SINGLE-ANTENNA CO-CHANNEL INTERFERENCE CANCELLATION FOR TDMA CELLULAR RADIO SYSTEMS

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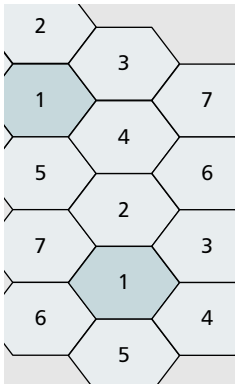

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ABSTRACT

Co-channel interference cancellation is particularly challenging in the downlink of cellular radio systems, because usually only one receive antenna is available at the mobile terminal. This tutorial provides an overview of promising single-antenna co-channel interference cancellation techniques. Focus is on the downlink of time-division multiple access systems. The results may, however, be extended to related applications, including interference suppression in multiple-input multiple-output systems.

INTRODUCTION

Large areas with a high user density cannot be served by just one base station. This problem can be solved by the well-known principle of cellularization:

- The service area is divided into cells.
- Resources are repeated in remote cells.

Figure 1 features a cellular network with two different cluster sizes. On the left side, the reuse factor is seven; that is, seven different channels (e.g., carrier frequencies in time/frequency-division multiple access, TDMA/FDMA, networks) have to be provided. On the right side, the reuse factor is three (i.e., the resources can be reused more than twice as often). Hence, the network capacity increases by decreasing the reuse factor. The drawback of decreasing reuse factor, however, is an increasing amount of interference from neighboring cells operating on the same channel (e.g., using the same carrier frequency). This type of interference is called co-channel interference (CCI). CCI can seriously impact performance, resulting in poor speech quality, lower data rates, dropouts, and even complete loss of voice calls. Due to channel reuse in neighboring cells, CCI is unavoidable. Techniques for reducing the performance degradation due to CCI include discontinuous transmission, dynamic power control, frequency hopping, dynamic channel allocation, adaptive multirate (AMR) speech transcoding, as well as CCI cancellation/suppression/reduction techniques:

- *Discontinuous transmission*: In discontinuous transmission, transmission is suspended when users are silent during voice calls.
- *Dynamic power control*: By continuously adjusting transmission power levels of mobile phones, interference is reduced.
- *Frequency hopping*: By changing the carrier frequency from burst to burst, frequencies can be reused more often in adjacent cells or cell sectors.
- *Dynamic channel allocation*: In dynamic channel allocation, resources (e.g., time slots and frequencies) are distributed dynamically.
- *Adaptive multirate speech transcoding*: By dynamically splitting the gross bit rates between speech and channel coding according to channel quality, almost wireline speech quality even for relatively poor radio conditions can be obtained. For good conditions, a higher speech quality can be achieved.
- *Co-channel interference cancellation*: By means of CCI cancellation techniques, CCI is removed from the desired signal. CCI cancellation techniques are implemented in the receiver without requirements to change the standard.

Current TDMA networks — Global System for Mobile Communications/General Packet Radio Service/Enhanced Data Rates for GSM Evolution (GSM/GPRS/EDGE), IS-54/IS-136, and Personal Digital Cellular (PDC) — are *interference-limited rather than noise-limited*, particularly in urban environments and hot spots like train stations and airports. Due to a growing number of users and high-rate applications, the demand for capacity is steadily increasing. As resources for wireless communications, the available frequency bands are limited and precious. Moreover, an allocation of new frequency bands is very complicated and associated with high costs. Although the efficient network capacity of existing TDMA networks can be improved by any of the

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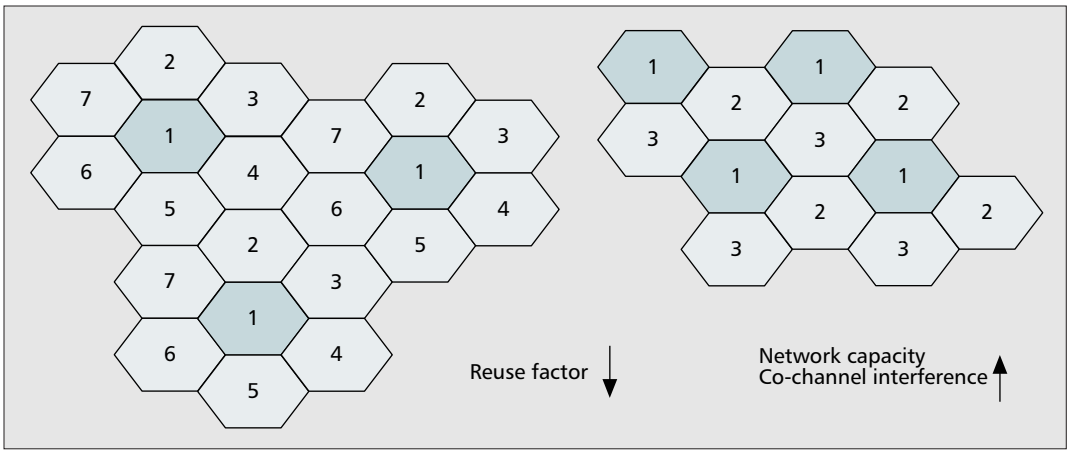


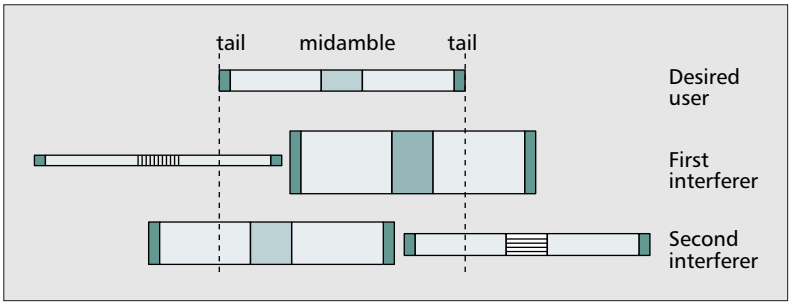
■ **Figure 1**. *A cellular network with different cluster sizes. Co-channel interference arises from neighboring cells operating at the same carrier frequency.*

techniques mentioned above, CCI remains the limiting factor for network capacity unless CCI cancellation is done.

