Decision-Directed MIMO Channel Tracking with Efficient Error Propagation Mitigation

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***Abstract*—We treat decision-directed tracking of fast-varying MIMO channels by applying the Kalman filter. The Kalman filter is considered but the suggested algorithm is applicable independently of the tracking technique. In the decision-directed mode, tracking filters suffer from error propagation caused by wrongly detected data. To mitigate the error propagation, a recently suggested pilot on request training is applied. Appropriate metrics to detect the filter divergence were developed in the past but these metrics strongly depend on the tracking algorithm. In this paper, we design a metric which solely depends on the estimated channel. The metric threshold is derived analytically and is shown to be SNR-independent on a large SNR range. We show the effectiveness of the pilot on request training with the novel metric in both reducing the BER and saving bandwidth.**

I. Introduction

To achieve high bit rates with wireless MIMO systems, algorithms for precise channel estimation are of paramount importance. Often periodic pilot-assisted channel estimation (PACE) is employed under the assumption that the channel is almost constant during a data block length. However, the increasing demand for high mobility support accentuates the time-varying nature of the radio link. In this case, PACE is not a resource-efficient method for tracking the fast channel variations. In order to preserve the spectral efficiency decision-directed (DD) channel tracking can be applied. By exploiting detected symbols that reflect the current channel state information (CSI), adaptive filtering techniques such as the Kalman filter (KF) can be used for channel tracking. A drawback of DD tracking filters is their sensitivity to wrongly detected data. To cope with this problem, periodic pilot patterns can be inserted to stop a potential filter divergence. Other solutions exploit reliability information on the detected data and select only reliable data for channel tracking. These approaches require however iterative receiver structures which introduce significant delay and complexity [1]. Alternatively forward error correction (FEC) can be used in the data detection loop which also results in undesirable complexity and latency.

In this paper, we perform channel tracking by means of hard detected data. Since we neither collect any reliability informations nor make use of FEC, our tracking algorithms are simple and do not necessitate iterative receivers. We improve the tracking by optimizing the training. Commonly, tracking algorithms are trained periodically. However, in conjunction with frame-wise data transmission, reinitilization at the beginning of each frame can be disadvantageous due to slow filter convergence. Furthermore, error propagations (EP) occuring at the beginning of a frame cause a large amount of data loss resulting in re-transmissions and more data traffic. Therefore, we suggest to apply training only when needed, i.e after an error propagation is signaled. The pilot on request training (PRQT) was first proposed in [2]. Appropriate metrics for EP detection were designed. A pilot request is initiated if the metrics are beyond a certain threshold[1]. However, the computation of these metrics is tightly integrated in the filtering process which makes them highly filter-specific. Furthermore, the threshold optimization shows strong SNR-dependency. Therefore, we develop in this paper a filter-independent metric for efficient EP detection. Motivated by the fact that unreliable detected symbols have often undergone a low instantaneous SNR, we design a metric depending on the estimated channel value, as it directly controls the instantaneous SNR. Thus, the novel metric allows for applying PRQT to computationally simple algorithms such as LMS which can be very attractive. Furthermore, the so-far suggested metrics fail in detecting some special effects inherent to the tracking filter and result in unperceived filter divergence. Such an effect is e.g. the reversal phenomenon [3], where the filter is triggered to track the channel with an opposite phase. We tackle this problem by introducing a buffer of a certain length to save the metric information. The EP detection rule is then imposed on all metrics stored in the buffer. We show that this measure increases the efficiency of EP detection.

