Blind ISI Mitigation

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Abstract— **In an outdoor communication environment a percentage of bandwidth is wasted sending a training sequence for channel estimation and equalization. For instance in GSM [1], 17.93% of bandwidth is dedicated to the transmission of such a known sequence. Therefore if a blind algorithm, using only the knowledge of input constellation and/or correlation[1], can achieve an acceptable performance, it will save the bandwidth considerably. In this paper, we present a robust blind adaptation structure for TDMA-based communication systems. Also, we include implementation issues such as differential coding and oversampling in our system modeling.**

I. Introduction

In any communication environment with delay spread comparable to the symbol period of the input signal, intersymbol interference (ISI) will occur. Since the receiver doesn't know both the channel and the input, there is a need for transmission of a known sequence for channel estimation. Transmission of such a sequence is a waste of bandwidth. This is more pronounced in a mobile environment due to the need for more frequent estimation. This initiated researches in the area of blind channel estimation/equalization. After the original work by Sato [2] and Godard [3], research has been conducted by different groups for different applications. In an outdoor wireless communication environment, blind equalization is a challenging task. Specifically in a building environment, where there is no LOS[2] path most of the time, channel power-delay profile can take any shape [4-5]. In this paper, we investigate blind equalization in such environments. We choose decision feedback (DF) structures due to their low complexity and robust behavior in the non-blind case. However, unconstrained blind adaptation of a DF structure with both feedforward (FF) and feedback (FB) taps has an undesirable minimum [6]. Exploiting a DFE structure with only a feedback section would not work either due to the existence of precursors in the channel [7-8]. Therefore, we use the 2-stage blind structure introduced in [6] as a channel estimator. The structure will converge to its best estimates after some iterations. To retrieve the input bits at the initial iterations, one can rerun the structure initializing it with the estimates from the previous run. However, a better performance will be achieved if the 2-stage structure is used as a Channel Estimator (CE) followed by another structure for input retrieval. This limits error propagation hence producing a more reliable result. Here, we use the structure in [6] as a CE followed by a DFE with only a feedback section (we call it FB-DFE[3] throughout the paper) for input retrieval. While a FB-DFE when initialized randomly, fails to converge in case of channels with precursors with high probability, it will produce a robust estimate of input bits if its coefficients are initialized close to their optimum values (these initial values are acquired from the 2-stage CE). Also we use the diversity introduced by oversampling to produce a robust estimate of the input stream.

[1]If the receiver doesn't have these information, blind adaptation would not be feasible with reasonable complexity

[2]Line of Sight

[3]FeedBack-Decision Feedback Equalizer

II. System Model

Consider a passband transmission system. The baseband model of such a system is depicted in Fig. 1. In this figure, $I(k)$, a 4-PSK modulated stream, passes through a differential coder to avoid phase ambiguity at the receiver. It then passes through a pulse shaper which we have chosen to be a square root of raised cosine with $\alpha^4 = .5$. The communication environment is represented by a multipath fading channel with coherence bandwidth smaller than T^{-1}, where T represents the symbol period. The first path of this channel has a delay of T_0 representing the random delay that the receiver will experience with respect to its reference time. The delay spread of the channel is also random, on the order of microsecond, depending on the position of the transmitter. Each time-sample of this channel is represented by a rayleigh-distributed amplitude and a uniformly distributed phase. In the receiver, noise is added to the received signal which then passes through a replica of the pulse shaper. At this point, the signal will be oversampled (with period $T/4$) to form a discrete sequence, $Y(k)$. We partition $Y(k)$ into four groups, $Y_i(k) = Y(i+4k), i = 0, \ldots, 3$. Define $C(t)$ to be the convolution of the continuous channel and the raised cosine pulse. It can be shown easily that each $Y_i(k)$ results from $I(k)$ passing through $C_i(k) = C(iT/4 + kT)$ and being disturbed by symbol spaced noise samples. Since $C_i(k)$s vary in their ISI severity, equalizing each $Y_i(k)$ results in a different performance. By investigating $Y_i(k)$s, we can use the diversity introduced by $C_i(k)$s. This approach enables us to make a more solid estimate of the input.

