rise and fall time (T of Fig. 2) of 200ns, while the total period is 800ns. The two lower curves refer to reversible operation, with the PMOS substrate connected to V_{DD} or to power/clock. In this case, the energy consumption per cycle is only slightly dependent on the connection of the PMOS substrate. For non-reversible operation, instead, the reduction of the recovery diode voltage provided by such connection (Fig. 3) gives a substantial improvement over the use of a diode connected NMOS (Fig. 3).

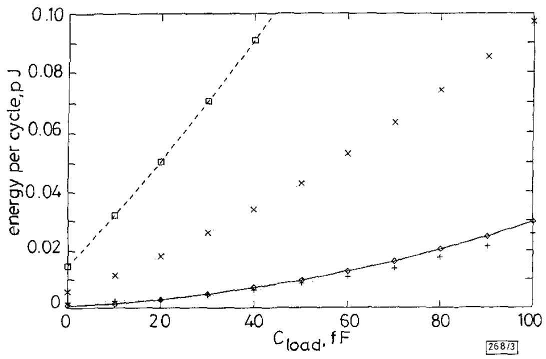

Fig. 3 *Energy dissipation of single buffer/inverter against additional load C_{load}*

◇ reversible, substrate to V_{DD}
+ reversible, substrate to clock
□ non-reversible, substrate to V_{DD}
× non-reversible, substrate to clock

From the data of Fig. 3, the parameters of eqns. 1 and 3 can be fitted, obtaining for K_{rev} 2.3 × 10^6pJ/(fF)^2, for K_{rev}* 4.2 × 10^6pJ/(fF)^2. Rough theoretical estimations based on eqn. 2 give 1.4 × 10^6pJ/(fF)^2 and 2.3 × 10^6pJ/(fF)^2, respectively.

K_{irr} strongly depends on the recovery method and varies from 1.7V^2, with a diode connected MOS transistor (Fig. 3) to 0.55V^2 with the substrate diode (Fig. 3). These values are close to the theoretical value of $^1/_2V_T^2$. E_{PD} is, in every configuration, <2fJ.

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References

1 ATHAS, W.C., SVENSSON, L.J., KOLLER, J.G., TZARTZANIS, N., and CHOU, E.: 'Low power digital systems based on adiabatic-switching principles', *IEEE Trans. Very Large Scale Integration (VLSI)*, 1994, **2**, (4), pp. 398–407

2 YOUNIS, S.G., and KNIGHT, T.F.: 'Asymptotically zero energy split-level charge recovery logic'. Proc. Int. Workshop on Low Power Design, 1994, pp. 177–182

3 ATHAS, W.C., SVENSSON, L.J., KOLLER, J.G., TZARTZANIS, N., and CHOU, E.: 'A framework for practical low-power digital CMOS system using adiabatic-switching principles'. Proc. Int. Workshop on Low-Power Design, 1994, pp. 189–194

Adaptive lattice-form IIR blind equaliser

Fang-Biau Ueng

Indexing terms: Equalisers, IIR filters

The author describes incorporation of the lattice-form structure in the blind infinite impulse response (IIR) algorithm, based on a cost function which is a modified version of that proposed by Shalvi and Weinstein. The proposed IIR blind equaliser has the advantage of lower complexity; simulation results also indicate that the proposed IIR blind equaliser has a faster convergence rate and a smaller mean square error (MSE).

Introduction: Conventional equalisation algorithms generally require an initial training period during which a known data sequence is transmitted, so that the receiver can use this *a priori* information to calibrate the tap weights of the equaliser. However, there are circumstances under which transmitting a training sequence is impossible or impractical, and thus blind equalisation, i.e. equalisation without training sequences, is required. Many finite-impulse-response (FIR)-type blind algorithms have been used to deal with such a problem.

The application of IIR adaptive filtering has recently attracted the interest of many researchers. This is due to its potential advantage of achieving better performance with a lower computational load, when compared with the FIR filtering technique. Most adaptive IIR algorithms have been derived for a direct-form implementation of the filter coefficients. Some disadvantages of the direct-form, such as the finite-precision effect and the complexity of stability monitoring, have led to the development of algorithms for lattice structures. The primary advantage of the lattice structure is its simple stability monitoring. Another advantage is that it does not have any saddle points. In this Letter, the lattice-form structure is incorporated in the blind IIR algorithm, based on a cost function which is a modified version of that proposed in [1]. We first discuss a cost function in a blind situation and then apply it to the above IIR structure. Some simulations are proposed to demonstrate the superiority of the IIR structure to the FIR structure.