CCI cancellation is particularly challenging in the downlink, where usually (due to cost, volume, power consumption, and design reasons) only one receive antenna is available. Corresponding techniques are called *single-antenna* (*co-channel*) *interference cancellation* (SAIC) techniques. An uncoded TDMA system in conjunction with a reuse factor of one can be interpreted as a narrowband code-division multiple access (CDMA) system without spreading. This analogy illustrates the difficulty in suppressing CCI, particularly if only one receive antenna is available.

For more than two years, the Third Generation Partnership Project, Technical Specification Group, GSM/EDGE Radio Access Network (3GPP TSG GERAN) has carried out a feasibility study on SAIC for GSM networks (Release 6) [1], aimed at reducing the reuse factor of GSM/GPRS/EDGE networks. A *reuse factor of one* is under discussion, in conjunction with a fractional load as high as possible. United States network operators suggest a fractional load of up to 70 percent (i.e., up to 70 percent of the time slots shall be occupied at the same time). In such a scenario, CCI and adjacent channel interference will be severe. As a consequence, the next GERAN release will be extended with respect to interference requirements, and interference cancellation will become necessary. Since November 2003, a new work item, Downlink Advanced Receiver Performance (DARP), has been set up within 3GPP TSG GERAN to specify the (tightened) performance requirements for mobile terminals from Release 6 onward. In field trails, significant gains due to interference cancellation have already been demonstrated [2].

The outline of the remainder of this article is as follows. An overview of CCI cancellation techniques suitable for TDMA systems is introduced next. Then the channel model under consideration is presented. Subsequently, decoupled linear CCI cancellation/nonlinear equalization is studied, representing a powerful receiver technique among the class of filter-based approaches. Afterward, joint multi-user detection is investigated, as it represents a high-performance multi-user detection technique. Both receivers are compatible with state-of-the-art TDMA receivers, which is an important aspect from an implementation point of view. Also of essential importance is channel estimation, which is more demanding than in single-user receivers, particularly in asynchronous networks. Finally, numerical results are presented before conclusions are drawn.



■ **Figure 2**. *An illustration of asynchronous bursts in the presence of frequency hopping.*

An Overview of CCI Cancellation Techniques for TDMA Systems

SAIC techniques should be applicable in asynchronous networks (Fig. 2) as well as in synchronous networks, as in novel networks the base stations are likely to be synchronized. Another challenge is frequency hopping. Due to frequency hopping, physical layer signal processing has to be done on a burst-by-burst basis, which prohibits excessive averaging. Last but not least, modeling errors have to be taken into account. For example, EDGE interference may occur in a GSM network and vice versa. Under any condition, the performance with SAIC should not be worse than that of a conventional receiver.

Co-channel interference cancellation techniques can be classified into filter-based approaches and multi-user detection techniques:

Compared to filter-based approaches, multiuser-based techniques are, generally speaking, more sensitive with respect to model errors. This implies that in the case of multiuser detection much attention should be paid to channel estimation.

- *Filter-based approaches* include the following methods:
- –Linear CCI and intersymbol interference (ISI) cancellation
  –Decoupled linear CCI cancellation/nonlinear equalization
  –Predictive CCI cancellation in conjunction with auto-regressive interference modeling
- *Multi-user detection techniques* include the following methods:
  –Joint multi-user detection
  • Full-state trellis-based detection
  • Reduced-state trellis-based detection
  • Sequential detection
  –Successive CCI cancellation
  –Parallel CCI cancellation

Perhaps the most simple filter-based approach is a *linear filter*, the coefficients of which are designed so that CCI and ISI are mitigated jointly (see, e.g., [3]). In the context of SAIC, linear CCI cancellation is capable of cancelling a single interferer if and only if the data sequences are real valued, that is, the modulation scheme is one-dimensional (e.g., Gaussian minimum shift keying in GSM). When the desired signal occupies two dimensions (real/imaginary) per transmitted symbol (e.g. 8-ary phase shift keying, 8-PSK in EDGE), linear single-antenna CCI cancellation is not applicable because we run out of dimensions for interference suppression. Given baud rate sampling, only a single complex-valued data stream (as in EDGE) or two real-valued data streams (as in GSM) can be resolved per receive antenna. Since the excess bandwidth in GSM and EDGE is approximately zero, oversampling does not allow resolving more data streams. Any performance improvement observed with oversampling is due to the use of finite filter lengths.

In *decoupled linear CCI cancellation/nonlinear equalization*, the tasks of CCI suppression and ISI cancellation are done separately [4–6]. This imposes fewer constraints on the linear filter. Besides CCI suppression, the linear filter may be designed to shorten the overall impulse response seen by the cascaded nonlinear equalizer. The overall receiver is nonlinear and more powerful than a linear receiver. This type of receiver structure has attracted much attention over the past few years.

