NONCOHERENT LMS ALGORITHM FOR NONCOHERENT SEQUENCE ESTIMATION

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***Abstract* — In this paper, a novel noncoherent adaptive algorithm for channel estimation is introduced. The proposed noncoherent least–mean–square (NC–LMS) algorithm can be combined easily with noncoherent sequence estimation (NSE) for M–ary differential phase–shift keying (MDPSK) signals transmitted over intersymbol interference (ISI) channels. For zero frequency offset the convergence speed and the steady–state error of the novel noncoherent adaptive algorithm are similar to those of a conventional (coherent) LMS algorithm. However, the conventional LMS algorithm diverges even for relatively small frequency offsets, whereas the proposed NC–LMS algorithm also converges for relatively large frequency offsets. Simulations confirm the good performance of NSE combined with noncoherent adaptive channel estimation in time–variant (fading) ISI channels.**

1. Introduction

In many existing communication systems (e.g., Global System for Mobile Communication (GSM), United States Digital Cellular (IS–54, IS–136)) coherent maximum–likelihood sequence estimation (MLSE) [1] is used for equalization of intersymbol interference (ISI) channels. MLSE requires knowledge of the possibly time–variant channel impulse response and therefore, adaptive channel estimation algorithms have to be employed. In practice, the least–mean–square (LMS) algorithm is often preferred for this purpose because of its simplicity [2, 3].

Recently, noncoherent sequence estimation (NSE) schemes for ISI channels have been proposed [4, 5, 6, 7]. Although, in principle, NSE is also applicable to multi–amplitude signals [5], for simplicity, in this paper we restrict ourselves to M–ary differential phase–shift keying (MDPSK) signals. In contrast to coherent sequence estimation schemes, NSE schemes do not require knowledge of the carrier phase and they are robust against frequency offset. On the other hand, NSE can only be applied if the impulse response of the channel is known up to a constant phase term. The conventional LMS algorithm cannot be used in this case since it is very sensitive to carrier phase variations and it is not able to perform a reliable channel estimation even for relatively small frequency offsets. For these reasons, it is necessary to employ a robust noncoherent adaptive channel estimation algorithm especially tailored for NSE. Although noncoherent linear and nonlinear adaptive equalization schemes have already been proposed in literature [8, 9, 10, 11, 12], a noncoherent adaptive algorithm for channel estimation has not been reported so far.

In this paper, we design a noncoherent LMS (NC–LMS) algorithm which delivers – up to a constant phase term – an estimate of the channel impulse response. This novel algorithm is very robust against frequency offsets and simulations confirm that its convergence speed is similar to that of its conventional (coherent) counterpart. For NSE, the so–called *Forney approach* proposed by Colavolpe and Raheli [4, 5] is employed because of its high performance. Our simulations confirm the good performance of NSE combined with the proposed NC–LMS algorithm for reception of MDPSK transmitted over time–variant ISI channels with frequency offset.

2. Transmission Model and Receiver Structure

2.1. Transmission Model

Fig. 1 shows a block diagram of the discrete–time transmission model. All signals are represented by their complex–valued baseband equivalents. At the transmitter, the MDPSK symbols $a[\cdot] \in \mathcal{A} = \{e^{j2\pi\nu/M} | \nu \in \{0, 1, \ldots, M-1\}\}$ are differentially encoded. The resulting MPSK symbols $b[\cdot] \in \mathcal{A}$ are given by

$$b[k] = a[k]b[k-1], \quad k \in \mathbb{Z}. \tag{1}$$

The coefficients of the possibly time–variant combined discrete–time impulse response of transmit filter, channel, and receiver input filter are denoted by $h_\nu[k]$, $0 \le \nu \le L-1$. L is the length of the impulse response. Θ denotes an unknown, constant, uniformly distributed phase shift introduced by the channel. The effects of an uncompensated phase drift caused by a demodulator frequency offset Δf are modeled by a multiplicative factor $e^{j2\pi\Delta f T k}$ (T is the symbol interval). We assume a square–root Nyquist frequency response for the receiver input filter[1], and thus, the zero mean complex Gaussian noise $n[\cdot]$ is white. Due to an appropriate normalization, the variance of $n[\cdot]$ is $\sigma_n^2 = \mathcal{E}\{|n[k]|^2\} = N_0/E_S$, where $\mathcal{E}\{\cdot\}$ denotes expectation. E_S and N_0 are the mean received energy per symbol and the single–sided power spectral density of the underlying passband noise process, respectively. The discrete–time received signal, sampled at times kT at the output of the receiver input filter can be written as

$$r[k] = e^{j\Theta} e^{j2\pi\Delta f T k} \sum_{\nu=0}^{L-1} h_\nu[k] b[k-\nu] + n[k]. \tag{2}$$

