Channel Estimator for Multiple Co-channel Demodulation in TDMA Mobile Systems

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***Abstract* – The suppression of the dominant co-channel interference by joint demodulation is a potential technique to enhance the performance of the future TDMA based mobile systems. The requirements for joint demodulation are that the dominant interfering signal is identified in the receiver and reliable channel estimates are provided for both co-channel signals. In practice to meet both requirements the channel estimation should be based on unique training sequences transmitted in each co-channel. In this paper, we propose new optimised training sequence sets and an algorithm for the identification of the dominant interferer. The performance of the sequences is analysed in terms of the bit error rate after joint channel estimation and detection using the GSM platform.**

I. INTRODUCTION

The requirements of the third generation mobile systems claim substantial improvement to the performance of the current mobile networks. The most obvious way to achieve this goal is to improve the receiver performance with co-channel interference by exploiting interference cancellation (IC) methods. IC techniques considered in the literature are either based on adaptive antennas or joint demodulation of cochannel signals. A major difficulty in the application of IC methods is the estimation of the channel parameters both for the desired and interfering signal(s).

In this paper we focus on the problem of joint demodulation of cochannel signals although the results can be exploited in the application of adaptive antennas, too. Joint detection of cochannel signals applied for the GSM system has been studied previously in [1,2,3]. In those papers the dominant interfering signal is cancelled requiring joint channel estimation of cochannel signals. The joint channel estimation is accomplished by frame synchronous cochannel signals with unique training sequences.

The performance of joint channel estimation depends strongly on the correlation properties of the training sequences. Lower auto- and cross-correlation values give smaller channel estimation error. Unfortunately, the current GSM training sequences are not optimised by their cross-correlation but only autocorrelation properties. This causes problems for the joint channel estimation as well as identification of dominant interfering signal.

In this paper, we propose new training sequence sets constructed from two basic families for the purpose of interference cancellation. In addition an algorithm for the identification of the dominant interferer is presented. The first family consists of the length 31 Gold sequences and the second family consists of length 20-bit sequences. The latter sequence set has an advantage that they fit to the GSM frame structure.

The paper is organised as follows. The co-channel communication system considered in this paper is first described. Next the joint channel estimation and joint detection algorithms are shortly presented. Then the methodology for selecting the sequence sets is described and appropriate training sequence sets are proposed. Next the dominant interferer identification algorithm is presented and its performance is analysed. After that the performance of the sequence sets is analysed by link level simulations. Finally, the results are discussed and conclusions are drawn.

II. SYSTEM MODEL

The co-channel communications system considered in this paper is depicted in Fig. 1. It consists of N synchronous co-channel signals with independent complex channel impulse responses $\mathbf{h}_{L,n} = \left(h_{0,n},\ h_{1,n}, \ldots,\ h_{L,n}\right)$ where L is the length of the channel memory. The sum of the signals is added up with independent white Gaussian noise and received by TDMA mobile or base station. The bits are transmitted burstwise through the channels, and the training information is located in the middle of transmission bursts. An example of the transmission burst structure is given in Fig. 2. The GSM system uses training sequences with 16 reference and 10 guard bits [4].

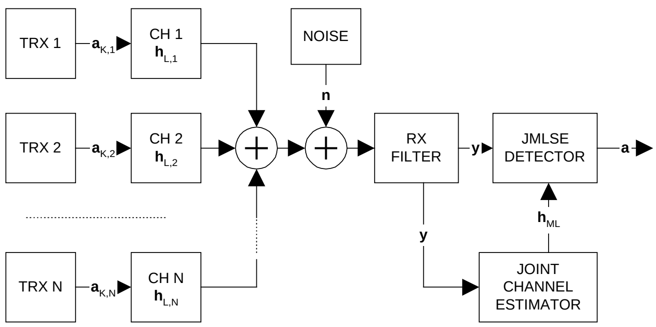

Fig. 1   Communications system with *N* co-channel signals.

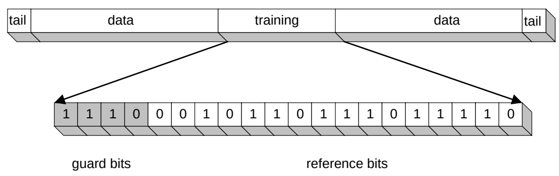

Fig. 2   TDMA burst structure (example).

