Performance Analysis of Error Propagation Effects in the DFE for ATSC DTV Receivers

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***Abstract*—This paper analyzes the error propagation phenomenon in the decision feedback equalizer (DFE) for the receivers of Advanced Television Systems Committee (ATSC) digital television (DTV) and presents the performance upper-limits of the DFE by comparing various error propagation cases and the no-error propagation case. As one approach to the performance limit, we consider a blind DFE, adopting a trellis decoder with a trace-back depth of 1 as a decision device. Through simulation, we show how much the DFE performance in ATSC DTV receivers is affected by error propagation. We found that while blind equalization is preferable to decision-directed (DD) equalization at signal-to-noise ratio (SNR) values less than 18 dB, DD equalization is superior to blind equalization at SNR values greater than 18 dB. In addition, symbol error rate curves quantitatively show that the performance difference in the DFE caused by error propagation becomes clearer at the trellis decoder following the DFE. The analysis results presented in this paper will be very informative for developing equalization algorithms for ATSC DTV receivers.**

***Index Terms*—ATSC, blind equalization, DFE, DTV, error propagation.**

I. Introduction

DECISION FEEDBACK EQUALIZERS (DFEs) are commonly used in digital communication systems to suppress intersymbol interference. Advanced Television Systems Committee (ATSC) digital TV (DTV) receivers have also used DFEs to equalize the 8-vestigial sideband (VSB) signal which is the transmission standard of the ATSC terrestrial DTV [1]. In a conventional DFE, the data passed into the feedback section is the slicer output and hence no longer contains any noise, thus increasing the accuracy of the interference cancellation. However, this advantage is meaningful only when the slicer output is correct. When there is no training signal and the eyes of the equalizer output are closed, the DFE may have a problem converging its tap coefficients since the decision-error probability of the slicer increases. This decision error results in error propagation through the feedback loop.

In the DFE for ATSC DTV receivers, the error propagation phenomenon may seriously affect the convergence performance because blind equalization or decision-directed equalization using slicer outputs has to be carried out in most received symbols. When the training sequence exists, the DFE uses the training sequence for the feedback filter input. However, when there is no training sequence during the data segments, the slicer output is generally fed into the feedback section. As the symbol error rate (SER) can be as high as 0.2 and the training sequence is very short in the terrestrial DTV receiver, error propagation is unavoidable during the data symbols [2]. This results in deterioration of the performance in terms of the convergence speed and residual mean-square error (MSE). The advantage of the DFE is no longer valid.

We analyze the error propagation phenomenon existing in the DFE of ATSC DTV receivers and present performance upper-limits of the DFE by comparing error propagation and no-error propagation cases. As one approach to the performance limit, we consider a blind DFE, adopting a trellis decoder with a trace-back depth of 1 as a decision device.

This paper is organized as follows. In Section II, we introduce the DFE commonly used for ATSC DTV receivers and analyze the error propagation effects in the DFE. As an effective method to overcome the error propagation, the DFE adopting a Viterbi decoder for the decision device is investigated in Section III. The performance differences of the DFE according to the error propagation are presented through simulation results in Section IV. Finally, Section V concludes this paper.

II. DFE for ATSC DTV Receivers

The 8-VSB signal is transmitted in "frames," as shown in Fig. 1. Each data frame is composed of two data fields, each containing 313 "segments," of which the first segment is the "field sync" segment, followed by 312 "data segments." Each data segment is composed of 832 symbols, of which the first four symbols are the "segment sync" symbols $(5, -5, -5, 5)$ and the remaining 828 symbols are Reed-Solomon (RS)-encoded, interleaved, and trellis-encoded symbols drawn from the 8 level pulse amplitude modulation constellation $(\pm 1, \pm 3, \pm 5, \pm 7)$ [1]. The field sync segment is used for the training sequence of the equalizer.

During the field sync segment, the DFE operates without error propagation because the known signal is fed into the feedback filter. However, since the field sync segment arrives only once every field corresponding to 24 ms, the overall rate of convergence of the equalizer can be quite slow if the adaptation of the equalizer is carried out only during the field sync segment. In addition, such an adaptation policy is not efficient for time-varying channels. Decision-directed (DD) adaptation at the data segments does not work well. Since the SER at the equalizer output is about 0.2 at the threshold of visibility (TOV) [2] and the DFE has 200 more taps, one error feedback can affect

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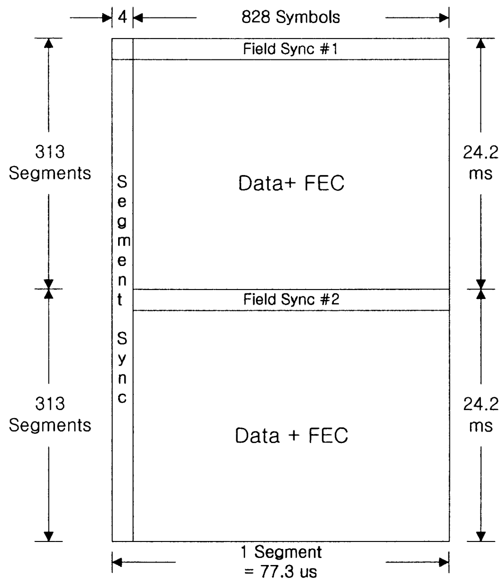


Fig. 1. An 8-VSB data frame.

200 more outputs. To deal with time-varying channels and compensate for the shortness of the training sequence, blind equalization algorithms has been introduced for the DFE during the data segments [2], [3].

The DFE can be adapted by using the least-mean square (LMS) or the recursive-least square (RLS) algorithm in the training mode and using one of the blind algorithms, such as the constant modulus algorithm (CMA), the stop-and-go (SAG) algorithm, or the SAG dual-mode CMA, for the data segments [3]. Let $x[k]$ be the equalizer input, the output of the DFE at time $k, y[k]$, is given by

$$y[k] = \sum_{i=0}^{N_b-1} b_i[k]x[k-i] - \sum_{j=1}^{N_a} c_j[k]\hat{y}[k-j], \qquad (1)$$

where $b_i[k](i = 0, \ldots, N_b - 1)$ are the forward equalizer taps at time $k, c_j[k](j = 1, \ldots, N_a)$ are the feedback taps at time k, and $\hat{y}[k]$ is the slicer output which is the constellation point closest to $y[k]$. The LMS update algorithm for the feedforward and feedback filter taps are given by

$$\begin{cases} b_i[k+1] = b_i[k] - \mu e_D[k]x[k-i] \\ c_j[k+1] = c_j[k] + \mu e_D[k]\hat{y}[k-j], \end{cases} . \qquad (2)$$

where μ is the renewing step size and

$$e_D[k] = y[k] - \hat{y}[k] \qquad (3)$$

is the decision-directed (DD) error.