III. Blind Estimation/Equalization

We divide the blind adaptation process into two phases. In phase I, the estimate of the channel is acquired using the 2-stage decision feedback structure. This structure was introduced in [6] and its adaptation was derived for the case of real input and baseband channels. We extend that work to the complex input and passband channels. Furthermore, to utilize the diversity introduced by $C_i(k)$s, channel estimation is performed over all $C_i(k)$s. For input retrieval a FB-DFE is chosen. The best channel estimate from the 2-stage CE will serve as the coefficients of the FB-DFE. Blind adaptation of the FB-DFE, when initialized randomly, will not converge globally with high probability [7-8]. However, if the coefficients are set close to their optimum solution, they will stay around it and the output will produce an estimate of $I(k)$.

[4]α is the roll-off factor of the raised cosine pulse

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IV. CHANNEL ESTIMATOR STRUCTURE

This section provides enough background for the CE of [6]. Consider the FB-DFE structure in Fig. 2 . If channel has no pre-cursors (which means that the first path is the strongest), with high probability blind FB-DFE will converge to its optimum solution. When the channel has its strongest path at time index p, FB-DFE tries to catch the first path and remove other paths some of which are now stronger than the first path. Hence, it fails with high probability. In the case of a channel of length N with both pre- and post-cursors and the strongest path at p, we can write $y(k)$ as follows,

$$y(k) = h(p) \times I(k-p) + \vec{I}_{post}(k) \times \vec{H}^t_{pre} + \vec{I}_{pre}(k) \times \vec{H}^t_{post} \quad (1)$$

Where $\vec{I}_{post}(k) = [I(k-p+1) \ldots I(k)]$,
$\vec{I}_{pre}(k) = [I(k-p-1) \ldots I(k-N)]$,
$\vec{H}_{post} = [h(p+1) \ldots h(N)], \vec{H}_{pre} = [h(p-1) \ldots h(0)]$
In the above equations, $\vec{H}_{post}$ and $\vec{H}_{pre}$ represent post- and pre-cursors of the channel respectively. Since h_p is the strongest path, the goal is to design a structure which estimates and removes the effect of $\vec{H}_{post}$ and $\vec{H}_{pre}$ from y_k. In other words, the first term on the right-hand side of Eq. 1 is the desirable term and the effect of the last two terms should be removed. We know that a FB-DFE structure can handle a pre-cursor free channel. Consider the post-cursor free channel, depicted in Fig. 3a. It is easy to see that for a received block of length M the reverse of the input passing through the reverse of the channel will produce the reverse of the output sequence as shown in Fig. 3b. Define $h_{r,new}(k)$ to be $h_r(-k)$. Since $h_{r,new}(k)$ represents a pre-cursor free channel, we can pass $y(M-k)$ to a FB-DFE. Then the output and the coefficients of FB-DFE will estimate I_{M-k} (the reverse of the input bits) and $h_{r,new}(k)$ respectively.

A. Final Structure

The new structure for estimating channels with both pre- and post-cursors is depicted in Fig. 4. This structure consists of a forward and a backward stage. The principle behind it is the observation that if a channel has no pre-cursor, it can be handled with FB-DFE with high global convergence probability. If a channel has no post-cursor, its time-reversal representation can be viewed as a pre-cursor free channel [9], which can then be estimated with a FB-DFE as well. Hence, we split a channel with both pre- and post-cursors into a pre- and post-cursor free channel. The goal is to estimate and remove the last two terms on the right-hand side of Eq. 1, hence capturing the strongest path. The forward stage acts similar to a FB-DFE. Its input is the received sequence $y(k)$. Its coefficients and output estimate $\vec{H}_{post}$ and $\vec{I}_{pre}$ respectively hence removing the effect of the third term on the right hand side of Eq. 1 from $y(k)$. The backward stage acts similar to the reverse structure. Eq. 2 shows the input to this stage, $y(M-k) =$

$$h(p) \times I(M-k-p) + \vec{I}_{rev,post}(k) \times \vec{H}^t_{pre} + \vec{I}_{rev,pre}(k) \times \vec{H}^t_{post} \quad (2)$$

where $\vec{I}_{rev,post}(k) = [I(M-k-p+1) \ldots I(M-k)]$,
$\vec{I}_{rev,pre}(k) = [I(M-k-p-1) \ldots I(M-k-N)]$