2.2. Receiver Structure

In this paper, we exclusively use the NSE scheme proposed by Colavolpe and Raheli [4, 5] (referred to as *Forney approach* in [5]) because of its high performance. Nevertheless, the proposed NC–LMS algorithm can be applied also to

[1] This also contains the whitened matched filter [1] as a special case.

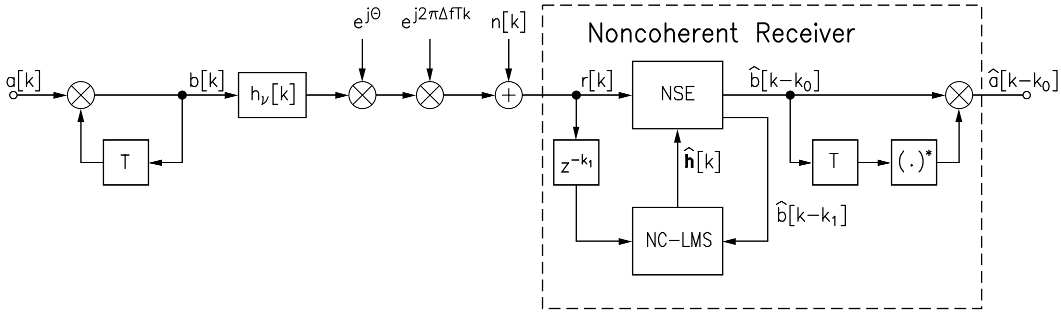

Figure 1: Block diagram of the discrete–time transmission and receiver model under consideration.

other kinds of NSE schemes, of course. In particular, it may be employed in combination with the efficient NSE scheme recently proposed in [7].

The accumulated metric $\Lambda[k]$ to be minimized for the NSE scheme of Colavolpe and Raheli is given by [4, 5]

$$\Lambda[k] \triangleq \sum_{\nu=0}^{k-1} \lambda[\nu], \qquad (3)$$

where

$$\lambda[k] \;\triangleq\; |\tilde{y}[k]|^2 + 2\left|\sum_{\nu=1}^{N-1} r[k-\nu]\tilde{y}^*[k-\nu]\right| -2\left|\sum_{\nu=0}^{N-1} r[k-\nu]\tilde{y}^*[k-\nu]\right| \qquad (4)$$

is the branch metric ($(\cdot)^*$ denotes complex conjugation). Here, N, $N \geq 2$, denotes the number of received samples $r[\cdot]$ used for calculation of $\lambda[k]$. Note that the original branch metric $\lambda'[k]$ in [5] is $\lambda'[k] = -\frac{1}{2}\lambda[k]$. The modification used here has no influence on the performance of the resulting NSE scheme, however, it facilitates the derivation of the NC–LMS algorithm (cf. Section 3). $\tilde{y}[k]$ is given by

$$\tilde{y}[k] \triangleq \sum_{\nu=0}^{L-1} \hat{h}_\nu[k]\tilde{b}[k-\nu], \qquad (5)$$

where $\hat{h}_\nu[k]$, $0 \leq \nu \leq L-1$, are the coefficients of the estimated channel impulse response. For $0 \leq \nu \leq K$ (K denotes the number of symbols used for trellis definition), the hypothetical symbols $\tilde{b}[k-\nu] \in \mathcal{A}$ are defined by the transition $t[k] \triangleq (\tilde{b}[k], \tilde{b}[k-1], \ldots, \tilde{b}[k-K])$ from state $S[k] \triangleq (\tilde{b}[k-1], \tilde{b}[k-2], \ldots, \tilde{b}[k-K])$ to state $S[k+1]$ in the underlying trellis diagram. The number of states is $Z = M^K$. For $\nu \geq K+1$, the symbols $\tilde{b}[k-\nu]$ are taken from the surviving path terminating in state $S[k]$, i.e., decision–feedback sequence estimation (DFSE) [13] is employed to limit complexity of NSE [5]. Note that this is necessary for a fair comparison with coherent MLSE since, in general, the full–state NSE scheme requires a larger number of states than the full–state Viterbi algorithm in the coherent case.