In *predictive CCI cancellation in conjunction with auto-regressive interference modeling*, the interference plus noise process is modeled by an auto-regressive model. The corresponding receiver is matched to this auto-regressive model in a clever way [7]. In SAIC, decoupled linear CCI cancellation/nonlinear equalization outperforms predictive CCI cancellation in conjunction with auto-regressive interference modeling, due to the inherent model mismatch in the latter approach.

Multi-user detection algorithms are different from filter-based approaches in the sense that the signals of all cochannels are estimated explicitly. Either the data of the co-channels can be estimated jointly, or the interference is subtracted off the received signal in either a sequential or parallel fashion.

The computational complexity of an optimal *joint multi-user detection* [8–10] is prohibitive, however, because it exponentially increases with the number of co-channels. An alternative to full-state trellis-based detection is reduced-state trellis-based joint detection [11–13] and sequential detection, respectively. These algorithms offer an adjustable performance/complexity trade-off. Particularly with reduced-state trellis-based detection, we obtained excellent results from a performance/complexity point of view.

In *successive CCI cancellation*, the interference is subtracted off the received signal sequentially, starting with the strongest interferer [14]. An alternative is *parallel CCI cancellation*, where interference is subtracted off in parallel.

Compared to filter-based approaches, multi-user-based techniques are, generally speaking, more sensitive with respect to model errors. This implies that in multi-user detection much attention should be paid to channel estimation. In effect, channel estimation appears to be the bottleneck, particularly in asynchronous networks with frequency hopping (Fig. 2).

The Channel Model

Throughout this article the complex baseband notation is used. Vectors are regarded as column vectors and are written in lower case boldface. For matrices upper case boldface is used. The transpose, complex conjugate transpose, and expected value are denoted $(.)^T$, $(.)^H$, and $E\{.\}$, respectively. Estimates and hypotheses are identified by $\hat{(.)}$ and $\tilde{(.)}$, respectively.

In the presence of CCI with J interferers, the equivalent discrete-time channel model can be written as

$$y[k] = \sum_{j=0}^{J} \sum_{l=0}^{L} h_{j,l}[k] a_j[k-l] + n[k], \quad 0 \le k \le K-1, \tag{1}$$

where $y[k]$ is the kth baud rate output sample of the analog receive filter, L is the effective memory length of the discrete-time channel model, $\mathbf{h}_j[k] := [h_{j,0}[k], \ldots, h_{j,L}[k]]^T$ are the channel coefficients of the jth co-channel, $0 \le j \le J$, $a_j[k]$ is the kth data symbol of the jth co-channel randomly drawn from an M-ary alphabet, $n[k]$ is the kth sample of a Gaussian noise process, k is the time index, and K is the number of M-ary data symbols per burst. All random processes are assumed to be mutually independent. Without loss of generality, index $j = 0$ refers to the desired user and indices $1 \ldots J$ refer to the J interferers. The channel coefficients $\mathbf{h}_j[k]$ comprise pulse shaping, the respective physical channel, analog receive filtering, sampling phase, and sampling rate. The signal-to-interference power ratio is defined as $C/I := E\{||\mathbf{h}_0[k]||^2\}/\Sigma_{j=1}^{J} E\{||\mathbf{h}_j[k]||^2\}$. In case of square-root Nyquist receive filtering and baud rate sampling, the Gaussian noise process is white. In case of N-times oversampling, where N is an integer, any of the N polyphase channels can be represented by Eq. 1. The equivalent discrete-time channel model is suitable for both synchronous as well as asynchronous TDMA networks.

Decoupled Linear CCI Cancellation/Nonlinear Equalization

A decoupled linear filter/nonlinear equalizer (Fig. 3) performs two tasks:

- CCI reduction by means of a linear filter
- ISI reduction by means of a nonlinear equalizer

According to the equivalent discrete-time channel model of Eq. 1, the received signal can be split into a desired user term, an other users' term representing CCI, and a noise term. The linear filter suppresses only the other users' term. The remaining ISI of the desired user is canceled by the nonlinear equalizer. This receiver structure is compatible with state-of-the-art TDMA receivers, where just the linear filter (called a prefilter) is missing

In the following, a finite impulse response (FIR) filter $\mathbf{w}$ is considered. The optimum filter coefficients in the sense of maximizing the signal-to-interference-plus-noise ratio (SINR) can be obtained as

$$\mathbf{w}^H = \mathbf{r}_{ya_0}^H[\mathbf{R}_{yy} - \mathbf{R}_{ya_0}^H\mathbf{R}_{ya_0}]^{-1}, \qquad (2)$$

if the data symbols are independent and identically distributed (i.i.d.). In Eq. 2, $\mathbf{R}_{yy} = E\{\mathbf{y}\mathbf{y}^H\}$ is the autocorrelation matrix of the received samples, $\mathbf{R}_{ya_0} := E\{\mathbf{a}_0\,\mathbf{y}^H\}$ is the cross-correlation matrix between the received samples and the data sequence of the desired user, $\mathbf{T}_{ya_0} := E\{a_0^*[k-k_0]\mathbf{y}\}$ is a cross-correlation vector; k_0 is the decision delay of the prefilter $\mathbf{w}$. The prefilter coefficients are either symbol-spaced or fractionally spaced, depending on whether oversampling is applied or not. In case of one-dimensional modulation schemes (such as binary phase shift keying, linearized Gaussian minimum shift keying, or M-ary amplitude shift keying), performance can be boosted by means of real-valued processing [15]. As opposed to alternative solutions available in the literature derived for the same optimization criterion, no eigenvalue problem has to be solved in Eq. 2 in order to compute the prefilter coefficients. This significantly simplifies the computational complexity.

