high to allow even the harsh mechanical processing of the bonded wafers.

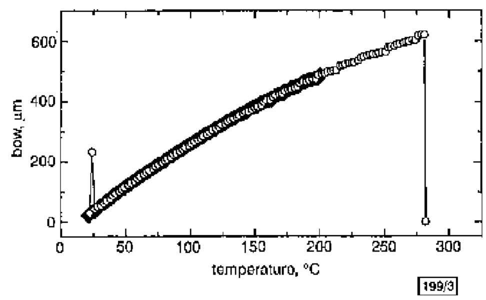

Fig. 3 *Bow measurements of GaAs/Si bonded sample during initial thermal annealing and second run after cooling*

■ initial thermal annealing
○ second run after cooling

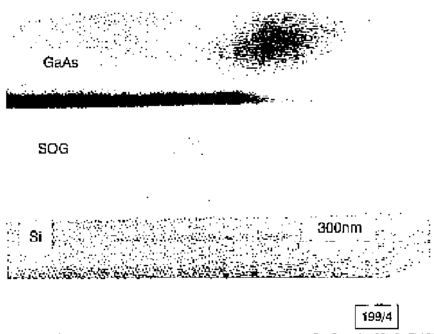

Fig. 4 *Typical cross-section TEM image of GaAs/SOG/Si interface after annealing at 200°C for 10h*

Conclusions: We have demonstrated a true low temperature bonding process using commercially available spin-on glass layers as an intermediate layer. SOG bonding is a simple, versatile and electronically clean process and it can be applied for gallium arsenide-to-silicon bonding and as well for silicon-to-silicon bonding. The interface energy achieved for SOG bonded GaAs/Si is ~1.7 J/m^2 after annealing at 200°C.

Acknowledgments: This work was funded by EC Project BONTEC (ESPRIT no. 28998) and TMWFK Project no. B609-97036.

23 December 1999
Electronics Letters Online No: 20000507
DOI: 10.1049/el:20000507

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Adaptive MLSE receiver: hybrid of per-survivor processing and tentative decision MLSE

Jung Suk Joo, Seung Chul Hong and Yong Hoon Lee

An adaptive maximum likelihood sequence estimation (MLSE) receiver is proposed that employs both per-survivor processing (PSP)-MLSE and tentative decision (TD)-MLSE by selecting one of them based on the instantaneous signal-to-noise ratio (SNR). Since the instantaneous SNR varies according to the channel, the proposed hybrid receiver can automatically control its complexity relative to the channel environment. Computer simulation results indicate that when compared with the PSP-MLSE, the proposed receiver can significantly reduce complexity with only a slight degradation in performance.

Introduction: Recently, an algorithm [1] that can reduce the computational complexity of per-survivor processing-maximum likelihood sequence estimation (PSP-MLSE) [2, 3], a powerful technique for sequence detection in uncertain environments, has been introduced. In contrast to PSP-MLSE, in which estimates of unknown parameters are made for every survivor in the trellis paths, the algorithm presented in [1] selects the N best survivors at each detection step and then only estimates parameters for those N survivors, where $1 \leq N \leq Q$ and Q denotes the number of trellis states. The remaining $Q - N$ survivors are assigned the parameter estimate associated with the best survivor. Accordingly, this algorithm, which will be referred to as N-survivor processing (NSP)-MLSE, is able to make a compromise between complexity and performance by adjusting the parameter N. NSP-MLSE is equivalent to PSP-MLSE when $N = Q$, and TD-MLSE [4, 5] when $N = 1$.

In this Letter, we propose an alternative approach to reducing the complexity of PSP-MLSE. The proposed method, called hybrid-MLSE, employs both PSP-MLSE and TD-MLSE by selecting one of them based on a comparison of the instantaneous SNR with a threshold. Owing to the fact that the instantaneous SNR varies according to the channel, in hybrid-MLSE, automatic control over the complexity relative to the channel environment is possible, without the need to adjust the threshold. As a result, hybrid-MLSE offers a compromise between complexity and performance more efficiently than NSP-MLSE. Computer simulation results indicate that a hybrid-MLSE receiver can significantly reduce computational complexity, while maintaining a performance comparable to that of a PSP-MLSE receiver.