II. System Model

We consider an $M \times N$ MIMO system. The $N \times 1$ receive signal vector at time instant n is given by:

$$\mathbf{y}(n) = \mathbf{H}(n)\mathbf{s}(n) + \mathbf{w}(n) \tag{1}$$

where $\mathbf{s}(n)$ denotes the $M \times 1$ sent signal vector with covariance $\mathbf{R}_{ss} = E_s \mathbf{I}_M$, $\mathbf{H}(n)$ the $N \times M$ flat fading channel matrix and $\mathbf{w}(n)$ the $N \times 1$ additive white Gaussian noise vector (AWGN) whose complex elements are i.i.d and $CN(0, 2\sigma_0^2)$ distributed. Without loss of generality, we assume spatially uncorrelated MIMO Rayleigh fading. An entry $h_{ij}(n)$ of $\mathbf{H}(n)$ is $CN(0,1)$ distributed and satisfies:

$$E\left\{h_{ij}(n)h_{ij}(n')^*\right\} = J_0(2\pi f_d(n-n')) \tag{2}$$

where f_d stands for the normalized Doppler frequency and J_0 is the Bessel function of first kind and order zero. In order to

[1] Pilot request and transmission are assumed to be delay-free. The impact of pilot feedback delay is analyzed in an article submitted for publication.

TABLE I
KALMAN FILTER ALGORITHM

Variable	Equation
Predicted channel state $\hat{\mathbf{z}}(n\|n-1)$	$\mathbf{F}\hat{\mathbf{z}}(n-1\|n-1)$
Predicted MSE $\mathbf{P}(n\|n-1)$	$\mathbf{F}\mathbf{P}(n-1\|n-1)\mathbf{F}^H + \mathbf{B}\mathbf{B}^H$
Innovation $\mathbf{e}(n)$	$\mathbf{y}(n) - \mathbf{X}(n)\hat{\mathbf{z}}(n\|n-1)$
Autocorrelation of innovation $\mathbf{R}_{ee}(n)$	$\mathbf{X}(n)\mathbf{P}(n\|n-1)\mathbf{X}^H(n) + \mathbf{R}_{ww}$
Kalman Gain $\mathbf{K}(n)$	$\mathbf{P}(n\|n-1)\mathbf{X}^H(n)\mathbf{R}_{ee}(n)^{-1}$
Corrected channel state $\hat{\mathbf{z}}(n\|n)$	$\hat{\mathbf{z}}(n\|n-1) + \mathbf{K}(n)\mathbf{e}(n)$
Corrected MSE $\mathbf{P}(n\|n)$	$(\mathbf{I} - \mathbf{K}(n)\mathbf{X}(n))\mathbf{P}(n\|n-1)$

estimate the channel at the receiver, orthogonal pilot symbol vectors $\mathbf{s}_p$ are periodically sent during the training period that takes L_p symbol periods T_s. At the end of the training phase, a channel estimate $\hat{\mathbf{H}}_p$ is computed by means of the received pilots. The training phase is followed by a data transmission phase where L_d symbol vectors are sent. In the absence of tracking, the PACE estimate is used for detection during the subsequent L_d symbol periods. In case of channel tracking, the PACE estimate can be used as good initial value for the tracking algorithm at the start of every training interval. A basic prerequisite for doing so is a recursive tracking algorithm such as the KF.

III. THE KALMAN TRACKING ALGORITHM

If the fading channel can be modeled as an autoregressive process of order p (AR(p)), the KF is the optimal MMSE estimator. Since the first few channel correlation terms in (2) are basically important for symbolwise tracking, an AR(2) model is adopted as in [4]. The Kalman algorithm relies on the observation equation (3) and the process equation (4),

$$\mathbf{y}(n) = \mathbf{X}(n)\cdot\mathbf{z}(n) + \mathbf{w}(n) \tag{3}$$

$$\mathbf{z}(n) = \mathbf{F}\mathbf{z}(n-1) + \mathbf{B}\mathbf{u}(n) \tag{4}$$

where $\mathbf{z}(n) = [\mathbf{h}^T(n) \quad \mathbf{h}^T(n-1) \quad \cdots \quad \mathbf{h}^T(n-p+1)]^T$ with $\mathbf{h}(n) = vec(\mathbf{H}(n))$ and $\mathbf{F}$ is the state transition matrix. $\mathbf{X}(n)$ contains the detected symbols $\hat{\mathbf{s}}(n)$ according to $\mathbf{X}(n) = [\hat{\mathbf{s}}^T(n)\otimes\mathbf{I}_N \quad \mathbf{O}_{N\times NM(p-1)}]$, where $\otimes$ refers to the kronecker product. $\mathbf{u}$ is the driving noise with $E[\mathbf{u}(n)\mathbf{u}(n)^H] = \mathbf{I}_{MN}$ [2]. The Kalman algorithm is described in Table I.

