Joint Equalization and Interference Suppression for High Data Rate Wireless Systems

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***Abstract*—Enhanced Data Rates for Global Evolution (EDGE) is currently being standardized as an evolution of GSM in Europe and of IS-136 in the United States as an air interface for high speed data services for third generation mobile systems. In this paper, we study space-time processing for EDGE to provide interference suppression. We consider the use of two receive antennas and propose a joint equalization and diversity receiver. This receiver uses feedforward filters on each diversity branch to perform minimum mean-square error cochannel interference suppression, while leaving the intersymbol interference to be mitigated by the subsequent equalizer. The equalizer is a delayed decision feedback sequence estimator, consisting of a reduced-state Viterbi processor and a feedback filter. The equalizer provides soft output to the channel decoder after deinterleaving. We describe a novel weight generation algorithm and present simulation results on the link performance of EDGE with interference suppression. These results show a significant improvement in the signal-to-interference ratio (SIR) performance due to both diversity (against fading) and interference suppression. At a 10% block error rate, the proposed receiver provides a 20 dB improvement in SIR for both the typical urban and hilly terrain profiles.**

***Index Terms*—Adaptive arrays, adaptive equalizers, cochannel interference, diversity, intersymbol interference (ISI).**

I. Introduction

ENHANCED Data Rates for Global Evolution (EDGE) is currently being standardized as an evolution of GSM in Europe and of IS-136 in the United States as an air interface for high speed data services [1]. EDGE reuses the GSM time slot structure, carrier bandwidth (180.05 kHz), and symbol rate (270.833 kbaud), but can provide a 3 times higher data rate through the use of 8-PSK modulation with partial response pulse shaping. EDGE is being introduced as an IS-136 and GSM overlay using a 1/3, 3/9, or 4/12 reuse pattern (instead of the 7/21 reuse pattern in current IS-136 systems); thus, cochannel interference (CCI) severely limits the radio link performance. Adaptive array techniques, using multiple receive antennas for interference suppression (as used in IS-136, see, e.g., [2]), can mitigate this problem.

In this paper, we study the use of a joint equalization and diversity receiver to provide interference suppression in EDGE. The proposed receiver is similar to the original EDGE receiver [1], except for an additional receiving branch. The feedforward filters of the diversity receiver perform minimum mean-square error (MMSE) CCI suppression, while leaving the intersymbol interference (ISI) to be mitigated by the subsequent equalizer. This equalizer is a delayed decision feedback sequence estimator (DDFSE) [3]–[5], consisting of a reduced-state Viterbi processor and a feedback filter. This equalizer provides soft output to the channel decoder after deinterleaving. We describe a novel weight generation algorithm, which is based partially on the results of [6], and present simulation results on the link performance of EDGE with interference suppression. Our results show a significant improvement in the signal-to-interference power ratio (SIR) performance due to both diversity (against fading) and interference suppression. At 10% block error rate (BLER), the proposed receiver provides a 20 dB improvement in SIR for both typical urban and hilly terrain profiles.

In Section II we describe the system, and in Section III describe the computer simulation model. In Section IV we present performance results. Conclusions are presented in Section V.

II. System Model

A. EDGE System Parameters

The EDGE system (see, e.g., [1]) uses a time-division multiple-access (TDMA) format with a burst length of 576.92 μs and a frame of 8 bursts (5 ms). Each burst contains 116 payload symbols, with 26 training symbols as a midamble, and 6 tail and 8.25 guard symbols. Each user occupies one burst out of each frame, and the data for each frame are interleaved over 4 frames. Therefore, one interleaving block contains 116 $\times$ 4 (464) data symbols. The modulation currently being considered is 8-PSK with linearized GMSK pulse shaping, with a symbol rate of 270.833 kbaud (symbol period $T = 3.692\,\mu$s), and a carrier separation of 200 kHz. The receiver filter that we consider is a square-root Nyquist filter with a bandwidth of 180.05 kHz and a rolloff factor of 0.5. Coding is 1/3 rate convolutional coding with a constraint length of 7, with block interleaving over (5 $\times$ 4) 20 ms.

