# BLIND GSM CHANNEL ESTIMATION

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**Abstract:** The bandwidth efficiency of many comm. systems could be improved if the transmission channel was estimated *blindly*, i.e. without resort to training sequences. As an example, we investigate in this paper the applicability of two algorithms for the blind identification of mixed-phase linear time-invariant FIR systems to the estimation of mobile radio channels on GSM conditions. Both approaches exploit *Higher Order Statistics (HOS)* of the received signal sampled at symbol rate. Although this class of algorithms is said to require an excessive number of samples to achieve acceptable performance levels, we demonstrate that it *is* possible with the EIGENVECTOR APPROACH TO BLIND IDENTIFICATION (EVI) to blindly estimate realistic COST-207 channels from one GSM burst (142 samples). At a signal-to-noise ratio of 7 dB, all sample channels are identified within a normalized mean square error bound of 5 per cent.

## 1. INTRODUCTION

OPTIMUM receivers in digital communication systems require the knowledge of the transmission channel's equivalent baseband impulse response. As this knowledge is not available in many cases, the problem of *channel estimation* arises. From the point of view of system theory, channel estimation is a particular form of (linear) *system identification* which, in our case, is complicated by two main properties of the multipath radio channel: *(i)* its discrete-time impulse response may be mixed-phase and *(ii)* in a *mobile* environment, it is *time-variant*. As for the latter property, time-variance is relatively slow in many applications so that the channel can be estimated repeatedly in periods of time where it can be assumed time-*in*variant *(piecewise* or *quasi* time-invariant).

According to Figure 1, there are two principal possibilities to identify a mixed-phase linear (quasi) time-invariant system: with or without reference data (training sequences).

As an example for an approach based on training sequences, consider the channel estimation scheme used in state-of-the-art mobile communication systems according to the GSM standard [1]. Information symbols are transmitted in *bursts* where each "normal" burst (see Figure 2) contains two packets of 58 data symbols (bits) surrounding a training sequence of 26 bits.

This research is supported by the German NSF (DFG-contract #Ka 841/2). *Matlab* programs and compressed postscript files of our publications are also available from our WWW server `http://www.comm.uni-bremen.de`.

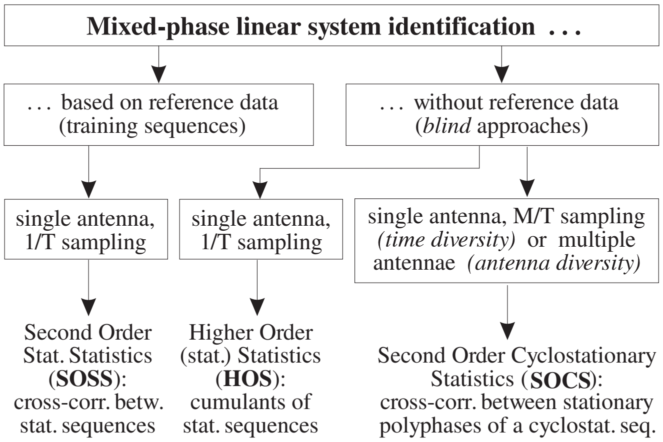


**Figure 1:** The principal ways to identify a mixed-phase linear system

On the assumption of time-invariance over 26 bit periods, linear[1] channel estimates can be derived from the received sequence sampled at symbol-rate by using the cross-correlation between the demodulated (corrupted) and the stored (ideal) training sequences, i.e. from a second order statistical property of (quasi) stationary sequences (refer to the left branch in Fig. 1). However, the repeated transmission of training sequences leaves a GSM system with an overhead capacity of $26/116 = 22.4\%$ which could be used for other purposes such as channel coding (thus enhancing overall GSM system performance) if the channel estimation problem was solved *blindly*.