IV. PERIODIC TRAINING

To lauch the recursive Kalman algorithm, initial values for some variables must be chosen. In [2], we have shown the importance of an appropriate initialization for the KF algorithm, especially in case of frame-wise data transmission. A full training analysis has proven that the algorithm convergence speed is drastically increased if we initialize the algorithm with the PACE estimate. Therefore, we proposed to devide the periodically sent pilots into two sequences. The first sequence of length L_p provides the tracking algorithm with a PACE initial estimate. The second one trains the algorithm and takes L_t samples. The optimal training length $L_{p,opt}$ which minimizes the PACE MSE was derived in [2]. These results show that $L_{p,opt}$ increases with increasing σ_0^2 and decreases with increasing f_d or M. Keeping in mind that $L_p \geq M$ must be satisfied in case of maximum likelihood PACE estimation, this means that for high SNR and/or fast fading rate f_d, we shoud invest only M pilots for the PACE initialization and spend the remaining pilots at hand for training the algorithm. Periodic training with optimized (L_p, L_t) so that $L_p + L_t = 8$ and $L_d = 100$, so-called 8% training, is adopted in this paper for comparison with the aperiodic training.

When applying periodic training, we notice that the MSE at the end of a frame can be smaller than the MSE at the beginning of a frame. This happens for example at high SNR when the detected data is mostly correct. In this case, reinitilization is disadvantageous. This gave birth to the idea of applying training only when needed, which is described next.

V. PILOTS ON REQUEST TRAINING

We briefly explain the principle of PRQT as first suggested in [2]. In the DD mode, KF works robustly as long as almost all detected symbols are correct. In case of misdetections, we have a model-mismatch and the channel estimation quality deteriorates resulting in more misdetections in the following steps, i.e. in error propagation. An accurate EP detection is a key issue for PRQT in order to preserve the spectral efficiency. Therefore, appropriate metrics for EP detection are of paramount importance. If the metric exceeds a certain threshold M_d an EP is signaled and pilots are requested to stop it. The threshold optimization minimizes the BER satisfying a certain spectral efficiency constraint.

A. *Filter-Dependent Metric for PRQT*

Closer analysis of different statistical quantities involved in the KF algorithm suggests that a filter divergence occurs in most of the cases just after a steep peak has appeared in their progress. This is for example the case for the innovation process norm $|\mathbf{e}(n)|^2$. Fig. 1 shows the true and estimated channel for the channel entry h_{11}, the difference between the transmit and the detected symbol $s_1(n) - \hat{s}_1(n)$, the innovation squared m_1 and the NIS m_2 as a function of the discrete time n for $f_d = 0.004$, $L_t = 2$ and $L_d = 200$. We can see that a large $|\mathbf{e}(n)|^2$ due to an instantaneous high noise value gives birth to a series of wrong detections resulting in a filter divergence. The error propagates until the beginning of the next frame where the estimate is set to the PACE value.

Armed with these observations, a first metric m_1 to detect a filter divergence was defined as $m_1 = |\mathbf{e}(n)|^2$. The threshold M_d imposed on m_1 depends on the SNR. In [2], an empirical approach to describe M_d as a function of the SNR was presented but this method requires the optimization of two parameters for each SNR value, which can be a tedious task. A second metric m_2 referred to as the normalized innovation squared (NIS) proved to be more practical as it is less SNR-dependent. m_2 is also depicted in Fig. 1 and is defined as:

$$m_2 = \mathbf{e}(n)^H\mathbf{R}_{ee}^{-1}(n)\mathbf{e}(n) \tag{5}$$

Under the assumption of correctly detected data, m_2 follows a chi-square pdf. Thus $\mathbf{e}(n)^H\mathbf{R}_{ee}^{-1}\mathbf{e}(n) < M_d$ means that for

[2] $\mathbf{F}$ and $\mathbf{B}$ are assumed to be known at the receiver. Please refer to [4] for explicit definition.