To improve the convergence speed at the expense of computational complexity, the RLS algorithm may be used in the training mode. The RLS update algorithm is as follows [4]:

$$\begin{cases} \mathbf{k}[k+1] = \frac{\lambda^{-1}\mathbf{P}[k]\mathbf{u}[k]}{1+\lambda^{-1}\mathbf{u}^T[k]\mathbf{P}[k]\mathbf{u}[k]} \\ \mathbf{w}[k+1] = \mathbf{w}[k] - \mathbf{k}[k+1]e_D[k] \\ \mathbf{P}[k+1] = \lambda^{-1}\mathbf{P}[k] - \lambda^{-1}\mathbf{k}[k+1]\mathbf{u}^T[k]\mathbf{P}[k], \end{cases} \qquad (4)$$

where λ is the forgetting factor and

$$\mathbf{w}[k] = \begin{bmatrix} \mathbf{b}[k] \\ \mathbf{c}[k] \end{bmatrix} = \begin{bmatrix} [b_0[k] & b_1[k] & \cdots & b_{N_b-1}[k]]^T \\ [c_1[k] & c_2[k] & \cdots & c_{N_a}[k]]^T \end{bmatrix} \qquad (5)$$

$$\mathbf{u}[k] = \begin{bmatrix} \mathbf{x}[k] \\ -\hat{\mathbf{y}}[k] \end{bmatrix} = \begin{bmatrix} [x[k] & x[k-1] & \cdots & x[k-N_b+1]]^T \\ [-\hat{y}[k-1] & -\hat{y}[k-2] & \cdots & -\hat{y}[k-N_a]]^T \end{bmatrix}. \qquad (6)$$

Note that (1) through (2) are the DD adaptation equations using the slicer output, which may be useful for the blind mode where there is no training sequence. During the training mode, however, the slicer output is replaced with the training symbol.

In the blind mode, using the SAG algorithm, the filter tap coefficients are updated via

$$\begin{cases} b_i[k+1] = b_i[k] - \mu f[k]e_D[k]x[k-i] \\ c_j[k+1] = c_j[k] + \mu f[k]e_D[k]\hat{y}[k-j]. \end{cases} \qquad (7)$$

The SAG flag $f[k]$ is defined as

$$f[k] = \begin{cases} 1 & \text{if } \operatorname{sgn}\{e_D[k]\} = \operatorname{sgn}\{e_S[k]\} \\ 0 & \text{if } \operatorname{sgn}\{e_D[k]\} \neq \operatorname{sgn}\{e_S[k]\}, \end{cases} \qquad (8)$$

where $e_S[k]$ is the Sato error given by

$$e_S[k] = y[k] - \gamma \operatorname{sgn}\{y[k]\}. \qquad (9)$$

Here, γ is a constant defined by

$$\gamma = \frac{E[|a[k]|^2]}{E[|a[k]|]}, \qquad (10)$$

where $a[k]$ is the transmitted symbol.

In many cases of DTV receivers, the DFE operates under the additive white Gaussian noise condition of SNR values between 20 dB and 30 dB. When we consider multi-path fading channels, the SNR condition becomes worse at the equalizer output because the DFE does not completely compensate for the multi-path channel effect. Fig. 2 shows the scatter diagrams of the equalizer output at various output SNR values of 17, 18, 19, 20 dB. When the SNR is lower than about 18 dB, the eyes of the 8-VSB signal are closed and thus error propagation occurs during the data segments. This results in deterioration of the convergence performance of the blind DFE.

To overcome this problem, it is necessary to analyze the error propagation effect and reduce it. In [3], a selective feedback

