Channel Estimation with Hard Limiter Receiver as Key Technology for Low Cost Wireless Systems

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***Abstract*—Future wireless indoor network applications will require technologies that allow high data rate transmission in multipath propagation environment. The acceptance of new technologies will depend essentially on the expense of its realization. A key technology for link level cost reduction is the use of hard (amplitude) limiting receiver structures that substantially save the costs for the analogue domain of the receivers [1][2]. Technologies suited for multipath propagation, such as ML based detection or smart antennas training, require the knowledge of the complex channel impulse response (CIR) [3][4]. Up to now, there is no method known how to estimate the complex CIR in case of a hard limited receiver structure. In this paper an estimation method is presented that allows an estimation of the complex CIR on basis of phase samples. The new estimation technique is a two level approach which exploits the finite-state nature of the transmission system. With the help of an appropriate training sequence an estimate of the desired phase and amplitude is performed. The second level procedure performs a subspace approach to estimate the CIR which yields a well treatable over determined linear equation system. Simulation results for a GMSK transmission system highlight the suitability of this estimation method.**

I. Introduction

Considering wireless indoor networks, low cost systems such as Bluetooth provide only low data rates ≤ 1 Mbps and high quality systems as WLANs provide high data rates > 10Mbps. However, the costs for such higher data rate systems is increased by orders magnitude: Linear receiver systems with high dynamic range and power consumption are used to handle the intersymbol interference (ISI) of the multipath propagation channel. This paper makes a contribution to the extension of low cost systems to higher data rates as illustrated in Fig 1.

One of the most effective technology to reduce these costs are hard amplitude limiting receiver structures. Compared to linear systems power consumption and hardware effort can be drastically reduced. Due to the amplitude limitation the dynamic range of those systems is minimized and no adaptive gain control (AGC) circuit is required. However, as linear receivers, these receivers also need equalizer techniques to handle the ISI. In [2] training of an adaptive antenna array is emphasized as low cost technology to combat the ISI in such systems. This and further technologies suited for multipath propagation, e.g. Maximum Likelihood (ML) based detection, require the knowledge of the complex channel impulse response (CIR). Up to now, a useful estimation of the CIR can only be performed by linear receivers. To the author's knowledge no method to estimate the complex CIR with hard limiting receivers has been proposed up to now.

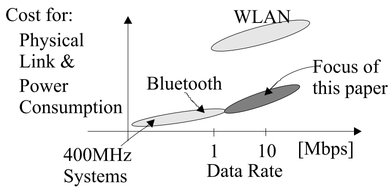


Fig. 1. Focus of the paper

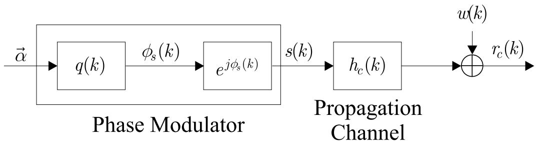
In this paper we present a technique to estimate the complex CIR on basis of phase samples. As will be shown a quite short training sequence, for example according to the HIPERLAN I standard, is sufficient to achieve a nearly perfect estimate.

In the next section, the considered system model is described. Section III and IV present the new estimation method. BER simulation results for a GMSK transmission system are depicted in Section V.

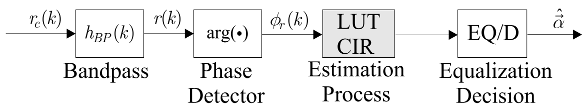
II. System Model

The system is described in discrete equivalent baseband representation. Fig. 2 shows a block diagram of the system model. It is assumed that the modulation scheme has finite memory (or can be described as a finite state process). The CIR of the bandpass filter $h_{BP}(k)$ and of the multipath channel $h_c(k)$ have finite memory, too. $h_c(k)$ is a highly frequency selective channel which is assumed to be stationary for the data burst duration. $w(k)$ is zero-mean circularly symmetric complex additive white Gaussian noise (AWGN) with variance σ_w^2. The bandpass is assumed to have Nyquist characteristic which means the noise samples at its output to be statistically independent. The phase samples $\phi_r(k)$ at the output of the phase detector are limited to the interval $\phi_r(k) \in [-\pi, \pi]$.