III. RECEIVER ALGORITHM

The received signal $\mathbf{y}$, corresponding to the training sequence information, sampled once per symbol in the presence of additive noise $\mathbf{n}$ can be written in matrix form as follows

$$\mathbf{y} = \mathbf{M}\mathbf{h} + \mathbf{n} \tag{1}$$

where all the radio channels are organised as a vector

$$\mathbf{h} = \left(\mathbf{h}_{L1,1}^T \ \ \mathbf{h}_{L,2}^T \ \ \dots \ \ \mathbf{h}_{L,N}^T \right)^T \tag{2}$$

and the known training bits as a matrix

$$\mathbf{M} = \left[\mathbf{M}_1 \ \ \mathbf{M}_2 \ \dots \ \mathbf{M}_N \right] \tag{3}$$

where

$$\mathbf{M}_n = \begin{bmatrix} m_{L,n} & \cdots & m_{1,n} & m_{0,n} \\ m_{L+1,n} & \cdots & m_{2,n} & m_{1,n} \\ \vdots & & \vdots & \vdots \\ m_{L+K-1,n} & \cdots & m_{K,n} & m_{K-1,n} \end{bmatrix}. \tag{4}$$

With the assumption of white Gaussian noise the maximum likelihood channel estimate is given by

$$\hat{\mathbf{h}}_{ML} = (\mathbf{M}^H \mathbf{M})^{-1} \mathbf{M}^H \mathbf{y}. \tag{5}$$

The channel estimates are passed to the joint detector based on the maximum likelihood sequence estimation (MLSE) principle. Joint MLSE can be straightforwardly implemented via the Viterbi algorithm and the detected data bits $\hat{\mathbf{a}}$ are found by [1,3]

$$\hat{\mathbf{a}} = \arg\min_{\mathbf{A}} \left[\left(\mathbf{r} - \mathbf{A}\hat{\mathbf{h}}_{ML} \right)^T \left(\mathbf{r} - \mathbf{A}\hat{\mathbf{h}}_{ML} \right) \right] \tag{6}$$

where $\mathbf{r}$ is the received signal during the whole burst and $\mathbf{A}$ is constructed from the tentative data bits like $\mathbf{M}$ in Eq. (3) and (4).

IV. NEW TRAINING SEQUENCES

In this paper, we consider training sequence structure similar to that depicted in Fig. 2, i.e. the sequence is divided into guard and reference parts. Guard bits are used to cover propagation and multipath delays between the nearest co-channels. Replicas of the last reference bits can be chosen to guard bits to optimise periodic correlation properties.

A sequence set for joint detection should meet the following requirements:

1. Set size is large enough to assure distinct codes for the nearest co-channels.
2. The length of the sequence is as short as possible to minimise the amount of overhead bits but long enough to enable estimation of adequate number of channel coefficients.
3. Sequence pairs in the set have low cross- and autocorrelation properties.

In the following sections we propose two larger sets from which the actual training sequence sets with a smaller size are selected.

A. Length 20-bit sequences

The first proposed basic set consists of length 20-bit sequences that are optimised by their autocorrelation function (ACF). Wolfmann [5] reports two sequences of length 20 bits having all out of phase components zero except one, i.e. there are 9 zeros after the main peak in ACF. Relaxing the requirement to 7 consecutive zeros in ACF gives a set of 22 sequences. This basic set is presented in Table I and it can be divided into three classes based on ACF:

- 2 sequences with 9 zeros in ACF
- 8 sequences with 8 zeros in ACF
- 12 sequences with 7 zeros in ACF

The total length of these sequences can be set to 26 by choosing guard length of 6 bits. Thus they fit to the current GSM frame structure.

TABLE I
Length 20-bit sequences

0.	02CEB	1.	035CD	2.	046D7
3.	04A27	4.	04B9D	5.	04C2B
6.	05A23	7.	05CE9	8.	0622D
9.	06A19	10.	07229	11.	075B1
12.	089AF	13.	08B3D	14.	08BCD
15.	08BD3	16.	09BC5	17.	09BD7
18.	0A6EF	19.	0B3D1	20.	0BBCD
21.	0BCD1				

Autocorrelation:

9 zeros	{14,19}
8 zeros	{2,3,6,8,10,11,12,18}
7 zeros	{0,1,4,5,7,9,13,15,16,17,20,21}

Subsets:

subset 7	{1,6,8,13,15,18,21}
subset 10	{1,2,3,8,9,11,13,15,17,19}
subset 15	{1,2,3,5,6,8,9,10,11,13,15,16,17,18,19}

TABLE II

SNR degradation values (dB) of training sequence sets. The worst and best sequence pair from each set is given.