Fig. 1 shows a block diagram of our receiver. It is similar to the original EDGE receiver [1], except for an additional receiving branch. The feedforward filters of the diversity receiver perform MMSE CCI suppression, while leaving the ISI to be mitigated by the subsequent equalizer. This equalizer is a DDFSE [3]–[5], consisting of a reduced-state Viterbi processor and a feedback filter. This equalizer provides soft output to the channel decoder after deinterleaving. As shown in [4], the DDFSE offers improved performance over a decision feedback equalizer (DFE), primarily due to a reduction in the effect of

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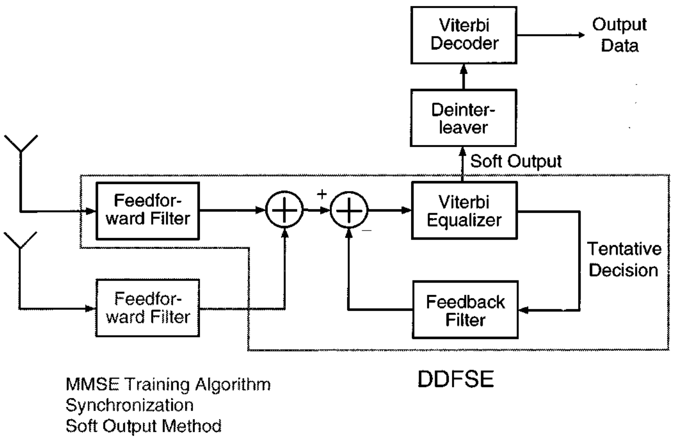

Fig. 1. Receiver structure.

error propagation, with a significant complexity reduction over a full Viterbi processor. The DDFSE of [4] was a single branch receiver without a feedforward filter, and therefore was suitable only for minimum phase channels. Here we have added a feedforward filter to handle dispersive channels (which may be nonminimum phase as well as minimum phase) with a second branch to provide CCI suppression.

B. Algorithms

The three key techniques used with this receiver are the soft output method, the timing recovery algorithm, and the equalizer weight training algorithm. These techniques are briefly described as follows.

1) Soft-Output DDFSE: A Viterbi processor normally produces only hard outputs. However, various kinds of soft information may be obtained either directly through the survivor path history or as byproducts of the metric computations required by the Viterbi algorithm [7]–[10]. An optimum soft output $\tilde{x}_n$ based on the MMSE criterion is computed by averaging all possible values of the transmit symbols x_n's, weighted by their *a posteriori* probabilities (APP's) [9]:

$$\tilde{x}_n = \sum_{x_n} x_n P(x_n|Y_n) \tag{1}$$

where $Y_n = (y_0, y_1, \cdots, y_n)$ is the sequence of the Viterbi equalizer inputs y_i up to time n, and $P(x_n|Y_n)$ is the APP of x_n, which can be computed using methods such as Lee [11] or Bahl *et al.* [12].

We adopt this optimum soft output approach in this study. In addition to providing tentative decisions to the feedback filter, the Viterbi processor in the DDFSE computes the soft output (using the Lee algorithm [11] for computing the APP's) as in (2), shown at the bottom of the page [13], where s_n is a state in the Viterbi decoding trellis at time n, $\pi(s_n)$ is all previous states of $s_n, x(s_{n-1}, s_n)$ is the transmitted 8-PSK symbol corresponding to the path between s_{n-1} and s_n, γ_o is the output SNR estimated during equalizer training, as described below, and $P(Y_{n-1}, s_{n-1})$ is computed recursively as

$$P(Y_{n-1}, s_{n-1}) = \sum_{s_{n-2}\in\pi(s_{n-1})} P(Y_{n-2}, s_{n-2}) e^{-\gamma_o|y_{n-1}-x(s_{n-2},s_{n-1})|^2}. \tag{3}$$