Proposed hybrid-MLSE: A baseband received signal sampled at $t = kT$ can be written as

$$r_k = \mathbf{d}_k^T \mathbf{h}_k + \eta_k \qquad (1)$$

where $\mathbf{d}_k = [d_k, d_{k-1}, ..., d_{k-L-1}]^T$; d_k represents an M-ary PSK (or DPSK) symbol; $\mathbf{h}_k = [h_{k,0}, h_{k,1}, ..., h_{k,L-1}]^T$; $h_{k,n}$ is the impulse response of the equivalent channel at time k due to an impulse that was applied n time units earlier; η_k is additive white Gaussian noise (AWGN) with variance σ^2.

Since $|d_k| = 1$, the signal power at the receiver is written as $\mathbf{h}_k^H \mathbf{h}_k$ where H denotes the Hermitian transposition. When a channel estimate $\hat{\mathbf{h}}_k$ is given, the instantaneous SNR at the receiver can be defined as

$$\Gamma_k = \frac{\hat{\mathbf{h}}_k^H \hat{\mathbf{h}}_k}{N_k} \qquad (2)$$

where $N_k = E[|r_k - \mathbf{d}^T\hat{\mathbf{h}}_k|^2]$ and $E[\cdot]$ denotes the expectation. The instantaneous noise power N_k reduces to σ^2, when $\hat{\mathbf{h}}_k = \mathbf{h}_k$. In general, N_k increases as either σ^2 or the estimation error associated with $\hat{\mathbf{h}}_k$ increases.

Consider a trellis diagram with Q states for sequence detection. Let $S = \{\mathbf{s}_1, \mathbf{s}_2, ..., \mathbf{s}_Q\}$ denote the set of states, $\hat{\mathbf{h}}_k(\mathbf{s}_i)$ be the channel estimate for state $\mathbf{s}_i$ at time k, and $\hat{\mathbf{s}}^k$ be the state having the smallest metric. At each instance, in TD-MLSE only one channel estimate is obtained, say $\hat{\mathbf{h}}_k$, by using a tentative decision and is then assigned to all states. Therefore, $\hat{\mathbf{h}}_k(\mathbf{s}_i) = \hat{\mathbf{h}}_k$ for all $\mathbf{s}_i$. In PSP-MLSE, the estimate $\hat{\mathbf{h}}_k(\mathbf{s}_i)$ is obtained for the hypothesised input vector associated with the survivor of $\mathbf{s}_i$ at time k. The operation of hybrid-MLSE in which a recursive least squares (RLS) algorithm is employed for channel updates is described in the following steps.

(i) *Step 1 (channel update):* Suppose that an estimate of Γ_k, say $\hat{\Gamma}_k$, is given. If $\hat{\Gamma}_k > \zeta$, where ζ is a threshold, then for hybrid-MLSE, the TD mode is chosen. The channel is updated by

$$\hat{\mathbf{h}}_k = \hat{\mathbf{h}}_{k-1} + \mathbf{G}_k\left[r_{k-1-D} - \hat{\mathbf{d}}_{k-1-D}^T\hat{\mathbf{h}}_{k-1}\right] \qquad (3)$$

where $\mathbf{G}_k$ is the RLS gain matrix [6], D is the decision delay, and $\hat{\mathbf{d}}_{k-1-D}$ is the tentative decision obtained by tracing back the survival path at time $k-1$. If for hybrid-MLSE the PSP mode was the chosen mode at time $k-1$, then $\{\hat{\mathbf{h}}_{k-1}(\mathbf{s}_i), i = 1, ..., Q\}$ and the one associated with the smallest metric, $\hat{\mathbf{h}}_{k-1}(\hat{\mathbf{s}}^{k-1})$, is used as $\hat{\mathbf{h}}_{k-1}$ in eqn. 3. Now assume that $\hat{\Gamma}_k < \zeta$. Then for hybrid-MLSE, the PSP mode is the chosen mode and the channel vector for each state is updated by

$$\hat{\mathbf{h}}_k(\mathbf{s}_i) = \hat{\mathbf{h}}_{k-1}(\mathbf{s}_{i_o}) + \mathbf{G}_k(\mathbf{s}_i)\left[r_{k-1} - \hat{\mathbf{d}}_{k-1}^T(\mathbf{s}_i)\hat{\mathbf{h}}_{k-1}(\mathbf{s}_{i_o})\right] \qquad (4)$$

where $\mathbf{s}_{i_o}$ is the state for which the path from $\mathbf{s}_{i_o}$ to $\mathbf{s}_i$ yields the smallest branch metric, among the paths entering state $\mathbf{s}_i$. If for hybrid-MLSE the TD mode was chosen at time $k-1$, then $\hat{\mathbf{h}}_{k-1}$ is used as $\hat{\mathbf{h}}_{k-1}(\mathbf{s}_{i_o})$ in eqn. 4 for all $\mathbf{s}_i$.