Lattice-form IIR blind equaliser: Let the input sequence $a(n)$ consist of zero-mean independently and identically distributed (iid) real random variables, with an arbitrary discrete probability distribution. Let $z(n)$ be the equaliser output and $\mathbf{S} \stackrel{\text{def}}{=} [\dots s_{-1}\ s_0\ s_1 \dots]$ be the combined channel-equaliser impulse response. To achieve zero intersymbol interference (ISI), $z(n)$ must be identical to the input $a(n)$ up to a constant delay. That is, $\mathbf{S}$ must be the following form:

$$\mathbf{S} = (0 \cdots 1 \cdots 0) \quad (1)$$

Since

$$\sum_l |s_l|^4 \leq \left(\sum_l |s_l|^2 \right)^2 \quad (2)$$

with equality holds if and only if $\{s_l\}$ has at most one nonzero component, perfect equalisation implies that $\Sigma_l |s_l|^4 = 1$ if and only if $\Sigma_l |s_l|^2 = 1$. We can minimise the following cost function to achieve the above result:

$$C(s) = \left[\sum_l |s_l|^2 \right]^2 \quad (3)$$

subject to $\Sigma_l |s_l|^4 = 1$. Define a cost function

$$J_c = \left[\sum_l |s_l|^2 \right]^2 + f\left(\sum_l |s_l|^4 \right) \quad (4)$$

We then have

$$J_c \geq \sum_l |s_l|^4 + f\left(\sum_l |s_l|^4 \right) \quad (5)$$

If we choose a function $f(x)$ such that $x + f(x)$ monotonically decreases in $0 \leq x \leq 1$ and monotonically increases in $x > 1$, then the minimisation of J_c will establish that $\mathbf{S}$ has at most one nonzero component, whose magnitude equals 1, and has a unique minimum point. Let $f(x) = x^2 - 3x$; we then have the following cost function:

$$J_c = \left(\sum_l |s_l|^2 \right)^2 + \left(\sum_l |s_l|^4 \right)^2 - 3\left(\sum_l |s_l|^4 \right) \quad (6)$$

By applying the two equations derived by Shalvi and Weinstein [1]

$$E[z^2(n)] = E[a^2(n)] \sum_l |s_l|^2 \quad (7)$$

$$C_4[z(n)] = C_4[a(n)] \sum_l |s_l|^4 \quad (8)$$

where $E[\cdot]$ denotes the expectation operator, and the fourth-order cumulant $C_4[v]$ defined by

$$C_4[v] = E[v^4] - 3E^2[v^2] \quad (9)$$

we obtain the following cost function:

$$J_c = \left[\frac{E[z(n)^2]}{E[a(n)^2]}\right]^2 + \left[\frac{C_4[z(n)]}{C_4[a(n)]}\right]^2 - 3\left[\frac{C_4[z(n)]}{C_4[a(n)]}\right] \quad (10)$$

We consider the lattice-form IIR filter proposed in [2] which comprises N+1 sections, each of which is characterised by two identical reflection coefficients G_p, $0 \leq p \leq N$. The overall output $z(n)$ is weighted sum of the backward residuals as follows:

$$z(n) = \sum_{i=0}^{N} q_i(n) K_i(n) \quad (11)$$

where $\{q_i(n)\}$ and $\{K_i(n)\}$ are the backward residuals and the feedforward coefficients, respectively. The IIR lattice filter can also be described by the following section input/output equations:

$$q_m(n) = q_{m-1}(n-1) + G_m(n) f_{m-1}(n) \quad (12)$$

$$f_{m-1}(n) = f_m(n) - G_m(n) q_{m-1}(n-1) \quad (13)$$

These equations require that $f_0(n) = q_0(n)$ and the input is given by $f_N(n) = y(n)$, where $y(n)$ is the filter input. Define

$$\Theta(n) = [\mathbf{G}(n)\ \mathbf{K}(n)]^T = [G_1(n) \cdots G_N(n)\ K_0(n) \cdots K_N(n)]^T \quad (14)$$

$$\mathbf{Q}(n) = [q_0(n) \cdots q_N(n)]^T \quad (15)$$

$$\Psi(n) = [\gamma(n)\mathbf{K}(n)\ \mathbf{Q}(n)]^T \quad (16)$$

where $\gamma(n)$ is a matrix composed of the derivatives of $\mathbf{Q}(n)$ with respect to $\mathbf{G}(n)$. Applying the cost function J_c, we then obtain the lattice-form IIR blind algorithm described as

$$\begin{aligned}\Theta(n) = \Theta(n-1) - \mu\Big[&(4\gamma_1 + 36\gamma_3)E[z^2(n)] \\ &- 24\gamma_2 E[z^2(n)]\big[E[z^4(n)] - 3E^2[z^2(n)]\big] z(n) \\ &+ \big[8\gamma_2(E[z^4(n)] - 3E^2[z^2(n)]) - 12\gamma_3\big] z^3(n)\Big]\Psi(n)\end{aligned} \quad (17)$$

where

$$\gamma_{ij}(n) = \gamma_{i,j-1}(n-1) + G_j(n)\theta_{i,j-1}(n) + \delta_{ij} f_{j-1}(n) \quad (18)$$

$\gamma_{ij}(n)$ is the ijth component of $\gamma(n)$, δ_{ij} is the Kronecker delta function and

$$\theta_{i,j-1}(n) = \theta_{ij}(n) - G_j(n)\gamma_{i,j-1}(n-1) - \delta_{i,j} q_{j-1}(n-1) \quad (19)$$

These expressions require that $\theta_{i0}(n) = \gamma_{i0}(n)$ and $\theta_{iN}(n) = 0$.

