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A Dual-mode Blind Equalization with the Variable Decision Region

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요 약

블라인드 등화 알고리듬은 빠른 수렴 속도를 얻기위해서 결정지향방식으로 전환되어야한다. 본 논문에서는 결정지향방식으로 자동으로 전환되는 새로운 블라인드 등화 방식을 제안한다. 제안된 방식은 블라인드 등화 모드와 결정지향 모드의 두가지 모드에서 동작한다. 동작 모드는 등화기의 출력값이 어느 영역에 들어가는가를 판단하여 결정되고, 이 영역은 등화기가 수렴해감에 따라 변화되며, 추정된 오차의 분산 값에 대한 함수이다. 실험 결과로부터, 제안된 블라인드 등화 방식은 빠른 수렴 속도와 작은 자승평균오차 값을 가짐을 확인하였다.

ABSTRACT

A blind equalization algorithm may be switched to a decision-directed(DD) scheme in order to speed up the convergence rate. In this paper, we propose a new blind equalization scheme that automatically switches to the DD mode. The proposed scheme operates in two mode: blind equalization mode and a DD mode. The mode is determined by the region in which the equalizer output lies, and the region varies as a function of the estimate value of the error variance. From simulation results, it is shown that this scheme can achieve faster convergence and small MSE.

I. Introduction

The blind equalization is an important technique in digital communication systems in which sending training signals is inappropriate. After Sato's pioneering work[1], many techniques have been developed to improve its performance[2]. However, compared to the conventional equalization techniques, the blind equalization schemes have very slow convergence rate. In order to speed up the convergence process, it is necessary that a blind equalizer switch over to the Decision-Directed(DD) equalization mode once the error level is reasonably low. But considerable attention has to be paid in determining the point at which this switch-over is made to avoid the error propagation effects associated with the DD equalization technique or a long delay in the convergence process.

A few techniques with an automatic switching from the blind startup mode to the DD equalization mode have been reported in the literature. Benveniste and Goursat[3] combined Sato's idea with DD algorithm, and Weerackody[4]

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presented dual-mode techniques which may be switched to DD equalization mode. Picchi and Prati[5] introduced a "Stop and Go" DD blind equalization that uses a stop-and-go adaptation rule based on a Sato-like error signal. Another practical DD blind equalizer was named as the Maximum Level Error(MLE) algorithm[6]. It also uses a stop-and-go adaptation rule. In this algorithm, the data signal constellation is divided into two regions by a threshold boundary determined by the outermost symbols. The adaptation stops if the equalizer output falls within the threshold boundary, and it continues if the equalizer output lies outside of the threshold boundary. For the latter case the sign of error of the DD scheme is almost always correct. Therefore the MLE algorithm updates the filter taps in the correct direction most of the time, but its disadvantage is that the frequency of update is small because most of the equalizer output fall into the region within the threshold boundary. And Ross and Taylor[7] modified the MLE algorithm. The soft decision-directed equalization algorithm[8][9], or blind clustering algorithm, was proposed. In this algorithm the equalizer output is modelled by M Gaussian clusters, of which mean is the symbols of the constellation set.

We propose a new blind equalization scheme that smoothly switches to a DD mode. We set the region of high confidence as in the MLE algorithm, and we calculate the variance of the error using the signal that lies in that region. The proposed scheme operates in two mode : a blind equalization mode and a DD mode. The mode is determined by the region in which the equalizer output lies, and the region varies as a function of the estimated variance of error. This scheme can achieve faster convergence and small MSE. We applied this technique to the Generalized Sato Algorithm(GSA). The remainder of this paper is organized as follows; In section II, we explain the system model. In section III, we explain the proposed algorithm. In section IV we present some simulation results with 64-QAM constellation set, and section V concludes this paper.

Ⅱ. System model

Consider the baseband model of a digital communication channel characterized by a finite impulse response(FIR) filter and an additive white noise source as depicted in fig. 1. The received signal is given by

$$x(k) = \sum_{l=0}^{L-1} h(l)a(k-l) + n(k), \qquad (1)$$

where L is the length of the channel impulse response, and h(i) is the complex channel impulse response. The complex symbol sequence a(k) is given by a(k)= $a_r(k)$+j $a_i(k)$ and assumed to be i. i. d., and n(k) is a complex Gaussian white noise.

