band density of states whereas the higher energy side is determined by the thermal distribution. With increasing temperature, the broadening of the distribution function increases. In addition, the spectrum shifts to longer wavelengths due to the temperature dependence of the bandgap. The magnitude of the emission decreases with increasing temperature due to the dominance of nonradiative recombination processes. We also measured the temperature dependence of the external quantum efficiency of an LED (Fig. 3). This measurement was calibrated by placing a large area ($0 \cdot 5\,cm^2$) InSb detector in

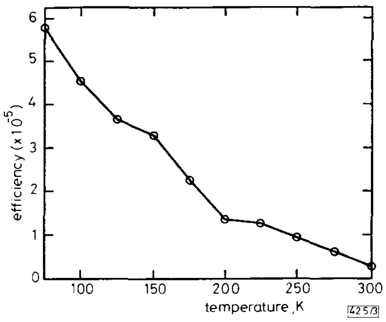

Fig. 3 *Temperature dependence of external efficiency of $InAs_{1-x}Sb_x$ light emitting diode for current $I = 200\,mA$*

front of a small ($10^{-4}\,cm^2$) LED so that most of the emitted light reaches the detector. At low temperature the efficiency reaches a maximal value of the order of 0·01%. This value could be improved significantly by using a heterostructure diode as in Reference 2 for the case of an InGaAsSb.

The operation as a gas sensor is illustrated in Fig. 4 which shows the spectrum (*a*) for an optical path of $\sim 2\,m$ through the atmosphere and (*b*) after purging the gas container with dry nitrogen, which leads to a decrease of the CO_2 absorption dip.

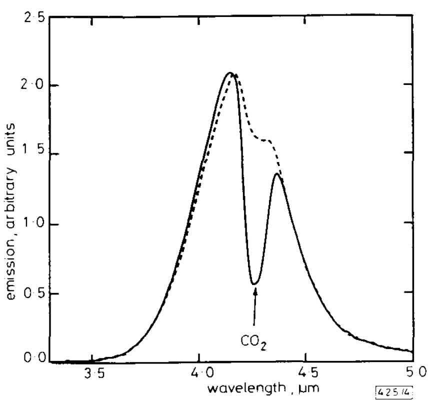

Fig. 4 *Demonstration of the application of an $InAs_{1-x}Sb_x$ light emitting diode as a CO_2 sensor*

——— measured using a monochromator filled with air
– – – – obtained after purging the monochromator with dry nitrogen

In conclusion we have demonstrated for the first time that $InAs_{1-x}Sb_x$ can be used to fabricate light emitting diodes on GaAs or Si substrates. The devices readily result in a new generation of infra-red gas sensors.

Acknowledgments: The authors would like to thank W. Van De Graaf and P. Heremans for their contributions to this work. W. Dobbelaere thanks the 'Instituut tot Aanmoediging van het Wetenschappelijk Onderzoek in de Nijverheid en Landbouw (IWONL)' for financial support.

22nd March 1993

W. Dobbelaere, J. De Boeck, C. Bruynseraede, R. Mertens and G. Borghs (*Interuniversity Micro-Electronics Center vzw Kapeldreef 75, B-3001 Leuven, Belgium*)

References

1 DOBBELAERE, W., DE BOECK, J., HEREMANS, P., BORGHS, G., LUYTEN, W., and VAN LANDUYT, J.: 'InAsSb infrared photodiodes grown on GaAs and GaAs-coated Si by molecular beam epitaxy', *Appl. Phys. Lett.*, 1992, **60**, pp. 3256–3258

2 CHOI, H. K., and EGLASH, S. J.: 'High-power multiple-quantum-well GaInAsSb/AlGaAsSb diode laser emitting at $2 \cdot 1\,\mu m$ with low threshold current density', *Appl. Phys. Lett.*, 1992, **61**, pp. 1154–1156

FAST BLIND EQUALISATION BASED ON A BAYESIAN DECISION FEEDBACK EQUALISER

S. Chen, S. McLaughlin, P. M. Grant and B. Mulgrew

Indexing terms: Equalisers, Algorithms, Digital communication systems

A blind Bayesian decision feedback equaliser is derived for joint channel and data estimation. The nature of this algorithm leads to an efficient parallel implementation. Convergence can be achieved in less than 50 symbols when a binary symbol constellation is used.