The coefficients of this stage estimate $\vec{H}_{pre}$ and its output produces an estimate of $\vec{I}_{rev,post}$, hence removing the effect of the second term on the right hand side of Eq. 2. To remove the effect of the second term on the right hand side of Eq. 1 from the input to the forward stage, the forward stage needs the estimates of $\vec{H}_{pre}$ and I_{post} which it does not produce itself. These estimates can be acquired from the backward stage since its coefficients estimate $\vec{H}_{pre}$ and its output estimates $\vec{I}_{rev,post}(k)$ which is equal to $\vec{I}_{post}(M-k)$. In Fig. 4, $O(M-k)$ represents an estimate of $\vec{I}_{post}(k) \times \vec{H}^t_{pre}$ which is acquired from the backward stage. In the same manner, the backward stage needs the estimate of the third term on the right hand side of Eq. 2 which it does not produce itself. It hence acquires it from the forward stage. $Q(M-k)$ in Fig. 4 represents this estimate. This results in complete ISI removal. Both stages function the same except for the direction in which the data is processed and the order in which the estimates of $I(k)$ are produced.
At time instant k, the forward stage needs the estimate of $\vec{I}_{post}(k)$ which is $[I(k-p+1) \ldots I(k)]$. At the same time instant, the backward stage has produced the estimates of $I(M-(k-1)-p), I(M-(k-2)-p), \ldots, I(M)$. Hence the estimates from the backward stage will be available for the forward stage to use when $k \geq (M+1-p)/2$ which happens approximately when k passes the midpoint of the received block ($M/2$ samples of $y(k)$) . The same argument holds for the backward stage. In other words, $O(M-k)$ and $Q(M-k)$ become available for the other stage to use after the midpoint. Therefore both stages perform partial ISI estimation and reduction before the midpoint and begin to remove the ISI completely afterward. After processing the whole received block, the coefficients of the forward and backward stages have estimates of post- and pre-cursor channels respectively. Furthermore, both stages have an estimate of input bits at their output. Since ISI levels on the two sides of the channel may differ noticeably, the performance of the stages are not necessarily the same. For instance, consider a channel in which $\vec{H}_{post}$ has higher ISI level than $\vec{H}_{pre}$. When in partial ISI removal (up to the midpoint of the received block), both stages act independently so forward and backward stages do not have an estimate of $\vec{H}_{pre}$ and $\vec{H}_{post}$ respectively and have to tolerate the ISI caused by them. Since in our example, $\vec{H}_{pre}$ has lower ISI level than $\vec{H}_{post}$, the forward stage has to tolerate less uncompensated ISI than backward stage. Therefore, it is more probable that forward stage produces more reliable results. To avoid error propagation, we can choose to feed the estimates of a stage to the other one after the midpoint, only if it has produced an agreeable performance. In other words, if we can measure the performance of each stage based on its behavior up to the midpoint, we can choose to feed only the reliable estimates to the other stage. This will limit the error propagation hence producing a better overall performance. The next sub-section will discuss different ways to get a reliable measure of the performance of a stage.

B. Decision at Midpoint

There are different measures that can be used to evaluate the performance of a stage at midpoint. One such measure

is the variance of convergence. The smaller the variance of convergence is, the better the performance of a stage would be. Also, the knowledge we have about input constellation can serve as a good measure. For instance consider a PSK modulated waveform with amplitude one. In this case, the smaller the ISI in a stage is, the closer the absolute value of the signal before the slicer would be to one. Hence the deviation of the amplitude of the signal before the slicer ($A(k)$ and $B(k)$) from 1 can serve as a good measure to compare the performance of the stages.
If the values produced by a measure function for both stages differ considerably, only the estimates of the more reliable stage will be used by the other stage.

C. Adaptation Algorithm

The coefficients of both stages are updated through a Decision Directed-based (DD) algorithm with cost functions $E|w_{0f}^{(k)*} \times (A(k) - \hat{A}(k))|^2$ and $E|w_{0b}^{(k)*} \times (B(k) - \hat{B}(k))|^2$. Hence, the adaptation formulas for the coefficients will be

$$w_f^{(k+1)}(i) = w_f^{(k)}(i) + \Delta \times w_{0f}^{(k)} \times (A(k) - \hat{A}(k))^* \times \hat{A}(k-i)$$

$$w_b^{(k+1)}(i) = w_b^{(k)}(i) + \Delta \times w_{0b}^{(k)} \times (B(k) - \hat{B}(k))^* \times \hat{B}(k-i)$$