2) Timing Recovery: The receiver timing includes both symbol timing and sequence timing. In general, the output v_n of each feedforward filter (assumed here to be symbol-spaced) at time n can be given as

$$v_n^l = \sum_{q=0}^{F-1} w_q^l r^l((n+j+q)T+\tau) \tag{4}$$

where

- w_q^l — qth filter coefficient in the lth branch of the receiver;
- F — total number of filter taps;
- $r^l(iT+\tau)$ — ith received signal sample in the lth branch of the receiver;
- T — symbol period;
- τ — symbol timing phase.

As can be seen, the filter output is a function of both the symbol timing τ and the sequence timing j. The Viterbi equalizer input that we referred to earlier is given as

$$y_n = \sum_{l=1}^{M} v_n^l - \sum_{m=\mu+1}^{B} b_m \hat{x}_{n-m} \tag{5}$$

where

- M — total number of antennas (diversity branches);
- μ — Viterbi equalizer memory;
- b_m — mth coefficient of the feedback filter with a total of $B-\mu$ taps;
- $\hat{x}_i$ — ith tentative decision from the Viterbi equalizer.

We have implied in (5) that all feedforward filters use the same symbol timing and sequence timing, although this is not a necessary condition.

Accurate symbol timing may not be required if the feedforward filters have fractional tap spacing. However, the choice of the sequence timing is critical to the equalizer performance, since it determines the subset $\{r^l((n+j)T), r^l((n+j+1)T), \cdots, r^l((n+j+F-1)T)\}$ of the received signal samples from which the receiver can extract symbol energy, while suppressing interference, for the detection of the nth transmit symbol.

In the case of unknown CCI, the receiver can estimate the sequence timing based on the measured impulse response of the desired channel (e.g., using the method described below) and then offset this timing by a certain amount to permit the use of

$$\tilde{x}_n = \frac{\displaystyle\sum_{s_n}\sum_{s_{n-1}\in\pi(s_n)} x(s_{n-1},s_n)P(Y_{n-1},s_{n-1})e^{-\gamma_o|y_n-x(x_{n-1},s_n)|^2}}{\displaystyle\sum_{s_n}\sum_{s_{n-1}\in\pi(s_n)} P(Y_{n-1},s_{n-1})e^{-\gamma_o|y_n-x(s_{n-1},s_n)|^2}} \tag{2}$$

"causal taps" (taps that contain signal energy only of past data symbols as described in [6]).

Note that without CCI casual taps are not needed in the feedforward filter of a Viterbi equalizer or a DFE. The use of causal taps only benefits the receiver when CCI is present. Furthermore, it only gives performance benefits when the feedforward filters have a sufficient span (e.g., twice the maximum length of the impulse response of the desired and interference channels), which may not be the case in the EDGE system scenario. In this scenario, we found that the receiver performance is, in general, more sensitive to the number of *anti*-causal taps than the number of causal taps. Thus, we base our timing recovery method on existing approaches for time-domain equalization (i.e., for no CCI and no causal taps).

The method we use is based on the technique described in [3] for a DFE receiver (see the rationale in Section II-A). This method finds the sequence and symbol timing (j, τ) that maximizes the following output SNR index:

$$\gamma_{j\tau} = \frac{\sum_{l=1}^{M} |h^l(jT+\tau)|^2}{\sum_{k=-K_1}^{j-1} \sum_{l=1}^{M} |h^l(kT+\tau)|^2 + N_o} \tag{6}$$

where $h^l(kT+\tau)$, for $k = -K_1, \cdots, K_2$, is the kth sample of the estimated channel impulse response of the desired signal on the lth antenna, and N_o is the estimated noise power, which can be set to a fixed small value (e.g., 0.001) without requiring an accurate estimate. The first term in the denominator of (6) is the estimated precursor ISI power at sequence timing j.

