Channel-Estimation-Based Adaptive Equalization of Underwater Acoustic Signals

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Abstract - To reduce computational complexity of signal processing and improve performance of data detection, receiver structures that are matched to the physical channel characteristics are investigates. A decision-feedback equalizer is designed which relies on an adaptive channel estimator to compute its parameters. The channel estimate is reduced in size by selecting only the significant components, whose delay span is often much shorter than the multipath spread of the channel. This estimate is used to cancel the post-cursor ISI prior to linear equalization. Optimal coefficient selection (sparsing) is performed by truncation in magnitude. The advantages of this approach are reduction in the number of receiver parameters, optimal implementation of sparse feedback, and efficient parallel implementation of adaptive algorithms for the multichannel pre-combiner, the fractionally-spaced channel estimators and the short feedforward equalizer filters. Receiver algorithm is demonstrated using real data transmitted at 10 kbps over 3 km in shallow water.

I. INTRODUCTION

Bandwidth-efficient digital underwater acoustic communications can be achieved by employing spatial diversity combining and equalization of PSK or QAM signals. The receiver structure that has been found useful in many applications is a multichannel decision-feedback equalizer (DFE) [1]. Due to the nature of the propagation channel, the required signal processing is often prohibitively complex. Reduction in computational complexity can be achieved by using efficient adaptive algorithms, such as the low-complexity LMS algorithms with improved tracking properties [2, 3, 4], and by reducing the number of adaptively adjusted receiver parameters [4, 5, 6]. The major focus of the present paper is on the latter form of complexity reduction.

Our goal is to consider a receiver structure that is matched to the physical characteristics of an underwater acoustic channel. Towards this goal, reduced-complexity spatial combining of [5] is used with a decision-feedback equalization method that is based on channel estimation. By tracking the channel explicitly, rather than implicitly through the equalizer coefficients, it is possible to design a receiver that uses only the significant channel components. The composite time span of these components is often much shorter than the overall multipath spread, leading to the desired reduction in complexity. In addition, elimination of unnecessary receiver parameters may lead to better performance as well as faster tracking of the channel time-variations.

Sparse, or tap-selective equalization has been considered for communications over horizontal underwater acoustic channels where multipath spread is extremely large, e.g., on the order of a hundred of symbol intervals [4, 6], and for broad-band wireless radio channels [7, 8]. An *ad hoc* sparse DFE [4] determines the positions of significant taps by computing the full-size equalizer solution (feedforward and the feedback filter) initially, but keeping only those taps whose magnitude exceeds a pre-determined threshold. This tap selection method is not optimal, because the input signal to the equalizer is not white. On the other hand, a sequence of uncorrelated data symbols at the input to a channel estimator is white, and optimal tap selection can easily be performed by truncation in magnitude. This fact serves as a motivation for developing a channel-estimation-based equalizer.

The method of determining the equalizer coefficients from a channel estimate is based on an alternative interpretation of the an optimal (MMSE) DFE, which is given in Sec.II. Adaptive implementations are discussed and a low-complexity channel estimator is proposed in Sec.III. Tap selection is addressed in Sec.IV. In Sec.V. the design principles of are extended to the multichannel receiver, which is necessary for the majority of underwater communication scenarios. The algorithm is demonstrated on real data transmitted using QPSK at 10 kilobits per second over 3 km in shallow water, as described in Sec.VI. The conclusions are summarized in Sec.VII.