Where $i = 1, \ldots, L$, Δ is the adaptation step and

$$w_{0f}^{(k+1)} = w_{0f}^{(k)} + \Delta \times (\beta 1 - w_{0f}^{(k)} \times |A(k) - \hat{A}(k)|^2)$$

$$w_{0b}^{(k+1)} = w_{0b}^{(k)} + \Delta \times (\beta 2 - w_{0b}^{(k)} \times |B(k) - \hat{B}(k)|^2)$$

$$\beta 1 = w_{0f}^{(k)} \times A(k) \times (A(k) - \hat{A}(k))^*$$

$$\beta 2 = w_{0b}^{(k)} \times B(k) \times (B(k) - \hat{B}(k))^*$$

D. Performance of the 2-stage structure

Consider the symbol-spaced channels depicted in fig. 5-6(a,b). They can represent one of the over-sampled channels, $C_i(k)$s. Convergence of the absolute value of the coefficients of feedforward and feedback stages of the 2-stage structure for these channels (except for w_{0f} and w_{0b}) is depicted in Fig. 5-6(c,d). Since in this part the speed of convergence is not of concern, we chose an arbitrary M (length of the received block, in our case 1000) long enough to reach steady state. The input modulation is 4PSK and the adaptation algorithm is DD. In this part, noise is not considered. The number of the feedforward and feedback coefficients was each set to ten. The extra coefficients (not shown in the figures) converge to zero. The initial points for the coefficients are all zero except for w_{0f} and w_{0b} which should be set non-zero and are initialized at one. We observe the deep nulls in the frequency response of the channels, especially channel 2. For midpoint decision, exploiting both measuring functions of sub-section B will produce similar results. As can be seen from the figures, the 2-stage starts with partial ISI removal. After the midpoint (500 here), the effect of switching from partial to complete ISI removal is noticeable. The dashed lines indicate the optimum solutions and the coefficients converge toward them after the midpoint. This shows that the new 2-stage structure can estimate channels with severe ISI.

E. Minima of the 2-Stage Structure

If $[h(0)\ h(1)\ \ldots\ h(N)]$ represents a channel profile with its most powerful path at $p \leq N$, a desirable minimum is reached when w_{0f}^* and w_{0b}^* reach $h(p)$ and the backward and forward stages estimate $[h(p-1)\ h(p-2)\ \ldots h(0)]$ and $[h(p+1)\ h(p+2)\ \ldots\ h(N)]$ respectively. But there are other *acceptable* minima too. In general, the 2-stage structure breaks the channel into two complementary parts and estimates each part with one of the stages. Theoretically, the break point can be any point from 0 to N. If the 2-stage coefficients produce two sides of any of these break points, the ISI will be removed completely. For instance, consider the case in which backward and forward stage coefficients estimate $[h(m-1)\ h(m-2)\ \ldots\ h(0)]$ and $[h(m+1)\ h(m+2)\ \ldots\ h(N)]$ respectively and w_{0f}^* and w_{0b}^* converge to $h(m)$ where m (break point) ranges from 0 to N. This will result in complete ISI removal. Therefore these minima are all acceptable. In practice, however, it is easier to converge to some of these minima than others. The choice of the channel and how two stages interact at the midpoint (that is which stage is fed to the other) are important factors in determining which minimum the structure will eventually converge too. In most of the cases, w_{0f}^* and w_{0b}^* converge to $h(p)$ and backward and forward stages estimate $[h(p-1)\ h(p-2)\ \ldots\ h(0)]$ and $[h(p+1)\ h(p+2)\ \ldots\ h(N)]$ respectively. But there can be cases that due to the channel shape reaching another one of the mentioned minima is easier for the structure. Since all the minima mentioned are acceptable, it does not change the performance if any of them is reached. To illustrate this with an example, consider the channel delay profile depicted in Fig. 6a. Let $[h(0)\ h(1)\ \ldots\ h(4)]$ represent channel samples. As can be seen from the figure, $h(2)$ and $h(4)$ are close in their values. When in partial ISI removal mode, each stage chooses to estimate a part of the channel. The decision regarding which channel portion to estimate is forced by the minimization algorithm and will result in finding the easiest part to equalize while minimizing the ISI from the rest of the channel. For instance, for the aforementioned channel, in partial ISI removal, forward stage estimates $[h(3)\ h(4)]$ with w_{0f}^* converging to $h(2)$. Meanwhile, the backward stage finds $[h(3)\ h(2)\ \ldots\ h(0)\ ]$ easier to converge to, with w_{0b}^* converging to $h(4)$. These decisions by two stages seem reasonable based on the factors mentioned above and the shape of the channel. In complete ISI removal mode, the structure may converge to different minima, depending on the decision at midpoint. For the channel in Fig. 6a, if only backward stage uses the results of the forward stage, the forward stage forces the backward stage to estimate the part of the channel that it had not which is $[h(1)\ h(0)]$ in this case ($m = 2$). In the same manner, if only the forward stage uses the results of the backward stage, the backward stage enforces its estimates resulting in the break point $m = 4$. Therefore depending on the shape of the channel and the decision at midpoint, the 2-stage will choose one of the mentioned minima. Since in most of the cases, the two sides of the channel are decreasing profiles, the 2-stage will choose the most powerful path as the breakpoint ($m = p$).