The estimated MPSK symbol $\hat{b}[k-k_0]$ (k_0: decision delay) is taken from the surviving path with minimum accumulated metric $\Lambda[k]$. For coherent MLSE usually a decision delay $k_0 = 5\cdot(L-1)$ ($L-1$ is the memory length of the channel) is employed [2]. We use the same decision delay for NSE since our simulations have confirmed that performance cannot be improved by a larger value for k_0. As typical for noncoherent detection schemes, the estimated MPSK symbols may be shifted by a constant phase. Thus, differential encoding is necessary and the estimated MDPSK symbols are obtained from $\hat{a}[k-k_0] = \hat{b}[k-k_0]\hat{b}^*[k-k_0-1]$.

Like the conventional LMS algorithm, the proposed NC–LMS algorithm requires knowledge of the transmitted symbol sequence. Thus, in the decision–directed mode the estimated transmitted symbols are also delivered to the channel estimator. Especially, for fast time–variant channels the decision delay k_0 may be too large for reliable tracking of the channel impulse response. Therefore, like in the coherent case, a smaller decision delay $k_1 \leq k_0$ may be used for channel estimation (cf. Fig. 1). Since the estimated transmitted symbols are the less reliable the smaller k_1 is chosen, while the tracking properties are improved for smaller values of k_1, there is a trade–off and k_1 has to be optimized for the particular channel. For convenience the (conjugated) coefficients of the estimated channel impulse response are organized in a vector

$$\hat{\boldsymbol{h}}[k] \triangleq [\hat{h}_0[k] \;\; \hat{h}_1[k] \;\; \ldots \;\; \hat{h}_{L-1}[k]]^H \qquad (6)$$

($[\cdot]^H$ denotes Hermitian transposition). We also would like to mention that, like in the coherent case, for noncoherent channel estimation the decision delay could be avoided by application of *per–survivor processing* [14] at the expense of a higher receiver complexity.

3. Noncoherent LMS Algorithm

In this section, the NC–LMS algorithm for estimation and tracking of the channel impulse response is derived and some properties of the novel adaptive algorithm are investigated.

3.1. *Derivation of the NC–LMS Algorithm*

For simplicity, the decision delay k_1 is not taken into account for derivation of the NC–LMS algorithm. A gradient adaptation algorithm is obtained if the coefficients of the estimated impulse response are updated according to the recursive relation [2, 3]

$$\hat{\boldsymbol{h}}[k+1] = \hat{\boldsymbol{h}}[k] - \delta_{\mathrm{LMS}} \frac{\partial}{\partial \hat{\boldsymbol{h}}^*[k]} J(\hat{\boldsymbol{h}}[k]), \tag{7}$$

where δ_{LMS} denotes the adaptation step size and $J(\hat{\boldsymbol{h}}[k])$ is an appropriate cost function.

For the conventional (coherent) LMS algorithm $J_{\mathrm{CLMS}}(\hat{\boldsymbol{h}}[k]) \triangleq |r[k] - \hat{\boldsymbol{h}}^H[k]\boldsymbol{b}[k]|^2$ ($\boldsymbol{b}[k] \triangleq [b[k]\ b[k-1]\ \ldots\ b[k-L+1]]^T$; $[\cdot]^T$ denotes transposition) is used as cost function, i.e., $J_{\mathrm{CLMS}}(\hat{\boldsymbol{h}}[k])$ is minimized recursively with respect to $\hat{\boldsymbol{h}}[k]$ provided that $\boldsymbol{b}[k]$ is known. On the other hand, for coherent MLSE $J_{\mathrm{CLMS}}[k]$ is used as branch metric and minimized with respect to $\boldsymbol{b}[k]$ provided that the impulse response $\hat{\boldsymbol{h}}[k]$ is known.

