NONCOHERENT SEQUENCE ESTIMATION COMBINED WITH NONCOHERENT ADAPTIVE CHANNEL ESTIMATION

Robert Schober, Lutz Lampe, and Wolfgang H. Gerstacker

Lehrstuhl für Nachrichtentechnik II, Universität Erlangen–Nürnberg
Cauerstraße 7, D–91058 Erlangen, Germany
e-mail: {*schober, LLampe, gersta*}*@LNT.de*, WWW: *http://www.LNT.de/LNT2*

Abstract

In this paper, $\underline{M}$–ary differential phase–shift keying (MDPSK) transmission over possibly time–variant intersymbol interference (ISI) channels is considered. For equalization, we combine noncoherent sequence estimation (NSE) with noncoherent adaptive channel estimation. For this, a novel noncoherent least–mean–square (NLMS) algorithm is derived. It is shown that the resulting noncoherent receiver is very robust against carrier phase variations. For zero frequency offset the convergence speed and the steady–state error of the novel noncoherent adaptive algorithm are similar to that of a conventional (coherent) LMS algorithm. However, the conventional LMS algorithm diverges even for relatively small frequency offsets, whereas the proposed NLMS algorithm also converges for relatively large frequency offsets. Simulations confirm the good performance of NSE combined with noncoherent adaptive channel estimation for both time–invariant and 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, 2] 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 [3, 4, 5].

Recently, noncoherent sequence estimation (NSE) schemes for ISI channels have been proposed [6, 7, 8]. Although, in principle, NSE is also applicable to multi–amplitude signals [6], we restrict ourselves to $\underline{M}$–ary differential phase–shift keying (MDPSK) modulation which is of most practical relevance. In contrast to coherent sequence estimation, NSE schemes do not require knowledge of the carrier phase. In addition, NSE has the advantage of being much more robust against frequency offset than coherent MLSE [7], i.e., complex phase and frequency synchronization circuits (e.g., phase–locked loops (PLLs)) can be avoided. However, NSE can only be applied if the impulse response of the channel is known up to a constant phase term. The conventional (coherent) LMS algorithm should not be used for channel estimation in this case since it is sensitive to carrier phase variations and is not able to deliver a reliable estimate even for relatively small frequency offsets. Thus, 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 [9, 10, 11, 12, 13], a *noncoherent* adaptive algorithm for *channel estimation* has not been reported so far.

In this paper, we design a noncoherent LMS (NLMS[1]) algorithm which delivers – up to a constant phase term – an estimate of the channel impulse response. This novel algorithm is very robust against frequency offset and simulations confirm that its convergence speed is similar to that of its conventional (coherent) counterpart. For NSE, the metrics proposed by Colavolpe et al. [6] and Schober et al. [8] are employed because of their high performance. Our simulations show that, in the presence of frequency offset, NSE combined with the proposed NLMS algorithm outperforms coherent MLSE combined with the conventional LMS algorithm in both time–invariant and time–variant ISI channels.

2. 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 $h_\nu[k]$, $0 \leq$

[1] Note that usually, in literature, NLMS refers to the *normalized* LMS algorithm [5]. However, since in this paper the normalized LMS algorithm is not employed, the different definition adopted here should cause no confusion.

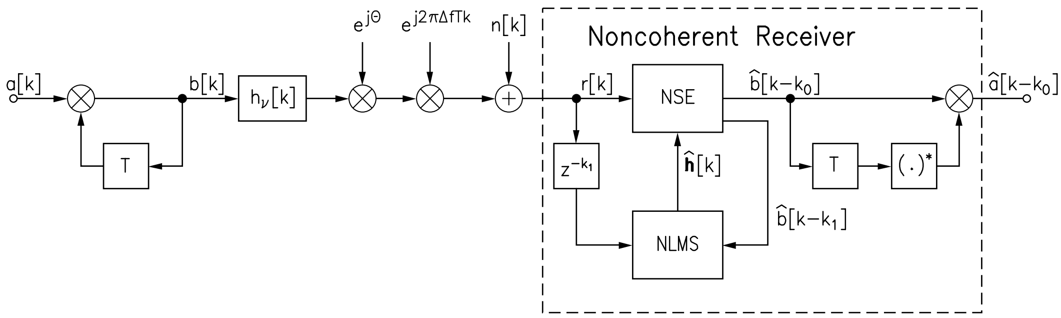

Figure 1: Block diagram of the discrete–time transmission and receiver model under consideration.

