

Minimum Symbol-Error-Rate Equalisation

Sheng Chen

Department of Electronics and Computer Science
University of Southampton
Southampton SO17 1BJ, U.K.
E-mail: sqc@ecs.soton.ac.uk

Presented at Non-linear and Non-Gaussian Signal Processing Workshop
Peebles Hydro, Scotland, July 8-9 2002

Some Previous Works

- “MBER” almost as old as “adaptive equalisation”
Yao, *IEEE Trans. Information Theory* 1972, Shamash & Yao, *ICC'74*
- More recently
Chen *et al.*, *ICC'96, IEE Proc. Communications* 1998;
Yeh & Barry, *ICC'97, IEEE Trans. Communications* 2000;
Mulgrew & Chen, *IEEE Symp. ASSPCC 2000, Signal Processing* 2001

Mostly on binary modulation (BPSK)

★ This work: multilevel modulation schemes (PAM and QAM)

Motivations

Linear filtering at receiver (equalisation, multiuser detection, beam-forming)

$$y(k) = \bar{y}(k) + e(k)$$

Filter output generally non-Gaussian (sum of Gaussian distributions)

- Zero forcing: Gaussian but noise enhancement too serious
- MMSE: classically regarded as optimal → non-optimal in terms of symbol error rate!
- Adopt to non-Gaussian view naturally leads to MSER approach

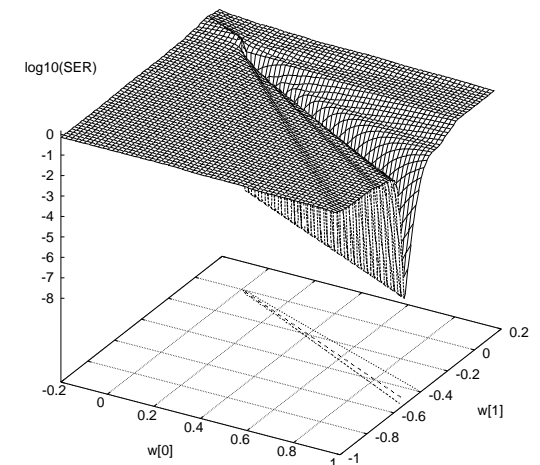
A Toy Example

Two-tap channel $1.0 + 0.5z^{-1}$
with 4-PAM and SNR= 35 dB

Two-tap $m = 2$ linear equaliser
with decision delay $d = 0$

Normalized MMSE:
 $\mathbf{w}_{\text{MMSE}}^T = [0.9285 \quad -0.3713]$
with $\log_{10}(\text{SER}) = -2.7593$

MSER ($\alpha > 0$):
 $\mathbf{w}_{\text{MSER}}^T = \alpha[0.8957 \quad -0.4447]$
with $\log_{10}(\text{SER}) = -7.1566$



- MSER solutions form a half line, origin is singular point

Real-Valued L -PAM Channel

- Channel of length n_h

$$r(k) = \sum_{i=0}^{n_h-1} h_i s(k-i) + n(k)$$

$$s(k) \in \mathcal{S} \triangleq \{s_l = 2l - L - 1, 1 \leq l \leq L\}$$

- Linear equaliser of order m

$$y(k) = \mathbf{w}^T \mathbf{r}(k) = \bar{y}(k) + e(k)$$

$$\mathbf{r}(k) = [r(k) \cdots r(k-m+1)]^T, \mathbf{w} = [w_0 \cdots w_{m-1}]^T, \text{ and decision delay } d$$

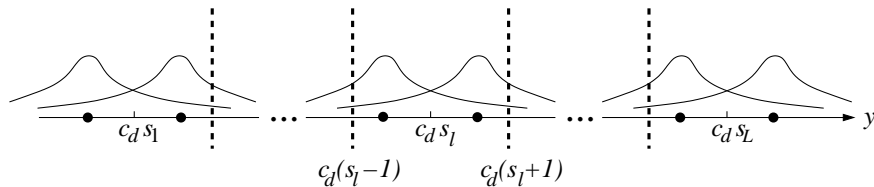
* $e(k)$: Gaussian with zero mean and variance $\sigma_n^2 \mathbf{w}^T \mathbf{w}$, σ_n^2 being variance of $n(k)$