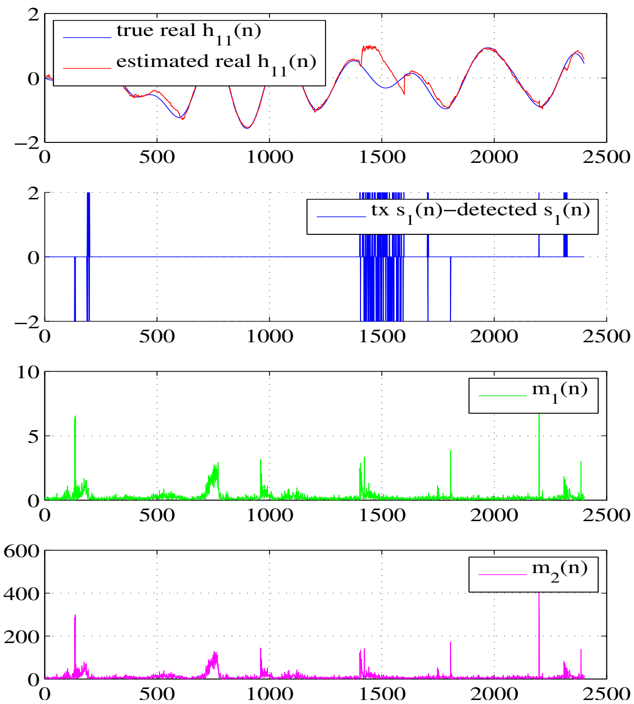

Fig. 1. EP detection metrics m_1 and m_2 as function of the discrete time n

a probability that p% of detected symbols are accepted, M_d can be computed from

$$\frac{p}{100} = P(\frac{N}{2}, \frac{M_d}{2}) = \frac{1}{\Gamma(N/2)} \int_0^{M_d/2} e^{-t} t^{N/2-1}\, dt \quad (6)$$

where Γ is the Gamma function. However, the SNR-independency of m_2 was shown to hold only beyond a certain SNR. Given that the chi-square distribution is only valid for perfectly detected data, which is increasingly true when the SNR grows, the pilot requirement α becomes constant only at high SNR.

The afore-mentioned metrics are computed along the tracking process. Whereas the first metric is in common adaptive algorithms automatically computed, the second is not and fits well to KF or to the RLS algorithm. However, if we consider the simple LMS algorithm for example, no knowlege about the innovation autocorrelation $\mathbf{R}_{ee}$ is available, which is a prerequistite for the NIS computation in (5). Therefore, we aim in the next section at designing a metric that is independent of the tracking algorithm. PRQT with the NIS metric will represent the benchmark performance for PRQT with the novel filter-independent metric.

B. Filter-Independent Metric for PRQT

The idea behind this metric is that symbols that have been detected with a high instantaneous SNR are more likely to be correct, i.e more reliable, than those symbols that have been undergoing deep fades. Given that the instantaneous SNR is governed by the instantaneous CSI, the novel metric depends on the channel estimate itself. This idea was first suggested in [5] to perform a symbol selection algorithm for OFDM systems. The assumption was however made that the channel is constant during several OFDM symbols. Despite down-selecting unreliable symbols, there were still enough observations to estimate the channel. In our task of symbol-wise tracking and due to the considered fast fading, we make use of this metric to signal an EP. If the metric underruns a certain threshold M_{th}, the data is not reliable. A potential EP is signaled and pilots are requested to stop it. In [5], only SISO and SIMO systems were considered. We develop the metric for EP detection for the general MIMO case. Instantaneous SNR expressions for MIMO systems can be found in [6] for different receivers. In case of a zero-forcing (ZF) receiver, the instantaneous SNR $\gamma_k(n)$ for the detection of a symbol $s_k(n)$ out of the tx vector $\mathbf{s}(n) = [s_1(n), \cdots, s_M(n)]$ is given by