To have a practical application in mind we consider a de-



(a) Sender and propagation channel



(b) Phase detection receiver

Fig. 2. System model

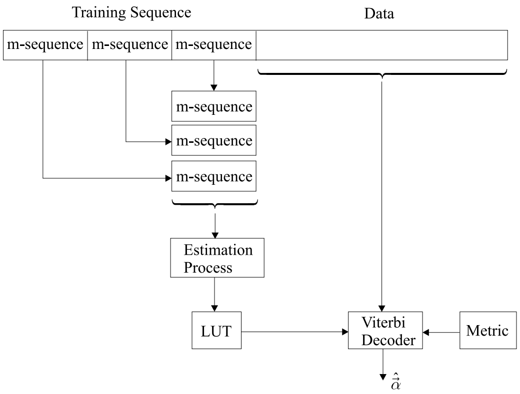


Fig. 3. Decoding of a data burst

coding of a data burst as shown in Fig. 3. With help of an appropriate training sequence a complex Look-Up-Table (LUT) is estimated which includes the desired amplitude and phase values. A Viterbi decoder uses a metric which is based on the complex LUT [5] to decode the data.
The training sequence is composed by a number of M concatenated m-sequences. Each m-sequence includes all possible symbol sequences according to the memory size of the system. The results which are shown in the next sections are achieved by simulations. The simulation parameters are summarized in Table I. The symbol period is denoted T_S.

III. A First Complex Estimate of the LUT

A. Direct approach to estimate the desired phase

In a first step the estimation of the phase LUT is considered. The LUT is described as a vector of length K:

$$[\phi_d(1), \phi_d(2), ..., \phi_d(K)]$$

The training sequence (TS) consists of M repetitions of the m-sequence which ideally is adapted to the system memory. That means, for every value $\phi_d(k)$ a number of M

TABLE I
Simulation parameters

Parameter	Name	Value
Modulation type	GMSK	$BT = 0.3$
Signal to noise ratio	E_b/N_0	10dB
Sampling period	T_{SA}	$T_S/8$
Number of m-sequences	M	4
Model Channel	$1 - D$	$\delta(t) - \delta(t - T_S)$

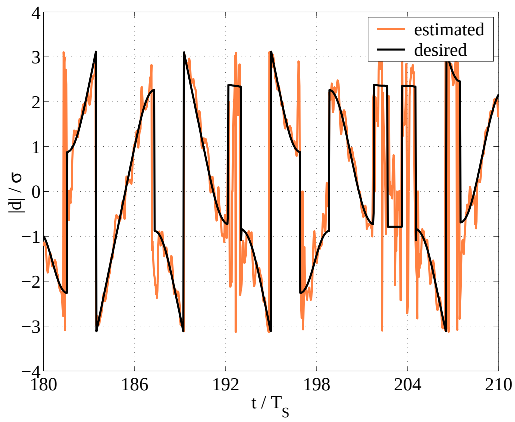


Fig. 4. First phase estimate, $1 - D$-channel

observations $\phi_r^{(m)}(k)$ are received during the TS. Each observation is perturbed by a noise component $\Delta\phi^{(m)}(k)$: $\phi_r^{(m)}(k) = \phi_d(k) + \Delta\phi^{(m)}(k)$. All realizations are summarized in one vector:

$$\vec{\phi}_r(k) = [\phi_r^{(1)}(k), \phi_r^{(2)}(k), ..., \phi_r^{(M)}(k)]^T \qquad (1)$$

An intuitive approach is to perform an averaging process to determine $\phi_d(k)$. A vectorial averaging is proposed here: The phase values $\phi_r^{(m)}(k)$ are written as complex phasors of length 1 and summarized:

$$\hat{\phi}_d(k) = \arg\left\{\sum_{m=1}^{M} \exp\left(j\phi_r^{(m)}(k)\right)\right\} \qquad (2)$$

This way, $\mod 2\pi$ steps do not disturb the phase mean. In Fig. 4 the result of this estimation is shown. The shape of the estimated phase looks very noisy and requires an improvement.

B. Direct approach to estimate the desired amplitude

The key idea of the amplitude estimation is to use the phase variance as relation to the desired amplitude. High values of the desired amplitude cause a low variance of the phase and vice versa: Consider a complex noise sample n with arbitrary phase and determined amplitude. The noise sample superposes the noiseless desired sample d.