$\nu \leq L-1$. L is the length of the impulse response. Θ denotes an unknown, constant, uniformly distributed phase shift introduced by the channel. We assume that the demodulator frequency offset Δf is small and thus, its effect on the discrete–time model can be approximately represented by a multiplicative factor $\mathrm{e}^{j2\pi\Delta f T k}$ (T is the symbol interval). Furthermore, the receiver input filter has a square–root Nyquist frequency response[2], i.e., 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

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

The estimates $\hat{b}[k-k_0]$ of the transmitted symbols are determined via NSE, where k_0 is a decision delay (cf. Fig. 1). As typical for noncoherent detection schemes, the estimated MPSK symbols may be shifted by a constant phase compared to the transmitted symbols. Thus, differential encoding is necessary and the estimated MDPSK symbols are obtained from $\hat{a}[k-k_0] = \hat{b}[k-k_0]\hat{b}^*[k-k_0-1]$. Since NSE still requires knowledge of the channel impulse response (up to a constant phase shift), we employ a novel NLMS algorithm for channel estimation.

3. Noncoherent Sequence Estimation

In this paper, we use the NSE schemes proposed in [6, 8]. Nevertheless, the proposed NLMS algorithm can be applied also to other kinds of NSE schemes, of course.

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

The accumulated noncoherent metric $\Lambda[k]$ to be minimized is given by

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

where

$$\lambda[k] \triangleq |\tilde{y}[k]|^2 + 2\,|\tilde{q}_{\mathrm{ref}}[k-1]| - 2\,|r[k]\tilde{y}^*[k] + \tilde{q}_{\mathrm{ref}}[k-1]| \qquad (4)$$

is the branch metric ($(\cdot)^*$ denotes complex conjugation). The *reference symbol* $\tilde{q}_{\mathrm{ref}}[k-1]$ may be calculated nonrecursively [6]

$$\tilde{q}_{\mathrm{ref}}[k-1] \triangleq \sum_{\nu=1}^{N-1} r[k-\nu]\tilde{y}^*[k-\nu] \qquad (5)$$

or recursively [8]

$$\tilde{q}_{\mathrm{ref}}[k-1] \triangleq \alpha\,\tilde{q}_{\mathrm{ref}}[k-2] + r[k-1]\tilde{y}^*[k-1]. \qquad (6)$$

Here, N, $N \geq 2$, and α, $0 \leq \alpha \leq 1$, denote the so–called observation window size and a forgetting factor, respectively. $\tilde{y}[k]$ is given by

$$\tilde{y}[k] \triangleq \sum_{\nu=0}^{L-1} \hat{h}_\nu[k]\tilde{b}[k-\nu], \qquad (7)$$

where $\tilde{b}[\cdot]$ and $\hat{h}_\nu[k]$, $0 \leq \nu \leq L-1$, are equalizer trial symbols and the coefficients of the estimated channel impulse response, respectively. If per–survivor processing [14] is employed, the NSE metric can be minimized using the Viterbi algorithm on a trellis with $Z = M^K$ states (cf. [6, 8]). $0 \leq K \leq N+L-3$ and $0 \leq K \leq \infty$ are valid for the nonrecursive and the recursive metric, respectively. In this work, $K = L-1$ is considered exclusively, i.e., the same number of states as for coherent full–state MLSE results [1].

Introducing a decision delay of k_0 time steps the estimated MPSK symbol $\hat{b}[k-k_0]$ 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

[4]. 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.

4. Noncoherent LMS Algorithm

In this section, an NLMS algorithm for estimation and tracking of the channel impulse response is derived and its convergence behaviour is investigated.

Like the conventional LMS algorithm, the proposed NLMS algorithm requires knowledge of the transmitted symbol sequence. Thus, 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 [15], 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.

