The value of the Hooge parameter α estimated for MESFETs was of the same order of magnitude as for TLM structures, $\alpha = (2\text{–}3) \times 10^{-3}$. This value of α is three orders of magnitude smaller than that reported for thin GaN films earlier [1 – 4]. We also found that the value of α in MESFETs does not depend on the gate voltage V_g, i.e. on the channel volume (thickness). Since α does not depend on the device geometry and volume, we conclude that the $1/f$ noise in thin GaN films is of bulk origin. Note that electrons in these GaN films are not degenerate, since the electron density of states in GaN at room temperature $N_c \simeq 2.3 \times 10^{18}\,\text{cm}^{-3}$ (i.e larger than the electron concentration).

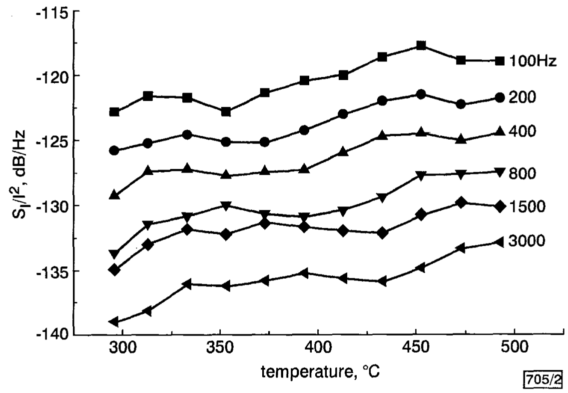

Fig. 2 *Temperature dependence of noise S_I/I_d^2 for MESFET at different frequencies of analysis*

Conclusion: Measurements of low-frequency noise in GaN TLM and MESFETs structures fabricated on 60 nm thick film have shown that, at room temperature, the noise has the form of $1/f$-like noise. The temperature dependence of the noise shows the weak contribution of generation-recombination noise at elevated temperatures. The Hooge parameter α for TLM structures and MESFETs is approximately the same and does not exceed $\alpha = (2\text{–}3) \times 10^{-3}$. This value of α is three orders of magnitude smaller than that reported for thin GaN films earlier and is of the same order of magnitude as for GaN/AlGaN HFETs. In GaN MESFETs, α does not depend on the gate voltage, indicating that the noise originates in the bulk.

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S.L. Rumyantsev, N. Pala, M.S. Shur and R. Gaska (*Department of Electrical, Computer and Systems Engineering and Center for Integrated Electronics and Electronics Manufacturing, CII 9017, Rensselaer Polytechnic Institute, Troy, NY 12180-3590, USA*)

M.E. Levinshtein (*Solid State Electronics Division, The Ioffe Physical-Technical Institute of Russian Academy of Sciences, 194021, St. Petersburg, Russia*)

M. Asif Khan, G. Simin, X. Hu and J. Yang (*Department of Electrical and Computer Engineering, University of South Carolina, Columbia, SC 29208, USA*)

R. Gaska: Also with Sensor Electronic Technology, Inc., 21 Cavalier Way, Latham, NY 12110, USA

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Adaptive minimum-BER linear multiuser detection for CDMA signals in multipath channels with 4-QAM constellation

A.K. Samingan, S. Chen and L. Hanzo

An adaptive minimum-BER linear multiuser detector called the least BER (LBER) algorithm, originally developed for BPSK modulation, is extended to 4-QAM modulation.

Introduction: The design of linear multiuser detectors is often based on the minimum mean square error (MMSE) principle. Adaptive MMSE detectors can readily be implemented using the LMS algorithm [1]. However, it is well known that the MMSE solution can in certain cases be distinctly inferior to the optimal minimum bit error rate (MBER) solution. Adaptive MBER linear multiuser detectors have recently been developed [2, 3]. These two adaptive MBER multiuser detectors were inspired, respectively, by the two adaptive MBER linear equalisers called the approximate MBER (AMBER) algorithm [4] and the LBER algorithm [5], and they are both designed for a binary signalling scheme. Previous studies [3, 5] have shown that the LBER algorithm performs better than the AMBER algorithm in terms of convergence speed and steady-state BER. We extend the LBER detector to complex-valued signalling schemes. The 4-QAM modulation scheme is used for this extension.