* $\bar{y}(k) \in \mathcal{Y} \triangleq \{\bar{y}_q, 1 \leq q \leq N_s = L^{m+n_h-1}\}$, which can be divided into L subsets

$$\mathcal{Y}_l \triangleq \{\bar{y}_q^{(l)} \in \mathcal{Y} | s(k-d) = s_l\}, 1 \leq l \leq L$$

Two Useful Properties

- Shifting: $\mathcal{Y}_{l+1} = \mathcal{Y}_l + 2c_d$
- Symmetry: distribution of \mathcal{Y}_l is symmetric around $c_d s_l$.



* For linear equaliser to work, $\mathcal{Y}_l, 1 \leq l \leq L$, must be *linearly separable*

This is not guaranteed

* In DFE, linear separability is guaranteed

Observation vector

$$\mathbf{r}(k) = \mathbf{H}\mathbf{s}(k) + \mathbf{n}(k)$$

- Combined impulse response $\mathbf{c}^T = \mathbf{w}^T \mathbf{H} = [c_0 \ c_1 \ \cdots \ c_{m+n_h-2}]$. Then

$$y(k) = c_d s(k-d) + \sum_{i \neq d} c_i s(k-i) + e(k)$$

- Optimal decision making

$$\hat{s}(k-d) = \begin{cases} s_1, & \text{if } y(k) \leq (s_1+1)c_d, \\ s_l, & \text{if } (s_l-1)c_d < y(k) \leq (s_l+1)c_d \\ & \text{for } l = 2, \dots, L-1, \\ s_L, & \text{if } y(k) > (s_L-1)c_d. \end{cases}$$

Unlike binary case, main tap of combined impulse response c_d needed!

SER Expression

PDF of $y(k)$

$$p_y(x) = \frac{1}{\sqrt{2\pi}\sigma_n \sqrt{\mathbf{w}^T \mathbf{w}}} \frac{1}{N_s} \sum_{l=1}^L \sum_{i=1}^{N_{sb}} \exp\left(-\frac{(x - \bar{y}_i^{(l)})^2}{2\sigma_n^2 \mathbf{w}^T \mathbf{w}}\right)$$

where $N_{sb} = N_s/L$ is number of points in \mathcal{Y}_l and $\bar{y}_i^{(l)} \in \mathcal{Y}_l$.

Utilizing shifting and symmetric properties, SER of equaliser \mathbf{w} is:

$$P_E(\mathbf{w}) = \frac{\gamma}{N_{sb}} \sum_{i=1}^{N_{sb}} Q(g_{l,i}(\mathbf{w}))$$

where Q is usual Q -function, $\gamma = 2(L-1)/L$, and

$$g_{l,i}(\mathbf{w}) = \frac{\bar{y}_i^{(l)} - c_d(s_l-1)}{\sigma_n \sqrt{\mathbf{w}^T \mathbf{w}}}$$

MSER Solution

○ MSER solution is defined as:

$$\mathbf{w}_{\text{MSER}} = \arg \min_{\mathbf{w}} P_E(\mathbf{w})$$

- Use simplified conjugated gradient algorithm with periodically resetting search direction to negative gradient
- Computation is on single subset \mathcal{Y}_l , and further simplification by using \mathcal{Y}_l with $s_l = 1$
- SER is invariant to a positive scaling of \mathbf{w} , computationally advantageous to normalize weight vector to $\mathbf{w}^T \mathbf{w} = 1$.