(ii) *Step 2 (branch metric calculation):* The branch metrics are computed using either $\hat{\mathbf{h}}_k$ (TD mode) or $\hat{\mathbf{h}}_k(\mathbf{s}_i)$ (PSP mode). A survivor for each state in the Viterbi algorithm is determined depending on the branch metrics.

(iii) *Step 3 (SNR estimation):* In the TD mode, $\hat{\Gamma}_{k+1}$ is predicted by $\hat{\Gamma}_{k+1} = \hat{\mathbf{h}}_k^H \hat{\mathbf{h}}_k / \hat{N}_k$, where the estimated noise power $\hat{N}_k$ is obtained recursively by using $\hat{N}_k = (1-\gamma)\hat{N}_{k-1} + \gamma|r_{k-D} - \hat{\mathbf{d}}_{k-D}^T \cdot \hat{\mathbf{h}}_k|^2$, where $0 < \gamma < 1$. In the PSP mode, $\hat{\Gamma}_{k+1}$ is predicted by $\hat{\Gamma}_{k+1} = \hat{\mathbf{h}}_k(\hat{\mathbf{s}}^k)^H\hat{\mathbf{h}}_k(\hat{\mathbf{s}}^k)/\hat{N}_k$, in which $\hat{N}_k$ is obtained by $\hat{N}_k = (1-\gamma)\hat{N}_{k-1} + \gamma|r_k - \hat{\mathbf{d}}_k(\hat{\mathbf{s}}^k)^T \cdot \hat{\mathbf{h}}_k(\hat{\mathbf{s}}^k)|^2$, and $\hat{\mathbf{d}}_k(\hat{\mathbf{s}}^k)$ is the symbol vector assumed by the survivor of $\hat{\mathbf{s}}^k$.

It is interesting to note that in hybrid-MLSE the complexity is automatically controlled relative to the channel environment, without necessitating a change in the threshold ζ. In a hostile environment caused by fading, $\hat{\Gamma}_k$ tends to decrease [Note 1]; thus the PSP mode is selected more frequently. In this case, the complexity is automatically increased to maintain system performance. In contrast, if the channel conditions become favourable, then $\hat{\Gamma}_k$ is increased. As a result, the TD mode is more advantageous and the complexity of the hybrid-MLSE is decreased.

Note 1: Fading causes a reduction in the signal power estimate $\hat{\mathbf{h}}_k^H \hat{\mathbf{h}}_k$; furthermore, fast time-varying fading causes an increase in the channel estimation error, which in turn increases the noise power estimate $\hat{N}_k$.

Simulation results: To examine the performance of the proposed receiver, computer simulations were performed for a time division multiple access (TDMA) system over frequency-selective Rayleigh fading channels. The modulation scheme was DQPSK with a symbol rate of 24.3 ksymbol/s and 900MHz carrier frequency. The data sequence was arranged into 200 symbol frames, in which the first 20 symbols of each frame were a training sequence. A total of 5000 frames were generated and transmitted through a two-ray Rayleigh fading channel with a uniform delay power profile. It was assumed that the time delay between the two rays was $2T$, which requires 16 state MLSE receivers. The channel parameters were estimated by the RLS algorithm with a forgetting factor of 0.65.