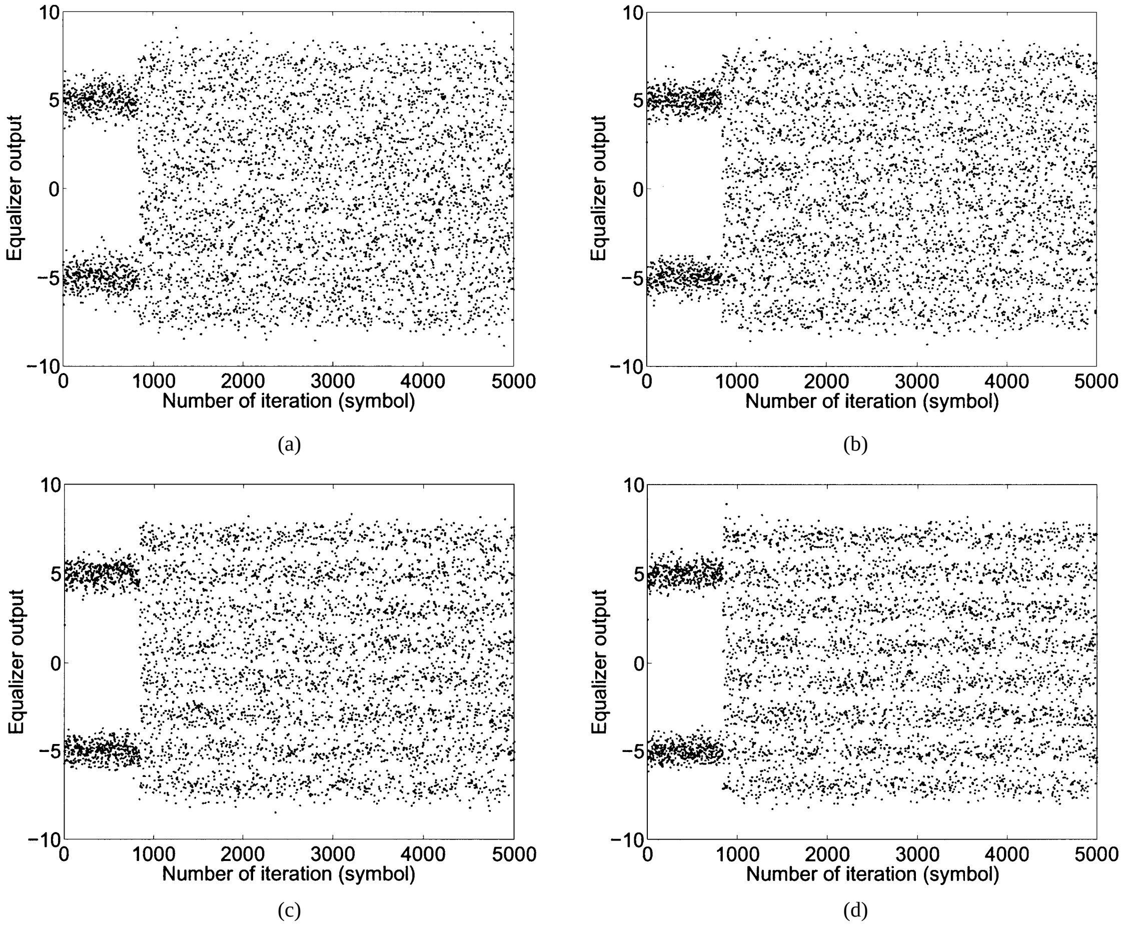


Fig. 2. Equalizer output SNR (a) 17 dB, (b) 18 dB, (c) 19 dB, (d) 20 dB.

scheme was proposed to reduce the performance degradation of the blind DFE caused by error propagation. However, though the performance of the blind DFE can be improved by introducing the selective feedback scheme, the degree of improvement is not large and error propagation still exists. From our analysis by simulation which will be shown in Section IV, we found that the SER performance can be improved by more than 2 dB if we minimize error propagation. Thus, if more feedback inputs are managed so that they are correct, the performance of the blind DFE will be improved.

III. Blind DFE With the Trellis Decoder

The slicer output is usually determined by searching for the symbol closest to the equalizer output $y[k]$ in a predetermined transmit symbol constellation. This kind of decision device has the lowest computational complexity but may result in error propagation when the eyes are closed. To improve the probability of the correct-decision of the slicer, the Viterbi decoder may be a good candidate as a decision device to replace the slicer [5]. It is well known that a trace back depth (TBD) $\delta \geq 5K$ results in a negligible degradation in the performance relative to the optimum Viterbi algorithm [6], where K is the constraint length. Since K is 3 in the ATSC DTV system, the TBD should be not less than 15. Unfortunately, because of the long delay[1] caused by the TBD and the trellis code de-interleaver [7], using a trellis decoder (TD), such as the Viterbi decoder, with a TBD of 15 may not be effective for the DFE of ATSC DTV receivers. To adopt the TD as a decision device in the blind DFE, the delay caused by the TD has to be minimized because the low-order tap coefficients of the feedback filter have a large impact on the equalizer performance.

According to coding theory, the trellis-coded 8-VSB has better performance than the uncoded 4-VSB at a TBD setting of about 15 as shown in Fig. 3. In the case of the DFE, however, it is already valuable if the output of the TD has better performance than the output of the slicer. Fig. 3 shows that the TD with a TBD of 1 has better SER performance than the slicer output by more than 5 dB at an SER of about 0.03. The more important fact is that the TD with a TBD of 1 does not cause any delay in using the output of the TD for the blind DFE. If we achieve the output SNR of the DFE only to 17 dB, the TD with a TBD of 1 produces an SER of about 0.003. Provided that this SER value would be given, the DFE could avoid being deteriorated by error propagation and approach a state of no error propagation. However, in the case of the slicer, when we achieve an output SNR of the DFE to 17 dB, the SER becomes 0.1 (Fig. 3) and thus results in error propagation. This error propagation makes the convergence speed slow and the residual MSE increase.

Now we consider the adaptation of the blind DFE adopting the TD with a TBD of 1 shown in Fig. 4. When we use the LMS

[1] The delay becomes $(N-1) \times 12$, where N is the TBD. A TBD of 15 produces a 168-symbol delay.

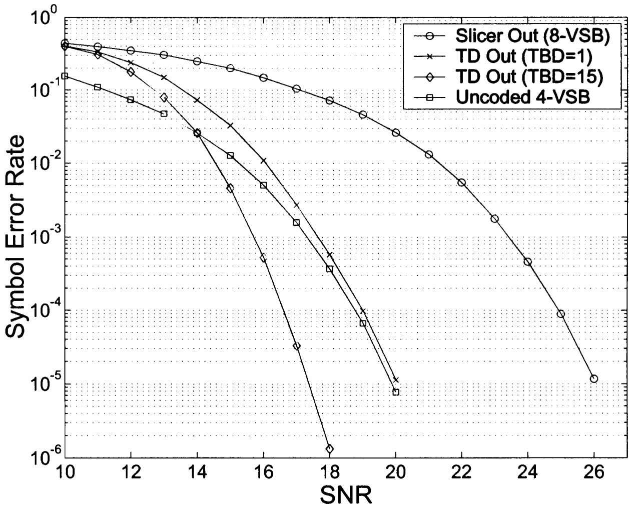


Fig. 3. Symbol error rates of the trellis-coded 8-VSB, the trellis decoder, and the uncoded 4-VSB.

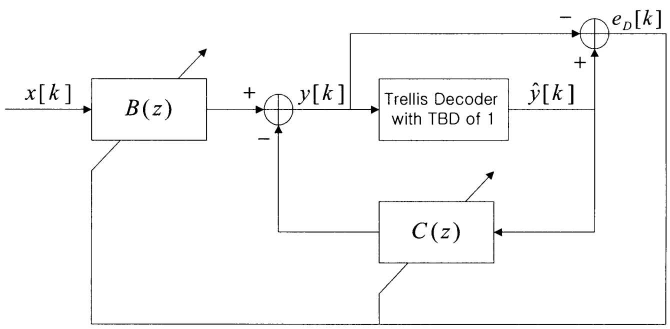


Fig. 4. DFE with the trellis decoder.

algorithm in the training mode, the output SNR of the equalizer at the end of the training mode fails to reach 17 dB. In this case, to raise the SNR, the use of blind algorithms in the data segments is required. On the other hand, with fast algorithms, such as the RLS, we can obtain an SNR of higher than 17 dB only in the training mode. In such a case, we can use DD equalization for the DFE instead of blind algorithms.