II. DFE: AN ALTERNATIVE INTERPRETATION

Let the input signal to the equalizer be the phasesynchronous baseband signal, coarsely aligned in time:

$$v(t) = \sum_n d(n)h(t-nT) + w(t) \tag{1}$$

where $d(n)$ is an i.i.d. sequence of unit-variance data symbols transmitted at times nT, $h(t)$ is the overall channel response, including transmitter and receiver filtering, and $w(t)$ is the additive noise. This signal is sampled at the Nyqist or higher rate. Without the loss of generality, we assume a sampling rate of $2/T$ for a signal bandlimited to $1/T$. The signal samples taken at times $(nT - M_2T/2)$ ... $(nT + M_1T/2)$ are arranged in a vector $\mathbf{v}(n)$, which is given as

$$\mathbf{v}(n) = \sum_k \mathbf{h}(k)d(n-k) + \mathbf{w}(n) \tag{2}$$

where $\mathbf{h}(k) = [h(kT + M_1T/2) \ldots h(kT - M_2T/2)]^T$. The reference channel vector $\mathbf{h}(0)$ has a the time span $(-M_2T/2, M_1T/2)$ which is chosen to capture all of the channel response $h(t)$. Coarse alignment is normally performed such that $h(0)$ is the channel coefficient with maximal amplitude.

The DFE with feedforward filter coefficient vector $\mathbf{a}$ and feedback coefficients b_k estimates the data symbol as

$$\hat{d}(n) = \mathbf{a}'\mathbf{v}(n) - \sum_{k>0} b_k^* \tilde{d}(n-k) \tag{3}$$

where $\tilde{d}(n)$ is the correct data symbol in the training mode or the symbol decision in the decision-directed mode. Prime denotes conjugate transpose, and all the vectors are defined as column vectors.

In the absence of decision errors, the optimal choice of the feedback taps is the one for which post-cursor ISI is completely cancelled:

$$b_k^* = \mathbf{a}'\mathbf{h}(\mathbf{k}), \ k > 0 \tag{4}$$

For this choice, the decision variable is expressed as

$$\hat{d}(n) = \mathbf{a}'[\sum_{k\leq 0} \mathbf{h}(k)d(n-k) + \mathbf{w}(n)] = \mathbf{a}'\mathbf{v}_f(n) \tag{5}$$

This expression is used to determine the MMSE solution for the feedforward filter in terms of the channel vector shifts $h(k)$ and the noise covariance $\mathbf{N} = E\{w(n)w^l(n)\}$. The solution is given by

$$\mathbf{a} = \mathbf{R}_f^{-1}\mathbf{h}(0) \tag{6}$$

where

$$\mathbf{R}_f = E\{\mathbf{v}_f(n)\mathbf{v}_f'(n)\} = \sum_{k<0} \mathbf{h}(k)\mathbf{h}'(k) + \mathbf{N} \tag{7}$$

Expressions (7), (6) and (4) define the conventional MMSE DFE. They also provide insight into the needed sizes of equalizer filters.

A usual approach to implementing an adaptive DFE is to group the feedforward and the feedback filter taps in a composite vector, and apply a least-squares algorithm to compute this vector recursively from the input signal vector $\mathbf{v}(n)$ and the previous decisions $\tilde{d}(n - k)$, $k > 0$, using the data estimation error $e(n) = d(n) - \hat{d}(n)$. The so-obtained equalizer taps are used to filter the received signal, and subtract the post-cursors ISI term according to the expression (3).

An alternative implementation is based on the expression (5). For this implementation, the equivalent feedforward signal $v_f(n)$ has to be obtained first. However, this signal cannot be measured directly. Instead, it can be reconstructed as

$$\mathbf{v}_f(n) = \mathbf{v}(n) - \mathbf{v}_b(n) \tag{8}$$

where

$$\mathbf{v}_b(n) = \sum_{k>0} \mathbf{h}(k)d(n-k) \tag{9}$$

is the equivalent feedback signal that can be obtained from the previous decisions and a channel estimate. The modified DFE implementation is defined as follows:

1. Using a channel estimate $\hat{\mathbf{h}}(0)$, its shifts $\hat{\mathbf{h}}(k)$, $k > 0$, and previous decisions, determine the equivalent feedforward input signal as

$$\hat{\mathbf{v}}_f(n) = \mathbf{v}(n) - \sum_{k>0} \hat{\mathbf{h}}(k)\tilde{d}(n-k) \tag{10}$$

2. Apply an adaptive linear equalizer $\mathbf{a}(n)$ to this signal to obtain the data symbol estimate

$$\hat{d}(n) = \mathbf{a}'(n)\hat{\mathbf{v}}_f(n) \tag{11}$$

Any adaptation algorithm may be considered.