V. Phase I: Channel Estimation

In this phase the 2-stage structure of the previous part is used as a channel estimator. To utilize the diversity introduced by oversampling, each $Y_i(k)$ is fed to the channel estimator. Global convergence would be achieved if the coefficients of the estimator converge to $C_i(k)$. If for any i, the estimation error measured by Measure1 is below a defined threshold, the process will be stopped and the corresponding channel estimates and $Y_i(k)$ will proceed to phase II for input retrieval. Otherwise, among $Y_i(k)$s, the one that results in the least error is chosen and its estimates pass on to phase II. This process is shown in fig. 7. Measure1 can be any of the performance monitoring functions introduced in sub-section B of IV.

VI. Phase II: Input Retrieval

It is possible to get an estimate of the input bits from $\hat{A}(k)$ and $\hat{B}(k)$ at the output of the channel estimator. Since the output estimates are more reliable at final iterations, there is a need to get a better estimate of the input bits at the beginning iterations. One possibility is to rerun the structure and initialize it at the estimates acquired from the past run. Therefore, the performance would rely on both the estimate of the channel and input bits. To reduce the probability of error propagation, another possibility is to use only the estimate of the channel. For instance the channel estimate can serve as the coefficients of another structure whose output would produce an estimate of input bits with smaller probability of error. This will limit error propagation since only the estimate of the channel is fed to the input retrieval structure. One possible structure for input retrieval is a FB-DFE. Without any knowledge of the channel and input, a FB-DFE will not converge for severe ISI channels. However, when an estimate of the channel is available, the coefficients can be initialized close to their optimum solution (assuming that the estimation error of the 2-stage structure was low). This initialization will result in a close to zero convergence time for most of the channels, since the coefficients are already close to their optimum values. By feeding the corresponding $Y_i(k)$ determined by phase I to the FB-DFE, the output will produce an estimate of the input stream. This input estimate is more reliable than the one produced at the output of the channel estimator. Fig. 8 shows how two phases interact. If in a mobile environment, after a time comparable to the channel coherence time, channel will change from the estimate that was acquired in phase I. In phase II, FB-DFE will track the changes in the channel. Its performance is monitored by a measure function (Measure2 in Fig. 8). If channel variations start to degrade the performance of the FB-DFE, Measure2 will signal a need for another channel estimation. Hence, the process will switch to phase I. Measure2 can be any of those defined in sub-section B of IV.

VII. Simulations

Sub-section D of IV showed a sample of the performance of the 2-stage structure of fig. 4 as a channel estimator. Also, it was shown in [6] that both aforementioned measuring functions, when used for midpoint decision, will produce similar reliable performances. In this part we show how the combined channel estimator and equalizer work together. Consider the system depicted in fig. 1. After differential coding and pulse shaping, the input passes through a complex channel which represents a baseband equivalent of a passband channel. Fig. 9a shows the convolution of the channel and two pulse shapers and represents the equivalent media that the input $I(k)$ passes through. Fig. 9b shows the amplitude of the frequency response of the absolute value of this channel. We observe the deep nulls of the channel. The noise in Fig. 1 is an AWGN[5] which becomes correlated when it passes through a pulse shaper at the receiver. The continuous received signal is oversampled with period $T/4$ to form $Y_i(k)$s. To see the performance of phase I, the output signal is generated at different SNRs and passed to phase I. SNR represents the received signal power through all the paths over the received noise power. At each SNR, simulations are repeated 200 times to get an average of the estimation error of phase I. At each iteration, the variance of convergence serves as a measuring function for midpoint decision. Also, Measure1 in fig. 7 is the closeness of the amplitude before the slicer to one. Fig. 9c shows the % of normalized estimation error of this phase. As can be seen from the graph, for SNR greater than 15db, the estimation error is under 0.5%. At each SNR and iteration, the best estimate of phase I serves as the coefficients of the FB-DFE of phase II. To see the performance of phase II, fig. 9d shows the steady state probability of error of phase II at each SNR. As seen from the graph, initializing the FB-DFE with the estimates of phase I results in near to zero probability of error at SNR greater than 20db. This shows that the combination of the two phases can produce a reliable result in a harsh channel environment with no training sequence. The size of the received packet for these simulations was chosen 1000 to guarantee convergence. To see the effect of the size of the received packet on the performance, we simulate the performance of phase I for different received packet sizes at SNR of 20db. Fig. 10 shows the % of the normalized estimation error of phase I vs. length of the received block. As can be seen from the graph, for lengths greater than 500, the % of error is under 1%. Also, our algorithm did not optimize for Δ. Optimization of Δ can result in a smaller required length as well. Overall, our simulations showed that the introduced combined structure can serve as a reliable candidate for blind ISI mitigation.