Set	Length	Set size	SNR degr. (dB)	
			worst	best
GSM	16 bits	7	8.0	3.2
20-BIT	20 bits	7	3.5	2.5
		10	5.0	2.3
		15	5.7	2.2
GOLD	31 bits	7	1.9	1.6
		10	2.0	1.6
		15	2.1	1.6

B. Gold sequences

One binary sequence family with considerably low correlation values is Gold sequences [6]. They are constructed from a pair of *m*-sequences with a help of shift registers. The period of *m*-sequences is $N = 2^n - 1$, n = 1,2,... and the constructed set consists of $2^n + 1$ Gold sequences including those two *m*-sequences. The whole set has a period of $2^n - 1$. There is only one *m*-sequence of period 15, thus no Gold sequences of that length can be constructed. The next possible period length 31 is therefore selected, corresponding best to the GSM training sequence (period 16). The cross-correlation spectrum of Gold sequences of length 31 is three-valued having values

$$-\frac{9}{31}\ ,\quad -\frac{1}{31}\ ,\quad \frac{7}{31}\ . \tag{7}$$

The autocorrelation of Gold sequences has also the same spectrum.

In the next section we consider the problem of selecting the best subsets among the basic sets.

C. Selection of subsets

The proposed basic sets have low autocorrelation properties, but in order to exclude the worst cross-correlations from the sets, we select smaller subsets. In this paper, we consider subsets of 7, 10 and 15 sequences and compare them to a subset of 7 GSM sequences. The subsets of length 20-bit sequences are listed in Table I above.

The selection method is based on the properties of the correlation matrix. The goodness of the set is evaluated by the degradation of the signal-to-noise ratio (SNR). The formula for the degradation d_{ce} is as follows [7]

$$d_{ce}\ /\ dB = 10 \cdot \log_{10}\left(1 + \mathrm{tr}\left\{\left(\mathbf{M}^H \mathbf{M}\right)^{-1}\right\}\right) \tag{8}$$

where the matrix $\mathbf{M}$ is formed from the training bits like in Eq. (3). This criterion tells us how much SNR degrades due to the errors in the channel estimation process. Hence, low degradation values are more desirable. Table II summarises the SNR degradation values for the best and worst pairs in the selected subsets.

The GSM training sequences perform well when used for conventional single channel estimation but some degradation can be seen in multiple channel estimation. Table II shows that the best GSM pair achieves a tolerable performance whereas the worst pair performs 5-6 dB worse than the worst 20-bit or Gold sequence pairs. However, the average performance is still reasonably good. It should be noted that this analysis is for a subset of seven GSM sequences. The eighth sequence causes a very severe cross-correlation peak which corresponds to a degradation value of over 12 dB.

The 20-bit sequences perform better than the GSM sequences on average, and the channel estimation accuracy depends much less on the particular pair of training sequences that are used. However, the relatively small size of the basic set (22 sequences) limits the performance of the larger subsets. All the bad pairs cannot be any more avoided, and hence a few undesirable degradation values occur in the subsets. Still, all the subsets look promising in terms of channel estimation accuracy on the average.

The Gold sequences look excellent for the joint channel estimation purposes. The degradation values are small and, what is more, the values appear to be very much alike for the whole set, which is due to the very even correlation properties of the set. One consequence is the minimal improvement achieved by shrinking the subset size since there are no particularly poor Gold sequence pairs.

V. DOMINANT INTERFERER

The maximum number of simultaneously estimated channel tap coefficients is strictly limited by the reference length of the training sequence, e.g. with GSM sequences can be estimated no more than 16 channel taps. This implies that the dominant interferer cannot be found just by performing joint channel estimation for all the signals as in Eq. 5. In the following we propose a new suboptimum algorithm to find the dominant interferer and thus avoid this inconvenience.

A. Identification of dominant interferer

The identification algorithm of dominant interferer is included in the channel estimation process presented in Ch. III. This algorithm is based on the channel estimates resulted from an estimation of two signals at a time, the desired signal and one of the interfering signals. All the other signals are considered as a noise during the process.