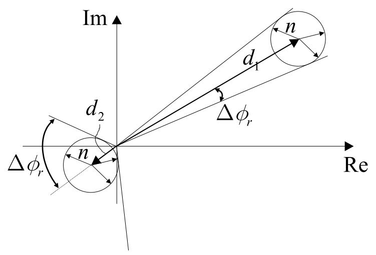


Fig. 5. Phase error for high and low amplitude

For high amplitude values $|d_1| \gg |n|$ the phase error $\Delta\phi_r$ is small (see Fig. 5). For low amplitudes ($|d_2| \lesssim |n|$) the phase error is high. The maximum phase error is indicated in the plot. To estimate the amplitude, first the variance is estimated from vector $\vec{\phi}_r(k)$:

$$\hat{\sigma}^2_{\phi_r}(k) = \hat{\sigma}^2_{\Delta\phi}(k) = \frac{1}{M-1}\sum_{m=1}^{M} \min\left\{|\Delta\phi^{(m)}(k)|^2, \left(2\pi - |\Delta\phi^{(m)}(k)|\right)^2\right\} \tag{3}$$

with

$$\Delta\phi^{(m)}(k) = \phi_r^{(m)}(k) - \hat{\phi}_d(k) \tag{4}$$

and $\hat{\phi}_d(k)$ from (2). The minimum operation in (3) prevents noise errors that are higher than π.
The relation between the desired amplitude and the associated variance of the phase is given in (5) with $\overline{\Delta\phi} \equiv 0$:

$$\sigma^2_{\Delta\phi}(k) = E\{\Delta\phi^2\} = \int_{-\pi}^{\pi} \Delta\phi^2 p_{\Delta\phi|\rho}\left(\Delta\phi|\rho(k)\right) d\Delta\phi \tag{5}$$

With $p_{\Delta\phi|\rho}$ given in [6]:

$$p_{\Delta\phi|\rho}(\Delta\phi|\rho(k)) = \frac{\exp\left(-\rho(k)\right)}{2\pi} + \sqrt{\frac{\rho(k)}{4\pi}} \cdot \exp\left(-\rho(k)\sin^2(\Delta\phi)\right) \cdot \cos(\Delta\phi) \cdot \mathrm{erfc}\left(-\sqrt{\rho(k)}\cos(\Delta\phi)\right) \tag{6}$$

the variance $\sigma^2_{\Delta\phi}(k)$ is a function of the instantaneous SNR $\rho(k)$, where:

$$\rho(k) = \frac{|d(k)|^2}{\sigma_w^2}$$

The variance of the complex noise σ_w^2 is a system parameter which is determined by the quality of the amplifier stages of the receiver. So, it can be assumed to be approximately known and with it the relation between the desired amplitude and the variance is given. A quasi optimum phase detection receiver is presented in [5] which uses $\rho(k)$ to perform the sequence estimation. This shows

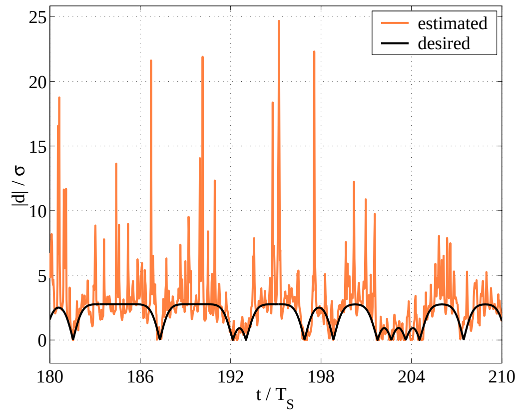


Fig. 6. First amplitude estimate, $1-D$-channel

an advantage of this estimation technique because fluctuations of σ_w^2 caused by temperature fluctuations are compensated by the estimation process. A numerical evaluation of (5) yields a function that gives the relation between the estimated (relative) amplitude $|\hat{d}(k)|/\sigma_w$ and the estimated variance, denoted by f_d:

$$\frac{|\hat{d}(k)|}{\sigma_w} = f_d\left(\sigma^2_{\Delta\phi}(k)\right) \tag{7}$$

The result of the amplitude estimation is shown in Fig. 6. The desired amplitude is difficult to recognize. Frequently, the estimates are much higher than the desired values. An explanation of this problem and a correction method is given in [5].
With the estimated phase from (2) and the estimated amplitude from (7) a first estimate of the complex desired signal can be composed:

$$\hat{d}(k) = \frac{|\hat{d}(k)|}{\sigma_w} \cdot \exp\left(j\hat{\phi}_d(k)\right) \tag{8}$$

IV. A Subspace Approach to Estimate the LUT and CIR

The subspace approach proposed in this section improves the performance of the first estimate from (8). It is assumed that the following signals and parameters are known a priori: a) Shape of sent signal during TS $s(k)$, b) Impulse response of the bandpass filter $h_{BP}(k)$ and c) Length of the CIR of the propagation channel by number of Taps N_c. The sent signal and the bandpass filter are generally known because they are invariable system parameters. The length of $h_c(k)$ is usually not known, because $h_c(k)$ is variable. Simulations have shown that the estimation process is not sensitive to small deviations of N_c. A method to estimate N_c has been developed in a companion work which is out of the scope of this paper. At first, the discrete linear time invariant model from Fig. 7 is considered. The desired