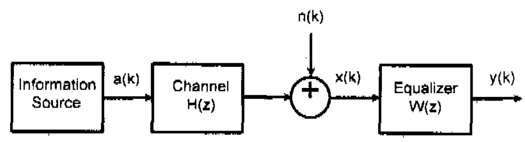

Fig 1. The equivalent baseband communication system.

To remove the intersymbol interference caused by channel distortion, an equalizer is employed. The equalizer has a FIR structure, and its output is represented by

$$y(k) = \sum_{l=-N}^{N} w_l(k)x(k-l) = W^T(k)X(k), \qquad (2)$$

where y(k) = $y_r(k)$+j $y_i(k)$ is the output of the equalizer, and W(k)=($w_{-N}(k)$, ⋯, $w_N(k)$)^T is the equalizer tap weight vector, and X(k)=(x(k+N), ⋯, x(k-N))^T is the equalizer input data vector.

In the data-aided equalization, the adaptation of the equalizer taps is carried out by minimizing the mean square value of the difference between the equalizer output and the desired symbol, which is made available from a training sequence. However, in blind equalizations the receiver does not have any knowledge of the transmitted symbol. Under this equalization scheme the equalizer taps are updated by an algorithm that minimizes a certain error function, which is

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formed by observing the equalizer output and by employing some a priori information of the transmitted data constellation statistics. The error function used in the Generalized Sato Algorithm (GSA) is similar to that used in a decision-directed equalization scheme but has a coarser quantization of the equalizer output to accommodate the "closed eye" situations encountered in blind equalization. The error function in the case of the GSA is given by

$$E\{e_S^2(k)\} = E\{[y_r(k) - \gamma \operatorname{sgn}(y_r(k))]^2 + [y_i(k) - \gamma \operatorname{sgn}(y_i(k))]^2\}, \quad (3)$$

where γ is a suitably chosen constant. By considering the stochastic gradients of the above error function with respect to the tap weight vector W(k), we have the following algorithm

$$W(k+1) = W(k) - \alpha[(y_r(k) - \gamma \operatorname{sgn}(y_r(k))) + j(y_i(k) - \gamma \operatorname{sgn}(y_i(k)))]X^*(k), \quad (4)$$

where α is the step-size parameter and superscript * denotes the complex conjugate. The value of γ can be evaluated considering the steady states of eq. (4), and is given as[2]

$$\gamma = \frac{E\{|a_r(k)|^2\}}{E\{|a_r(k)|\}} = \frac{E\{|a_i(k)|^2\}}{E\{|a_i(k)|\}}. \quad (5)$$

Ⅲ. The proposed algorithm

A. The estimation of the error variance

In blind equalizations, in order to speed up the convergence process, it is necessary that a blind equalizer is switched over to the DD equalization mode once the error level is reasonably low. Switching may be occurred according to the convergence rate, which can be estimated by the variance of the error signal. However, because the receiver does not have the knowledge of the transmitted symbol, the estimate of the error variance cannot be obtained. The receiver knows only the estimated value $\hat{a}(k)$=D(y(k)), which is the decision device's estimate of a(k) given y(k), and the estimated error, $\hat{e}(k) = y(k) - \hat{a}(k)$. Therefore, we may calculate the variance of the error with the equalizer output having a high confidence.

During the startup phase of the blind equalization, if the output of the equalizer is smaller than the caution level, the decision based on the equalizer output is most likely to be incorrect due to the effect of the random noise and the channel distortion. Therefore the confidence in the correctness of the sign of the decision directed error is lower. Otherwise, higher confidence exists when the output of the equalizer is larger than the caution level.

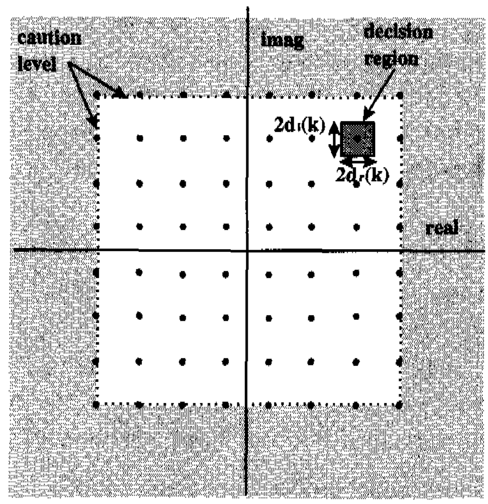

Fig 2. Decision region and caution level for the proposed algorithm.

