PERFORMANCE BOUNDS FOR CHANNEL TRACKING ALGORITHMS FOR MIMO SYSTEMS

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ABSTRACT

In this paper[1] we derive performance bounds for tracking time-varying OFDM multiple-input multiple-output (MIMO) communication channel in the presence of additive white Gaussian noise (AWGN). We discuss two channel tracking schemes. The first tracks the filter coefficients directly in time-domain, while the second separately tracks each tone in the frequency-domain. The Kalman filter, with known channel statistics, is utilized for evaluating the performance bounds. It is shown that the time-domain tracking scheme, which exploits the sparseness of the channel impulse response, outperforms the computationally more efficient, frequency-domain tracking scheme, which does not exploit the smooth frequency response of the channel.

Index Terms— Time-varying Channels, Communication system performance, Tracking, Kalman filtering, MIMO systems

1. INTRODUCTION

In recent years, MIMO OFDM schemes have gained increased interest in both theoretical and practical aspects. Channel tracking in MIMO regime is a more complicated task than in the commonly used single-input-single-output (SISO) case. Recently, several blind estimation methods for channel tracking were proposed. Dahl *et al.* [1] and Gannot *et al.* [2] propose to track the singular value decomposition (SVD) of the channel matrix. The proposed algorithms differ in the algebraic structure used. Komninakis *et al.* [3] use the Kalman filter in the time-domain to track the channel coefficients. The unknown input signals are replaced by the output of a decision feedback equalizer (FDE). Bulumulla *et al.* [4] replace the time-domain formulation by its frequency-domain counterpart, exploiting the channel smooth frequency response. Cheng and Dahlhaus [5] compare a time-domain scheme, similar to [3], and a frequency-domain scheme, similar to [4], and show their equivalence. Haeb-Umbach and Bevermeier [6] use time-domain Kalman filtering (during the preamble) for the initialization of frequency-domain Wiener filter, used for blindly tracking the channel impulse response.

Our contribution does not aim at the design of an actual channel tracking method, but rather establishes performance bounds for any tracking algorithm. Specifically, we compare time- and frequency-domain schemes assuming that the transmitted data is given. We show that frequency-domain tracking algorithms which does not exploit the smooth channel frequency response are inferior to the, computationally more expensive, time-domain tracking schemes.

The structure of this work is as follows. In Sec. 2 we introduce the problem. The use of the Kalman filter for evaluating the channel tracking performance bounds is motivated in Sec. 3. The channel model and measurement equations are restated in state-space presentation in Sec. 4. Finally, the superiority of the time-domain scheme over the frequency-domain scheme is experimentally demonstrated in Sec. 5. We draw final conclusions in Sec. 6.

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2. PROBLEM FORMULATION

In this section, the MIMO channel in the orthogonal frequency-division multiplexing (OFDM) framework is presented. We start by formulating the problem in the time-domain and proceed to the frequency-domain presentation. We describe only the downlink of the MIMO channel, as the derivation of the uplink channel is equivalent.

2.1. Time-Domain Presentation

Let N denote the OFDM symbol length. Assume that the number of transmit antennas is N_t, and the number of the received antennas is N_r. Each of the $N_t \times N_r$ MIMO channels is assumed to be fading channels with L coefficients $h^{ij}(\ell, n)$, where $1 \leq i \leq N_t$ are the transmit antenna indexes, $1 \leq j \leq N_r$ are the receive antenna indexes, and $\ell = 0, \ldots, L-1$ are the coefficients indexes. We assume the filters to be time-variant, and hence, their values depend on n, the symbol index. However, the channels are assumed to be time-invariant within the OFDM symbol.

The ith antenna in the downlink transmits a sequence of OFDM symbols $x^i(m, n)$, where $-\infty < n < \infty$ is the symbol index, and $m = 0, \ldots, N-1$ denotes the time index *within* the OFDM symbol. For the OFDM assumption to hold, each symbol of the transmitted signal is comprised of the data samples preceded by a cyclic prefix (CP). The length of the CP should be greater than or equal to the channel spread L, to guarantee proper operation of the OFDM system.