In this approach, the feedback filter taps b_k are not computed explicitly at all. The feedforward filter operates on the equivalent signal $\mathbf{v}_f(n)$ from which the postcursors ISI has been removed.

A feature worth noting is that the estimate of the feedback signal,

$$\hat{\mathbf{v}}_b(n) = \sum_{k>0} \hat{\mathbf{h}}(k)\tilde{d}(n-k) \tag{12}$$

obeys a shifting law:

$$\hat{\mathbf{v}}_b(n) = \downarrow \hat{\mathbf{v}}_b(n-1) + \hat{\mathbf{h}}(1)\tilde{d}(n-1) \tag{13}$$

where $\downarrow$ indicates shifting of the vector downwards by two (in general, by as many samples as there are per one symbol interval) and filling the top by zeros. This property eliminates the need to carry out the entire summation for determining the post-cursor ISI every time a new data decision becomes available. It was shown originally in [7] for a T-spaced equalizer.

III. ADAPTIVE CHANNEL ESTIMATOR AND EQUALIZER IMPLEMENTATION

There are many possibilities for implementing the channel estimator and the equalizer adaptively. Each should be chosen according to the channel at hand. Some scenarios are the following:

1. Fixed channel estimate / adaptive equalizer.

Channel is estimated from the packet *preamble, and* this *estimate is* frozen for the duration of the packet. Short feedforward equalizer is adapted throughout the packet. This approach is suitable for high speed radio receivers, *where computational* complexity is of paramount importance, but the channel can safely be assumed constant over the packet duration.

2. Adaptive channel estimate / adaptive equalizer.

Channel estimator and the short equalizer are updated throughout the packet. Channel estimation is independent of equalization, except that it relies on the symbol decisions in decision-directed mode. This approach may be chosen for underwater communications with packets long enough to support significant channel changes. The receiver structure allows arbitrary choice of updating intervals.

The equalizer and the channel estimator are updated separately. Thus, they may use different adaptive algorithms. For channel estimation, a number of adaptive algorithms can be devised based on the modeling equation (1). For a fractional spacing of *T/2*, two estimators are needed to generate a *T/2* spaced channel response. Since computational complexity is the focal point of this work, and the channel responses are expected to be of considerable length as measured in the number of samples *M,* it is of interest to use a computationally simple algorithm. The algorithm proposed below is based on the modeling equation (2). From this expression it follows that

$$\mathbf{h}(0) = E\{\mathbf{v}(n)d^*(n)\} \tag{14}$$

To obtain an estimate of the above vector, a simple stochastic approximation can be used:

$$\hat{\mathbf{h}}[n] = (1-\lambda_{ch})\sum_{i=0}^{n}\lambda_{ch}^{n-i}\mathbf{v}(i)d^*(i) \tag{15}$$

where $\hat{\mathbf{h}}[n]$ denotes the estimate of $\mathbf{h}(0)$ obtained in the *n*th iteration, λ_{ch} *is* an exponential forgetting factor, and the scaling factor $(1 - \lambda_{ch})$ ensures an asymptotically unbiased estimate. This expression gives way to a very simple recursion:

$$\mathbf{h}[n] = \lambda_{ch}\mathbf{h}[n-1] + (1-\lambda_{ch})\mathbf{v}(n)d^*(n) \tag{16}$$

The estimate $\hat{\mathbf{h}}[n]$ *is* chosen to span all of the significant channel response, but it suffices to keep only the channel coefficients with significant amplitude. A key feature of this algorithm is that various channel coefficients are updated independently. While such a method is suboptimal if there is correlation between the channel coefficients, it allows fast tracking of the channel response. The fact that channel estimation is decoupled from equalization allows easy instantaneous change of the feedback tap positions without having to change the feedforward filter tap positions.