$$\gamma_k(n) = \frac{\gamma}{\left[\left(\mathbf{H}^H(n)\mathbf{H}(n)\right)^{-1}\right]_{kk}} \quad (7)$$

where $\gamma = \frac{E_s}{2\sigma_0^2}$ and $[\cdot]_{kk}$ refers to the kth diagonal entry of a matrix. Therefore, we propose (8) as a metric for ZF receivers[3]. Analogously, (9) describes the metric for an MMSE receiver.

$$M_k^{ZF}(n) = \frac{1}{\left[\left(\hat{\mathbf{H}}^H(n)\hat{\mathbf{H}}(n)\right)^{-1}\right]_{kk}} \quad (8)$$

$$M_k^{MMSE}(n) = \frac{1}{\left[\left(\hat{\mathbf{H}}^H(n)\hat{\mathbf{H}}(n) + \frac{1}{\gamma}\mathbf{I}_N\right)^{-1}\right]_{kk}} \quad (9)$$

Given that the instantaneous SNR varies depending on the receiver, the metric should be adapted accordingly. However, the ZF metric in (8) can be considered as a conservative "worst case " approximation for other receivers. The resulting mismatch can cause unjustified pilot requests. However, if $M_k^{MMSE} \leq M_{th}$, due to $M_k^{ZF} \leq M_k^{MMSE}$, $M_k^{ZF} \leq M_{th}$ holds and a justified pilot request is actually started. We adopt M_k^{ZF} independently of the receiver and omit the superscript^{ZF}.

Fig. 2 shows M_k as a function of the discrete time n. We can see that an EP occurs just after the metric has undertaken a deep fade which shows its adequacy for EP detection. In [6], the pdf f_{γ_k} of $\gamma_k(n)$ was derived for Rayleigh fading for a general $M \times N$ MIMO system. It was proven that f_{γ_k} is a Γ-distribution with $N' = N - L + 1$ degrees of freedom, where L is the rank of $\mathbf{H}$. This means that under the assumption of full-rank channel matrix $\mathbf{H}$, we obtain

$$f_{\gamma_k}(\xi) = \frac{1}{\gamma} exp\left(-\frac{\xi}{\gamma}\right) \quad (10)$$

According to (8), (7), and (10), the pdf f_{M_k} of M_k is given by $f_{M_k}(\xi) = exp(-\xi)$. Having defined the metric pdf, the threshold derivation is now straightforward. Similar to the validation gating in (6), the threshold M_{th} is defined such that for a probability $p\%$ the metric is larger than M_{th}, yielding the constant threshold:

$$M_{th} = -ln(p) \quad (11)$$

[3]It is straightforward to derive the metric for the SISO and SIMO cases. The resulting metric is the channel envelope square or the sum of channel envelopes squares respectively, which is in agreement with [5].