Let there be N simultaneous co-channel users transmitting over independent radio channels with a memory of L taps. If there is no noise in the system, the received signal is

$$\mathbf{y} = \mathbf{M}\mathbf{h} = \mathbf{M}_e\mathbf{h}_e + \mathbf{M}_r\mathbf{h}_r \quad , \tag{9}$$

where

$$\mathbf{M}_e = \begin{bmatrix} \mathbf{M}_1 & \mathbf{M}_i \end{bmatrix} \; , \; i = 2,3,...,N \tag{10}$$
$$\mathbf{M}_r = \begin{bmatrix} \mathbf{M}_2 & \mathbf{M}_3 & \cdots & \mathbf{M}_{i-1} & \mathbf{M}_{i+1} & \cdots & \mathbf{M}_N \end{bmatrix}$$

and $\mathbf{M}_i$ consists of the training sequence bits as in Eq. 4 and

$$\mathbf{h}_e = \begin{bmatrix} \mathbf{h}_{L,1}^T & \mathbf{h}_{L,i}^T \end{bmatrix}^T \; , \; i = 2,3,...,N \tag{11}$$
$$\mathbf{h}_r = \begin{bmatrix} \mathbf{h}_{L,2}^T & \mathbf{h}_{L,3}^T & \cdots & \mathbf{h}_{L,i-1}^T & \mathbf{h}_{L,i+1}^T & \cdots & \mathbf{h}_{L,N}^T \end{bmatrix}^T$$

The desired signal has the index 1 and the interfering signals have indices from 2 to N.

The channel tap coefficients in vector $\mathbf{h}_e$ are the parameters that are currently estimated. The rest of the signals are supposed to give only noise to the system, thus the channel estimate is

$$\hat{\mathbf{h}}_e = \left(\mathbf{M}_e{}^H\mathbf{M}_e\right)^{-1}\mathbf{M}_e{}^H\mathbf{y} \quad . \tag{12}$$

The estimation (12) is repeated for each interferer yielding channel estimates for them. A straightforward method to find out the strongest interference is to calculate power estimates based on the channel estimates as follows

$$\hat{P}_i = \sum_{k=0}^{L} h_{k,i}^2 \quad , \; i = 2,3,...,N. \tag{13}$$

The signal having the biggest power estimate $\hat{P}_i$ is determined to be the dominant one.

A more elaborate method to determine the dominant interferer is to reconstruct the received signal and compare that with the real received signal. Using the channel estimates given by Eq. (12) the estimated received signal is

$$\begin{aligned}\hat{\mathbf{y}} = \mathbf{M}_e\hat{\mathbf{h}}_e &= \mathbf{M}_e\left(\mathbf{M}_e{}^H\mathbf{M}_e\right)^{-1}\mathbf{M}_e{}^H\mathbf{y} \\ &= \mathbf{M}_e\left(\mathbf{M}_e{}^H\mathbf{M}_e\right)^{-1}\mathbf{M}_e{}^H\left(\mathbf{M}_e\mathbf{h}_e + \mathbf{M}_r\mathbf{h}_r\right) \\ &= \mathbf{M}_e\mathbf{h}_e + \mathbf{M}_e\left(\mathbf{M}_e{}^H\mathbf{M}_e\right)^{-1}\mathbf{M}_e{}^H\mathbf{M}_r\mathbf{h}_r\end{aligned} \tag{14}$$

The mean squared error (MSE) of the reconstructed signal is given by

$$\left\|\mathbf{y} - \hat{\mathbf{y}}\right\|^2 = \left\|(\mathbf{I} - \mathbf{A})\mathbf{M}_r\mathbf{h}_r\right\|^2 \tag{15}$$

where

$$\mathbf{A} = \mathbf{M}_e\left(\mathbf{M}_e{}^H\mathbf{M}_e\right)^{-1}\mathbf{M}_e{}^H \tag{16}$$

and $\mathbf{I}$ is the identity matrix. It can be seen that small error term implies also small $\mathbf{h}_r$ as there exists a linear dependence between them. Hence, MSE is most likely to reach the minimum value when the most powerful signals are taken into estimation matrix $\mathbf{M}_e$ and the other signals are weak ($\mathbf{h}_r$ is small). The signal having the smallest MSE is chosen to be the dominant.