The above method is optimum for a DFE with a single feedforward tap, but it was also found to give near-optimum performance over all multipath delay profiles that we have tested [3], compared to a brute-force timing search method. Therefore, fractionally spaced taps are not needed, i.e., the feedforward filter can use symbol spaced taps. We use the same sequence and symbol timing for all diversity branches.

3) Equalizer Training: The feedforward filter in Fig. 1 has F symbol-spaced taps, while the Viterbi equalizer has a memory of μ, and the feedback filter has $B-\mu$ taps. Our receiver is trained as if it was a DFE with F feedforward taps per branch and B feedback taps, using the MMSE criterion. The method we use is based on the recursive least square (RLS) algorithm, where the weights are calculated using the training sequence, and then held fixed over the TDMA burst. After training, the feedforward filter coefficients are used as the coefficients of the feedforward filter, the first μ feedback coefficients $b_1, b_2, \cdots, b_\mu$ are used to compute the metrics in the Viterbi equalizer, and the remaining coefficients $b_{\mu+1}, \cdots, b_B$ are used to set the feedback filter of the DDFSE. The rationale for this training method is as follows.

C. Rationale for the Space-Time Equalizer Training Algorithm

For the infinite-length case, according to [6, (54)], the optimum maximum likelihood sequence estimation (MLSE) and DFE filters have the following relationship:

$$\boldsymbol{W}_{\mathrm{MLSE}} = \boldsymbol{W}_{\mathrm{DFE}} \frac{1+\Gamma(f)}{C[1+\Gamma(f)]} \cdot \frac{C[\Gamma(f)]}{\Gamma(f)} \tag{7}$$

where $\Gamma(f)$ is the signal-to-interference-plus-noise power density ratio (SINR) at frequency f, and $C[\cdot]$ denotes the *canonical* factor as defined in [6].

Applying the results of [6, (16)] or [6, (43)] to the case of 2 antennas $(M=2)$ and 1 interferer $(L=1)$, we obtain

$$\Gamma(f) = \frac{\alpha+\beta}{N_o(|I_1(f)|^2 + |I_2(f)|^2 + N_o)} \tag{8}$$

where

$$\alpha = N_o(|H_1(f)|^2 + |H_2(f)|^2) \tag{9}$$

$$\beta = |H_1(f)I_2(f) - H_2(f)I_1(f)|^2 \tag{10}$$

$H_i(f)$ is the transfer function of the desired channel on the ith antenna, and $I_i(f)$ is the transfer function of the interference channel on the ith antenna.

We see from (8) that, at high signal-to-noise ratio (SNR), i.e., as $N_o \to 0$,

$$\Gamma(f) \approx 1 + \Gamma(f) \to \frac{|H_1(f)I_2(f) - H_2(f)I_1(f)|^2}{N_o(|I_1(f)|^2 + |I_2(f)|^2 + N_o)}. \tag{11}$$

Therefore,[1]

$$\boldsymbol{W}_{\mathrm{MLSE}} \approx \boldsymbol{W}_{\mathrm{DFE}}. \tag{12}$$

We have shown above that, for an ideal receiver with infinite complexity, the feedforward filter of the MLSE behaves similarly to the feedforward filter of the DFE at high SNR. This proof, however, does not extend to the finite-length case, and certainly not to the case of DDFSE. In these practical cases, we need to consider the tradeoff between maximizing the output SINR of the feedforward filter and the ability to suppress both the ISI and CCI with a short postfiltering equalizer. This has been studied before in other publications (e.g., [14]), but no optimum solution has been found. In our case, we have no guarantee that our training method is optimum, and we have no benchmark for the finite-length case with which to compare the performance of our receiver (since there is no optimum solution available to date). However, we are confident that, based on our training method, the receiver at least performs better than a receiver that uses DFE for both training and data detection. This is because the Viterbi equalizer part of the DDFSE always provides more accurate estimates of the received symbols than a hard slicer. Moreover, since there is only a small gap (1–2 dB) in the ideal performance (with infinite length) between the DFE and MLSE (see, e.g., [6, Fig. 5]), and this is also generally the case for practical receivers, we deduce that our training method is close to optimum (not to mention that it is simple and standard techniques for convergence can be used, since it employs a quadratic function).