4.1. Derivation of the NLMS Algorithm

For derivation of the NLMS algorithm, for clarity of presentation, the decision delay k_1 is not taken into account. A gradient adaptation algorithm is obtained if the vector of (complex–conjugated) estimated impulse response coefficients

$$\hat{\boldsymbol{h}}[k] \triangleq [\hat{h}_0[k] \; \hat{h}_1[k] \; \ldots \; \hat{h}_{L-1}[k]]^H \tag{8}$$

($[\cdot]^H$ denotes Hermitian transposition) is updated according to the recursive relation [4, 5]

$$\hat{\boldsymbol{h}}[k+1] = \hat{\boldsymbol{h}}[k] - \delta_{\text{LMS}} \frac{\partial}{\partial \hat{\boldsymbol{h}}^*[k]} J(\hat{\boldsymbol{h}}[k]), \tag{9}$$

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

$$J_{\text{CLMS}}(\hat{\boldsymbol{h}}[k]) \triangleq |r[k] - \hat{\boldsymbol{h}}^H[k]\boldsymbol{b}[k]|^2 \tag{10}$$

with

$$\boldsymbol{b}[k] \triangleq [b[k] \; b[k-1] \; \ldots \; b[k-L+1]]^T \tag{11}$$

($[\cdot]^T$ denotes transposition) is used as cost function, i.e., $J_{\text{CLMS}}(\hat{\boldsymbol{h}}[k])$ is minimized recursively with respect to $\hat{\boldsymbol{h}}[k]$ provided that $\boldsymbol{b}[k]$ is known. On the other hand, for coherent MLSE $J_{\text{CLMS}}[k]$ 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 $J_{\text{NLMS}}(\hat{\boldsymbol{h}}[k])$ for the NLMS algorithm. For the following derivation, we only consider the nonrecursive reference symbol (cf. Eq. (5)) and define

$$J_{\text{NLMS}}(\hat{\boldsymbol{h}}[k]) \triangleq |y[k]|^2 + 2\left|\sum_{\nu=1}^{N_{\text{NLMS}}-1} r[k-\nu]y^*[k-\nu]\right| - 2\left|\sum_{\nu=0}^{N_{\text{NLMS}}-1} r[k-\nu]y^*[k-\nu]\right|, \tag{12}$$

with

$$y[k] \triangleq \hat{\boldsymbol{h}}^H[k]\boldsymbol{b}[k]. \tag{13}$$

N_{NLMS}, $N_{\text{NLMS}} \geq 2$, denotes the number of received signal samples $r[\cdot]$ used for calculation of $J_{\text{NLMS}}(\hat{\boldsymbol{h}}[k])$. Note that N_{NLMS} does not have to coincide with N used for NSE. Using the method for complex differentiation described in [5, Appendix B] and the rule

$$\frac{\partial}{\partial \boldsymbol{w}^*}|z(\boldsymbol{w})| = \frac{\partial}{\partial \boldsymbol{w}^*}\frac{\partial(z(\boldsymbol{w})z^*(\boldsymbol{w}))}{\partial(z(\boldsymbol{w})z^*(\boldsymbol{w}))}\sqrt{z(\boldsymbol{w})z^*(\boldsymbol{w})} = \frac{1}{2}\frac{1}{|z(\boldsymbol{w})|}\frac{\partial(z(\boldsymbol{w})z^*(\boldsymbol{w}))}{\partial \boldsymbol{w}^*}, \tag{14}$$

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

$$\frac{\partial}{\partial \hat{\boldsymbol{h}}^*[k]} J_{\text{NLMS}}(\hat{\boldsymbol{h}}[k]) = \left(y[k] - \frac{q^*_{N_{\text{NLMS}}}[k]}{|q_{N_{\text{NLMS}}}[k]|} r[k]\right)^* \boldsymbol{b}[k], \tag{15}$$

with the definition

$$q_{N_{\text{NLMS}}}[k] \triangleq \sum_{\nu=0}^{N_{\text{NLMS}}-1} r[k-\nu]y^*[k-\nu]. \tag{16}$$

Note that for differentiation of $J_{\text{NLMS}}(\hat{\boldsymbol{h}}[k])$ 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 [9, 10, 11, 12, 13]). The dependence of the noncoherent cost function on $\hat{\boldsymbol{h}}[k-\nu]$, $\nu \geq 1$, is an important difference between the NLMS and the conventional coherent LMS algorithm.