Finally, note that the blind DFE with the TD does not cause any problem in the correlation of the noise sequence at the DFE output addressed in [2], because we do not assume any no-error propagation. Therefore, the analysis result given in [2] suggests that this DFE will converge to the minimum-mean-square-error taps derived using the error propagation model, actually reduces the noise correlation at the DFE output; hence, the loss through the trellis decoder is reduced.

IV. Simulation Results

Extensive computer simulations were carried out to analyze the equalization performance according to the error propagation in the blind DFE for ATSC DTV receivers. The channel profile used for this simulation was Ensemble D of five echoes with amplitudes, delays, and phases as specified by the ATTC [8], which is shown in Table I. The received SNR was obtained from

TABLE I
Multi-Path Profile

Delay (μs)	Amplitude (dB)	Phase (degree)
-1.8	-20	90
+0.15	-20	55
+1.80	-18	25
+5.70	-14	80
+18.0	-10	90

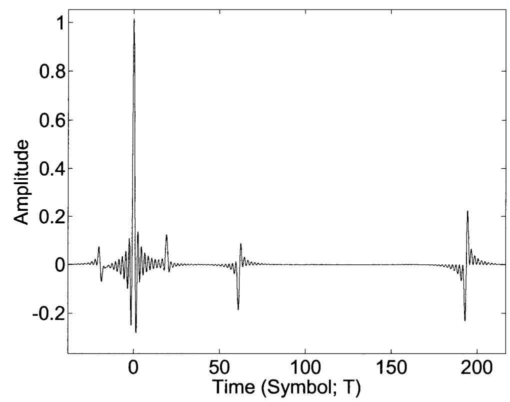


Fig. 5. Impulse response of the equivalent VSB channel corresponding to Ensemble D.

the baseband equivalent VSB channel model presented in [9] and is defined as

$$\mathrm{SNR} = \frac{E[|h_R[k] * g[k] * a[k]|^2]}{E[|\sqrt{g}[k] * 2\sqrt{g}[k]\cos\omega_1 n * w[k]|^2]}, \tag{11}$$

where $h_R[k]$ is an impulse response of the baseband-equivalent VSB channel model, $g[k]$ is the pulse-shaping filter of the raised cosine filter with the roll-off factor[2] of 0.0576, $\sqrt{g}[k]$ is the square-root raised cosine filter corresponding to $g[k], a[k]$ is a transmit symbol sequence, $w[k]$ is a white Gaussian noise process, and $\omega_1 = 2\pi \times 5.38$ (Refer to [9] for a detailed description). In our simulations based on the VSB channel model, we considered VSB modulation and passband-related effects, such as phase information and a carrier frequency under Korean DTV CH 15 for which the center frequency is 479 MHz. The impulse response of the baseband-equivalent VSB channel corresponding to Ensemble D is shown in Fig. 5.

The DFE with 40 feedforward and 216 feedback taps was adapted using the LMS or RLS algorithm in the field sync segment and blind equalization algorithms in the data segments. The step sizes of μ in the field sync segment and the data segments were 2.0×10^{-4} and 2.0×10^{-5} (1.0×10^{-5} for the DD algorithm under SNR values of less than 21 dB), respectively.

[2]The roll-off factor for the ATSC system is 11.5% which corresponds to the RF channel response with bandwidth of 5.38 MHz [1]. However, pulse-shaping in the baseband is performed based on the symbol rate of 10.76 MHz and thus the roll-off factor of the pulse-shaping filter becomes $11.5/2 = 5.76$%.