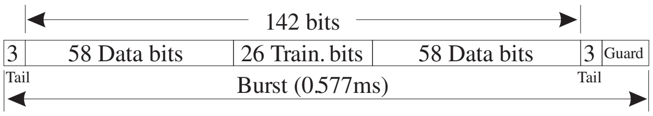


**Figure 2:** GSM "normal" burst

The fundamental idea of *blind* system identification is to derive the channel characteristics from the received signal only, i.e. *without* training sequences. Depending on the different ways to extract information from the received signal, two classes of algorithms can be distinguished:

- **Class HOS** (middle branch in Fig. 1): When the received signal is sampled at symbol rate $1/T$, the resulting sequence is (quasi) stationary. Since second order statistics of a stationary signal are inadequate for the identification of the

[1] Although GSM prescribes *non-linear* GMSK modulation *(Gaussian Min. Shift Keying)*, typical channel estimation schemes assume linearity of the composite channel by using the *Laurent* approximation [2].

complete channel characteristics (including phase information), class HOS methods are based on *Higher Order Statistics*. Higher order *cumulants* contain the complete information on the channel's magnitude and phase provided that the distribution of the channel input signal is non-Gaussian (which is true for applications in digital communications). Excellent overviews on HOS and their applications can be found in [3, 4, 5, 6].

- **Class SOCS** (right branch in Fig. 1): When the sampling period is a fraction of $T$ *(time diversity)*, or alternatively, the symbol-rate sampled signals received by several sensors are interleaved *(antenna diversity)*, the resulting received sequence is (quasi) *cyclostationary*. Generally, *2nd Order Cyclostationary Statistics* (SOCS) are sufficient to retrieve the complete channel characteristics, but there are "singular" channel classes which can *not* be identified this way. They include channels with common subsystems in all polyphase subchannels (refer to [7, 8] for details).

N.B.: Although the GSM channel estimation scheme assumes time-*in*variance of the channel during the transmission of the 26 training bits only, the resulting estimate is used for MLSE *(Max. Likelihood Sequence Estimation)* on the adjacent data fields. As the channel coefficients might already have changed in the data fields, there is an implicit assumption of *quasi time-invariance over one burst* in this non-blind concept. Therefore, blind channel estimation approaches may also suppose this.

With the objective 'blind GSM channel estimation' in mind, the following criteria were used to select appropriate algorithms:

(1) As the eff. channel order is unknown (and just *quasi* time-invariant), an overestimation must not represent a problem.

(2) **Reliable complex channel estimates must be obtained from 142 symbol-rate samples of the received signal.**

(3) This should apply to arbitrary channels (even if there are zeros 'on' or 'close to' the complex plane's unit circle).

(4) The estimates should be as robust as possible with respect to additive Gaussian noise ($S/N$ down to $7 \ldots 10$ dB).

The algorithms we apply in this paper are class HOS methods based on 4th order statistics. SOCS-based schemes were neglected on account of the fact that their performance level is heavily affected by "singular" channels which can not be prevented from occurring in mobile environments [9]. Algorithms based on 3rd order statistics were discarded due to the zero skewness of digital communication signals.

Within the HOS class, two approaches were found to meet criterion (1), and apparently (2) to (4): the W-SLICE (WS) algorithm by Fonollosa and Vidal [10] and the EIGENVECTOR APPROACH TO BLIND IDENTIFICATION (EVI) by Jelonnek, Boss and Kammeyer [11, 12]. While the former is a linear one-step scheme, the latter is a non-linear iterative procedure.

Upon the precise statement of the assumptions and our objective in section 2, we will demonstrate in section 3 how WS and EVI perform on realistic mobile radio channels.

## 2. PROBLEM STATEMENT

Assuming for the moment a motionless scenario, the equivalent baseband representation of the composite channel (physical channel as well as pulse shaping and receive filters) is given by the time-invariant impulse response[2]

$$h_c(\tau) \stackrel{\Delta}{=} c(\tau) * g_{TR}(\tau)\,, \tag{1}$$

where $c(\tau)$ represents the impulse response of the physical multipath radio channel, $g_{TR}(\tau)$ stands for the combined transmit/receive filter impulse response, "$*$" denotes the convolution operator, and the subscript 'c' stands for "continuous-time".

