A 2-Stage Soft-Output Equalizer for EDGE

Hanks H. Zeng[1], Ye (Geoffrey) Li[1], Jack H. Winters[1] and Hamid R. Sadjadpour[2]
[1]Wireless Systems Research Department
AT&T Labs-Research, Red Bank, NJ 07701 USA
[2]AT&T Labs-Research, Florham Park, NJ 07932 USA
Email: {zeng, liye, jhw}@research.att.com, sadjadpour@att.com

Abstract— **In this paper, we propose a new 2-stage soft-output equalizer (TSSOE) structure for spatial-temporal processing in EDGE. The TSSOE is the cascade of a delayed decision-feedback sequence estimator (DDFSE) and maximum *a posteriori* probability (MAP) estimator. The TSSOE uses the final-decision symbols from the DDFSE to estimate the noise variance and truncates the channel memory for the following MAP estimator. Compared with the soft-output DDFSE, the TSSOE reduces both the feedback symbol errors and the noise variance estimation error. At 10% block error rate and 20 dB signal-to-noise ratio, the TSSOE requires about 10 dB lower signal-to-interference ratio than the soft-output DDFSE for the GSM typical urban channel profile.**

I. Introduction

The radio interface EDGE, Enhanced Data rates for Global Evolution, has been standardized as an evolutionary path from GSM and TDMA-IS136 for third-generation high-speed data wireless systems [1]. A major limitation on the system range and capacity of wireless systems such as EDGE is intersymbol interference (ISI), caused by multipath fading, and co-channel interference (CCI). Spatial-temporal equalization (STE) using multiple antennas is an effective approach to jointly suppress ISI and CCI [2], [3].

A popular STE structure uses space-time prefilters for combining, followed by a temporal equalizer for signal detection (see Figure 1). For the temporal equalizer, the optimal solution in the sense of minimum bit error rate is the symbol-by-symbol maximum *a posteriori* probability (MAP) estimator which delivers soft-output information to the outer convolutional decoder. In EDGE, the 8-PSK modulation and long channel memory (about 7 taps) result in a computationally complex MAP estimator. For complexity reduction, one can use suboptimal approaches such as the soft-output Viterbi algorithm (SOVA) [4], Max-Log-MAP [5], Log-MAP [6], reduced-state soft-output equalization [7], and soft-output delayed decision-feedback sequence estimator (SO-DDFSE) [2], [8]. Among the above approaches, SOVA is not as effective in nonbinary modulation [9]. The other approaches perform well only when good noise variance estimation is provided prior to equalization, and mismatch of the noise variance significantly degrades the decoder performance [10].

In this paper, we first study the performance of the SO-DDFSE. Next we propose a new 2-stage soft-output equalizer (TSSOE) which is the cascade of a DDFSE and MAP estimator. The TSSOE uses the final-decision symbols from the DDFSE to estimate the noise variance and and truncates the channel memory for the following MAP estimator. Compared with the SO-DDFSE, the TSSOE reduces both the feedback symbol errors and the noise variance estimation error. The TSSOE is evaluated for EDGE under different channel conditions. For the GSM typical urban channel profile, 20dB SNR and 10% block error rate (BLER), the required signal-to-interference ratio (SIR) with the TSSOE is 7.5 dB which is 10 dB lower than that required with SO-DDFSE.

II. Soft-Output DDFSE

As shown in Figure 1, the STE has prefilters followed by a temporal equalizer. The prefilters suppress noise and cochannel interference and also shorten the overall system impulse response to reduce the computational complexity of the temporal equalizer. At the prefilter combiner output, the received signal channel can be viewed as an ISI channel given by:

$$y(k) \triangleq \sum_{i=0}^{L_b} g(i)s(k-i) + w(k) \qquad (1)$$

where $s(k)$ is the transmitted 8-PSK symbol, $\{g(i)\}$ is the shortened channel impulse response, and $w(k)$ is the noise including residual ISI, CCI and AWGN.

