain briefly the details of the Sequential Importance Resampling algorithm for a known channel order. We begin with the Importance Sampling (IS) scheme. First, we obtain M particles from a trial pmf, i.e,

$$\mathbf{x}_{0:N}^{(i)} \sim q[\mathbf{x}_{0:N}|\mathbf{y}_{0:N}] \tag{17}$$

where $q[\mathbf{x}_{0:N}|\mathbf{y}_{0:N}]$ has the same support as the true posterior probability of the data sequence conditional on the corresponding series of observations $p[\mathbf{x}_{0:N}|\mathbf{y}_{0:N}]$ but is easier to sample from. The particles will be weighted according to

$$\begin{aligned} \tilde{w}^{(i)} &= \frac{p[\mathbf{x}_{0:N}^{(i)}|\mathbf{y}_{0:N}]}{q[\mathbf{x}_{0:N}^{(i)}|\mathbf{y}_{0:N}]} \\ w^{(i)} &= \frac{\tilde{w}^{(i)}}{\sum_{k=1}^{M}\tilde{w}^{(k)}} \end{aligned} \tag{18}$$

These particles and their normalized weights provide an MC approximation of the true posterior pmf,

$$p[\mathbf{x}_{0:N}|\mathbf{y}_{0:N}] \approx \hat{p}[\mathbf{x}_{0:N}|\mathbf{y}_{0:N}] = \sum_{i=1}^{M}\delta_i w^{(i)} \tag{19}$$

where $\delta_i = 1$ if $\mathbf{x}_{0:N} = \mathbf{x}_{0:N}^{(i)}$ and $\delta_i = 0$ otherwise.

The IS method can be modified to construct the particles and their associate weights sequentially as new observations arrive. Let us consider the following factorization of the importance pmf

$$q[\mathbf{x}_{0:n}|\mathbf{y}_{0:n}] \propto q[\mathbf{x}_n|\mathbf{x}_{0:n-1},\mathbf{y}_{0:n}]q[\mathbf{x}_{0:n-1}|\mathbf{y}_{0:n-1}], \quad \forall t. \tag{20}$$

Using (20), the IS principle and the following descomposition of the posterior pmf,

$$p[\mathbf{x}_{0:n}|\mathbf{y}_{0:n}] \propto p[\mathbf{y}_n|\mathbf{x}_{0:n},\mathbf{y}_{0:n-1}]p[\mathbf{x}_{0:n-1}|\mathbf{y}_{0:n-1}], \tag{21}$$

it is simple to see that the importance weights can be evaluated recursively in time, leading to the Sequential Importance Sampling (SIS) algorithm

$$\begin{aligned} \mathbf{x}_n^{(i)} &\propto q[\mathbf{x}_n|\mathbf{x}_{0:n-1}^{(i)},\mathbf{y}_{0:n}] \\ \tilde{w}_n^{(i)} &= w_{n-1}^{(i)}\frac{p[\mathbf{y}_n|\mathbf{x}_{0:n}^{(i)},\mathbf{y}_{0:n-1}]}{q[\mathbf{x}_n^{(i)}|\mathbf{x}_{0:n-1}^{(i)},\mathbf{y}_{0:n}]} \\ w_n^{(i)} &= \frac{\tilde{w}_n^{(i)}}{\sum_{k=1}^{M}\tilde{w}_n^{(k)}} \end{aligned} \tag{22}$$

for $i = 1,\ldots,M$. The set of particles and normalized weights at time n,

$$\{\mathbf{x}_{0:n}^{(i)}, w_n^{(i)}\}_{i=1}^{M}, \tag{23}$$

allow to approximate the *a posteriori* pmf in a way analogous to (19), namely

$$p[\mathbf{x}_{0:n}|\mathbf{y}_{0:n}] \approx \hat{p}[\mathbf{x}_{0:n}|\mathbf{y}_{0:n}] = \sum_{i=1}^{M}\delta_i w_n^{(i)}. \tag{24}$$

It can be shown [13] that this approximate probability obtained by means of the method described above converges to the true probability $p[\mathbf{x}_{0:n}|\mathbf{y}_{0:n}]$ as $M \to \infty$. We could also obtain estimates of the data sequence using the particles with the largest importance weights [4]

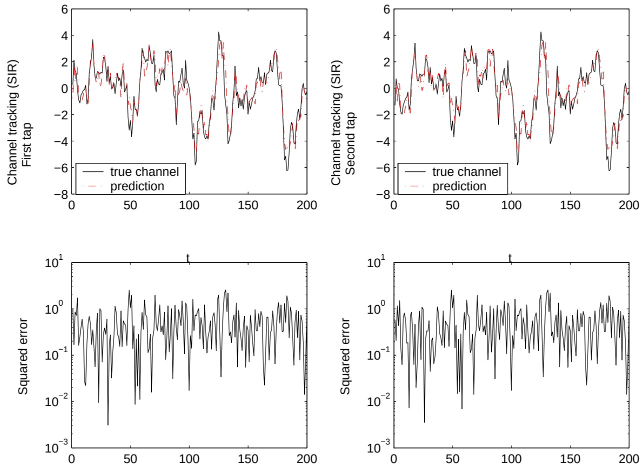

Fig. 2. Channel tracking using Sequential Importance Resampling.