The received signal at the jth antenna is thus a linear combination of transmitted sequences:

$$y^j(m, n) = \sum_{i=1}^{N_t} \sum_{\ell=0}^{L-1} h^{ij}(\ell, n) x^i(m - \ell, n) + z^j(m, n) \qquad (1)$$

where the additive term $z^j(m, n)$ is assumed to be temporarily-white Gaussian noise. Due to the CP, $x^i(m - \ell, n) = x^i(mod(m - \ell, N), n)$. The received signals can be compactly described in a matrix notation:

$$\boldsymbol{y}_n = (\mathbf{I}_{N_r} \otimes \mathbf{X}_n)\, \boldsymbol{h}_n + \boldsymbol{z}_n \qquad (2)$$

where $\otimes$ is the Kronecker product and

$$\begin{aligned} \boldsymbol{h}_n^{ij} &\triangleq \begin{bmatrix} h^{ij}(0, n) & h^{ij}(1, n) & \ldots & h^{ij}(L-1, n) \end{bmatrix}^T \\ \boldsymbol{h}_n &\triangleq \Big[(\boldsymbol{h}_n^{11})^T \quad \ldots \quad (\boldsymbol{h}_n^{N_t 1})^T \ldots \\ &\qquad (\boldsymbol{h}_n^{1 N_r})^T \quad \ldots \quad (\boldsymbol{h}_n^{N_t N_r})^T \Big]^T \end{aligned}$$

$$\begin{aligned}\boldsymbol{y}_n &\triangleq \left[\begin{array}{ccccc} y^1(0,n) & \dots & y^1(N-1,n) & \dots \\ y^{N_r}(0,n) & \dots & y^{N_r}(N-1,n) \end{array}\right]^T \\ \boldsymbol{z}_n &\triangleq \left[\begin{array}{ccccc} z^1(0,n) & \dots & z^1(N-1,n) & \dots \\ z^{N_r}(0,n) & \dots & z^{N_r}(N-1,n) \end{array}\right]^T\end{aligned}$$

and

$$\mathbf{X}_n^i \triangleq \begin{bmatrix} x^i(0,n) & \dots & x^i(-L+1,n) \\ x^i(1,n) & \dots & x^i(-L+2,n) \\ & \vdots & \\ x^i(N-1,n) & \dots & x^i(N-L,n) \end{bmatrix}_{N\times L}$$

$$\mathbf{X}_n \triangleq \begin{bmatrix} X_n^1 & X_n^2 & \dots & X_n^{N_t} \end{bmatrix}_{N\times(LN_t)}.$$

$\boldsymbol{z}_n$, comprised of concatenated noise samples, is a zero-mean, temporarily-white, circular symmetric complex, Gaussian distributed random vector, $\boldsymbol{z}_n \sim \mathcal{CN}(0, \mathbf{R}_n^t)$, where $\mathbf{R}_n^t \in \mathbb{C}^{(N_r N)\times(N_r N)}$ is the time-domain noise covariance matrix. If the measurement noise is also spatially-white, i.e. the noise signals received by the antennas are uncorrelated, the covariance matrix $\mathbf{R}_n^t$ becomes diagonal.

2.2. Frequency-Domain Presentation

If the CP is larger than or equal the channel order L, the channel effect is converted into a circular convolution, and hence can be conveniently expressed as a multiplication in the frequency-domain:

$$\boldsymbol{y}_n(\omega) = \mathbf{H}_n(\omega)\,\boldsymbol{x}_n(\omega) + \boldsymbol{z}_n(\omega) \tag{3}$$

where ω is the frequency bin, $\boldsymbol{x}_n(\omega) \in \mathbb{C}^{N_t\times 1}$ is the channel input vector, $\boldsymbol{y}_n(\omega) \in \mathbb{C}^{N_r\times 1}$ is the channel output vector, $\mathbf{H}_n(\omega) \in \mathbb{C}^{N_r\times N_t}$ is the channel matrix, and $\boldsymbol{z}_n(\omega)$ is a circular symmetric complex AWGN $\boldsymbol{z}_n(\omega) \sim \mathcal{CN}(0, \mathbf{R}_n^f(\omega))$. In the frequency-domain formulation, the frequency bins are decoupled, hence yielding instantaneous rather than convolutive mixing.

