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비선형 적응 여파기 설계를 위한 최소평균자승에러의 알고리듬 수학적 표현

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<요 약>

본 논문에서는 최소평균자승에러 (MMSE)을 이용한 비선형 적응 여파기 (non-linear filter with ISI canceller) 시스템 설계를 위한 알고리듬을 수학적으로 표현하고자한다. 또한 무선통신 전송상에서 발생하는 신호 다중경로지연 확산 현상을 고려하여 다중 안테나 시스템(dual diversity antenna)을 적용하였다. 일반적으로 채널 모델을 가우시안으로 설정하여 시스을 설계한다. 그러나 무선통신 시스템은 자연환경 또는 지역적인 작은 변화에 의해 신호의 세기가 다양하게 변조되기 때문에 일정한 패턴의 잡음 모델설정으로 한 시스템 설계는 다소 무리가 따를 것으로 본다. 본 논문에서는 좀더 현실적인 상황을 고려하여 일정한 패턴을 지니지 않는 모델(nongaussian)을 설정하여 시스템 구현에 필요한 알고리듬을 수학적으로 표현하였다. 이는 어떠한 환경에서도 적용이 가능할 것이며 다양한 분야에 응용이 될 것으로 본다. 본 논문의 내용을 간략하게 정리해보면, 비가우시안 잡음 모델이므로 수신된 표본 (observables)의 분포가 유한한 집합(mean, variance)으로 정의 될 수 없기 때문에, 대신 r-차의 표본 공간을 quantiles에 바탕을 둔 벡터 양자화 (vector quantization)를 이용하여 유한개의 같은 확률을 갖는 독립적인 영역으로 나눈다. 여기에서 이용될 알고리듬은 Robbins Monro Stochastic Approximation (RMSA)이며 이 알고리듬에 의해 추정된 quantiles와 조건부의 부분 평균치(conditional partition moments)을 이용하여 감쇄함수 (regression function)을 구분 근사화(piecewise approximation)로 변형하고 이를 바탕으로 하여 시스템의 계수를 구한다. 성능 실험을 위하여 Monte-Carlo 시뮬레이션 방법을 이용하였다.

Numerical Expression of MMSE Algorithm in Designing of Non-Linear Adaptive Filter with ISI canceller

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<Abstract>

In this paper, we show how to derive non-linear minimum mean square error (MMSE) algorithm (including ISI canceller) numerically for designing an adaptive filter combined with postdetection diversity reception. Due to intersymbol interference (ISI) produced by multipath channel delay spread and irregular additive noise in mobile communication, we assume nongaussian noise as a channel model in this paper. Because of nongaussian noise, it is very difficult to obtain the functional form of the underlying distributions associated with the observables. Instead of trying to find a finite set of parameters, we use the sample space which is equiprobably partitioned into finite number of independent regions based on vector quantization (VQ) and quantiles which is estimated by Robbins Monro Stochastic Approximation (RMSA). We use the 6^{th} *Chebychev filter to generate ISI components for computer simulation. Monte-Carlo simulation was used to show the performance of system suggested here.*