The main problem with particle filtering is that most of the particles are assigned weights very close to zero after just a few time steps. To avoid the loss in performance, a modified version of the algorithm known as Sequential Importance sampling with Resampling (SIR) is employed. It includes a resampling step in the SIS algorithm, which consists of stochastically discarding the particles with the smallest weights while those with higher weights are replicated.

To illustrate the goodness of the SIR algorithm for the channel tracking application, Figure 2 shows an example when $M = 200$ particles are considered.

4. SNR PERFORMANCE

In order to evaluate the performance of the proposed adaptive TH precoding technique, the signal to noise ratio is an important parameter [5].

When we are not employing precoding at transmission and with Zero–Forcing Equalization (ZFE) in the receiver, the ratio of total receiver power to total noise power at the detector input at time instant n reads

$$\begin{aligned} SNR(n) &= \frac{E_a\{\mathbf{a}\mathbf{a}^H\}}{E_v\{trace(\mathbf{H}^{-1}\mathbf{v}\mathbf{v}^H\mathbf{H}^{-H})\}} \\ &= \frac{n_r\sigma_a^2}{\sigma_v^2}\cdot\frac{1}{\sum_{i=1}^{n_r}\sum_{j=1}^{n_t}\sum_{k=0}^{L-1}|h_{ij}^k(n)^{-1}|^2} \end{aligned} \tag{25}$$

In case of precoding (if we ignore the modulo loss) and perfect CSI at transmission, we will have the following expresions for the SNR at this point,

$$\begin{aligned} SNR(n) &= \frac{E_a\{\mathbf{a}\mathbf{a}^H\}}{E_v\{trace(\mathbf{G}\mathbf{v}\mathbf{v}^H\mathbf{G}^H)\}} \\ &= \frac{n_r\sigma_a^2}{\sigma_v^2}\cdot\frac{1}{\sum_{i=1}^{n_r}\sum_{j=1}^{n_t}\sum_{k=0}^{L-1}|g_{ij}^k(n)|^2} \end{aligned} \tag{26}$$

Finally, if we have not perfect CSI at the transmitter side and residual ZFE at the detector input is considered, the SNR is defined as

$$\begin{aligned} SNR(n) &= \frac{E_a\{\mathbf{a}\mathbf{a}^H\}}{E_v\{trace(\mathbf{H_t}\mathbf{v}\mathbf{v}^H\mathbf{H}_t^H)\}} \\ &= \frac{n_r\sigma_a^2}{\sigma_v^2}\cdot\frac{1}{\sum_{i=1}^{n_r}\sum_{j=1}^{n_t}\sum_{k=0}^{L-1}|h_{t_{ij}}^k(n)|^2} \end{aligned} \tag{27}$$

with $\mathbf{H}_t = (\mathbf{G}\mathbf{H}\hat{\mathbf{F}}\hat{\mathbf{B}}^{-1})^{-1}\mathbf{G}$, where $\hat{(\cdot)}$ implies channel prediction, i.e, no perfect CSI available, and with $h_{t_{ij}}^k(n)$ containing the predicted fading gain from transmit antenna j to receive antenna i for the kth tap. The average SNR, i.e., $E_H\{SNR(n)\}$ will be calculated in all cases by means of Monte Carlo simulations.

5. RESULTS

In this section we present the results of several simulations that were carried out to illustrate the robustness of THP methods. We implemented Kalman and SIR algorithms and compare the performance of the system measured in terms of BER, when transmitting with BPSK modulation in MIMO Rayleigh fading channels.

We set $n_t = n_r$ for maximum spatial multiplexing gain with Zero Forcing (ZF) THP, and, specifically, in these simulations, $n_t = n_r = 2$ with $L = 2$. Simulations are averaged over $2,000$ channel realizations, wherein the channel is constant across a space–time block code of 50 symbols, and changes according to the model explained in Section II from one block to another. The SIR algorithm is evaluated with $M = 200$ particles and all the transmitted symbols are assumed known for Kalman filtering. With σ_v^2 being the noise variance at each receiver, the SNR plotted is given by $SNR = 10\,log\,P_T/\sigma_v^2$, where P_T is the transmit power in each slot, i.e., for a BPSK modulation, $P_T = \sigma_a^2 = E|a(k)|^2 = 1$. Coincidently, this SNR value will be the SNR at the detector input with linear pre–equalization and perfect CSI at transmission, i.e., multiplying the data vector $\mathbf{a}$ with the right(seudo)inverse of the channel matrix $\mathbf{H}$ at the transmitter.