○ Readily extend to DFE (with lower bound SER)

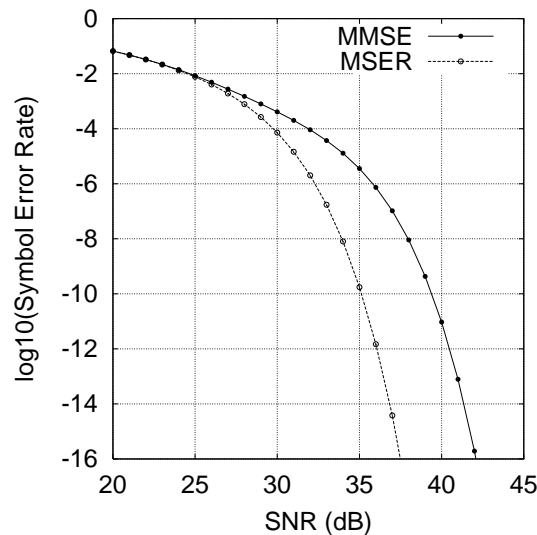
○ Block adaptation: identify channel or Parzen window estimate of PDF $p_y(x) \rightarrow P_E(\mathbf{w}) \rightarrow$ optimisation

An 8-PAM DFE Example

- Lower-Bound SER Comparison

Channel:
 $0.3 + 1.0z^{-1} - 0.3z^{-2}$
 with 8-PAM

DFE:
 $m = 3, d = 2, n_b = 2$



Stochastic Adaptation

Single-sample estimate of $p_y(x)$

$$\hat{p}_y(x, k) = \frac{1}{\sqrt{2\pi}\rho_n} \exp\left(-\frac{(x - y(k))^2}{2\rho_n^2}\right)$$

Using instantaneous stochastic gradient \rightarrow LSER:

$$\mathbf{w}(k+1) = \mathbf{w}(k) + \mu \frac{\gamma}{\sqrt{2\pi}\rho_n} \exp\left(-\frac{(y(k) - \hat{c}_d(k)(s(k-d) - 1))^2}{2\rho_n^2}\right) \times (\mathbf{r}(k) - (s(k-d) - 1)\hat{\mathbf{h}}_d(k))$$

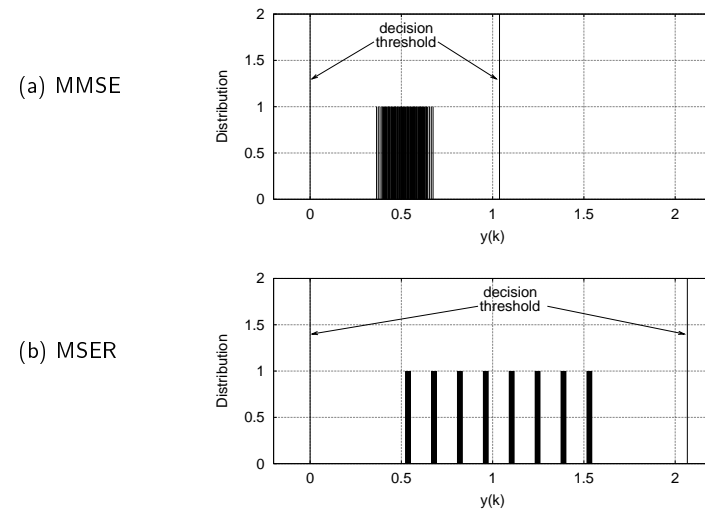
$\hat{c}_d(k)$: estimate of c_d

$\hat{\mathbf{h}}_d(k)$: estimate of d -th column of \mathbf{H}

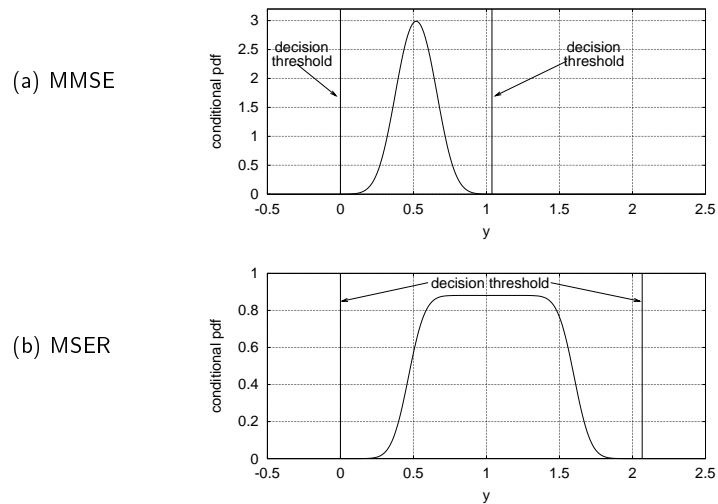
Adaptive gain μ and kernel width ρ_n need to be set appropriately