In order to compute the prefilter coefficients, $\mathbf{R}_{yy}$, $\mathbf{R}_{ya_0}$, and $\mathbf{r}_{ya_0}$ have to be estimated. Toward this end, conventionally the expected values $E\{.\}$ are replaced by mean values. Due to the finite length of the training sequence of the desired user, the estimation is poor. As an alternative, channel estimates may be used in order to compute the prefilter coefficients, since for i.i.d. data $\mathbf{R}_{yy}$, $\mathbf{R}_{ya_0}$, and $\mathbf{r}_{ya_0}$ only depend on the channel coefficients and the variance of the Gaussian noise term. If reliable channel estimates are available, the estimation is usually better than in the conventional approach. The following cases can be distinguished:

- Case A: Channel estimates are available for the desired user and the interferer(s).
- Case B: Channel estimates are available only for the desired user.
- Case C: Channel estimates are not available at all (conventional approach).

All three cases are considered in the numerical results shown below. Since the prefilter mitigates the CCI, the cascaded nonlinear equalizer has to be matched to the ISI channel of the desired user (modified by the linear CCI canceler) only. Trellis-based, tree-based, and graph-based equalizers are suitable, preferably delivering reliability information in conjunction with the detected data symbols. As mentioned earlier, only one complex-valued data stream or two real-valued data streams can be resolved per receive antenna by means of a linear filter. This motivates us to investigate the more complex trellis-based approaches studied next.

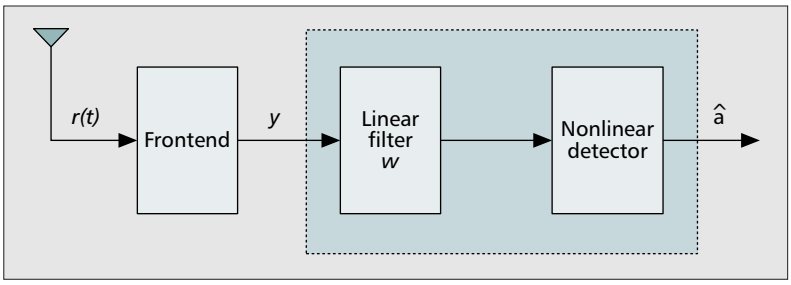


Figure 3. *A block diagram of decoupled linear CCI cancellation/nonlinear detection.*

Joint Multi-User Detection

Given perfect knowledge of the channel coefficients of all co-channels, the optimal receiver in terms of maximum likelihood sequence estimation is the joint maximum-likelihood sequence estimator (JMLSE). The JMLSE is based on the equivalent discrete-time channel model (Eq. 1. The data symbols of all co-channels are estimated jointly. For white Gaussian noise, the JMLSE selects the $J+1$ data sequences that minimize the squared Euclidean distance between the noisy observations and all possible hypotheses of the noiseless received sequence. In this case, the JMLSE can formally be written as

$$(\hat{\mathbf{a}}_0,\ldots,\hat{\mathbf{a}}_J) = \arg\min_{\tilde{\mathbf{a}}_0,\ldots,\tilde{\mathbf{a}}_J} \underbrace{\sum_{k=0}^{K-1}\underbrace{\left|y[k]-\sum_{j=0}^{J}\sum_{l=0}^{L}h_{j,l}[k]\tilde{a}_j[k-l]\right|^2}_{\text{branch metric}}}_{\text{path metric}}, \qquad (3)$$

where $\mathbf{a}_j := [a_j[0],\ldots,a_j[K-1]]$.

The term *branch metric* is the squared Euclidean distance between the kth noisy observation and all possible hypotheses of the kth noiseless received sample. By comparing Eqs. 1 and 3 it is easy to see that only the noise term remains if the symbol hypotheses $\tilde{a}_j[k-l]$ and the actually transmitted data symbols $a_j[k-l]$ are identical. For each time index k, $M^{(J+1)(L+1)}$ possible hypotheses exist according to Eq. 3. The number of hypotheses depends on the effective memory length of the equivalent discrete-time channel model, L, the number of interferers, J, and the cardinality of the symbol alphabet, M. Note that the cardinality of the symbol space is $M = 2$ for GSM/GPRS, $M = 4$ for IS-54/IS-136, and $M = 8$ for EDGE. The effective memory length for these systems is about $L = 2 \ldots 7$, depending on the morphology of the environment. In Fig. 4, all $M^{(J+1)(L+1)}$ possible hypotheses that affect the J

The JDDFSE is a simplification of a JMLSE; the performance loss is small if the past decisions are reliable or if the channel coefficients occurring in the second part of the branch metric tend to be small.