The estimated BER curves are shown in Figure 3 for a normalized Doppler frequency $f_DT = 0.02$. From the figure, it can be seen that Kalman filtering performs better than

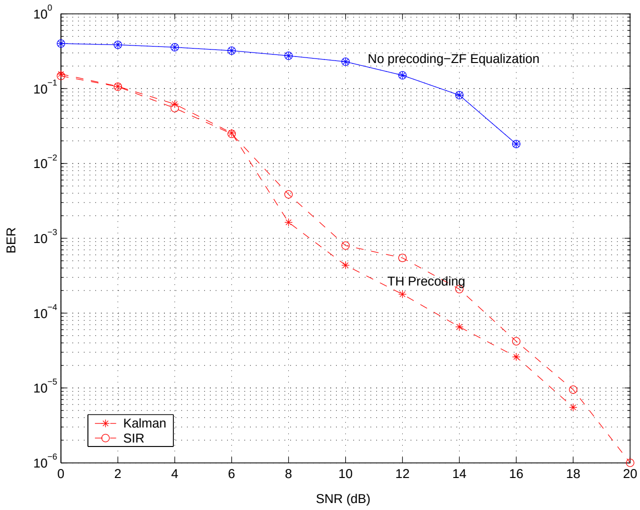

Fig. 3. BER vs. SNR for a Normalized Doppler Frequency equal to 0.02.

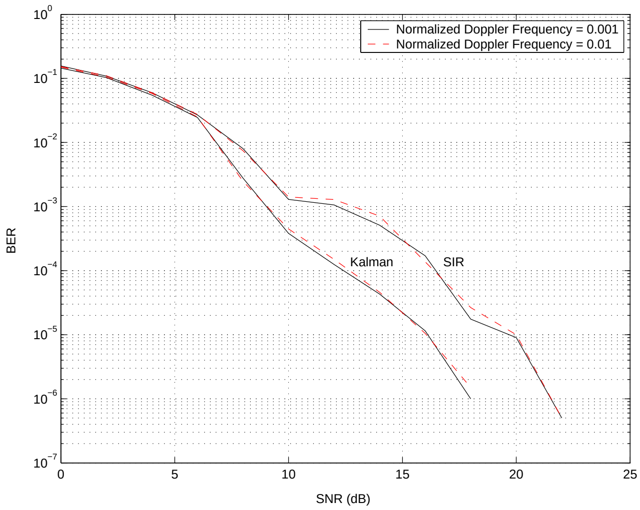

Fig. 4. BER vs. SNR depends on the Normalized Doppler Frequency.

Sequential Importance Resampling, but the loss in terms of BER when SIR is employed is very small. It is shown too the good performance obtained when the predicted channel is employed in the precoder design and if the mismatch beetween the true channel and the predicted one is compensated by means of a linear adaptive residual equalization at the receiver. The figure also reveals how the use of precoding is advantageous over the simple receiver equalization.

The simulation results in Figure 4 provide some insight on the issue of how the magnitude and speed of the channel variation affects the system performance. The figure plots the BER for two different values of normalized Doppler frequency, $f_d T = 0.001$ (slow fading) and $f_d T = 0.01$ (fast fading). We observe that slightly higher SNR is required to achieve a BER of 10^{-3} as the Doppler rate $f_D T$ increases. Thus, the performance is similar in both cases which indicates that our precoding method is capable of correctly adapting to varying channel conditions. In addition, there is a small loss in performance for employing SIR techniques with regard to Kalman filtering.

Finally, in the Figure 5 the SNR at the detector input when SIR is employed is plotted as a function of the normalized Doppler frequency for an SNR=15 dB. It is clearly seen how the performance is very similar if perfect CSI is not available at transmission. Evidently the SNR values decrease with the Doppler frequency but very lightly, as you can see in the picture. This loss is caused by the prediction errors whose variance increases with the channel Doppler rate.

6. CONCLUSIONS

In this work we have demonstrated the feasibility of adaptive Tomlinson-Harashima precoding over frequency–selective channels. We have investigated two channel prediction methods to implement the precoding strategy, namely Kalman Filtering (KF) and Sequential Importance Resampling (SIR). Although Kalman filtering provides better results it is of limited applicability because it requires knowledge of the transmitted symbols. This assumption is not necessary when SIR is employed and the loss in performance is small. Thus, employing SIR yields to more bandwidth efficient communication links.

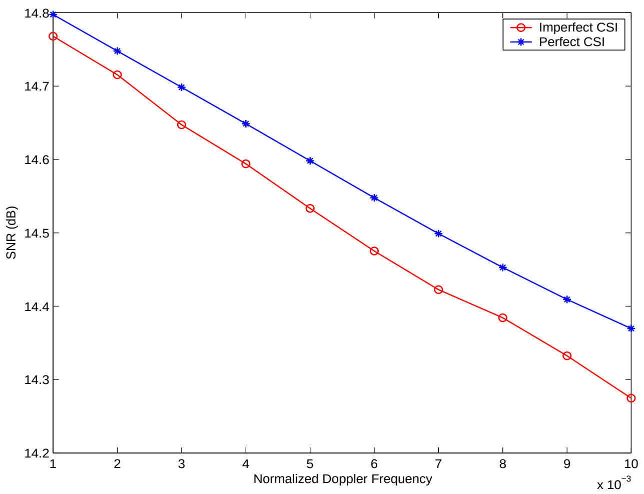

Fig. 5. SNR vs. Normalized Doppler Frequency.

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