Introduction: Since the pioneering work of Sato [1], three classes or blind equalisation techniques for nonminimum phase channels have emerged. The first class of blind adaptive algorithms constructs a transversal equaliser directly [1–3]. The second class of blind adaptive algorithms identifies a channel model using higher order cumulants and then designs an equaliser based on the identified channel model [4–6]. The third class of blind adaptive algorithms employs some blind approximation of maximum likelihood sequence estimation for joint channel and data estimation [7, 8, *].

We derive a novel blind Bayesian decision feedback equaliser (DFE) for joint data and channel estimation. The channel is modelled as a finite impulse response filter with an additive noise source. Specifically, the received signal is given by

$$r(k) = \hat{r}(k) + e(t) = \sum_{i=0}^{n_a-1} a_i s(k-i) + e(k) \qquad (1)$$

where $\hat{r}(k)$ denotes the noiseless channel output, n_a is the channel order, a_i are the channel taps, the symbol sequence $\{s(k)\}$ is independently identically distributed (*iid*) and $e(k)$ is an *iid* Gaussian noise with zero mean and variance σ_e^2.

Bayesian decision feedback equaliser: A generic DFE is depicted in Fig. 1, where d is the decision delay, m is the feedforward order and n is the feedback order. In practice, $d = n_a - 1$, $m = n_a$ and $n = n_a - 1$. For the symbol constellation $\{s_i,\ 1 \le i \le M\}$, $s_f(k) = [s(k) \ldots s(k-d)]^T$ has $N_s = M^{d+1}$ combinations and, therefore, $\hat{r}(k) = [\hat{r}(k) \ldots \hat{r}(k-m+1)]^T$ has N_s states. The states of $\hat{r}(k)$ can be grouped into M sets according to the value of $s(k-d)$:

$$R_f^{(i)} = \{\hat{r}(k) = r_f^{(i)} \mid s(k-d) = s_i\} \qquad 1 \le i \le M \quad (2)$$

Each $R_f^{(i)}$ contains $N_s^{(i)} = M^d$ states. The feedback vector

* SESHADRI, N.: 'Joint data and channel estimation using blind trellis search techniques', submitted to *IEEE Trans. Commun.*, 1991

$\hat{s}_b(k) = [\hat{s}(k-d-1) \ldots \hat{s}(k-d-n)]^T$ is usually assumed to be correct to simplify the analysis.

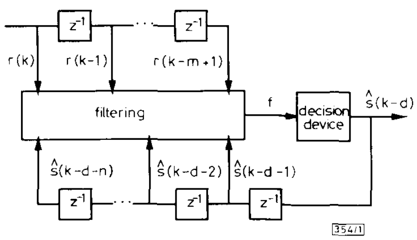

Fig. 1 *Schematic diagram of generic symbol-by-symbol decision feedback equaliser*

Because all the channel states are assumed to be equiprobable and the noise is Gaussian, applying the Bayes decision rule leads to the following Bayesian DFE [9]: Given the channel $\boldsymbol{a} = [a_0 \ldots a_{n_a-1}]^T$, compute the M Bayesian decision variables

$$\eta_i(k, \boldsymbol{a}) = \sum_{j=1}^{N_s(i)} \exp\left(-\|\boldsymbol{r}(k'') - \boldsymbol{r}_j^{(i)}\|^2 / 2\sigma_e^2\right) \quad 1 \le i \le M \qquad (3)$$

where $\boldsymbol{r}(k) = [r(k) \ldots (k-m+1)]^T$. The decision is then made according to the rule

$$\hat{s}(k-d) = s_{i^*} \text{ if } \eta_{i^*}(k, \boldsymbol{a}) = \max\{\eta_i(k, \boldsymbol{a}), 1 \le i \le M\} \qquad (4)$$

Blind implementation: At sample k, assume that $\hat{s}_b(k)$, an 'unconditional' channel estimate $\hat{\boldsymbol{a}}(k-1-d)$ and an estimated mean square error (MSE) $\sigma_\varepsilon^2(k-1-d)$ are given. The operations of the blind Bayesian DFE are as follows:

(i) N_s 'conditional' least mean square estimators update N_s 'conditional' channel estimates. Given $\hat{\boldsymbol{a}}_l(k-1-d) = \hat{\boldsymbol{a}}(k-1-d)$, the lth estimator forms $\hat{\boldsymbol{a}}_l(k)$ from $[\boldsymbol{s}_{f,l}^T(k)\hat{\boldsymbol{s}}_b^T(k)]^T$ and $\boldsymbol{r}(k)$, where $\boldsymbol{s}_{f,l}(k)$ is the lth sequence of $\boldsymbol{s}_f(k)$.