B. Performance analysis

In this section, the probability of finding dominant interferer with the proposed algorithms is evaluated in MATLAB environment. The three families of training sequences, GSM, 20-bit and Gold, with the optimised subsets of 7, 10 and 15 sequences are used in the simulations. The intercell interference from the nearest cochannel cells is modelled with lognormal distribution as the shadowing effect dominates also the path loss variations. Intersymbol interference (ISI) is generated according to Typical Urban (TU) multipath channel profile and 5 channel taps per signal are estimated in the receiver. Interference limited situation is studied, thus noise is assumed to be negligible compared to the interference.

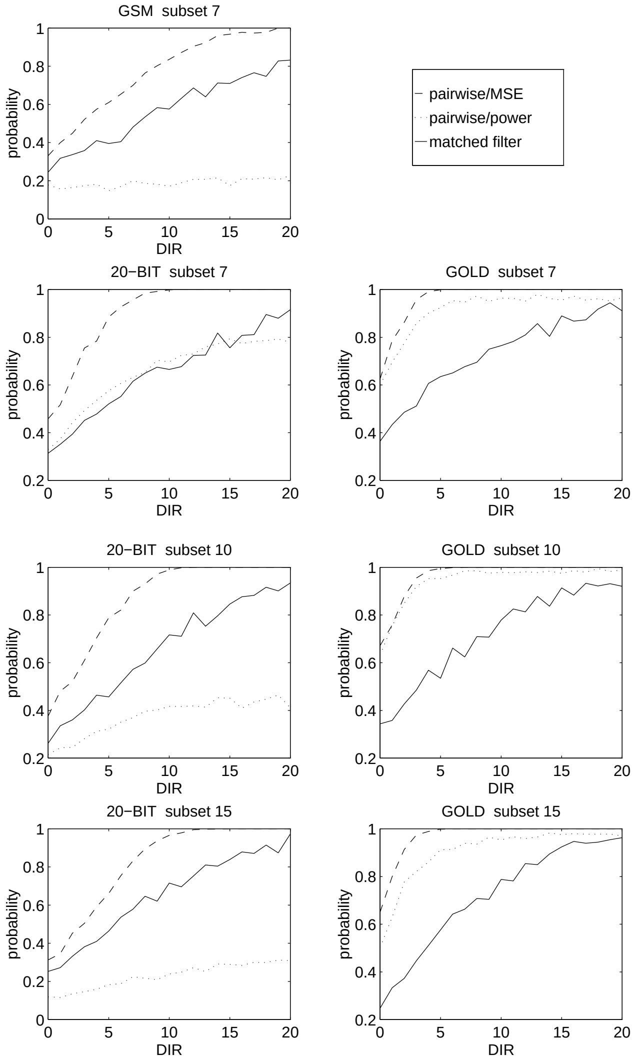

Fig. 3 Probability of finding dominant interferer with respect to power ratio between the dominant and other interfering signals (DIR).

During the simulation, the power ratio between the dominant interferer and the sum of the other interferers (DIR) is calculated, the DI identification is performed with the proposed pairwise method using both strict power estimates and MSE based techniques. As a comparison, matched filter (MF) estimation for all the signals simultaneously is also performed.

The simulated average performance over all possible sequence pairs, i.e. the percentage of the successful identifications, with respect to DIR is presented with graphs in Fig. 3. Note that the simulation cases are classified according to the DIR ratio, i.e. there is no variance in the ratio values. This approach corresponds to a frequency hopping network in which the consecutive bursts are independent of each other and we are usually interested in the average performance characteristics of the system. However, if a non-hopping network is assumed, the same interfering signal may dominate for a period of several successive bursts, and the average performance may not be informative enough. The real performance depends on the particular training sequences that are allocated for the cochannel signals, and it can be either worse or better than that in Fig. 3.

The proposed MSE algorithm is affected by the training sequences as it exploits their correlation properties. Graphs show that to achieve 100 % certainty of finding DI it requires DIR to be at least 5 dB with Gold sequences, 10 dB with length 20-bit sequences and 20 dB with GSM sequences. On the other hand, the pairwise channel estimation with direct power estimate performs poorly in many cases. Only with the Gold sequences this algorithm seems to work adequately because of the desirable cross-correlation properties of the sequences.