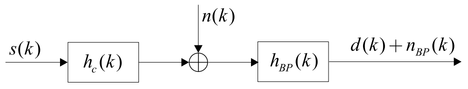


Fig. 7. Discrete LTI system model

signal $d(k)$ can be written as:

$$d(k) = s(k) * h_c(k) * h_{BP}(k) \\ = s_{BP}(k) * h_c(k) \qquad (9)$$

$$s_{BP}(k) = s(k) * h_{BP}(k) \qquad (10)$$

In vector representation the convolution can be replaced by a matrix multiplication:

$$\vec{d} = \mathbf{S}_{BP}\vec{h}_c \qquad (11)$$

$\mathbf{S}_{BP}$ is the convolution matrix of $\vec{s}_{BP}$. If $\vec{s}_{BP}$ has length K the dimension of $\mathbf{S}_{BP}$ is $(K + N_c - 1) \times N_c$:

$$\mathbf{S}_{BP}(k,n) = \begin{cases} \vec{s}_{BP}[k-n+1], \text{for } 1 \leq k-n+1 \leq K \\ 0, \text{else} \end{cases} \qquad (12)$$

S_{BP} is a priori known at the receiver because $h_{BP}(k)$ and $s(k)$ do not depend on the propagation channel. $d(k)$ and $h_c(k)$ are not known. The idea of the subspace approach is to estimate $\vec{h}_c$ by replacing $\vec{d}$ with $\hat{\vec{d}}$. $\hat{\vec{d}}$ is given by the first estimate from (8).

$$\hat{\vec{d}} = \mathbf{S}_{BP}\hat{\vec{h}}_c \qquad (13)$$

Since the dimension of $\hat{\vec{d}}$ is generally higher than the dimension of $\vec{h}_c$, the linear equation system of (13) is over determined. Usually, it has not a unique solution. Therefore, the quadratic norm of the error vector is minimized:

$$\left|\mathbf{S}_{BP}\hat{\vec{h}}_c - \hat{\vec{d}}\right|^2 \stackrel{!}{=} \min \qquad (14)$$

The solution of (14) is the orthogonal projection of $\hat{\vec{d}}$ on the subspace M_c [7]. M_c is spanned by the column vectors of $\mathbf{S}_{BP}$:[1]

$$M_c = \text{span}\{\mathbf{S}_{BP}[:,1], \ldots, \mathbf{S}_{BP}[:,N_c]\} \qquad (15)$$

There are several mathematical methods that solve (14). Numerically robust solutions are achieved with help of a QR-decomposition of $\mathbf{S}_{BP}$ [8].

With help of the estimated CIR $\hat{\vec{h}}_c$ a better estimate of $\vec{d}$ can be performed. This "second level" estimate is:

$$\tilde{\vec{d}} = \mathbf{S}_{BP}\hat{\vec{h}}_c \qquad (16)$$

[1] In MATLAB-notation $\mathbf{S}_{BP}[:,i]$ denotes the i-th column vector of $\mathbf{S}_{BP}$

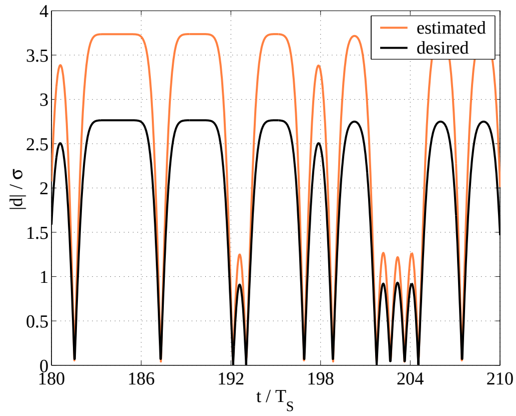


Fig. 8. Subspace amplitude estimate, $1-D$-channel

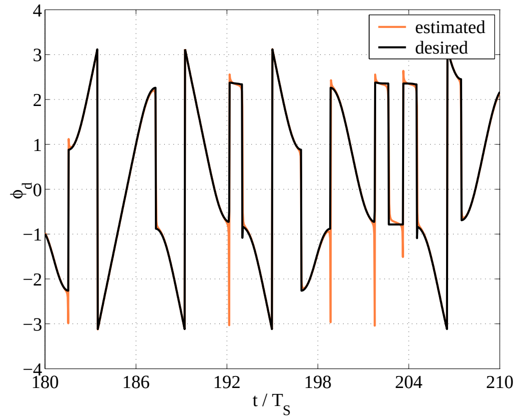


Fig. 9. Subspace phase estimate, $1-D$-channel

This way, the statistical basis for the estimation of $d(k)$ is not limited to M but all samples of the TS contribute to all $d(k)$. As a direct advantage, the TS does not necessarily have to contain all symbol combinations. Combinations which are not part of the TS can be reconstructed. The major advantage is that the used m-sequences do not have to be adapted to the system memory which is generally not known to the sender. Furthermore, shorter m-sequences can be used.