This brief review of the coherent receiver suggests to use the branch metric (cf. Eq. (4)) of NSE as (noncoherent) cost function $J_{\mathrm{NC-LMS}}(\hat{\boldsymbol{h}}[k])$ for the NC–LMS algorithm. Thus, we define

$$J_{\mathrm{NC-LMS}}(\hat{\boldsymbol{h}}[k]) \triangleq |y[k]|^2 + 2\left|\sum_{\nu=1}^{N_{\mathrm{NC-LMS}}-1} r[k-\nu]y^*[k-\nu]\right| - 2\left|\sum_{\nu=0}^{N_{\mathrm{NC-LMS}}-1} r[k-\nu]y^*[k-\nu]\right|, \tag{8}$$

with

$$y[k] \triangleq \hat{\boldsymbol{h}}^H[k]\boldsymbol{b}[k]. \tag{9}$$

$N_{\mathrm{NC-LMS}}$, $N_{\mathrm{NC-LMS}} \geq 2$, denotes the number of received signal samples $r[\cdot]$ used for calculation of $J_{\mathrm{NC-LMS}}(\hat{\boldsymbol{h}}[k])$. Note that $N_{\mathrm{NC-LMS}}$ does not have to coincide with N used for NSE. Using the method for complex differentiation described in [3, Appendix B] and the rule

$$\begin{aligned} \frac{\partial}{\partial \boldsymbol{w}^*}|z(\boldsymbol{w})| &= \frac{\partial}{\partial \boldsymbol{w}^*}\frac{\partial(z(\boldsymbol{w})z^*(\boldsymbol{w}))}{\partial(z(\boldsymbol{w})z^*(\boldsymbol{w}))}\sqrt{z(\boldsymbol{w})z^*(\boldsymbol{w})} \\ &= \frac{1}{2}\frac{1}{|z(\boldsymbol{w})|}\frac{\partial(z(\boldsymbol{w})z^*(\boldsymbol{w}))}{\partial \boldsymbol{w}^*}, \end{aligned} \tag{10}$$

where $z(\boldsymbol{w}) \neq 0$ denotes a complex–valued function of a complex–valued vector $\boldsymbol{w}$, the derivative $\partial J_{\mathrm{NC-LMS}}(\hat{\boldsymbol{h}}[k])/\partial \hat{\boldsymbol{h}}^*[k]$ may be calculated to:

$$\frac{\partial J_{\mathrm{NC-LMS}}(\hat{\boldsymbol{h}}[k])}{\partial \hat{\boldsymbol{h}}^*[k]} = \left(y[k] - \frac{q^*_{N_{\mathrm{NC-LMS}}}[k]}{|q_{N_{\mathrm{NC-LMS}}}[k]|}r[k]\right)^* \boldsymbol{b}[k], \tag{11}$$

with the definition

$$q_{N_{\mathrm{NC-LMS}}}[k] \triangleq \sum_{\nu=0}^{N_{\mathrm{NC-LMS}}-1} r[k-\nu]y^*[k-\nu]. \tag{12}$$

Note that for differentiation of $J_{\mathrm{NC-LMS}}(\hat{\boldsymbol{h}}[k])$ with respect to the current estimated channel impulse response $\hat{\boldsymbol{h}}[k]$ previously estimated channel impulse responses $\hat{\boldsymbol{h}}[k-\nu]$, $\nu \geq 1$, have to be treated as constants (cf. also [8, 9, 10, 11, 12]). The dependence of the noncoherent cost function on $\hat{\boldsymbol{h}}[k-\nu]$, $\nu \geq 1$, is an important difference between the NC–LMS and the conventional LMS algorithm.

The NC–LMS algorithm can be obtained by inserting $\partial J_{\mathrm{NC-LMS}}(\hat{\boldsymbol{h}}[k])/\partial \hat{\boldsymbol{h}}^*[k]$ from Eq. (11) into Eq. (7):

$$\hat{\boldsymbol{h}}[k+1] = \hat{\boldsymbol{h}}[k] + \delta_{\mathrm{LMS}} \cdot e^*_{\mathrm{NC-LMS}}[k]\boldsymbol{b}[k], \tag{13}$$

where the definition

$$e_{\mathrm{NC-LMS}}[k] \triangleq \frac{q^*_{N_{\mathrm{NC-LMS}}}[k]}{|q_{N_{\mathrm{NC-LMS}}}[k]|}r[k] - y[k] \tag{14}$$

is used. A comparison of the NC–LMS with the conventional LMS algorithm shows that the only difference is the additional factor $q^*_{N_{\mathrm{NC-LMS}}}[k]/|q_{N_{\mathrm{NC-LMS}}}[k]|$ in Eq. (14). This factor is the maximum–likelihood (ML) estimate of the phase difference between $r[\cdot]$ and $y[\cdot]$ [5]. Thus, the proposed NC–LMS algorithm can be interpreted as conventional LMS algorithm with incorporated ML phase estimation.