To mitigate the ISI and noise in (1), the SO-DDFSE was developed [2]. Basically, the SO-DDFSE is a reduced-state MAP algorithm which applies a MAP estimator in the MLSE portion of the DDFSE. As shown in Figure 2 (a), the first part of the channel ($\mathbf{g}_\mu$) is handled by the MLSE via the Viterbi algorithm (VA), while the remaining postcursors ($\mathbf{g}_b$) are cancelled by delayed tentative decisions for each state. Thus, the channel state is reduced to a hyperstate corresponding to $\mathbf{g}_\mu$. In parallel to the MLSE, the MAP estimator computes the soft-outputs based on these hyperstates in the MLSE. In computing the soft-outputs, the variance of the noise $w(k)$ prior to the equalization is required. The noise variance is estimated during the equalizer training period [2].

The performance of the SO-DDFSE is affected by the following factors: (a) white Gaussian assumption for the noise; (b) equalizer parameter generation error; (c) feedback symbol errors (e.g., incorrect tentative decisions); and (d) noise variance estimation error. Among the above factors, (b) and (c) enhance residual ISI and reduce the input SNR of the MAP estimator, and (d) is a very sensitive factor for the MAP estimator [10]. In particular, we have shown that the noise variance estimation in [2] is biased, which results in a substantial performance degradation.

III. 2-Stage Soft-Output Equalizer

To overcome the drawbacks of the SO-DDFSE, we propose a new 2-stage soft-output equalizer structure which reduces the feedback symbol errors and the noise variance estimation error. As shown in Figure 2 (b), the proposed structure is the cascade of a DDFSE and MAP estimator. The DDFSE produces hard-decision outputs $\hat{s}(k)$ and noise variance estimates $\hat{\sigma}^2$. The shortened channel impulse response $\mathbf{g}$ is further truncated using hard-decisions. The truncated channel $\mathbf{g}_{\mu'}$ is then handled by a MAP estimator.

Noise variance estimation:

The equivalent model at the input of the MAP is given by

$$\begin{aligned} z(k) &= y(k) - \sum_{i=\mu'+1}^{L_b} g(i)\hat{s}(k-i) \\ &= \sum_{i=0}^{\mu'} g(i)s(k-i) + \bar{w}(k) \end{aligned} \tag{2}$$

where

$$\bar{w}(k) = \sum_{i=\mu'+1}^{L_b} g(i)(\hat{s}(k-i) - s(k-i)) + w(k).$$

The above noise $\bar{w}(k)$ includes the additive noise at the prefilter output and the decision errors. It can be estimated by averaging over only the data as follows:

$$\begin{aligned} \sigma^2 &\triangleq E\{|\bar{w}(k)|^2\} \approx \frac{1}{N}\sum_{k=1}^{N}|\bar{w}(k)|^2 \\ &\approx \frac{1}{N}\sum_{k=1}^{N}|\bar{w}(k) + \sum_{i=0}^{\mu'} g(i)(\hat{s}(k-i) - s(k-i))|^2 \\ &= \frac{1}{N}\sum_{k=1}^{N}|\sum_{i=0}^{L_b} g(i)\hat{s}(k-i)) - y(k)|^2 \triangleq \hat{\sigma}^2 \end{aligned} \tag{3}$$

Eq. (3) is the accumulated error metric corresponding to the final decision symbols which can be computed using the hard-decisions of the DDFSE.

Soft-output recursion:

The soft-output of the MAP estimator is derived using Lee's algorithm [11]. In particular, the transmitted 8-PSK symbol can be expressed as

$$s(k) = F(b_0(k), b_1(k), b_2(k)), \tag{4}$$

where $b_i(k) = \{0, 1\}$, and the function F performs the 8-PSK modulation and Gray mapping. The soft-output is the *a posteriori* probability (APP) defined as the conditional probability of each bit $b_i(k)$ given the received samples $z_1^k \triangleq \{z(1), \cdots, z(k)\}$, i.e,

$$\begin{aligned} &\hat{b}_i(k) = Pr(b_i(k) = 1|z_1^k) \\ = &\sum_{b_i(k)=1, b_j(k)=0,1, j\neq i} \\ &Pr(s(k) = F(b_0(k), b_1(k), b_2(k))|z_1^k) \end{aligned} \tag{5}$$

where

$$Pr(s(k)|z_1^k) = \frac{Pr(s(k), z_1^k)}{Pr(z_1^k)} \tag{6}$$

$$= \frac{\sum_{s_{k-\mu'+1}^{k-1}} Pr(s_{k-\mu'+1}^{k}, z_1^k)}{\sum_{s_{k-\mu'+1}^{k}} Pr(s_{k-\mu'+1}^{k}, z_1^k)}. \quad (7)$$