Figure 3 shows an equivalent discrete-time model of a digital communication system. In the transmitter, each symbol period $T$, the independent identically distributed (i.i.d.) random sequence $d(k)$ takes a (possibly complex) value from a finite set[3]. We assume the equivalent symbol-rate impulse response

$$h(k) = h_c(\tau)|_{\tau=kT} \tag{2}$$

of the composite channel to have finite length with $q$ denoting its order. In the sequel, $h(k)$ will simply be termed "channel". The channel output sequence $x(k)$ is corrupted by independent stationary additive Gaussian noise $n(k)$, which has possibly been colored by the receive filter.

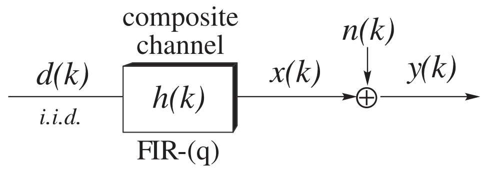


**Figure 3:** Equivalent discrete-time model of a comm. system

In a *mobile* setting, however, the phys. channel is *time-variant*. Thus, its impulse response $c(\cdot)$ [and hence $h_c(\cdot)$] not only depends on the time difference $\tau$ between the observation and excitation instants, but also on the (absolute) observation time $t$. We adopt the stochastic *Gaussian Stationary Uncorrelated Scattering (GSUS)* model for the physical multipath radio channel

$$c(\tau, t) = \frac{1}{\sqrt{N_e}} \sum_{\nu=1}^{N_e} e^{j(2\pi f_{d,\nu} t + \Theta_\nu)} \cdot \delta(\tau - \tau_\nu)\,, \tag{3}$$

where the $\nu$-th elementary echo path is characterized by a Doppler frequency $f_{d,\nu}$, an initial phase $\Theta_\nu$, and an echo delay time $\tau_\nu$. For *slow* time-variance, the composite channel's equivalent baseband impulse response can be approximated by [13]

$$\begin{aligned} h_c(\tau, t) &\approx c(\tau, t) * g_{TR}(\tau) \\ &= \frac{1}{\sqrt{N_e}} \sum_{\nu=1}^{N_e} e^{j(2\pi f_{d,\nu} t + \Theta_\nu)} \cdot g_{TR}(\tau - \tau_\nu)\,. \end{aligned} \tag{4}$$

Sample channel impulse responses can be calculated from (4) by independently drawing *(i)* $N_e$ Doppler frequencies $f_{d,\nu}$ from

[2]Just as typical GSM receivers, we assume a *linear* composite channel.
[3]For notational simplicity, we assume zero mean processes.

a random variable with Jakes probability density function (pdf), *(ii)* $N_e$ initial phases $\Theta_\nu$ from a uniformly distributed random variable in $[0, 2\pi)$, and *(iii)* $N_e$ echo delay times $\tau_\nu$ from a random variable with a pdf proportional to the mean power delay spectrum of a propagation environment such as those defined by COST-207[4], for instance: *Typical Urban (TU)*, *Bad Urban (BU)*, *Hilly Terrain (HT) ...*

Fig. 4 shows a (non-causal) sample magnitude impulse response $|h_c(\tau, t)|$, obtained from (4) with $N_e = 100$, of a *Bad Urban* channel with raised cosine transmit and receive filters ($r = 0.5$). Both time axes are normalized to the GSM symbol (bit) period $T \approx 3.7\,\mu$s. The velocity of the mobile unit is $v = 100\,\mathrm{km/h}$. Assuming a carrier frequency of 950 MHz, this leads to a max. Doppler shift of $f_{d,max} = 88$ Hz. Equation (4) was evaluated over a $t$ range covering one minimum Doppler period $T_{d,min} = 1/f_{d,max} = 3080T = 11.4\,\mathrm{ms}$.