- Distribution of Subset \mathcal{Y}_5 ($s_5 = 1$), 64 points, SNR=34 dB

Weight vector has been normalized to a unit length, a point plotted as a unit impulse.

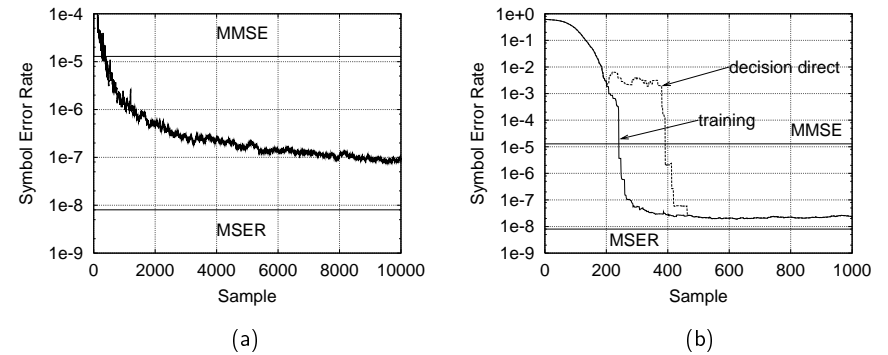


- Conditional PDF given $s(k-d) = 1$, SNR=34 dB. Weight vector normalized, $\mathbf{w}_{\text{MMSE}}^T = [-0.0578 \ 0.2085 \ 0.9763]$, $\mathbf{w}_{\text{MSER}}^T = [-0.2365 \ 0.7946 \ 0.5592]$



- Learning Curves of LSER Averaged Over 100 Runs, SNR=34 dB

Initial weight: (a) \mathbf{w}_{MMSE} , (b) $[-0.01 \ 0.01 \ 0.01]^T$



In (a) training and decision directed indistinguishable, in (b) dashed curve: after 200-sample training, switched to decision-directed with $\hat{s}(k-d)$ substituting $s(k-d)$

Initial value is critical for convergence, MMSE not necessarily good initial choice

Complex-Valued Channel and QAM

Recall $\mathbf{c} = \mathbf{w}^T \mathbf{H}$,

$$y(k) = c_d s(k-d) + \sum_{i \neq d} c_i s(k-i) + e(k)$$

Generally $c_d = c_{R_d} + j c_{I_d}$, advisable always perform a rotation to be sure $c_{I_d} = 0$:

$$\mathbf{w} = \frac{|c_d| \mathbf{w}}{c_d}$$

○ Then I and Q decisions decoupled, real and imaginary parts are PAMs and

$$P_E(\mathbf{w}) = P_{E_R}(\mathbf{w}) + P_{E_I}(\mathbf{w}) - P_{E_R}(\mathbf{w}) P_{E_I}(\mathbf{w})$$

○ MSER defined as solution that minimises upper-bound SER:

$$P_{E_B}(\mathbf{w}) = P_{E_R}(\mathbf{w}) + P_{E_I}(\mathbf{w})$$

Conclusions

- MSER equalisation solution for high-level modulation schemes
 - Effective sample-by-sample adaptation has been developed
 - Unlike MSE surface which is quadratic, SER surface is highly complex
 - Initial equaliser weight values can influence convergence speed
- Generalization to adaptive filtering at various communication receivers
 - Traditional MMSE filtering sub-optimal because conditional filter output is non-Gaussian
 - Proposed approach is based on non-Gaussian nature and can be referred to as adaptive minimum error rate filtering