[1]In our experience, the only special case where $\boldsymbol{W}_{\mathrm{MLSE}}$ cannot be approximated by $\boldsymbol{W}_{\mathrm{DFE}}$ at high SNR is the case where $L=1$ and $M=1$, which is not relevant here, and assuming no excess bandwidth in this case,

$$\Gamma(f) = \frac{|H(f)|^2}{|I(f)|^2 + N_o}$$

and

$$I + \Gamma(f) = \frac{|H(f)|^2 + |I(f)|^2 + N_o}{|I(f)|^2 + N_o}.$$

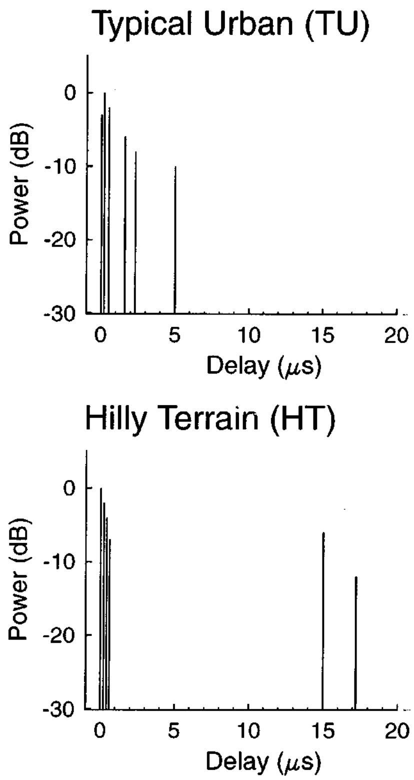

Fig. 2. Delay profiles for the typical urban and hilly terrain models.

III. Simulation Model

The simulation assumptions are similar to those used in [1] for the EDGE system as described above. Exceptions include the following. First, the number of payload symbols in each burst was reduced to 80 (for the convenience of simulation only). Second, the number of training symbols was variable to study the effects of a longer training sequence. Third, a preamble instead of midamble training sequence was used (this results in more pessimistic performance in fast fading).

The channel models are the typical urban (TU) and hilly terrain (HT)—with the maximum delay spread $\tau_{\max} = 17.2\,\mu$s—models, as shown in Fig. 2, with Doppler frequency f_D up to 200 Hz, corresponding to 108 km/h at 2 GHz. The equalizer uses an 8-state Viterbi algorithm with 5 prefilter and 4 feedback taps. Therefore, $F = 5$ and $B = 5$ in our case. We consider a single dominant interferer with random symbol alignment relative to the desired signal. All the imperfections associated with the above timing and weight estimations/training are included in the simulations.

IV. Performance Results

The measure of performance is the BLER, where each block is interleaved over 4 TDMA frames. Overall, we found the proposed 8-PSK scheme performs about 5 dB poorer than standard QPSK with Nyquist filtering. The use of linearized GMSK pulse shaping results in only a small degradation (within 1 dB) compared to square-root raised cosine filtering due to the ISI reduction of the equalizer.

Fig. 3 shows the SIR performance for the TU profile at a Doppler frequency of 4 Hz. Three groups of results are given.

