A (SEMI)-BLIND EQUALIZATION TECHNIQUE FOR WIRELESS BURST TRANSMISSION SYSTEMS

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ABSTRACT

In this paper a new indirect channel equalization technique, suitable for wireless burst transmission systems, is proposed. The technique consists of two distinct parts. The first part comprises a parametric method for estimating the unknown channel impulse response (CIR) in a blind or semi-blind manner. The main trait of this method is that instead of seeking the whole CIR sequence only the unknown time delays and attenuation factors of the physical channel multipath components are estimated. The involved CIR estimation method, for the same degree of estimation accuracy, is much simpler as compared to the existing methods. In the second part, a fixed DFE is applied on the current burst yielding the unknown transmitted symbols. The DFE filters are computed in terms of the estimated CIR values via a recently proposed efficient scheme. It should be noted that, since no training or a small number of training symbols are used, the whole technique offers significant bandwidth savings at a reasonable computational cost.

1. INTRODUCTION

In this paper we address the channel equalization problem in wireless burst transmission systems. Equalization in wireless systems, especially in high-speed applications, is very often a major task since the introduced intersymbol interference (ISI), mainly due to multipath, may cause a severe probability of error, [1],[2]. It should be noted that, the higher the symbol rate the more the symbols spanned by the channel impulse response. Thus, if training-based equalization techniques are employed, the training sequence has to be relatively long and in such a case the overall system throughput is reduced.

A useful characteristic in burst transmission systems is that a packet of channel output samples can be buffered in the receiver before applying any detection scheme. Transmission in bursts of data is a trait encountered in many wireless systems, such as, wireless ATM networks, TDMA-based mobile systems, reverse link of MMDS systems etc. When the burst is relatively short and the channel is considered stationary within the burst then batch equalization may be preferable as compared to adaptive equalization. The equalizer coefficients can be computed either directly or indirectly. In the latter case the required coefficients are computed in terms of the CIR which has to be estimated first, [3]. Channel estimation has to be adequately accurate, otherwise the resulting equalizer performs poorly.

In this paper, a novel indirect equalization method is proposed consisting of the following two parts. In the first part the unknown CIR is estimated based on a new parametric technique. More specifically, assuming that the multipath CIR has a discrete form, the channel estimation task is reduced to that of estimating the time delays and attenuation factors of the physical channel components. Therefore, the size of the estimation problem is smaller since it now depends only on the number of delayed components and not on the length of the CIR. The benefit of this alternative parametrization is twofold. First, a significant saving in complexity is achieved, and, second (and perhaps more important in case of a short burst) the number of the required channel output samples is correspondingly reduced. The proposed CIR estimation technique can be blind or semi-blind and is based on the well-known Subchannel Response Matching criterion (SRM) [6].

Applying the SRM criterion to the problem at hand we end up with a least squares (LS) problem, which is separable with respect to the unknown parameters, i.e. the time delays and the attenuation factors. The Golub-Pereyra method [7] is then applied in order to separate the optimization problem to two different sub-problems. A sub-problem which is non-linear with respect to the time delays and a sub-problem which is linear with respect to the attenuation parameters. Based on the special structure of the nonlinear problem a computationally efficient linear search method for the estimation of the unknown time delays has been developed. Subsequently, the Gauss-Newton algorithm may be applied in order to further improve the accuracy of the estimated values. Finally, the attenuation parameters are estimated by solving a linear LS problem. The method of the first part is very simple to implement and for the same degree of estimation accuracy has a computational complexity which is much lower as compared to other related channel parameter estimation methods [5], [4]. Moreover the method yields good estimates even in cases of closely spaced time delays, especially when the semi-blind approach is used.

In the second part, a fixed Decision Feedback Equalizer (DFE) is employed. The DFE structure has been widely ac-

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cepted as an effective one for reducing ISI [1],[2]. It turns out to be particularly suitable for multipath channels, since most part of ISI is due to the long postcursor portion of the CIR and can be successfully canceled by the feedback filter. The feedforward (FF) and feedback (FB) filters of the DFE are computed in terms of the estimated channel values via an efficient scheme which has been proposed recently in [8].

Since the channel estimation task is performed in a (semi)-blind manner, the whole technique offers significant bandwidth savings. The performance of the method has been tested via extensive simulations.

The paper is organized as follows. In Section 2 the parametric CIR estimation problem is formulated and the method of the first part is presented. In Section 3 the DFE filters computation in terms of the CIR values is discussed. Finally, in Section 4 some indicative simulation results verifying the performance of the new technique are provided.