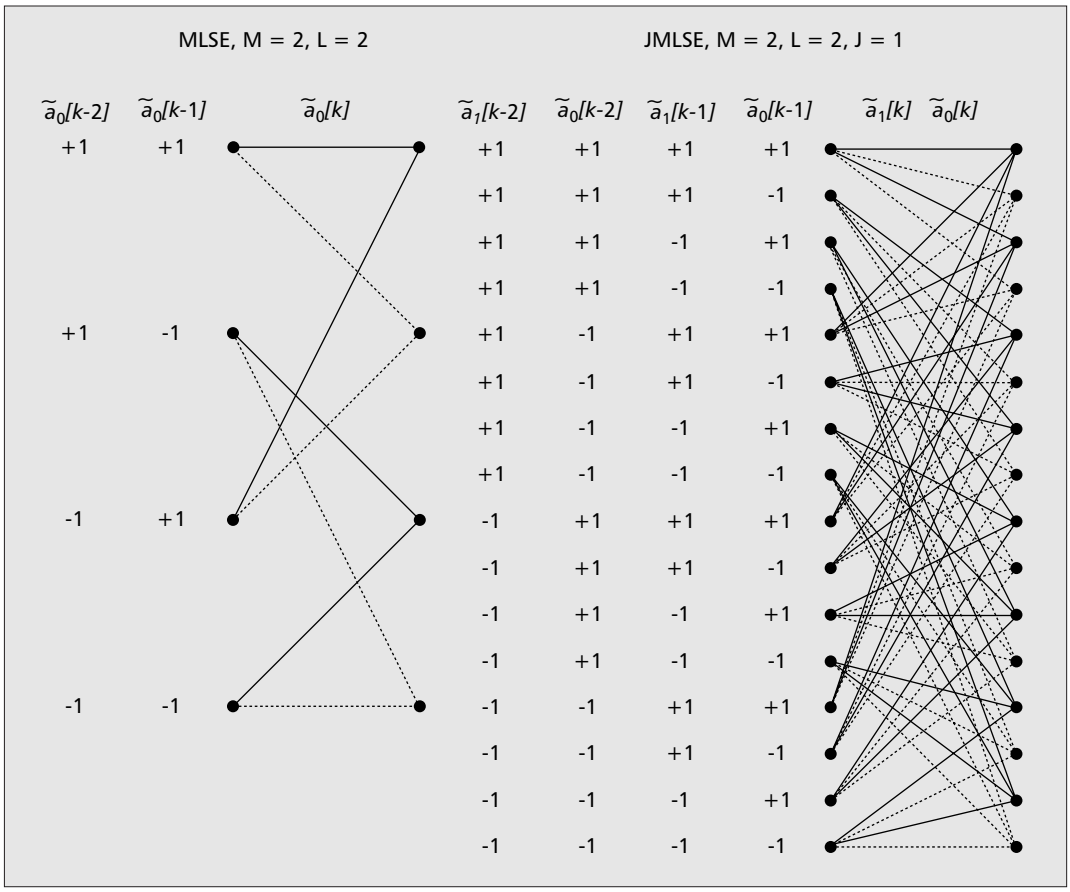


Figure 4. *Trellis segment for MLSE and JMLSE.*

+1 data symbols at time index k are plotted in the form of a trellis segment. The trellis segment consists of $M^{(J+1)L}$ states, which represent the symbol history due to the channel memory, and $M(J+1)$ branches per state, which represent the current symbol hypotheses. Each branch (also called transition or edge) is associated with the branch metric according to Eq. 3. For illustrative reasons, in Fig. 4 the simple case of binary antipodal modulation ($M = 2$), an effective memory length of $L = 2$, and one interferer ($J = 1$) is considered on the right side. For comparison, the case without interference is plotted on the left side. Even in this simple case it is obvious that the complexity explodes in the presence of one or more interferers.

By concatenating K trellis segments (i.e., one segment per time index k), a trellis diagram is obtained. A consecutive sequence of branches is called a path. Each path is associated with the corresponding accumulated branch metrics, called *path metric* in Eq. 3. The maximum likelihood path is the path with the smallest metric. This path is finally selected. Finding the best path is related to the well-known traveling salesman problem. Even though a recursive computation can be done by means of the Viterbi algorithm and related techniques, the computational complexity is usually prohibitive with one or more interferers ($J \geq 1$), even for binary systems ($M = 2$).

This problem can be solved by reducing the number of hypotheses taken into account, for example, by means of *joint reduced-state sequence estimation* (JRSSE). A special case of JRSSE is *joint delayed-decision feedback sequence estimation* (JDDFSE). JDDFSE is obtained from JMLSE by applying the principle of parallel decision feedback [16] in order to reduce the computational effort. JDDFSE can be written as [13]

$$(\hat{\mathbf{a}}_0,\ldots,\hat{\mathbf{a}}_J) = \arg\min_{\tilde{\mathbf{a}}_0,\ldots\tilde{\mathbf{a}}_J} \underbrace{\sum_{k=0}^{K-1} \underbrace{\left| y[k] - \sum_{j=0}^{J}\sum_{l=0}^{\ell_j} h_{j,l}[k]\tilde{a}_j[k-l] - \sum_{j=0}^{J}\sum_{l=\ell_j+1}^{L} h_{j,l}[k]\hat{a}_j[k-l] \right|^2}_{\text{branch metric}}}_{\text{path metric}} . \quad (4)$$