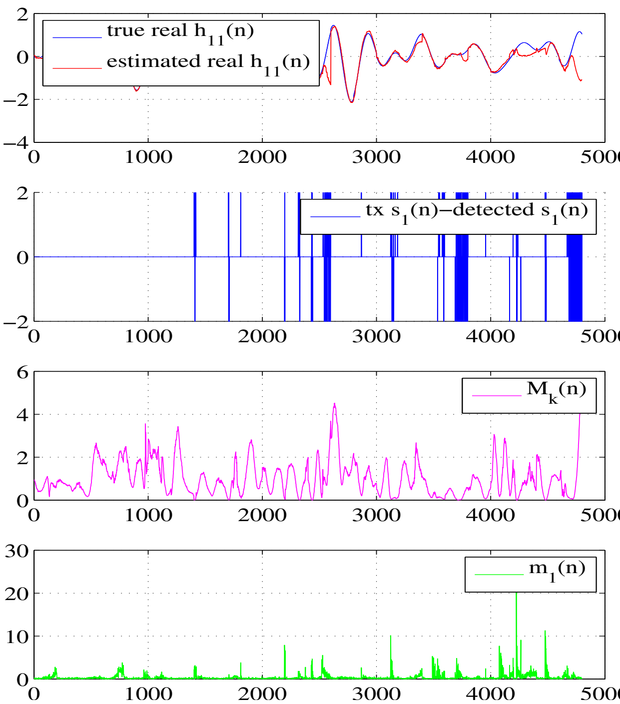

Fig. 2. m_1 and the novel metric M_k as a function of the discrete time n

Further to the right of Fig. 2 at $n \approx 4700$, we see that an EP occurs whereas m_1 is not notably large. In this case, the EP is not caused by a large noise value but rather by a deep channel fade. Interestingly, the consequence is a series of detection errors combined by estimating the opposite or negative sign of the channel. This effect, first termed *reversal phenomenon* in [3], is explained in the next section.

VI. The Reversal Phenomenon

For the sake of completeness, we recall the state space formulation if the driving noise $\mathbf{u}(n)$ and the observation AWGN noise $\mathbf{w}(n)$ are negligible.

$$\mathbf{z}(n) = \mathbf{F}\mathbf{z}(n-1) \tag{12}$$

$$\mathbf{y}(n) = \mathbf{X}(n)\cdot \mathbf{z}(n) \tag{13}$$

Assume some components of the detected vector $\hat{\mathbf{s}}$ were subject to wrong decisions so that $\hat{\mathbf{X}}(n) = -\mathbf{X}(n)$. Plugging this and (13) in the corrected channel state expression of Table I yields

$$\hat{\mathbf{z}}(n|n) = \hat{\mathbf{z}}(n|n-1) + \mathbf{K}(n)\mathbf{X}(n)(\mathbf{z}(n) + \hat{\mathbf{z}}(n|n-1)) \tag{14}$$

Adding $\mathbf{z}(n)$ to both sides of (14) and using (12) leads to

$$\hat{\mathbf{z}}(n|n) + \mathbf{z}(n) = (\mathbf{I} + \mathbf{K}(n)\mathbf{X}(n))(\mathbf{z}(n) + \hat{\mathbf{z}}(n|n-1)) \tag{15}$$

Now, with (12), we finally obtain

$$\hat{\mathbf{z}}(n|n)+\mathbf{z}(n) = (\mathbf{I}+\mathbf{K}(n)\mathbf{X}(n))\mathbf{F}(\hat{\mathbf{z}}(n-1|n-1)+\mathbf{z}(n-1)) \tag{16}$$

If the Kalman filter is stable, i.e. the magnitudes of all eigenvalues of $(\mathbf{I} + \mathbf{K}(n)\mathbf{X}(n))\mathbf{F}$ are less than 1, the iteration outcome of (16) goes to zero. This implies that $\hat{\mathbf{z}}(n|n) = -\mathbf{z}(n)$. In other words, a series of wrong detections triggers the reversal phenomenon. Analogously a sequence of correct detections will result in the tracking of $\hat{\mathbf{z}}(n|n)$ to $\mathbf{z}(n)$ provided that all noise terms are small. Since the filter divergence is not mainly caused by a large noise value, the EP would remain unperceived by m_1 and m_2. A closer look on Fig. 2 reveals that the reversal phenomenon arises after a persisting deep fade in the metric M_k. Therefore, we suggest to consider not only a single metric value at a time but a certain number, defined as B_L, of previously computed metrics. To this end, the metric information is stored in a FIFO buffer of length B_L and is updated at each time instant. An EP is signaled if all buffered metrics are below a certain threshold[4].