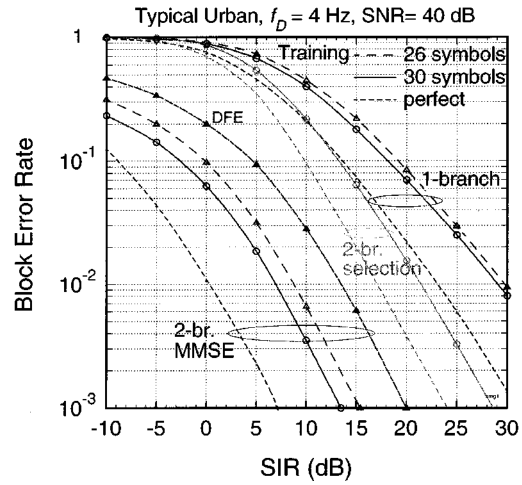

Fig. 3. The SIR performance for the typical urban profile at a Doppler frequency of 4 Hz.

"1-branch" represents our version of the original EDGE results. "2-branch MMSE" represents the results of our interference suppression technique. "2-branch selection" assumes selection diversity based on the total received signal power. The performance differences between these results and the "2-branch MMSE" results approximately indicate the interference suppression gain. Furthermore, for the results with "2-branch MMSE," we provide the performance of a standard space-time DFE [6] (with soft output and hard decision feedback) with the same number of feedforward and feedback taps (for a 26 symbol training sequence). This is to show the improvement provided by the use of delayed decisions and Viterbi sequence estimation in the DDFSE. Note that the DFE requires about 5 dB higher SIR for the same block error rate.

Each group of curves includes results for two different numbers of training symbols: 26 symbols (the EDGE standard) and 30 symbols, as well as "perfect training," which assumes perfect knowledge of all the channel impulse responses for the desired and interfering signals, and perfect training based on the MMSE criterion.

Although "2-branch selection" provides some improvement (about 5 dB) over "1-branch," "2-branch MMSE" provides about 20 dB improvement. The results for 30 training symbols and perfect training show that additional gain (up to 8 dB) could be provided by better weight estimation. Compared to the case without diversity, the BLER with MMSE diversity is more sensitive to the number of training symbols.

This effect is further illustrated in Fig. 4, which shows results for MMSE diversity as a function of the number of training symbols. The training sequence used in each case was chosen to have zero autocorrelation sidelobes—this is considered optimum for space-time equalization with unknown interference. For every four symbols added, the results show an improvement by 2–3 dB in the required SIR.

We note that our equalizer uses five feedforward taps $(F = 5)$ on each branch and four feedback taps, along with the one symbol Viterbi equalizer $(B = 5)$. Thus, the weight training algorithm estimates 15 weights $(2F + B)$ using the training symbols. From [15], using the Direct Matrix Algorithm for weight

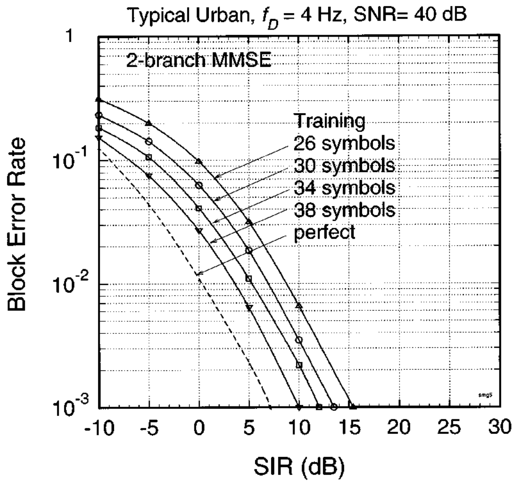

Fig. 4. The SIR performance for MMSE diversity as a function of the number of training symbols.