Each term of the above equation is obtained recursively by

$$\begin{aligned} & Pr(s_{k-\mu'+1}^{k}, z_1^k) \\ = & \sum_{s(k-\mu')} Cexp(\frac{|z(k) - \sum_{i=0}^{\mu'} g(i)s(k-i)|^2}{2\hat{\sigma}^2}) \\ & \cdot Pr(s_{k-\mu'}^{k-1}, z_1^{k-1}) \end{aligned} \quad (8)$$

where C is a constant.

Compared with the SO-DDFSE, the TSSOE uses the final decisions instead of the tentative decisions, thus reducing the feedback error. Furthermore, the noise variance estimation in the TSSOE is averaged over more samples since it is obtained in the data period. It also utilizes the results of the DDFSE, and therefore is more accurate.

IV. Simulation

The performance of the TSSOE was evaluated for the EDGE system shown in Figure 1. Modulation and coding scheme 5 (MCS-5) was chosen in the simulation [1]. In particular, a rate 1/3 convolutional code with constraint length of 7 was used. The burst format is the same as GSM. The modulation is 8-PSK with linearized GMSK pulse shaping, and the baud rate is 279.833 ksps The channel model is a multipath fading channel with a single interferer, a Doppler frequency of 4Hz, and no frequency hopping. In the receiver, the timing recovery algorithm determines the estimated burst timing and processing direction [12]. The two prefilters have 5 taps each, and the shortened channel impulse response ($\mathbf{g}$) has 6 taps. The equalizer uses an 8-state DDFSE and 8-state MAP ($\mu = \mu' = 1$).

First, we study the effect of the noise estimation and feedback errors. Figure 3 shows the BLER versus SIR with a single interferer for the TSSOE, the SO-DDFSE, the SO-DDFSE with perfect noise variance estimation, and the SO-DDFSE with perfect noise variance estimation plus perfect feedback. The last technique corresponds to the best achievable 8-state (reduced-state) soft-output equalizer. For the SO-DDFSE, the noise variance estimation error and feedback errors cause about a 13 dB loss in required SIR for a 10% BLER. With perfect noise variance estimation, the required SIR is reduced by 5 dB. On the other hand, the TSSOE significantly reduces both the noise variance estimation error and feedback errors. The performance improvement over the SO-DDFSE is about 10 dB, which is within 3 dB of that of the SO-DDFSE with perfect noise variance estimation and feedback.

Second, we study the performance of the TSSOE for different channel conditions. Figure 4 shows the BLER versus signal-to-interference-plus-noise ratio (SINR) for the TSSOE with the typical urban (TU) and hilly terrain (HT) profiles. In the interference dominant cases (SNR=30dB), the required SINR for 10% BLER is -7.5 dB for TU, and 10 dB for HT. On the other hand, in the noise dominant case (SIR=30 dB), the required SINR is about 15 dB for both TU and HT. Thus, the proposed TSSOE with a 2-branch receiver can handle strong CCI, and therefor provides an efficient means for EDGE capacity enhancement.

V. Conclusion

In this paper, we proposed a new 2-stage soft-output equalizer (TSSOE) structure which is the cascade of a DDFSE and a MAP estimator. The TSSOE uses the final-decision symbols from the DDFSE to estimate the noise variance and truncates the channel memory for the subsequent MAP estimator. The TSSOE reduces both the feedback symbol errors and the noise variance estimation error. We applied the TSSOE for spatial-temporal equalization in EDGE. Compared with the previous approach, the TSSOE significantly improves the BLER performance. Furthermore, the TSSOE with a 2-branch receiver can handle strong CCI, especially in the typical urban environment, therefore is an efficient technique for EDGE capacity enhancement.