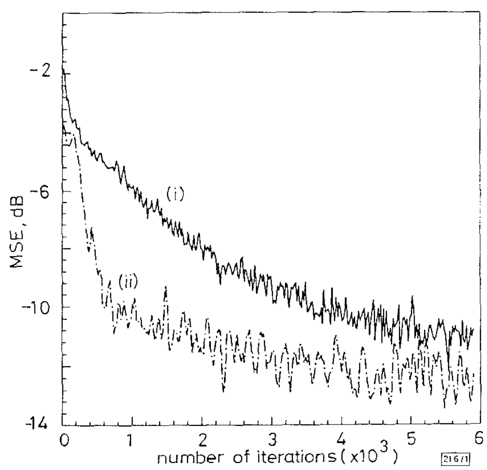

Fig. 1 *MSE performance of proposed lattice-form IIR blind equaliser and its FIR counterpart*

(i) FIR
(ii) lattice-form IIR

Simulation results: In this Section we present some Monte-Carlo simulations of the proposed blind algorithms. Binary PSK data are transmitted. The channel defined below is used in the simulations:

channel : $y(n) = a(n) + 0.9a(n-1)$

The step size μ is chosen to be 5×10^{-4}, the length N of the IIR equaliser is 6. The number of taps M for the FIR equaliser under comparison is 20. Fig. 1 shows the learning curves for the lattice-form IIR equaliser and its FIR version equaliser, respectively, for binary PSK data in the channel. These curves indicated that the proposed IIR blind algorithm not only has a faster convergence speed, but also yields a smaller steady state MSE than its FIR counterpart.

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References

1 SHALVI, O., and WEINSTEIN, E.: 'New criteria for blind deconvolution of nonminimum phase systems (channel)', *IEEE Trans. Info. Theory*, 1990, pp. 312–321
2 SHYNK, J.J.: 'On lattice-form algorithms for adaptive IIR filtering'. Proc. Int. Conf. Acoust., Speech, Signal Processing, 1998, New York, pp. 1554–1557

EBTC: An economical method for searching the threshold of BTC compression

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Indexing terms: Data compression, Image processing, Image coding

An economical method for obtaining a nearly-optimal threshold for the block truncation coding (BTC) image compression algorithm is presented. Simulation results show that the PSNR performance of the proposed economic BTC (EBTC) method is very close to that of the optimised BTC (OBTC) algorithm, but EBTC only takes about half the computation time required by the OBTC algorithm.

Introduction: Block truncation coding (BTC) [1, 2] is a simple and fast compression technique for digitised images. To reduce the mean square error (MSE) further, Kamel *et al.* [3] presented an algorithm which used a (partially) optimal threshold to quantise the block. However, as was pointed out in [4], the MSE generated by the method of Kamel *et al.* did not obtain a minimum value because the quantised error was neglected. Chen and Liu [4] suggested the optimised BTC (OBTC) algorithm to minimise the MSE, using a new threshold value searching policy. The PSNR performance of the OBTC algorithm is slightly better than that of [3], and the computation speed is also faster than that of [3], although the computation cost of [4] is still a heavy burden. In this Letter we develop an economical BTC (EBTC) algorithm whose PSNR is high (MSE is minimised) but the computation time is reduced significantly. Experiments showed that there is an effective tradeoff between the PSNR and computation time. We note that the nearly-optimal threshold is obtained by only searching a small portion of the input data for each block.

EBTC algorithm: Partition the image into blocks of size $n \times n$. For each block, let $G = \{g_i | i = 1, 2, ..., |G|\}$ be the $|G| = n^2$ given grey values to be split into two classes $H = \{g_i \geq Q\}$ and $L = \{g_i < Q\}$ where Q is a threshold value to be determined. The MSE of the block is defined by

$$MSE = \sum_{g_i \in H}(g_i - \bar{h})^2 + \sum_{g_i \in L}(g_i - \bar{l})^2 \quad (1)$$

where $\bar{h}$ and $\bar{l}$ are the average grey values of H and L, respectively. We try to obtain a Q for which the MSE is small. The procedure is as follows: The centroid O of G is evaluated by $O = (\Sigma_{i=1}^{|G|} g_i)/|G|$. The radius weighted mean [5] R of G is then evaluated by $R = (\Sigma_{i=1}^{|G|} r_i g_i)/\Sigma_{i=1}^{|G|} r_i$, with $r_i = |g_i - \bar{g}|$ for all i. If O equals R, then the value of R is assigned directly to the final threshold Q (that is, the threshold is obtained quickly without any searching operation). Otherwise, the data set is divided into two (temporary) subsets, say G_1 and G_2, by using the (temporary) threshold R. Let $G_k \in$