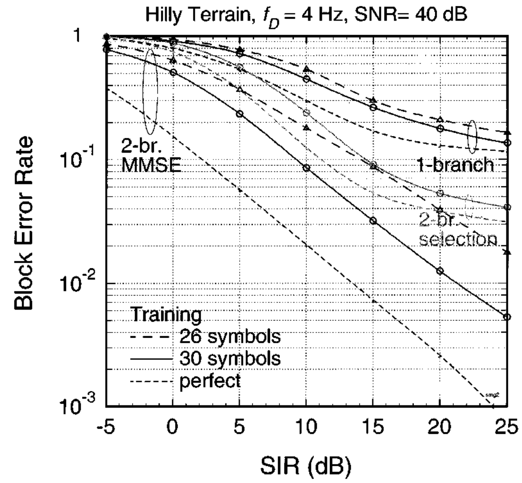

Fig. 6. The SIR performance for the hilly terrain profile at a Doppler frequency of 4 Hz.

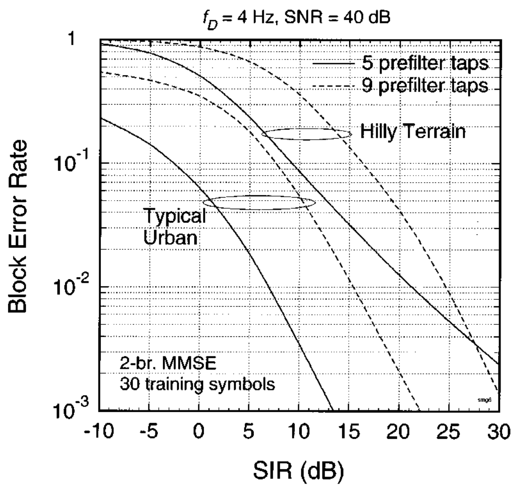

Fig. 5. Comparison of results using 5 and 9 prefilter taps on each diversity branch.

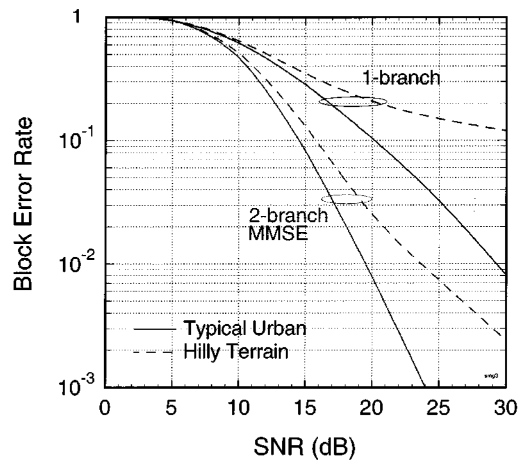

Fig. 7. The SNR performance with and without MMSE diversity.

estimation (note that we are using RLS, however, which should give similar results), one would expect a 3-dB degradation in SNR as compared to perfect estimation when the number of training symbols is twice the number of weights. Here, we see about a 7-dB degradation in SIR with 30 symbols, which is in line with [15].

With perfect training, the performance should improve with the number of feedforward taps. However, with a fixed training sequence length, this is not always the case, since the weight estimation error increases with the number of feedforward taps. This is illustrated in Fig. 5, where we show that even with 30 training symbols, a 9-tap feedforward filter does substantially worse than a 5-tap feedforward filter. This is to be expected since, with nine feedforward taps, 23 weights must be calculated using only 30 symbols, which leads to such a large weight estimation error that the gain due to diversity is lost (see Fig. 3). Thus, the above results indicate the potential for even better performance with further improvements in the weight tracking algorithm.

Fig. 6 shows the results for the HT profile. Here, the performance with MMSE diversity is even more sensitive to the number of training symbols—increasing the number of training symbols from 26 to 30 provides a 4 dB improvement in the required SIR at a 20% BLER.

Note that the results for "1-branch" and "2-branch selection" in Fig. 6 exhibit error floors. This indicates that there are not nearly enough equalizer taps in the receiver when the HT profile is assumed. The results for "2-branch MMSE," however, do not have these floors. This is because MMSE diversity is effective against both CCI and ISI.