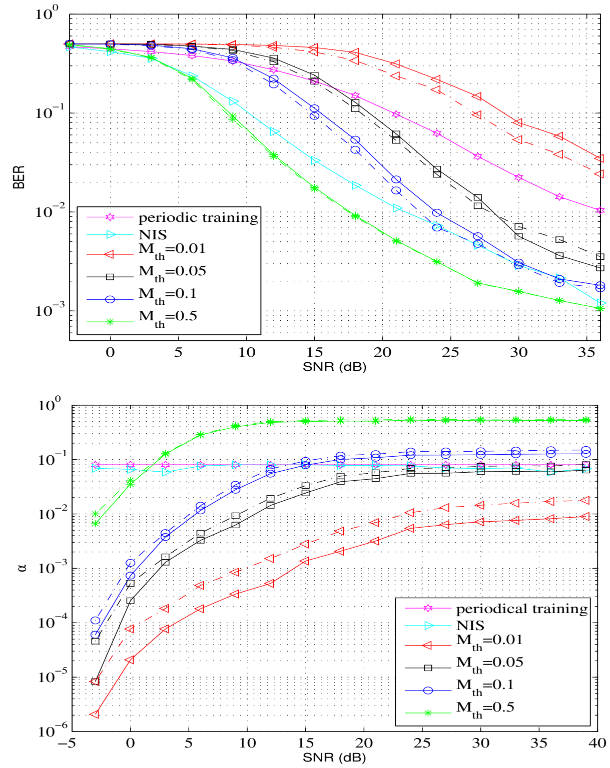

Fig. 3. BER for different thresholds M_{th} with $B_L = 1$ (dashed line) and $B_L = 3$ (continuous line) (top). Ratio α of pilots over data (bottom)

VII. Simulation Results

We consider a 2×2 MIMO system with BPSK and ZF receiver. Fig. 3 presents the BER results for PRQT with various thresholds M_{th} and the corresponding ratio α of pilots over data as a function of the SNR at $f_d = 0.01$. It is plain to see that α depends on the SNR for small SNR values and becomes constant with increasing SNR. This can be explained as follows. The pdf in (10) holds for Rayleigh channels. Given that the metric is built upon the estimated and not the true channel, (10) does not hold anymore. It becomes however increasingly true as the channel estimation errors diminish which is the case for increasing SNR and/or decreasing f_d. For SNR>18dB, we notice that $M_{th} = 0.05$, corresponding to a probability $p = 95\%$ is a good heuristic

[4] $B_L = 1$ means that only the current metric is cosidered for EP detection which corresponds to the buffer-free case.

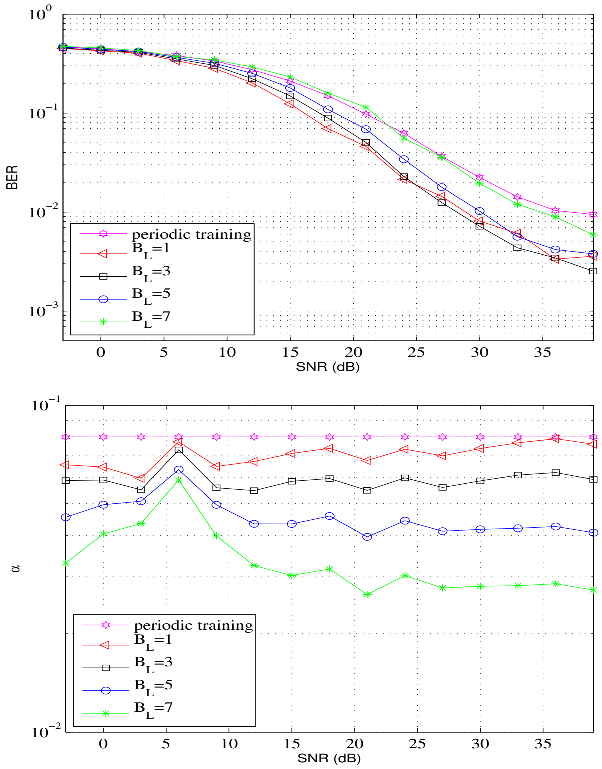

Fig. 4. BER as function of the SNR for different Buffer lengths B_L at $f_d = 0.01$ (top). Corresponding ratio α of pilots over data (bottom)