Note that there is a choice when it comes to channel estimation: to update the entire channel estimate vectors, or to update only the selected taps. Updating the entire vectors provides constant on-line monitoring of the time-variations in the channel (even though all of the taps are not used for post-cursor ISI suppression). Updating only the selected taps provides reduction in complexity. The choice should be made based on the properties of a particular channel, and the desired performance. The algorithm presented above serves to somewhat reconcile the two requirements.

An MMSE algorithm, such as LMS or RLS, for the equalizer vector **a** will operate on the equivalent input signal $\mathbf{v}_f(n)$, driven by the error $e(n)$. There is also a possibility that the feedforward equalizer be calculated from the channel estimate, making use of the relation (6). The matrix inverse in this case would be computed recursively, and possibly frozen for the packet duration on the grounds that the channel covariance changes more slowly than the channel realization. However, the advantage of running the equalizer independently is that it may compensate to some degree for the channel estimation errors.

IV. TAP SELECTION

Because the feedback is implemented implicitly through the channel estimate, the optimal feedback tap selection is obviously made by choosing only the channel coefficients whose amplitude is above some threshold.

Selection of the best feedforward filter taps, however, remains a difficult problem. In general, as it is desired to use only a short feedforward filter, not all the *M* coefficients will be updated in the equalizer vector, but only $N \leq M$. The question is how to choose the *N* equalizer taps. Three approaches come to mind:

1. Optimally sparsed filter.

Finding the optimal sparsing pattern involves an exhaustive search whose complexity is prohibitive for a practical implementation. The search is conducted among all the sparsing patterns to find the one which minimizes the the minimum mean squared data estimation error obtained with the filter of given size.

2. Approximation of the optimization criterion to allow for a more efficient search.

One such approximation was investigated in [8]. In this reference, a T-spaced feedforward filter is considered and the approximation is made by searching among all the single-tap filters and selecting those N consecutive solutions which result in the lowest MMSEs.

3. An *ad hoc* method.

A feedforward filter can be chosen with contiguous taps, but of total length much shorter than the length of the channel estimate. The method seems to be effective for channels with decaying multipath intensity profile as long as N is large enough to capture sufficient signal energy. Another *ad hoc* method is to assign feedforward filter taps to match the significant taps of the estimate of the channel $\mathbf{h}(0)$. This approach was suggested in [6]; however, its effectiveness is not obvious except in special cases of distinctly sparse channels with comparable energy of multipath arrivals.

In summary, a total of M signal samples are used to obtain the M channel coefficients, but a number of those coefficients, say M_{off}, are set to zero when evaluating the post-cursor ISI. At the same time, only $N \leq M$ signal samples are used for linear equalization. The positions of the M_{off} taps are determined by thresholding. The positions of the N equalizer taps are determined by any of the above three methods. An analysis of these methods can be found in [9].