Usually, $\hat{\boldsymbol{h}}[k]$ is initialized with the all zero vector at time $k=0$. Since in this case $q_{N_{\mathrm{NC-LMS}}}[0] = 0$ follows, $q_{N_{\mathrm{NC-LMS}}}[0]/|q_{N_{\mathrm{NC-LMS}}}[0]|$ is not defined. Therefore, we suggest to use the initialization $q_{N_{\mathrm{NC-LMS}}}[0]/|q_{N_{\mathrm{NC-LMS}}}[0]| = 1$ in Eq. (14) at time $k=0$.

Due to the nonlinearity of the magnitude operator in Eqs. (8) and (14), a theoretical analysis of the NC–LMS algorithm is very difficult if not impossible. Nevertheless, for a better understanding of the novel algorithm, we investigate some of its properties.

3.2. *Influence of Phase Shift and Frequency Offset*

In order to investigate the influence of phase shift and frequency offset on the conventional LMS algorithm, the corresponding error signal $e_{\mathrm{CLMS}}[k] \triangleq r[k] - y[k]$ [3] may be considered. For simplicity, here the channel noise is neglected. If $r[k]$ and $y[k]$ given by Eqs. (2) and (9), respectively, are applied,

$$e_{\mathrm{CLMS}}[k] = \left(\mathrm{e}^{j\Theta}\mathrm{e}^{j2\pi\Delta f T k}\boldsymbol{h}^H[k] - \hat{\boldsymbol{h}}^H[k]\right)\boldsymbol{b}[k] \tag{15}$$

is obtained. Eq. (15) clearly shows that the error $e_{\mathrm{CLMS}}[k]$ depends on both phase shift Θ and frequency offset Δf. Thus, in order to minimize $e_{\mathrm{CLMS}}[k]$, the conventional LMS algorithm has to estimate not only the channel impulse response $\boldsymbol{h}[k]$ but implicitly also Θ and more importantly, it has to track the frequency offset. Our simulations in Section 3.3 show that even for relatively small frequency offsets the conventional LMS algorithm is not able to perform this difficult task.

The error signal $e_{\mathrm{NC-LMS}}[k]$ (cf. Eq. (14)) of the NC–LMS algorithm may be rewritten to

$$e_{\mathrm{NC-LMS}}[k] = \left(f_{\Delta f}[k] \cdot \boldsymbol{h}^H[k] - \hat{\boldsymbol{h}}^H[k]\right)\boldsymbol{b}[k] \tag{16}$$

with

$$f_{\Delta f}[k] = \frac{\left(\sum\limits_{\nu=0}^{N_{\mathrm{NC-LMS}}-1} \mathrm{e}^{-j2\pi\Delta fT\nu}\boldsymbol{h}^H[k-\nu]\boldsymbol{b}[k-\nu]\,\boldsymbol{b}^H[k-\nu]\hat{\boldsymbol{h}}[k-\nu]\right)^*}{\left|\sum\limits_{\nu=0}^{N_{\mathrm{NC-LMS}}-1} \mathrm{e}^{-j2\pi\Delta fT\nu}\boldsymbol{h}^H[k-\nu]\boldsymbol{b}[k-\nu]\,\boldsymbol{b}^H[k-\nu]\hat{\boldsymbol{h}}[k-\nu]\right|}. \qquad (17)$$

Eq. (16) demonstrates that $e_{\mathrm{NC-LMS}}[k]$ is independent of Θ which underlines the noncoherent character of the proposed NC–LMS algorithm. On the other hand, the influence of the frequency offset is limited to the factor $f_{\Delta f}[k]$, where only frequency offset dependent terms of the form $\mathrm{e}^{-j2\pi\Delta fT\nu}$, $0 \leq \nu \leq N_{\mathrm{NC-LMS}} - 1$, are involved. Thus, it can be expected that small frequency offsets do not influence the estimated impulse response $\hat{\boldsymbol{h}}[k]$ as long as $N_{\mathrm{NC-LMS}}$ is not chosen too large (the proper choice of $N_{\mathrm{NC-LMS}}$ will be discussed in Section 3.3). Even for relatively large frequency offsets (i.e., $\Delta fT \geq 0.01$), the NC–LMS algorithm does not diverge (cf. Section 3.3) since it does not attempt to track the frequency offset. The only effect is an increased estimation error, especially for large $N_{\mathrm{NC-LMS}}$.