2. PARAMETRIC CIR ESTIMATION PART

A trait encountered in many wireless applications, particularly the high-speed ones, is that the multipath channel tends to be of a discrete form (i.e. it consists of a number of dominant multipath components). More specifically, if the physical CIR is assumed to be time invariant within a small-scale time interval then it may be written in the form

$$h_c(t) = \alpha_0 \delta(t) + \sum_{i=1}^{p-1} \alpha_i \delta(t-\tau_i) \tag{1}$$

where a_i and τ_i are the complex attenuation factor and the delay, respectively, of the $i-th$ multipath component. The delay τ_0 is considered to be 0, while for the other delays it is assumed that $\tau_0 < \tau_1 < \ldots < \tau_{p-1}$. Therefore the problem of the multipath CIR estimation is reduced to the smaller problem of the complex attenuation and delay parameters estimation. Let $g(t)$ be the pulse shape filter (convolution of transmitter and receiver filters). The overall impulse response $h(t)$ of the communication system is then given as the convolution of $h_c(t)$ with $g(t)$. Furthermore, we consider the multichannel model, according to which the channel output is oversampled by a factor of N_s samples per symbol period. For the sake of simplicity, we consider that the channel output is oversampled by a factor of two samples per symbol period. As a result, the sampled overall CIR is expressed by two vectors, one for each subchannel, i.e. for $i = 1, 2$

$$\boldsymbol{h}_i^T = \left[\; h(\tfrac{(i-1)}{2}T) \;\; h(T + \tfrac{(i-1)}{2}T) \;\ldots\; h(LT + \tfrac{(i-1)}{2}T) \;\right] \tag{2}$$

where LT is the span of the overall CIR, with T standing for the symbol period. It is straightforward that the subchannels' IRs can be expressed in terms of the multipath channel parameters as follows

$$\boldsymbol{h}_i = G_i(\boldsymbol{\tau})\boldsymbol{\alpha}, \quad i = 1, 2 \tag{3}$$

where $\boldsymbol{\tau} = [\tau_0 \; \tau_1 \; \ldots \; \tau_{p-1}]^T$ and $\boldsymbol{\alpha} = [\alpha_0 \; \alpha_1 \; \ldots \; \alpha_{p-1}]^T$. Finally $G_i(\boldsymbol{\tau})$ is an $(L+1)\times p$ matrix with the following form

$$G_i(\boldsymbol{\tau}) = \begin{bmatrix} g(\frac{i-1}{2}T - \tau_0) & \ldots & g(\frac{i-1}{2}T - \tau_{p-1}) \\ g(T + \frac{i-1}{2}T - \tau_0) & \ldots & g(T + \frac{i-1}{2}T - \tau_{p-1}) \\ \vdots & \ddots & \vdots \\ g(LT + \frac{i-1}{2}T - \tau_0) & \ldots & g(LT + \frac{i-1}{2}T - \tau_{p-1}) \end{bmatrix} \tag{4}$$

We see from (3) that in order to blindly estimate the overall CIR, it suffices to estimate the unknown multipath parameters $\boldsymbol{\alpha}$ and $\boldsymbol{\tau}$ solely from the subchannels' output samples. The above parametric formulation of the channel estimation problem has also been exploited recently in [5], in a manner completely different than the one presented here.

To proceed further, the subchannel response matching concept [6] is applied and the channel parameters are estimated in a two steps procedure. More specifically, it can be easily shown that in the two-channels, noise-free case the following relation holds

$$\begin{bmatrix} Y_2 & -Y_1 \end{bmatrix} \begin{bmatrix} \mathbf{h}_1 \\ \mathbf{h}_2 \end{bmatrix} = \mathbf{0} \tag{5}$$

where Y_i for $i = 1, 2$ are matrices of the two subchannels' output samples, which have the following form

$$Y_i = \begin{bmatrix} y_i(L+n) & \cdots & y_i(n) \\ y_i(L+n+1) & \cdots & y_i(n+1) \\ \vdots & \vdots & \vdots \\ y_i(n+K-1) & \cdots & y_i(n+K-L-1) \end{bmatrix} \tag{6}$$

By imposing the channel parametric structure, (5) is written as follows

$$YG(\boldsymbol{\tau})\boldsymbol{\alpha} = \mathbf{0} \tag{7}$$

where

$$Y = \begin{bmatrix} Y_2 & -Y_1 \end{bmatrix}, \quad G(\boldsymbol{\tau}) = \begin{bmatrix} G_1(\boldsymbol{\tau}) \\ G_2(\boldsymbol{\tau}) \end{bmatrix}$$