Fig. 2 illustrates the caution level for 64-QAM. When the equalizer output lies to the right side or to the left side of the constellation, that is, $|y_r|>$ caution level, it can be assumed that high confidence in the correctness of the sign of the real error exists. Similarly, the equalized data lying in the areas above or below the constellation, that is, $|y_i|>$ caution level, generate error signal with high confidence in the correctness of the sign of the imaginary error. In [6], the caution level was set to the outermost signal magnitude. In [7] the caution level was placed to the just slightly beyond the outermost magnitude.

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Here we set the caution level as the magnitude of the outermost symbol. Thus for the 64-QAM the caution value is 7.

We estimate the error variance using the equalizer output which has larger magnitude than the caution level. That is, if the output of the equalizer falls in the region of the high confidence, we calculate the variance of the error of the decision directed mode. In order to make an estimate of the error variance, we define the time-averaged variance as

$$\begin{aligned} var(k) &= E[\,|a(k)-y(k)|^2] \\ &\approx \frac{1}{k}\sum_{n=1}^{k}|\,\hat{a}(n)-y(n)|^2. \end{aligned} \quad (6)$$

An alternative approach is to filter the squared magnitude of equalizer output error by a lowpass filter and use the output of the filter as an estimate of error variance. A simple lowpass filter for the error variance yields as an output

$$var(k) = \beta\, var(k-1) + (1-\beta)\,|\,\hat{a}(k)-y(k)|^2, \quad (7)$$

where the choice of $0 \le \beta < 1$ determines the bandwidth of the lowpass filter. When β is close to unity, the filter bandwidth is small and the effective averaging is performed[12]. Therefore, the variance of the error signal can be calculated as

$$\begin{aligned} var_r(k) &= \beta var_r(k-1) + (1-\beta)|\,\hat{a}_r(k)-y_r(k)|^2 \\ &\qquad \text{if } |y_r| > \text{caution level} \\ var_i(k) &= \beta var_i(k-1) + (1-\beta)|\,\hat{a}_i(k)-y_i(k)|^2 \\ &\qquad \text{if } |y_i| > \text{caution level}\,. \end{aligned} \quad (8)$$

The error variance is estimated using eq. (8) only when the real part or the imaginary part of the equalizer output is larger than the caution level. Otherwise, The estimated error variance does not updated. At this point, the decision device decide the equalizer output as the outermost one. Since the decision error may occur, the estimated value of the error variance is smaller than the actual one. We use this estimated error variance as a criterion to determine the decision region of the dual-mode algorithm.

B. The switching over technique to the DD mode

The proposed algorithm switches the usual blind equalization scheme to the DD mode gradually. We use the equalizer output model of the blind clustering algorithm. The equalizer output can be expressed as a(n)+ $\nu(n)$, with $\nu(n)$ following approximately Gaussian probability density function (pdf). For $\nu(n)$ is the convolutional noise, and if the number of multipath of channel is large enough, by the central limit theorem the distribution of convolutional noise can be assumed to have Gaussian distribution[10]. Thus when the equalization is accomplished, the output of equalizer can be modeled approximately by Gaussian processes with mean a(k), which is the value of the transmitted symbol.

If we model the equalizer output as Gaussian clusters, the conditional probability $P\{\hat{a}(k)=a(k)|y(k)\}$is high in the region around the data point. So we devised a technique which, when the probability is larger than arbitrary value δ ($0<\delta<1$), forces the blind equalization algorithm to operate in decision directed mode. For the simplicity of the explanation, without the loss of generality, only the binary case is considered, that is $a(k)=\pm 1$, and assuming $\hat{a}(k)=1$. The conditional probability $P(a(k)=1\mid y(k))$ is given by

$$\begin{aligned} &P(a(k)=1\mid y(k)) = \\ &\frac{P(y(k)\mid a(k)=1)P(a(k)=1)}{P(y(k))} \\ &= \frac{P(y(k)\mid a(k)=1)P(a(k)=1)}{P(y(k)\mid a(k)=1)P(a(k)=1)+P(y(k)\mid a(k)=-1)P(a(k)=-1)} \\ &= \frac{1}{1+\frac{P(y(k)\mid a(k)=-1)}{P(y(k)\mid a(k)=1)}} \end{aligned} \quad (9)$$