(ii) For each $\hat{\boldsymbol{a}}_l(k)$, a Bayesian DFE is designed with the required σ_e^2 being substituted by $\sigma_\varepsilon^2(k-1-d)$. The lth 'conditional' Bayesian DFE provides a tentative decision $\hat{s}^{(l)}(k-d) = s_{i_l}$ with the corresponding Bayesian decision variable $\eta_{i_l}(k, \hat{\boldsymbol{a}}_l(k))$.

(iii) The detected symbol $\hat{s}(k-d)$ is then chosen to be the best solution of the N_s tentative decisions according to

$$\hat{s}(k-d) = \hat{s}^{(l^*)}(k-d) \text{ if } \eta_{i_{l^*}}(k, \hat{\boldsymbol{a}}_{l^*}) = \max\{\eta_{i_l}(k, \hat{\boldsymbol{a}}_l), 1 \le l \le N_s\}$$

(iv) Given $r(k-d)$ and $[\hat{s}(k-d) \ldots \hat{s}(k-d-n_a+1)]^T$, $\hat{\boldsymbol{a}}(k-1-d)$ is updated to $\hat{\boldsymbol{a}}(k-d)$ using the recursive least squares algorithm. The estimated MSE is adjusted according to the adaptive rule

$$\left.\begin{aligned} \varepsilon(k-d) &= r(k-d) - \sum_{i=0}^{n_a-1} \hat{a}_i(k-d)\hat{s}(k-d-i) \\ \sigma_\varepsilon^2(k-d) &= (1-\mu_\varepsilon)\sigma_\varepsilon^2(k-1-d) + \mu_\varepsilon \varepsilon^2(k-d) \end{aligned}\right\} \qquad (5)$$

where $0 < \mu_\varepsilon < 1$ is an adaptive gain. Steps (i) and (ii) consist of N_s identical components and are suitable for parallel implementation.

Given $\hat{\boldsymbol{a}}(-1-d) = [0 \ldots 0]^T$ and $\hat{s}_b(0) = [0 \ldots 0]^T$, the above blind algorithm tends to converge falsely to an 'equivalent' minimum phase channel. If the ith channel tap a_i is known to have the largest amplitude, setting $\hat{a}_i(-1-d)$ to 1·0 and the rest of $\hat{\boldsymbol{a}}(-1-d)$ to zeros is a better initialisation. This suggests an expansion of the blind equaliser to include several units of the basic algorithm. In theory, n_a units are needed to cover the n_a initial estimates, and the ith unit, $0 \le i \le n_a - 1$, is given the initial channel estimate

$$\begin{aligned} &\hat{a}_i(-1-d) = 1 \\ &\hat{a}_j(-1-d) = 0 \qquad 0 \le j \le n_a - 1 \quad \text{and} \quad j \ne i \end{aligned} \qquad (6)$$

If a unit converges, its channel estimate converges either to $\boldsymbol{a}$ or to $-\boldsymbol{a}$, and its estimated MSE σ_ε^2 will be significantly smaller than those of the units which do not achieve convergence. Thus those units which perform poorly in terms of estimated MSE can then be switched off. Similar expansion can be applied to the initial feedback vector.