When the channel is corrupted by noise, we can estimate the channel parameters $\boldsymbol{\alpha}, \boldsymbol{\tau}$ by solving the following least squares (LS) problem

$$\min_{\boldsymbol{\alpha},\boldsymbol{\tau}} ||YG(\boldsymbol{\tau})\boldsymbol{\alpha}||^2 \tag{8}$$

where we assume that $\boldsymbol{\alpha}$ is subject to the constraint $\boldsymbol{\alpha}^T\mathbf{e}_1 = 1$, with $\mathbf{e}_1^T = [1, 0, \ldots, 0]$. Then, the optimization problem takes the form

$$\min_{\hat{\boldsymbol{\alpha}},\hat{\boldsymbol{\tau}}} ||\mathbf{z} + \Phi(\hat{\boldsymbol{\tau}})\hat{\boldsymbol{\alpha}}||^2, \quad \Phi(\hat{\boldsymbol{\tau}}) = Y\hat{G}(\hat{\boldsymbol{\tau}}) \tag{9}$$

where

$$\hat{\boldsymbol{\tau}}^T = [\tau_1, \tau_2, \ldots, \tau_{p-1}], \quad \hat{\boldsymbol{\alpha}}^T = [\alpha_1, \alpha_2, \ldots, \alpha_{p-1}]$$

$$\mathbf{z} = Y\mathbf{g}(\tau_0), \quad G(\boldsymbol{\tau}) = \begin{bmatrix} \mathbf{g}(\tau_0) & \hat{G}(\hat{\boldsymbol{\tau}}) \end{bmatrix}$$

Note that $\mathbf{z}$ is a quantity that can be computed from the data.

The non-linear LS problem in (9) is separable with respect to the unknown parameters $\hat{\boldsymbol{\tau}}$ and $\hat{\boldsymbol{\alpha}}$. In particular, the problem is nonlinear with respect to $\hat{\boldsymbol{\tau}}$ and linear with respect to $\hat{\boldsymbol{\alpha}}$. As a result, the optimization process can be conducted separately with respect to the distinct parameter sets $\hat{\boldsymbol{\tau}}$ and $\hat{\boldsymbol{\alpha}}$ respectively, [7]. More specifically

- The delay parameters $\hat{\boldsymbol{\tau}}$ are obtained from the solution of the following non-linear optimization problem

$$\hat{\boldsymbol{\tau}}_{opt} = arg \min_{\hat{\tau}} \{f(\hat{\boldsymbol{\tau}})\} \tag{10}$$

  where $f(\hat{\boldsymbol{\tau}}) = ||(I - \Phi(\hat{\boldsymbol{\tau}})\Phi^{\dagger}(\hat{\boldsymbol{\tau}}))\mathbf{z}||^2$ and † denotes the pseudoinverse of a matrix

- The attenuation parameters $\hat{\boldsymbol{\alpha}}$ are determined by the linear LS method as

$$\hat{\boldsymbol{\alpha}}_{opt} = -\Phi^{\dagger}(\hat{\boldsymbol{\tau}}_{opt})\mathbf{z} \tag{11}$$

The first step of the optimization procedure, concerning the time delays, appears to be a complicated non-linear optimization problem. However, by properly exploiting the special form of the cost function in (10), an efficient method for the estimation of parameter vector $\boldsymbol{\tau}$ arises. Indeed, it can be shown that the special form of the function under consideration allows for a linear search to be performed for the estimation of the global minimum. More specifically, it can be proved that this function is decoupled with respect to the delay parameters $\tau_i, i = 1, 2, \ldots, p-1$, i.e., the optimization search can be performed separately for each τ_i and independently of the other delay parameters. Due to this decoupling, the resulting method offers significant computational savings.

The basic steps of the blind channel estimation method are summarized below.

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1. Set values $\hat{L}, \hat{p}$ for unknown L, p, respectively.
2. Initialize $\tau_i,\ i = 1, 2, \ldots, p-1$ with distinct random values in the interval $[0, LT]$.
3. Choose a linear search step size, δ and set $i = 1$.
4. Minimize $f(\hat{\boldsymbol{\tau}})$ with respect to τ_i. Find $\tau_{i,opt}$ by evaluating the function at $\tau_i = j\delta,\ \ j = 0, 1, \ldots, \frac{\hat{L}T}{\delta}$
5. Set $\tau_i = \tau_{i,opt}$, $i = i + 1$ and repeat from step 3 until $i = \hat{p}$.
6. Run a Gauss-Newton search in the neighborhood of $\hat{\boldsymbol{\tau}}_{opt}$ to improve the estimation accuracy.
7. Obtain the attenuation parameters from (11).