The results given in Figs. 7 and 8 and Table I assume the use of 30 training symbols. Fig. 7 shows the SNR performance with and without MMSE diversity when interference is not present. The SNR at a 10% BLER is decreased by 10 dB for the TU model with MMSE diversity, and even more for the HT model.

Fig. 8 shows the performance (with MMSE diversity) as a function of the Doppler frequency. The SIR and SNR values were chosen to provide BLER's between 10 and 20% at a low fading rate. Due to the use of coding and interleaving, the receiver is seen to be quite robust against fast fading.

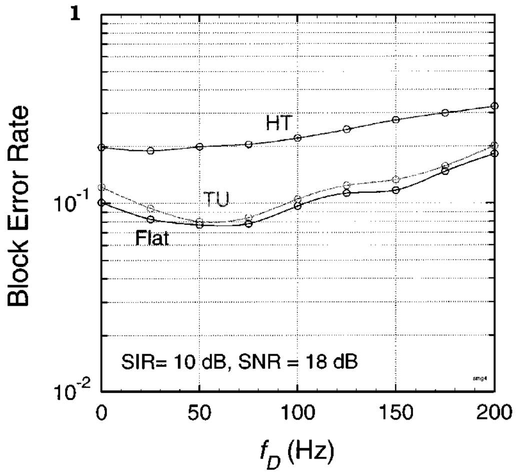

Fig. 8. The performance with MMSE diversity as a function of the Doppler frequency.

TABLE I
REQUIRED SIR AND SNR

1-Branch (f_D = 4 Hz)

Channel	SIR	SNR	BLER
Flat Fading	20	20	11.2%
TU Profile	20	20	18.6%
HT Profile	20	20	26.2%

2-Branch (f_D = 4 Hz)

Channel	SIR	SNR	BLER
Flat Fading	10	18	9.7%
TU Profile	10	18	11.8%
HT Profile	10	18	19.4%

Table I lists the values of the required SNR and SIR to achieve BLER's around 10–20% when the SNR and SIR are comparable. With interference suppression, the system can operate at an SIR of 10 dB and an SNR of 18 dB; whereas the original EDGE system would require an SNR and SIR of 20 dB. Thus, we conclude that in environments where the noise and interference levels are comparable MMSE diversity provides a 10 dB improvement in SIR performance and a 2 dB improvement in SNR performance.

V. CONCLUSION

In this paper we presented a receiver structure and algorithms for joint interference suppression and equalization with 2 antennas in EDGE. This receiver provided from 10 to 20 dB interference suppression and from 2 to 10 dB improvement in SNR performance (with and without interference, respectively). We also showed improved robustness against delay spread and the effect of increased training sequence length.

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Dr. Ariyavisitakul has served as Editor of the IEEE TRANSACTIONS ON COMMUNICATIONS since 1995, and the Secretary of the Communication Theory Technical Committee of the IEEE Communications Society since 1997. He has organized and chaired technical sessions in a number of IEEE conferences. He received the 1988 Niwa Memorial Award in Tokyo, Japan, for outstanding research and publication. He is a member of the Institute of Electronics, Information, and Communication Engineers of Japan.

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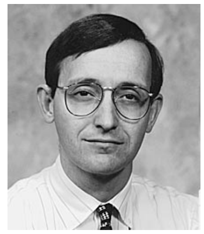

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He heads the Wireless Systems Research Department at AT&T. His department performs research on next generation wireless systems concepts and technologies including high speed transmission methods, smart antennas and adaptive signal processing, system architectures and radio link techniques to support wireless multimedia and advanced voice services. From 1979 to 1986, he was a member of the cellular radio development organization at Bell Laboratories. At Bell Laboratories, he investigated spectrally efficient analog and digital technologies for second-generation cellular radio systems. In 1987, he joined the radio research department at Bellcore, and was the head of that department from 1993 to 1995. At Bellcore, he investigated concepts for PACS, the Personal Access Communications System. In 1995, he joined AT&T.