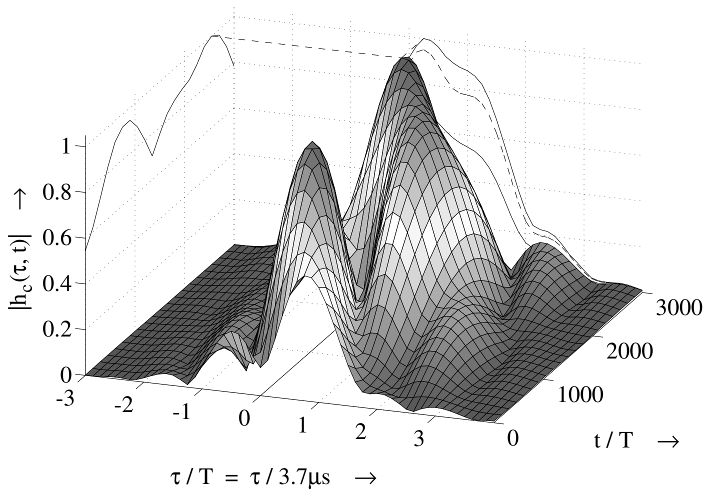


**Figure 4:** Impulse response of a *Bad Urban* channel

Assuming *quasi time-invariance over one burst*, $h_c(\tau, t)$ is sampled on the $t$ axis each 150 symbols (c.f. Fig. 2). This produces 21 slices within the $t$ range of $3080T$, which can be seen in Fig. 4 as surface lines parallel to the $\tau$ axis. Each slice is sampled at $\tau = kT$ and then constrained to the range $\mathcal{I}$ of adjacent indices $k$ where the associated sample power delay spectrum exceeds the threshold of 1% of its peak value.

$$h(k, \xi) \triangleq h_c(\tau, t) \;\; \text{for} \;\; \begin{cases} \tau = kT & \text{with } k \in \mathcal{I} \\ t = \xi\, 150T & \text{with } \xi = 0, \cdots, 20. \end{cases} \qquad (5)$$

**Objective:** Refer to Figure 3 with $h(k, \xi)$ from (5) substituted for $h(k)$. Given solely $L$ samples of $y(k)$, estimate the channel slices $h(k, \xi)$ for $\xi = 0, \cdots, 20$.

As channel estimation is our primary concern in this paper and both the blind and the non-blind schemes under investigation assume the composite channel to be *linear*, we use linear modulation for the simulation results we present in the following section in order to avoid systematic errors in the channel estimates. However, as linearity is also assumed in typical GSM receivers, the results for GMSK are not expected to change much.

[4]Cooperation in the field of Scientific and Technical research.

## 3. SIMULATION RESULTS

On the assumptions[5] stated in section 2, nine different sample GSUS composite channels $h_c(\tau, t)$ were obtained from (4) by combining three COST-207 propagation environments *(TU, BU, HT)* with three raised cosine transmit/receive filters: roll-off factors $r \in \{0.9, 0.5, 0.1\}$. Let *"BU–(0.5)"* denote the *Bad Urban* channel with roll-off factor $r = 0.5$, e.g.. According to (5), each channel $h_c(\tau, t)$ was decomposed into 21 slices $h(k, \xi)$. Referring to Fig. 3 with $h(k, \xi)$ substituted for $h(k)$, a burst of 150 i.i.d. *BASK (Binary Amplitude Shift Keying)* symbols $d(k)$ was propagated through each channel slice. Each resulting sequence $x(k)$ was limited to a block of $L = 142$ steady state samples. Finally, independent stationary additive white Gaussian noise (AWGN) $n(k)$ was added according to a given signal-to-noise ratio $S/N$ to obtain $L$ samples of $y(k)$.

Then, WS and EVI were applied to $y(k)$. In either case, $L = 142$ samples of $y(k)$ were taken into account for the estimation of the required cumulant and correlation sequences by unbiased sample averaging. Both algorithms were given the effective length of the sample power delay spectrum (ranging from $3T$ to $5T$ for a relative threshold of 1%) as the expected channel length $\hat{q} + 1$. Note that the actual effective length of a channel slice may well be shorter due to time selective fading. With WS, the complete set of 4th order (auto)cumulants was exploited while EVI uses both 4th order (cross)cumulants and autocorrelation estimates. EVI did not attempt to compensate for the noise influence by subtracting the noise correlation sequence.

