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EM 及各種 LS 演算法之相互關係及其在通訊系統中同步器及等化器設計之應用(1/2)

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中文摘要

(關鍵詞:EM、LS、ACM、插補器、等化器)

本期中報告目的是說明及檢討本計畫執行之結果。本計畫目的是研究建立 EM 演算法及最小平方 (LS) 家族群之演算法的關係, 並應用 EM 及 LS 演算法到數位通訊系統中同步器與等化器之設計。本計畫執行已近一年, 其成果之一是我們已提出使用應用 EM 及 LS 相關的演算法來設計一數位通訊系統中同步器的插補器與等化器。其設計方法與推導過程是本報告的主要內容。此外在探討 EM 演算法可以使用來解 LS 的問題時, 我們在文獻中發現另一方法稱座標交替最小化 (ACM), 其解問題方式亦如 EM 方法, 將所要解決問題分成二個小問題來解決。但 ACM 方法亦如同 LS 方法是用來處理決定性資料 (Deterministic data)。其也可用來估計一模式參數使得某些使用者定義的誤差標準值 (Error criterion) 爲最小。我們知道 EM 演算法是定義在統計環境下透過計算期望值及最大值的重覆過程以求取參數使得一可能性函數值 (Likelihood function) 爲最大。而 ACM 演算法則是定義在非統計環境下透過座標交替的重覆過程以求取參數使得一誤差標準值 (Error criterion) 爲最小。我們並應用此方法來判別一非線性磁頭之參數, 也發表一文章參加國際研討會並已爲 IEEE Trans. Magnetics 接受。這項成果另附錄在出席國際會議發表論文中。

Abstract

Keywords: EM, LS, ACM, Interpolator, Equalizer

The purpose of this report is to report and discuss the progress of the project. This project aims to uncover relations between algorithms of least squares (LS) family and the algorithm of expectation maximization (EM) and develop new applications of these algorithms for the design of interpolator of the synchronizer and equalizer in communication systems. This project has been executed for one year. One result of ths result is that we have successfully applied the EM and LS related algorithm to develop a new approach for designing an interpolator and decision feedback equalizer. The design approach and derivation constitutes the main content of this report. Along with the research to investigate the LS and EM related algorithms, we observe an algorithm called alternating coordinates minimization (ACM). This algorithm, similar to the EM algorithm, also divides a problem into two small problems and solve them iteratively. The ACM algorithm, similar to the LS algorithms, deals with the deterministic data and can be used to identify model parameters in the sense of user-defined error criterion. It is known that the EM algorithm, defined in statistical sense, is an iterative algorithm of the expectation and maximization for solving the problem of maximum likelihood (ML) estimation. Similarly, the ACM algorithm, defined in the deterministic sense, is also an iterative algorithm of minimization of different coordinates for solving the problem to minimize a user-defined error criterion. Therefore, it is as useful as the EM algorithm. We have applied this algorithm for identifying model parameters of a nonlinear magnetic read head and written a paper to attend the international conference. The paper also has been accepted by the IEEE Trans. Magnetics. This result is appended in the report.

一：報告內容：數位通訊系統中同步器的插補器與等化器，Optimal Joint Design of Interpolation Filters and Decision Feedback Equalizers

abstract

This paper presents an algorithm to design jointly optimal interpolation filters and decision feedback equalizers in the sense of minimum mean-square error such that the joint capacity which is neglected in conventional design is explored to improve the receiver performance. The algorithm comprises an iteration of two alternating simple quadratic minimizing operations and ensures convergence. A simulation example for the raised-cosine channel demonstrates that via this approach an improvement over the conventional design can be achieved.

1.1 Introduction

In a digital baseband communication receiver, a timing recovery system is used to compensate for the timing offset between the transmitted data and the received sample while an equalizer serves to balance the channel effect for reducing the intersymbol interference (ISI). The timing recovery system is commonly realized by a timing offset estimator combined with either a voltage control oscillator (VCO) or an interpolation filter [1] and the commonly used equalizer is the decision-feedback equalizer (DFE) [2]. It is known that in the receiver, the timing recovery and the equalizer do not work independently of each other and the interaction has been studied [3, 4, 5]. The single-sideband AM digital communication system is studied in [3, 4] to jointly design an analog timing loop for carrier recovery and an FIR equalizer in the receiver. In [5], a single adaptive fractionally-spaced FIR filter is used to realize the functions of both the timing recovery and the equalizer. In the present paper, we consider the digital baseband communication systems with a receiver containing a timing recovery system as well as a DFE and concentrate on the joint design of the interpolation filter and the DFE.