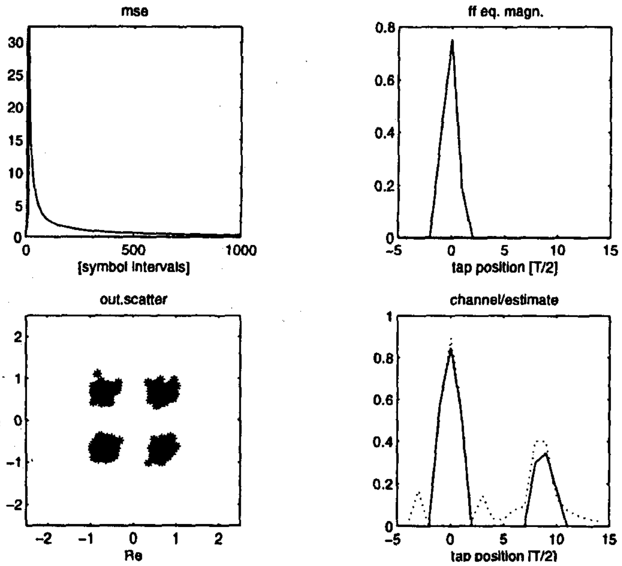

Figure 1. DFE performance. *Ad hoc* sparsing of the feedforward filter using 3 taps around the main arrival. SNR=20 dB, $N = 3$, $M = 19$, $N_t = 38$, $G_0 = 1/6$, $\lambda_e = 0.999$, $\lambda_{ch} = 0.99$.

The design concept is demonstrated below through a numerical example. A two-path time-invariant channel is considered with path amplitude ratio 2/1, and relative delay of 4.25 symbols. The transmitter filter is a spectral raised cosine with roll-off factor 0.25 and truncation length of ±4 symbol intervals. (This is the actual filter used to generate experimental signals of Sec.VI.) The channel introduces additive white Gaussian noise, with SNR=20 dB. The channel estimator looks 2 symbols (M_2=4 taps) to the left and 7 symbols (M_f=14 taps) to the right of the reference tap. The feedforward filter uses 3 taps and an RLS algorithm. The DFE performance is shown in Fig. 1. The figure shows the estimated MSE; the output scatter plot; the tap magnitudes of the feedforward filter; the channel (dotted) and its sparse estimate (solid). The receiver is trained during the first 38 data symbols, and then switched into the decisiondirected mode. There are no decision errors. The channel taps whose magnitude is less than 1/6 of the main tap magnitude are set to zero. In this manner, out of the total of M = 19 taps, 5 are kept to be used for post-cursor ISI cancellation. An *ad hoc* choice of few taps around the main arrival works very well in this type of channel.

V. THE MULTICHANNEL CASE

In the majority of underwater channels, the SNR observed by a single sensor is not sufficient for a reliable equalizer performance. The principles of channelestimation-based DFE thus need to be extended to the case of multiple input sensors. The question that arises in the multichannel receiver design is how many channel estimates are needed, or, equivalently, at which point in the receiver do we want to remove the post-cursor ISI. If the channel responses $h_k(t)$ from the transmitter to each of the receiving elements were known, this could be done directly on the input signals $v_k(t)$. However, we already know that a single input signal does not yield sufficient SNR for data detection (hence multichannel processing), and consequently, it is not suitable for individual channel estimation either. Thus, a processing gain must be extracted *before* channel estimation is attempted. The approach of pre-combining, proposed in [5] is precisely suited for this purpose.

The multichannel receiver that we consider is shown in Fig.2. The K spatially distributed input channels are first pre-combined into a smaller number of channels, P. No temporal processing (filtering) is used in doing so, but only weighted combining. The resulting P channels are then equalized. The approach of pre-combining has proven very effective in processing different types of real data. What is interesting to note, is that a small value of P, usually only two channels (but rarely one) is sufficient for extracting the multichannel processing gain. In addition to multichannel combining, a practical receiver incorporates a phase-locked loop (PLL). Phase tracking can be performed at the input, after pre-combining, or after linear equalization. In Fig.2, the second choice is shown, which is also used for the experimental results.

The analysis of the multichannel DFE closely follows that of a single channel DFE given in Sec.II. The complete algorithm, which includes the adaptation of the K x P pre-combiner weights and the multichannel decision-directed **PLL** is rather lengthy. The complete algorithm can be found in [9].