**Estimation quality measure:** Let $\hat{h}^{(1)}(k, \xi)$ denote the estimate of $h(k, \xi)$ based on a given input burst. In the frame of Monte-Carlo simulations, a total of $\mathrm{MC} = 100$ different BASK bursts was propagated through each channel slice to obtain MC estimates $\hat{h}^{(\gamma)}(k, \xi)$, $\gamma = 1, \cdots, \mathrm{MC}$. For each slice index $\xi$, estimation quality was assessed on the basis of the averaged *Normalized Mean Square Error (NMSE)*[6]

$$\mathrm{NMSE}(\xi) \;\triangleq\; \frac{1}{\mathrm{MC}} \sum_{\gamma=1}^{\mathrm{MC}} \frac{\sum_k |\hat{h}^{(\gamma)}(k, \xi) - h(k, \xi)|^2}{\sum_k |h(k, \xi)|^2} \,. \qquad (6)$$

**Figure 5:** From the set of nine sample channels described above, we have selected six examples by combining the propagation environments *TU*, *BU* and *HT* with the roll-off factors $r = 0.5$ (Fig. a to c) and $0.1$ (Fig. d to f). For each channel, Figure 5 shows the $\mathrm{NMSE}(\xi)$-values (in per cent) of WS' and EVI's estimates for different values of $S/N$, where the noiseless case is marked by "$\circ$" symbols, while "$\times$" and "$+$" stand for $S/N =$ 10 dB and 7 dB, respectively. The $\mathrm{NMSE}(\xi)$-values for WS are connected by dotted lines, those for EVI by solid lines. Note the different scaling on the $\mathrm{NMSE}(\xi)$ axes of Figure 5.

From Fig. 5a and d, we realize that EVI can estimate the *TU* channels very well, even at $S/N = 7$ dB ("$+$"): the $\mathrm{NMSE}(\xi)$ values are below 3% for most slices. Conversely, assuming an

[5]$N_e = 100$, $T = 3.7\,\mu$s, $f_{d,max} = 88$ Hz, $t/T = 0, \cdots, 3080$.

[6]As blind system identification methods can *not* identify one complex factor, each estimate was multiplied with the optimum complex constant (minimizing the Euclidean distance from the true channel slice) before (6) was calculated.