3. THE USE OF THE KALMAN FILTER FOR PERFORMANCE EVALUATION

The need for establishing a proper communication link necessitates the development of channel tracking algorithms. The current contribution *is not concerned* with the derivation of such an algorithm. Our aim is to present performance bounds which can be applicable to any tracking method. The goal of time-domain tracking algorithms is the estimation of $\boldsymbol{h}_n$ using the measurements given in (2). The outcome of frequency-domain tracking algorithms, using the measurements given by (3), is an estimate of $\mathbf{H}_n(\omega)$.

We propose a Bayesian framework for evaluating the upper performance bound for the ability of algorithms to track the channel coefficients. The Kalman filter [7] is the optimal linear minimum mean square error (MSE) estimator of a state-vector from measurements up to that time-instant; moreover, it is the optimal minimum MSE estimator in general (i.e., among all linear and nonlinear estimators), when the states and the measurements are jointly Gaussian.

For our tracking scheme, the channel coefficients are therefore treated as stochastic processes, while the terms related to the input signal (either $\mathbf{X}_n$ in the time-domain or $\boldsymbol{x}_n(\omega)$ in the frequency-domain) are *assumed to be known*. Naturally, this assumption cannot be met in practice. However, since this contribution does not aim at deriving new algorithms, but rather evaluating performance bounds, we will assume that the input signal are indeed known. It should be stressed that the tightness of the derived bounds is not claimed.

The Kalman filter is based on state-space formulation of the system's dynamics. Assume that the underlying process of interest $\boldsymbol{d}_n$ satisfies the following recursive model equation:

$$\boldsymbol{d}_n = \boldsymbol{\Phi}_n \boldsymbol{d}_{n-1} + \boldsymbol{w}_n. \tag{4}$$

Assume further, that the measurement $\boldsymbol{y}_n$ is related to the state-vector $\boldsymbol{d}_n$ via the following measurement equation:

$$\boldsymbol{y}_n = \mathbf{G}_n \boldsymbol{d}_n + \boldsymbol{v}_n. \tag{5}$$

Proper definitions of the model (4) and measurement (5) equations will be discussed in Sec. 4.1 (time-domain) and in Sec. 4.2 (frequency-domain), where the involved terms $\boldsymbol{d}_n$, $\boldsymbol{y}_n$, the transition matrix $\boldsymbol{\Phi}_n$, the innovation process $\boldsymbol{w}_n$, the measurement matrix $\mathbf{G}_n$, and the noise process $\boldsymbol{v}_n$ will be identified.

We assume that the exact statistical model governing the production of the channel coefficients is known in advance. Since, usually, the actual models are replaced by their estimated values, this assumption further restricts the application of the proposed method to the evaluation of merely an upper bound for the tracking ability.

Define $\hat{\boldsymbol{d}}_{n|n}$ the minimum MSE estimator of $\boldsymbol{d}_n$ in (4) based on the measurements $\boldsymbol{y}_n$, $n = 0, 1, \dots$ in (5), and let $\mathbf{P}_{n|n} = E\left\{(\hat{\boldsymbol{d}}_{n|n} - \boldsymbol{d}_n)(\hat{\boldsymbol{d}}_{n|n} - \boldsymbol{d}_n)^H\right\}$ be its respective error covariance matrix. The Kalman procedure is initialized with $\hat{\boldsymbol{d}}_{0|0} = \boldsymbol{m}_0$, and $\mathbf{P}_{0|0} = \mathbf{P}_0$ (algorithm initialization schemes are out of the scope of this paper.). It then proceeds for $n = 1, 2, \dots$ with the following *propagation* and *update* equations.