The MF estimation gives a steady and similar performance with all the training sequences. The cross-correlations have a significant role, especially when DI is not very distinguishable they impair the MF performance clearly. As DIR ratio grows, the probability of finding DI slowly increases.

With the subsets of 10 and 15 sequences the MSE method still performs very well and also MF estimation gives reasonable results. Hence, these two methods seem to be insensitive against increasing number of users and the DIR ratio is the dominating factor in performance. Only the pairwise method with power estimates is considerably degraded if the length 20-bit sequences are used.

The noise in the pairwise estimation is not necessarily white Gaussian because of the residual interference and therefore the pairwise channel estimates in Eq. (12) are not optimum. Furthermore, the power estimates (13) may be highly biased degrading the performance. Instead, the proposed MSE method can perform more reliably in the presence of coloured noise.

VI. SIMULATION RESULTS

In this section, the performance of the training sequences is evaluated by link level simulations. A comparison between the sequences is performed by jointly demodulating two cochannel signals in the presence of Gaussian noise. Simulation results with different training sequences are given in Fig. 4 - Fig. 7. Subsets of 7 and 15 sequences are used, and the best and worst sequence pairs are evaluated from each subset.

Simulation model is a standard GSM simulation model where the receiver is updated with joint channel estimator and joint detector presented in Ch. III. There are two cochannel signals corresponding to the desired and interfering signals, respectively. The signals are equally strong

(SIR = 0 dB) and they have independent Rayleigh fading multipath channels. The joint detection of the cochannel signals is performed in the receiver and bit error rate (BER) is measured. As a reference the conventional detection of single signal with no interference (SIR infinite) is performed. In the both conventional and joint detection cases additive white Gaussian noise (AWGN) is present.

The cross-correlation properties of the training sequences have a major impact on the joint detection performance as the simulation results show. GSM sequences have a large variance in performance depending which particular sequence pair is used since there is over 6 dB difference at BER level of 10^{-2} between the best and worst sequence pair. The other sets are more uniform, thus the gain for the best 20-bit sequence pair is under 1 dB but up to 6 dB for the worst pair compared to the corresponding GSM pairs in the subset of size 7. Gold sequences perform still over 1 dB better both with the best and worst pairs compared to the 20-bit sequences, and their performance depends also least on the chosen sequence pair. As they achieve more gain from the longer sequence, this is also expected.

In the subset of size 15 the Gold sequences perform only slightly worse than in the smaller subset and the average performance of the length 20-bit sequences is still reasonable. However, the worst pair of 20-bit sequences is degraded being more than 2 dB worse at BER level of 10^{-2} than the worst Gold sequence pair.

VII. CONCLUSIONS

The suppression of the dominant cochannel interference by joint detection technique requires identification of the dominant interferer and accurate channel estimation for the cochannel signals. To improve the estimation accuracy new training sequence sets with low cross-correlation properties are proposed, and the simulations show that the performance of the system can be improved by the new sequences. By the length 20-bit sequences can be achieved 6 dB and by Gold sequences over 7 dB gain compared to the worst GSM sequence pair at BER 10^{-2}. Even though, GSM sequences are still applicable for the joint detection, too, since they have a reasonable average performance.

Burstwise identification of the dominant interferer is required in frequency hopping network where the interference in consecutive bursts is independent. The identification algorithms are integrated as a part of the joint channel estimation process exploiting distinct training sequences of the users. The simulations show that the algorithm which is based on the pairwise channel estimation and MSE criterion finds the dominant interferer reliably if it is 5 dB / 10 dB / 20 dB above the interference left over with Gold / 20-bit / GSM sequences. The algorithm outperforms the other identification algorithms that are the pairwise channel estimation with strict power estimation and matched filter estimation. Proper training sequence design is also essential for the identification algorithms.

GSM training sequences can be replaced by the length 20-bit sequences as they both fit to the frame of 26 bits (including guard bits). By that replacement IC works more efficiently but the payload of the system is kept unchanged. Gold sequences have slightly better performance, but on the other hand, they take more bits in the frame structure.