The NLMS algorithm can be obtained by inserting $\partial J_{\text{NLMS}}(\hat{\boldsymbol{h}}[k])/\partial \hat{\boldsymbol{h}}^*[k]$ according to Eq. (15) into Eq. (9):

$$\hat{\boldsymbol{h}}[k+1] = \hat{\boldsymbol{h}}[k] + \delta_{\text{LMS}} e^*_{\text{NLMS}}[k]\boldsymbol{b}[k], \tag{17}$$

where the definition

$$e_{\text{NLMS}}[k] \triangleq \frac{q^*_{N_{\text{NLMS}}}[k]}{|q_{N_{\text{NLMS}}}[k]|} r[k] - y[k] \tag{18}$$

is used. A comparison of the NLMS with the conventional LMS algorithm shows that the only difference is the additional factor $q^*_{N_{\text{NLMS}}}[k]/|q_{N_{\text{NLMS}}}[k]|$ in

Eq. (18). This factor is the maximum–likelihood (ML) estimate of the phase difference between $r[\cdot]$ and $y[\cdot]$ [6]. Thus, the proposed NLMS algorithm can be interpreted as conventional LMS algorithm with incorporated ML phase estimation.
If we initialize $\hat{\boldsymbol{h}}[0]$ with the all zero vector, $q_{N_{\rm NLMS}}[0] = 0$ follows and $q_{N_{\rm NLMS}}[0]/|q_{N_{\rm NLMS}}[0]|$ is not defined. Therefore, in this case, we suggest to use the initialization $q_{N_{\rm NLMS}}[0]/|q_{N_{\rm NLMS}}[0]| = 1$ in Eq. (18).

4.2. Convergence of the NLMS Algorithm

A theoretical 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 $\delta_{\rm LMS}$ of the NLMS algorithm has to fulfill similar conditions like the step size parameter of the coherent LMS algorithm [5].
In the following, the convergence speed of the NLMS algorithm will be compared with that of the conventional LMS algorithm. For this, a constant ISI channel (specified in [4]) 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 [5] 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 for the proposed NLMS and the conventional LMS algorithm for normalized frequency offsets of $\Delta fT = 0$ and $\Delta fT = 0.02$, respectively. The step size parameter $\delta_{\rm LMS} = 0.05$ is adopted in all cases. For the NLMS algorithm $J'_{\rm LMS}[k]$ is defined as $J'_{\rm LMS}[k] \triangleq \mathcal{E}\{|e_{\rm NLMS}[k]|^2\}$, whereas for the conventional LMS algorithm the usual definition (cf. e.g. [5]) is employed. Fig. 2a) shows that, in the absence of frequency offset, the NLMS algorithm has a similar convergence speed and causes a similar steady–state error like the conventional LMS algorithm. In addition, the performance of the NLMS algorithm is almost independent of $N_{\rm NLMS}$. 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 for the frequency offset. The proposed NLMS algorithm, however, converges in all cases. The frequency offset only increases the steady–state error, while the convergence speed is hardly influenced. It should be mentioned that the performance of the conventional LMS algorithm can only be marginally improved by increasing $\delta_{\rm LMS}$. Since for $\Delta fT > 0$ the steady–state error is higher for larger $N_{\rm NLMS}$, $N_{\rm NLMS} = 2$ will be used exclusively in our simulations presented in Section 5.

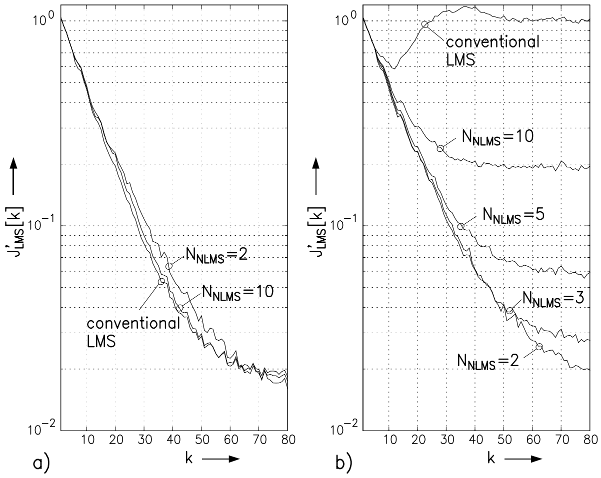

Figure 2: Learning curves for NLMS and conventional LMS algorithm with a) $\Delta fT = 0$, and b) $\Delta fT = 0.02$. For both figures $h_0[k] = 1/\sqrt{19}$, $h_1[k] = 2/\sqrt{19}$, $h_2[k] = 3/\sqrt{19}$, $h_3[k] = 2/\sqrt{19}$, $h_4[k] = 1/\sqrt{19}$, $\forall\, k$, $10\log_{10}(E_b/N_0) = 15$ dB, and $\delta_{\rm LMS} = 0.05$ are adopted.