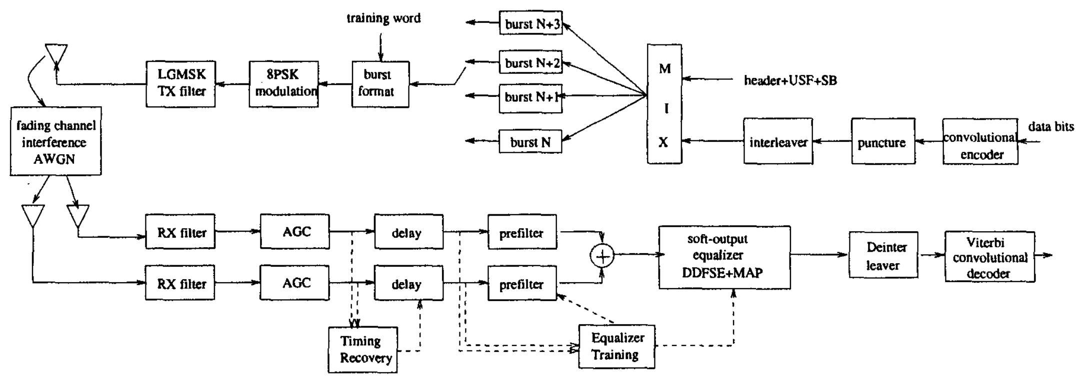
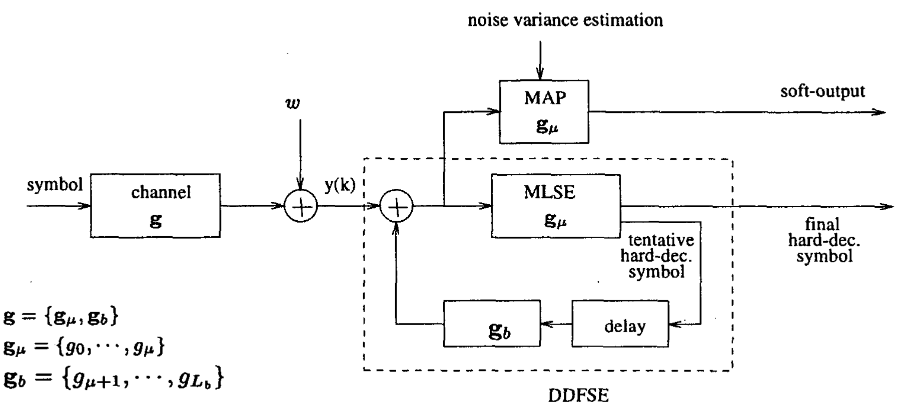
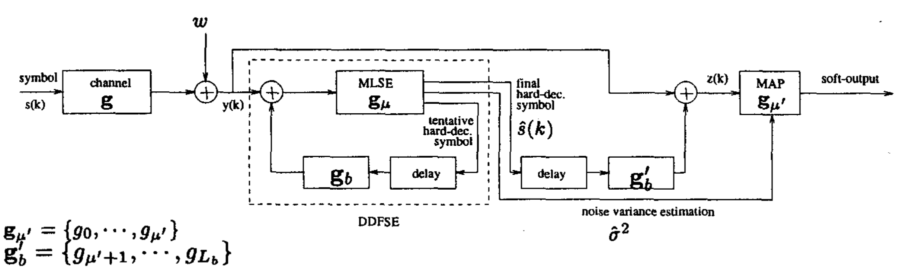


Fig. 1. EDGE system diagram.



(a)



(b)

Fig. 2. (a) Soft-output DDFSE; (b) Two-stage soft-output equalizer.

REFERENCES

[1] N. R. Sollenberger, N. Seshadri, and R. Cox, "The evolution of IS-136 TDMA for third-generation wireless services", *IEEE Personal Communications*, vol. 6, pp. 8–18, June 1999.

[2] S. Ariyavisitakul, J. H. Winters, and N. R. Sollenberger, "Joint equalization and interference suppression for high data rate wireless systems", in *VTC1999 Spring*, vol. 1, pp. 700–706, 1999.

[3] D. Baldsjo, A. Furuskar, S. Javerbring, and E. Larsson, "Interference cancellation using antenna diversity for EDGE - enhanced data rates in GSM and TDMA/136", in *VTC1999 Fall*, vol. 4, pp. 1956–1960, 1999.