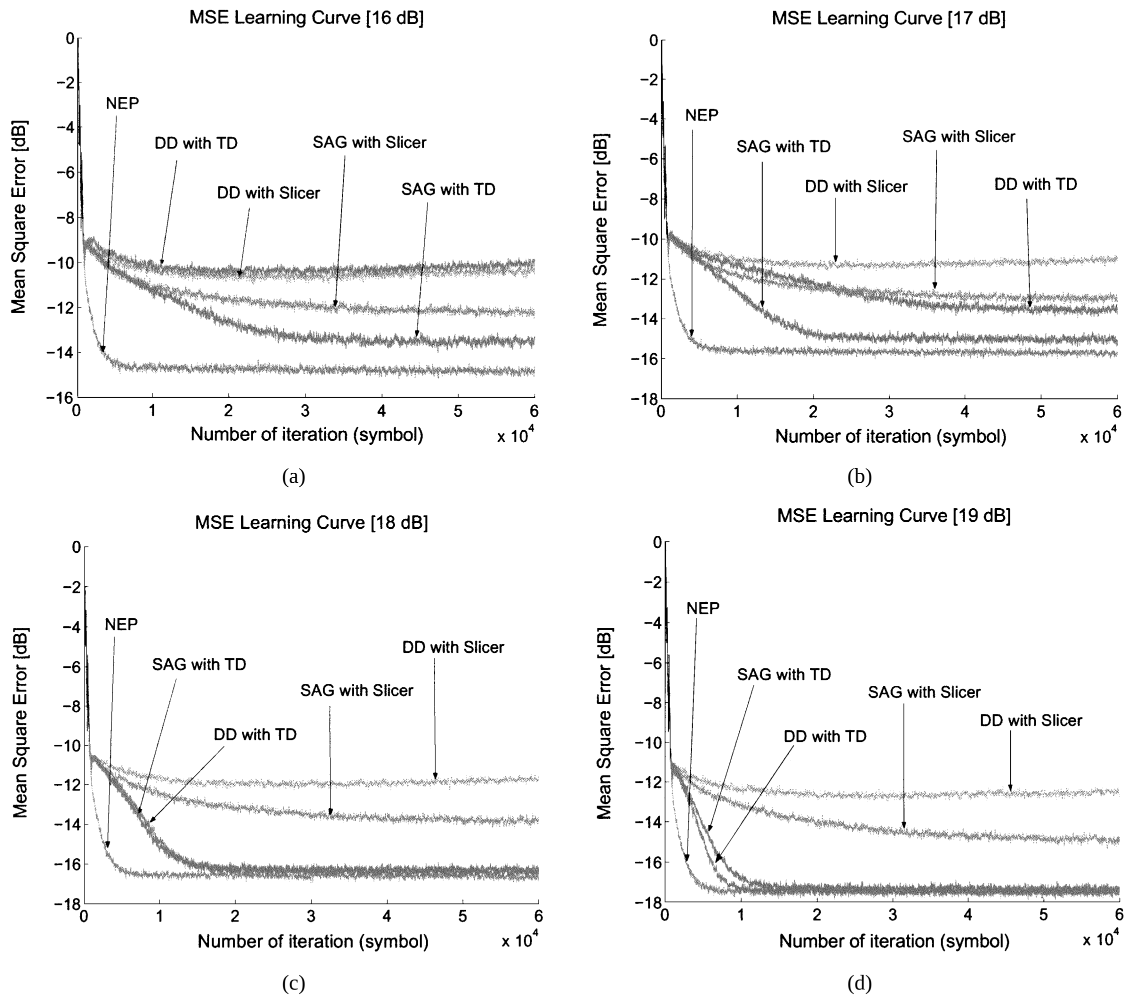


Fig. 6. Mean-square error convergence of the DFE (LMS with $\mu = 0.0002$ in the field sync segment, SAG or DD with $\mu = 0.000\,02$ in the data segments). (a) 16 dB (b) 17 dB (c) 18 dB (d) 19 dB.

A. Convergence Performance

The convergence performance was checked by the MSE of the equalizer output, which was computed as follows:

$$\mathrm{MSE}[k] = E[|y[k] - a[k]|^2]. \tag{12}$$

The statistical results come from the average of 100 independent ensembles. For ease of performance view, we also used the time average of 50 symbols.

1) LMS in the Training Mode: Figs. 6 and 7 show the MSE learning curves of the DFE with the conventional slicer, the TD, and no error propagation (NEP) at the SNRs of 16–23 dB. The LMS algorithm was applied in the training mode and the SAG and DD algorithms were used during the data segments. The result shows that the error propagation degrades the convergence performance in terms of both the convergence speed and the residual error.

At an SNR of 16 dB (Fig. 6(a)), the output SNR at the end of the training mode[3] was about 10 dB, where the SER of the TD with a TBD of 1 was almost the same as that of the slicer and was greater than 0.4 (Fig. 3). Thus, at the start point of the blind adaptation, error propagation is inevitable even though we use the TD with a TBD of 1 instead of the slicer for a decision device. However, blind adaptation using the SAG algorithm makes the output SNR improve and thus the performance is better than when the DD algorithm is used. As the blind adaptation using the SAG algorithm proceeds, the output SNR increases and thus the effect of adopting the TD is prominent compared with the slicer because the difference between the SER of the TD and that of the slicer becomes large.

The effect of error propagation on the equalization performance becomes clearer in Fig. 6(b). Though error propagation exists at the start of blind adaptation, the SAG algorithm with the TD enhances the output SNR of the DFE and thus makes the error propagation decrease. On the other hand, when we use the DD algorithm with the slicer, error propagation caused by slicing error seriously affects the convergence performance. The SAG with the slicer is comparable to the DD with the TD because blind adaptation of the SAG algorithm in the SAG with the slicer compensates for the slicing error and the TD decreases the decision error probability in the DD with the TD.

In conclusion, as the SNR increases from the low SNRs in Fig. 6 to the high SNRs in Fig. 7, the DFE with the TD ap-

[3]This corresponds to an 832-symbol time. Actually, the number of the training symbols is 820. In addition, the number may be shortened to 728 if we do not use the reserved symbols. Anyway, this number is not critical for analyzing the performance trend of the DFE.