The key idea is to define adjustable design parameters ℓ_j, $0 \leq j \leq J$, where $0 \leq \ell_j \leq L$. The first part of the branch metric is similar to the branch metric of JMLSE (Eq. 3) except that fewer terms are considered. As a consequence, for each data symbol according to Eq. 4 only $\Pi_{j=0}^{J} M^{(\ell_j+1)}$ instead of $\Pi_{j=0}^{J} M^{(L+1)}$ hypotheses are taken into account. Note that the number of hypotheses only depends on the design parameters, ℓ_j, the number of interferers, J, and the cardinality of the symbol alphabet, M, but not on the effective memory length of the equivalent discrete-time channel model, L. In the second part of the branch metric, the remaining (past)

data symbols are considered. The important difference between the first and second parts of the branch metric is as follows. In the first part, all possible hypotheses (denoted $\tilde{a}_j[k]$) are tested. Processing can be done along the same lines as for JMLSE, with a reduced number of states. In the second part, tentative decisions are used (denoted $\hat{a}_j[k]$), since the second part represents past symbols. The second part is related to the feedback filter of a decision feedback equalizer. Only this part of the branch metric is subject to error propagation. The path metrics can be computed recursively (e.g., by means of the Viterbi algorithm). JDDFSE is a simplification of JMLSE; the performance loss is small if the past decisions are reliable or the channel coefficients occurring in the second part of the branch metric tend to be small. JDDFSE is compatible with state-of-the-art TDMA receivers, since only the computation of the branch metric is modified.

An optimization of the design parameters ι_j corresponds to a trade-off between complexity and performance. One extreme is $\iota_j = L$ for all j, in which case JDDFSE corresponds to JMLSE. The other extreme is $\iota_j = 0$ for all j, which corresponds to joint decision feedback equalization. In practice, ι_j should be chosen such that the dominant fraction of the power is contained in the coefficients $h_{j,0}, \ldots, h_{j,\iota_j}$ in order to minimize error propagation. This condition can be relaxed by using an adaptive prefilter, which is able to jointly shorten the impulse responses of all co-channels [12]. The design parameter can be made adaptive [13]. In case of a nonbinary data alphabet, the complexity can be further reduced by applying the principle of set partitioning [17].

Channel Estimation

Channel estimation is more demanding than in single-user receivers, because more channel coefficients have to be estimated. Channel estimation is particularly difficult in asynchronous systems with frequency hopping (Fig. 2) because of short observation intervals and nonoverlapping training sequences.

For simplicity, let us consider the synchronous case first. The presentation is simplified if the equivalent discrete-time channel model, Eq. 1, is written in vector/matrix form:

$$\mathbf{y} = \sum_{j=0}^{J} \mathbf{A}_j \cdot \mathbf{h}_j + \mathbf{n} = \mathbf{X} \cdot \mathbf{f} + \mathbf{n}, \qquad (5)$$

where $\mathbf{X} := [\mathbf{A}_0, \ldots, \mathbf{A}_J]$ and $\mathbf{f} := [\mathbf{h}_0^T, \ldots, \mathbf{h}_J^T]^T$. Given the right side of Eq. 5, the so-called *joint least-squares channel estimator* (JLSCE) can be formulated for TDMA systems as [9]

$$\hat{\mathbf{f}} = (\mathbf{X}^H \cdot \mathbf{X})^{-1} \cdot \mathbf{X}^H \cdot \mathbf{y}, \qquad (6)$$

where $\hat{\mathbf{f}} := [\hat{\mathbf{h}}_0^T, \ldots, \hat{\mathbf{h}}_J^T]^T$ are the channel estimates. JLSCE is particularly simple if the matrix $(\mathbf{X}^H \cdot \mathbf{X})^{-1} \cdot \mathbf{X}^H$ can be precomputed. The first drawback of JLSCE is that the training sequences should overlap. Due to different propagation delays, even for ideally synchronized base stations the co-channels cannot be made synchronous for all users. The second drawback of JLSCE is that the training sequences of all active users should be known. In many cases, however, only the training sequence of the desired user is known to the receiver. Possible solutions for both drawbacks are prevailing research topics.

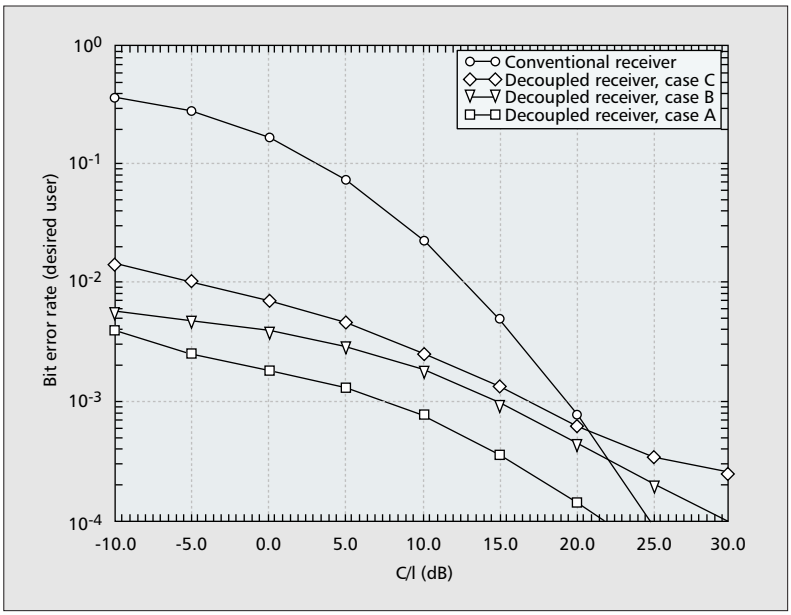


Figure 5. *Simulation results for decoupled linear CCI cancellation/nonlinear detection (TU0 channel model, perfect channel knowledge,* E_s/N_0 *= 25 dB, one dominant interferer, synchronous GSM network).*

In case of asynchronous networks with frequency hopping, according to Fig. 2 the channel coefficients have to be computed piecewise. If the training sequence of the desired user is known and the training sequences of the interferers are unknown, *semi-blind channel estimation* can be done. In semi-blind channel estimation, information coming from known symbols as well as information obtained by blind methods is combined. Solutions for this scenario have been studied extensively in the literature (e.g., [18, references therein]).