VIII. Conclusion

We have introduced a combined structure for blind channel estimation/equalization. This structure uses the 2-stage structure introduced in [6] as a channel estimator. This estimate would serve as the coefficients of a FB-DFE for input retrieval. Also, we utilize the diversity introduced by oversampling to further improve the performance. Our simulations showed the robust behavior of the combined structure for different SNRs and block sizes and proved it to be a qualified candidate for blind ISI mitigation.

IX. References

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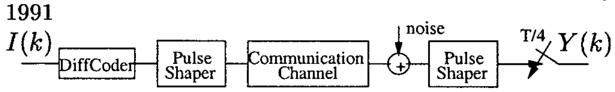


Fig. 1 System Model

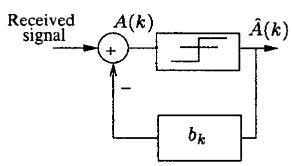


Fig. 2 FB–DFE Structure

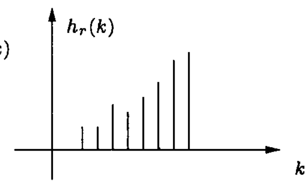


Fig. 3a Post-Cursor Free Channel

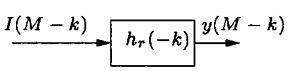


Fig. 3b Reverse Channel Model

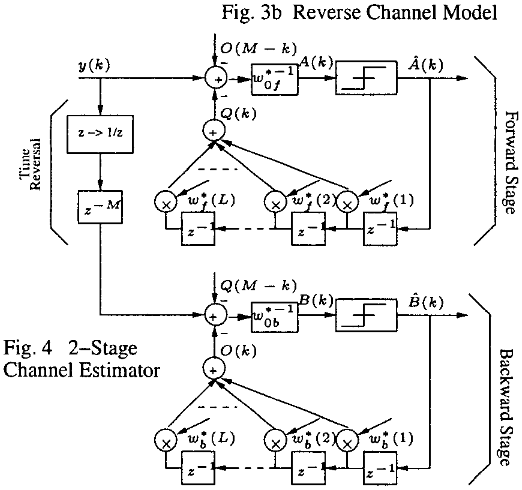
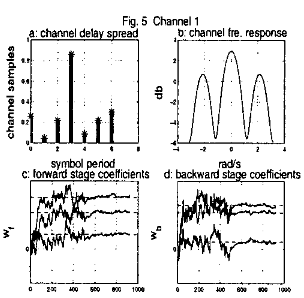
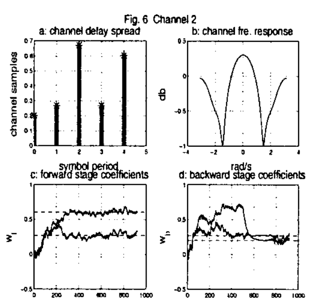


Fig. 4 2-Stage Channel Estimator





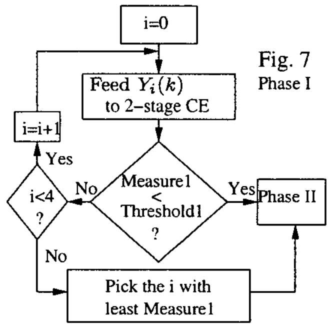


Fig. 7 Phase I

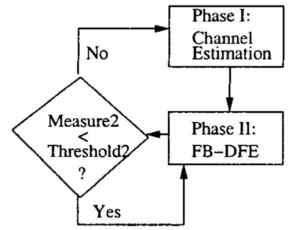


Fig. 8 Phase I & II