In convention, the interpolation filter and equalizer are designed separately: the interpolation filter is designed assuming the channel is known and fixed [6, 7] and the DFE is designed assuming the timing offset has been completely compensated [2]. The reason for designing each independently is mainly the simplicity because the joint design of both requires to solve a nonlinear optimization problem. The price, however, is that the joint capability is sacrificed. Investigating closely this problem, we observe that the complexity for solution of joint design does not seem so formidable. While the design of interpolation filter and DFE independently requires only solving a quadratic minimization problem each, an algorithm for optimal joint design, presented in this paper, requires only an iteration of two quadratic minimizing operations. Therefore, the capacities of the interpolation filter and DFE can be further employed for improving the receiver performance. Specifically, we formulate together the interpolation filter and the DFE to minimize a mean-square error (MSE) and present an algorithm for solution. The algorithm comprises only an iteration of two simple quadratic minimizations and thus is simple to realize; it also ensures convergence and the convergence solution, by choosing a proper initial estimate, guarantees better than those obtained from conventional designs. A simulation example for the raised-cosine channel is performed to illustrate the design and the performance improvement.

1.2 Problem Formulation

The received signal of a digital baseband communication system can be expressed as

$$x(t) = \sum_{k=-\infty}^{\infty} d_k h(t-kT) + n(t) \tag{1.1}$$

where d_k is the transmitted data symbol with period T, $h(t)$ is the cascaded impulse response of the transmission filter, the channel, and the receiver filter, and $n(t)$ is an additive noise which may be white or colored depending on applications. Assume baud-rate sampling with a normalized sampling timing offset represented by μ, the received sample is given by

$$x_k(\mu) = \sum_{i=-\infty}^{\infty} d_{k-i} h((i-\mu)T) + n_k \tag{1.2}$$

$$= \sum_{i=-\infty}^{\infty} d_{k-i} h_i(\mu) + n_k \tag{1.3}$$

where $x_k(\mu) = x((k-\mu)T)$, $h_i(\mu) = h((i-\mu)T)$, and n_k is the noise sample. We also assume that the timing offset μ is uniformly distributed within the range $[-0.5, 0.5]$, as is commonly done. Note that the baud-rate sampling is assumed here for simplicity; the interpolation filter with a higher sampling rate can be similarly formulated but requires further mechanism for down-sampling processing.

Fig. 1.1 depicts an equivalent discrete-time model of a digital baseband communication receiver; the receiver consists of a timing recovery system, a decision-feedback equalizer (DFE), and a detector. The timing recovery system includes a timing offset estimator and an interpolation filter. Like conventional designs, the timing offset estimator is assumed to obtain correctly the timing offset μ and the detector obtains correct decision, i.e., $\hat{d}_k = d_k$. The purpose of this paper is to design the interpolation filter and DFE such that the mean square of the error between the transmitted data and the DFE output is minimized.

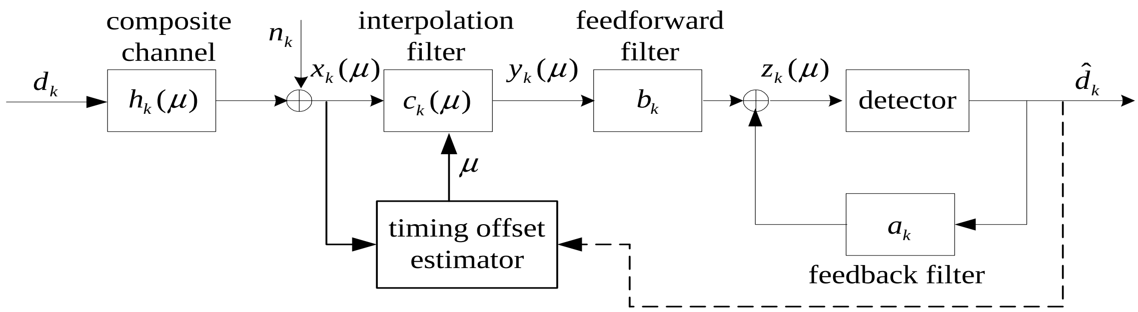

Figure 1.1: An equivalent discrete-time model of a digital baseband communication system