5. 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 [5] of the channel impulse response as it is customary in mobile communications [3]. 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. Since the NLMS algorithm is more robust against frequency offset for small $N_{\rm NLMS}$, in the following, we will use exclusively $N_{\rm NLMS} = 2$.
The impulse response length is $L = 3$ for all examples presented below. In the coherent case, a full–state Viterbi algorithm [1] is employed, i.e., the number of states is $Z = 16$. For NSE the same number of states is used. The decision delay k_1 for conventional LMS and NLMS algorithm is $k_1 = 2$ in all cases since this value yields the best result for the time–variant channel considered below.
In our first example, a static channel with impulse response $h_0[k] = 0.304$, $h_1[k] = 0.903$, and $h_2[k] =$

0.304, $\forall k$, specified in [4] is used. Fig. 3 shows the bit error rate (BER) vs. $10\log_{10}(E_b/N_0)$ for coherent MLSE with conventional LMS algorithm and NSE (nonrecursive reference symbol, cf. Eq. (5)) with NLMS algorithm. For $\Delta fT = 0$ the step size parameter $\delta_{\text{LMS}} = 0.01$ is employed for both LMS and NLMS algorithm. It can be observed that the gap between coherent MLSE and NSE decreases with increasing block size N. Although for $\Delta fT = 0.01$ the step size parameter of the conventional LMS algorithm is increased to $\delta_{\text{LMS}} = 0.1$, the coherent receiver degrades severely and causes a high error floor (BER > 0.1). The step size parameter for the NLMS algorithm is the same as for zero frequency offset. The noncoherent receiver does not degrade significantly under frequency offset. As can be seen, the loss compared to $\Delta fT = 0$ is larger for larger N.

In our second example, a frequency–selective time–variant three–tap Rayleigh fading channel is considered. All three taps fade independently according to Jakes Model. The normalized fading bandwidth of all taps is $B_f T = 0.001$, where B_f denotes the single–sided bandwidth of the underlying continuous–time fading process. The second and the third tap are attenuated by 3 dB and 6 dB in comparison to the first tap, respectively. Fig. 4 shows BER vs. $10\log_{10}(E_b/N_0)$ for coherent MLSE combined with the conventional LMS algorithm and NSE (recursive reference symbol, cf. Eq. (6)) combined with the NLMS algorithm. $\delta_{\text{LMS}} = 0.1$ is used for all curves. Clearly, the coherent receiver degrades severely for $\Delta fT = 0.01$ and causes a high error floor, i.e., in practice, an additional frequency synchronization circuit is necessary. For the noncoherent receiver, however, frequency offset causes only a small loss in power efficiency.

From the above examples it can be seen that 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 (α), the sensitivity to carrier phase variations increases, too. Thus, in a practical application the proper choice of N (α) depends on the maximum expected frequency offset in the system.

6. Conclusions

The combination of NSE and noncoherent adaptive channel estimation has been considered in this paper. An NLMS algorithm has been derived and its robustness against carrier phase variations has been demonstrated. It has been shown that in the absence of frequency offset the proposed adaptive algorithm has a similar performance as the conventional coherent LMS algorithm. On the other hand, the novel noncoherent algorithm also converges under frequency offset,