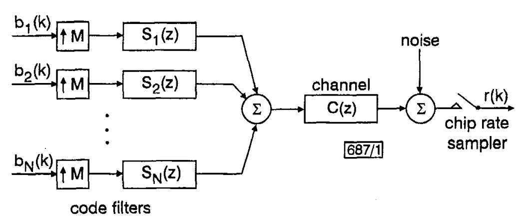

Fig. 1 *Discrete-time model of synchronous CDMA downlink*

System model: The discrete-time model of the synchronous CDMA downlink system with N users and M chips per symbol is depicted in Fig. 1, where $b_i(k) = b_{R,i}(k) + jb_{I,i}(k) \in \{\pm1 \pm j\}$ denotes the kth symbol of user i, the unit-length spreading code for user i is $\bar{\mathbf{s}}_i = [\bar{s}_{i,1} \dots \bar{s}_{i,M}]^T$, and the channel impulse response (CIR) is defined by $C(z) = c_0 + c_1 z^{-1} + \dots + c_{n_c-1} z^{-n_c+1}$ with $\{c_i\}$ denoting the complex-valued channel taps. The received signal sampled at the chip rate is given by

$$\mathbf{r}(k) = \mathbf{P} \begin{bmatrix} \mathbf{b}(k) \\ \mathbf{b}(k-1) \\ \vdots \\ \mathbf{b}(k-L+1) \end{bmatrix} + \mathbf{n}(k) = \bar{\mathbf{r}}(k) + \mathbf{n}(k) \qquad (1)$$

where the complex Gaussian channel noise vector $\mathbf{n}(k) = [n_1(k) \dots n_M(k)]^T$ with $E[\mathbf{n}(k)\mathbf{n}^H(k)] = 2\sigma_n^2 \mathbf{I}$, $\mathbf{b}(k) = [b_1(k) \dots b_N(k)]^T$ is the user symbol vector, and the $M \times LN$ system matrix

$$\mathbf{P} = \mathbf{C}\begin{bmatrix} \bar{\mathbf{S}}\mathbf{A} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \bar{\mathbf{S}}\mathbf{A} & \ddots & \vdots \\ \vdots & \ddots & \ddots & \mathbf{0} \\ \mathbf{0} & \cdots & \mathbf{0} & \bar{\mathbf{S}}\mathbf{A} \end{bmatrix} \tag{2}$$

with $\bar{\mathbf{S}} = [\bar{\mathbf{s}}_1 \ldots \bar{\mathbf{s}}_N]$, the user amplitude matrix $\mathbf{A} = \text{diag}\{A_1 \ldots A_N\}$, and the $M \times LM$ CIR matrix

$$\mathbf{C} = \begin{bmatrix} c_0 & c_1 & \cdots & c_{n_c-1} & & & \\ & c_0 & c_1 & \cdots & c_{n_c-1} & & \\ & & \ddots & \ddots & \cdots & \ddots & \\ & & & c_0 & c_1 & \cdots & c_{n_c-1} \end{bmatrix} \tag{3}$$

The intersymbol interference span L depends on n_c and M: $n_c = 1$, $L = 1$; $1 < n_c \leq M$, $L = 2$; $M < n_c \leq 2M$, $L = 3$; and so on. The linear detector for user i is given by

$$\hat{b}_i(k) = \text{sgn}(y_R(k)) + j\text{sgn}(y_I(k)) \quad \text{with}$$
$$y(k) = y_R(k) + j\, y_I(k) = \mathbf{w}^H \mathbf{r}(k) \tag{4}$$

Let the $N_b = 4^{LN}$ possible combinations of $[\mathbf{b}^T(k)\ \mathbf{b}^T(k-1) \ldots \mathbf{b}^T(k-L+1)]^T$ be

$$\mathbf{b}^{(l)} = \begin{bmatrix} \mathbf{b}^{(l)}(k) \\ \mathbf{b}^{(l)}(k-1) \\ \vdots \\ \mathbf{b}^{(l)}(k-L+1) \end{bmatrix} \quad 1 \leq l \leq N_b \tag{5}$$

and $b_i^{(l)} = b_{R,i}^{(l)} + jb_{I,i}^{(l)}$ the ith element of $\mathbf{b}^{(l)}(k)$. We define the N_b noise-free received signal states $\mathbf{r}_l = \mathbf{r}_{R,l} + j\mathbf{r}_{I,l} = \mathbf{P}\mathbf{b}^{(l)}$, $1 \leq l \leq N_b$, and the set of N_b scalars $y_l = y_{R,l} + jy_{I,l} = \mathbf{w}^H\mathbf{r}_l$, $1 < l < N_b$.