3.3. *Convergence of the NC–LMS Algorithm*

An analytical stability and convergence analysis of the proposed noncoherent adaptive algorithm is very difficult if not impossible due to its nonlinear character. Therefore, we have to restrict ourselves to computer simulations. As far as the stability is concerned, our simulations showed that the step size parameter δ_{LMS} of the NC–LMS algorithm has to fulfill similar conditions like the step size parameter of the coherent LMS algorithm [3].

In the following, the convergence speed of the NC–LMS algorithm will be compared with that of the conventional LMS algorithm. For this, a constant ISI channel specified in [2] with $L = 5$ and $h_0[k] = 1/\sqrt{19}$, $h_1[k] = 2/\sqrt{19}$, $h_2[k] = 3/\sqrt{19}$, $h_3[k] = 2/\sqrt{19}$, $h_4[k] = 1/\sqrt{19}$, $\forall\, k$, is used. For all simulations presented in this section, a training sequence of QDPSK symbols (i.e., $M = 4$) is employed and all learning curves [3] are the result of averaging over 1000 adaptation processes. Furthermore, $10\log_{10}(E_b/N_0) = 15$ dB is valid, where $E_b = E_S/2$ denotes the mean received energy per bit. Figs. 2a) and b) show the learning curves $J'_{\mathrm{LMS}}[k]$ for the proposed NC–LMS and the conventional LMS algorithm for normalized frequency offsets of $\Delta fT = 0$ and $\Delta fT = 0.02$, respectively. The step size parameter $\delta_{\mathrm{LMS}} = 0.05$ is used in all cases. For the NC–LMS algorithm $J'_{\mathrm{LMS}}[k]$ is defined as $J'_{\mathrm{LMS}}[k] \triangleq \mathcal{E}\{|e_{\mathrm{NC-LMS}}[k]|^2\}$, whereas for the conventional LMS algorithm the usual definition (cf. e.g. [3]) is employed. Fig. 2a) shows that, in the absence of frequency offset, the NC–LMS algorithm has a similar convergence speed and causes a similar steady–state error like the conventional LMS algorithm. In addition, the performance of the NC–LMS algorithm is almost independent of $N_{\mathrm{NC-LMS}}$. On the other hand, for $\Delta fT = 0.02$, Fig. 2b) clearly illustrates that the conventional LMS algorithm does not converge to a reasonable solution; it is not able to compensate the frequency offset. The proposed NC–LMS algorithm, however, converges in all cases. The frequency offset only increases the steady–state error, while the convergence speed is hardly influenced. Since for $\Delta fT > 0$ the steady–state error is higher for larger $N_{\mathrm{NC-LMS}}$, $N_{\mathrm{NC-LMS}} = 2$ will be used exclusively in our simulations presented in Section 4.

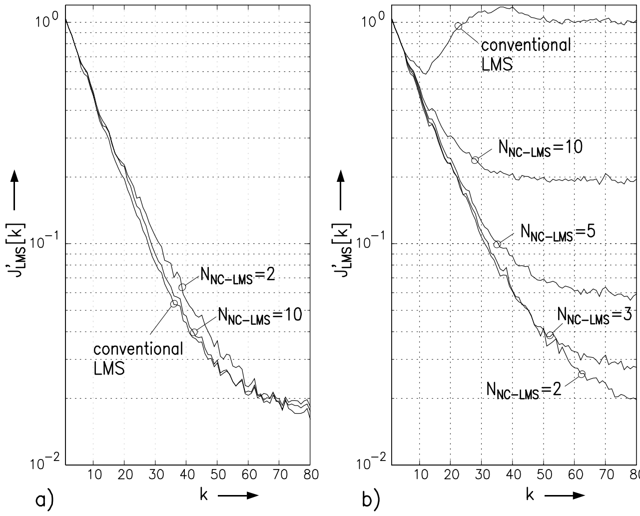

Figure 2: Learning curves for NC–LMS and conventional LMS algorithm with a) $\Delta fT = 0$, and b) $\Delta fT = 0.02$. For both figures $10\log_{10}(E_b/N_0) = 15$ dB and $\delta_{\mathrm{LMS}} = 0.05$ are valid.