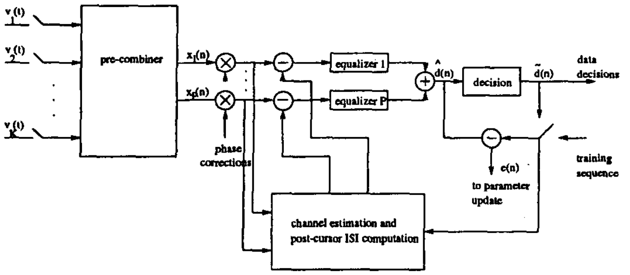

Figure 2. Reduced complexity multichannel DFE incorporates a *K* to *P* pre-combiner and a *P*-channel DFE. The DFE is based on channel estimation and sparsing.

In the following section, the multichannel DFE algorithm is applied to real data. The algorithm consists of three parts, implemented in parallel: a standard RLS for the pre-combiner weights, a channel estimation algorithm of Sec.III. extended to *P* channels, and a standard RLS (form II [10]) used for the feedforward equalizer filters. Feedback tap selection is performed on-line, by thresholding. Feedforward tap selection is an *ad hoc* one, with a pre-specified number of contiguous taps. Phase tracking is accomplished by a second-order PLL.

VI. EXPERIMENTAL RESULTS

The experimental data, provided by the Woods Hole Oceanographic Institution, was collected during a 1997 experiment, conducted in the Continental Shelf region near the coast of New England. The water depth was between 100 m and 200 m. The signals were transmitted using a carrier frequency of 25 KHz, over the range of 3 km. The modulation format was QPSK, and the signals were transmitted at 10 kilobits per second. The vertical receiver array consisted of eight onmidirectional hydrophones, spaced by approximately half a wavelength (0.027 m). The recorded signals were processed off-line using Matlab. In this section, results of signal processing are demonstrated using an average quality data set.

The channel responses, observed by four of the input sensors, are shown in Fig.3. The channel consists of two groups of concentrated energy arrivals. These groups are separated by approximately 225 symbol intervals. Within each clustered arrival, there are several distinct peaks of the response magnitude. The relative energy of clusters varies with the sensor location.

Fig.4 shows the results of data processing. The input data is the raw baseband signal, frame synchronized using a Barker code. No phase synchronization is performed on this signal. The 8 input channels are precombined into 2, which are fed into 2 channel estimators that accompany the 2 feedforward filters. The channel estimates obtained after pre-combining are shown in the upper right corner, together with the thresholds. The channel responses are estimated over a total length of $M = 25$ taps. This value is sufficient because the precombiner apparently succeeds in suppressing the distant arrivals. The truncation threshold for channel estimate sparsing is set to $G_0 = 1/6$. This procedure results in $M_{off} = 18$ taps being turned off in each of the channel estimators. The remaining 7 taps are used in post-cursor ISI estimation. The feedforward filters have $N = 17$ taps per channel. L_e, L_c, and L_{ch} are the forgetting factors of the equalizer, pre-combiner and the channel estimators, respectively. These factors can be chosen independently. K_{f1} and K_{f2} are the PLL tracking constants. The PLL tracks a -15 Hz Doppler shift with good accuracy, and the MSE indicates a steady convergence. The scatter plot shows no errors in the detection of the data block.

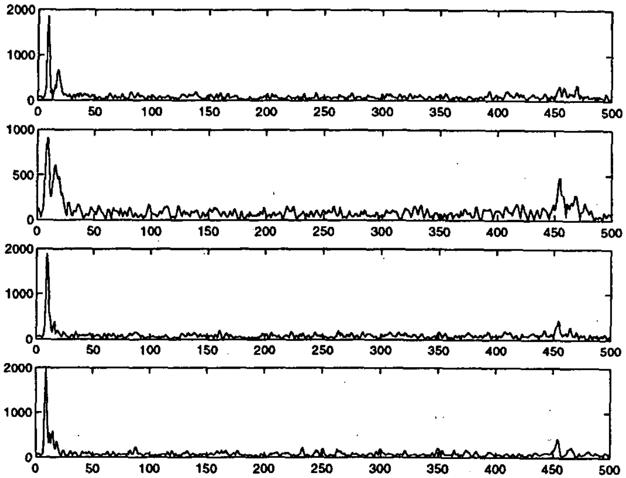

Figure 3. Channel responses observed at the receiver input. Estimates are obtained by matched filtering to the channel probe (a pseudo-random sequence).