1.2.1 MSE criterion

As usual, an FIR interpolation filter with coefficients $c_k(\mu)$ is used to compensate for the timing offset [8], yielding its output sample $y_k(\mu)$,

$$y_k(\mu) = \sum_{i=-L_1}^{L_2} c_i(\mu) x_{k-i}(\mu) \tag{1.4}$$

where integers L_1 and L_2 indicate the lengths of non-causal and causal parts of the interpolation filter. Each coefficient is usually characterized by a polynomial of degree M in μ,

$$c_k(\mu) = \sum_{m=0}^{M} f_{k,m} \mu^m \tag{1.5}$$

Farrow [9] have proposed an efficient structure to realize such an interpolation filter and thus $f_{k,m}$'s are also called the Farrow coefficients [7]. The DFE including a feedforward filter of order K_1 and a decision feedback filter of order K_2 is then used to combat the ISI, yielding the output $z_k(\mu)$,

$$z_k(\mu) = \sum_{i=0}^{K_1} b_i y_{k-i}(\mu) + \sum_{i=1}^{K_2} a_i d_{k-i} \tag{1.6}$$

The MSE criterion J, therefore, is given by

$$J = \mathrm{E}[d_k - z_k(\mu)]^2 \tag{1.7}$$

where the expectation operation $\mathrm{E}[\cdot]$ is taken with respect to the randomness of the input data, the noise sample and the timing offset μ.

It is more convenient to express the MSE in the frequency domain. Let $H(\omega,\mu)$, $C(\omega,\mu)$, $B(\omega)$, and $A(\omega)$ denote, respectively, the frequency responses of the composite channel, the interpolation filter, the feedforward filter, and the decision feedback filter; that is $H(\omega,\mu) = \sum_{n=-\infty}^{\infty} h_n(\mu)e^{-jn\omega}$, $C(\omega,\mu) = \sum_{n=-L_1}^{L_2} c_n(\mu)e^{-jn\omega}$, $B(\omega) = \sum_{n=0}^{K_1} b_n e^{-jn\omega}$, and $A(\omega) = \sum_{n=1}^{K_2} a_n e^{-jn\omega}$. Then, via the Parseval's theorem [2], the MSE in frequency domain can be derived,

$$\begin{aligned} J &= \frac{1}{2\pi}\int_{-0.5}^{0.5}\int_{-\pi}^{\pi}\Big[D(\omega)|1 - H(\omega,\mu)C(\omega,\mu)B(\omega) - A(\omega)|^2 + N(\omega)|C(\omega,\mu)B(\omega)|^2\Big]\,d\omega d\mu & (1.8)\\ &= \int_{-0.5}^{0.5} J_\mu d\mu & (1.9)\end{aligned}$$

where $D(\omega)$ is the power spectrum density (PSD) of d_k and $N(\omega)$ is the PSD of n_k. Note that J_μ in (1.9) is the MSE of a given fixed μ, which will be used later to illustrate performance difference between various designs.

The frequency response of the interpolation filter can be represented in a more compact form using (1.5) [10],

$$C(\omega,\mu) = \boldsymbol{f}^T(\boldsymbol{\mu}\otimes\boldsymbol{\omega}_c) \tag{1.10}$$

where $\boldsymbol{f} = [f_{-L_1,0},\ldots,f_{L_2,0},\ldots,f_{-L_1,M},\ldots,f_{L_2,M}]^T$, $\boldsymbol{\mu} = [1,\mu,\ \ldots,\mu^M]^T$, $\boldsymbol{\omega}_c = [e^{j\omega L_1},\ \ldots,\ 1,\ldots, e^{-j\omega L_2}]^T$, the superscript T denotes the transpose operation and the notation $\otimes$ represents the right Kronecker product [11]. Similarly, the frequency responses of the feedforward and decision feedback filters can be represented in a vector form,

$$\begin{aligned} B(\omega) &= \boldsymbol{b}^T\boldsymbol{\omega}_b & (1.11)\\ A(\omega) &= \boldsymbol{a}^T\boldsymbol{\omega}_a & (1.12)\end{aligned}$$

where $\boldsymbol{b} = [b_0, b_1, \ldots, b_{K_1}]^T$, $\boldsymbol{a} = [a_1, a_2, \ldots, a_{K_2}]^T$, $\boldsymbol{\omega}_b = [1, e^{-j\omega}, \ldots, e^{-j\omega K_1}]^T$, and $\boldsymbol{\omega}_a = [e^{-j\omega},\ e^{-j\omega 2} \ldots, e^{-j\omega K_2}]^T$.