I. Introduction

In many radio communication environments frequency selectivity caused by multipath propagation degrades the performance of digital communication channel by causing ISI which imposes limitations of the data transmission rate [4]. How much ISI a given amount of delay spread causes depends on the symbol duration. Due to unknown characteristics of multipath channel in mobile communication, the objective of the receiver is to identify the channel characteristics in order to reduce the ISI component and additive noise. The bit error rate *(BER)* represents the performance index associated with the modulated signal (in this paper : *QDPSK)* transmitted over multipath fading channel in the presence of additive noise and ISI [6]. In order to improve BER, two methods (direct or indirect) have been studied in the past. In direct method, the optimal detector is designed by estimating the noise probability density function *(pdf)* and conditional probability density function(cpdf). In indirect method, the optimal equalizer followed by a detector is designed to minimize the mean square error *(MSE)*. The purpose of this paper is to design non-linear adaptive filter *(with ISI canceller and called equalizer)* which have the ability to alleviate problems associated with nongaussian noise. The structure of the non-linear adaptive filter is chosen to minimize the MSE with respect to transmitted information. The non-linear MMSE equalizer is based on piecewise approximations to a regression function involving only quantiles and partition moments which are estimated by a RMSA. algorithm [5]. For each partition, the coefficients of the non-linear MMSE equalizer are evaluated by using the conditional minimum mean square estimation criterion. In our system, we employ a quarternary differential phase shift keying *(QDPSK)* as a modulation and detection scheme. Mobile radio channels are characterized by fading caused by interference among multipath waves with different time delays. Fading severely degrades the BER performance. Diversity reception is one of the most powerful techniques to combat fading. There are many possible implementations of diversity reception systems, but for mobile radio postdetection diversity is attractive because the cophasing function necessary in predetection combining is not required and because switching noise due to an abrupt phase change is not produced. In postdetection diversity, diversity outputs are weighted according to each branch's channel conditions before combining so that the contribution of the weaker signal branch is minimized. In this paper, we employ a postdetection phase combining *(PC)* scheme [1]-[2].

II. System Description

II-1. System Model Description

In this paper, we employ a diversity reception providing a viable solution, because of the presence of a diversity path. In postdetection diversity, detector outputs are weighted according to each branch's channel condition before combining so that the contribution of the weaker signal branch is minimized [1],[7]-[8]. The combiner output can be expressed by

$$I+jQ=\sum_{k}X_k(nT)\cdot X_k^*((n-1)T) \tag{1}$$

where $X_k(t)$ is the k^{th} branch received faded signal.

In this paper, we consider rician fading channel as a channel model and express three components as $x_{dk,}\ x_{fk,}\ x_{nk}$ separately as the differential phase detection *(DPD)* detector input components. In general, $M-ary$ DPSK transmitted signal can be expressed as

$$S(t)=\sum_{n=-\infty}^{\infty}a_n\cdot p(t-nT)\cos(w_ct+\theta_n) \tag{2}$$

The DPD detector input $x_k(t)$ of the k^{th} $(k=1,2)$ branch can be expressed as

$$x_k=x_{dk}(t)+x_{fk}(t)+x_{nk}(t)$$

$$x_{dk}(t)=\sum a_nq(t-nT)\cos(w_ct+\theta_n(t))$$

$$x_{fk}(t)=\frac{1}{\beta}\sum_{n=-\infty}^{\infty}a_n\,c(t)\ q(t-nT)\cdot\cos[w_c(t-\tau(t))+\theta_n(t)]$$

$$q(t) = h(t) * p(t), \quad h(t)\text{: channel filter} \tag{3}$$

and $x(t)$ can be expressed by in-phase and quadrature components representing the input to the detector of the signal

$$\begin{aligned} x_k(t) &= x_{ki}(t)\cos w_c t - x_{kq}(t)\sin w_c t \\ &= \sqrt{x_{ki}^2(t) + x_{kq}^2(t)}\cos[w_c t + \tan^{-1}(\frac{x_{kq}(t)}{x_{ki}(t)})] \\ &= R_k(t)\cos[w_c t + \tan^{-1}(\frac{x_{kq}(t)}{x_{ki}(t)})] \end{aligned} \tag{4}$$

II-2. RMSA Algorithm

The main idea is that using a training mode, we estimate quantiles by the RMSA procedure and then partition the observation space into Q regions using the VQ. Next, for each partition, the partition moments are estimated. These moments are required to calculate the coefficients of the MMSE equalizer. In the following part, we will consider RMSA algorithm used in calculating the quantiles and partition moments which are required in VQ.