MBER detector: The probability density functions of the signed decision variables $\text{sgn}(b_{R,i}^{(l)})\, y_R(k)$ and $\text{sgn}(b_{I,i}^{(l)})\, y_I(k)$ are

$$p_{R,s}(x) = \frac{1}{N_b\sqrt{2\pi}\sigma_n\sqrt{\mathbf{w}^H\mathbf{w}}} \sum_{l=1}^{N_b} \exp\left(-\frac{(x - \text{sgn}(b_{R,i}^{(l)})y_{R,l})^2}{2\sigma_n^2\mathbf{w}^H\mathbf{w}}\right) \tag{6}$$

and

$$p_{I,s}(x) = \frac{1}{N_b\sqrt{2\pi}\sigma_n\sqrt{\mathbf{w}^H\mathbf{w}}} \sum_{l=1}^{N_b} \exp\left(-\frac{(x - \text{sgn}(b_{I,i}^{(l)})y_{I,l})^2}{2\sigma_n^2\mathbf{w}^H\mathbf{w}}\right) \tag{7}$$

respectively. The BER of the linear detector (eqn. 4) is $P_E(\mathbf{w}) = \frac{1}{2}(P_{E,R}(\mathbf{w}) + P_{E,I}(\mathbf{w}))$, where

$$P_{E,R}(\mathbf{w}) = \int_{-\infty}^{0} p_{R,s}(x)dx \quad \text{and}$$
$$P_{E,I}(\mathbf{w}) = \int_{-\infty}^{0} p_{I,s}(x)dx \tag{8}$$

After some manipulations and with the help of weight normalisation $\mathbf{w}^H\mathbf{w} = 1$, it can be shown that

$$\nabla P_{E,R}(\mathbf{w}) = \frac{1}{N_b\sqrt{2\pi}\sigma_n} \sum_{l=1}^{N_b} \exp\left(-\frac{y_{R,l}^2}{2\sigma_n^2}\right) \text{sgn}(b_{R,i}^{(l)})(y_{R,l}\mathbf{w} - \mathbf{r}_l) \tag{9}$$

$$\nabla P_{E,I}(\mathbf{w}) = \frac{1}{N_b\sqrt{2\pi}\sigma_n} \sum_{l=1}^{N_b} \exp\left(-\frac{y_{I,l}^2}{2\sigma_n^2}\right) \text{sgn}(b_{I,i}^{(l)})(y_{I,l}\mathbf{w} + j\mathbf{r}_l) \tag{10}$$

The exact MBER solution can thus be obtained using the gradient descent algorithm (where t denotes the iteration number)

$$\mathbf{w}(t+1) = \mathbf{w}(t) - \frac{\mu}{2}(\nabla P_{E,R}(\mathbf{w}(t)) + \nabla P_{E,I}(\mathbf{w}(t))) \tag{11}$$

LBER detector: We will follow the approach in [3, 5] to derive a stochastic gradient adaptive MBER algorithm. One-sample estimates of $p_{R,s}(x)$ and $p_{I,s}(x)$ are

$$\hat{p}_{R,s}(x;k) = \frac{1}{\sqrt{2\pi}\rho_n\sqrt{\mathbf{w}^H(k)\mathbf{w}(k)}} \exp\left(-\frac{(x - \text{sgn}(b_{R,i}(k))y_R(k))^2}{2\rho_n^2\mathbf{w}^H(k)\mathbf{w}(k)}\right) \tag{12}$$

and

$$\hat{p}_{I,s}(x;k) = \frac{1}{\sqrt{2\pi}\rho_n\sqrt{\mathbf{w}^H(k)\mathbf{w}(k)}} \exp\left(-\frac{(x - \text{sgn}(b_{I,i}(k))y_I(k))^2}{2\rho_n^2\mathbf{w}^H(k)\mathbf{w}(k)}\right) \tag{13}$$

respectively, where ρ_n is the width for a kernel density estimation. Re-scaling after each sample update to ensure $\mathbf{w}^H(k)\mathbf{w}(k) = 1$ and using instantaneous gradients

$$\nabla\hat{P}_{E,R}(\mathbf{w}(k);k) = \frac{1}{\sqrt{2\pi}\rho_n} \exp\left(-\frac{y_R^2(k)}{2\rho_n^2}\right) \text{sgn}(b_{R,i}(k))(y_R(k)\mathbf{w}(k) - \mathbf{r}(k)) \tag{14}$$

$$\nabla\hat{P}_{E,I}(\mathbf{w}(k);k) = \frac{1}{\sqrt{2\pi}\rho_n} \exp\left(-\frac{y_I^2(k)}{2\rho_n^2}\right) \text{sgn}(b_{I,i}(k))(y_I(k)\mathbf{w}(k) + j\mathbf{r}(k)) \tag{15}$$