4. Simulation Results

For the simulations presented in this section, a burst transmission is assumed. Each burst contains a preamble of 14 QDPSK training symbols and 160 QDPSK data symbols. The training sequence (TS) is used for least–squares (LS) estimation [3] of the channel impulse response as it is customary in mobile communications [15]. Note that the LS approach for initial impulse response estimation is suitable for both coherent and noncoherent sequence estimation since it does not degrade severely under carrier phase variations. In time–variant environments, the initial estimate delivered by the LS estimator may be considered as the *mean* channel impulse response during the TS. Hence, the NC–LMS algorithm starts in the middle of the TS. First, it works in a training mode, then at the beginning of the data sequence we switch to the decision–directed mode. Since the NC–LMS algorithm is the more robust against frequency offset the smaller $N_{\mathrm{NC-LMS}}$ is chosen, in the following, we will use exclusively $N_{\mathrm{NC-LMS}} = 2$. In our example, a frequency–selective time–variant three–tap Rayleigh fading channel is employed ($L = 3$). All three taps fade independently according to Jakes model. The normalized fading bandwidth of all taps is $B_fT = 0.001$, where B_f denotes the single–sided bandwidth of the underlying conti-

nuous–time fading process. The second and the third tap are attenuated by 3 dB and 6 dB in comparison to the first tap, respectively. For coherent MLSE, the Forney metric [1] and a full–state Viterbi algorithm are employed, i.e., the number of states is $Z = 16$. For NSE the same number of states is used, i.e., DFSE [13, 5] is applied. A decision delay of $k_1 = 2$ is chosen for both conventional LMS and NC–LMS algorithm since this value yields the best results.
Fig. 3 shows BER vs. $10\log_{10}(E_b/N_0)$ for coherent MLSE combined with the conventional LMS algorithm and NSE combined with the NC–LMS algorithm. $\delta_{\rm LMS} = 0.1$ is used for all curves. For zero frequency offset, the noncoherent receiver approaches the performance of the coherent receiver as N increases. On the other hand, the frequency offset causes only a small loss in power efficiency if the noncoherent receiver is employed. Note that the coherent receiver would need an additional synchronization circuit in order to cope with the frequency offset.
Obviously, for the noncoherent receiver there is a trade–off between power efficiency for $\Delta fT = 0$ and robustness against frequency offset. Although power efficiency for zero frequency offset increases with increasing N, the sensitivity to carrier phase variations increases, too. Thus, in a practical application the proper choice of N depends on the maximum expected frequency offset in the system.

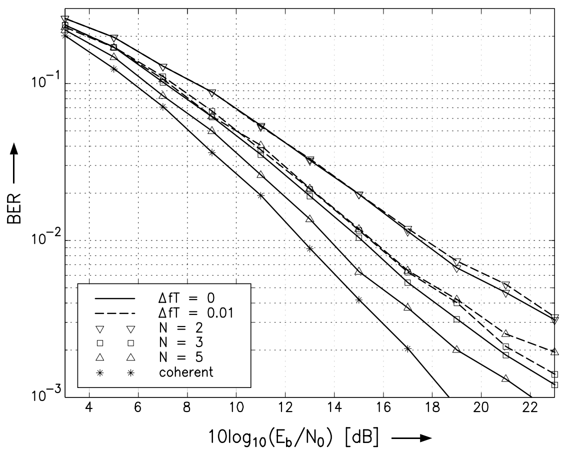

Figure 3: BER vs. $10\log_{10}(E_b/N_0)$ for NSE combined with the NC–LMS algorithm and coherent MLSE combined with the conventional LMS algorithm. A three–tap Rayleigh fading channel is used.

5. Conclusions

Noncoherent adaptive channel estimation has been introduced in this paper. An NC–LMS algorithm has been derived and its robustness against carrier phase variations has been demonstrated. In the absence of frequency offset, the proposed adaptive algorithm has a similar performance as the conventional LMS algorithm. On the other hand, the novel noncoherent algorithm also converges under frequency offset, whereas its coherent counterpart diverges. It has also been shown that the optimum value for the block size $N_{\rm NC-LMS}$ of the NC–LMS algorithm is 2.
Moreover, it was confirmed by computer simulations that the combination of NSE and NC–LMS algorithm provides a robust receiver, which does not degrade under frequency offset. For zero frequency offset, the loss of the noncoherent receiver in comparison to coherent MLSE combined with the conventional LMS algorithm is small.

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