We seek an estimate of the quantile k that satisfies $\Pr[x_n < k] = F(k) = p$ for a given value of p. The available data is the sequence $[x_n]$, for n= 0, 1, 2, ⋯. The proposed recursive estimation is, for n=0, 1, 2, ⋯.

$$V_{n+1} = V_n - g_n[U(V_n - X_{n-1}) - p] \tag{5}$$

where $U(\cdot)$ is the *Heaviside stepfunction.* and $[g_n]$ is the sequence of positive numbers having the following conditions ;

$$g_n \Downarrow 0, \ n \Rightarrow \infty; \quad \sum_{n=0}^{\infty} g_n = \infty; \quad \sum_{n=0}^{\infty} g_n^2 < \infty$$ (6), (g_n is usually $\frac{1}{n}$)

Before processing further, we will consider the modification of quantile estimators because of the overlapping tails at the center having a bad influence on the quantile estimation for high *SNR* case which corresponds to a more confined *P.D.F* than in case of low *SNR*. We modify the quantile estimators suggested by Lomp [21], namely, the data $[x_n]$ are grouped into two subgroups under

$(H_0 : (S(n) = 1),\ H_1 : (S(n) = -1 \text{ is transmitted}))$ hypothesis.

$[x_n]$ is equiprobably partitioned by quantiles $\eta_{i,j}$ using (1), where *i=0 or 1, j=1, 2, ⋯, l-1 (l* : odd number).

$$\nu_{i,j} \ : \ \Pr[x_n < \nu_{i,j} | H_i] = \frac{j}{l}$$

$$\eta_k \ : \ \Pr[x_n < \eta_k] = \frac{k}{l}, \quad where \ \ k = 1, 2, \cdots, l-1$$

$$\eta_1 = \nu_{0,2}\ ,\ \eta_2 = \nu_{0,4}\ ,\ \cdots,\ \eta_{\frac{l-1}{3}} = \nu_{0,l-1}$$

$$\eta_{\frac{l+1}{2}} = \nu_{1,1}\ ,\ \cdots, \eta_{l-1} = \nu_{1,l-2} \tag{7}$$

If $\nu_{0,l-1} \geq 0$, or $\nu_{1,1} \leq 0, \eta_k$'s are obtained from $\Pr[x_n < k] = F(k) = p$

Now we also establish a recursive estimation scheme for estimating the partition moments defined by

$$m_i\ (a,b] = E\ [\chi_{(a,b]}(x)x^i],\ i = 1, 2, \cdots \tag{8}$$

where $\chi_{(a,b]}$ is the indicator function of the interval $(a,b]$, and $\chi_{(a,b]}x^i$ will also be denoted by H. From the available sequence $[x_n]$, $n = 0, 1, 2, \cdots$, the proposed partition moments are

$$W_{n+1} = W_n + g_n[H_{n+1} - W_n] \tag{9}$$

where $H_{n+1} = \chi_{(a,b]}(x)x^i$ and g_n satisfies the previous conditions described.

II-3. Non-Linear MMSE Structure

Let's discuss the problem a modulated signal imbedded in nongaussian noise (dependent noise).

Consider MMSE estimation of the transmitted signal, a_n, from $(r+1)$ present and past received signals. The optimum estimate is the well-known regression function

$$E[a_n | x_n,\ x_{n-1}, \cdots,\ x_{n-r}] \tag{10}$$

In general, this function is nonlinear, and often suboptimal linear estimator is used, i.e.,

$$a' = \sum_{k=0}^{r} c_k\ x_{n-k} \tag{11}$$

Let's consider the linear estimate case first and assume the input to the conventional equalizer as

$x(t) = x_d(t) + x_f(t) + x_n(t)$ and sampled at time kT, i.e., $x_k = x_{dk} + x_{fk} + x_{nk}$. Denoting the r-equalizer coefficients at time kT by the column vector c_k, the equalizer output is give by $z_k = c_k' x_k$.