As mentioned above, if we model $P(y(k)\mid a(k)=1)$ as a Gaussian distribution with variance σ^2, then

$$\begin{aligned} P(a(k)=1\mid y(k)) &= \frac{1}{1+\mathrm{EXP}\{[-(y(k)+1)^2+(y(k)-1)^2]/\sigma^2\}} \\ &= \frac{1}{1+\mathrm{EXP}[-4y(k)/\sigma^2]} \end{aligned} \quad (10)$$

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If we set an arbitrary value δ, then the set of y(k) satisfying eq. (11) becomes the decision region in which blind equalizer operates DD mode.

$$\frac{1}{1+\mathrm{EXP}[-4y(k)/\sigma^2]} > \delta$$
$$y(k) > \frac{\sigma^2}{4}\ln\left(\frac{\delta}{1-\delta}\right) = \delta\sigma^2 \qquad (11)$$

Since for the QAM constellation in-phase and quadrature-phase component are independent of each other, each component can be considered respectively. Suppose that D_k are the decision region enclosing the data points of the QAM constellation and consider the GSA described by eq. (4). We choose a square size of $d_r(k) \times d_i(k)$ enclosing each data point in the QAM constellation as the decision region D_k as depicted in Fig. 2. In general, for an M-QAM constellation there will be M such square regions. As noted previously, in the decision regions, the estimated value, $\hat{a}(k)$=D(y(k)), is given by the data point enclosed by the decision region D_k. In the proposed technique, if the variance gets smaller, the decision region becomes wider. Thus, we have approximated the relationship between the decision region and the variance as follows.

$$d_r(k) = 1 - \delta' var_r(k)$$
$$d_i(k) = 1 - \delta' var_i(k) \qquad (10)$$

Higher value of δ' corresponds to the higher value of δ. The proposed algorithm employs two mode of operation: the decision directed mode in the decision region, and the usual blind equalization mode in other regions. Then the proposed algorithm operates as

$$W(k+1) = W(k) - \alpha[(y_r(k) - \hat{a}_r(k)) + j(y_i(k) - \hat{a}_i(k))]X^*(k), \quad \text{if } y(k) \in D_k$$
$$W(k+1) = W(k) - \alpha[(y_r(k) - \gamma\,\mathrm{sgn}(y_r(k))) + j(y_i(k) - \gamma\,\mathrm{sgn}(y_i(k)))]X^*(k), \quad \text{if } y(k) \notin D_k. \qquad (11)$$

Initially the decision regions do not exist, that is, $d_r(0) = d_i(0) = 0$. Therefore, at first this algorithm operates in GSA mode. As the equalization process continues, the decision regions become wider. That is, the algorithm comes to operate in the dual mode, and finally switches to the DD mode. The proposed algorithm can be regarded as the dual mode algorithm[4] with variable decision region.

In the case of $var(k)$=0, the proposed algorithm leads to the conventional decision directed algorithm. Since the decision-directed algorithm converges to the minimun mean square error when the eye pattern of the equalizer output is opened to some extent, the proposed algorithm has small mean square error(MSE).

Ⅳ. Simulation results

We have performed several simulations using 64-QAM data constellations with the channel whose impulse response is shown in [2]. We have used equalizers of the length 11. In all simulations the center-tap initialization strategy is used. The coefficients are initially set to 0+j0 except for the center tap, which is set to 2+j0. For the parameters in the proposed technique, β is set to 0.9, and initial value of the variance is set to 10 for both real and imaginaty part. The signal to noise ratio is fixed at 30dB. The SNR is computed at the input to the equalizer and is given as the ratio of the received signal power to that of the additive Gaussian noise component. As the measure of performance, we used the MSE at the equalizer output.

To show the validity of the estimation of the error variance, we compare the MSE curve with the estimated variance. Fig 3. shows the MSE of the proposed algorithm and the estimate of the error variance. In fig. 3, MSE curves are the ensemble averaged values (over 500 independent trials) for 64-QAM constellations, where γ = 5.25, and the step size is 0.0001. We can see that the estimated value of the error variance follows and is smaller than the real squared error.