Propagation Equations:

$$\begin{aligned}\hat{\boldsymbol{d}}_{n|n-1} &= \boldsymbol{\Phi}_n \hat{\boldsymbol{d}}_{n-1|n-1} \\ \mathbf{P}_{n|n-1} &= \boldsymbol{\Phi}_n \mathbf{P}_{n-1|n-1} \boldsymbol{\Phi}_n^H + \mathbf{Q}_n.\end{aligned} \tag{6}$$

Update Equations:

$$\begin{aligned}\mathbf{K}_n &= \mathbf{P}_{n|n-1}\mathbf{G}_n^H(\mathbf{G}_n\mathbf{P}_{n|n-1}\mathbf{G}_n^H + \mathbf{R}_n)^{-1} \\ \hat{\boldsymbol{d}}_{n|n} &= \hat{\boldsymbol{d}}_{n|n-1} + \mathbf{K}_n(\boldsymbol{y}_n - \mathbf{G}_n\hat{\boldsymbol{d}}_{n|n-1}) \\ \mathbf{P}_{n|n} &= (\mathbf{I} - \mathbf{K}_n\mathbf{G}_n)\mathbf{P}_{n|n-1}.\end{aligned} \tag{7}$$

where, $\mathbf{Q}_n \triangleq E\left\{\boldsymbol{w}_n\boldsymbol{w}_n^H\right\}$ is the innovation noise covariance matrix, $\mathbf{R}_n \triangleq E\left\{\boldsymbol{v}_n\boldsymbol{v}_n^H\right\}$ is the measurement noise covariance matrix, and $\mathbf{K}_n$ is the Kalman gain.

In the rest of the paper we will discuss different instances of (4) and (5) which will enable the application of the Kalman filter for evaluating a upper performance bound for the channel tracking algorithms.

4. CHANNEL MODEL AND STATE-SPACE FORMULATION

In many cases the channel coefficients trajectory can be approximately modeled as an auto-regressive (AR) process of order P. Hence the ℓth tap of the ijth time-varying channel is given by

$$h^{ij}(\ell,n) = \sum_{p=1}^{P} \alpha_\ell^{ij}(p) h^{ij}(\ell,n-p) + w^{ij}(\ell,n). \tag{8}$$

We assume that the frame-dependent filter coefficients can be modeled as a wide-sense-stationary (WSS) AR(P) process. Hence, the driving noise signals $w^{ij}(\ell,n)$ are independently identically distributed (i.i.d.). We further assume that all $N_t \times N_r \times L$ processes $w^{ij}(\ell,n)$ are uncorrelated.

Outdoor fading channels are often modeled as AR processes [4]. The AR coefficients $\alpha_\ell^{ij}(p)$ and the variance of the innovation process $w^{ij}(\ell,n)$ can be determined in advance by solving the Yule-Walker equations using the channel correlation matrix. Following Komninakis [3], we assume that the mean of all channel coefficients is zero, and that their autocorrelation sequences are governed by the Doppler shift f_D:

$$E\left\{h^{ij}(\ell,n)\left(h^{ij}(\ell,n-m)\right)^*\right\} \sim J_0(2\Pi f_D mT) \tag{9}$$

where T is the duration of a transmitted symbol, $T = \frac{1}{\Delta f}$. Δf is the frequency spacing between the OFDM sub-carriers. It was shown empirically that AR modeling fits measured indoor channels as well [2]. Given that the geographic route is identical for all the channel reflections, we can also assume that the taps do not depend on the coefficient index, i.e. $\alpha_\ell^{ij}(p) = \alpha^{ij}(p), \forall\ p = 1,\ldots,P$. For the clarity of the exposition we will assume that the order of all AR processes is $P = 1$.