Minimizing the mean square error $(MSE)\ E[|a_n - z_k|^2]$ leads to the set of suboptimum equalizer coefficients ;

$$c = A^{-1} \cdot a \quad where \quad A = E[x_k x_l],\ a = E[a_k x_l],\ c' = [c_0, c_1, \cdots, c_r] \tag{12}$$

We present a method that is of similar complexity but which yields better performance using Taylor series expansion, we approximate the function $E[a_n \mid x_n,\ x_{n-1}, \cdots, x_{n-m}]$ in the neighborhood of a point $(x_n^*,\ x_{n-1}^*, \cdots,\ x_{n-m}^*)$ as

$$E[a_n|x_n, x_{n-1}, \cdots, x_{n-r}] = E[a_n|x_n^*, x_{n-1}^*, \cdots, x_{n-r}^*] + \nabla E[a_n|x_n, x_{n-1}, \cdots, x_{n-r}]|_{(x_n^* \cdots x_{n-r}^*)} \cdot [x_n - x_n^*, \ x_{n-1} - x_{n-1}^*, \cdots, \ x_{n-r} - x_{n-r}^*] \tag{13}$$

The suggested estimate is represented by

$$E[a_n|x_n, x_{n-1}, \cdots, x_{n-m}] = \beta(x_n^*, \cdots, x_{n-m}^*) + \sum_{k=0}^{r} a_{xk}(x_n^*, \cdots, x_{n-m}^*) x_{n-k} \tag{14}$$

Now, we consider data-blocks that are *(r+1)*-dimensional vectors. We replace the conditioning vector $(x_n, x_{n-1}, \cdots, x_{n-r})$ by the output of a VQ. The VQ maps from S^{r+1} to $Q=\rho_0, \rho_1, \cdots, \rho_l$, where Q is a finite set with elements called pseudo-states of $(x_n, x_{n-1}, \cdots, x_{n-r})$. The method is defined as follows

- Space S^{r+1} be partitioned : Q : $S^{r+1} = U_{i=1}^{l} S_i$, $S_i \bigcap S_j = \emptyset$, $i \neq j$
- If $(x_n, x_{n-1}, \cdots, x_{n-r}) \in S_t$ then $VQ(y_n, y_{n-1}, \cdots, y_{n-r}) = \rho$ (15)

If the partition ζ_s quantizes the vector $(x_n, x_{n-1}, \cdots, x_{n-r})$ into equally likely outputs $(\rho_0, \rho_1, \cdots, \rho_l)$, then the partition ζ_{s+1} is obtained by determining the conditional quantiles, $[\eta_{j,k}^{s+1}]$, i.e., each s-dimensional part in ζ_s becomes an *(s+1)*-dimensional part in ζ_{s+1}. The determination of the $[\eta_{j,k}^{s+1}]$ is accomplished by parsing the data sequence $[x_{n-s-1}]$, using the *VQ* for ζ_s, into η_i substreams. Each substream $[x_{n-s-1}^k]$ is then processed by the recursive quantile estimator

$$V_{n+1} = V_n - g_n[U(x_{n-s-1}^{(k)} - V_n) - \frac{j}{m}], \quad where \ j = 1, 2, \cdots, m-1 \tag{16}$$

In here, we utilizes the extracted noise $(g(n))$ and the combination of already detected (known) symbols to suppress the interference based on assuming *SNR(dB) > 0*. Through the assuming high *SNR*, we can obtain almost correct past symbols during the real transmitting mode. The conditional MSE with ISI canceller, called *MMSE-I*, can be expressed by

$$MSE = E\ [(a_n - (a_{qk} + \beta_{qk} x_n + \sum_{j=1}^{r} \gamma_{qk,j}\ g_{n-j} + \sum_{i=1}^{r} \xi_{qk,i}\ a'_{n-i}))^2\ |S_k] \tag{17}$$

where a' is past detected symbols. As done in suboptimum case, using the orthogonality principle we can get following forms respectively to solve each partitioned space coefficients ;