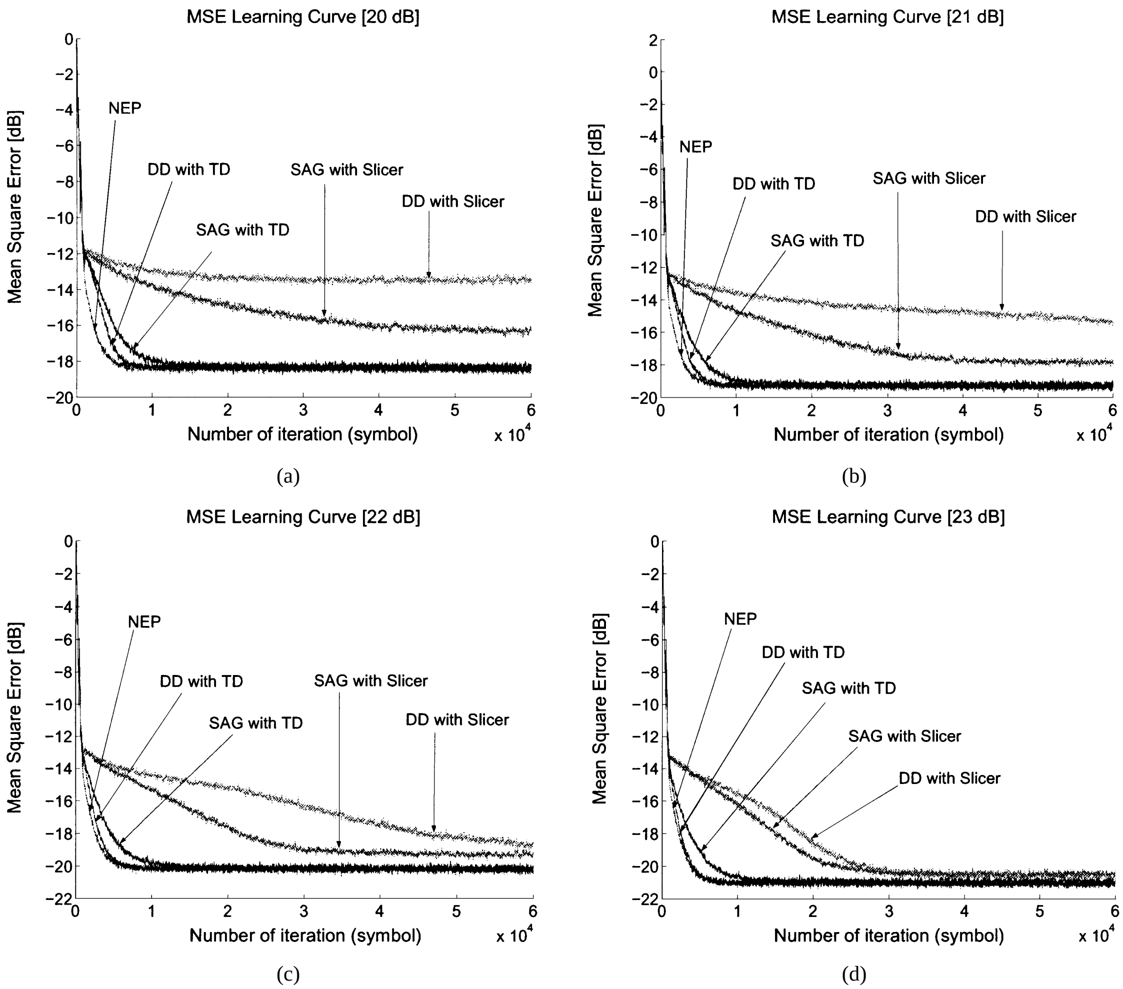


Fig. 7. Mean-square error convergence of the DFE (LMS with $\mu = 0.0002$ in the field sync segment, SAG or DD with $\mu = 0.000\,02$ in the data segments). (a) 20 dB (b) 21 dB (c) 22 dB (d) 23 dB.

proaches the DFE with NEP. We can see that blind equalization is preferable to DD equalization at low SNRs (less than about 18 dB) while DD equalization is superior to blind equalization at high SNRs (more than about 19 dB).

2) RLS in the Training Mode: To raise the output SNR at the end of the training mode, the RLS algorithm was used and the results are shown in Figs. 8 and 9. Though the RLS enhanced the output SNR over the LMS, there was still an SNR loss between the input and the output of the DFE. This is because training was not complete. If the coefficients are trained sufficiently, there should be no SNR loss at the equalizer. Under an SNR of 16 dB (Fig. 8(a)), the output SNR at the end of the training mode was about 13.7 dB, where the SER of the DFE with the TD was 0.08 (Fig. 3). This SER value was smaller than that of the DFE with the slicer, which was about 0.25 (Fig. 3), but still caused error propagation. Accordingly, the performance of the DFE with the TD was close to the DFE with the slicer.

The performance of the DFE with the TD approached the DFE with NEP at an SNR of 17 dB (Fig. 8(b)). In this case, the output SNR at the training mode was about 14.7 dB corresponding to an SER of 0.04. When the SNR was greater than 17 dB, the performance of the DFE with the TD was almost the same as that of the DFE with NEP. From these results, we found that if the output SNR of the DFE with the TD at the end of the training mode was greater than 15.6 dB corresponding to an SER of 0.02, error propagation did not affect the convergence performance. However, the DFE with the slicer suffered from error propagation even when the output SNR was about 19 dB (Fig. 8(d)) because the SER of the slicer output was about 0.05 (Fig. 3).

Note that the optimal solution of LMS-type algorithms is different from that of LS-type algorithms. This causes discontinuity between the training mode and blind mode in the MSE learning curves when we use LS-type algorithms, such as the RLS in the training mode, and LMS-type algorithms, such as DD and SAG in the blind mode. The discontinuity becomes more obvious when error propagation caused by slicing error in the DFE with the slicer or a low output SNR exists. Figs. 8 and 9 clearly show the relationship between the MSE discontinuity and error propagation.

We also found that the DD adaptation and the blind adaptation had the almost the same performance when we used the TD. In the case of the conventional slicer, however, the blind adaptation showed a little better performance than the DD adaptation in terms of residual MSE at low SNRs, which will be clearly shown in the SER plots presented in the next section.