Substituting (1.10), (1.11), and (1.12) into (1.8), we obtain the MSE J as a nonlinear function of the interpolation filter coefficients $\boldsymbol{f}$ and the DFE parameters $\boldsymbol{\theta} = [\boldsymbol{b}^T, \boldsymbol{a}^T]^T$. The nonlinear optimization approaches [12] can be used for solution but are complicated. In this paper, the alternating coordinates minimization (ACM) [13] algorithm is applied for solution such that simple realization is obtained. Before discussing the detail of the algorithm, note that since the interpolation filter and the feedforward filter are cascaded, a constant factor redundancy thus exists between $\boldsymbol{f}$ and $\boldsymbol{b}$. Hence an extra constraint $f_{0,0} = 1$ is imposed to remove this redundancy. The optimization problem, therefore, is given by

$$\mathrm{Min}_{\boldsymbol{f},\boldsymbol{\theta}}\ J \quad \text{subject to } f_{0,0} = 1 \tag{1.13}$$

1.3 ACM Algorithm for Optimal Joint Design

The ACM algorithm for solving this optimization problem involves iterations of two alternating optimizing operations; in the p-th iteration, the first operation solves $\boldsymbol{\theta}^{(p)}$ of (1.13) given $\boldsymbol{f} = \boldsymbol{f}^{(p-1)}$, and then the second operation solves $\boldsymbol{f}^{(p)}$ of (1.13) given $\boldsymbol{\theta} = \boldsymbol{\theta}^{(p)}$ which is obtained from the first operation. The iteration continues until the convergence of $\boldsymbol{f}^{(p)}$ and $\boldsymbol{\theta}^{(p)}$. Each optimizing operation, shown below, only requires solving a simple quadratic optimization and thus its solution is unique. Also the two operations solve the coefficients $\boldsymbol{\theta}^{(p)}$, $\boldsymbol{f}^{(p)}$ alternatingly, the obtained MSE J is therefore guaranteed non-increasing in every iteration. Since the MSE J is non-negative and thus bounded from below, the ACM algorithm always converges. The derivations of two optimizing operations are described in the following subsections.

1.3.1 First optimizing operation: solve $\boldsymbol{\theta}^{(p)}$ of (1.13) given $\boldsymbol{f} = \boldsymbol{f}^{(p-1)}$.

Since $\boldsymbol{f}$ is given and fixed, the constraint is naturally satisfied and $C(\omega, \mu)$, for a given ω and μ, is a fixed scalar; the MSE, after substituting (1.12) and (1.11) into (1.8), turns into a quadratic function of $\boldsymbol{\theta}$,

$$J = \frac{1}{2\pi}\int_{-0.5}^{0.5}\int_{-\pi}^{\pi}\left[D(\omega)|1 - H(\omega,\mu)C(\omega,\mu)\boldsymbol{b}^T\boldsymbol{\omega}_b - \boldsymbol{a}^T\boldsymbol{\omega}_a|^2 + N(\omega)|C(\omega,\mu)\boldsymbol{b}^T\boldsymbol{\omega}_b|^2\right]d\omega d\mu \quad (1.14)$$

$$= \frac{1}{2\pi}\int_{-0.5}^{0.5}\int_{-\pi}^{\pi}\left[D(\omega)|1 - \boldsymbol{\theta}^T\boldsymbol{R}\boldsymbol{\omega}_\theta|^2 + N(\omega)|\boldsymbol{\theta}^T\boldsymbol{Q}\boldsymbol{\omega}_\theta|^2\right]d\omega d\mu \quad (1.15)$$

where $\boldsymbol{\omega}_\theta = [\boldsymbol{\omega}_b^T, \boldsymbol{\omega}_a^T]^T$,

$$\boldsymbol{R} = \begin{bmatrix} H(\omega,\mu)C(\omega,\mu)\boldsymbol{I}_{K_1+1} & \boldsymbol{0}_{(K_1+1)\times K_2} \\ \boldsymbol{0}_{K_2\times(K_1+1)} & \boldsymbol{I}_{K_2} \end{bmatrix}, \quad \boldsymbol{Q} = \begin{bmatrix} C(\omega,\mu)\boldsymbol{I}_{K_1+1} & \boldsymbol{0}_{(K_1+1)\times K_2} \\ \boldsymbol{0}_{K_2\times(K_1+1)} & \boldsymbol{0}_{K_2\times K_2} \end{bmatrix}$$