$$\cdot \quad \frac{de}{da_{qk}} \ : \ E\ [(a_n - (a_{qk} + \beta_{qk} x_n + \sum_{j=1}^{r} \gamma_{qk,j}\ g_{n-j} + \sum_{i=1}^{r} \xi_{qk,i}\ a'_{n-i}))\ (-1)|S_k] = 0$$

$$E\,[a_n|S_k] = \alpha_{qk} + \beta_{qk}E[x_n|S_k] + \sum_{i=1}^{r}\gamma_{qk,i}\,E[g_{n-i}|S_k] + \sum_{i=1}^{r}\xi_{qk}\,E[a'_{n-i}|S_k]$$

- $\dfrac{de}{d\beta_{qk}}$: $E\,[(a_n - (\alpha_{qk} + \beta_{qk}x_n + \sum_{j=1}^{r}\gamma_{qk,j}\,g_{n-j} + \sum_{i=1}^{r}\xi_{qk,i}\,a'_{n-i}))\,(-x_n)|S_k] = 0$

$$E\,[a_nx_n|S_k] = \alpha_{qk}E[x_n|S_k] + \beta_{qk}E[x_n^2|S_k] + \sum_{i=1}^{r}\gamma_{qk,i}\,E[x_ng_{n-i}|S_k] + \sum_{i=1}^{r}\xi_{qk}\,E[a'_{n-i}x_n|S_k]$$

- $\dfrac{de}{d\gamma_{qk}}$: $E\,[(a_n - (\alpha_{qk} + \beta_{qk}x_n + \sum_{j=1}^{r}\gamma_{qk,j}\,g_{n-j} + \sum_{i=1}^{r}\xi_{qk,i}\,a'_{n-i}))\,(-g_{n-j})|S_k] = 0$

$$E\,[a_ng_{n-j}|S_k] = \alpha_{qk}E[g_{n-j}|S_k] + \beta_{qk}E[x_ng_{n-j}|S_k] + \sum_{i=1}^{r}\gamma_{qk,i}\,E[g_{n-i}g_{n-j}|S_k] + \sum_{i=1}^{r}\xi_{qk}\,E[a'_{n-i}g_{n-j}|S_k]$$

- $\dfrac{de}{d\xi_{qk}}$: $E\,[(a_n - (\alpha_{qk} + \beta_{qk}x_n + \sum_{j=1}^{r}\gamma_{qk,j}\,g_{n-j} + \sum_{i=1}^{r}\xi_{qk,i}\,a'_{n-i}))\,(-a'_{n-j})|S_k] = 0$

$$E\,[a_na'_{n-j}|S_k] = \alpha_{qk}E[a'_{n-j}|S_k] + \beta_{qk}E[x_na'_{n-j}|S_k] + \sum_{i=1}^{r}\gamma_{qk,i}\,E[g_{n-i}a'_{n-j}|S_k] + \sum_{i=1}^{r}\xi_{qk}\,E[a'_{n-i}a'_{n-j}|S_k] \quad (18)$$

Those partition moments in (14) can be estimated from (5). Thus, for each partition, q_k, the coefficients can be obtained by using following matrix form. Let's assume $r=3$;

$$\begin{pmatrix} a_{11}, & a_{12}, & \cdot & \cdot & \cdot & a_{18} \\ a_{21} & a_{22} & \cdot & \cdot & \cdot & a_{28} \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ a_{81}, & a_{82}, & \cdot & \cdot & \cdot & a_{88} \end{pmatrix} \begin{pmatrix} y_1 \\ y_2 \\ \cdot \\ \cdot \\ \cdot \\ y_8 \end{pmatrix} = \begin{pmatrix} z_1 \\ z_2 \\ \cdot \\ \cdot \\ \cdot \\ z_8 \end{pmatrix} \quad (19)$$