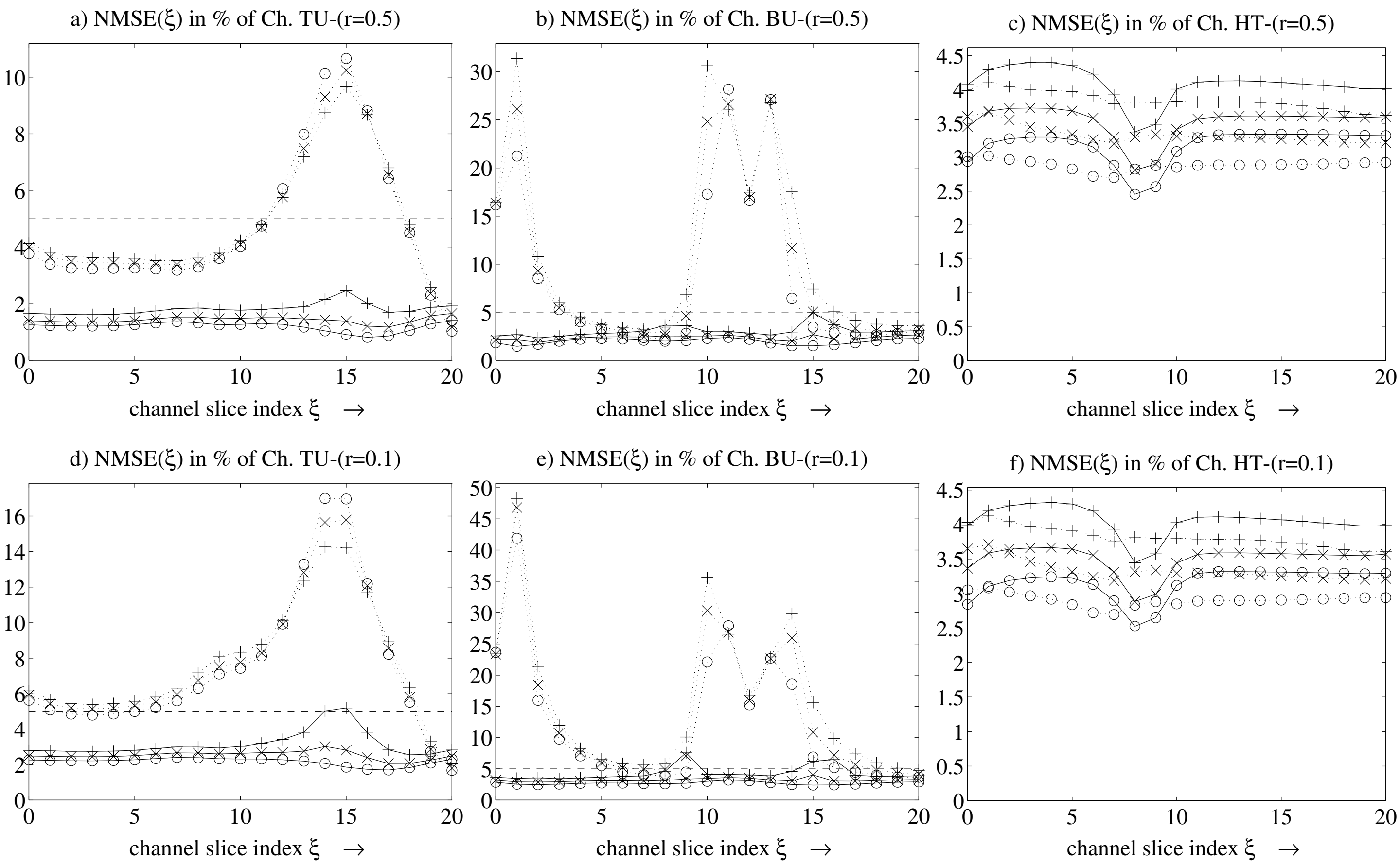


**Figure 5:** $\mathrm{NMSE}(\xi)$ [in per cent] of WS (dotted) and EVI (solid) from $L = 142$ samples: "∘": $S/N = \infty$, "×": 10 dB, "+": 7 dB;
a, d) *Typical Urban (TU)*, b, e): *Bad Urban (BU)*, c, f): *Hilly Terrain (HT)*;
a, b, c): Roll-off factor $r = 0.5$, d, e, f): roll-off factor $r = 0.1$

acceptance threshold value of 5% (dashed lines), WS can *not* identify slices $\xi = 12$ to 17 of channel *TU-(0.5)* (Fig. a) and all but the last two slices of *TU-(0.1)* (Fig. d). Apart from the last slice ($\xi = 20$), EVI largely outperforms WS at any given $S/N$.

Comparable statements can be made for the *BU* channels in Fig. 5b and e (note that the channel used for Fig. 5b was shown in Fig. 4): although there are channel slices, where WS and EVI perform almost equally well ($\xi = 6$ to 8 and 18 to 20), there is a huge performance gap for other channel slices ($\xi = 0$ to 2 and 10 to 14). For all slices of *BU-(0.5)* and 18 out of 21 slices of *BU-(0.1)*, EVI's $\mathrm{NMSE}(\xi)$-values remain below 5%, while this is true for WS' estimates for 10 (*BU-(0.5)*) and 2 (*BU-(0.1)*) slices, only. Again, for all slices and $S/N$ ratios, EVI's performance is superior to that of WS.

In case of the *HT* channels, we can see from Fig. 5c and f that both approaches successfully identify all slices: all $\mathrm{NMSE}(\xi)$-values are around 3% in the noiseless case and 4% at 7 dB. It should be noted that these two sample *HT* channels are uncritical because the zeros of $\mathcal{Z}\{h(k,\xi)\}$ do not approach the unit circle of the complex plane too closely. Besides, Fig. 5c and f are almost identical. We attribute this to the fact that, as opposed to the *TU* and *BU* channels, the length of the *HT* channel did not increase when the roll-off factor $r$ was reduced to 0.1.