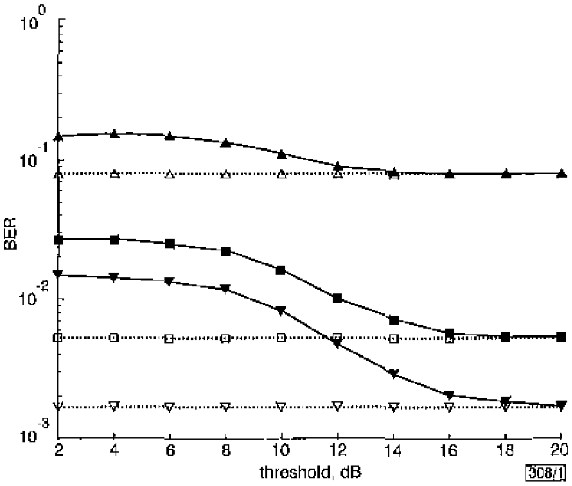

Fig. 1 *BER against threshold* ζ (v = *100km/h*)

Parameter γ for hybrid MLSE was 0.35
△ PSP-MLSE (E_b/N_o = 10dB)
□ PSP-MLSE (E_b/N_o = 20dB)
▽ PSP-MLSE (E_b/N_o = 30dB)
▲ hybrid-MLSE (E_b/N_o = 10dB)
■ hybrid-MLSE (E_b/N_o = 20dB)
▼ hybrid-MLSE (E_b/N_o = 30dB)

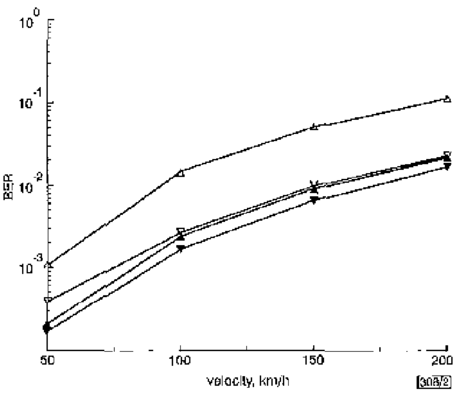

Fig. 2 *BER against vehicle speed*

E_b/N_o set at 30dB
△ TD-MLSE (D = 2)
▽ NSP-MLSE (N = 12)
▲ hybrid-MLSE (ζ = 15dB, γ = 0.35)
▼ PSP-MLSE

Fig. 1 shows the empirically estimated bit error rate (BER) values of the hybrid-MLSE against the threshold ζ. In this simulation, three cases with E_b/N_o = 10, 20 and 30dB were considered, while the vehicle speed was fixed at 100km/h. The hybrid algorithm performance was almost the same as that of the PSP-MLSE algorithm when ζ was greater than: 14dB when E_b/N_o = 10dB; 16dB when E_b/N_o = 20dB; 18dB when E_b/N_o = 30dB. However, as demonstrated by the curves in Fig. 1, it was not necessary to carefully adjust the threshold according to the channel characteristics. For example, the use of ζ = 16dB looks suitable for all three cases. The percentage of the PSP mode, indicating the complexity of the hybrid algorithm, when ζ = 16dB was: 92% when E_b/N_o = 10dB; 30% when E_b/N_o = 20dB; and 13% when E_b/N_o = 30dB.

Fig. 2 shows a comparison of the performances of the TD-, PSP-, NSP- and hybrid-MLSE algorithms against vehicle speed. The NSP- and hybrid-MLSE algorithms exhibited similar performances, which were much closer to the performance of the PSP-MLSE algorithm than that of the TD-MLSE algorithm. The percentage of time spent in the PSP mode in the hybrid algorithm was: 1.49% when the velocity v = 50km/h; 9.36% when v = 100km/h; 24.9% when v = 150km/h; and 42.92% when v = 200km/h. The complexity of the hybrid algorithm increased as the vehicle speed increased, because a fast time-varying channel causes an increase in channel estimation errors. It is interesting to note that the hybrid-MLSE algorithm required fewer computations than the NSP-MLSE algorithm, which always required ~75% (N/Q where N = 12 and Q = 16) of the computational load of the PSP-MLSE.

Conclusion: In an attempt to reduce the complexity of PSP-MLSE receivers, a hybrid-MLSE receiver has been developed that employs both TD- and PSP-MLSE by selecting one of them based on an instantaneous SNR level. This hybrid-MLSE receiver can automatically control its complexity relative to the channel environment and form a compromise between complexity and performance more efficiently than NSP-MLSE receivers. Simulation results indicate that when compared with a PSP receiver, the hybrid receiver can significantly reduce computational complexity with only a slight degradation in performance.

6 January 2000
Electronics Letters Online No: 20000472
DOI: 10.1049/el:20000472

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Blind signal separation in teleconferencing using ICA mixture model

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An algorithm for separating several sources with fewer sensors in a nonstationary environment is presented. The nonstationary environment is modelled by tracking unmixing matrix classes and the optimal class number is determined using a modified split and merge algorithm. Its usefulness is demonstrated by considering a teleconferencing problem.