where

$a_{11}=1$ $a_{12}=E[x_n|S_k]$, $a_{13}=E[g_{n-1}|S_k]$, $a_{14}=E[g_{n-2}|S_k]$, $a_{15}=E[g_{n-3}|S_k]$, $a_{16}=E[a'_{n-1}|S_k]$, $a_{17}=E[a'_{n-2}|S_k]$, $a_{18}=E[a'_{n-3}|S_k]$, $a_{21}=E[x_n|S_k]$, $a_{22}=E[x_n^2|S_k]$, $a_{23}=E[x_ng_{n-1}|S_k]$, $a_{24}=E[x_ng_{n-2}|S_k]$, $a_{25}=E[x_ng_{n-3}|S_k]$,

$$a_{26}=E[x_n a'_{n-1}|S_k],\ a_{27}=E[x_n a'_{n-2}|S_k], a_{28}=E[x_n a'_{n-3}|S_k]\cdots$$
$$z_1=E[a_n|S_k],\ z_2=E[a_n x_n|S_k],\ z_3=E[a_n g_{n-1}|S_k],\ z_4=E[a_n g_{n-2}|S_k],$$
$$z_5=E[a_n g_{n-3}|S_k],\ z_6=E[a_n a'_{n-1}|S_k],\ z_7=E[a_n a'_{n-2}|S_k],$$
$$z_8=E[a_n a'_{n-3}|S_k] \tag{20}$$

To obtain unknown values of $(y_1, y_2, y_3, \cdots, y_8)$, we use the Cramer's law and transform (15) into n equations

$$\begin{aligned} a_{11}y_1+a_{12}y_2+a_{13}y_3+a_{14}y_4+a_{15}y_5+a_{16}y_6+a_{17}y_7+a_{18}y_8 &= z_1 \\ a_{21}y_1+a_{22}y_{22}+a_{23}y_3+ \cdots\cdots\cdots\cdots\cdots + a_{28}y_8 &= z_2 \\ &\vdots \\ a_{81}y_1+a_{82}y_{22}+a_{83}y_3+ \cdots\cdots\cdots\cdots\cdots + a_{88}y_8 &= z_8 \end{aligned} \tag{21}$$

If the determinant $D=det\ A$ of a system of n equations (17) in the same number of unknowns $y_1, y_2, \ldots, y_8$ is not zero, the system has precisely one solution (*Cramer's Theorem*). This solution is given by the formula

$$y_1=\frac{D_1}{D}, y_2=\frac{D_2}{D}, \cdots, y_8=\frac{D_8}{D} \tag{22}$$

where D_k is the determinant obtained from D by replacing in D the k^{th} column by the column with the entries $z_1, z_2, \cdots, z_8$. Through the Cramer's rule we can get the coefficients of non-linear MMSE, (compare (13) with (18)) i.e. ;

$$MSE=E\ [\ (a_n-\ (a_{qk}+\beta_{qk}x_n+\sum_{j=1}^{r}\gamma_{qk,j}\ g_{n-j}+\sum_{i=1}^{r}\xi_{qk,i}\ a'_{n-i}))^2\ |S_k]$$
$$\begin{aligned} \textit{where}\ \ & y_1=a_{qk},\ y_2=\beta_{qk},\ y_3=\gamma_{qk,1},\ y_4=\gamma_{qk,2},\ y_5=\gamma_{qk,3} \\ & y_6=\xi_{qk,1},\ y_7=\xi_{qk,2},\ y_8=\xi_{qk,3} \end{aligned} \tag{23}$$

As stated before, we employ the postdetection diversity system so to avoid the problem that the combiner output phase might fall outside the phase region sandwiched between $\triangle\phi_1$, $\triangle\phi_2$ where

$$\triangle\phi_l=\ (\phi_l(n)-\phi_l(n-1),\ \mathrm{mod}\ 2\pi) \tag{24}$$

we must consider the phase correction procedure before combining phases, [2]-[3]

$$\triangle\phi_2=\begin{pmatrix} \triangle\phi_2+2\pi, & (\triangle\phi_1-\triangle\phi_2)>\pi \\ \triangle\phi_2-2\pi, & (\triangle\phi_1-\triangle\phi_2)<-\pi \end{pmatrix} \tag{25}$$