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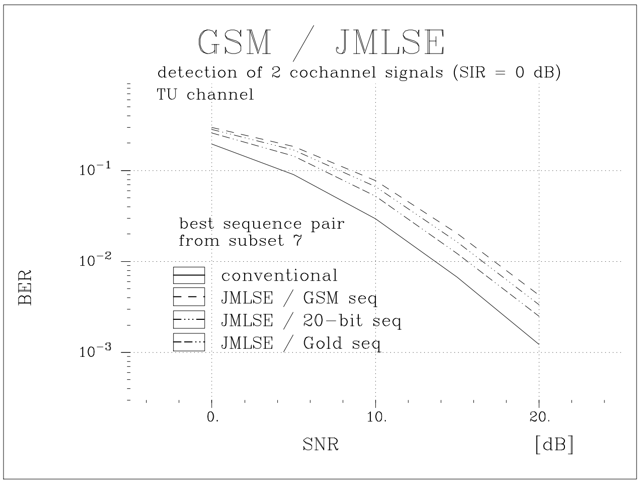

Fig. 4 Performance of joint detection of two cochannel signals. Best sequence pairs from subset 7 used.

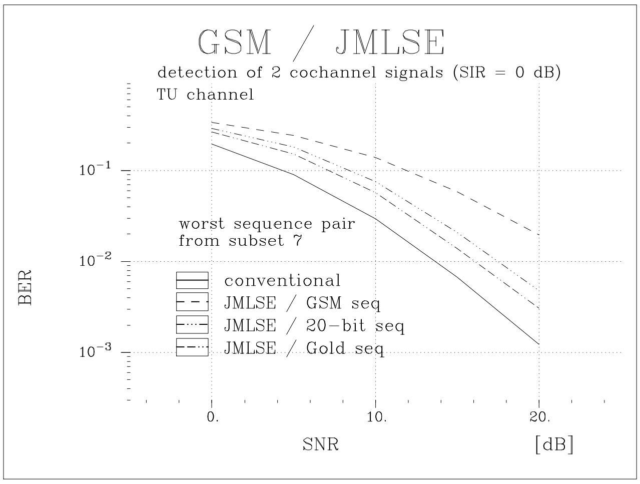

Fig. 5 Performance of joint detection of two cochannel signals. Worst sequence pairs from subset 7 used.

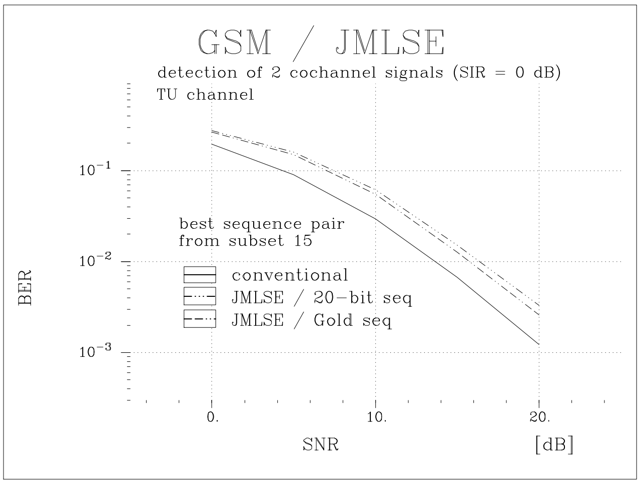

Fig. 6 Performance of joint detection of two cochannel signals. Best sequence pairs from subset 15 used.

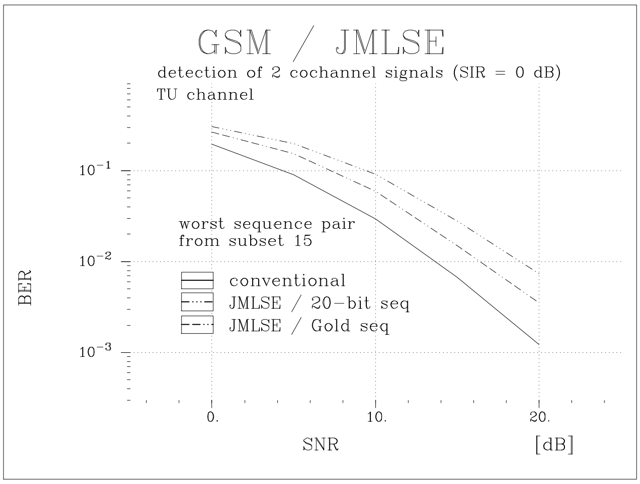

Fig. 7 Performance of joint detection of two cochannel signals. Worst sequence pairs from subset 15 used.