Simulation example: A simulated channel involving a binary symbol constellation is used to illustrate the proposed blind equaliser. The channel had five taps

$$\boldsymbol{a} = [-0{\cdot}205 \;\; -0{\cdot}513 \;\; 0{\cdot}719 \;\; 0{\cdot}369 \;\; 0{\cdot}205]^T \qquad (7)$$

and the signal to noise ratio was 15dB. Fig. 2 depicts the estimated MSEs of the blind adaptive algorithm starting from different initial channel estimates (eqn. 6), where the label I_i indicates that the nonzero element of the initial estimate was $\hat{a}_i(-1-d)$. From Fig. 2, it can be seen that the blind adaptive unit I_2 achieved convergence. The channel estimate of this converged unit, averaged over 30 different runs, is plotted in Fig. 3, where the dashed lines indicate the true channel taps.

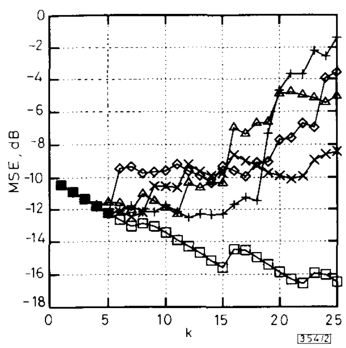

Fig. 2 *Estimated mean square errors of blind adaptive units with different initial estimates*

I_i indicates the ith unit
◇ I_0
+ I_1
□ I_2
× I_3
△ I_4

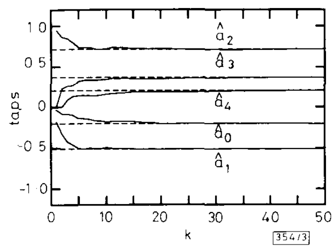

Fig. 3 *Channel estimate of converged unit over ensembles of 30 different runs*

Conclusions: A blind Bayesian decision feedback equaliser has been developed for joint channel estimation and symbol detection. It has been shown how the complete blind equaliser is built up with many identical adaptive units. Simulation results have demonstrated the very fast convergence property of this blind equaliser.

Acknowledgments: This work was supported by the UK SERC under award GR/G/72380. S. Mulgrew gratefully acknowledges financial support from the UK Royal Society.

 16th March 1993

S. Chen, S. McLaughlin, P. M. Grant and B. Mulgrew (*Department of Electrical Engineering, University of Edinburgh, King's Buildings, Edinburgh EH9 3JL, United Kingdom*)

References

1 SATO, Y.: 'A method of self-recovering equalization for multilevel amplitude-modulation systems', *IEEE Trans.*, 1975, **COM-23**, pp. 679–682

2 GODARD, D.: 'Self-recovering equalization and carrier tracking in two-dimensional data communication systems', *IEEE Trans.*, 1980, **COM-28**, pp. 1867–1875

3 TREICHLER, J. R., and AGEE, B. G.: 'A new approach to multipath correction of constant modulus signals', *IEEE Trans.*, 1983, **ASSP-31**, (2), pp. 459–472

4 GIANNAKIS, G. B., and MENDEL, J. M.: 'Identification of nonminimum phase system using higher order statistics', *IEEE Trans.*, 1989, **ASSP-37**, pp. 360–377

5 HATZINAKOS, D., and NIKIAS, C. L.: 'Blind equalization using a tricepstrum-based algorithm', *IEEE Trans.*, 1991, **COM-39**, (5), pp. 669–682

6 ZHENG, F.-C., MCLAUGHLIN, S., and MULGREW, B.: 'Blind equalization of nonminimum phase channels: higher order cumulant based algorithm', *IEEE Trans.*, 1993, **SP-41**, (2), pp. 681–691

7 GHOSH, M., and WEBER, C. L.: 'Maximum-likelihood blind equalization'. Proc. *SPIE (San Diego)*, 1991, Vol. 1565, pp. 188–195

8 ZERVAS, E., PROAKIS, J., and EYUBOGLU, V.: 'A quantized channel approach to blind equalization'. Proc. ICC'92 (Chicago), 1992, Vol. 3, pp. 351.8.1–351.8.5

9 CHEN, S., MULGREW, B., and MCLAUGHLIN, S.: 'Adaptive Bayesian equaliser with decision feedback', to be published in *IEEE Trans. Signal Processing*, September, 1993

NEW PSEUDORANDOM CODE READING METHOD APPLIED TO POSITION ENCODERS

M. Arsić and D. Denić

Indexing terms: Pseudorandom binary sequences, Codes and coding, Measurement

A new code reading method using two reading heads is proposed for use in pseudorandom position encoders. This method provides pseudorandom n-tuple formation continuity and eliminates systematic errors in code reading. Such an approach additionally enables simple realisation of a permanent checking of code reading correctness.