The performance of the proposed technique is improved by assuming that a small number of information symbols are known at the receiver. In such a case the optimization problem takes the following form [9]

$$\min_{\boldsymbol{\alpha},\boldsymbol{\tau}} ||\mathbf{z} - Y_S G(\boldsymbol{\tau})\boldsymbol{\alpha}||^2 \tag{12}$$

where

$$Y_S = \begin{bmatrix} Y_2 & -Y_1 \\ S & 0 \\ 0 & S \end{bmatrix}, \quad \mathbf{z} = \begin{bmatrix} \mathbf{0} \\ \mathbf{y}_1 \\ \mathbf{y}_2 \end{bmatrix}$$

S is the information symbols matrix and $\mathbf{y}_1$, $\mathbf{y}_2$ are the corresponding subchannels' output vectors. It can be shown, [9], that a similar analysis can be applied to yield a method that retains the advantages of the blind approach, offering at the same time significant performance improvement.

3. EQUALIZATION PART

After estimating the multipath channel parameters, as described in the previous section, an estimate of the CIR can be directly obtained from (3). As stated in literature (e.g. [4], [5]) the channel estimation error is expected to be much smaller compared to methods that do not take into account the knowledge of the pulse-shaping filters. Based on the CIR estimate, the optimum values, in the MSE sense, of the DFE coefficients can be computed by solving the resulting system of normal equations. Nevertheless, such computation can require large processing power, because the associated system matrix is unstructured. An efficient algorithm for the extraction of the DFE coefficients was derived in [3]. This algorithm involves a Cholesky factorization method and a backsubstitution procedure for the computation of FB and FF filter coefficients respectively. In this work, we adopt an alternative approach which is simple to implement and is proposed in [8].

Specifically, the MMSE FF filter $\mathbf{a}$ and FB filter $\mathbf{b}$ of corresponding lengths M and N, can be computed by solving the following system of equations

$$\begin{bmatrix} R_{xx} & R_{xd} \\ (R_{xd})^H & R_{dd} \end{bmatrix} \cdot \begin{bmatrix} \mathbf{a} \\ \mathbf{b} \end{bmatrix} = \begin{bmatrix} \boldsymbol{r}_{xs} \\ \mathbf{0} \end{bmatrix} \tag{13}$$

where R_{xx}, R_{dd} and R_{xd} are the autocorrelation and crosscorrelation matrices of the FF filter input sequence $\boldsymbol{x}$ and the FB filter input sequence of decisions $\boldsymbol{d}$ and $\boldsymbol{r}_{xs}$ is the crosscorrelation of the FF filter input sequence with the current transmitted symbol.

As it is shown in [8], all the quantities that appear in the above system of equations can be expressed as functions of the CIR coefficients, leading to the following solution

$$\mathbf{a} = (H_1 H_1^H + \sigma^2 I_{2M})^{-1} H_1 \mathbf{e}_{M+L_1} \tag{14}$$

$$\mathbf{b} = \begin{bmatrix} -H_2^H \mathbf{a} \\ \mathbf{0}_{(N-L_2)\times 1} \end{bmatrix} \tag{15}$$

where $\sigma^2 = \sigma_w^2 / \sigma_s^2$ is the ratio of the noise and the transmitted sequence powers , I_{2M} is the $2M \times 2M$ identity matrix and $\mathbf{e}_{M+L_1} = [0 \ldots 0\ 1]$. L_1 stands for the length of non-causal part of the CIR, i.e. the part that precedes the main peak of the estimated CIR. Similarly, $L_2 + 1$ is the length of the causal part of the channel IR. Clearly $L = L_1 + L_2 + 1$. Matrices H_1 and H_2 of dimensions $2M \times (M + L_1)$ and $2M \times L_2$ respectively are formed by the estimated CIR coefficients as follows

$$H_1 = \begin{bmatrix} \bar{\boldsymbol{h}}_{(-L_1)} & \bar{\boldsymbol{h}}_{(-L_1+1)} & \cdots & & \bar{\boldsymbol{h}}_{(M-1)} \\ 0 & \bar{\boldsymbol{h}}_{(-L_1)} & \cdots & & \bar{\boldsymbol{h}}_{(M-2)} \\ \vdots & \ddots & & \ddots & \vdots \\ 0 & 0 & \bar{\boldsymbol{h}}_{(-L_1)} & \cdots & \bar{\boldsymbol{h}}_{(0)} \end{bmatrix}$$