Introduction: The independent component analysis (ICA) mixture model [1] can be used for blind signal separation (BSS) in a nonstationary environment by assigning the class membership to changes in the environment. Each class can then separate independent sources. In other words, the ICA mixture model can separate more sources than sensors if the sources are in different mixing classes. Then, the required number of sensors is not the total number of sources, but the maximum number of sources in a class. Lee *et al.* [1] showed that the ICA mixture model can separate two speech signals and a background music signal with only two microphones when two different mixing classes exist. One of the most important requirements of the model is that the number of classes is known *a priori*, which is rarely the case in real world applications. Since the ICA mixture model is an extension of the Gaussian mixture model and both learning algorithms are derived using maximum likelihood principles, they both suffer from overfitting problems, and any increase in the number of classes will always increase the likelihood measure. To circumvent the overfitting problem, we considered the recently proposed split and merge EM algorithm (SMEM) by Ueda *et al.* [2]. They applied the SMEM algorithm to the training of Gaussian mixtures and mixtures of factor analysers, and showed the effectiveness of the split and merge operations. However, the problem of finding the optimum number of classes still remains because the number of classes in the SMEM algorithm has to be determined in advance, as in the ICA mixture model, and this number cannot be changed through the split and merge operations. The exact optimum number of classes is difficult to compute and is affected by many factors, such as the number of sources, the location of sources, and the similarities of mixing matrices. Moreover, it becomes a time-variant variable in a nonstationary environment.

In this Letter, we propose a modified split and merge ICA mixture model to solve these problems. The usefulness of this approach is demonstrated by considering a teleconferencing problem in which several people may speak simultaneously and an automatic transcription speech recognition system can track each speaker and thus improve the recognition performance.

Proposed algorithm: To find the optimal number of classes automatically, the proposed algorithm gradually increases the number of classes and checks the redundancy of the number of classes using the merge criterion in eqn. 1:

$$J_{merge}(i, j, \Theta) = P_i(\Theta)^T P_j(\Theta) \tag{1}$$

where $P_i(\Theta) = (p(C_i \mid \mathbf{x}_1, \Theta), ..., p(C_i \mid \mathbf{x}_T, \Theta))^T$ is the T-dimensional vector consisting of *a posteriori* probabilities for class C_i. This criterion implies that when two classes have almost equal *a posteriori* probabilities for the same data, they can be regarded as one class. The merge criterion is the same form as that of the SMEM algorithm [2], but the split and merge operations are different from those of the SMEM algorithm, which performs the following: it sorts the split and merge candidates using the split and merge criteria and then performs the EM procedure for each candidate to determine what improves the total log-likelihood. The threshold for deciding merging classes was set to zero. After the algorithm performs the procedure based on the ICA mixture model, two mutually exclusive classes will have disjoint data sets and the value of the merge criterion becomes zero.

The other problem is the local maxima in the ICA mixture model. Not only the large number of classes but also the large block sizes which provide more accurate estimation of the class conditional probability for each class lead to a local maximum problem. To overcome this problem, a method for initialising basis functions was proposed. Let C denote the number of classes. The proposed algorithm learns the basis function when $C = 1$, and uses it for the initial seed of the other basis functions when $C > 1$. This implies that the basis functions are initialised at the data mean of the classes so that they have almost equal probabilities of learning the data. Because the local maxima occur when a few classes have too many data components and the others are given only a few data samples, adjusting the initial basis functions is necessary so as to avoid local maxima.

The algorithm is summarised as follows.

(i) Set C to one and carry out the learning procedure of the ICA mixture model. Let $\mathbf{A}^*$ be the basis function when $C = 1$.

(ii) For $C = 2, ...$, set the initial value of $\mathbf{A}_k$ for each class as

$$\mathbf{A}_k = \mathbf{A}^* + \epsilon \tag{2}$$

where ϵ is a small random perturbation matrix (i.e. $\|\epsilon\| << \|\theta_k^*\|$). Then carry out the learning procedure of the ICA mixture model.

(iii) Compute the merge criterion in eqn. 1.

(iv) If all the values of the merge criterion for any two classes are zero, increase C and go to step (ii). Otherwise, decrease C and end the learning.