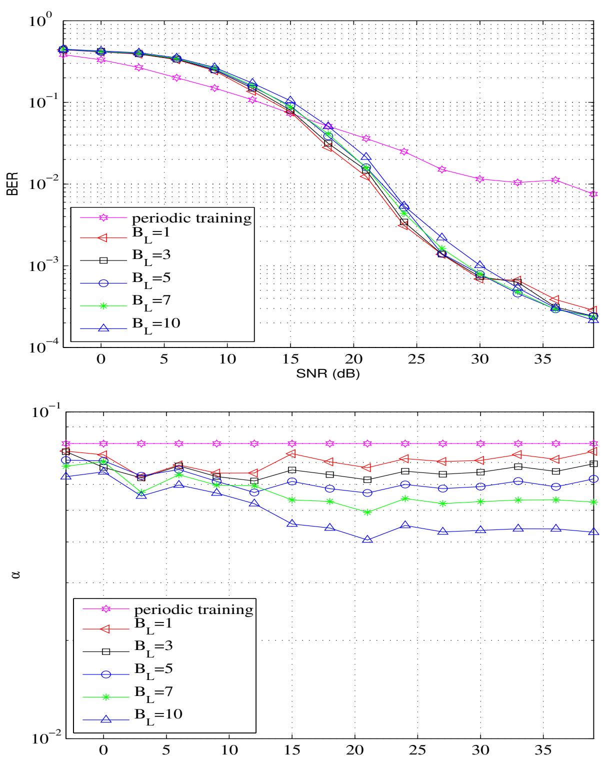

Fig. 5. BER as function of the SNR for different Buffer lengths B_L at $f_d = 0.004$ (top). Corresponding ratio α of pilots over data (bottom)

value for $f_d \in \{0.01, 0.004, 0.001\}$. It allows PRQT to outperform periodic training by far (7dB gain at BER=10^{-2}). For SNR<18dB, M_{th} is optimized to minimize the BER under the constraint that $\alpha \precsim 8\%$ for a fair comparison with 8% periodic training. The BER for PRQT with the NIS metric is also included in Fig. 3. NIS outperforms the filter-independent metric since it is well-adapted to the tracking algorithm.

In order to analyze the impact of the buffer length B_L, Fig. 4 and Fig. 5 show the optimized threshold BER curves for $f_d = 0.01$ and $f_d = 0.004$ respectively with various B_L. At $f_d = 0.01$, $B_L = 3$ outperforms the buffer-free case $B_L = 1$ beyond 24dB, whereas larger B_L degrade the performance. The benefit from using a buffer becomes more evident for smaller Doppler frequencies. At $f_d = 0.004$, $B_L = 10$ leads to 2dB gain in comparison to $B_L = 1$ at a BER of $0.5 \cdot 10^{-4}$. At the same time, α is reduced to less than 5%, which translates to a real bandwidth saving in comparison to 8% with periodic training and around 7% with $B_L = 1$. We can therefore conclude that introducing a buffer insures the correct detection of an EP caused by the reversal phenomenon as well as a high instantaneous noise value. The buffer length must be adjusted to f_d.

VIII. Conclusion

We deal with decision-directed tracking of fast-varying MIMO channels by applying adaptive filters taking the example of the Kalman algorithm. In order to mitigate the error propagation after a series of wrong detections, a pilot on request training (PRQT), scheme is applied. Previously designed metrics for error propagation detection depend strongly on the tracking filter. We design a novel metric which is applicable independently of the tracking algorithm. An analytical metric threshold is derived. Simulation results show that PRQT with the novel metric leads to significant performance improvement in comparison to conventional periodic training. For large SNR, similar BER performance is achieved as in the case of PRQT with the filter-adapted metric. We show that PRQT with the novel metric is efficient not only in decreasing the BER but also in reducing the number of required pilots.

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