with $\boldsymbol{I}_m$ representing the identity matrix of dimension m and $\boldsymbol{0}_{m\times n}$ the $m \times n$ zero matrix. The solution $\boldsymbol{\theta}^{(p)}$ can be obtained by setting the gradient vector of J in (1.15) with respect to $\boldsymbol{\theta}$ to zero and rearranging, yielding

$$\boldsymbol{\theta}^{(p)} = \boldsymbol{\Omega}_f^{-1}\boldsymbol{v}_f \quad (1.16)$$

where

$$\boldsymbol{\Omega}_f = \frac{1}{2\pi}\int_{-0.5}^{0.5}\int_{-\pi}^{\pi}\mathrm{Re}[D(\omega)\boldsymbol{R}\boldsymbol{w}_\theta\boldsymbol{w}_\theta^H\boldsymbol{R}^H + N(\omega)\boldsymbol{Q}\boldsymbol{w}_\theta\boldsymbol{w}_\theta^H\boldsymbol{Q}^H]d\omega d\mu \quad (1.17)$$

and

$$\boldsymbol{v}_f = \frac{1}{2\pi}\int_{-0.5}^{0.5}\int_{-\pi}^{\pi}D(\omega)\mathrm{Re}[\boldsymbol{R}\boldsymbol{\omega}_\theta]d\omega d\mu \quad (1.18)$$

with Re[·] representing the real part of a variable. The subscript f in $\boldsymbol{\Omega}_f, \boldsymbol{v}_f$ indicates that they are evaluated given a fixed interpolation filter $\boldsymbol{f}$. Note that the matrix $\boldsymbol{\Omega}_f$ is symmetric and some of its submatrices have a Toeplitz form; these properties can be used to simplify the matrix evaluation and are not elaborated further for brevity.

1.3.2 Second optimizing operation: solve $\boldsymbol{f}^{(p)}$ of (1.13) given $\boldsymbol{\theta} = \boldsymbol{\theta}^{(p)}$.

Note that the given $\boldsymbol{\theta}^{(p)}$ is obtained from the previous optimizing operation. Since $\boldsymbol{\theta}$ is known, $A(\omega)$ and $B(\omega)$ can be evaluated and hence the optimization problem (1.13) is turned into a simple constraint quadratic optimization problem,

$$\mathrm{Min}_{\boldsymbol{f}}\ J \quad \text{subject to } f_{0,0} = 1 \quad (1.19)$$

where

$$J = \frac{1}{2\pi}\int_{-0.5}^{0.5}\int_{-\pi}^{\pi}[D(\omega)|1 - H(\omega,\mu)B(\omega)\boldsymbol{f}^T(\boldsymbol{\mu}\otimes\boldsymbol{\omega}_c) - A(\omega)|^2 + N(\omega)|B(\omega)\boldsymbol{f}^T(\boldsymbol{\mu}\otimes\boldsymbol{\omega}_c)|^2]d\omega d\mu \quad (1.20)$$

Express the constraint as $\boldsymbol{f}^T\boldsymbol{i}_c = f_{0,0} = 1$ where $\boldsymbol{i}_c$ is a vector whose (L_1+1)th component is unity and whose other components are zero. Then, the solution $\boldsymbol{f}^{(p)}$ can be derived using the Lagrange multiplier technique [12], yielding

$$\boldsymbol{f}^{(p)} = \boldsymbol{\Omega}_\theta^{-1}\left(\boldsymbol{v}_\theta + \frac{1-\boldsymbol{i}_c^T\boldsymbol{\Omega}_\theta^{-1}\boldsymbol{v}_\theta}{\boldsymbol{i}_c^T\boldsymbol{\Omega}_\theta^{-1}\boldsymbol{i}_c}\boldsymbol{i}_c\right) \tag{1.21}$$

where

$$\boldsymbol{\Omega}_\theta = \frac{1}{2\pi}\int_{-0.5}^{0.5}\int_{-\pi}^{\pi}|B(\omega)|^2[D(\omega)|H(\omega,\mu)|^2+N(\omega)]\mathrm{Re}[(\boldsymbol{\mu}\otimes\boldsymbol{\omega}_c)(\boldsymbol{\mu}\otimes\boldsymbol{\omega}_c)^H]d\omega d\mu \tag{1.22}$$