leads to the LBER algorithm

$$\mathbf{w}(k+1) = \mathbf{w}(k) - \frac{\mu}{2}\left(\nabla\hat{P}_{E,R}(\mathbf{w}(k);k) + \nabla\hat{P}_{E,I}(\mathbf{w}(k);k)\right) \tag{16}$$

$$\mathbf{w}(k+1) = \frac{\mathbf{w}(k+1)}{\sqrt{\mathbf{w}^H(k+1)\mathbf{w}(k+1)}} \tag{17}$$

where the adaptive gain μ and the width parameter ρ_n should be chosen appropriately to ensure a best combined performance of convergence rate and steady-state BER misadjustment.

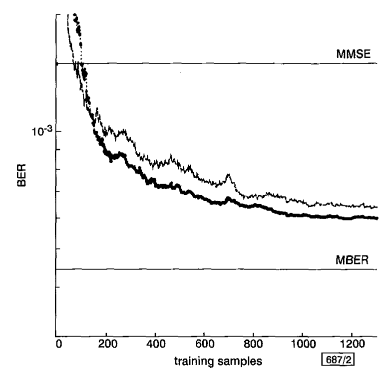

Fig. 2 *Learning curves of LBER and AMBER algorithms*

– – – – AMBER solution
- - - - - LBER solution

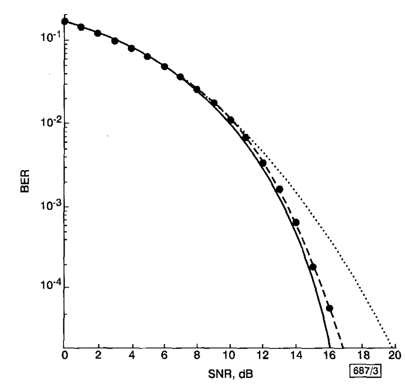

Fig. 3 *Performance comparison of MMSE, MBER and LBER detectors*

——— MBER solution
.... MMSE solution
– ● – LBER solution

Simulation example: A four-equal-power-user system with 4-QAM modulation was used in the simulation. The four-user spreading codes were (+1, +1, +1, +1, –1, –1, –1, –1), (+1, –1, +1, –1, –1, +1, –1, +1), (+1, +1, –1, –1, –1, –1, +1, +1) and (+1, –1, –1, +1, –1, +1, +1, –1), respectively. The CIR was $C(z) = (0.4 + 0.4j) + (0.7 + 0.7j)z^{-1} + (0.4 + 0.4j)z^{-2}$. For user 1 with an SNR = 14 dB, and $\mu = 5/k$ and $\rho_n = \sigma_n$, the convergence performance of the LBER algorithm is shown in Fig. 2, where the results are averaged on 10 runs. The AMBER algorithm [2] was also modified to work for 4-QAM, and its performance is also depicted in Fig. 2. It can be seen that the LBER algorithm has a faster convergence rate and a smaller steady-state BER. Fig. 3 compares the BER of the LBER detector with those of the MMSE and MBER detectors for user 1 over a range of SNR values.

Conclusion: A stochastic gradient adaptive MBER linear multiuser detector, originally developed for binary signalling schemes, has been extended to the complex-valued 4-QAM signalling scheme. Initial simulation results show that this proposed LBER detector has better performance, in terms of faster convergence rate and smaller steady-state BER, than the existing AMBER detector.

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A.K. Samingan, S. Chen and L. Hanzo (*Department of Electronics and Computer Science, University of Southampton, Southampton, SO17 1BJ, United Kingdom*)

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Missing data techniques using voicing probability for robust automatic speech recognition

L.Y. Kim, H.Y. Cho and Y.H. Oh

The authors propose a new method for detecting missing data by utilising voicing probability under a missing data theory. With the same level of distortion, people fail to recognise vowels more frequently than consonants. From this observation, we propose that consonants should not be classified into missing data. The experimental results showed that our method significantly improves the performance for isolated word recognition under various noise environments.

Introduction: The human auditory system is robust to spectral loss caused by band-limited noise sources [1]. Human beings can cope with unnatural, unseen degradation or deletion even though they are not trained *a priori*. They are able to reject a broad range of degradation or deletion in time or frequency domains, while still taking into account cue information for recognition. People are capable of utilising the partial information left in the degraded speech. This is the capability that a 'missing data' approach models. Ongoing robust speech recognition research is exploring more reliable features and speech recognition that uses these features. In previous work, a simple method of spectral subtraction has been widely used for classifying the features as reliable or unreliable [2, 3]. However, in the presence of severe noise, consonants with low energy are undoubtedly masked by louder noise. In isolated word recognition with many similar words, the recognition performance is degraded because consonants are likely to be labelled as missing data. We propose a new method of using voicing probability to indicate the reliability of detected missing data. Using the proposed method, we obtain better results than the baseline system using only spectral subtraction.