$$H_2 = \begin{bmatrix} \bar{\boldsymbol{h}}_{(M)} & \dots & \bar{\boldsymbol{h}}_{(L_2)} & 0 & \dots & 0 \\ \bar{\boldsymbol{h}}_{(M-1)} & \dots & \bar{\boldsymbol{h}}_{(L_2-1)} & \bar{\boldsymbol{h}}_{(L_2)} & \dots & 0 \\ \vdots & & \vdots & & \ddots & \vdots \\ \bar{\boldsymbol{h}}_{(1)} & \dots & \bar{\boldsymbol{h}}_{(L_2-M+1)} & \dots & & \bar{\boldsymbol{h}}_{(L_2)} \end{bmatrix}$$

where

$$\begin{aligned} \bar{\boldsymbol{h}}^T_{(m)} &= [h((L_1+m)T) \;\; h((L_1+m)T+\frac{T}{2})] \\ & \quad \text{for } \; m = -L_1, -L_1+1, \dots, L_2 \end{aligned}$$

Equation (14) can be efficiently solved by observing that, with the exception of the term $\sigma^2 I_{2M}$, it resembles a prewindowed least squares problem with H_1 as the data matrix and $\mathbf{e}_{M+L_1}$ as the desired response vector. In [8] a Levinson-type order-recursive algorithm is suggested for the efficient solution of (14). The total complexity of the algorithm is $O(M^2)$.

Once the FF is computed, the FB filter can be obtained either directly from (15) with complexity $O(L_2 M)$, or by using FFT in (15) with complexity $O(L_2 \log L_2)$ [8].

After computing the equalizer settings from the estimated CIR as described above, the transmitted symbols in the packet can be directly detected from the DFE. Note that due to the guard interval which always precedes the transmission of a data burst, the FB filter taps can be initially set to zeroes.

4. SIMULATION RESULTS

Extensive simulations to test the performance of the proposed equalization technique in different noise conditions were performed. The performance of a Burst Transmission System with bursts of 200 binary symbols transmitted through a four-ray multipath channel was simulated. The channel relative delays were $\boldsymbol{\tau} = [0 \;\; 4.2 \;\; 8.3 \;\; 19]^T$ and $\boldsymbol{\alpha} = [1 \;\; 2 \;\; -0.7 \;\; 0.5]^T$ was the vector of the corresponding attenuation factors. Note that this is a rather hostile noncausal channel, since the main peak is at relative delay $\tau_1 = 4.2$ and there is a strong anticausal ray of half power only 4 symbol periods before the main peak. Moreover the two causal rays are also quite strong, which renders the channel very difficult to equalize. The impulse response of the channel was convolved with a raised cosine filter, with a roll-off factor of 0.25, to give an overall CIR of length $L = 25$. The binary sequences were passed through the overall channel and white Gaussian noise was added so that the final SNR varied from 16 to 24dB. At the receiver, the 200 symbols were used to estimate the channel rays, by applying the parameter estimation method presented in Section 2. The estimated channel parameters were then used to synthesize the overall CIR, according to (3), from which the DFE filters were computed as described in Section 3. The delay of the DFE was adjusted according to the CIR coefficients, considering the one with the largest power as the main peak. In Table 1, the Bit Error Rate results for different SNRs, averaged over 2000 bursts are presented. As it is seen the proposed blind equalization scheme performs quite well in medium-to-high SNR conditions. The performance of the whole method deteriorates in low SNR conditions due to the sensitivity of the standard form of the SRM criterion to noise.

SNR (db)	BER
16	0.08834
18	0.00840
20	0.00086
22	0.00003
24	0

Table 1. BER Results for SNR=16-24dB

5. CONCLUSION

A new technique appropriate for (semi)-blind equalization of burst transmission systems has been developed. The technique offers the following advantages. First, a saving in bandwidth is achieved. This saving may be significant in high-speed applications where the CIR may span a large number of symbol periods. Second, the CIR estimation part is performed in a parametric manner therefore a high degree of estimation accuracy can be attained with a relatively small number of channel output samples, thus making the technique appropriate even for short bursts. Finally, the above performance merits are offered at an affordable computational cost due to the efficient schemes employed in both parts of the technique. Extensive simulations concerning the application of interest have confirmed the performance of the proposed technique.

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