$$= \frac{1}{2\pi}\int_{-0.5}^{0.5}\int_{-\pi}^{\pi}|B(\omega)|^2[D(\omega)|H(\omega,\mu)|^2+N(\omega)][(\boldsymbol{\mu}\boldsymbol{\mu}^H)\otimes\mathrm{Re}(\boldsymbol{\omega}_c\boldsymbol{\omega}_c^H)]d\omega d\mu \tag{1.23}$$

and

$$\boldsymbol{v}_\theta = \frac{1}{2\pi}\int_{-0.5}^{0.5}\int_{-\pi}^{\pi}D(\omega)\mathrm{Re}\left[H(\omega,\mu)B(\omega)(1-A^*(\omega))(\boldsymbol{\mu}\otimes\boldsymbol{\omega}_c)\right]d\omega d\mu \tag{1.24}$$

with the superscript * standing for the complex conjugate operation.

The algorithm starts with an initial guess $\boldsymbol{f}^{(0)}$ and iteratively performs the above two optimizations until convergence. Numerically, the algorithm terminates when the ratio of MSE improvement over MSE in previous iteration, $|J^{(l)} - J^{(l-1)}|/J^{(l-1)}$, is less than a predetermined small value ϵ.

Note that even the ACM algorithm ensures convergence, like most nonlinear optimization algorithms, it may converge to a local minimum. Therefore, a sensible initial estimate may be required. One good initial estimate is to take the $\boldsymbol{f}$ obtained from the conventional approach and normalizes it to obtain $f_{0,0} = 1$. The convergence solution using this initial estimate, because of the non-increasing MSE of the algorithm, is ensured to result in a lower MSE than that by the conventional design. Another good initial estimate is $\boldsymbol{f}^{(0)} = \boldsymbol{i}_c$, i.e., $f_{00}^{(0)} = 1$ and all other components are zero. The interpolation filter corresponding to this initial estimate is just a pure unity gain filter, hence the first operation will obtain a DFE without the intervention of interpolation filter.

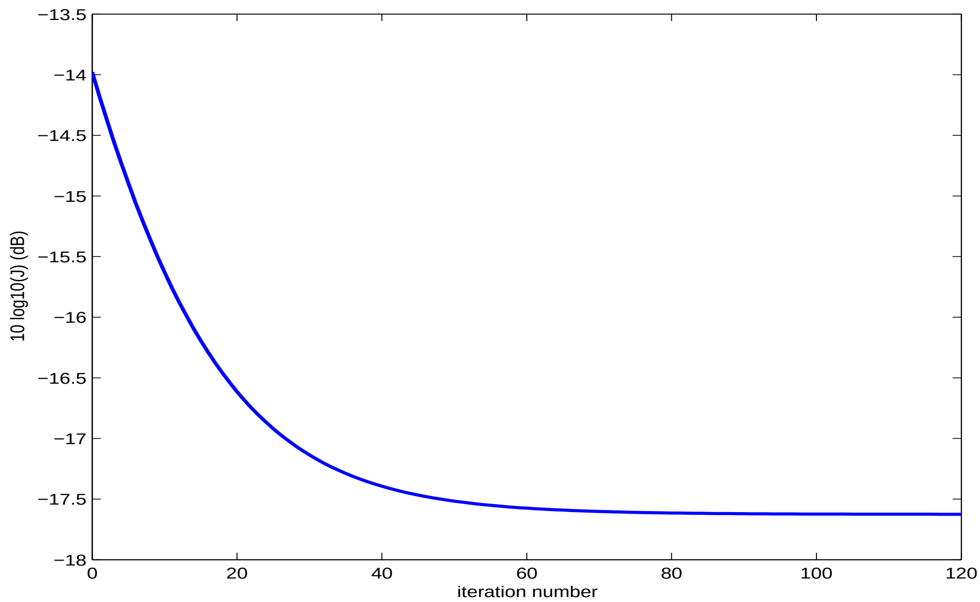

Figure 1.2: The obtained MSEs J at each iteration for SNR of 20 dB

1.4 Demonstration Example

One design example for standard raised-cosine channel is given to illustrate the advantage gained through the joint design approach. The channel impulse response with the symbol rate normalized as $T = 1$ is known to be

$$h(t) = \frac{\sin(\pi t)\cos(\beta\pi t)}{\pi t(1 - 4\beta^2 t^2)} \tag{1.25}$$