The resultant combiner output is $\triangle\phi=w_1\triangle\phi_1+w_2\triangle\phi_2$ and the decision rule is based on $\triangle\phi$;

$$S'(n)=\begin{bmatrix} (0,0); & 0\leq \Delta\phi & <\frac{\pi}{2} \\ (0,1); & \frac{\pi}{2}\leq \Delta\phi & \leq\pi \\ (0,0); & -\pi< \Delta\phi & <\frac{-\pi}{2} \\ (1,0); & \frac{-\pi}{2}\leq \Delta\phi & <0 \end{bmatrix} \quad (26)$$

III. Discussion of Results and Conclusion

We used the auto-regressive *(AR)* model to generate the dependent noise which is used in this paper as a nongaussian noise component in computer simulation. Fig.1 plots the comparison of the performance between the equalizer based on non-linear mmse in partitioned observables (without ISI canceller) and the conventional equalizer in non-partitioned observables and shows that the performance of the equalizer suggested here is much better than that of the conventional decision feedback equalizer in rician dependent noise. Fig.2 shows the performance of P_e versus total number of quantization levels for equalizer based on non-linear mmse and indicates that we need to find an appropriate number of quantization level in partitioning the received signal which will give an optimum result for arbitrary noise distribution. In this paper, we derive the numerical expression of a non-linear mmse for designing adaptive filter and show that the system suggested here have a better ability to suppress noise and ISI when compare to conventional equalizer and obtain coefficients of non-linear mmse which are used in real transmitted signal through training mode in computer simulation. *(Note : N.L-EQ* : Equalizer based on Non-Linear MMSE, *Con-DFB* : Conventional Equalizer)

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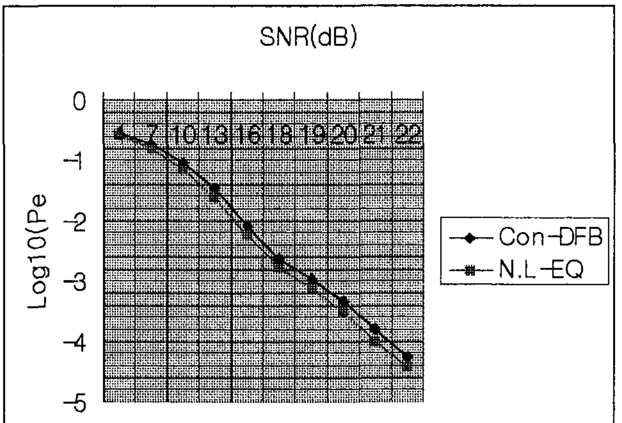

Fig1. Pe of N.L-EQ comparing to Con-DFB, k=22,m=2, rectangular pulse

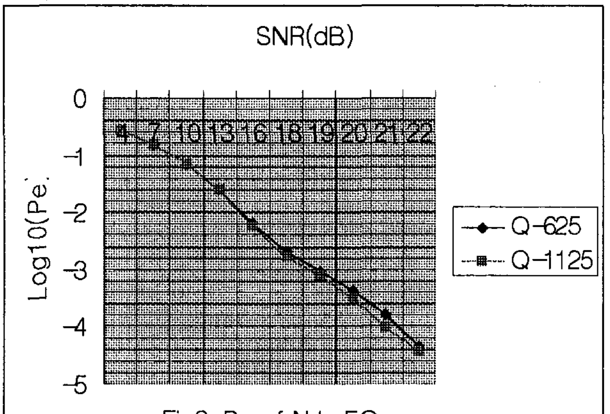

Fig2. Pe of N.L-EQ according to different number of partition, k-22, m=2