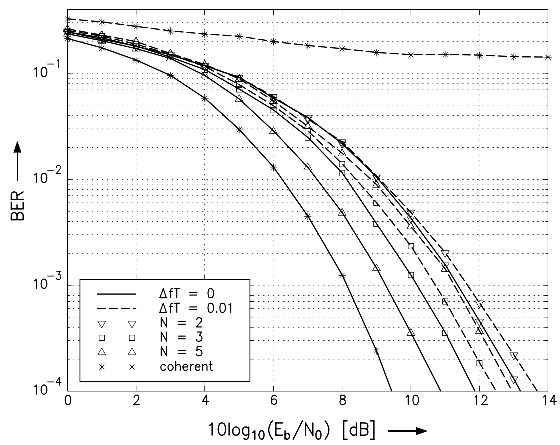

Figure 3: BER vs. $10\log_{10}(E_b/N_0)$ for NSE (nonrecursive reference symbol, cf. Eq. (5)) combined with the NLMS algorithm and coherent MLSE combined with the conventional LMS algorithm. Here, a static channel ($h_0[k] = 0.304$, $h_1[k] = 0.903$, $h_2[k] = 0.304$, $\forall k$) is used.

whereas its coherent counterpart diverges. It has also been shown that the optimum value for the block size N_{NLMS} of the NLMS algorithm is 2.

Moreover, it was confirmed by computer simulations that the combination of NSE and NLMS algorithm provides a robust receiver, which outperforms coherent MLSE combined with the conventional (coherent) LMS algorithm under frequency offset. For zero frequency offset, the loss of the noncoherent receiver in comparison to the coherent receiver is small.

Finally, it is worth mentioning that besides the presented NLMS algorithm also a faster converging noncoherent recursive least–squares (NRLS) algorithm can be derived [16].

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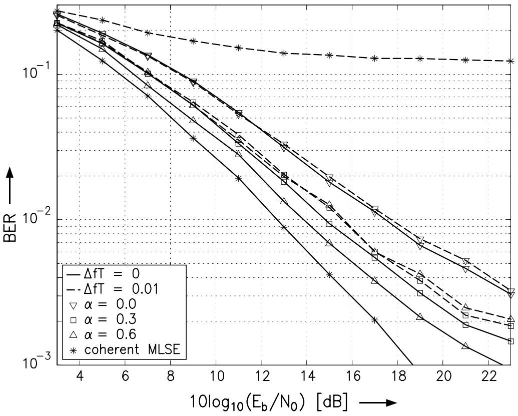

Figure 4: BER vs. $10\log_{10}(E_b/N_0)$ for NSE (recursive reference symbol, cf. Eq. (6)) combined with the NLMS algorithm and coherent MLSE combined with the conventional LMS algorithm. A three–tap Rayleigh fading channel is used. All taps fade independently and the second and the third tap are attenuated by 3 dB and 6 dB, respectively, in comparison to the first tap.

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Biographies

Robert Schober (S'97) was born in Neuendettelsau, Germany, in 1971. He received the Dipl.–Ing. degree in electrical engineering from the University of Erlangen–Nürnberg in 1997. He is now a Research Assistant at the Telecommunications Institute at the University of Erlangen–Nürnberg. His research interests include noncoherent detection, equalization, and CDMA.

Lutz Lampe (S'98) was born in Leipzig, Germany, in 1973. He received the Dipl.–Ing. degree in electrical engineering from the University of Erlangen–Nürnberg in 1998. He is now a Research Assistant at the Telecommunications Institute at the University of Erlangen–Nürnberg. Currently, his research is focused on high–rate digital transmission over power line distribution networks. His interests comprise general issues of information theory and digital communications, and especially multicarrier modulation and differentially encoded transmission.

Wolfgang H. Gerstacker (S'93, M'99) was born in Nürnberg, Germany, in 1966. He received the Dipl.-Ing. degree in electrical engineering from the University of Erlangen-Nürnberg in 1991. From 1992 to 1998 he was a Research Assistant at the Telecommunications Institute of the University of Erlangen-Nürnberg. In 1998, he received the Dr.–Ing. degree with a thesis on improved equalization concepts for transmission over twisted pair lines. Since 1998, he is a consultant working in the area of mobile communications and also performing joint work with the Telecommunications Institute of the University of Erlangen–Nürnberg. In 1999/2000, he was a Visiting Research Fellow for a six months period at the University of Canterbury, Christchurch, New Zealand, sponsored by a fellowship from the German Academic Exchange Service (DAAD). His research interests are (adaptive) equalization for high-rate baseband transmission schemes, such as xDSL, equalization and channel estimation for mobile communications systems, blind channel estimation, and noncoherent detection algorithms.