Numerical Results

In order to demonstrate the performance of SAIC receiver structures, a software simulator has been implemented. The numerical results reported in Figs. 5 and 6 are obtained for a synchronous GSM/GPRS network with one dominant interferer ($J = 1$). A typical urban (TU) environment is assumed, because urban environments are subject to strong CCI. The TU channel model (in conjunction with linearized Gaussian minimum shift keying and a square-root Nyquist receive filter) has an effective memory length of about $L = 3$. The training sequences of the desired user and the dominant interferer are uniformly distributed over the set of GSM training sequences (TSC0–TSC7). It is assumed that both training sequences are different. In all figures the raw bit error rate (BER) of the desired user is plotted vs. the average signal-to-interference ratio (C/I) given a fixed signal-to-noise ratio (E_s/N_0). The channel coefficients are assumed to be constant for the duration of a burst (block fading assumption). As a benchmark, the performance curve for a conventional

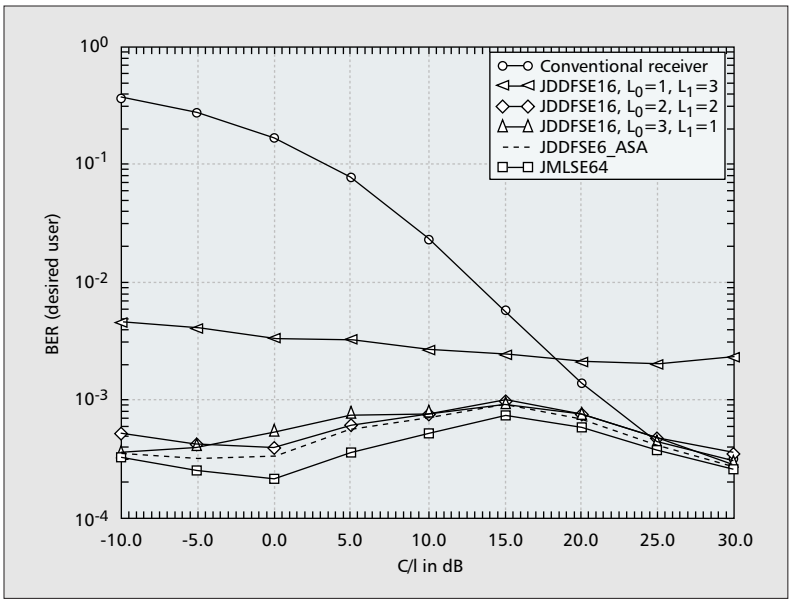


Figure 6. *Simulation results for JMLSE with 64 states and joint delayed decision feedback sequence estimation with 16 states (TU0 channel model, perfect channel knowledge,* E_s/N_0 *= 20 dB, one dominant interferer, synchronous GSM network).*

GSM receiver with $2^L = 8$ states is plotted as well. In all simulations, $5 \cdot 10^4$ statistical independent bursts were generated, emulating perfect frequency hopping.

Decoupled Linear CCI Cancellation/ Nonlinear Equalization

Performance results for decoupled linear CCI cancellation/nonlinear equalization as described above are shown in Fig. 5. The FIR prefilter is adjusted burst by burst according to Eq. 2. A fractionally spaced filter ($N = 2$) with 20 real-valued coefficients is used. Real-valued processing as proposed in [15] is done. The decision delay of the prefilter is chosen to be $k_0 = 4$. The prefilter is cascaded by a Viterbi detector with eight states. Numerical results are shown for all three cases, A, B, and C, defined above. In case A JLSCE is used, which is capable of performing channel estimation jointly for both co-channels, whereas in case B a conventional channel estimator for the desired user is applied in order to adapt the linear filter. In case C, the linear filter is adjusted without using a channel estimator. In all three cases, decoupled linear CCI cancellation/nonlinear equalization outperforms the conventional GSM receiver over a wide range of signal-to-interference ratios.

Joint Maximum Likelihood Sequence Estimation and Joint Delayed Decision Feedback Sequence Estimation

Figure 6 shows performance results for JMLSE and JDDFSE in conjunction with perfect channel knowledge. Since the typical urban channel model has an effective memory length of about $L = 3$, the joint maximum likelihood sequence estimator consists of $2^{2 \cdot 3} = 64$ states in case of one dominant interferer. In [19] a tight lower bound on the bit error rate performance of JMLSE has been published, which verifies the local maximum at about 15 dB.

For the joint delayed decision feedback sequence estimator, 16 states are assumed in Fig. 6. Different choices of the design parameters l_0 and l_1 are considered. Particularly with *adaptive state allocation* (ASA) [13], the performance gap with respect to JMLSE is negligible. For JDDFSE with just eight states, the results are similar. In case of GSM/GPRS an adaptive prefilter, which is able to jointly shorten the impulse responses of all co-channels, is only necessary if the number of states is four or less. In case of EDGE, however, a prefilter should always be used in conjunction with JDDFSE.

For (quasi-)synchronous GSM networks, JDDFSE outperforms decoupled linear CCI cancellation/nonlinear equalization even if channel estimation is taken into account. However, channel estimation is particularly difficult in asynchronous networks with multiple interferers. For this reason, decoupled linear CCI cancellation/nonlinear equalization (cases B and C) is a suitable alternative. Furthermore, JDDFSE is sensitive with respect to model errors.