4.1. State-Space Formulation in the Time-Domain

Identify the desired state-vector $\boldsymbol{d}_n$ as the channel vector $\boldsymbol{h}_n \in \mathbb{C}^{(LN_tN_r)\times 1}$. Hence, (2) can be easily restated as a proper measurement equation:

$$\boldsymbol{y}_n = (\mathbf{I}_{N_r} \otimes \mathbf{X}_n)\,\boldsymbol{d}_n + \boldsymbol{z}_n \tag{10}$$

i.e. $\mathbf{I}_{N_r} \otimes \mathbf{X}_n$ in (2) can be identified as $\mathbf{G}_n^t$, the measurement matrix.

Define $\boldsymbol{w}_n \in \mathbb{C}^{(LN_tN_r)\times 1}$, the innovation vector:

$$\begin{aligned} \boldsymbol{w}_n^{ij} &\triangleq \left[\begin{array}{cccc} w^{ij}(0,n) & w^{ij}(1,n) & \ldots & w^{ij}(L-1,n) \end{array}\right]^T \\ \boldsymbol{w}_n &\triangleq \left[\begin{array}{ccc} (\boldsymbol{w}_n^{11})^T & \ldots & (\boldsymbol{w}_n^{N_t1})^T \quad \ldots \\ (\boldsymbol{w}_n^{1N_r})^T & \ldots & (\boldsymbol{w}_n^{N_tN_r})^T \end{array}\right]^T. \end{aligned} \tag{11}$$

The driving noise covariance matrix is thus given by $\mathbf{Q}_n^t = E\{\boldsymbol{w}_n\boldsymbol{w}_n^H\}$. Due to the assumption that all driving noise processes are uncorrelated, $\mathbf{Q}_n^t$ is a diagonal matrix. We further assume that the coefficients obey a decaying power profile. Define also $\mathbf{A} \in \mathbb{C}^{(LN_tN_r)\times(LN_tN_r)}$, the AR(1) transition matrix:

$$\begin{aligned} \boldsymbol{\alpha}^{ij} &\triangleq \left[\begin{array}{ccc} \alpha^{ij} & \ldots & \alpha^{ij} \end{array}\right]_{L\times 1} \\ \mathbf{A} &\triangleq \operatorname{diag}\left(\left[\begin{array}{c} \boldsymbol{\alpha}^{11}\ldots\boldsymbol{\alpha}^{N_t1}\ldots\boldsymbol{\alpha}^{N_tN_r} \end{array}\right]\right). \end{aligned} \tag{12}$$

Using these definitions, it is easily verified that (8) can be reformulated into stat-space presentation (4) with $\boldsymbol{d}_n = \boldsymbol{h}_n$, $\boldsymbol{\Phi} = \mathbf{A}$, and $\mathbf{G}_n = \mathbf{G}_n^t$.

4.2. State-Space Formulation in the Frequency-Domain

An AR(P) model for the matrix $\mathbf{H}_n(\omega)$ in the frequency-domain can be derived from the time-domain model described in (8).

$$\begin{aligned} h^{ij}(\omega,n) &\triangleq \text{DTFT}\{h^{ij}(\ell,n)\} = \sum_{l=0}^{L-1} h^{ij}(\ell,n)e^{-j\omega\tau_l^{ij}} \\ &= \sum_{l=0}^{L-1}\left(\sum_{p=1}^{P}\alpha^{ij}(p)h^{ij}(\ell,n-p) + w^{ij}(,\ell,n)\right)e^{-j\omega\tau_l^{ij}} \\ &= \sum_{p=1}^{P}\alpha^{ij}(p)h^{ij}(\omega,n-p) + \sum_{l=0}^{L-1} w^{ij}(\ell,n)e^{-j\omega\tau_l^{ij}}. \end{aligned} \tag{13}$$

Collecting terms, we have:

$$h^{ij}(\omega,n) = \sum_{p=1}^{P}\alpha^{ij}(p)h^{ij}(\omega,n-p) + w^{ij}(\omega,n). \tag{14}$$