where $\beta \in [0, 1]$ is the roll-off factor. Since the channel has been ideally equalized, no equalizer is needed. For illustration, however, we assume that a first-order DFE $(K_1 = 0, K_2 = 1)$ is used. As discussed in [1], the interpolation FIR filters for timing offset compensation are normally short and the degree of polynomial to characterize the coefficients is also low. Hence, we choose six taps $(L_1 = 2, L_2 = 3)$ interpolation FIR filter with each coefficient characterized by a polynomial of degree 3 $(M = 3)$. Assume the input data are white such that its PSD $D(\omega) = 1$ for all ω. Generally, the noise is colored because of the receiving filter, but for simplicity, it is also assumed white. The raised-cosine channels of $\beta = 0.2$ with the output SNRs set to 15 dB, 20 dB, 25 dB, and 30 dB, respectively, are used in simulations. The conventional approach first designs the DFE for minimizing the MSE assuming exact sampling time and then designs the interpolation filter for minimizing J in (1.8). The joint approach normalizes the interpolation filter obtained via the conventional approach and uses it as the initial data, then the iteration terminates when the ratio of MSE improvement is less than $\epsilon = 10^{-5}$.

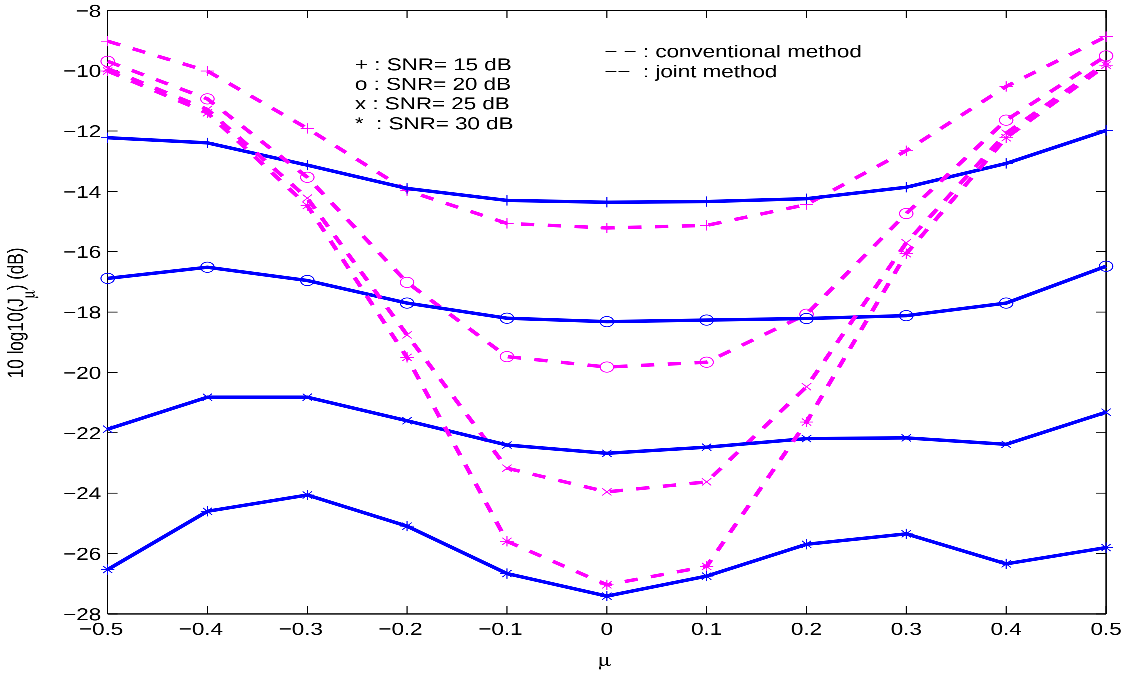

Figure 1.3: J_μ versus the timing offset μ for the joint method and conventional method in different output SNRs

For example, for the output SNR of 20 dB, the DFE via the conventional approach yields $b_0 = 0.9906, a_1 = 0$, the interpolation filter is then designed, yielding the minimum J of -13.51 dB. The joint design, in this case, obtains the MSEs at each iteration which is shown in Fig. 1.2; the algorithm takes 120 iterations to converge and the convergence MSE equals -17.63 dB. Therefore, the performance gain of 4.12 dB is achieved. Note that the obtained MSEs with respect to iteration, as expected, are non-increasing. To further illustrate the difference between the conventional approach and the joint method,

Table 1.1: The MSEs of conventional and joint methods for raised-cosine channel for various output SNRs