Introduction: Pseudorandom position encoders enable an absolute position measurement using one-bit wide code track. Different solutions to the scanning problem and pseudorandom/natural code conversion problems are possible [2, 4, 5]. However, little attention has been paid to the possibility that n bits of the position code are not read in parallel but assembled sequentially in an n-bit bidirectional shift register, using the technique described in Reference 4. These techniques have the advantage of using only one code reading head. The cost of applying this solution is loss of positional information for any change of direction of movement. We proposed a method that eliminates this drawback, as well as the systematic errors considered in Reference 4, and enables development of a reliable method for permanent checking of the code reading correctness.

Method: The solution is based on the idea of using two code reading heads, instead of one, being at distance $n \,.\, q$. As shown in Fig. 1, by means of simple logic consisting of two AND and one OR gate, a selection of one from two reading heads is made. Moving to the left the bits read off by the head $x(n)$ will be accepted, and so will be the bits read off by the head $x(0)$ moving to the right. In this way a pseudorandom n-tuple formed after the change of movement direction now responds to the current position of the movable system (MS).

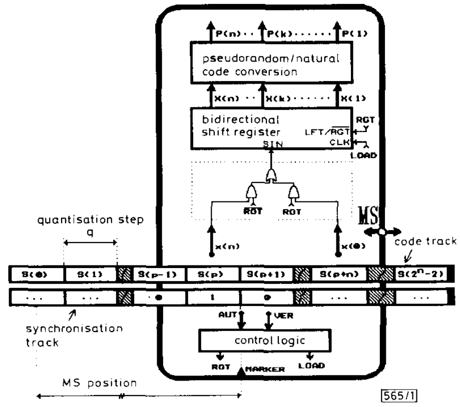

Fig. 1 *Example of application of suggested pseudorandom code reading method*

A protection circuit against measuring errors that occur when the MS changes the direction of movement on the guide path, described in Reference 4, is not necessary any more. The most important factor now is that continuity in forming the pseudorandom n-tuple is achieved even for the possible MS oscillations along the movement course. Application of this proposed code reading method is especially justified in systems where those MS oscillations can occur.

An example of a linear pseudorandom position encoder is shown in Fig. 1. The scanning problem is solved by using an external synchronisation track laid along the pseudorandom code track. By means of control logic, sensor heads AUT and VER provide the synchronisation pulses and information about the movement direction (RGT: right), as described in Reference 4. By using the code reading method proposed here, continual formation of pseudorandom n-tuples is carried out, that are then converted to natural code [3]. The new arrangement of the reading heads cancels the need for the correction element in the form of a parallel adder, because systematic errors at the code reading, considered in Reference 4, are eliminated.

Checking the code reading correctness: The proposed method of pseudorandom code reading enables a simple realisation for checking the code reading correctness, providing high reliability of the position transducer. While one code reading head serves to form the main pseudorandom n-tuple (corresponding to the current position), the other is used to form the control pseudorandom n-tuple. To realise permanent checking of code reading correctness, it is necessary to provide continuity in forming the control n-tuple. This can be achieved by applying the above described method, that is, by using one more code reading head $x(2n)$. The method for loading the code bits into the main code assembly register X (bidirectional shift register for forming the pseudorandom n-tuples corresponding to the current position) and into the control register Y, depending on the MS moving direction, is shown in Fig. 2. Checking is carried out at every reading of new bits by examining the equality of the register Y content, after it has been shifted to the left n times using the direct feedback equation [3], and content of register X.

Because of the uniqueness of the pseudorandom n-tuple [1], single errors (if the bit, read with one of two heads, is wrong) will always be detected. Only double errors, where both reading bits are wrong, should be considered. Let the MS move to the left. The register contents, after the code reading by the $x(n)$ and $x(2n)$ heads, will be $X = \{x'(n), x(n-1), \ldots, x(2), x(1)\}$ *i* $Y = \{y'(n), y(n-1), \ldots, y(2), y(1)\}$, where $x'(n)$ and