Conclusions

Single-antenna interference cancellation is more difficult than multiple-input multiple-output (MIMO) processing, since fewer degrees of freedom exist in order to suppress CCI. Nevertheless, with SAIC capacity gains of 40–70 percent are expected for the GSM/GPRS downlink. In this tutorial, suitable receiver structures have been presented that are particularly powerful with respect to compatibility, complexity, and performance. For asynchronous TDMA networks, decoupled filtering/equalization is a good choice. For synchronous TDMA networks, however, we propose using a joint reduced-state sequence estimator. Channel estimation is of vital importance, especially for multiple interferers and/or asynchronous networks with frequency hopping.

References

[1] 3GPP TSG GERAN TR, "DRAFT Feasibility Study on Single Antenna Interference Cancellation (SAIC) for GSM Networks (Release 6)," Apr. 2004.
[2] A. Mostafa *et al.*, "Single Antenna Interference Cancellation (SAIC) for GSM Networks," *Proc. IEEE VTC*, Orlando, FL, Oct. 2003, pp. 1089–93.
[3] J. H. Winters, "Optimum Combining in Digital Mobile Radio with Cochannel Interference," *IEEE JSAC*, vol. 2, no. 4, July 1984, pp. 528–39.
[4] D. T. M. Slock, "Spatio-Temporal Training-Sequence-Based Channel Equalization and Adaptive Interference Cancellation," *Proc. IEEE Int'l. Conf. Acoustics, Speech, & Sig. Proc.*, Atlanta, GA, May 1996, pp. 2714–17.
[5] J.-W. Liang, J.-T. Chen, and A. J. Paulraj, "A Two-Stage Hybrid Approach for CCI/ISI Reduction with Space-Time Processing," *IEEE Commun. Lett.*, vol. 1, no. 6, Nov. 1997, pp. 163–65.
[6] S. L. Ariyavistakul, J. H. Winters, and N. R. Sollenberger, "Joint Equalization and Interference Suppression for High Data Rate Wireless Systems," *IEEE JSAC*, vol. 18, no. 7, July 2000, pp. 1214–20.
[7] D. Asztely and B. Ottersten, "MLSE and Spatio-temporal Interference Rejection Combining with Antenna Arrays," *Proc. EUSIPCO '98*, Rhodes, Greece, Sept. 1998, pp. 1341–44.
[8] W. Etten, "Maximum Likelihood Receiver for Multiple

Channel Transmission Systems," *IEEE Trans. Commun.*, vol. 24, no. 2, Feb. 1976, pp. 276–83.
[9] P.A. Ranta, A. Hottinen, and Z.-C. Honkasalo, "Co-channel Interference Cancellation Receiver for TDMA Mobile Systems," *Proc. IEEE ICC '95*, Seattle, WA, June 1995, pp. 17–21.
[10] K. Giridhar *et al.*, "Nonlinear Techniques for the Joint Estimation of Cochannel Signals," *IEEE Trans. Commun.*, vol. 45, no. 4, Apr. 1997, pp. 473–84.
[11] J.-T. Chen *et al.*, "Low-complexity Joint MLSE Receiver in the Presence of CCI," *IEEE Commun. Lett.*, vol. 2, no. 5, May 1998, pp. 125–27.
[12] A. Hafeez, D. Hui, and H. Arslan, "Interference Cancellation for EDGE via Two-user Joint Demodulation," *Proc. IEEE Vehic. Tech. Conf.*, Orlando, FL, Oct. 2003, pp. 1025–29.
[13] P.A. Hoeher *et al.*, "Joint Delayed-Decision Feedback Sequence Estimation with Adaptive State Allocation," *Proc. IEEE Int'l. Symp. Info. Theory*, Chicago, IL, June/July 2004, p. 132.
[14] H. Arslan and K. Molnar, "Cochannel Interference Suppression with Successive Cancellation in Narrowband Systems," *IEEE Commun. Lett.*, vol. 5, no. 2, Feb. 2001, pp. 37–39.
[15] H. Trigui and D. T. M. Slock, "Performance Bounds for Cochannel Interference Cancellation within the Current GSM Standard," *EURASIP Sig. Proc.*, vol. 80, no. 7, July 2000, pp. 1335–46.
[16] A. Duel-Hallen and C. Heegard, "Delayed Decision-Feedback Sequence Estimation," *IEEE Trans. Commun.*, vol. 37, no. 5, May 1989, pp. 428–36.
[17] M.V. Eyuboglu and S.U. Qureshi, "Reduced-State Sequence Estimation with Set Partitioning and Decision Feedback," *IEEE Trans. Commun.*, vol. 36, no. 1, Jan. 1988, pp. 13–20.
[18] E. de Carvalho and D.T.M. Slock, "Blind and Semi-blind FIR Multichannel Estimation: (Global) Identifiability Conditions," *IEEE Trans. Signal Proc.*, vol. 52, no. 4, Apr. 2004, pp. 1053–64.
[19] H. Schoeneich and P.A. Hoeher, "Iterative Semi-Blind Single-Antenna Cochannel Interference Cancellation and Tight Lower Bound for Joint Maximum-likelihood Sequence Estimation," *EURASIP J. Adv. Sig. Proc.*, vol. 84, Oct. 2004, pp. 1991–2004.

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