Fig. 8 and 9 show the result of the subspace estimation for the above example. In contrast to the first estimate the amplitude values are very smooth. Areas with amplitudes near zero are estimated very exactly. Only the scaling of the amplitude seems to be worth to improve. The phase values are estimated very well, too. Only at small amplitude values they differ from the desired amplitudes.

In [5] an amplitude correction method is derived. It is shown that a simple linear scaling of the amplitude achieves a very good approximation of the desired values. This estimate achieves bit error ratios that are nearly perfect in the considered range (see Section V). Table II shows the nu-

TABLE II

PROPORTIONALITY FACTORS OF AMPLITUDE CORRECTION

M	a_M
2	$a_2 = 0.280$
4	$a_4 = 0.760$
10	$a_{10} = 0.917$
100	$a_{100} = 1.000$

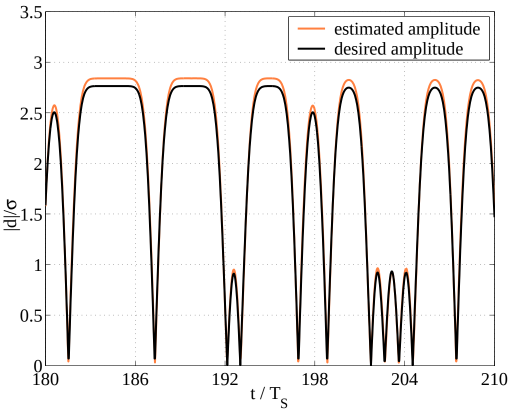


Fig. 10. Estimation result of amplitude correction

merically evaluated proportionalities. Fig. 10 pictures the result of the amplitude correction.

V. BER SIMULATION RESULTS

To compare the stages of the estimation process bit error ratios are shown in Fig. 11. Exemplarily the $1-D$-channel is examined with $T_{SA} = T_S/8$. The first estimation with $M = 4$ repetitions of the m-sequence has weak performance compared to the decoder with perfect CIR knowledge. The loss is about 9dB at BER=10^{-2}. An error floor appears at $\approx 4 \cdot 10^{-3}$. The subspace estimate achieves a high gain towards the first estimate. No error floor appears in the considered range. However, the loss to the perfect CIR still is 2.5dB at BER=10^{-2}. With amplitude correction the estimate is nearly perfect. The dotted line shows the performance of the State-of-the-art decoder of [9] which is based on a phase LUT only. This phase LUT is considered to be perfectly known in this simulation. The loss of this decoder compared to the best performance with complex LUT is about 5dB at BER=10^{-2}. Further simulations with critical channels have shown that even for $M = 2$ and $T_{SA} = T_S$ the loss of the performance compared to a perfect complex LUT is $\lesssim 1$dB @ 10^{-3}.

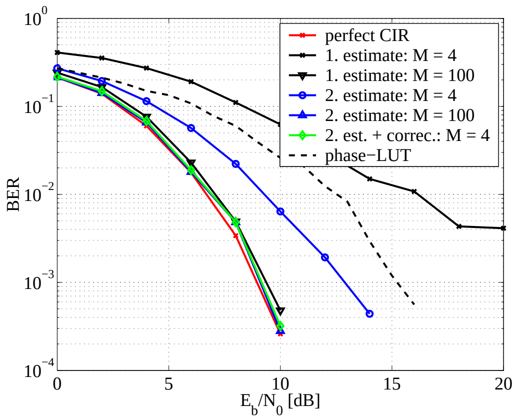


Fig. 11. Bit error ratios, $1 - D$-channel

VI. CONCLUSION

A new method to estimate the complex CIR for a hard limiting receiver structure was proposed. The two level estimation technique is based only on phase samples. Nearly perfect estimates can be achieved with short training sequences that are for example conform with the HIPERLAN I standard. This result makes it possible to combine the nonlinear low cost receiver structure with "linear" equalization technologies like beam forming and ML decoding. So, those receiver structures could become very attractive for high data rate wireless communications.

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