**Table 1** summarizes the $\overline{\mathrm{NMSE}}$-values for the entire set of sample channels, where those exceeding 5% are marked in boldface. The first value in each column refers to WS, while the second

| S/N | *TU-(0.9):* 3 | *TU-(0.5):* 3 | *TU-(0.1):* 4 |
|---|---|---|---|
| ∞ dB | 2.9 / 1.2 | 4.8 / 1.2 | **7.5** / 2.2 |
| 10 dB | 3.0 / 1.4 | 4.8 / 1.4 | **7.6** / 2.5 |
| 7 dB | 3.1 / 1.8 | 4.8 / 1.8 | **7.7** / 3.2 |
| **S/N** | ***BU-(0.9):*** 3 | ***BU-(0.5):*** 4 | ***BU-(0.1):*** 5 |
| ∞ dB | **7.1** / 1.2 | **8.6** / 2.0 | **12.2** / 2.7 |
| 10 dB | **8.3** / 1.5 | **9.9** / 2.3 | **14.0** / 3.2 |
| 7 dB | **9.5** / 2.0 | **11.2** / 3.0 | **15.6** / 4.3 |
| **S/N** | ***HT-(0.9):*** 5 | ***HT-(0.5):*** 5 | ***HT-(0.1):*** 5 |
| ∞ dB | 2.9 / 3.2 | 2.9 / 3.2 | 2.9 / 3.2 |
| 10 dB | 3.3 / 3.5 | 3.3 / 3.5 | 3.3 / 3.5 |
| 7 dB | 3.8 / 4.1 | 3.8 / 4.1 | 3.8 / 4.1 |

**Table 1:** $\overline{\mathrm{NMSE}}$ [in per cent] for WS's and EVI's estimates of *TU* (above), *BU* and *HT* (below) channels

number applies to EVI. We realize that WS can not identify satisfactorily the *BU* channels as well as *TU-(0.1)*. On the other hand, EVI is capable of estimating all channel examples from

142 samples at $S/N$ ratios down to 7 dB (10 dB) to within an outstanding $\overline{\mathrm{NMSE}}$ bound of 4.3% (3.5%).
Finally, from the numbers of channel coefficients (which are given in Table 1 after the channel indications), we realize that channels with a short impulse response (resulting from a propagation environment with a small delay spread and/or transmit/receive filters with a high roll-off factor) are less critical and therefore allow for superior estimation qualities.

It should be noted that EVI's estimates of critical channels (those with zeros 'on' or 'close to' the complex plane's unit circle) can be improved by adjusting EVI's parameters: in the initial equalization step, the equalizer order and/or the number of iterations could be increased. As for WS, second order statistics could be used in addition to cumulants in order to improve performance. However, this evokes the problem of how to weight correlation estimates against cumulants. Furthermore, for low $S/N$ ratios, the estimates will be biased.

## 4. CONCLUSIONS AND FURTHER WORK

We have demonstrated in this paper that it *is* possible with an algorithm exploiting HOS (EVI) to blindly estimate (within an $\overline{\mathrm{NMSE}}$-bound of about 4%) realistic mobile radio channels from 142 received samples at $S/N$ levels of 10 dB. Even at 7 dB, the considered channel examples can be identified to within 5%. Note that these values are remarkably low. To the knowledge of the authors, no other HOS-based algorithm is capable of achieving the cited $\overline{\mathrm{NMSE}}$ levels on the assumptions made in this paper. Furthermore, we have shown that the WS algorithm's performance level heavily depends on the actual channel impulse response. This behavior still needs to be explained.

While this paper concentrated on the quality of blind channel estimates in terms of their NMSE, further work will be directed towards a comparison of the post-MLSE *bit error rates (BER)* attainable from blind and non-blind channel estimates. First simulation results based on GMSK modulation were obtained recently [14, 15]. The decisive question is whether BER is lower *(i)* if non-blind estimates of the mean channel coefficients (averaged over 26 bit periods) are applied to MLSE of 116 data bits, or *(ii)* if blind estimates of the mean channel coefficients (averaged over $142T$) are utilized for the whole sequence of 142 data bits. The answer to this question will depend on the maximum Doppler frequency and remains to be found.

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