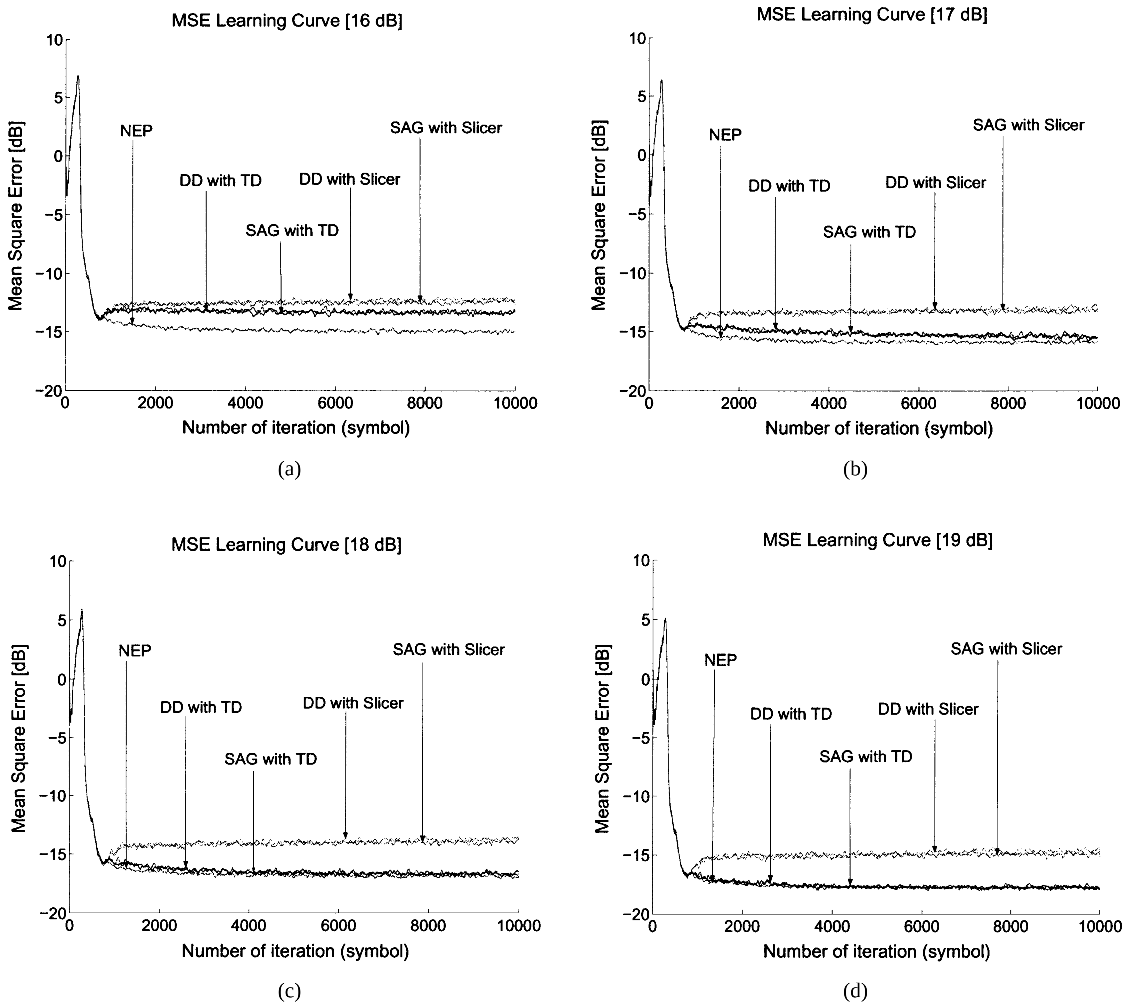


Fig. 8. Mean-square error convergence of the DFE (RLS in the field sync segment, SAG or DD with $\mu = 0.000\,02$ in the data segments). (a) 16 dB (b) 17 dB (c) 18 dB (d) 19 dB.

B. Symbol-Error Rate Performance

We carried out simulations to obtain the SER curves of the blind DFE to show the effect of error propagation on the residual error. The number of simulated segments including one field sync segment was 301, and thus that of the data segments was 300, which corresponded to 249 600 symbols. The SER was computed by counting the number of symbol errors existing in the last 180 000 symbols after the tap coefficients converged. In ATSC DTV receivers, we are interested in the performance at SNR values of not more than 25 dB, because the trellis decoder following the equalizer can correct most symbol errors at SNR values of greater than 25 dB.

Fig. 10 shows the SER curves using the LMS and RLS in the training mode. In both cases, the DFE with NEP had better performance by about 3 dB than the blind DFE with the slicer at an SER of 0.2 corresponding to the threshold of visibility (TOV). On the other hand, the DFE with the TD was about 2 dB better than the DFE with the slicer at the TOV. The performance of the DFE with the TD was similar to that of the NEP case at most SNR values but degraded to the level of the DFE with the slicer at very low SNR values when either the LMS or the RLS in the training mode was used. We found that when error propagation existed, blind adaptation was preferable to DD adaptation in the DFE for ATSC DTV receivers.

We have to note that the performance of the DFE affects the SER performance of the trellis decoder[4] following the DFE specified in the ATSC terrestrial DTV standard [7]. In the ATSC DTV systems, an RS decoder, which has 10-byte error correction capability, follows the trellis decoder. Hence, a byte error rate is more meaningful than an SER at the end of the trellis decoder. Fig. 11 shows the byte error rate curves of the trellis decoder, which receives the output of the DFE and then decodes it with a TBD of 15. While the SER performance of the DFE with the TD was similar to that of the DFE with NEP in the DFE, the byte error rate performance of the trellis decoder between the DFE with the TD and the DFE with NEP differed by 1 dB. In the DFE with the slicer, blind adaptation of the SAG algorithm had better performance than DD adaptation at SNR values of less than 22 dB. When the SNR was greater than 21 dB, the byte error rate was smaller than about 1.4×10^{-2}, the byte error

[4]This trellis decoder is different from the TD used as a decision device and generally has a TBD of about 15 to produce the maximum SER performance in the trellis-coded 8-VSB signal.