Hence, $h^{ij}(\omega,n)$ is an AR(P) model as well, with the same coefficients $\{\alpha^{ij}(p)\}_{p=1}^P$. Since the frequency-domain driving noise $w^{ij}(\omega,n)$ sequences are the DTFT of the respective time-domain driving noise sequences $w^{ij}(\ell,n)$, they are also i.i.d. sequences. The channels' independence also implies that $w^{ij}(\omega,n)$ are independent for different ij pairs. Finally, the channel matrix $\mathbf{H}_n(\omega)$ is given by

$$\mathbf{H}_n(\omega) \triangleq \begin{bmatrix} h^{11}(\omega,n) & \cdots & h^{N_t1}(\omega,n) \\ \vdots & & \vdots \\ h^{1N_r}(\omega,n) & \cdots & h^{N_tN_r}(\omega,n) \end{bmatrix}. \tag{15}$$

The state-space equation can now be stated. Again, for simplicity, we present only the results for AR(1) processes. Define $\boldsymbol{d}_n(\omega) \in \mathbb{C}^{(N_tN_r)\times 1}$ the desired vector:

$$\begin{aligned} \boldsymbol{d}_n(\omega) \triangleq \big[\ & h^{11}(\omega,n) \quad \ldots \quad h^{N_t1}(\omega,n)\ldots \\ & h^{1N_r}(\omega,n) \quad \ldots \quad h^{N_tN_r}(\omega,n)\ \big]^T. \end{aligned} \tag{16}$$

Using (3) we get the measurement equation:

$$\begin{aligned} \boldsymbol{y}_n(\omega) &= \left(I_{N_r} \otimes \boldsymbol{x}_n^T(\omega)\right)\boldsymbol{d}_n(\omega) + \boldsymbol{z}_n(\omega) \\ &\triangleq \mathbf{G}_n^f(\omega)\boldsymbol{d}_n(\omega) + \boldsymbol{z}_n(\omega). \end{aligned} \tag{17}$$

Further defining the innovation vector

$$\boldsymbol{w}_n(\omega) \triangleq \left[\begin{array}{cccc} w^{11}(\omega,n) & \ldots & \ldots & w^{N_tN_r}(\omega,n) \end{array}\right] \tag{18}$$

and the transition matrix

$$\mathbf{A} \triangleq \text{diag}([\,\alpha^{11}\cdots\alpha^{N_t1}\cdots\alpha^{N_tN_r}\,]). \tag{19}$$

the model equation is readily shown to be:

$$\boldsymbol{d}_n(\omega) = \mathbf{A}\boldsymbol{d}_{n-1}(\omega) + \boldsymbol{w}_n(\omega). \tag{20}$$

It is important to emphasize that the resulting Kalman filter will be applied in parallel to all frequency bins (i.e. the estimators are decoupled). The innovation noise vector $\boldsymbol{w}_n(\omega)$ is an i.i.d. process, with zero-mean and covariance matrix $E\{\boldsymbol{w}_n(\omega)\boldsymbol{w}_m^H(\omega)\} \triangleq \mathbf{Q}_n^f(\omega)\delta_{m,n}$. Assuming uncorrelated antennas $\mathbf{Q}_n^f(\omega)$ is a diagonal matrix. Following the assumption that the driving noise signals $w^{ij}(\ell,n)$ are uncorrelated it is easily shown that:

$$E\left\{|w^{ij}(\omega,n)|^2\right\} = \sum_{l=0}^{L-1} E\left\{|w^{ij}(\ell,n)|^2\right\} \tag{21}$$

5. EXPERIMENTAL STUDY

Simulations were conducted using an AR(1) fading model for the channel coefficients. We used sparse impulse responses with delay spread $L = 16$. The *known* input signal was white Gaussian noise, transmitted over $N = 128$ sub-carriers (the OFDM symbol length).

The performance measure was defined as the mean normalized estimation error (over all channels and all time indexes):

$$\mathrm{MSE} = \frac{E\left\{\|\hat{\boldsymbol{d}}_{n|n} - \boldsymbol{d}_n\|^2\right\}}{E\left\{\|\boldsymbol{d}_n\|^2\right\}} \tag{22}$$

where, $\boldsymbol{d}_n = \boldsymbol{h}_n$ for the time-domain algorithm and is given by (16) for the frequency-domain algorithm. We note that, using (6) and (7), $\mathbf{P}_{n|n}$ can be directly calculated, bypassing the need for calculating $\hat{\boldsymbol{d}}_{n|n}$. The solution of the resulting Riccati difference equation [7] is the desired MSE. However, we found it interesting to present the estimate $\hat{\boldsymbol{d}}_{n|n}$ as well.