Detection of missing data: Spectral subtraction is also used in our work for the case of speech corrupted by additive noise. Some spectral subtraction criteria have been proposed for identifying missing data [2, 3]. One of them is the SNR criterion. Let $y(n)$ be the speech samples affected by an additive stationary noise signal $d(n)$:

$$y(n) = s(n) + d(n) \qquad (1)$$

The short-time magnitude spectrum of enhanced speech is calculated by

$$|\hat{S}_m(\omega)| = \begin{cases} |Y_m(\omega)| - |\bar{N}(\omega)| & \text{if } |Y_m(\omega)| > |\bar{N}(\omega)| \\ 0 & \text{otherwise} \end{cases} \qquad (2)$$

where $|Y_m(\omega)|$ is the magnitude spectrum of the current noisy speech frame, and $|\bar{N}(\omega)|$ is the average magnitude spectrum of the noise. For the SNR criterion, features are regarded as being missed if the estimated SNR is smaller than 0 dB. This means

$$10\log\left(\frac{|\hat{S}_m(\omega)|^2}{|\bar{N}(\omega)|^2}\right) < 0 \quad \text{or} \quad |\hat{S}_m(\omega)|^2 < |\bar{N}(\omega)|^2 \qquad (3)$$

Marginalisation: In HMMs, each state is defined by observation and transition probabilities. For a single state model Γ, the likelihood function of the probability of observation vector $\mathbf{x} = [x(1), ..., x(\omega), ..., x(\Omega)]^T$ is expressed as

$$f(\mathbf{x}|\Gamma) = \sum_{i=1}^{M} w_i \prod_{\omega=1}^{\Omega} \Phi(x(\omega), \mu_{\Gamma_i}(\omega), \sigma^2_{\Gamma_i}(\omega)) \qquad (4)$$

where w_i is the weight for the ith Gaussian PDF, $\mathbf{x}$ a vector of the log-spectrum components of the critical bands and $\mu_{\Gamma_i}(\omega)$, $\sigma^2_{\Gamma_i}(\omega)$ the mean and variance for the ith Gaussian PDF in frequency band ω, respectively. The components of $\mathbf{x}$ can be divided into missing and present features. Eqn. 4 can be expressed as follows:

$$f(\mathbf{x}|\Gamma) = \sum_{i=1}^{M} w_i \left\{ \prod_{\omega,present} \Phi(x(\omega), \mu_{\Gamma_i}(\omega), \sigma^2_{\Gamma_i}(\omega)) \cdot \prod_{\omega,missing} \Phi(x(\omega), \mu_{\Gamma_i}(\omega), \sigma^2_{\Gamma_i}(\omega)) \right\} \qquad (5)$$

The modified likelihood function $f(\mathbf{x}_p|\Gamma)$ required to recognise speech with missing features can be obtained by integrating the original likelihood function $f(\mathbf{x}|\Gamma)$ over missing features, $f(\mathbf{x}_p|\Gamma) = \int f(\mathbf{x}|\Gamma)d\mathbf{x}_m$ where $\mathbf{x}_m$ represents all missing features. The desired modified likelihood is then given by

$$f(\mathbf{x}_p|\Gamma) = \sum_{i=1}^{M} w_i \prod_{\omega,present} \Phi(x(\omega), \mu_{\Gamma_i}(\omega), \sigma^2_{\Gamma_i}(\omega)) \qquad (6)$$

Using voicing probability for detecting missing data: In our research, we use a robust algorithm for pitch tracking (RAPT) [4] to obtain voicing probability. RAPT makes a binary voicing classification on the presence or the absence of voicing in speech. A consonant with low energy is easily masked by the background noise. We adopt a voicing probability in order to measure the reliability of detected missing data. A segmental SNR of a vowel region is higher than that of a consonant. If some frequency bands of a vowel frame are marked as missing data, their feature vector elements are ignored in the next likelihood calculation. However, labelled as unvoiced, consonants should not be classified as missing data. As shown in Fig. 1, for input speech, we perform spectral subtraction to find any unreliable frames. If the energy of the estimated noise is higher than that of the enhanced speech frame, it is labelled as missing data. The frame detected as missing data is