[4] J. Hagenauer, "Source-controlled channel decoding", *IEEE Trans. on Commun.*, vol. COM-43, pp. 2449–2457, Sept. 1995.

[5] W. Koch and A. Baier, "Optimum and sub-optimum detection of coded data disturbed by time-varying intersymbol interference", in *Proc. Globecom'90*, pp. 1679–1684, 1990.

[6] P. Robertson, E. Villebrun, and P. Hoeher, "A comparison of optimal and sub-optimal MAP decoding algorithms operating in the log domain ", in *Proc. 1995 IEEE Intl. Conf. Commun.*, (Seattle), pp. 1009 –1013, 1995.

[7] S. H. Muller, W. H. Gerstacker, and J. B. Huber, "Reduced-state soft-output trellis-equalization incorporating soft feedback", in *Proc. Globecom'96*, vol. 1, pp. 95–100, 1996.

[8] A. Duel-Hallen and C. Heegard, "Delayed decision-feedback sequence estimation", *IEEE Trans. Commun.*, vol. COM-37, pp. 428–436, May 1989.

[9] P. Hoeher, "TCM on frequency-selective fading channels: a comparison of soft-output probabilistic equalizers", in *Proc. Globecom'90*, vol. 1, pp. 376–381, 1990.

[10] T. Summers and S. Wilson, "SNR mismatch and online estimation in turbo decoding", *IEEE Trans. Commun.*, vol. 46, pp. 421–423, April 1998.

[11] L. Lee, "Real-time minimum-bit-error probability decoding of convolutional codes", *IEEE Trans. Commun.*, vol. COM-22, pp. 146–151, Feb. 1974.

[12] H. Zeng, Y. Li, and J. H. Winters, "A fast selective-direction MMSE timing recovery algorithm for spatial-temporal equalization in EDGE", in *VTC2000 Fall.*

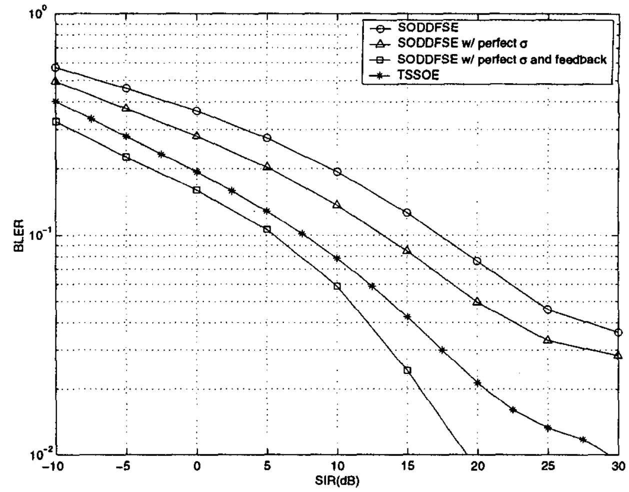


Fig. 3. Comparison of the SO-DDFSE and TSSOE. (TU profile. SNR=20dB)

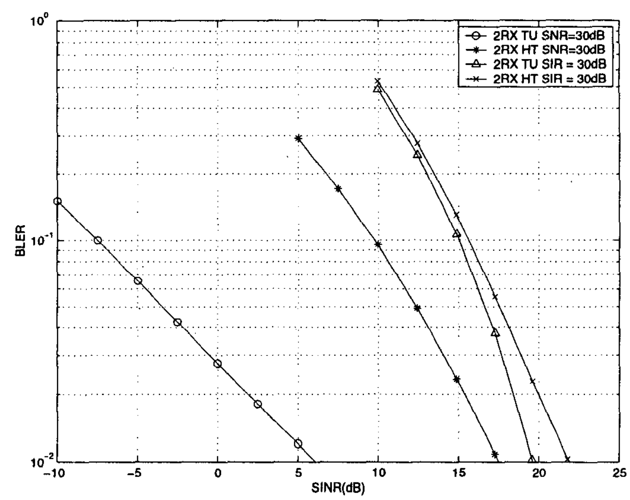


Fig. 4. SINR performance of the TSSOE.