The MSE as a function of the input signal-to-noise-ratio (SNR) is depicted in Fig. 1.

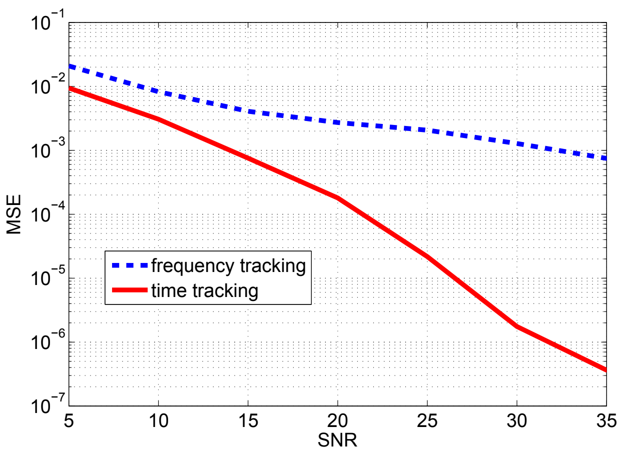

Fig. 1. MSE vs. SNR for time- and frequency-domain algorithms.

It is evident that the upper performance bound, obtained by the time-domain algorithm, outperforms the upper bound, obtained by the frequency-domain algorithm, over the entire SNR range. Above input SNR higher than 20 dB, the difference between the algorithms becomes significant.

We further demonstrate and compare the tracking ability of the algorithms. In Fig. 2 the tracking ability for a single OFDM sub-carrier is demonstrated for input SNR=15 dB. Again, it can be easily verified that the trace of the time-domain algorithm is closer than the trace of the frequency-domain algorithm to the real channel. Comparable results were obtained for the performance bounds for tracking single channel coefficients.

6. DISCUSSION

In this contribution we compared time-domain and frequency-domain performance bounds for channel tracking utilizing the Kalman filter. The frequency-domain formulation is much simpler than the time-domain formulation due to the sub-carrier decoupling.

However, while the number of estimated parameters in the frequency-domain is equal to $N_t N_r N$, the respective number of parameters in the time-domain is only $N_t N_r L$ (recall that N is the FFT length and L is the delay spread of the channel). Since the channel length in the time-domain is assumed to be significantly smaller

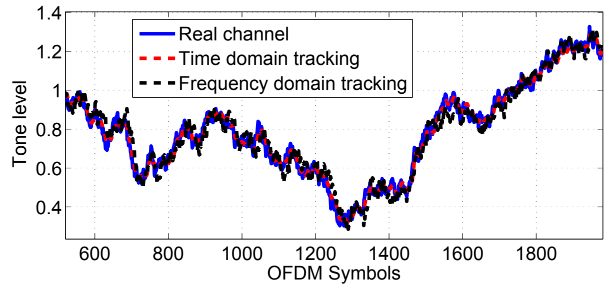

Fig. 2. Tracking trace for sub-carrier #17 as a function of the symbol index n.

than the FFT length, i.e $L \ll N$, the number of the time-domain parameters to be tracked is significantly smaller than the number of the frequency-domain parameters. Hence, as verified by the experimental study, the upper performance bound for time-domain algorithms is expected to be correspondingly higher than for the respective frequency-domain algorithms.

Moreover, the tracking ability of the frequency-domain algorithm saturates to non-zero MSE even for SNR approaching infinity. This phenomenon is also attributed to the large number of unknown parameters in comparison with the number of available equations.

For lower SNR values the tracking ability of both methods is comparable, and hence the more efficient frequency-domain algorithms may be preferred.

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