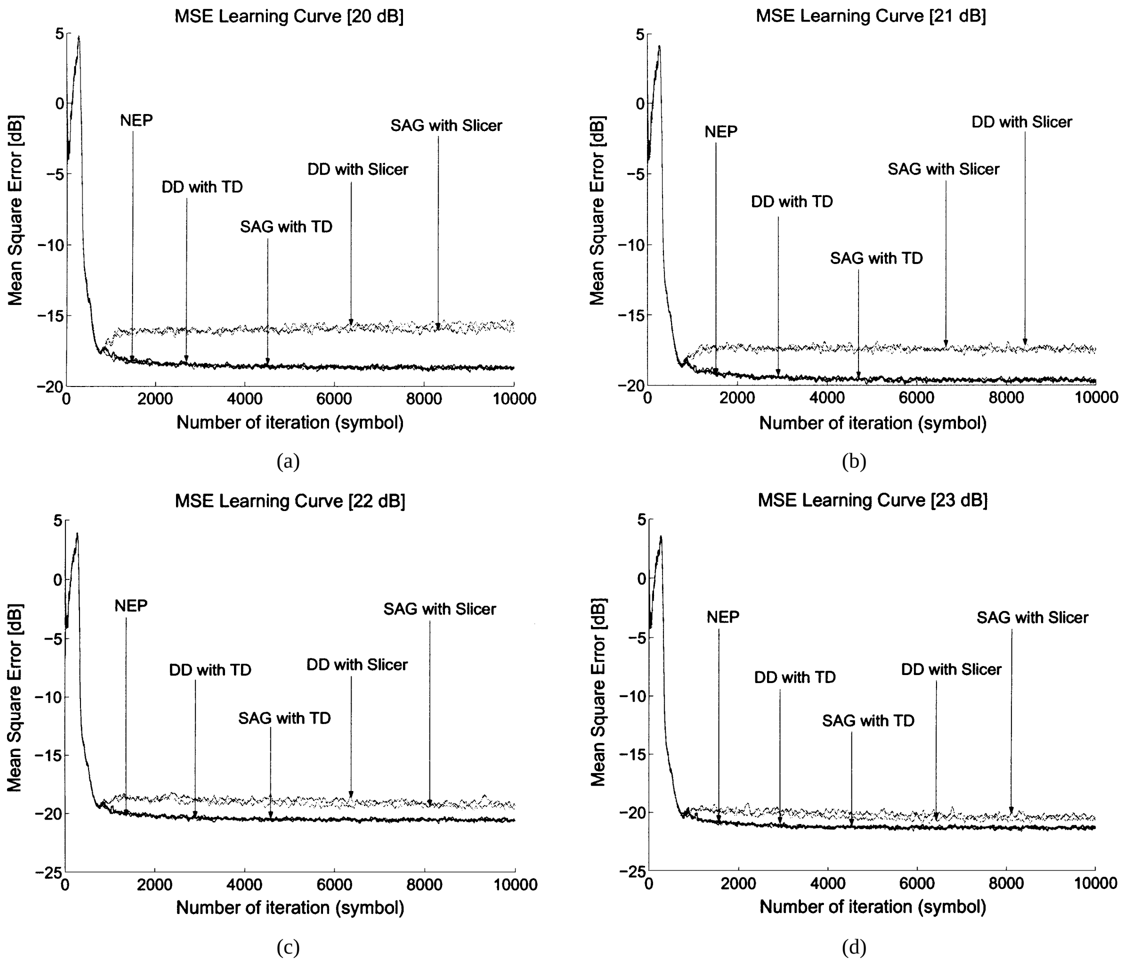


Fig. 9. Mean-square error convergence of the DFE (RLS in the field sync segment, SAG or DD with $\mu = 0.000\,02$ in the data segments). (a) 20 dB (b) 21 dB (c) 22 dB (d) 23 dB.

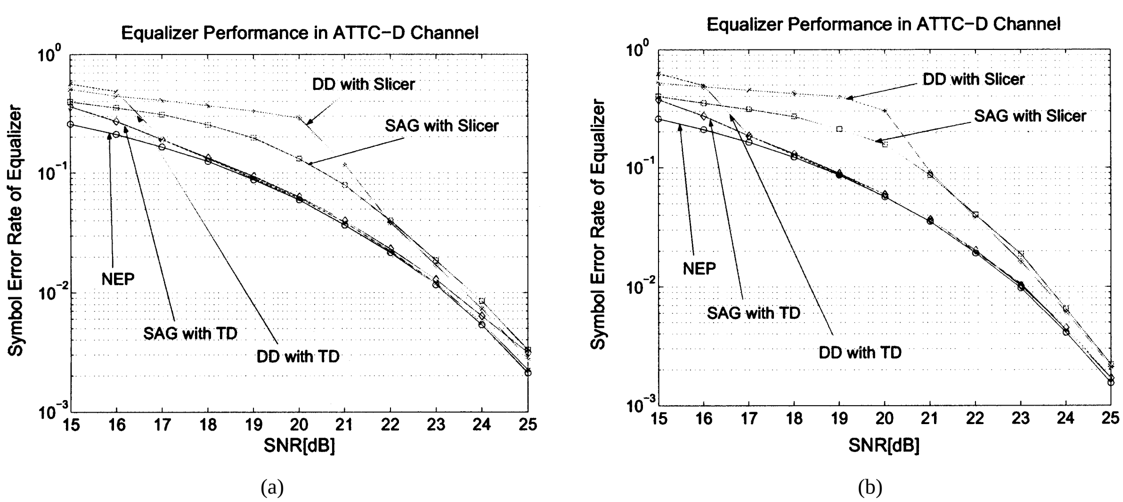
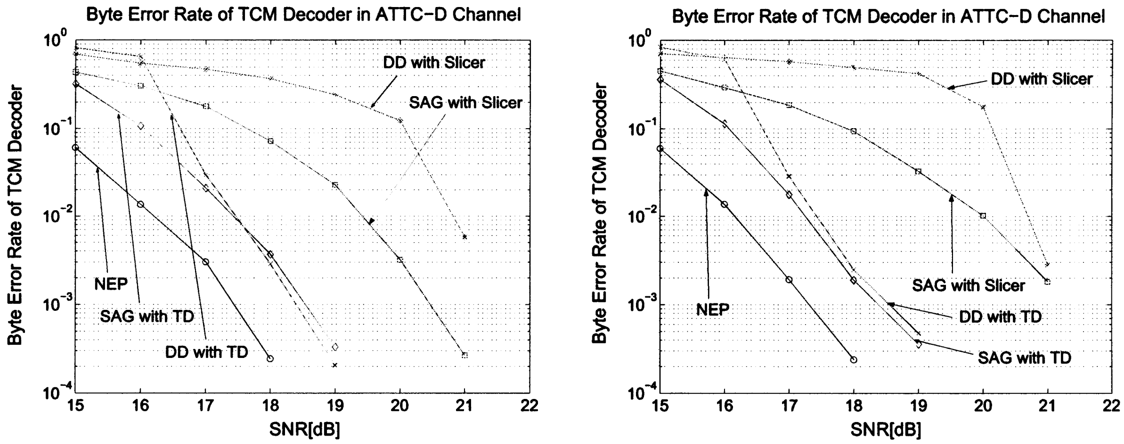


Fig. 10. Symbol error rate performance of the DFE. (a) LMS (b) RLS.

rate at TOV after the trellis decoder [2], and thus the comparison is meaningless.

V. Conclusion

The error propagation phenomenon is unavoidable in the DFE for ATSC DTV receivers because the training sequence is very short and the SER of the equalizer output can be as high as 0.2. We analyzed the convergence performance affected by error propagation by comparing error propagation and no-error propagation (NEP) cases. We found that by minimizing error propagation, the convergence speed became faster and the SER performance was improved by more than 2 dB. In view of implementing a realistic receiver, we considered a blind



(a) (b)

Fig. 11. Byte error rate performance of the trellis decoder following the DFE. (a) LMS (b) RLS.

DFE, adopting the trellis decoder (TD) with trace back depth of 1 for a decision device as one approach to the performance limit corresponding to the NEP case. As the SNR increased, the DFE with the TD approached the DFE with NEP. At low SNRs, blind equalization was preferable to decision-directed (DD) equalization while DD equalization was superior to blind equalization at high SNRs.

To reduce the error propagation and thus improve the performance of the DFE, it is important to raise the output SNR of the DFE with efficient and fast adaptation methods in the training mode and enhance the correct-decision probability with an advanced decision device, such as the TD in the blind mode. The analysis results presented in this paper will be very informative for developing equalization algorithms for ATSC DTV receivers.

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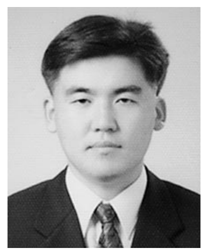

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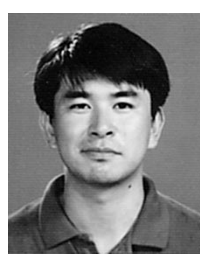

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