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Fig. 4 shows the convergence curves obtained from ensemble averages over 500 independent runs. Each curve represents the performance of the proposed algorithm with the values of the parameter, δ'=1, 0.84, 0.64, 0.3 respectively. The step size is set to 0.0001. As the value of δ' decrease, the switching to the DD mode occurs earlier, and the convergence rate gradually decreases and then starts to increase, because too many erroneously detected symbols are being used to update the equalizer.

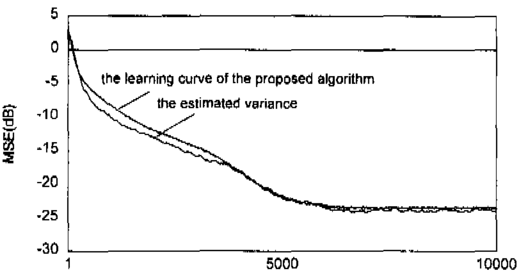

Fig 3. Comparison of learning curves of the proposed algorithm and the estimated variance(SNR=30dB, α=0.0001, δ'=0.64.)

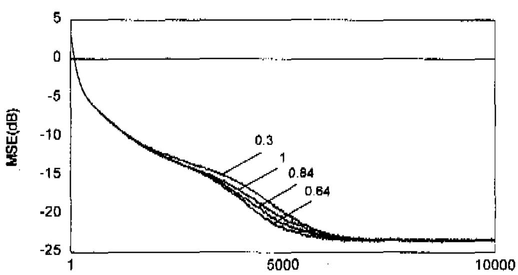

Fig 4. Learning curves for the proposed algorithm(α=0.0001, δ'=1, 0.84, 0.64, 0.3.)

In Fig. 5, the proposed algorithm is compared with the dual mode algorithm, Sato algorithm, and data-aided LMS. For the dual mode algorithm the step size is 0.0001, d=0.65. The proposed algorithm has faster convergence rate than the dual mode algorithm with the same step size. Initially this algorithm operates as Sato algorithm, and is switched over to the DD equalization mode gradually. Once the equalizer converges, it has the same steady-state performance as that of the LMS with training sequences because the automatic switch-over to the DD mode is accomplished.

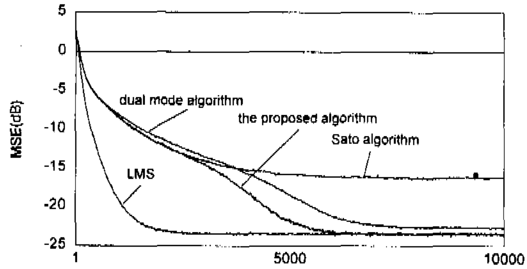

Fig 5. Learning curves for 64-QAM. SNR=30dB.
For dual mode algorithm : d=0.65, α=0.0001,
For the proposed algorithm : δ'=0.64, α=0.0001,
For Sato algorithm : γ=5.25, α=0.0001,
For lms algorithm : α=0.0001.

Next, we consider a switching channel in order to show the validity of the proposed algorithm. For this experiment, the channel impulse response is initially set to that of shown in [2] and forced to switch into the following channel response after 10000 symbols are received.

{0.0485-j0.0194, 0.0573+j0.0253, 0.0786-j0.0282, 0.0874-j0.0447, 0.922+j0.3031, 0.1427+j0.0349, 0.0835+j0.0157, 0.0621+j0.0078, 0.0359+j0.0049, 0.0214+j0.019}

As shown in fig. 6, we can see that when the channel is changed abruptly, the proposed algorithm is automatically switched to blind equalization mode because the estimated error variance enlarges. And as the equalizer converges, the proposed algorithm operates again in DD equalization mode.

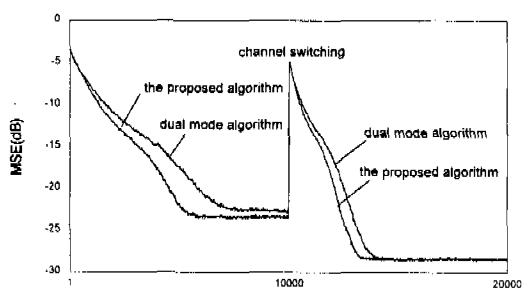

Fig 6. Learning curves for 64-QAM under a switching channel(SNR=30dB).
For dual mode algorithm : d=0.65, α=0.0001,
For the proposed algorithm : δ'=0.64, α=0.0001,