SNR(dB)	15	20	25	30
conventional method, MSE(dB)	-12.23	-13.98	-14.74	-15.02
joint method, MSE(dB)	-13.51	-17.63	-21.88	-25.72
improvement (dB)	1.28	3.65	7.14	10.7

Fig. 1.3 depicts the J_μ defined in (1.9) of both methods for μ increasing from -0.5 to 0.5 with the step size of 0.1 for various SNRs. The conventional approach obtains good performance only when the timing offset is small; the joint design, however, achieves lower and more uniform J_μ, resulting in a smaller MSE J. The MSEs (J) obtained from conventional and joint design methods under different output SNRs are listed in Table 1.1. Note that the improvement, as shown from the table, increases as the SNR is increasing. When the SNR equals 30 dB, the improvement in MSE attains 10.7 dB; the improvement, however, is only about 1.28 dB for SNR of 15 dB. These results explain that because the compensation of the timing offset does not reduce the effect of noise, the joint design has less room for improvement when the noise power is larger. Hence, the joint design obtains better improvement for higher SNR of the received signal. This simulation, therefore, demonstrates that the joint design may significantly improve the MSE performance over the conventional approach.

1.5 Summary

In this paper, we present an algorithm to design both the interpolation filter and the DEF such that the joint capability is explored to improve the performance of a communication receiver. The algorithm is simple to realize and ensures convergence; the convergence solution, for a proper initial estimate, guarantees better than that obtained from the conventional design. This approach exploits the joint capacity which is neglected in the conventional design and achieves the performance improvement without increasing the complexity of either the interpolation filter or the DFE.

Bibliography

[1] H. Meyr, M. Moeneclaey, and S. A. Fechtel, *Digital Communication Receivers, Synchronization: Channel Estimation, and Signal Processing.* John Wiley & Sons, Inc., 1998.

[2] J. G. Proakis, *Digital Communications*, 3rd ed. New York: McGraw-Hill, 1995.

[3] R. W. Chang, "Joint optimization of automatic equalization and carrier acquisition for digital communcation," *Bell Syst. Tech. J.*, vol. 49, pp. 1069–1104, July-Aug. 1970.

[4] R. W. Chang and R. Srinivasagopalan, "Carrier recovery for data communication systems with adaptive equalization," *IEEE Trans. Commun.*, vol. 28, no. 8, pp. 1142–1153, Aug. 1980.

[5] D. J. Artman, S. Chari, and R. P. Gooch, "Joint equalization and timing recovery in a fractionally-spaced equalizer," in *IEEE Twenty-Sixth Asilomar Conference on Signals, Systems and Computers*, Oct. 1992, pp. 25–29.

[6] D. Kim, M. J. Narasimha, and D. C. Cox, "Design of optimal interpolation filter for symbol timing recovery," *IEEE Trans. Commun.*, vol. 45, no. 7, pp. 877–884, July 1997.

[7] G. Watkins, "Optimal Farrow coefficients for symbol timing recovery," *IEEE Commun. Lett.*, vol. 5, no. 9, pp. 381–383, Sept. 2001.

[8] L. Erup, F. M. Gardner, and R. A. Harris, "Interpolation in digital modems- part II: implementation and performance," *IEEE Trans. Commun.*, vol. 41, no. 6, pp. 998–1008, June 1993.

[9] C. W. Farrow, "A continuously variable digital delay element," in *IEEE International Symposium on Circuits and Systems*, no. 3, June 1988.

[10] T. B. Deng, "Discretization-free design of variable fractional-delay FIR digital filters," *IEEE Trans. Circuits Syst. II*, vol. 48, no. 6, pp. 637–644, June 2001.

[11] P. Lancaster and M. Tismenetsky, *The Theory of Matrices*, 2nd ed. Academic Press, 1985.

[12] R. Fletcher, *Practical Methods of Optimization*, 2nd ed. John Wiley & Sons, 1987.

[13] I. Csiszár and G. Tusnády, "Information geometry and alternating minimization procedures," *Statistics and Decisions*, vol. supplement issue, pp. 205–237, 1984.

二、計畫成果自評

本計畫是二年期。目前第一年的研究進行結果似與原計畫內容之預估相接近。而在執行計畫中, 我們也對與 EM 及 LS 演算法之相關演算法有更深入的了解並加應用。因此有一些初步的成果。我們很感謝國科會的支持, 讓我們可以在研究中成長。也希望在明年此計畫能有好的成果展現。