One may wonder about the receiver performance with the span of channel estimators extendeded to include the distant multipath arrivals. The DFE performance in this case is again very good (practically the same as in Fig.4). The channel estimators capture the distant arrivals, 225 symbols away from the main arrival. However, the additional energy obtained in this way is negligible as compared to that of the coherently combined main arrivals, hence a small difference in performance. Nevertheless, this example demonstrates a powerful advantage of sparse channel estimation: the overall performance is not affected by the large extent of the feedback, because only the significant taps are used for ISI suppression. It is thus possible to constantly monitor the channel changes without affecting the equalizer size. If the feedback section of a conventional DFE were extended to cover 225 post-cursors, this would significantly slow the convergence, and also restrict the tracking speed (by constraining the choice of the LMS step size or the

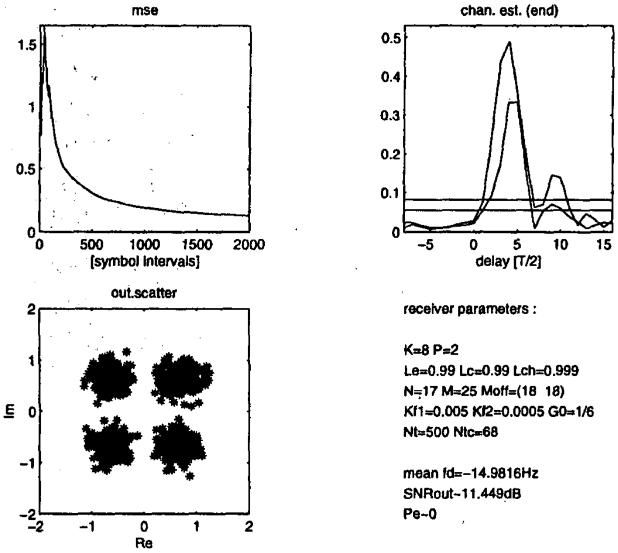

Figure 4. Results of reduced-complexity multichannel processing. DFE is implemented via channel estimation. Figure shows the MSE, the channel estimates, and the output scatter plot.

fast RLS forgetting factor). Because different channel taps are updated independently in the algorithm proposed, convergence remains fast, channel estimation is not overly sensitive to the choice of forgetting factor A,h, and this factor is not restricted by the estimator size.

VII. CONCLUSIONS

The method of channel-estimation-aided equalization was proposed in conjunction with multichannel pre combining. The channel estimates are sparsed, which accounts for eliminating the unnecessary noise and re ducing the receiver complexity. The ideas that govern the receiver implementation are:

1. Pre-combining of a larger number of input channels into a few that will be equalized.
2. Adaptive channel estimation and sparsing.
3. Subtraction of post-cursor ISI using the channel es timate feedback prior to adaptive feedforward equalization.

The advantages of this method are the following:

1. Preservation of the full multichannel processing gain without temporal processing in each channel.
2. Optimal selection of the channel taps by truncation in magnitude (rather than direct selection of the equalizer taps)
3. Efficient post-cursor ISI calculation using the shifting property (13).
4. Use of a short feedforward equalizer (much shorter than the multipath spread).
5. Efficient estimation of the fractionally-spaced channel response based on the recursion (16).
6. Continuous channel monitoring.
7. Flexibility to increase the feedback length on demand without affecting feedforward equalization.
8. Parallel implementation of the algorithms for channel estimation, equalization and pre-combining.

Further research in this area will likely concentrate on highly-mobile underwater acoustic communications. Signal processing based on channel estimation provides an interesting platform for the development of algorithms capable of dealing with motion-induced signal distortions.

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