Finally, we extended the proposed algorithm to

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the decision feedback structure. The channel impulse response used in this simulations is as follows : [11]

{0.041+j0.0109, 0.0495+ j0.0123, 0.0672+j0.0170, 0.0919+j0.0235, 0.792+j 0.1281, 0.396+j0.0871, 0.2715+j0.0498, 0.2291+j0.0414, 0.1287+j0.0154, 0.1032+j0.0119}

The proposed algorithm with decision feedback structure was compared with the dual mode algorithm with decision feedback structure. The proposed algorithm has faster convergence rate than the dual mode algorithm in this case too. And decision feedback equalizer has lower steady state MSE as shown in fig. 7.

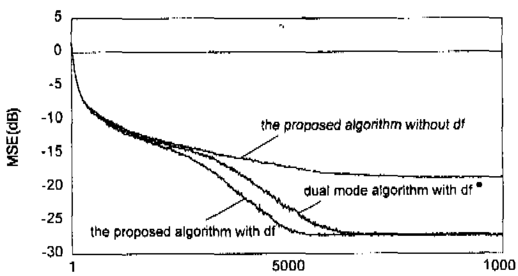

Fig 7. Learning curves of decision feedback equalizer. For dual mode algorithm, d=0.65, α =0.0001, For the proposed algorithm, δ'=0.64, α=0.0001.

V. Conclusion

The proposed algorithm make the decision regions of the dual-mode algorithm become gradually wider according to the estimated variance of the equalizer output error, resulting in smooth and automatic transition from blind equalization mode to the DD mode. Once the equalizer converges, it has the same steady-state performance as that of the LMS with trainning sequences. In order to esimate the variance of the error, the equalizer output with high confidence, which is larger than the caution level, is used. This technique is applied to the GSA blind algorithm to give a smooth transition toward the DD mode. The proposed scheme can achieve faster convergence and small MSE.

References

[1] Y. Sato, "A method of self-recovering equalization for mulitilevel amplitude-modulation systems," *IEEE Trans. Comm.*, Vol. 23, No. 6-, pp. 679- 682, June 1975.

[2] D. N. Godard, "Self-recovering equalization and carrier tracking in two dimensoinal data communication systems," *IEEE Trans. Comm.*, Vol. 28, No. 11, pp. 1867-1875, Nov. 1980.

[3] A. Benveniste, and M. Goursat, "Blind equalizers," *IEEE Trans. Comm.*, Vol. 32, No. 8, pp. 871-882, Aug. 1984.

[4] V. Weerackody, and S. Kassam, "Dual-mode type algorithms for blind equalization," *IEEE Trans. Comm.*, Vol. 42, No. 6, pp. 22-28, Jan. 1994.

[5] G. Picchi, and G. Prati, "Blind equalization and carrier recovery using a stop-and-go decision-directed algorithm," *IEEE Trans. Comm.*, Vol. 35, No. 9, pp. 877-887, Sep. 1987.

[6] R. Yatsuboshi, N. Sata and K. Aoki, "A Convergence of Automatic Equalizer by Maximum Level Error Control," in Nati. Conv. Rec., IEIC of Japan, No. 2192, 1974.

[7] Fergus J. Ross and Desmond P. Taylor, "An Enhancement to Blind Equalization Algorithms," *IEEE Tran. Comm.*, Vol. 39, No. 5, pp. 636-639, May 1991.

[8] Steven J. Nowlan and Geoffrey E. Hinton, "A Soft Decision-Directed Algorithm for Blind Equalization," *IEEE Trans. Comm.*, Vol. 41, No. 2, pp. 275-279, Feb. 1993.

[9] S. Chen, S. McLaughlin, P. M. Grant and B. Mulgrew, "Multi-Stage Blind Clustering Equaliser," *IEEE Trans. Comm.*, Vol. 43, No. 2/3/4, pp. 701-705, Feb./March/April 1995.

[10] S. Haykin, *Adaptive Filter Theory*, 2nd ed. Englewood Cliffs, NJ: Prentice Hall, 1991.

[11] E. Biglieri, D. Divsalar, P. J. Mclane, M. K. Simon, *Introduction to Trellis-Coded Modulation with Application*, Mcmillan

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Publishing Company, 1991.
[12] J. G. Proakis, *Digital Communications*, McGraw-Hill, 3rd ed., 1995.

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